Essays on Credit Risk and Credit Derivatives

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Preface

This thesis is the product of my Ph.D. studies in finance at Copenhagen Business School and Danmarks Nationalbank. The thesis has benefitted from comments from a number of persons, and they are mentioned in each chapter. However, a few deserve to be mentioned here. First of all I am grateful to my thesis advisor David Lando for his guidance and help throughout my years as a Ph.D. student. Secondly, I would like to thank Danmarks Nationalbank for financing the Ph.D. Thirdly, I thank Peter Tind Larsen for excellent cooperation on two of the papers. Without his drive and our endless discussions the thesis would not have reached its present form. Furthermore, I thank colleagues and fellow Ph.D. students both at the Department of Finance, Copenhagen Business School and at Danmarks Nationalbank for making the time spent pleasant and rewarding.

Outside academia I would like to thank my mom and dad and Jes and Annette for helping out and taking care of Sebastian and Hjalte during the last stressful months of the Ph.D.

Last but not least I am indebted to Line Simmelsgaard for being there at all times and for understanding my ups and downs. I thank you for your patience and I am grateful for the joy Sebastian and Hjalte have brought into our lives. They constantly remind me of what truly matters in life.

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Claus Bajlum

Introduction

This thesis is on credit risk, and more specifically on credit derivatives. Credit risk is the risk that an obligor does not honour his payment obligations, while a credit derivative could be defined as a security whose payoff is affected by credit risk. A credit derivative is primarily used to transfer, hedge or manage credit risk.

For modelling credit risk, two classes of models exist: structural models and reduced-form models. Structural models date back to the papers of Black & Scholes (1973) and Merton (1974). These papers demonstrated how option pricing formulas can be applied to the valuation of equity and corporate bonds. In these models equity, debt and other claims issued by a firm are viewed as contingent claims on the value of the firm's underlying assets. While the original models of Black & Scholes (1973) and Merton (1974) relied on a number of simplifying assumptions, there has been a large literature of extensions to the original framework, such as the inclusion of taxes, bankruptcy costs and a continuous default boundary. These features have made the models more realistic, and have e.g. made it possible to describe the firm's optimal capital structure. Default is modelled as the assets of the firm falling short of a default boundary and the probability of this occurring is determined by the amount of debt in the firm and the volatility of its assets. Structural models are extremely important for building intuition and for understanding how changes in a firm's capital structure or it's business risk affects the firm's cost of capital. Furthermore, the models are useful if one wants to understand the co-movement between debt and equity of the same firm, which is why the models are also used for relative value trading between credit and equity markets. The practical implementation of structural models is often done by calibrating the chosen model to the equity market, which makes it possible to estimate firm specific default probabilities. This type of calibration is widely used in industry models such as Creditgrades, and also forms the basis of Moody's Expected Default Frequency measure (EDF).

The second type of approach to the modelling of credit risk is the so-called reduced form (or intensity) models. In these models a firm's default time is unpredictable and driven by a default intensity, which is a function of a number of either latent or observed state variables. The focus in these models is more on consistent pricing across debt instruments, and the reason for default is not modelled. Thus, a reduced form model does not give any fundamental reason for the arrival of defaults, but instead a consistent description of the market implied distribution of default arrival times. These models can thus be used for relative value trading across debt instruments and credit derivatives. Lando (2004) and also Schönbucher (2003) contain a treatment of both types of models.

This thesis consists of three self-contained essays, which can be read independently. However, they are interrelated through their use of structural credit risk models. Chapter 1 estimates the impact of accounting transparency on the term structure of Credit Default Swap spreads (CDS spreads) for a large cross-section of firms. Using a newly developed measure of accounting transparency in Berger, Chen & Li (2006), we find a downward-sloping term structure of transparency spreads, which is in accordance with the theory in Duffie & Lando (2001). Chapter 2 analyzes the use of CDS's in a convergence-type trading strategy popular among hedge funds and proprietary trading desks. This strategy, termed capital structure arbitrage, takes advantage of a lack of synchronicity between equity and credit markets and is related to recent studies on the lead-lag relationship between bond, equity and CDS markets. Chapter 3 estimates the time-series behavior of credit risk premia in the market for Credit Default Swaps. The risk premium peaks in the third quarter of 2002, but the subsequent drop in the risk premium is not as dramatic, when expected losses are based on implied volatility instead of a historical volatility measure. The credit risk premium tends to be countercyclical when expected losses are based on implied volatility and the results of the paper also suggest that structural models should contain a time-varying risk premium.

Finally, English and Danish summaries of the three essays are provided at the back.

Chapter 1

Accounting Transparency and the Term Structure of Credit Default Swap Spreads

Coauthored with Peter Tind Larsen, School of Economics and Management, University of Aarhus

Abstract[1]

This paper estimates the impact of accounting transparency on the term structure of CDS spreads for a large cross-section of firms. Using a newly developed measure of accounting transparency in Berger et al. (2006), we find a downward-sloping term structure of transparency spreads. Estimating the gap between the high and low transparency credit curves at the 1, 3, 5, 7 and 10-year maturity, the transparency spread is insignificant in the long end but highly significant and robust at 20 bps at the 1-year maturity. Furthermore, the effect of accounting transparency on the term structure of CDS spreads is largest for the most risky firms. These results are strongly supportive of the model by Duffie & Lando (2001), and add an explanation to the underprediction of short-term credit spreads by traditional structural credit risk models.

[1]We thank Lombard Risk for access to the credit default swap data. We thank Christian Riis Flor, Peter Løchte Jørgensen, David Lando, Mads Stenbo Nielsen, Thomas Plenborg and participants at the Danish Doctoral School of Finance Workshop 2007 for valuable comments and insights. Any remaining errors are our own.

1.1 Introduction

Traditional structural credit risk models originating with Black & Scholes (1973) and Merton (1974) define default as the first passage of a perfectly measured asset value to a default barrier. While later extensions that allow for endogenous default and debt renegotiations have increased predicted spread levels, it is well-known in the empirical literature that structural models underpredict corporate bond credit spreads, particularly in the short end.[2] Reasons for the poor performance may lie in shortcomings in the models as well as factors other than default risk in the corporate bond credit spread.

As noted in Duffie & Lando (2001), it is typically difficult for investors in the secondary credit markets to observe a firm's assets directly, either because of noisy or delayed accounting reports or other barriers to monitoring. Instead, investors must draw inference from the available accounting data and other publicly available information. As a consequence they build a model where credit investors are not kept fully informed on the status of the firm, but receive noisy unbiased estimates of the asset value at selected times. This intuitively simple framework has a significant implication for the term structure of credit spreads.

In particular, for firms with perfectly measured assets credit spreads are relatively small at short maturities and zero at zero maturity, regardless of the riskiness of the firm. However, if firm assets periodically are observed with noise, credit spreads are strictly positive under the same limit because investors are uncertain about the distance of current assets to the default barrier.

This paper contributes to the existing literature by estimating the component of the term structure of credit spreads associated with a lack of accounting transparency.[3] To this end, credit default swap (CDS) spreads at the 1, 3, 5, 7 and 10-year maturity for a large cross-section of firms are used together with a newly developed measure of accounting transparency by Berger et al. (2006). We relate this transparency measure to CDS spreads in two ways.

First, it is used to estimate a gap between the high and low transparency credit curves. This gap interpreted as a transparency spread is estimated at 20 bps at

[2] See e.g. Jones, Mason & Rosenfeld (1984), Ogden (1987), Huang & Huang (2003) and Eom, Helwege & Huang (2004).

[3] Consistent with the literature, we use the terms "accounting noise" and "accounting transparency" interchangeably. If the noise in the reported asset value is low, the accounting transparency is high.

the 1-year maturity and narrows to 14, 8, 7 and 5 bps at the 3, 5, 7 and 10-year maturity, respectively. The downward-sloping term structure of transparency spreads is highly significant in the short end but most often insignificant above the 5-year maturity. Furthermore, the effect of accounting transparency is largest for the most risky firms. These results are robust across alternative econometric specifications controlling for within cluster correlations and a large set of control variables.

Second, we analyze each maturity class in isolation using the raw transparency measure and a rank transformation. In this specification, the equal maturities across firms fixed through time in the CDS data allow the control variables to impact spreads differently across maturity classes. Since insights from above are preserved, the results are supportive of hypotheses derived from Duffie & Lando (2001) and add an explanation to the underprediction of short-term credit spreads by traditional structural models.

However, the explanatory power of accounting transparency and a typical set of control variables is small for less risky firms. This observation is supportive of the problems in earlier studies, when explaining the credit spreads of low-yield firms using structural models. This paper suggests that variables other than accounting transparency are needed, also in the short end.

The results contradict an earlier study by Yu (2005), who analyzes corporate bond credit spreads in 1991 to 1996 using the AIMR analyst ranking of corporate disclosure. He attributes a u-shaped transparency spread with the largest affect at longer maturities to a discretionary disclosure hypothesis, where firms hide information that would adversely affect their long-term outlook. While Duffie & Lando (2001) assume an exogenous unbiased accounting noise, the theory of discretionary disclosure starting with Verrecchia (1983) suggests that withheld information may signal hidden bad news about a company. Consistent with the term structure implications in Duffie & Lando (2001), our study shows that the transparency spread is downward-sloping in the CDS market.

Although a close relation exists between corporate bond and CDS spreads (Duffie (1999)), the latter are preferable from several perspectives when analyzing the determinants of the shape of the credit curve. First, the fixed maturities in CDS contracts make term structures directly comparable across firms and time. There is no maturity shortening as there would be with corporate bonds, and we are not forced to interpolate maturities to compare spreads in the cross-section.

Second, quotes at different maturities should be compared on the same curve, and a study of multiple maturity observations for a given firm at a given date is in effect only possible in the CDS market. Third, a use of CDS spreads avoids any noise arising from a misspecified risk-free yield curve (Houweling & Vorst (2003)). Fourth, as shown in Lando & Mortensen (2005) and Agrawal & Bohn (2005), the shape of the corporate bond credit curve depends on deviations from par under the realistic recovery of face value assumption. As Yu (2005) focuses on secondary market yields this technical effect may influence his results. The same effect is not present in the CDS market as CDS spreads are closely related to par bond spreads.

Fifth, CDS contracts are less likely to be affected by differences in contractual arrangements such as embedded options, guarantees, covenants and coupon effects. Although bonds with e.g. call features may be deliverable in default, this effect is likely to be present across the term structure of CDS spreads.

Sixth, several recent studies find that CDS spreads are a purer measure of credit risk and represent more timely information than corporate bonds. Non-default components stemming from asymmetric taxation and illiquidity have been compared across corporate bond and CDS markets.[4] However, the component due to imprecisely observed assets, let alone the term structure implications, is much less understood.

A reason for the lack of evidence on the impact of accounting transparency is the difficulty in constructing an empirical measure of a firm's overall information quality. The accounting literature explaining e.g. the cost of capital has relied on the AIMR analyst ranking of corporate disclosure. Analyzing the cost of debt, Sengupta (1998) finds a negative relationship between the AIMR measure and offering yields. This measure is also adopted by Yu (2005), with a resulting sample almost entirely made up of investment grade firms. As the measure ends in 1996, it cannot be related to CDS curves.

However, a newly developed measure of accounting transparency by Berger

[4] Blanco, Brennan & Marsh (2005) find that the CDS market leads the corporate bond market. Longstaff, Mithal & Neis (2005) find a significant non-default related component in the corporate bond credit spread correlated with illiquidity proxies. Ericsson, Reneby & Wang (2006) find this not to be present in CDSs. Elton, Gruber, Agrawal & Mann (2001) document a tax premium of 29 to 73 percent of the corporate bond credit spread, depending on the rating. Related studies on corporate bonds include Delianedis & Geske (2001) and Huang & Huang (2003).

et al. (2006) can be readily calculated for a large sample of firms. This allows us to study a large set of credit curves across rating categories. The idea behind the measure is that given the idiosyncratic cash flow volatility, the better a firm's information quality the higher its firm-specific equity return volatility. Berger et al. (2006) conduct several tests to assess their measure, and find results in accordance with intuition. Our application in the credit derivatives market provides additional evidence to the validity of the measure.

This paper is related to Sarga & Warga (1989), Fons (1994), Helwege & Turner (1999), Lando & Mortensen (2005) and Agrawal & Bohn (2005) who analyze the slope of the credit curve as a function of credit quality. Ignoring noisy asset reports, standard theory predicts an upward-sloping credit curve for high quality firms and a humped shaped or mostly downward-sloping credit curve for low quality firms. However, these papers are silent on decomposing the curve and the effect of accounting transparency.

Early studies mainly analyze the 5-year maturity, which is considered the most liquid point on the curve. This paper contributes to an increasing literature analyzing the entire term structure of CDS spreads. In addition to Lando & Mortensen (2005) and Agrawal & Bohn (2005) this includes Huang & Zhou (2007), who conduct a consistent specification analysis of traditional structural models. Although the 5-year maturity dominates our data, a significant number of observations are found at the 1, 3, 7 and 10-year maturity.

Finally, the paper is related to studies on the determinants of credit spreads such as Collin-Dufresne, Goldstein & Martin (2001), Campbell & Taksler (2003), Ericsson, Jacobs & Oviedo (2005), Cremers, Driessen, Maenhout & Weinbaum (2006) and Cao, Yu & Zhong (2006). These papers analyze the explanatory power of traditional structural variables such as leverage, asset volatility and risk-free interest rates, but are silent on different maturity classes and accounting transparency. Finally, Güntay & Hackbarth (2007) study the relation between corporate bond credit spreads and the dispersion of equity analysts' earnings forecasts.

The outline of the paper is as follows. Section 1.2 reviews the Duffie & Lando (2001) model and motivates the hypotheses. This section also shows a formula for the CDS spread that avoids a double integral and is easily comparable with the case of perfect information. Section 1.3 outlines the accounting transparency measure developed in Berger et al. (2006), while section 1.4 presents the data.

The descriptive statistics are presented in section 1.5, while section 1.6 and 1.7 contain the empirical results and a robustness analysis. Section 1.8 concludes. Appendix A and B give details behind the Duffie & Lando (2001) model and the transparency measure, respectively.

1.2 Hypotheses

In traditional structural credit risk models, default is defined as the first hitting time of a perfectly observed diffusion process on a default barrier. This default barrier can be exogenously determined as in e.g. Black & Cox (1976) and Longstaff & Schwartz (1995) or endogenously derived as in e.g. Leland (1994) and Leland & Toft (1996).

As shown in Leland (2004), these models do a reasonable job in predicting longer horizon default rates while the prediction of short-term default rates is far to low. The problem is that conditional on the firm value being above the barrier, the probability that it will cross the barrier in the next Δt is $o(\Delta t)$ and the conditional default probability converges to zero as time goes to zero.

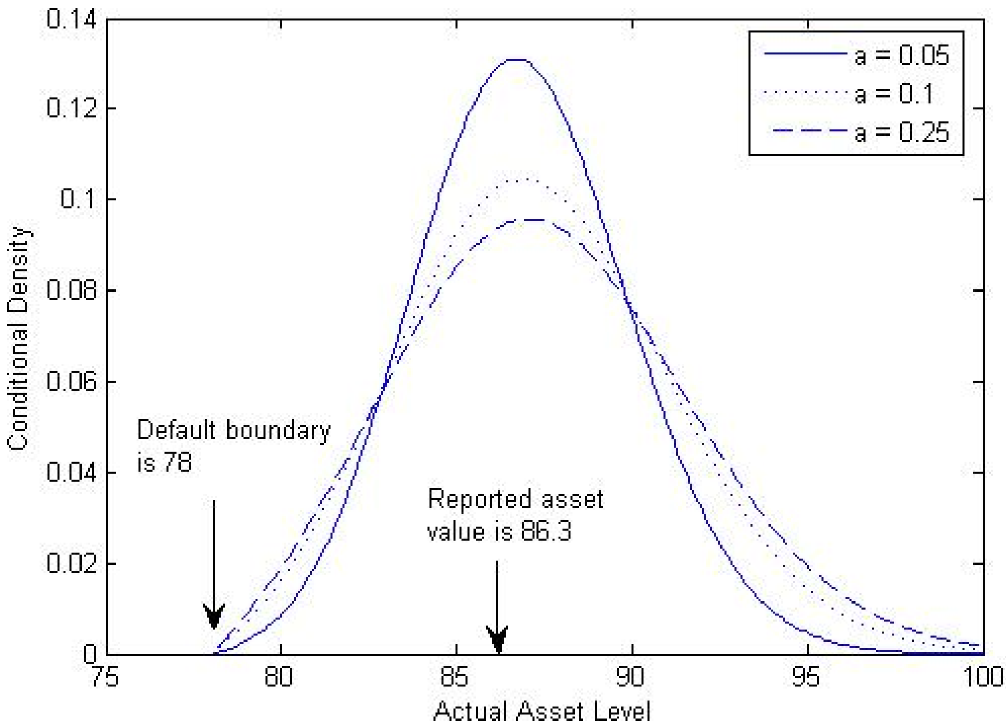
Duffie & Lando (2001) argue that it is typically difficult for investors in the secondary credit markets to perfectly observe the firm's assets and introduce accounting noise into a Leland (1994)-type model. More specifically, the value of the firm's assets is assumed to follow a geometric Brownian motion unobservable to the credit investors. Instead, the firm periodically issues noisy unbiased accounting reports, which makes investors uncertain about the distance of the assets to the default barrier.

Conditional on the accounting reports and the fact that the firm has not defaulted investors are able to compute a distribution of the value of assets. This conditional distribution of assets is reproduced in Figure 1.1 for various degrees of accounting noise a and a set of base case parameters. The crucial parameter a measures the standard deviation of the normal noise-term added to the true asset value. A lower a thus represents a higher degree of accounting transparency and less uncertainty about the true asset value. When a approaches zero the distribution will eventually collapse around the latest reported asset value.

According to Duffie & Lando (2001) this simple mechanism of uncertainty surrounding the true asset value is enough to produce a default probability within the next Δt that is of the same order as Δt. In fact, they show that the default stopping time τ has an intensity. The Duffie & Lando (2001) model is further described in appendix A.

Figure 1.1: Conditional Asset Density

The figure illustrates the conditional asset density for varying accounting precisions, reproducing the base case in Duffie & Lando (2001). The tax rate $\theta = 0.35$, volatility $\sigma = 0.05$, risk-free rate $r = 0.06$, drift $m = 0.01$, payout ratio $\delta = 0.05$ and default cost $\alpha = 0.3$. The coupon rate $C = 8.00$ and the default barrier $V_B(C) = 78$. A noise-free asset report $V(t-1) = \hat{V}(t-1) = 86.3$ is assumed together with a current noisy asset report $\hat{V}(t) = 86.3$. The standard deviation a is assumed at 0.05, 0.1 and 0.25 and measures the degree of accounting noise.



The payments in a CDS fit nicely into a continuous-time framework since the accrued premium must also be paid if a credit event occurs between two payment dates. In appendix A we show that with continuous payments the CDS spread with maturity T can be written as

$$c(0,T) = r(1-R)\frac{\int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx}{1 - e^{-rT}\int_{\underline{\upsilon}}^{\infty}\left(1-\pi\left(T, x-\underline{\upsilon}\right)\right)g\left(x\right)dx - \int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx}, \tag{1.1}$$

where r is the risk-free interest rate and R is the recovery rate.[5] $\pi\left(T, x-\underline{\upsilon}\right)$ denotes the probability of first passage time of a Brownian motion with constant drift and volatility parameter from an initial condition $(x-\underline{\upsilon}) > 0$ to a level below zero at time T, where x and $\underline{\upsilon}$ denote the logarithm of the asset value and default barrier, respectively. The formulas for $\pi\left(T, x-\underline{\upsilon}\right)$ and $G(x,T)$ are given in closed form in the appendix together with the conditional density function of the logarithm of assets $g\left(x\right)$ at the time of issuance of the CDS.

In the case of perfect information the integral and the density function $g\left(x\right)$ simply disappears, leading to a closed form solution for the CDS spread known from traditional structural credit risk models.

In Figure 1.2, the term structure of CDS spreads in equation (1.1) is shown for the associated conditional distribution of assets in Figure 1.1 and the various degrees of accounting noise a. Also depicted is the traditional case of perfect information $a = 0$, where the spread approaches zero as maturity goes to zero. However, this is not the case when noisy reports are introduced. As a becomes larger, the probability that the asset value is, in fact, close to the default barrier and may cross in a short period of time increases, resulting in higher short-term spreads. The difference in spreads due to a lack of accounting transparency is less pronounced at longer maturities.

Figure 1.3 and 1.4 depict the case of a lower leverage and a lower asset volatility, respectively. This captures the effect of accounting transparency on CDS spreads for less risky firms than the base case. The spreads are compressed compared to Figure 1.2, indicating that we should expect a lower absolute effect of accounting transparency for less risky firms.

[5] The formula in Duffie & Lando (2001) is based on semiannually payments and a double integral over time and the asset density. The assumption of continuous payments implies that it is only necessary to calculate a single integral numerically to evaluate the CDS spread.

Figure 1.2: CDS Spreads for Varying Accounting Precisions
The figure illustrates the CDS spreads associated with the conditional asset densities for varying accounting precisions, reproducing the base case in Duffie & Lando (2001). The tax rate $\theta = 0.35$, volatility $\sigma = 0.05$, risk-free rate $r = 0.06$, drift $m = 0.01$, payout ratio $\delta = 0.05$, default cost $\alpha = 0.3$ and recovery rate $R = 0.5$. The coupon rate $C = 8.00$ and the default barrier $V_B(C) = 78$. A noise-free asset report $V(t-1) = \hat{V}(t-1) = 86.3$ is assumed together with a current noisy asset report $\hat{V}(t) = 86.3$. The standard deviation a is assumed at 0.05, 0.1 and 0.25 and measures the degree of accounting noise.

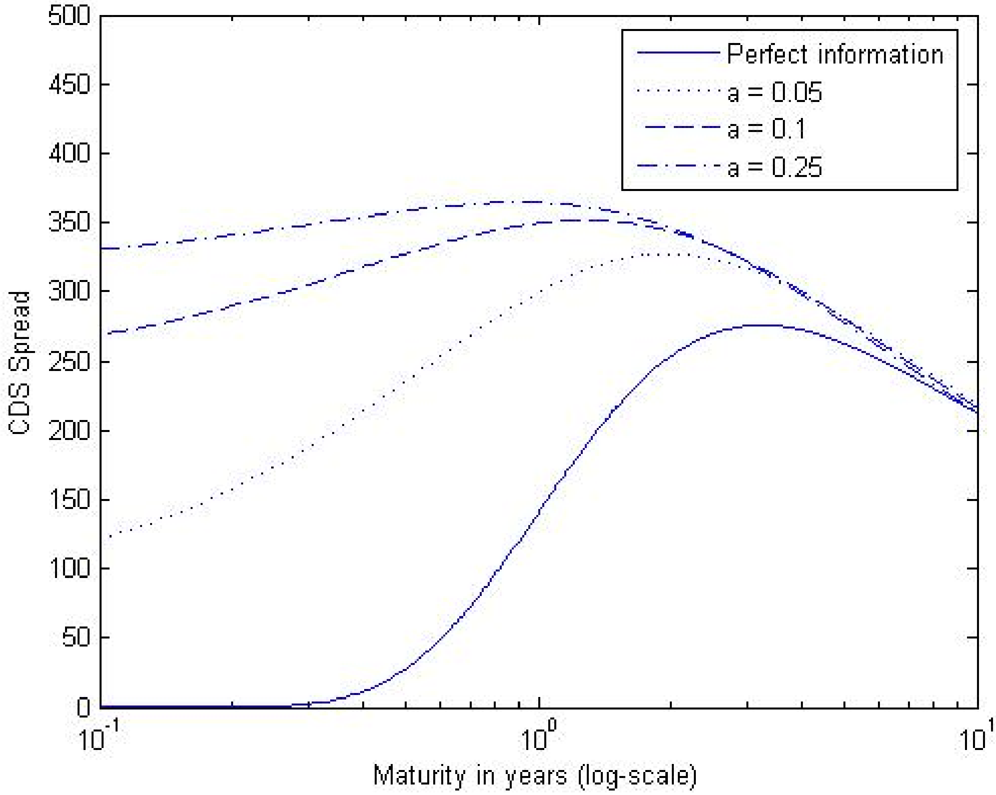


Figure 1.3: CDS Spreads For a Low Leverage Firm

The figure illustrates the CDS spreads for varying accounting precisions in Duffie & Lando (2001). A higher current and lagged asset report are assumed, capturing a lower leverage ratio. The tax rate $\theta = 0.35$, volatility $\sigma = 0.05$, risk-free rate $r = 0.06$, drift $m = 0.01$, payout ratio $\delta = 0.05$, default cost $\alpha = 0.3$ and recovery rate $R = 0.5$. The coupon rate $C = 8.00$ and the default barrier $V_B(C) = 78$. A noise-free asset report $V(t-1) = \hat{V}(t-1) = 90.0$ is assumed together with a current noisy asset report $\hat{V}(t) = 90.0$. The standard deviation a is assumed at 0.05, 0.1 and 0.25 and measures the degree of accounting noise.

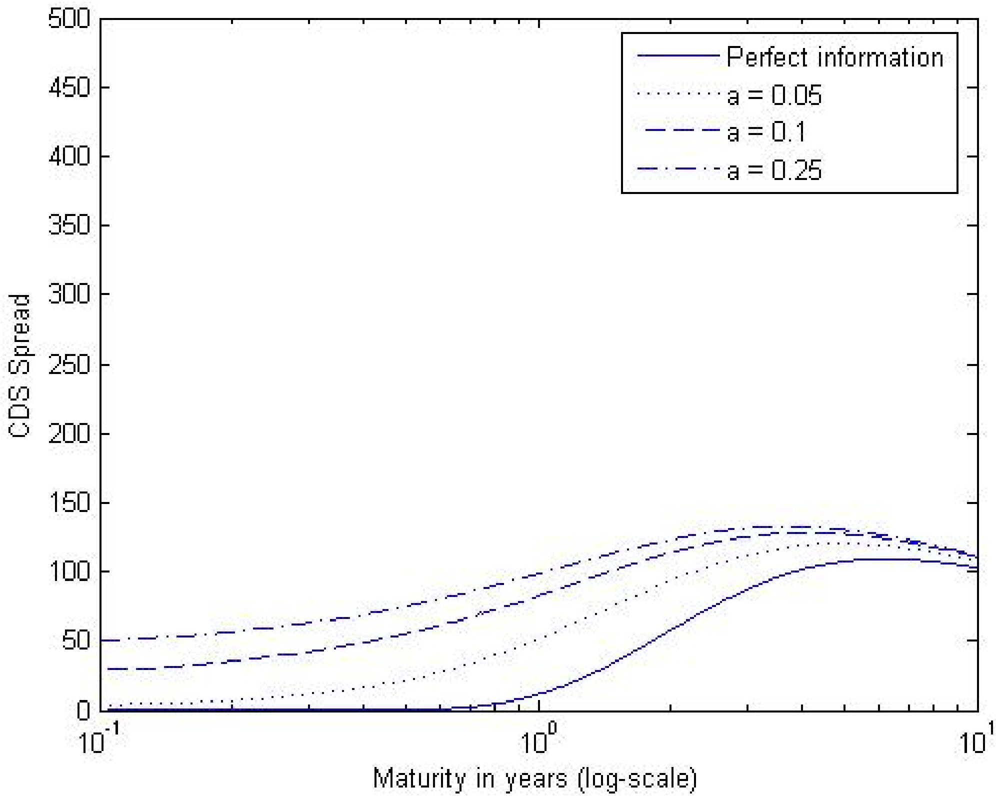
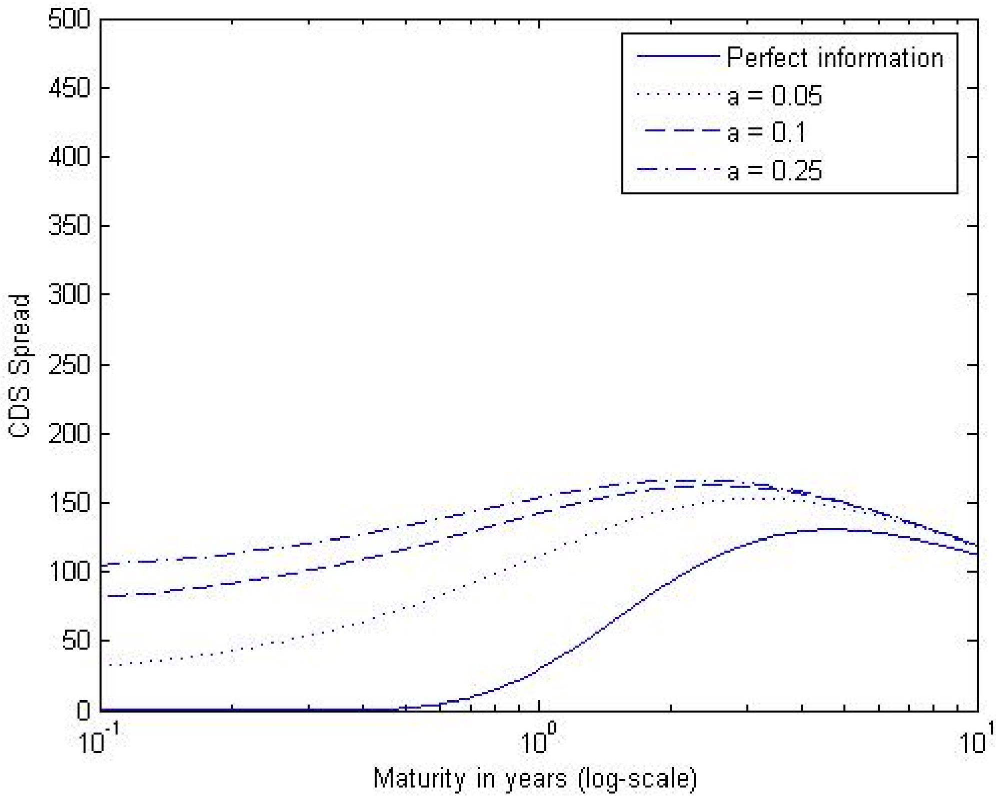


Figure 1.4: CDS Spreads For a Low Volatility Firm

The figure illustrates the CDS spreads for varying accounting precisions in Duffie & Lando (2001) for a firm with low volatility. The tax rate $\theta = 0.35$, volatility $\sigma = 0.04$, risk-free rate $r = 0.06$, drift $m = 0.01$, payout ratio $\delta = 0.05$, default cost $\alpha = 0.3$ and recovery rate $R = 0.5$. The coupon rate $C = 8.00$ and the default barrier $V_B(C) = 78$. A noise-free asset report $V(t-1) = \hat{V}(t-1) = 86.3$ is assumed together with a current noisy asset report $\hat{V}(t) = 86.3$. The standard deviation a is assumed at 0.05, 0.1 and 0.25 and measures the degree of accounting noise.



Finally, an adverse effect of the exogenous and unbiased accounting noise in the Duffie & Lando (2001) model, which is also addressed in Yu (2005), is depicted in Figure 1.5. In this case, the current report shows a substantially lower asset value than the lagged report, which leads to the counterintuitive result that a higher transparency is associated with higher spreads for most parts of the term structure. With perfect information the lagged report is irrelevant, but as a increases and transparency is reduced the current report becomes less reliable and more weight is put on the lagged report suggesting a higher asset value.[6] Hence, more mass of the conditional asset distribution is shifted towards higher asset values implying lower credit spreads. This example illustrates the need for structural models to incorporate accounting transparency as an endogenous choice. With discretionary disclosure this situation would not arise since the firm would choose not to reveal the bad news in the first place. The theory of discretionary disclosure starting with Verrecchia (1983) suggests that withheld information may signal hidden bad news about a company. As a result, a lower transparency is associated with higher credit spreads. The above intuition leads to the following hypotheses for the qualitative effect of accounting transparency on CDS spreads.

H1. Firms with a lower level of accounting transparency have higher CDS spreads.

H2. The effect of accounting transparency is more pronounced at shorter maturities, leading to a term structure effect.

H3. A stronger effect of accounting transparency is expected for more risky firms.

The level effect in the first hypothesis is due to the theory of discretionary disclosure, while the second and third hypotheses are due to Duffie & Lando (2001). At reasonable parameter values, Duffie & Lando (2001) do not predict a significant spread due to noisy reports above the 5-year maturity.

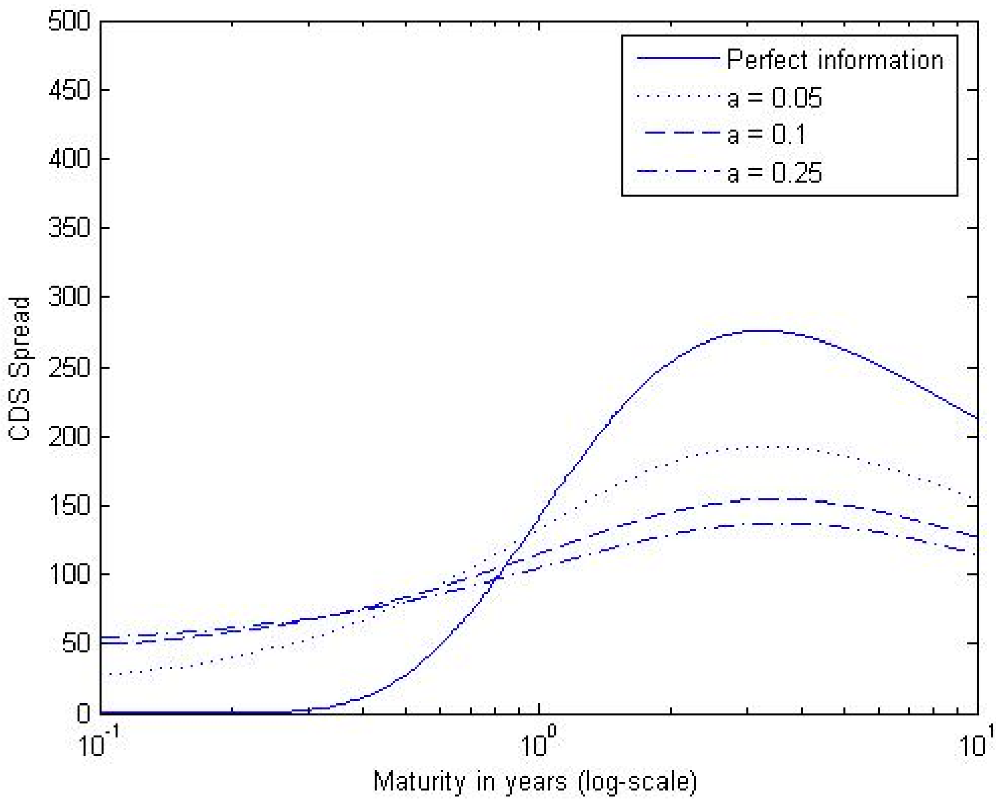
The term structure effect of discretionary disclosure is less obvious and depends on the nature of information that a firm tries to conceal. A temporary shock to the firm value affects short-term spreads, while a permanent shock such as a negative outlook on earnings growth affects long-term spreads. Yu (2005) notes that the positive net-worth requirement effectively present in short-term

[6] Under perfect information, the term structure of CDS spreads in Figure 1.2 and 1.5 are identical.

debt implies that firms have little incentive to conceal information that they are soon forced to reveal anyway.[7] Hence, he argues that discretionary disclosure is most likely to concern permanent shocks and long-term spreads.

Figure 1.5: CDS Spreads For a Higher Initial Firm Level

The figure illustrates the CDS spreads for varying accounting precisions in Duffie & Lando (2001). The current asset report is at it's base case level, while the lagged asset report is higher. The tax rate $\theta = 0.35$, volatility $\sigma = 0.05$, risk-free rate $r = 0.06$, drift $m = 0.01$, payout ratio $\delta = 0.05$, default cost $\alpha = 0.3$ and recovery rate $R = 0.5$. The coupon rate $C = 8.00$ and the default barrier $V_B(C) = 78$. A noise-free asset report $V(t-1) = \hat{V}(t-1) = 90.0$ is assumed together with a current noisy asset report $\hat{V}(t) = 86.3$. The standard deviation a is assumed at 0.05, 0.1 and 0.25 and measures the degree of accounting noise.



[7] See Leland (1994) for the relationship between short-term debt and positive net-worth requirements.

1.3 Measuring Accounting Transparency

To assess accounting transparency, we construct a newly developed measure by Berger et al. (2006) that can be readily calculated for a large sample firms. The idea behind the measure is that when pricing equity, investors use a weighted average of reported earnings and industry earnings. Investors put more weight on the firm's reported earnings when the accounting transparency is high. It turns out that the measure of accounting transparency is the ratio of idiosyncratic equity return volatility to the idiosyncratic volatility in earnings growth. Appendix B establishes the theoretical link between the measure and accounting transparency. The current section implements it as prescribed in Berger et al. (2006).

In particular, to measure transparency empirically in year t two regressions are performed for each firm. The first uses monthly data from year $t-5$ to $t-1$ to calculate the idiosyncratic volatility in equity returns

$$r_t^j = a_j^r + b_j^{r,M} r_t^M + b_j^{r,I} r_t^I + \varepsilon_t^{r,j}, \tag{1.2}$$

where r_t^j is firm $j's$ monthly equity return, r_t^M is the CRSP value-weighted market return and r_t^I is a value-weighted industry return using the 48 industries in Fama & French (1997).[8] To ensure the accuracy at least 50 valid monthly returns are required for each firm. The annualized idiosyncratic volatility of returns $IVOL_{t,j}^r$ is then calculated as $\sqrt{12} * std(\varepsilon^{r,j})$.

The second regression uses quarterly data from year $t-5$ to $t-1$ to calculate the idiosyncratic volatility in earnings growth

$$EG_t^j = a_j^{EG} + b_j^{EG,M} EG_t^M + b_j^{EG,I} EG_t^I + \varepsilon_t^{EG,j}, \tag{1.3}$$

where EG_t^j is the annual growth rate in firm $j's$ quarterly operating earnings calculated as $\frac{\text{operating earnings}_t}{\text{operating earnings}_{t-4}} - 1$.[9] The growth rate is measured between identical quarters to avoid complications that arise from seasonality. If the lagged earnings are negative the growth rate is not meaningful and that particular growth rate is

[8] Market capitalization is used as weights when calculating the market and industry returns. All firms in the CRSP database enter the return and later earnings growth calculations.

[9] The quarterly operating earnings is data item number 8 in the Compustat database.

dropped.[10] To ensure the accuracy, we require at least 15 quarters of data. EG_t^M is the earnings-weighted average market growth rate and EG_t^I is the earnings-weighted average growth rate in the Fama & French (1997) industries.

The idiosyncratic volatility in earnings growth $IVOL_{t,j}^{EG}$ is $std(\varepsilon^{EG,j})$, and the measure is finally constructed as the ratio of the idiosyncratic volatility in equity returns to the idiosyncratic volatility in earnings growth

$$\delta_{t,j} = \frac{IVOL_{t,j}^{r}}{IVOL_{t,j}^{EG}}. \tag{1.4}$$

Hence, the idiosyncratic volatility in equity returns is driven by the idiosyncratic volatility in earnings growth and the firm's information quality. The measure is theoretically constrained to the unit interval, and a higher score corresponds to a higher accounting transparency.

Berger et al. (2006) calculate the measure for 41,615 firm-years in 1980 to 2004 and find empirical evidence in accordance with intuition and theory. In particular, they assess the validity of the measure by relating it to different measures of disclosure quality and the cost of equity. First, the measure increased after two new regulations that increased mandatory disclosures in the pension and oil and gas sectors. Second, the measure is strongly correlated with the investor relations component of the AIMR measure and weakly correlated with the total AIMR measure. Third, firms with a higher measure are followed by more analysts and have a lower forecast dispersion of earnings per share. Finally, the measure is negatively related to three estimates of the cost of equity.

In the end, we necessarily test the joint hypotheses of the validity of the accounting transparency measure developed in Berger et al. (2006), and the term structure effects suggested in Duffie & Lando (2001). Our application in the credit derivatives market provides additional evidence to the validity of the measure.

1.4 Data

Data on CDS spreads is provided by the ValuSpread database from Lombard Risk Systems, dating back to July 1999. The number of entities and frequency of quotes increase significantly through time, reflecting the growth and improved

[10] Since operating income and not net income is used the loss of observations is small.

liquidity in the market. This data is also used by Lando & Mortensen (2005) and Berndt, Jarrow & Kang (2006). The data consists of mid-market CDS quotes on both sovereigns and corporates with varying maturity, restructuring clause, seniority and currency. For a given date, reference entity and contract specification, the database reports a composite CDS quote together with an intra-daily standard deviation of the collected quotes. The composite quote is calculated as a mid-market quote by obtaining quotes from up to 25 leading market makers. This offers a more reliable measure of the market spread than using a single source, and the standard deviation measures how representative the mid-market quote is for the overall market.

To test the effect of accounting transparency on the term structure of CDS spreads, contracts with a maturity of 1, 3, 5, 7 and 10 years are analyzed. We furthermore confine ourselves to composite CDS quotes on senior unsecured debt for North American corporate obligors with currencies denominated in US dollars. Regarding the specification of the credit event, we follow large parts of the literature in using contracts with a modified restructuring clause.

To generate a proper subsample, several filters are applied to the data. First, the CDS data is merged with quarterly balance sheet data from Compustat and daily stock market data from CRSP. The quarterly balance sheet data is lagged one month from the end of the quarter to avoid the look-ahead bias in using data not yet available in the market. Second, firms from the financial and utility sector are excluded as their capital structure is hard to interpret.

Third, the composite quote at a given maturity must have a certain quality. Therefore, we define the relative quote dispersion as the intra-daily standard deviation of collected quotes divided by the mid-market quote. We follow Lando & Mortensen (2005) and delete all daily mid-market quotes with an intra-daily quote dispersion of zero or above 20 percent. Fourth, 1, 3, 5, 7 and 10-year constant maturity treasury yields are obtained from the Federal Reserve Bank of St. Louis.

Fifth, we restrict the sample to end-of-month dates. This selection criteria is also applied by Lando & Mortensen (2005), as these dates have the highest number of quotes. This leaves us with 31,525 month-end consensus quotes distributed across 8,309 curves and 432 firms. Finally, for each year t the month-end curves are merged with the annual transparency measure calculated for each firm in section 1.3. The result is 25,599 quotes, 6,756 month-end curves and 890 annual transparency scores distributed across 368 firms from May 2002 to September 2004.[11]

1.5 Descriptive Statistics

Table 1.1 illustrates the distribution of the annual accounting transparency measure. Panel A represents statistics based on the pooled measure across firms and years, while statistics in Panel B are calculated after averaging the measure for each firm in the time-series. The pooled mean and median are 0.50 and 0.29, respectively. A few high transparency scores drive up the average, and about 10 percent of the sample firm-years have scores larger than the theoretical upper bound of 1. A similar result based on a larger set of firms is found in Berger et al. (2006), who attribute it to possible time-varying expected returns.

Table 1.1: Summary Statistics of Accounting Transparency

This table reports summary statistics for the accounting transparency measure developed in Berger, Chen & Li (2006) and calculated in section 1.3. Panel A represents statistics when pooling the measure across firms and years, while panel B displays statistics after averaging the measure in the time-series for each firm. In panel A, N denotes the number of firm-years with sufficient data to calculate the accounting transparency measure and with associated CDS data. In panel B, N denotes the number of unique firms.

N	Mean	Std.dev.	Min	25%	50%	75%	99%	Max
Panel A. Statistics on the pooled transparency measure								
890	0.50	0.61	0.00	0.16	0.29	0.60	3.23	5.65
Panel B. Statistics on the time-series average transparency measure								
368	0.50	0.57	0.01	0.16	0.30	0.62	2.84	4.44

[11] One firm is excluded, Colgate Palmolive, as the transparency measure is calculated at 10.23, 11.56 and 11.89 in year 2002-2004. This persistently large score far above the remaining firms might indicate a data problem specific to the firm.

The standard deviation is 0.61 and the inter-quartile range is 0.44. The same variation is observed in Panel B after averaging the measure in the time-series, indicating a large variation in accounting transparency across the firms. The data allow for a maximum of 3 consecutive annual transparency scores with associated CDS data for each firm. An untabulated mean and median annual absolute change of 0.17 and 0.04, respectively, indicate a somewhat persistent transparency measure in the time-series.

Table 1.2 presents summary statistics of key variables across the senior unsecured credit rating from Standard & Poor's. The variables presented are averages across time and across firms. Consistent with the predictions of structural credit risk models, a lower rating is associated with a higher credit spread level represented by the 5-year CDS spread, a higher equity volatility and a higher leverage. The equity volatility is calculated using 250 days of equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization.

Table 1.2: Summary Statistics of Major Variables

This table reports averages of key variables across firms and time. The statistics are presented across the senior unsecured credit rating from Standard & Poor's. The 5-year spread represents the overall spread level and is averaged over firms and end-of month observations. The volatility is calculated at month-end using 250-days of historical equity returns. The associated leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. NR means not rated.

	5yr spread	Volatility	Leverage	Transparency
AAA	23	0.29	0.28	0.92
AA	26	0.28	0.21	0.88
A	48	0.33	0.34	0.60
BBB	128	0.36	0.49	0.40
BB	392	0.49	0.61	0.39
B	658	0.74	0.76	0.20
NR	137	0.33	0.31	0.66

A better credit rating is associated with a higher accounting transparency. This observation and a correlation of 0.16 in Table 1.3 provide additional evidence to the validity of the transparency measure as documented empirically in Berger et al. (2006). As noted in Sengupta (1998) and Yu (2005), credit agencies claim to have incorporated the quality of information disclosure in the credit ratings. Hence, we follow Sengupta (1998) and Yu (2005) and use credit ratings with caution when controlling for the cross-sectional determinants of credit spreads other than accounting transparency. We use an alternative set of control variables from studies on the determinants of credit spreads such as equity volatility, leverage, liquidity and the risk-free yield curve. However, we also analyze whether credit ratings absorb the effect of accounting transparency on the term structure of CDS spreads.

As a final remark, the correlation between the accounting transparency measure and leverage and volatility, respectively, is estimated at -0.16 and -0.08. This is of similar sign and magnitude as the correlations found in Yu (2005) based on the AIMR measure in 1991 to 1996.

Table 1.3: Average Correlations Among Major Variables

This table reports the Spearman rank correlation coefficients between the major variables. The correlations are calculated each month, and the resulting average correlations are reported. The volatility is calculated at month-end using 250-days of historical equity returns. The associated leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned the highest number, AA the next highest and so forth.

	5yr spread	Volatility	Leverage	Transp
Volatility	0.57			
Leverage	0.62	0.25		
Transp.	-0.11	-0.08	-0.16	
Rating	-0.76	-0.41	-0.55	0.16

The distribution of the CDS spreads across credit ratings and maturities is illustrated in Table 1.4 Panel A. The mean consensus quote across time and firms is found in the first row, while the number of observations and the mean relative quote dispersion are found in the second and third row, respectively. Panel B contains the statistics for full month-end curves with observations at all maturities at month-end for a given firm. By considering full curves, the mean consensus quotes within a given rating class are comparable across maturities, since all averages are calculated from the same set of dates and firms. As expected, the mean consensus quotes increase monotonically with maturity for high credit quality firms and decrease monotonically with maturity for the lowest credit quality firms.[12]

The 5-year maturity accounts for the highest number of observations, but even the least observed 1-year maturity accounts for almost 15 percent of the observations. Across ratings the lower end of the investment grade segment has the highest number of observations. However, we are able to study a significant proportion of sample spreads across maturities in the low credit quality segment. For BB-rated firms the sample consists of 449 to 757 month-end quotes for each maturity and 342 full curves, while the number of quotes for B-rated firms ranges from 66 to 87 with 50 full curves.[13]

Lando & Mortensen (2005) interpret the relative quote dispersion as a proxy for liquidity. The more agreement about a quote, the higher the liquidity for that particular credit. Adopting this liquidity proxy, we see a liquidity smile for a fixed rating across maturities. This is consistent with the fact that the 5-year maturity is considered the most liquid point on the curve. However, the difference in the mean relative quote dispersion across maturities is small.

[12] Theory predicts an upward-sloping credit curve for high quality firms and a humped shaped or mostly downward-sloping credit curve for low quality firms. While the first is well-established in the empirical literature, the latter is more controversial. See Sarga & Warga (1989), Fons (1994), Helwege & Turner (1999), Lando & Mortensen (2005) and Agrawal & Bohn (2005).

[13] For comparison, Yu (2005) studies 0 speculative grade bonds in 1991-1994, 4 in 1995 and 15 in 1996.

Table 1.4: Summary Statistics by Credit Rating and Maturity
This table illustrates the distribution of month-end CDS quotes across credit ratings and maturities. The mean consensus quote across time and firms is found in the first row for each rating category, while the number of observations and the mean relative quote dispersion are found in the second and third row, respectively. The latter is calculated as the standard deviation of collected quotes divided by the consensus quote. Panel A reports the statistics for unrestricted curves, while Panel B reports statistics for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years.

	1yr	3yr	5yr	7yr	10yr	Total
	Panel A. Unrestricted curves					
AAA	24	25	25	33	38	29
	34	59	92	66	45	296
	0.13	0.13	0.13	0.13	0.13	0.13
AA	24	24	26	29	35	28
	146	264	351	297	226	1,284
	0.14	0.14	0.12	0.12	0.13	0.13
A	45	44	48	52	59	50
	1,177	1,930	2,136	1,856	1,658	8,757
	0.14	0.12	0.09	0.11	0.12	0.11
BBB	131	126	128	127	131	128
	1,732	2,568	2,736	2,365	2,234	11,635
	0.13	0.11	0.08	0.09	0.11	0.10
BB	419	407	392	390	368	395
	449	702	757	559	567	3,034
	0.11	0.10	0.09	0.09	0.10	0.10
B	761	712	658	613	615	672
	66	82	87	76	70	381
	0.12	0.11	0.08	0.09	0.10	0.10
NR	142	137	137	184	183	154
	31	53	55	35	38	212
	0.10	0.11	0.09	0.09	0.07	0.09
Total	141	136	133	129	139	
	3,635	5,658	6,214	5,254	4,838	
	0.13	0.12	0.09	0.10	0.11	

Table 1.4: Summary Statistics by Credit Rating and Maturity (cont.)

This table illustrates the distribution of month-end CDS quotes across credit ratings and maturities. The mean consensus quote across time and firms is found in the first row for each rating category, while the number of observations and the mean relative quote dispersion are found in the second and third row, respectively. The latter is calculated as the standard deviation of collected quotes divided by the consensus quote. Panel A reports the statistics for unrestricted curves, while Panel B reports statistics for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years.

	1yr	3yr	5yr	7yr	10yr	Total
			Panel B. Full curves			
AAA	33	44	54	56	61	49
	18	18	18	18	18	90
	0.14	0.12	0.09	0.11	0.12	0.12
AA	28	35	39	41	46	38
	94	94	94	94	94	470
	0.14	0.13	0.10	0.11	0.12	0.12
A	48	55	60	63	69	59
	893	893	893	893	893	4,465
	0.14	0.12	0.09	0.11	0.12	0.12
BBB	133	140	143	144	146	142
	1,428	1,428	1,428	1,428	1,428	7,140
	0.13	0.11	0.07	0.09	0.11	0.10
BB	428	425	413	403	390	412
	342	342	342	342	342	1,710
	0.11	0.10	0.08	0.08	0.10	0.10
B	690	690	668	642	626	663
	50	50	50	50	50	250
	0.12	0.10	0.08	0.09	0.10	0.10
NR	210	219	219	231	222	220
	12	12	12	12	12	60
	0.10	0.10	0.08	0.08	0.08	0.09
Total	148	154	155	155	157	
	2,837	2,837	2,837	2,837	2,837	
	0.13	0.11	0.08	0.10	0.11	

In the end, the measure developed in Berger et al. (2006) allows us to relate accounting transparency to CDS curves for a large cross-section of firms. Importantly, the distribution of CDS spread observations across credit quality and maturity is desirable in our attempt to understand the impact of accounting transparency on the term structure of CDS spreads. The accounting transparency varies considerably in the large cross-section but less in our relatively short time-series. Furthermore, some evidence indicates that credit spread changes in the time-series are mostly driven by market factors that tend to overwhelm the effect of firm-level characteristics.[14] Hence, cross-sectional regressions form our benchmark approach. This makes the results comparable to Yu (2005), as cross-sectional regressions constitute the only regression framework in his study. Later, various econometric specifications are introduced to ensure that the results are not driven by spurious correlations.

1.6 Empirical Results

First, we estimate a gap between the high and low transparency credit curves. This allows us to directly estimate the term structure of transparency spreads. We then study a restricted set of full curves and estimate the transparency spread term structure for high and low risk firms.

1.6.1 The Term Structure of Transparency Spreads

Duffie & Lando (2001) predict accounting transparency to be an important variable in explaining credit spreads in the short end. At reasonable parameter values, the model does not predict a significant impact of accounting transparency above the 5-year maturity. However, discretionary disclosure may still imply an effect in the long end.

The corporate bond data used in Yu (2005) consists of bonds with unequal and shortening maturities and durations. This forces him to construct a piecewise linear function of bond maturity across the firms at each month-end. He then estimates the level of the credit spread at the constructed and artificial knot points.

[14] The results in Collin-Dufresne et al. (2001) suggest that the time-series variation in corporate bond credit spreads is mainly determined by local supply and demand shocks independent of credit risk factors and liquidity proxies. Huang & Zhou (2007) find that five popular structural models cannot capture the time-series behavior of CDS spreads.

As a starting point, we adopt a comparable specification and estimate the gap between the high and low transparency credit curves. However, we estimate the gap between the two curves at the equal, fixed and therefore directly comparable maturities in the CDS data, and interpret the gap as a transparency spread term structure.

In particular, define d as a dummy variable that equals 1 if a firm's transparency measure calculated in equation (1.4) in a given year ranks above the median score. Furthermore, define m_T as a dummy variable that attains a value of 1 if the CDS spread has a maturity of T and zero otherwise. Hence, in the linear combination $\beta_1 m_1 + \beta_2 m_3 + \beta_3 m_5 + \beta_4 m_7 + \beta_5 m_{10}$ the coefficient β_i represents the level of the term structure at maturities 1, 3, 5, 7 and 10 years. Now, define dm_T as the product of the transparency dummy d and m_T. The regression coefficient in front of this term can be directly interpreted as the transparency spread, i.e. the gap between the high and low transparency credit curves at the given maturity.

Hence, we run monthly cross-sectional regressions of CDS spreads on the transparency variables, volatility (vol), leverage (lev) and relative quote dispersion (Qdisp)[15]

$$\begin{aligned} Spread_{itT} &= \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} \\ &\quad + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} \\ &\quad + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \varepsilon_{itT}. \end{aligned} \tag{1.5}$$

The coefficient estimates are averaged in the time-series and standard errors are calculated following Fama & MacBeth (1973). Table 1.5 displays the results. Focusing on the first column, the transparency spread is highly significant and estimated at 23 bps at the 1-year maturity and 20, 13, 13 and 11 bps at the remaining maturities. Particularly the transparency spread in the short end represents a considerable part of the average CDS spread level of 130 to 140 bps across maturities as reported in Table 1.4.

[15] To facilitate interpretation the regression equation does not include an intercept term. Hence, the R^2 is not reported under this empirical specification.

Table 1.5: Estimation of the Term Structure of Transparency Spreads
This table reports the results of monthly cross-sectional regressions when estimating the gap between high and low transparency CDS spread curves. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). d is a dummy variable equal to 1 if the transparency measure developed in Berger, Chen & Li (2006) and calculated in section 1.3 in a given year ranks above the median score. m_T is a dummy that attains a value of 1 if the CDS maturity equals T. The regression coefficient in front of the product dm_T can be directly interpreted as the transparency spread. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. Full curves are a restricted set of curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The monthly regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \varepsilon_{itT}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	(1)	(2)	(3)	(4)
	Unrestr.	Unrestr.	Full curves	Full curves
m_1	-293.64***	-299.10***	-315.01***	-333.24***
	(-11.21)	(-12.78)	(-11.48)	(-13.84)
m_3	-292.11***	-297.06***	-312.26***	-328.17***
	(-11.17)	(-12.66)	(-10.78)	(-12.54)
m_5	-293.64***	-297.26***	-316.80***	-328.18***
	(-10.87)	(-11.94)	(-10.82)	(-12.00)
m_7	-296.34***	-300.50***	-315.20***	-328.85***
	(-10.74)	(-11.87)	(-10.36)	(-11.74)
m_{10}	-295.43***	-300.12***	-311.45***	-327.26***
	(-10.37)	(-11.55)	(-9.90)	(-11.44)
dm_1	-22.66***	-22.35***	-23.56***	-24.31***
	(-4.22)	(-4.11)	(-3.91)	(-4.29)
dm_3	-20.04***	-19.98***	-20.52***	-20.94***
	(-6.58)	(-6.44)	(-3.57)	(-3.67)
dm_5	-13.15***	-13.24***	-17.61***	-18.18***
	(-5.56)	(-5.54)	(-3.11)	(-3.21)
dm_7	-12.88***	-13.05***	-14.67**	-15.78***
	(-5.98)	(-5.75)	(-2.71)	(-2.82)
dm_{10}	-10.94***	-10.82***	-13.08**	-14.06**
	(-5.26)	(-5.21)	(-2.47)	(-2.59)
Volatility	805.44***	805.59***	873.06***	874.86***
	(16.50)	(16.53)	(12.92)	(12.99)
Leverage	317.20***	318.99***	315.71***	321.00***
	(12.98)	(13.14)	(11.80)	(12.29)
Qdisp	-33.37		-122.68**	
	(-1.07)		(-2.37)	

As expected, the volatility and leverage are highly significant in explaining credit spreads. However, the relative quote dispersion varies in significance and has a negative coefficient estimate. If proxying for liquidity, the coefficient is expected to be positive. Hence, although the variable allows for reasonable interpretations on average as liquidity in Table 1.4, it is questionable whether the relative quote dispersion captures differences in liquidity as suggested in Lando & Mortensen (2005). As the control variable only has a minor impact on the remaining coefficient estimates and significance, we keep it in our future regressions[16].

Firms usually have corporate bonds outstanding with just a few (or one) maturities. Hence, studying multiple maturity observations for a given firm at a given date is in effect only possible in the CDS market, and therefore not pursued in Yu (2005). Table 1.5 also contains the regression results for a restricted set of full month-end curves with observations at all maturities at month-end for a given firm. This makes CDS spreads directly comparable across maturities as all observations are from the same set of dates and firms. As noted in Helwege & Turner (1999) firms with heterogenous credit quality are known to populate different ends of the corporate bond credit curve. This maturity bias is avoided when studying full curves in the CDS market.

A highly significant downward-sloping term structure of transparency spreads also emerges from a study of full curves. From a transparency spread of 24 bps at the 1-year maturity it decreases to 13 bps at the longest maturity.

The results in Table 1.5 to some extend support the findings in Yu (2005). While agreeing on the statistically and economically significant transparency spread in the short end, Yu (2005) finds a widening transparency spread at longer maturities. In fact, he finds the transparency spread larger in the long end than short end. He attributes this observation to the discretionary disclosure hypothesis where firms hide information that would adversely affect their long-term outlook.[17] In alternative econometric specifications building on the

[16]Unreported results show that the presence or omission of relative quote dispersion has no impact on any results reported in the paper.

[17]Although Yu (2005) has only few observations in the longest end, he calculates a transparency spread at the 30-year knot point coinciding with the maximum corporate bond maturity. Hence, this estimate is likely to be less reliable. However, while our transparency spread term-structure remains downward-sloping, his exhibits a u-shape already at the 10-year knot point. More precisely, he estimates a transparency spread of 11, 3, 9 and 13 bps at the 0, 5, 10 and 30-year knot points.

interpretation of dm_T as a transparency spread, we later show that the term structure of transparency spreads is not only strictly downward-sloping but most often insignificant in the long end.

As argued in section 1.2, a stronger effect of accounting transparency is expected for more risky firms. Therefore, each month the firms are separated into high and low leverage and volatility groups by the respective medians. The regression in (1.5) is then presented for each group in Table 1.6.[18]

For the low leverage and low volatility groups, the effect of accounting transparency on credit spreads is small and of varying significance. While the transparency spread term structure is insignificant for low leverage firms, it is most often significant for the low volatility firms. However, the transparency spread is estimated at around 3 to 7 bps, which constitutes a small part of the average CDS spread level for low volatility firms of 69 to 84 bps across maturities.

In contrast, the effect of accounting transparency is large for the high leverage and high volatility groups. For the high leverage group the term structure of transparency spreads is highly significant and estimated at 29, 34, 23, 22 and 14 bps across maturities. For the high volatility group it is estimated at 33, 26, 14, 12 and 7 bps. The transparency spread is highly significant in the short end but insignificant at longer maturities.

Finally, for firms with both a high leverage and a high volatility, the term structure of transparency spreads is very steep and estimated at 51, 40, 23, 22 and 15 bps. Again, the transparency spread is highly significant in the short end while weakly significant at the longest maturity. Compared to an average spread of 180 to 220 bps across maturities in both groups, the transparency spread constitutes a relatively larger component of the CDS spread level for risky firms. Unreported results on full curves support these insights.

[18] As noted in Table 1.3, the correlation between the transparency measure and leverage and volatility, respectively, is -0.16 and -0.08. As an extreme example, all firms with below median leverage or volatility could have above median accounting transparency. In such a case, the regression would not be able to identify a relation between transparency and CDS spreads. However, the summary statistics on accounting transparency for each high and low leverage or volatility group are not far from those reported in Table 1.1.

Table 1.6: Estimation of the Term Structure of Transparency Spreads for High and Low Risk Firms

This table reports the results of monthly cross-sectional regressions when estimating the gap between high and low transparency CDS spread curves. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). d is a dummy variable equal to 1 if the transparency measure developed in Berger, Chen & Li (2006) and calculated in section 1.3 in a given year ranks above the median score. m_T is a dummy that attains a value of 1 if the CDS maturity equals T. The regression coefficient in front of the product dm_T can be directly interpreted as the transparency spread. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. Full curves are a restricted set of curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The monthly regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \varepsilon_{itT}$. Each month, the firms are separated into high and low leverage and volatility groups by the respective medians. The regression is then performed for each group. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	(1) High Lev.	(2) Low Lev.	(3) High Vol.	(4) Low Vol.	(5) High-High	(6) Low-Low
m_1-m_{10}	supp.	supp.	supp.	supp.	supp.	supp.
dm_1	-28.52***	-13.31*	-33.45***	-2.91	-50.91***	-9.32***
	(-3.38)	(-1.96)	(-3.11)	(-1.21)	(-3.88)	(-2.81)
dm_3	-34.21***	-2.01	-25.56***	-7.57***	-40.21***	-5.95***
	(-5.90)	(-1.26)	(-4.24)	(-4.38)	(-4.02)	(-3.30)
dm_5	-22.69***	-1.44	-14.06***	-7.07***	-23.05***	-4.71**
	(-5.64)	(-0.78)	(-2.77)	(-3.92)	(-2.97)	(-2.69)
dm_7	-21.51***	-3.75*	-11.70*	-5.15***	-22.35**	-5.72***
	(-4.29)	(-1.98)	(-1.85)	(-4.10)	(-2.52)	(-3.13)
dm_{10}	-14.44***	-5.97**	-7.22	-5.47***	-14.61*	-6.18***
	(-3.22)	(-2.40)	(-1.32)	(-3.73)	(-1.73)	(-2.88)
Volatility	979.19***	338.10***	1045.61***	242.07***	1150.61***	200.79***
	(14.08)	(11.95)	(12.61)	(8.72)	(10.75)	(12.86)
Leverage	473.62***	171.83***	423.95***	122.31***	582.42***	109.80***
	(8.15)	(11.15)	(11.78)	(10.64)	(7.98)	(13.54)
Qdisp	-78.90	-177.14***	-22.81	-235.41***	11.49	-145.59***
	(-1.47)	(-7.29)	(-0.47)	(-12.22)	(0.18)	(-9.34)

To summarize at this point, we find a highly significant downward-sloping term structure of transparency spreads. Furthermore, the effect of accounting transparency on the term structure of CDS spreads is largest for the most risky firms. We now show that the term structure of transparency spreads remains downward-sloping under alternative econometric specifications. Furthermore, while highly significant in the short end, it is often insignificant at maturities exceeding 5 years. Hence, the findings are strongly supportive of hypotheses H2 and H3 from Duffie & Lando (2001). The findings only weakly support the overall level effect due to discretionary disclosure in hypothesis H1

1.7 Robustness Analysis

This section conducts various robustness tests, e.g. controlling for a residual dependence across a given credit curve. In a final specification, we allow the control variables to impact CDS spreads differently across maturities, which is possible since the CDS data consists of equal maturities across firms and time. This exercise is based on the raw transparency measure and a rank transformation.

1.7.1 Alternative Econometric Specifications

Table 1.7 presents the results of estimating the gap between the high and low transparency credit curves under different econometric specifications. The benchmark regression (1) is a pooled OLS regression with White standard errors. As standard errors in the remaining regressions are robust to heteroscedasticity, differences in standard errors across columns (1) to (8) are due to within cluster correlations - including the Fama & MacBeth (1973) standard errors in (7) and (8).[19]

Clustered standard errors (also called Rogers standard errors) account for a residual dependence created by a firm effect, time effect or similar. The correlation can be of any form as no parametric structure is assumed. Regression (2) controls for a possible correlation in residuals across maturities for a given firm and month, by allowing for within cluster correlation at the curve level. The clustered standard errors in regression (3) control for a possible time effect, where the residuals of a given month may be correlated across different firms and maturities.

[19] See the survey of panel data methods used in finance by Petersen (2007).

Regression (4) to (6) extend these specifications and control for a constant time effect. We do that by addressing the latter parametrically using monthly dummies. Clustering by month while including monthly dummies allows one to separate the time effect into a constant and non-constant part. A non-constant time effect is present, if a shock in a given month has a different effect on different firms.

The cross-sectional Fama & MacBeth (1973) regression from Table 1.5 is repeated in regression (7). This regression also accounts for a cross-correlation in residuals stemming from a time effect, and it assumes that the monthly coefficient estimates are independent of each other. However, when estimating the standard error of their mean the annual accounting transparency measure may imply a serial correlation in the monthly coefficient estimates. We adopt the method in Abarbanell & Bernard (2000) and present the adjusted standard errors in regression (8). This adjustment is designed to correct for a firm effect arising from persistent firm characteristics.[20][21]

The conclusion from Table 1.7 Panel A is that the transparency spread is very robust in the short end and estimated around 20 bps at the 1-year maturity. At longer maturities the transparency spread narrows and is estimated around 14, 8, 7 and 5 bps at the 3, 5, 7 and 10-year maturity, respectively. While highly significant in the short end across all specifications, the transparency spread is most often insignificant after the 7-year maturity. The same conclusion results from Panel B, where the different econometric specifications are applied on full curves[22].

[20] To be conservative, the adjustment is not applied when the estimated serial correlation is less than zero.

[21] We do not report standard errors after clustering at the firm level or introducing firm dummies for a number of reasons. First, the short time-series implies that we only have 1 year of data for a significant number of firms (as noted in Table 1.1 the data consists of 368 firms and 890 firm-years in 2002 to 2004). This makes an identification of a firm effect separate from accounting transparency impossible. Second, as shown in Petersen (2007) the bias from a firm effect is increasing in the number of periods. Third, the inclusion of firm fixed effects would force an identification of the transparency spread from time-series changes in accounting transparency, which is unreasonable.

[22] Other unreported specifications such as purely cross-sectional regressions and annual cross-sectional regressions based on the time-series average CDS spreads and control variables support these findings.

Table 1.7: The Term Structure of Transparency Spreads Under Various Econometric Specifications

This table estimates the gap between the high and low transparency CDS curves under various econometric specifications. (1) is a pooled OLS regression with White errors, while (2) and (3) control for residual dependence by estimating cluster-robust errors by curves and time, respectively. Regression (4) to (6) extend (1) to (3) by including monthly dummies. The Fama & MacBeth estimates are reported in (7), and Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000) are reported in (8). T-statistics are reported in parantheses. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \varepsilon_{itT}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

Panel A. Unrestricted curves

	(1) White	(2) Cluster	(3) Cluster	(4) White	(5) Cluster	(6) Cluster	(7) F-M	(8) Adj. F-M
m_1-m_{10}	supp.	supp.	supp.	supp.	supp.	supp.	supp.	supp.
dm_1	-20.08***	-20.08***	-20.08***	-17.12***	-17.12***	-17.12***	-22.66***	-22.66***
	(-3.43)	(-3.50)	(-3.29)	(-3.03)	(-3.11)	(-2.84)	(-4.22)	(-2.89)
dm_3	-14.44***	-14.44***	-14.44***	-13.93***	-13.93***	-13.93***	-20.04***	-20.04***
	(-3.68)	(-3.89)	(-3.57)	(-3.68)	(-3.92)	(-3.53)	(-6.58)	(-3.66)
dm_5	-9.05***	-9.05***	-9.05***	-7.66**	-7.66***	-7.66**	-13.15***	-13.15**
	(-2.83)	(-2.95)	(-2.85)	(-2.49)	(-2.64)	(-2.47)	(-5.56)	(-2.14)
dm_7	-8.49**	-8.49***	-8.49***	-7.47**	-7.47**	-7.47**	-12.88***	-12.88***
	(-2.49)	(-2.59)	(-2.94)	(-2.29)	(-2.39)	(-2.65)	(-5.98)	(-4.37)
dm_{10}	-6.34*	-6.34*	-6.34**	-3.53	-3.53	-3.53	-10.94***	-10.94***
	(-1.90)	(-1.91)	(-2.21)	(-1.10)	(-1.15)	(-1.29)	(-5.26)	(-3.81)
Volatility	686.82***	686.82***	686.82***	767.05***	767.05***	767.05***	805.44***	805.44***
	(34.28)	(20.99)	(10.49)	(28.69)	(18.58)	(10.52)	(16.50)	(5.24)
Leverage	355.97***	355.97***	355.97***	349.27***	349.27***	349.27***	317.20***	317.20***
	(54.58)	(29.19)	(12.65)	(53.41)	(29.20)	(12.98)	(12.98)	(3.37)
Qdisp	-63.04***	-63.04**	-63.04	12.11	12.11	12.11	-33.37	-33.37
	(-2.76)	(-2.01)	(-1.31)	(0.50)	(0.36)	(0.25)	(-1.07)	(-0.60)
Cluster	-	Curve	Month	-	Curve	Month	-	-
Dummy	-	-	-	Month	Month	Month	-	-

Table 1.7: The Term Structure of Transparency Spreads Under Various Econometric Specifications (cont.)

This table estimates the gap between the high and low transparency CDS curves under various econometric specifications. (1) is a pooled OLS regression with White errors, while (2) and (3) control for residual dependence by estimating cluster-robust errors by curves and time, respectively. Regression (4) to (6) extend (1) to (3) by including monthly dummies. The Fama & MacBeth estimates are reported in (7), and Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000) are reported in (8). T-statistics are reported in parantheses. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \varepsilon_{itT}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

Panel B. Full curves								
	(1) White	(2) Cluster	(3) Cluster	(4) White	(5) Cluster	(6) Cluster	(7) F-M	(8) Adj. F-M
m_1-m_{10}	supp.	supp.	supp.	supp.	supp.	supp.	supp.	supp.
dm_1	-21.35***	-21.35***	-21.35***	-19.33***	-19.33***	-19.33***	-23.56***	-23.56***
	(-3.43)	(-3.53)	(-4.13)	(-3.27)	(-3.39)	(-3.86)	(-3.91)	(-2.91)
dm_3	-16.54***	-16.54***	-16.54***	-14.48***	-14.48***	-14.48***	-20.52***	-20.52**
	(-3.01)	(-3.12)	(-3.33)	(-2.79	(-2.92)	(-2.98)	(-3.57)	(-2.59)
dm_5	-13.75***	-13.75***	-13.75***	-11.71**	-11.71***	-11.71***	-17.61***	-17.61**
	(-2.75)	(-2.86)	(-3.24)	(-2.50)	(-2.62)	(-2.84)	(-3.11)	(-2.47)
dm_7	-10.99**	-10.99**	-10.99**	-9.02**	-9.02**	-9.02**	-14.67**	-14.67**
	(-2.30)	(-2.39)	(-2.75)	(-2.00)	(-2.10)	(-2.33)	(-2.71)	(-2.24)
dm_{10}	-9.07**	-9.07**	-9.07**	-5.01*	-5.01*	-5.01*	-13.08**	-13.08**
	(-2.03)	(-2.09)	(-2.26)	(-1.66)	(-1.73)	(-1.78)	(-2.47)	(-2.06)
Volatility	712.37***	712.37***	712.37***	793.03***	793.03***	793.03***	873.06***	873.06***
	(38.52)	(18.72)	(8.83)	(37.96)	(18.68)	(9.40)	(12.92)	(5.94)
Leverage	368.84***	368.84***	368.84***	359.81***	359.81***	359.81***	315.71***	315.71***
	(47.12)	(21.59)	(12.65)	(47.46)	(21.77)	(12.80)	(11.80)	(5.71)
Qdisp	-93.68***	-93.68*	-93.68	-29.26	-29.26	-29.26	-122.68**	-122.68*
	(-2.68)	(-1.81)	(-1.17)	(-0.85)	(-0.59)	(-0.45)	(-2.37)	(-1.80)
Cluster	-	Curve	Month	-	Curve	Month	-	-
Dummy	-	-	-	Month	Month	Month	-	-

Table 1.8 repeats the specifications in Table 1.7, but includes the senior unsecured credit rating from Standard & Poor's as an additional control variable in equation (1.5). As noted in Sengupta (1998) and Yu (2005), credit agencies claim to have incorporated the quality of information disclosure in the credit ratings. The results show that credit ratings do not absorb the effect of accounting transparency on the term structure of credit spreads. After accounting for the information content in credit ratings, the transparency spread continues to be highly significant at the 1-year maturity and downward-sloping. However, now the gap between the high and low transparency credit curves is insignificant after the 5-year maturity. As expected, the credit rating is highly significant and a one notch increase in rating lowers the CDS spread by approximately 50 bps. Unreported results based on full curves support these findings.

Consistent with empirical findings in Duffee (1998), structural models such as Longstaff & Schwartz (1995) predict an inverse relationship between the risk-free rate and credit spreads. An increase in the risk-free rate increases the risk-neutral drift of the asset value process and reduces the risk-neutral default probability. If an increase in the slope of the risk-free yield curve increases the expected future short rate, then by the same argument as above it implies a decrease in credit spreads. From a different perspective, as noted in Collin-Dufresne et al. (2001), a decrease in the slope of the risk-free yield curve may imply a weakening economy with decreasing expected recovery rates and higher default rates. Once again, a negative relationship between the slope of the risk-free yield curve and credit spreads is expected. The risk-free term structure variables are constant across all firms in a given month. Hence, they cannot be included in the empirical specifications from Table 1.7 based on Fama & MacBeth (1973) or when including monthly dummies. Table 1.9 presents the results from including the slope of the yield curve in addition to credit ratings in equation (1.5). The slope is defined as the difference between the 10 and 1-year constant maturity treasury yields.[23] The slope of the risk-free yield curve is highly significant and estimated with a negative coefficient. However, the transparency spread continues to be highly significant in the short end, downward-sloping and insignificant after the 5-year maturity.

[23] The level of the risk-free yield curve is discussed in section 1.7.2, where individual maturity classes are studied.

Table 1.8: The Term Structure of Transparency Spreads and Credit Ratings

This table estimates the gap between the high and low transparency CDS curves under various econometric specifications. (1) is a pooled OLS regression with White errors, while (2) and (3) control for residual dependence by estimating cluster-robust errors by curves and time, respectively. Regression (4) to (6) extend (1) to (3) by including monthly dummies. The Fama & MacBeth estimates are reported in (7), and Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000) are reported in (8). T-statistics are reported in parantheses. The senior unsecured credit ratings from S&P are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \beta_{14} Rating_{it} + \varepsilon_{itT}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	(1) White	(2) Cluster	(3) Cluster	(4) White	(5) Cluster	(6) Cluster	(7) F-M	(8) Adj. F-M
m_1-m_{10}	supp.	supp.	supp.	supp.	supp.	supp.	supp.	supp.
dm_1	-15.93***	-15.93***	-15.93***	-14.28***	-14.28***	-14.28**	-18.90***	-18.90***
	(-2.76)	(-2.81)	(-2.89)	(-2.66)	(-2.62)	(-2.57)	(-3.52)	(-2.68)
dm_3	-11.76***	-11.76***	-11.76***	-11.83***	-11.83***	-11.83***	-17.23***	-17.23***
	(-3.07)	(-3.25)	(-3.24)	(-3.19)	(-3.41)	(-3.33)	(-6.18)	(-3.52)
dm_5	-6.43**	-6.43**	-6.43**	-5.69*	-5.69**	-5.69**	-10.16***	-10.16**
	(-2.09)	(-2.17)	(-2.45)	(-1.92)	(-2.02)	(-2.16)	(-5.17)	(-2.26)
dm_7	-4.77	-4.77	-4.77**	-4.48	-4.48	-4.48*	-8.87***	-8.87***
	(-1.45)	(-1.50)	(-2.10)	(-1.42)	(-1.48)	(-1.99)	(-4.88)	(-4.20)
dm_{10}	-3.02	-3.02	-3.02	-1.51	-1.51	-1.51	-7.45***	-7.45***
	(-0.94)	(-0.98)	(-1.30)	(-0.49)	(-0.51)	(-0.65)	(-3.80)	(-2.81)
Volatility	639.80***	639.80***	639.80***	694.29***	694.29***	694.29***	702.68***	702.68***
	(32.33)	(19.44)	(9.38)	(26.06)	(16.55)	(9.14)	(13.65)	(4.05)
Leverage	263.48***	263.48***	263.48***	262.34***	262.34***	262.34***	228.60***	228.60***
	(43.04)	(21.85)	(10.26)	(44.96)	(22.70)	(11.21)	(11.67)	(3.47)
Qdisp	74.71***	74.71**	74.71*	126.28***	126.28***	126.28***	72.30**	72.30
	(3.30)	(2.45)	(1.83)	(5.38)	(4.01)	(3.04)	(2.73)	(1.55)
Rating	-49.70***	-49.70***	-49.70***	-46.62***	-46.62***	-46.62***	-48.73***	-48.73***
	(-37.41)	(-20.70)	(-15.14)	(-27.60)	(-16.66)	(-12.73)	(-17.54)	(-5.96)
Cluster	-	Curve	Month	-	Curve	Month	-	-
Dummy	-	-	-	Month	Month	Month	-	-

Table 1.9: The Term Structure of Transparency Spreads and the Yield Curve

This table estimates the gap between the high and low transparency CDS curves under various econometric specifications. (1) is a pooled OLS regression with White errors, while (2) and (3) control for residual dependence by estimating cluster-robust errors by curves and time, respectively. T-statistics are reported in parantheses. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The slope of the yield curve is the difference between the 10 and 1-year constant maturity treasury rates. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The regressions are $Spread_{itT} = \beta_1 m_{1it} + \beta_2 m_{3it} + \beta_3 m_{5it} + \beta_4 m_{7it} + \beta_5 m_{10it} + \beta_6 dm_{1it} + \beta_7 dm_{3it} + \beta_8 dm_{5it} + \beta_9 dm_{7it} + \beta_{10} dm_{10it} + \beta_{11} Vol_{it} + \beta_{12} Lev_{it} + \beta_{13} Qdisp_{itT} + \beta_{14} Rating_{it} + \beta_{15} Slope_t + \varepsilon_{itT}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. Unrestricted curves			Panel B. Full curves		
	(1)	(2)	(3)	(1)	(2)	(3)
	White	Cluster	Cluster	White	Cluster	Cluster
m_1-m_{10}	supp.	supp.	supp.	supp.	supp.	supp.
dm_1	-15.48***	-15.48***	-15.48***	-13.93**	-13.93**	-13.93***
	(-2.70)	(-2.75)	(-2.77)	(-2.30)	(-2.35)	(-3.16)
dm_3	-11.60***	-11.60***	-11.60***	-9.02*	-9.02*	-9.02**
	(-3.05)	(-3.23)	(-3.20)	(-1.72)	(-1.78)	(-2.13)
dm_5	-6.27**	-6.27**	-6.27**	-6.22	-6.22	-6.22*
	(-2.05)	(-2.14)	(-2.37)	(-1.33)	(-1.38)	(-1.72)
dm_7	-4.68	-4.68	-4.68**	-3.76	-3.76	-3.76
	(-1.43)	(-1.49)	(-2.05)	(-0.84)	(-0.87)	(-1.10)
dm_{10}	-2.89	-2.89	-2.89	-1.50	-1.50	-1.50
	(-0.91)	(-0.95)	(-1.23)	(-0.36)	(-0.37)	(-0.42)
Volatility	649.90***	649.90***	649.90***	682.60***	682.60***	682.60***
	(32.52)	(19.57)	(9.56)	(35.31)	(17.12)	(7.99)
Leverage	263.51***	263.51***	263.51***	270.80***	270.80***	270.80***
	(43.31)	(22.04)	(10.83)	(34.71)	(15.91)	(10.58)
Qdisp	94.90***	94.90***	94.90**	75.96**	75.96	75.96
	(4.18)	(3.09)	(2.29)	(2.25)	(1.54)	(1.13)
Rating	-49.38***	-49.38***	-49.38***	-57.97***	-57.97***	-57.97***
	(-37.37)	(-20.74)	(-13.66)	(-35.79)	(-16.72)	(-13.58)
Slope	-0.51***	-0.51***	-0.51***	-0.65***	-0.65***	-0.65***
	(-22.26)	(-11.09)	(-3.19)	(-18.99)	(-8.89)	(-2.82)
Cluster	-	Curve	Month	-	Curve	Month
Dummy	-	-	-	-	-	-

1.7.2 Individual Maturity Classes

When included in equation (1.5), the control variables are only allowed to induce a parallel shift in the term structure of CDS spreads. As a final exercise, we allow the control variables to impact CDS spreads differently across maturities. For that purpose, we analyze each maturity class in isolation using the raw transparency measure calculated in equation (1.4) and a rank transformation. This is possible since the data consists of CDS spreads with equal and fixed maturities.

For each maturity class T, Table 1.10 Panel A presents the results of monthly cross-sectional regressions of CDS spreads on the transparency measure, volatility, leverage and relative quote dispersion

$$Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \varepsilon_{it}. \quad (1.6)$$

The coefficient estimates are averaged in the time-series and standard errors are calculated following Fama & MacBeth (1973). The average adjusted R^2 ranges from 0.58 to 0.60 and accounting transparency is significant or highly significant at all maturities. From a coefficient of -13.45 at the 1-year maturity, the coefficient on accounting transparency decreases to -6.75 and -6.68 at the 3 and 5-year maturity, respectively. After this point a u-shape kicks in with coefficients of -8.49 and -9.56 at the 7 and 10-year maturity, respectively. The variation in accounting transparency in each maturity class is similar to the variation reported in Table 1.1 for the entire sample. Hence, a one standard deviation increase in transparency reduces the spread by approximately 8, 4, 4, 5 and 6 bps across the curve.

Table 1.10 Panel B contains the regression results for the restricted set of full curves with observations at all maturities at month-end for a given firm. The resulting coefficients on accounting transparency are all highly significant and larger at -22.28, -21.32, -19.75, -12.15 and -17.90 at maturities of 1, 3, 5, 7 and 10 years, respectively. A one standard deviation increase in transparency reduces the spread by approximately 14, 13, 12, 7 and 11 bps across the curve, and main insights from the unrestricted curves in Panel A are preserved. Under alternative econometric specifications and a broader set of control variables, the impact of accounting transparency is later shown to strictly decrease with maturity.

Table 1.10: Fama & MacBeth Regressions on Isolated Maturity Classes

This table reports the results of monthly cross-sectional regressions when analyzing each maturity class in isolation. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The monthly regressions for each maturity class are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. Unrestricted curves									
	1-year maturity		3-year maturity		5-year maturity		7-year maturity		10-year maturity	
Intercept	-317.92***	-368.62***	-329.58***	-333.73***	-328.56***	-299.57***	-263.25***	-271.89***	-232.29***	-254.03***
	(-8.17)	(-10.24)	(-10.31)	(-12.47)	(-14.79)	(-15.71)	(-10.07)	(-12.80)	(-11.48)	(-14.72)
Transp	-13.45**	-10.92**	-6.75***	-6.92***	-6.68***	-6.57***	-8.49***	-8.62***	-9.56***	-9.51***
	(-2.58)	(-2.56)	(-2.86)	(-3.01)	(-4.01)	(-3.75)	(-4.27)	(-4.57)	(-4.20)	(-4.23)
Volatility	928.25***	941.46***	860.30***	861.16***	802.93***	802.58***	744.61***	749.34***	717.25***	716.69***
	(11.94)	(12.07)	(15.95)	(16.06)	(19.82)	(19.66)	(16.79)	(16.95)	(17.55)	(17.52)
Leverage	325.54***	331.19***	334.08***	335.64***	335.77***	325.38***	292.83***	296.24***	293.93***	298.19***
	(11.17)	(11.45)	(11.55)	(11.94)	(14.92)	(14.66)	(11.97)	(12.56)	(14.64)	(14.89)
Qdisp	-350.11***		-24.15		265.73***		-60.51		-172.06***	
	(-5.37)		(-0.43)		(5.08)		(-0.94)		(-3.29)	
Adj. R^2	0.59	0.58	0.59	0.59	0.60	0.60	0.59	0.59	0.60	0.60

Table 1.10: Fama & MacBeth Regressions on Isolated Maturity Classes (cont.)

This table reports the results of monthly cross-sectional regressions when analyzing each maturity class in isolation. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The monthly regressions for each maturity class are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel B. Full curves									
	1-year maturity		3-year maturity		5-year maturity		7-year maturity		10-year maturity	
Intercept	-311.87***	-382.08***	-347.54***	-358.88***	-373.66***	-331.24***	-293.47***	-308.58***	-257.89***	-285.08***
	(-7.83)	(-10.23)	(-10.20)	(-12.84)	(-14.03)	(-14.16)	(-11.71)	(-14.18)	(-10.63)	(-14.56)
Transp	-22.28***	-23.23***	-21.32***	-20.80***	-19.75***	-18.82***	-12.15**	-12.16***	-17.90***	-17.85***
	(-3.66)	(-4.15)	(-3.66)	(-3.81)	(-4.97)	(-3.72)	(-2.08)	(-3.71)	(-3.75)	(-3.78)
Volatility	956.21***	968.14***	907.03***	930.93***	872.92***	874.33***	812.82***	830.24***	790.30***	792.69***
	(11.28)	(11.44)	(13.14)	(13.18)	(13.33)	(13.63)	(12.31)	(13.26)	(13.32)	(13.37)
Leverage	310.69***	321.69***	337.53***	331.23***	340.91***	328.65***	320.43***	321.37***	302.95***	309.63***
	(9.31)	(9.85)	(11.19)	(11.74)	(12.97)	(13.00)	(13.96)	(13.53)	(13.85)	(14.47)
Qdisp	-468.32***		-66.81		452.42***		-126.51		-198.98***	
	(-7.63)		(-0.56)		(3.75)		(-1.10)		(-3.33)	
Adj. R^2	0.62	0.61	0.63	0.63	0.64	0.64	0.63	0.63	0.64	0.64

A concern is that the accounting transparency measure is a noisy estimate of "true" accounting transparency, where an interpretation of the distance between two scores in a cardinal manner is unreasonable. Hence, we transform the annual accounting transparency measure to evenly spaced observations on the unit interval [0,1], and only interpret the annual ranking ordinally. A transformed score of 1(0) in a given year is assigned to the firm with highest(lowest) transparency.

Table 1.11 Panel A presents highly significant coefficient estimates of -36.69, -27.73, -20.11, -26.93 and -26.89 across the curve. If a firm is able to improve its accounting transparency from the lowest to a median ranking, say, the result is a reduction in CDS spreads of 18, 14, 10, 13 and 13 bps at maturities of 1, 3, 5, 7 and 10 years, respectively. A similar conclusion is reached from full curves in Panel B.

Table 1.12 analyzes the impact of accounting transparency for high and low risk firms using the annual transparency ranks. Consistent with the results in the previous section, the effect of accounting transparency is small and most often insignificant when based on firms with a low leverage and a low volatility in Panel B. However, for the most risky firms with a high leverage and a high volatility in Panel A, the coefficient estimates are -99.02, -83.78, -68.09, -70.84 and -66.29 and highly significant. Hence, if a risky firm is able to improve its accounting transparency from the lowest to a median ranking, say, the result is a reduction in CDS spreads of 50, 42, 34, 35 and 33 bps at maturities of 1, 3, 5, 7 and 10 years, respectively.

Note the large R^2 of 0.59 to 0.63 for the risky firms and the much smaller R^2 of 0.14 to 0.20 for the firms with low leverage and low volatility. This observation is supportive of the problems in earlier studies when explaining the credit spreads of low-yield firms using structural models. This paper suggests that variables other than accounting transparency are needed - also in the short end.

Table 1.11: Fama & MacBeth Regressions on Isolated Maturity Classes Based on Transparency Rankings
This table reports the results of monthly cross-sectional regressions when analyzing each maturity class in isolation. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. A transformed score of 1(0) in a given year is assigned to the firm with highest(lowest) transparency. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. Panel A displays the results for unrestricted curves, while Panel B displays results for full curves with an observation at a maturity of 1, 3, 5, 7 and 10 years. The monthly regressions for each maturity class are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. Unrestricted curves					Panel B. Full curves				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	-302.23***	-316.63***	-320.59***	-252.54***	-221.81***	-295.67***	-333.10***	-360.83***	-283.41***	-246.09***
	(-7.91)	(-10.02)	(-14.41)	(-9.85)	(-11.04)	(-7.55)	(-9.65)	(-13.41)	(-11.37)	(-10.23)
Transp	-36.69***	-27.73***	-20.11***	-26.93***	-26.89***	-39.91***	-37.48***	-33.06***	-25.87***	-31.33***
	(-4.33)	(-6.60)	(-9.14)	(-7.15)	(-6.74)	(-3.85)	(-4.89)	(-6.43)	(-3.23)	(-4.13)
Volatility	928.39***	858.59***	802.09***	743.96***	715.29***	947.32***	902.76***	869.96***	810.88***	786.03***
	(11.87)	(15.90)	(19.74)	(16.80)	(17.54)	(11.27)	(13.11)	(13.27)	(12.41)	(13.26)
Leverage	317.56***	331.05***	334.49***	290.78***	292.83***	308.24***	333.69***	337.15***	317.24***	300.85***
	(10.70)	(11.35)	(14.74)	(11.79)	(14.72)	(9.22)	(11.04)	(12.58)	(13.79)	(13.78)
Qdisp	-346.94***	-27.19	263.40***	-62.00	-176.22***	-483.29***	-79.69	425.67***	-132.83	-212.79***
	(-5.53)	(-0.49)	(5.01)	(-0.96)	(-3.33)	(-8.02)	(-0.68)	(3.50)	(-1.17)	(-3.56)
Adj. R^2	0.59	0.59	0.61	0.59	0.60	0.63	0.64	0.64	0.64	0.64

Table 1.12: Isolated Maturity Classes and High and Low Risk Firms

This table reports the results of monthly cross-sectional regressions when analyzing each maturity class in isolation. The coefficient estimates are averaged in the time-series. T-statistics are reported in parentheses and are based on the standard error in Fama & MacBeth (1973). The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. A transformed score of 1(0) in a given year is assigned to the firm with highest(lowest) transparency. The volatility is calculated using 250 days of historical equity returns, and leverage is total liabilities divided by the sum of total liabilities and equity market capitalization. Quote dispersion is the standard deviation of collected quotes divided by the consensus quote. The monthly regressions for each maturity class are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \varepsilon_{it}$. Each month, the firms are separated into high and low leverage and volatility groups by the respective medians. Pabel A displays the results when running the regression on firms with both a high leverage and a high volatility, while Panel B is for firms with low leverage and low volatility. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. High leverage, high volatility					Panel B. Low leverage, low volatility				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	-579.49***	-643.09***	-563.56***	-546.239***	-469.89***	-22.81	-12.14	-22.77***	-13.20**	-7.49
	(-6.70)	(-9.98)	(-14.30)	(-9.78)	(-12.93)	(-1.64)	(-1.12)	(-2.94)	(-2.36)	(-0.7)
Transp	-99.02***	-83.78***	-68.09***	-70.84***	-66.29***	-2.72	-7.05**	-3.60	-6.57***	-11.62*
	(-3.55)	(-5.60)	(-8.06)	(-5.61)	(-5.37)	(-0.39)	(-2.29)	(-1.28)	(-3.18)	(-1.81)
Volatility	1193.6***	1210.0***	1123.5***	1028.4***	1027.6***	129.47**	178.10***	206.55***	211.15***	207.01***
	(10.47)	(10.38)	(10.73)	(10.13)	(9.91)	(2.33)	(7.97)	(12.58)	(11.54)	(5.72)
Leverage	625.08***	622.28***	548.87***	588.45***	507.47***	160.80***	105.85***	91.88***	99.34***	127.57***
	(6.76)	(6.85)	(8.14)	(8.23)	(7.85)	(5.80)	(10.36)	(10.89)	(10.30)	(10.33)
Qdisp	-593.92***	133.95	298.77**	8.946	-73.94	-186.42***	-170.67***	-135.06***	-187.27***	-189.97***
	(-4.00)	(0.81)	(2.72)	(0.06)	(-0.54)	(-2.91)	(-4.10)	(-4.83)	(-6.65)	(-7.58)
Adj. R^2	0.62	0.62	0.63	0.60	0.59	0.16	0.14	0.16	0.20	0.18

Finally, we allow the broader set of control variables to impact spreads differently across the curve under the alternative econometric specifications introduced earlier.[24] The conclusion is a downward-sloping impact of accounting transparency across maturities that is highly robust in the short end. Across all specifications, a move from the lowest to a median transparency ranking, say, reduces the 1-year spread by approximately 15 bps.

In particular, Table 1.13 presents the results from including the credit rating as a control variable. In the cross-sectional regressions in Panel A and B, the coefficients on accounting transparency are insignificant or only weakly significant after the 5-year maturity. The remaining specifications in Panel C to F support a highly significant effect of accounting transparency at the 1-year maturity and a declining coefficient with varying significance at longer maturities. The credit rating is highly significant in all specifications, and R^2 increases to 0.68 compared to an R^2 around 0.60 without credit ratings in the Fama & MacBeth (1973) regressions in Table 1.10.

Table 1.14 presents the results from including the slope of the yield curve in addition to credit ratings.[25] As before, this variable can only be included in a subset of the empirical specifications. While estimated with a highly significant negative coefficient, the slope of the yield curve only increases R^2 marginally. Accounting transparency continues to be highly significant in the short end, and the impact continues to decline as maturity increases.

[24] As each maturity class is analyzed in isolation, the various econometric specifications do not include standard errors robust to within cluster correlation at the curve level.

[25] Including the maturity-matched constant maturity treasury yield in addition to the slope implies that both are estimated insignificantly. However, coefficients and significance of the transparency gap are unchanged.

Table 1.13: Isolated Maturity Classes and Alternative Econometric Specifications

This table analyzes each maturity class in isolation using various econometric specifications. Panel A reports the Fama & MacBeth estimates, and Panel B reports the Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000). Panel C is a pooled OLS regression with White standard errors, while Panel D reports standard errors clustered by month. Panel E and F display the White and cluster-robust errors, respectively, after including monthly dummy variables. T-statistics are reported in parantheses. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The monthly regressions are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \beta_5 Rating_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. F-M					Panel B. Adj. F-M				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	158.87***	175.80***	147.19***	200.43***	223.31***	158.87*	175.80**	147.19**	200.43***	223.31***
	(3.29)	(3.89)	(3.81)	(5.18)	(5.89)	(1.87)	(1.98)	(2.38)	(4.37)	(4.71)
Transp.	-24.90**	-21.37**	-17.64**	-12.09	-17.21*	-24.90**	-21.37*	-17.64*	-12.09	-17.21*
	(-2.40)	(-2.55)	(-2.59)	(-1.34)	(-1.84)	(-1.96)	(-1.72)	(-1.78)	(-1.21)	(-1.74)
Volatility	844.17***	782.40***	748.86***	693.37***	670.04***	844.17***	782.40***	748.86***	693.37***	670.04***
	(9.65)	(11.04)	(11.28)	(10.50)	(11.49)	(3.26)	(4.77)	(5.97)	(7.00)	(6.76)
Leverage	218.91***	234.16***	238.24***	225.07***	210.69***	218.91***	234.16***	238.24***	225.07***	210.69***
	(8.12)	(9.80)	(11.32)	(12.17)	(12.23)	(3.08)	(5.32)	(6.15)	(6.16)	(6.76)
Quote disp.	-350.50***	26.45	441.94***	-23.13	-108.91*	-350.50***	26.45	441.94***	-23.13	-108.91
	(-5.47)	(0.24)	(3.91)	(-0.23)	(-1.85)	(-4.79)	(0.30)	(3.13)	(-0.16)	(-1.41)
Rating	-55.62***	-60.91***	-59.30***	-57.69***	-56.27***	-55.62***	-60.91***	-59.30***	-57.69***	-56.27***
	(-9.94)	(-13.09)	(-13.78)	(-15.38)	(-14.13)	(-6.95)	(-7.75)	(-9.78)	(-11.99)	(-12.28)
Cluster	-	-	-	-	-	-	-	-	-	-
Dummy	-	-	-	-	-	-	-	-	-	-
Adj. R^2	0.67	0.68	0.69	0.68	0.68	0.67	0.68	0.69	0.68	0.68

Table 1.13: Isolated Maturity Classes and Alternative Econometric Specifications (cont.)

This table analyzes each maturity class in isolation using various econometric specifications. Panel A reports the Fama & MacBeth estimates, and Panel B reports the Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000). Panel C is a pooled OLS regression with White standard errors, while Panel D reports standard errors clustered by month. Panel E and F display the White and cluster-robust errors, respectively, after including monthly dummy variables. T-statistics are reported in parantheses. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The monthly regressions are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \beta_5 Rating_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel C. White					Panel D. Cluster				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	86.50*	137.59***	181.35***	234.19***	253.11***	86.50	137.59**	181.35***	234.19***	253.11***
	(1.96)	(3.53)	(5.68)	(7.82)	(9.02)	(1.31)	(2.28)	(3.39)	(5.06)	(5.97)
Transp	-29.48***	-18.61**	-17.83**	-15.47**	-15.24**	-29.48***	-18.61***	-17.83***	-15.47***	-15.24***
	(-2.66)	(-1.97)	(-2.17)	(-1.99)	(-2.12)	(-3.68)	(-3.10)	(-3.66)	(-2.96)	(-3.19)
Volatility	834.54***	726.83***	620.53***	588.01***	558.21***	834.54***	726.83***	620.53***	588.01***	558.21***
	(14.56)	(17.19)	(17.38)	(17.02)	(17.65)	(7.18)	(8.17)	(8.29)	(8.32)	(8.67)
Leverage	280.18***	285.95***	287.00***	259.58***	243.71***	280.18***	285.95***	287.00***	259.58***	243.71***
	(13.54)	(14.76)	(16.62)	(16.05)	(16.85)	(8.21)	(9.54)	(10.54)	(10.66)	(11.18)
Qdisp	-167.77**	292.87***	627.25***	0.77	-165.96***	-167.77*	292.87**	627.25***	0.77	-165.96***
	(-1.99)	(2.89)	(7.75)	(0.01)	(-3.17)	(-1.95)	(2.31)	(4.17)	(0.01)	(-2.88)
Rating	-50.63***	-59.78***	-62.35***	-59.31***	-56.31***	-50.63***	-59.78***	-62.35***	-59.31***	-56.31***
	(-11.45)	(-15.46)	(-18.03)	(-17.23)	(-17.30)	(-9.30)	(-13.61)	(-16.68)	(-16.75)	(-15.91)
Cluster	-	-	-	-	-	Month	Month	Month	Month	Month
Dummy	-	-	-	-	-	-	-	-	-	-
Adj. R^2	0.58	0.61	0.62	0.62	0.64	0.58	0.62	0.62	0.62	0.64

Table 1.13: Isolated Maturity Classes and Alternative Econometric Specifications (cont.)

This table analyzes each maturity class in isolation using various econometric specifications. Panel A reports the Fama & MacBeth estimates, and Panel B reports the Fama & MacBeth standard errors adjusted for a dependence between the cross-sections by Abarbanell & Bernard (2000). Panel C is a pooled OLS regression with White standard errors, while Panel D reports standard errors clustered by month. Panel E and F display the White and cluster-robust errors, respectively, after including monthly dummy variables. T-statistics are reported in parantheses. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The monthly regressions are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \beta_5 Rating_{it} + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel E. White					Panel F. Cluster				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	74.66	132.02***	157.85***	223.21***	243.41***	74.66	132.02**	157.85***	223.21***	243.41***
	(1.61)	(3.25)	(4.63)	(7.04)	(8.28)	(1.15)	(2.41)	(3.75)	(5.54)	(6.67)
Transp	-21.27**	-11.34	-10.88	-8.98	-9.24	-21.27***	-11.34**	-10.88**	-8.98*	-9.24**
	(-2.27)	(-1.29)	(-1.43)	(-1.25)	(-1.39)	(-2.91)	(-2.01)	(-2.39)	(-1.88)	(-2.13)
Volatility	892.73***	776.95***	687.62***	636.69***	601.23***	892.73***	776.95***	687.62***	636.69***	601.23***
	(13.81)	(16.16)	(16.62)	(15.92)	(16.58)	(7.17)	(8.23)	(8.63)	(8.47)	(8.87)
Leverage	275.79***	279.90***	287.85***	259.36***	242.47***	275.79***	279.90***	287.85***	259.36***	242.47***
	(13.85)	(15.03)	(17.02)	(16.50)	(17.37)	(8.59)	(10.25)	(12.08)	(12.07)	(12.56)
Qdisp	-142.37*	269.74***	664.12***	87.32	-86.26*	-142.37*	269.74**	664.12***	87.32	-86.26
	(-1.75)	(2.77)	(7.88)	(1.24)	(-1.66)	(-1.84)	(2.34)	(5.27)	(1.10)	(-1.60)
Rating	-48.75***	-57.55***	-57.29***	-57.08***	-54.39***	-48.75***	-57.55***	-57.29***	-57.08***	-54.39***
	(-10.29)	(-14.11)	(-16.06)	(-16.43)	(-16.54)	(-8.67)	(-12.89)	(-16.10)	(-17.14)	(-17.75)
Cluster	-	-	-	-	-	Month	Month	Month	Month	Month
Dummy	Month	Month	Month	Month	Month	Month	Month	Month	Month	Month
Adj. R^2	0.64	0.65	0.67	0.66	0.67	0.64	0.65	0.67	0.66	0.67

Table 1.14: Isolated Maturity Classes and the Yield Curve

This table analyzes each maturity class in isolation using various econometric specifications. Panel A is a pooled OLS regression with White standard errors, while Panel B reports standard errors clustered by month. T-statistics are reported in parantheses. The accounting transparency measure is developed in Berger, Chen & Li (2006) and calculated in section 1.3. The transparency measure is subsequently transformed to evenly spaced observations on the unit interval [0,1]. The senior unsecured credit ratings from Standard & Poor's are transformed to a numerical scale, where firms rated AAA are assigned a score of 10, AA a score of 9 and so forth. The slope of the yield curve is the difference between the 10 and 1-year constant maturity treasury rates. The monthly regressions are $Spread_{it} = \beta_0 + \beta_1 Transp_{it} + \beta_2 Vol_{it} + \beta_3 Lev_{it} + \beta_4 Qdisp_{it} + \beta_5 Rating_{it} + \beta_6 Slope_t + \varepsilon_{it}$. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A. White					Panel B. Cluster				
	1-year	3-year	5-year	7-year	10-year	1-year	3-year	5-year	7-year	10-year
Intercept	263.28***	299.30***	341.79***	380.46***	389.46***	263.28***	299.30***	341.79***	380.46***	389.46***
	(6.53)	(8.15)	(11.35)	(13.44)	(14.48)	(4.26)	(5.95)	(9.16)	(10.22)	(10.95)
Transp	-28.14***	-17.33*	-16.63**	-14.43*	-14.23**	-28.14***	-17.33***	-16.63***	-14.43**	-14.23***
	(-2.61)	(-1.86)	(-2.06)	(-1.89)	(-2.02)	(-3.44)	(-2.81)	(-3.31)	(-2.69)	(-2.91)
Volatility	852.17***	742.92***	636.22***	601.25***	570.57***	852.17***	742.92***	636.22***	601.25***	570.57***
	(14.71)	(17.29)	(17.53)	(17.12)	(17.76)	(7.14)	(8.10)	(8.35)	(8.30)	(8.65)
Leverage	280.79***	285.22***	288.04***	261.68***	245.31***	280.79***	285.22***	288.04***	261.68***	245.31***
	(13.67)	(14.86)	(16.87)	(16.35)	(17.15)	(8.63)	(10.11)	(11.57)	(11.50)	(12.01)
Qdisp	-174.62**	248.43**	642.58***	60.29	-112.59**	-174.62**	248.43**	642.58***	60.29	-112.59*
	(-2.09)	(2.50)	(8.04)	(0.88)	(-2.16)	(-2.10)	(2.20)	(4.91)	(0.74)	(-1.94)
Rating	-49.99***	-59.01***	-61.86***	-59.34***	-56.33***	-49.99***	-59.01***	-61.86***	-59.34***	-56.33***
	(-11.39)	(-15.40)	(-18.16)	(-17.51)	(-17.58)	(-8.20)	(-12.13)	(-16.62)	(-16.66)	(-16.05)
Slope	-0.73***	-0.65***	-0.67***	-0.61***	-0.57***	-0.73**	-0.65**	-0.67***	-0.61***	-0.57***
	(-7.82)	(-8.25)	(-9.62)	(-9.13)	(-9.39)	(-2.47)	(-2.65)	(-3.18)	(-3.00)	(-3.07)
Cluster	-	-	-	-	-	Month	Month	Month	Month	Month
Dummy	-	-	-	-	-	-	-	-	-	-
Adj. R^2	0.59	0.62	0.65	0.63	0.65	0.59	0.63	0.65	0.63	0.65

1.8 Conclusion

Motivated by the theoretical contribution in Duffie & Lando (2001), this paper relates a newly developed empirical measure of accounting transparency by Berger et al. (2006) to the term structure of CDS spreads for a large cross-section of firms.

We find a highly significant effect of accounting transparency at the 1-year maturity, and a declining impact at longer maturities. Estimating the gap between the high and low transparency credit curves, the transparency spread is estimated around 20 bps at the 1-year maturity. At longer maturities, the transparency spread narrows and is estimated at 14, 8, 7 and 5 bps at the 3, 5, 7 and 10-year maturity, respectively. While highly significant in the short end and robust across alternative econometric specifications and control variables, the impact of accounting transparency is not robust and most often insignificant for maturities exceeding 5 years. Finally, the effect of accounting transparency on the term structure of CDS spreads is largest for the most risky firms.

Thus, the results are strongly supportive of hypotheses H2 and H3 derived from Duffie & Lando (2001), and add an explanation to the underprediction of short-term credit spreads by traditional structural credit risk models. Only weak evidence supports the presence of an overall level effect as suggested in hypothesis H1.

The results contrast an earlier study by Yu (2005), who analyzes corporate bond credit spreads using the AIMR analyst ranking of corporate disclosure in 1991 to 1996. He attributes a strongly u-shaped transparency spread with the largest effect at longer maturities to the theory of discretionary disclosure, where firms hide information that would adversely affect their long-term outlook.

Liquid CDS contracts are highly desirable when studying the determinants of the shape of the credit curve. As opposed to corporate bonds, this allows us to study multiple maturity observations for a given firm at a given day, and maturities are equal across firms and fixed through time. Furthermore, technical effects are known to impact the slope of the credit curve for corporate bonds trading off par. Hence, findings based on CDS spreads are likely to be more reliable than studies based on corporate bonds. Our study shows that the term structure of transparency spreads is downward-sloping in the CDS market across alternative econometric specifications.

A Duffie & Lando (2001)

The setup and results on optimal capital structure and default are close to Leland (1994) and Leland & Toft (1996). The firm's assets V are modeled as a geometric Brownian motion, which is defined on a fixed probability space $(\Omega, \mathcal{F}, Q)$. More specifically, $V(t) = \exp(Z(t))$ where

$$Z_t = Z_0 + mt + \sigma W_t, \tag{1.7}$$

for a standard Brownian motion W, a volatility parameter σ and a parameter m that determines the expected asset growth rate

$$\mu = \frac{\log[E\left(V_t/V_0\right)]}{t} = m + \sigma^2/2. \tag{1.8}$$

The firm generates cash flow at the rate δV_t at time t and issues debt to take advantage of the tax shields offered for interest expense at the tax rate θ. The debt is modeled as a consol bond with a constant coupon rate C. Hence, the tax benefits are θC until default, where $\alpha \in [0,1]$ of the asset value is lost as a frictional cost. All agents in the model are risk-neutral and discount cash flows at a constant market interest rate r.

The firm is operated by its equity owners, who are completely informed at all times on the value of the assets V and choose when to liquidate the firm.[26] The default time is chosen endogenously by the equity owners to maximize the value of equity, and is given as the first time $\tau(V_B) = \inf\{t : V_t \leq V_B\}$ the asset value falls to the default barrier

$$V_B\left(C\right) = \frac{\left(1-\theta\right)C\gamma\left(r-\mu\right)}{r(1+\gamma)\delta}, \tag{1.9}$$

where

$$\gamma = \frac{m + \sqrt{m^2 + 2r\sigma^2}}{\sigma^2}. \tag{1.10}$$

[26] This means that the equity owners have the information filtration $(\mathcal{F}_t)$ generated by V, where $\mathcal{F}_t$ is the σ-algebra generated by $\{V_s : 0 \leq s \leq t\}$.

The resulting equity value is

$$S(V,C)=\frac{\delta V}{r-\mu}-\frac{V_B\left(C\right)\delta}{r-\mu}\left(\frac{V}{V_B\left(C\right)}\right)^{-\gamma}+\left(\theta-1\right)\frac{C}{r}\left[1-\left(\frac{V}{V_B\left(C\right)}\right)^{-\gamma}\right], \tag{1.11}$$

while the value of the consol bond is

$$d\left(V,C\right)=\frac{\left(1-\alpha\right)V_B\left(C\right)\delta}{r-\mu}\left(\frac{V}{V_B\left(C\right)}\right)^{-\gamma}+\frac{C}{r}\left[1-\left(\frac{V}{V_B\left(C\right)}\right)^{-\gamma}\right]. \tag{1.12}$$

Finally, the optimal coupon is chosen such that the initial total value of the firm $S(V,C)+d\left(V,C\right)$ is maximized.

After issuance, bond and CDS investors are not kept fully informed on the status of the firm. They do understand that equity owners will force liquidation when the asset value falls to V_B, but they cannot observe the asset process V directly. Instead, they receive an accounting report at selected times $t_1, t_2..., t_i < t$ in terms of a noisy estimate of the asset value given by $\widehat{V}_t$, where $\log\widehat{V}_t$ and $\log V_t$ are joint normal. Specifically,

$$Y\left(t\right)=\log\widehat{V}_t=Z(t)+U\left(t\right), \tag{1.13}$$

where $U\left(t\right)$ is independent of $Z(t)$ and normally distributed with mean $\overline{u}=-\frac{a^2}{2}=E\left(U_t\right)$ and variance $a^2=Var(U_t)$. Hence, the standard deviation a of U_t measures the degree of accounting noise. Also observed at each t is whether the firm has defaulted or not. For simplicity, it is assumed that equity is not traded in the public market and equity owners are precluded from trading in the credit market.[27]

Based on the information available, it is possible for the investors to calculate the conditional distribution of assets V_t. With the simple case of having observed only a single noisy asset report at time $t=t_1$, the density $g\left(\cdot\mid Y_t,z_0,t\right)$ of Z_t can be computed conditional on the noisy observation Y_t, a lagged noise-free report z_0 and $\tau>t$. With $\widetilde{y}=y-\underline{v}-\overline{u}$, $\widetilde{x}=x-\underline{v}$ and $\widetilde{z}=z_0-\underline{v}$, where $\log(V_B)=\underline{v}$,

[27] Hence, the information filtration in the credit market is defined as $\mathcal{H}_t=\sigma\left(\left\{Y\left(t_1\right),....,Y\left(t_n\right),1_{\{\tau(V_B)\leq s\}}:0\leq s\leq t\right\}\right)$ for the largest n such that $t_n\leq t$.

the density is shown to be

$$g\left(x \mid y, z_0, t\right) = \frac{\sqrt{\frac{\beta_0}{\pi}} \exp\left(-J\left(\widetilde{y}, \widetilde{x}, \widetilde{z}_0\right)\right)\left[1 - \exp\left(\frac{-2\widetilde{x}\widetilde{z}_0}{\sigma^2 t}\right)\right]}{\exp\left(\frac{\beta_1^2}{4\beta_0} - \beta_3\right)\Phi\left(\frac{\beta_1}{\sqrt{2\beta_0}}\right) - \exp\left(\frac{\beta_2^2}{4\beta_0} - \beta_3\right)\Phi\left(-\frac{\beta_2}{\sqrt{2\beta_0}}\right)}, \tag{1.14}$$

where

$$J\left(\widetilde{y}, \widetilde{x}, \widetilde{z}_0\right) = \frac{\left(\widetilde{y} - \widetilde{x}\right)^2}{2a^2} + \frac{\left(\widetilde{z}_0 + mt - \widetilde{x}\right)^2}{2\sigma^2 t}, \tag{1.15}$$

$$\beta_0 = \frac{a^2 + \sigma^2 t}{2a^2\sigma^2 t}, \tag{1.16}$$

$$\beta_1 = \frac{\widetilde{y}}{a^2} + \frac{\widetilde{z}_0 + mt}{\sigma^2 t}, \tag{1.17}$$

$$\beta_2 = -\beta_1 + 2\frac{\widetilde{z}_0}{\sigma^2 t}, \tag{1.18}$$

$$\beta_3 = \frac{1}{2}\left(\frac{\widetilde{y}}{a^2} + \frac{\left(\widetilde{z}_0 + mt\right)^2}{\sigma^2 t}\right) \tag{1.19}$$

and Φ is the standard normal distribution function. Conditional on survival up to time t, this density gives us the conditional distribution of assets as $g(V)/V$, depicted in Figure 1.1. The conditional survival probability $q(t, s) = Q\left(\tau > s \mid \mathcal{H}_t\right)$ to some future time $s > t$ is

$$q(t, s) = \int_{\underline{v}}^{\infty} \left(1 - \pi\left(s - t, x - \underline{v}\right)\right) g\left(x \mid Y_t, z_0, t\right) dx. \tag{1.20}$$

$\pi\left(s - t, x - \underline{v}\right)$ at time t denotes the probability of the first passage of a Brownian motion with drift m and volatility parameter σ from an initial condition $(x - \underline{v}) > 0$ to a level below zero at time s. This probability is known as

$$\begin{aligned} &1 - \pi\left(s - t, x - \underline{v}\right) && (1.21)\\ &= \Phi\left(\frac{\left(x - \underline{v}\right) + m\left(s - t\right)}{\sigma\sqrt{(s - t)}}\right) - \exp\left(-\frac{2m\left(x - \underline{v}\right)}{\sigma^2}\right)\Phi\left(\frac{-\left(x - \underline{v}\right) + m\left(s - t\right)}{\sigma\sqrt{(s - t)}}\right). \end{aligned}$$

A.1 Pricing the CDS

A CDS is an insurance contract against credit events such as the default on a corporate bond (the reference obligation) by a specific issuer (reference entity).

In case of a credit event, the seller of insurance is obligated to buy the reference obligation from the protection buyer at par. For this protection, the buyer pays a periodic premium to the protection seller until the maturity of the contract or the credit event, whichever comes first. Since the accrued premium must also be paid if a credit event occurs between two payment dates, the payments fit nicely into a continuous-time framework. The present value of the premium payments can be calculated as

$$E^Q\left(c\int_0^T \exp\left(-\int_0^s r_u du\right) 1_{\{\tau>s\}} ds\right), \tag{1.22}$$

where c denotes the annual premium known as the CDS spread, T the maturity of the contract, r the risk-free interest rate, τ the default time of the obligor and E^Q denotes the expectation under the risk-neutral pricing measure. Assuming independence between the default time and the risk-free interest rate, this can be written as

$$c\int_0^T P(0,s)q(0,s)ds, \tag{1.23}$$

where $P(0,s)$ is the price of a default-free zero-coupon bond with maturity s, and $q(0,s)$ is the risk-neutral survival probability until time s at the time of issuance, derived in equation (1.20). The present value of the credit protection is equal to

$$E^Q\left((1-R)\exp\left(-\int_0^\tau r_u du\right) 1_{\{\tau<T\}}\right), \tag{1.24}$$

where R is the recovery of bond market value measured as a percentage of par in the event of default. Maintaining the assumption of independence between the default time and the risk-free interest rate and assuming a constant R, this can be written as

$$-(1-R)\int_0^T P(0,s)q'(0,s)ds, \tag{1.25}$$

where $-\ q'(0,t) = -dq(0,t)/dt$ is the probability density function of the default time. The CDS spread is determined such that the value of the contract is zero at initiation

$$0 = c\int_0^T P(0,s)q(0,s)ds + (1-R)\int_0^T P(0,s)q'(0,s)ds, \tag{1.26}$$

and hence

$$c(0,T) = -\frac{(1-R)\int_0^T P(0,s)q'(0,s)ds}{\int_0^T P(0,s)q(0,s)ds}. \tag{1.27}$$

As mentioned, the model assumes a constant interest rate r, implying that

$$c(0,T) = -\frac{(1-R)\int_0^T e^{-rs}q'(0,s)ds}{\int_0^T e^{-rs}q(0,s)ds}. \tag{1.28}$$

Integrating the denominator by parts yields

$$c(0,T) = -r(1-R)\frac{\int_0^T e^{-rs}q'(0,s)ds}{1-e^{-rT}q(0,T)+\int_0^T e^{-rs}q'(0,s)ds}. \tag{1.29}$$

We find $q'(0,s)$ by differentiating equation (1.20) inside the integral. To ease notation, we denote $b = x - \underline{v}$, $g(x) = g(x \mid Y_t, z_0, t)$ and $t = 0$, implying that a noise-free report is received one period before. Since $g(x)$ does not depend on s, we only need to differentiate $1 - \pi(s,b)$ with respect to s yielding

$$\frac{\partial(1-\pi(s,b))}{\partial s} = \frac{-b}{\sigma\sqrt{2\pi s^3}}\exp\left(-\frac{1}{2}\left(\frac{(b+ms)}{\sigma\sqrt{s}}\right)^2\right) = -f(x,s), \tag{1.30}$$

where $f(x,s)$ is the first hitting time density of a Brownian motion with drift m and volatility parameter σ. Therefore,

$$q'(0,s) = -\int_{\underline{v}}^{\infty} f(x,s)\, g(x)dx, \tag{1.31}$$

and hence

$$\begin{aligned}\int_0^T e^{-rs}q'(0,s)ds &= -\int_0^T e^{-rs}\int_{\underline{v}}^{\infty} f(x,s)\, g(x)dxds \\ &= -\int_{\underline{v}}^{\infty} g(x)\int_0^T e^{-rs}f(x,s)\, dsdx,\end{aligned} \tag{1.32}$$

again since $g(x)$ does not depend on s. The inner integral $\int_0^T e^{-rs}f(x,s)\,ds$ is the integral of a discounted first hitting time density known from Reiner & Rubinstein

(1991) and Leland & Toft (1996) in closed form as

$$\begin{aligned} G(x,T) &= \int_0^T e^{-rs} f(x,s)\, ds \\ &= \exp\left(\left(-c+z\right)b\right)\Phi\left(h_1\left(T\right)\right) + \exp\left(\left(-c-z\right)b\right)\Phi\left(h_2\left(T\right)\right), \end{aligned} \tag{1.33}$$

where

$$h_1\left(T\right) = \frac{\left(-b - z\sigma^2 T\right)}{\sigma\sqrt{T}}, \tag{1.34}$$

$$h_2\left(T\right) = \frac{\left(-b + z\sigma^2 T\right)}{\sigma\sqrt{T}}, \tag{1.35}$$

$$c = \frac{m}{\sigma^2}, \tag{1.36}$$

and

$$z = \frac{\left(m^2 + 2r\sigma^2\right)^{\frac{1}{2}}}{\sigma^2}. \tag{1.37}$$

In the end, to calculate the CDS spread we only need to evaluate a single integral numerically

$$\begin{aligned} c(0,T) &= r(1-R)\frac{\int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx}{1 - e^{-rT}q(0,T) - \int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx} \\ &= r(1-R)\frac{\int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx}{1 - e^{-rT}\int_{\underline{\upsilon}}^{\infty}\left(1 - \pi\left(T, x - \underline{\upsilon}\right)\right)g\left(x\right)dx - \int_{\underline{\upsilon}}^{\infty} G(x,T)g(x)dx}. \end{aligned} \tag{1.38}$$

B The Accounting Transparency Measure

The basic idea in Berger et al. (2006) is that when pricing equity, investors perceive a firm's permanent earnings as a geometrically weighted average of reported earnings and industry average earnings. Investors put more weight on the firm's reported earnings when the accounting transparency is high.

Denote $\widetilde{E}_{j,t}$ as investors' perception of firm $j's$ permanent earnings in year t, $E_{j,t}$ as the firm's reported earnings and $E_{I,t}$ as the industry average earnings. Scaling the earnings by firm asset $A_{j,t}$ and industry assets $A_{I,t}$, the permanent earnings perceived by investors is formally written as

$$\frac{\widetilde{E}_{j,t}}{A_{j,t-1}} = \left(\frac{E_{j,t}}{A_{j,t-1}}\right)^{\delta}\left(\frac{E_{I,t}}{A_{I,t-1}}\right)^{1-\delta}, \tag{1.39}$$

where $\delta \in [0,1]$ is the weight put on firm-specific information. Taking logarithms and first-order differences yields

$$\widetilde{e}_{j,t} = \delta e_{j,t} + (1-\delta)\, e_{I,t} + (1-\delta)\left(\ln\left(\frac{A_{j,t-1}}{A_{I,t-1}}\right) - \ln\left(\frac{A_{j,t-2}}{A_{I,t-2}}\right)\right). \qquad (1.40)$$

Lower case letters denote the log-growth rate of the variable $\widetilde{e}_{j,t} = \ln\left(\frac{\widetilde{E}_{j,t}}{\widetilde{E}_{j,t-1}}\right)$, $e_{j,t} = \ln\left(\frac{E_{j,t}}{E_{j,t-1}}\right)$, $e_{I,t} = \ln\left(\frac{E_{I,t}}{E_{I,t-1}}\right)$ and $\frac{A_{j,t}}{A_{I,t}}$ represents the firm's share of the industry assets. Assuming this share does not change much from year $t-2$ to $t-1$, we approximately have

$$\widetilde{e}_{j,t} = \delta e_{j,t} + (1-\delta)\, e_{I,t}. \qquad (1.41)$$

The equity price $P_{j,t}$ is determined by investors' perception of permanent earnings, and with the assumption of a constant cost of capital μ_j and a constant expected growth rate g_j, we have

$$P_{j,t} = \frac{\widetilde{E}_{j,t}}{\mu_j - g_j}. \qquad (1.42)$$

Hence, a firm's equity return equals its permanent earnings growth rate $r_{j,t} = \widetilde{e}_{j,t}$, implying that the idiosyncratic variance of the return must equal the idiosyncratic variance of the perceived permanent earnings. Idiosyncratic is defined relative to the industry, and the following relations between firm and industry returns and between firm and industry earnings, respectively, are assumed

$$r_{j,t} = \widetilde{e}_{j,t} = \alpha^r + \beta r_{I,t} + \varepsilon^r_{j,t} \qquad (1.43)$$

$$e_{j,t} = a^e + b e_{I,t} + \varepsilon^e_{j,t}. \qquad (1.44)$$

Finally, using equations (1.41), (1.43) and (1.44), the idiosyncratic variance of the perceived earnings growth equals δ^2 times the idiosyncratic variance of the reported earnings growth

$$var(\varepsilon^r_j) = \delta^2 var(\varepsilon^e_j), \qquad (1.45)$$

and the measure of accounting transparency δ is calculated as the idiosyncratic volatility of equity returns divided by the idiosyncratic volatility in earnings growth

$$\delta = \frac{vol(\varepsilon_j^r)}{vol(\varepsilon_j^e)}. \tag{1.46}$$

Chapter 2

Capital Structure Arbitrage: Model Choice and Volatility Calibration

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Abstract[1]

When identifying relative value opportunities across credit and equity markets, the arbitrageur faces two major problems, namely positions based on model misspecification and mismeasured inputs. Using credit default swap data, this paper addresses both concerns in a convergence-type trading strategy. In spite of differences in assumptions governing default and calibration, we find the exact structural model linking the markets second to timely key inputs. Studying an equally-weighted portfolio of all relative value positions, the excess returns are insignificant when based on a historical volatility. However, relying on an implied volatility from equity options results in highly significant excess returns. The gain is largest in the speculative grade segment, and cannot be explained from systematic market risk factors. Although the strategy may seem attractive at an aggregate level, positions on individual obligors can be very risky.

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2.1 Introduction

Capital structure arbitrage refers to trading strategies that take advantage of the relative mispricing across different security classes traded on the same capital structure. As the exponential growth in the credit default swap (CDS) market has made credit much more tradable and traditional hedge fund strategies have suffered declining returns (Skorecki (2004)), important questions arise for hedge funds and proprietary trading desks. In particular, do credit and equity markets ever diverge in opinion on the quality of an obligor? What is the risk and return of exploiting divergent views in relative value strategies? Although trading strategies founded in a lack of synchronicity between equity and credit markets have gained huge popularity in recent years (Currie & Morris (2002) and Zuckerman (2005)), the academic literature addressing capital structure arbitrage is very sparse.

This paper conducts a comprehensive analysis of the risk and return of capital structure arbitrage using CDS data on 221 North American obligors in 2002 to 2004. When looking at one security in order to signal the sale or purchase of another, the resulting link and initiation of a trade depends on the chosen model relating the markets. We address two major problems facing the arbitrageur, namely relative value opportunities driven by model misspecification or mismeasured inputs.

Duarte, Longstaff & Yu (2005) analyze traditional fixed income arbitrage strategies such as the swap spread arbitrage, but also briefly address capital structure arbitrage. Yu (2006) cites a complete lack of evidence in favor of or against strategies trading equity instruments against CDSs. Hence, he conducts the first analysis of the strategy by implementing the industry benchmark CreditGrades using a historical volatility, which is a popular choice among professionals.[2]

We show that the more comprehensive model by Leland & Toft (1996) only adds an excess return of secondary order. However, when exploiting a wider array of inputs and securities in model calibration and identification of relative value opportunities, the result is a substantial improvement in strategy execution and returns.

[2] That CreditGrades is the preferred framework among professionals is argued in Currie & Morris (2002) and Yu (2006), while the CreditGrades Technical Document by Finger (2002) advocates for the 1000-day historical volatility.

When searching for relative value opportunities, the arbitrageur uses a structural model to gauge the richness and cheapness of the 5-year CDS spread. Using the market value of equity, an associated volatility measure and the liability structure of the obligor, he compares the spread implied from the model with the market spread. When the market spread is substantially larger(smaller) than the theoretical counterpart, he sells(buys) a CDS and sells(buys) equity. If the market and equity-implied spread from the model subsequently converge, he profits. Hence, a model that links firm fundamentals with different security classes helps to identify credits that either offer a discount against equities or trade at a very high level.

In fact, the chosen underlying model relating equity with credit plays a central role in all parts of the strategy. First, it is used to calculate equity-implied CDS spreads governing entry and exit decisions in equity and credit markets. Second, to calculate daily returns on an open position, it is necessary to keep track on the total value of an outstanding CDS position. This is done from the model-based term structure of survival probabilities. Third, the model is used to calculate the equity hedge by a numerical differentiation of the value of the CDS position wrt. the equity price.

CreditGrades loosely builds on Black & Cox (1976), with default defined as the first passage time of firm assets to an unobserved default barrier. This model, like other structural models, is based on a set of restrictive assumptions regarding the default mechanism and capital structure characteristics.

Although allowing for a random recovery, CreditGrades belongs to the class of models with an exogenous default barrier. However, Leland (1994) subsequently extended in Leland & Toft (1996) has pioneered models with endogenous default. In these models, the default barrier is chosen by managers as the asset value where it is no longer optimal for the equityholders to meet the promised debt service payments. Hence, the default barrier and survival probability are determined not only by debt principal but a number of structural variables.

As a result of model variations, differences in model calibration exist. For structural models, this is particularly relevant as many key inputs are difficult to measure. Bypassing strict definitions CreditGrades is developed for immediate application, while the calibration of Leland & Toft (1996) is more extensive. Hence, the number and characteristics of parameters to be estimated, as well as the method to infer the underlying asset value process and default barrier, differ across models.

Duarte et al. (2005) and Yu (2006) solely rely on CreditGrades calibrated with a 1000-day historical volatility. When based on a large divergence between markets, both find that capital structure arbitrage is profitable on average. At the aggregate level, the strategy appears to offer attractive Sharpe ratios and a positive average return with positive skewness. Yet, individual positions can be very risky and most losses occur when the arbitrageur shorts CDSs but subsequently find the market spread rapidly increasing and the equity hedge ineffective.

Due to the substantial differences in model assumptions and calibration, the key observed gap between the market and model spread fueling the arbitrageur may be driven by model misspecification. Furthermore, key inputs may be mismeasured sending the arbitrageur a false signal of relative mispricing. Hence, there is a need to understand how the risk and return vary with model choice and calibration. These caveats are unexplored in Duarte et al. (2005) and Yu (2006).

We address these two problems facing the arbitrageur, and study how the characteristics of capital structure arbitrage vary with model choice and asset volatility calibration. For this purpose, we apply the CreditGrades model and Leland & Toft (1996). As the volatility measure is a key input to the pricing of credit, we identify relative value opportunities from a traditional 250-day historical volatility used extensively in the bond pricing literature and a volatility measure implied from equity options.

Based on anecdotal evidence using CreditGrades, Finger & Stamicar (2005*a*) and Finger & Stamicar (2005*b*) show how model spreads based on historical volatilities lag the market when spreads increase, while overpredicting the market as spreads recover. However, the more responsive option-implied volatility substantially improves the pricing performance. Cremers et al. (2006) and Cao et al. (2006) analyze the information content of equity options for corporate bond and CDS pricing. They find the forward-looking option-implied volatility to dominate the historical measure in explaining credit spreads, and the gain is particularly pronounced among firms with lower credit ratings. Only analyzing the determinants of credit spreads, they are silent on the risk and return of capital structure arbitrage.

As the arbitrageur feeds on large variations in credit and equity markets, these insights suggest the implied volatility to lead to superior entry and exit decisions and trading returns. Furthermore, the gain from a more timely credit signal is expected to be largest for the obligors of most interest to the arbitrageur, namely those in the speculative grade segment.

Hence, we implement the strategy on 221 North American industrial obligors in 2002 to 2004. Case studies illustrate that while model choice certainly matters in identifying relative value opportunities, the volatility input is of primary importance. The historical volatility may severely lag the market, sending the arbitrageur a false signal of relatively cheap protection in the aftermath of a crisis. The result is large losses for the arbitrageur as market spreads continue to tighten. Indeed, the implied volatility may result in the exact opposite positions, with obvious consequences for the arbitrageur.

When studying the risk and return at an aggregate level, we focus on holding period returns and a capital structure arbitrage index of monthly excess returns. Both models generally result in insignificant excess returns, when calibrated with a traditional volatility from historical equity returns. However, the gain from identifying relative value opportunities from option-implied volatilities is substantial.

In a variant of the strategy based on CreditGrades, the mean holding period return for speculative grade obligors increases from 2.64 percent to 4.61 percent when implemented with option-implied volatilities. The similar numbers based on Leland & Toft (1996) are 3.14 versus 5.47 percent. However, the incremental return is much smaller for investment grade obligors.

Additionally, the corresponding excess returns are highly significant when option-implied volatilities are used to identify opportunities. Based on CreditGrades, the mean excess return is 0.44 percent on investment grade and 1.33 percent on speculative grade obligors, both highly significant. The similar numbers when Leland & Toft (1996) is used to identify relative value opportunities are 0.27 and 2.39 percent, both highly significant. At a low threshold for strategy initiation, the excess return may turn negative and significant based on the historical measure, while it continues to be positive and significant based on implied volatilities. Finally, we do not find the excess returns to represent compensation for exposure to systematic market factors.

However, irrespective of model choice and volatility calibration, the strategy is very risky at the level of individual obligors. Convergence may never happen and the equity hedge may be ineffective. This may force the arbitrageur to liquidate positions early and suffer large losses.

We conclude that while model choice matters for the arbitrageur, it is second to properly measured key inputs in the calibration. Hence, if the arbitrageur relies on the dynamics of option prices when identifying relative value opportunities across equity and credit markets, the result is a substantial aggregate gain in trading returns above the benchmark application of capital structure arbitrage in Duarte et al. (2005) and Yu (2006).

This paper is based on the premise that structural models price CDSs reasonably well. Ericsson et al. (2006) find that Leland (1994), Leland & Toft (1996) and Fan & Sundaresan (2000) underestimate bond spreads consistent with previous studies. However, the models perform much better in predicting CDS spreads, particularly Leland & Toft (1996). The resulting residual CDS spreads are found to be uncorrelated with default proxies as well as non-default proxies. Furthermore, this paper is related to Schaefer & Strebulaev (2004), who show that structural models produce hedge ratios of equity to debt that cannot be rejected in empirical tests.

Since the rationale for the strategy is to exploit a lack of integration between various markets, capital structure arbitrage is also related to studies on the lead-lag relationship among bond, equity and CDS markets like Hull, Predescu & White (2004), Norden & Weber (2004), Longstaff et al. (2005) and Blanco et al. (2005). While the CDS is found to lead the bond market, no definitive lead-lag relationship exists between equity and CDS markets. Finally, Hogan, Jarrow, Teo & Warachka (2004) study statistical arbitrages, while Mitchell & Pulvino (2001) and Mitchell, Pulvino & Stafford (2002) are important studies on merger and equity arbitrage.

The outline of the paper is as follows. Section 2.2 outlines the trading strategy, while the data is presented in section 2.3. Section 2.4 presents the underlying models and calibration, and section 2.5 illustrates some case studies. Section 2.6 presents the aggregate results of the strategy, and section 2.7 concludes.

2.2 Trading Strategy

This section describes the trading strategy underlying capital structure arbitrage. The implementation closely follows Duarte et al. (2005) and Yu (2006), to whom we refer for a more elaborate description. Since a time-series of predicted CDS spreads forms the basis of the strategy, we start with a short description of how to price a CDS.

2.2.1 CDS Pricing

A CDS is an insurance contract against credit events such as the default on a corporate bond (the reference obligation) by a specific issuer (reference entity). In case of a credit event, the seller of insurance is obligated to buy the reference obligation from the protection buyer at par.[3] For this protection, the buyer pays a periodic premium to the protection seller until the maturity of the contract or the credit event, whichever comes first. There is no requirement that the protection buyer actually owns the reference obligation, in which case the CDS is used more for speculation rather than protection. Since the accrued premium must also be paid if a credit event occurs between two payment dates, the payments fit nicely into a continuous-time framework.

First, the present value of the premium payments from a contract initated at time 0 with maturity date T can be calculated as

$$E^Q \left(c(0,T) \int_0^T \exp\left(- \int_0^s r_u du \right) 1_{\{\tau > s\}} ds \right), \tag{2.1}$$

where $c(0,T)$ denotes the annual premium known as the CDS spread, r the risk-free interest rate, and τ the default time of the obligor. E^Q denotes the expectation under the risk-neutral pricing measure. Assuming independence between the default time and the risk-free interest rate, this can be written as

$$c(0,T) \int_0^T P(0,s) q_0(s) ds, \tag{2.2}$$

where $P(0,s)$ is the price of a default-free zero-coupon bond with maturity s, and $q_0(s)$ is the risk-neutral survival probability of the obligor, $P(\tau > s)$, at $t = 0$[4].

[3] In practice, there may be cash settlement or physical settlement, as well as a possible cheapest-to-deliver option embedded in the spread. However, we refrain from this complication. Credit events can include bankruptcy, failure to pay or restructuring.

[4] Later, we focus on constant risk-free interest rates. This assumption allows us to concentrate on the relationship between the equity price and the CDS spread. This is exactly the relationship exploited in the relative value strategy.

Second, the present value of the credit protection is equal to

$$E^Q\left((1-R)\exp\left(-\int_0^\tau r_u du\right)1_{\{\tau<T\}}\right), \tag{2.3}$$

where R is the recovery of bond market value measured as a percentage of par in the event of default. Maintaining the assumption of independence between the default time and the risk-free interest rate and assuming a constant R, this can be written as

$$-(1-R)\int_0^T P(0,s)q_0'(s)ds, \tag{2.4}$$

where $-\ q_0'(t) = -dq_0(t)/dt$ is the probability density function of the default time. The CDS spread is determined such that the value of the credit default swap is zero at initiation

$$0 = c(0,T)\int_0^T P(0,s)q_0(s)ds + (1-R)\int_0^T P(0,s)q_0'(s)ds, \tag{2.5}$$

and hence

$$c(0,T) = -\frac{(1-R)\int_0^T P(0,s)q_0'(s)ds}{\int_0^T P(0,s)q_0(s)ds}. \tag{2.6}$$

The preceding is the CDS spread on a newly minted contract. To calculate daily returns to the arbitrageur on open trades, the relevant issue is the value of the contract as market conditions change and the contract is subsequently held. To someone who holds a long position from time 0 to t, this is equal to

$$\pi(t,T) = (c(t,T)-c(0,T))\int_t^T P(t,s)q_t(s)ds, \tag{2.7}$$

where $c(t,T)$ is the CDS spread on a contract initiated at t with maturity date T. The value of the open CDS position $\pi(t,T)$ can be interpreted as a survival-contingent annuity maturing at date T, which depends on the term-structure of survival probabilities $q_t(s)$ through s at time t. The survival probability $q_t(s)$ depends on the market value of equity S_t through the underlying structural model, and we follow Yu (2006) in defining the hedge ratio δ_t as

$$\delta_t = N * \frac{\partial \pi(t,T)}{\partial S_t}, \tag{2.8}$$

where N is the number of shares outstanding.[5] Hence, δ_t is defined as the dollar-amount of shares bought per dollar notional in the CDS. The choice of underlying model-framework and calibration is discussed in section 2.4.

2.2.2 Implementation of the Strategy

Using the market value of equity, an associated volatility measure and the liability structure of the obligor, the arbitrageur uses a structural model to gauge the richness and cheapness of the CDS spread. Comparing the daily spread observed in the market with the equity-implied spread from the model, the model helps identify credits that either offer a discount against equities or trade at a very high level.

If e.g. the market spread at a point in time has grown substantially larger than the model spread, the arbitrageur sees an opportunity. It might be that the credit market is gripped by fear and the equity market is more objective. Alternatively, he might think that the equity market is slow to react and the CDS spread is priced fairly. If the first view is correct, he should sell protection and if the second view is correct, he should sell equity. Either way, the arbitrageur is counting on the normal relationship between the two markets to return. He therefore takes on both short positions and profits if the spreads converge. In the opposite case with a larger model spread, the arbitrageur buys protection and equity.

This relative value strategy is supposed to be less risky than a naked position in either market, but is of course far from a textbook definition of arbitrage. Two important caveats to the strategy are positions initiated based on model misspecification or mismeasured inputs. Such potential false signals of relative mispricing are exactly what this paper addresses.

We conduct a simulated trading exercise based on this idea across all obligors. Letting α be the trading trigger, c_t' the CDS spread observed in the market at date t and c_t short-hand notation for the equity-implied model spread, we initiate

[5] This calculation deviates slightly from the one in Yu (2006), since we formulate all models on a total value basis and not per share. Equation (2.8) follows from a simple application of the chain rule.

a trade each day if one of the following conditions are satisfied

$$c'_t > (1+\alpha)\,c_t \text{ or } c_t > (1+\alpha)\,c'_t. \tag{2.9}$$

In the first case, a CDS with a notional of \$1 and shares worth $\$ - \delta_t * 1$ are shorted.[6] In the second case, the arbitrageur buys a CDS with a notional of \$1 and buys shares worth $\$ - \delta_t * 1$ as a hedge.

Since Yu (2006) finds his results insensitive to daily rebalancing of the equity position, we follow his base case and adopt a static hedging scheme. The hedge ratio in equation (2.8) is therefore fixed throughout the trade and based on the model CDS spread c_t when entering the position.

Knowing when to enter positions, the arbitrageur must also decide when to liquidate. We assume that exit occurs when the spreads converge defined as $c_t = c'_t$ or by the end of a pre-specified holding period, which ever comes first. In principle, the obligor can also default or be acquired by another company during the holding period. Yu (2006) notes that in most cases the CDS market will reflect these events long before the actual occurrences, and the arbitrageur will have ample time to make exit decisions.[7] Specifically, it is reasonable to assume that the arbitrageur will be forced to close his positions once the liquidity dries up in the underlying obligor. Such incidents are bound to impose losses on the arbitrageur.

2.2.3 Trading returns

The calculation of trading returns is fundamental to analyze how the risk and return differ across model assumptions and calibration methods. Since the CDS position has a zero market value at initiation, trading returns must be calculated by assuming that the arbitrageur has a certain level of initial capital. This assumption allows us to hold fixed the effects of leverage on the analysis. The initial capital is used to finance the equity hedge, and is credited or deducted as a result of intermediate payments such as dividends or CDS premia. Each trade

[6] δ_t is, of course, negative.

[7] This argument seems to be supported in Arora, Bohn & Zhu (2005), who study the surprise effect of distress announcements. Conditional on market information, they find only 11 percent of the distressed firms' equities and 18 percent of the distressed bonds to respond significantly. The vast majority of prices are found to reflect the credit deterioration well before the distress announcement.

is equipped with this initial capital and a limited liability assumption to ensure well-defined returns. Hence, each trade can be thought of as an individual hedge fund subject to a forced liquidation when the total value of the portfolio becomes zero.[8]

Through the holding period the value of the equity position is straightforward, but the value of the CDS position has to be calculated using equation (2.7) and market CDS spreads $c'(t, T)$ and $c'(0, T)$. Since secondary market trading is very limited in the CDS market and not covered by our dataset, we adopt the same simplifying assumption as Yu (2006), and approximate $c'(t, T)$ with $c'(t, t + T)$. That is, we approximate a CDS contract maturing in four years and ten months, say, with a freshly issued 5-year spread. This should not pose a problem since the difference between to points on the curve is likely to be much smaller than the time-variation in spreads.

Yu (2006) finds his results insensitive to the exact size of transaction costs for trading CDSs. We adopt his base case, and assume a 5 percent proportional bid-ask spread on the CDS spread. The CDS market is likely to be the largest single source of transaction costs for the arbitrageur. We therefore ignore transaction costs on equities, which is reasonable under the static hedging scheme.

2.3 Data

Data on CDS spreads is provided by the ValuSpread database from Lombard Risk Systems, dating back to July 1999. This data is also used by Lando & Mortensen (2005) and Berndt, Jarrow & Kang (2006). The data consists of mid-market CDS quotes on both sovereigns and corporates, with varying maturity, restructuring clause, seniority and currency. For a given date, reference entity and contract specification, the database reports a composite CDS quote together with an intra-daily standard deviation of collected quotes. The composite quote is calculated as a mid-market quote by obtaining quotes from up to 25 leading market makers. This offers a more reliable measure of the market spread than using a single source, and the standard deviation measures how representative the mid-market quote is for the overall market.

[8] This is reminiscent of potential large losses when marked to market, triggering margin calls and forcing an early liquidation of positions.

We confine ourselves to 5-year composite CDS quotes on senior unsecured debt for North American corporate obligors with currencies denominated in US dollars. Indeed, the 5-year maturity is the most liquid point on the credit curve (see e.g. Blanco et al. (2005)). Regarding the specification of the credit event, we follow Yu (2006) and large parts of the literature in using contracts with a modified restructuring clause. The frequency of data on CDS quotes increases significantly through time, reflecting the growth and improved liquidity in the market. To generate a subsample of the data suitable for capital structure arbitrage, we apply several filters.

First, we merge the CDS data with quarterly balance sheet data from Compustat and daily stock market data from CRSP. The quarterly balance sheet data is lagged one month from the end of the quarter to avoid the look-ahead bias in using data not yet available in the market. We then exclude firms from the financial and utility sector.

Second, for each obligor in the sample, daily data on the 30-day at-the-money put-implied volatility is obtained from OptionMetrics. OptionMetrics is a comprehensive database of daily information on exchange-listed equity options in the U.S. since 1996. OptionMetrics generates the 30-day at-the-money put-implied volatility by interpolation.

Third, in order to conduct the simulated trading exercise, a reasonably continuous time-series of CDS quotes must be available. In addition, the composite quote must have a certain quality. Therefore, we define the relative quote dispersion as the intra-daily standard deviation of collected quotes divided by the mid-market quote. All daily mid-market quotes with an intra-daily quote dispersion of zero or above 40 percent are then deleted.[9] For each obligor, we next search for the longest string of more than 100 daily quotes no more than 14 calender days apart, which have all information available on balance sheet variables, equity market and equity options data.[10] As noted in Yu (2006), this should also yield the most liquid part of coverage for the obligor, forcing the arbitrageur to

[9] One could argue for a cut-off point at a lower relative dispersion, but on the other hand a trader is likely to take advantage of high uncertainty in the market. The vast majority of quotes have a relative dispersion below 20 percent.

[10] As discussed below, this may give rise to a survivorship issue. However, we try to minimize this by requiring a string of only 100 spreads, far less than Yu (2006). In any case, this should not pose a problem, since the focus of the paper is on relative risk and return across models and calibration methods, and not absolute measures.

close his positions once the liquidity vanishes.

Finally, the 5-year constant maturity treasury rate and the 3-month treasury bill rate are obtained from the Federal Reserve Bank of St. Louis. The 5-year interest rate is used to calculate the equity-implied 5-year CDS spread, while the 3-month interest rate is chosen when calculating daily excess returns from the trading strategy[11]. Applying this filtration to the merged dataset results in 221 obligors with 65,476 daily composite quotes, dating back to July 2002 and onwards to the end of September 2004.

Table 2.1 presents summary statistics for the obligors across the senior unsecured credit rating from Standard & Poor's when entering the sample. The variables presented are averages over time and then firms. The majority of firms are BBB rated, and 16 firms are in the speculative grade segment, including one non-rated obligor. A lower spread is associated with a lower leverage and volatility, which is in line with predictions of structural credit risk models.

We implement the trading strategy using the implied volatility from equity options (IV), and a 250-day volatility from a historical time-series of equity values (HV). On average these volatilities are similar, but it turns out that the dynamics of option prices provide the arbitrageur with superior information. The average correlation between changes in the spread and the equity value is negative as expected from a structural viewpoint, but fairly low. This is consistent with Yu (2006) and correlations ranging from minus 5 to minus 15 percent quoted by traders in Currie & Morris (2002). This indicates that the two markets may drift apart and hold divergent views on obligors, which fuels the arbitrageur ex ante. Ex post, it suggests that the equity hedge may be ineffective.

[11] This choice of short-term interest rate is consistent with Yu (2006). Changes in shorter maturity rates are to a larger extend driven by idiosyncratic variation (see Dufee (1996)).

Table 2.1: Sample Characteristics

This table reports sample characteristics for the 221 obligors. First, the average characteristics are calculated for each obligor over time, then averaged across firms. The statistics are presented across the senior unsecured credit rating from Standard & Poor's. N is the number of obligors and spread is the 5-year composite CDS quote. While the historical equity volatility HV is calculated from a 250-day rolling window of equity returns, the implied equity volatility IV is inferred from 30-day at-the-money put options. The leverage ratio lev is total liabilities divided by the sum of total liabilities and equity market capitalization, and size is the sum of total liabilities and equity market capitalization in millions of dollars. Finally, $corr$ is the correlation between changes in the CDS spread and the equity value, averaged across ratings.

Rating	N	Spread	HV	IV	Lev.	Size	Corr.
AAA	4	16	0.284	0.227	0.197	142,619	-0.107
AA	11	23	0.267	0.257	0.216	95,237	-0.050
A	80	40	0.305	0.293	0.354	40,274	-0.089
BBB	109	103	0.346	0.337	0.502	25,431	-0.124
BB	15	270	0.386	0.377	0.524	13,667	-0.056
B	1	355	0.554	0.555	0.564	34,173	-0.261
NR	1	172	0.229	0.219	0.450	11,766	-0.129

2.4 Model Choice and Volatility Calibration

Having the trading strategy and data explained, next we introduce the two underlying models and the associated calibration. The formulas for each model including the risk-neutral survival probability $q_t(s)$, the CDS spread $c(0,T)$, the contract value $\pi(t,T)$ and the equity delta $\delta(t,T)$ are described in the appendix. Further details on the models can be found in Finger (2002) and Leland & Toft (1996).

2.4.1 CreditGrades

The CreditGrades model is jointly developed by RiskMetrics, JP Morgan, Goldman Sachs and Deutsche Bank with the purpose to establish a simple framework linking credit and equity markets. As noted by Currie & Morris (2002) and Yu (2006), this model has become an industry benchmark widely used by traders, preferably calibrated with a rolling 1000-day historical volatility as advocated in

Finger (2002). It loosely builds on Black & Cox (1976), with default defined as the first passage time of firm assets to an unobserved default barrier. Hence, deviating from traditional structural models, it assumes that the default barrier is an unknown constant drawn from a known distribution. This element of uncertain recovery increases short-term spreads, but cannot do so consistently through time.[12]

Originally, the model is built on a per-share basis taking into account preferred shares and the differences between short-term versus long-term and financial versus non-financial obligations, when calculating debt per share. Like Yu (2006), we only work with total liabilities and common shares outstanding. Therefore, we formulate the model based on total liabilities and market value of equity.

Under the risk-neutral measure, the firm assets V are assumed to follow

$$dV_t = \sigma_V V_t dW_t, \tag{2.10}$$

where σ_V is the asset volatility and W_t is a standard Brownian motion. The zero drift is consistent with the observation of stationary leverage ratios in Collin-Dufresne & Goldstein (2001). The default barrier is LD, where L is a random recovery rate given default, and D denotes total liabilities. The recovery rate L follows a lognormal distribution with mean $\bar{L}$, interpreted as the mean global recovery rate on all liabilities, and standard deviation λ. Then, R in equation (2.6) is the recovery rate on the specific debt issue underlying the CDS.

Instead of working with a full formula for the value of equity S, CreditGrades uses the linear approximation

$$V = S + \bar{L}D, \tag{2.11}$$

which also gives a relation between asset volatility σ_V and equity volatility σ_S

$$\sigma_V = \sigma_S \frac{S}{S + \bar{L}D}. \tag{2.12}$$

The model is easy to implement in practice. In particular, D is the total liabilities from quarterly balance sheet data, S is the market value of equity calculated as the number of shares outstanding multiplied by the closing price,

[12] A theoretically more appealing approach is given by Duffie & Lando (2001).

and r is the 5-year constant maturity treasury yield. Furthermore, the bond-specific recovery rate R is assumed to be 0.5 and the standard deviation of the global recovery rate λ is 0.3. All parameters are motivated in Finger (2002) and Yu (2006).

The volatility measure is a key input to the pricing of credit. Instead of using a rolling 1000-day volatility σ_S from historical equity values as Yu (2006), we implement the strategy using a 250-day historical volatility and the implied volatility from equity options. According to Cremers et al. (2006) and Cao et al. (2006), the implied volatility contains important and timely information about credit risk different from the historical measure. This may potentially lead the arbitrageur to superior entry and exit decisions and trading returns. We expect the gain to be mostly pronounced for the speculative grade sample, where obligors typically experience large variations in spreads. Here, historical volatilities may lag true market levels and send a false signal of mispricing to the arbitrageur.

Finally, we follow Yu (2006) in using the mean global recovery rate $\bar{L}$ to align the model with the credit market before conducting the trading exercise. In particular, we infer $\bar{L}$ by minimizing the sum of squared pricing errors using the first 10 CDS spreads in the sample for each firm. Now, all parameters are in place to calculate the time-series of CDS spreads underlying the analysis, together with hedge ratios and values of open CDS positions.

2.4.2 Leland & Toft (1996)

This model assumes that the decision to default is made by a manager, who acts to maximize the value of equity. At each moment, the manager must address the question if meeting promised debt service payments is optimal for the equityholders, thereby keeping their call option alive. If the asset value exceeds the endogenously derived default barrier V_B, the firm will optimally continue to service the debt - even if the asset value is below the principal value or if cash flow available for payout is insufficient to finance the net debt service, requiring additional equity contributions.

In particular, firm assets V are assumed to follow a geometric Brownian motion under the risk-neutral measure

$$dV_t = (r - \rho)V_t dt + \sigma_V V_t dW_t, \tag{2.13}$$

where r is the constant risk-free interest rate, ρ is the fraction of asset value paid out to security holders, σ_V is the asset volatility and W_t is a standard Brownian motion. Debt of constant maturity Υ is continuously rolled over, implying that at any time s the total outstanding debt principal P will have a uniform distribution over maturities in the interval $(s, s+\Upsilon)$. Each debt contract in the multi-layered structure is serviced by a continuous coupon. The resulting total coupon payments C are tax deductible at a rate τ, and the realized costs of financial distress amount to a fraction α of the value of assets in default V_B. Rolling over finite maturity debt in the way prescribed implies a stationary capital structure, where the total outstanding principal P, total coupon C, average maturity $\frac{\Upsilon}{2}$ and default barrier V_B remain constant through time.

To determine the total value of the levered firm $v(V_t)$, the model follows Leland (1994) in valuing bankruptcy costs $BC(V_t)$ and tax benefits resulting from debt issuance $TB(V_t)$ as time-independent securities. It follows, that

$$\begin{aligned} v(V_t) &= V_t + TB(V_t) - BC(V_t) \\ &= S(V_t) + D(V_t), \end{aligned} \tag{2.14}$$

where $S(V_t)$ is the market value of equity and $D(V_t)$ the market value of total debt.

To implement the model, we follow Ericsson et al. (2006) in setting the realized bankruptcy cost fraction $\alpha = 0.15$, the tax rate $\tau = 0.20$ and the average debt maturity $\frac{\Upsilon}{2} = 3.38$.[13] Furthermore, as above, P is the total liabilities from quarterly balance sheet data, S is the market value of equity and r is the 5-year constant maturity treasury yield. We also follow Ericsson et al. (2006) in assuming that the average coupon paid out to all debtholders equals the risk-free interest rate, $C = rP$.[14] The asset payout rate ρ is calculated as a time-series mean of the weighted average historical dividend yield and relative interest expense from

[13]The choice of 15 percent bankruptcy costs lies well within the range estimated by Andrade & Kaplan (1998). 20 percent as an effective tax rate is below the corporate tax rate to reflect the personal tax rate advantage of equity returns. Stohs & Mauer (1996) find an average debt maturity of 3.38 years using a panel of 328 industrial firms with detailed debt information in Moody's Industrial Manuals in 1980-1989.

[14]A firm's debt consists of more than market bonds, and usually a substantial fraction of total debt is non-interest bearing such as accrued taxes and supplier credits. Furthermore, corporate bonds may be issued below par, which also opens up for this approximation.

balance sheet data

$$\rho = \left(\frac{Interest\ expenses}{Total\ liabilities}\right) \times L\ + (Dividend\ yield) \times (1 - L) \tag{2.15}$$

$$L = \frac{Total\ liabilities}{Total\ liabilities + Market\ equity}.$$

Contrary to CreditGrades, the default barrier V_B is endogenously determined and varies with fundamental characteristics of the firm such as leverage, asset volatility, debt maturity and asset payout rates. Due to the full-blown relationship between equity and assets, the estimation of the asset value V and asset volatility σ_V is a more troublesome exercise in Leland & Toft (1996). Hence, when analyzing the trading strategy with a 250-day historical volatility, we use the iterative algorithm of Moody's KMV outlined in Crosbie & Bohn (2003) and Vassalou & Xing (2004) to infer the unobserved time-series of asset values and asset volatility. This iterative algorithm is preferable over an instantaneous relationship between asset volatility σ_V and equity volatility σ_S, governed by Ito's lemma. The latter underlies the implementation of CreditGrades in equation (2.12), and is used in Jones et al. (1984). As noted in Lando (2004), the iterative algorithm is particularly preferable when changes in leverage are significant over the estimation period.

In short, the iterative scheme goes as follows. The value of equity S_t is a function of the asset value V_t, asset volatility σ_V and a set of parameters θ in equation (2.31), i.e. $S_t = f(V_t, \sigma_V, \theta)$. We use a 250-day window of historical equity values to obtain an estimate of the equity volatility σ_S, by viewing the value of equity as a geometric Brownian motion. Given this initial estimate of the asset volatility σ_V and quarterly balance sheet data, we calculate the value of the default barrier. Using the daily market values of equity and the equity pricing formula we then back out an implied time-series of asset values $V_t(\sigma_V) = f^{-1}(S_t, \sigma_V, \theta)$. Next, the daily asset values allow us to obtain an improved estimate of the asset volatility σ_V, which is used in the next iteration. This procedure is repeated until the values of σ_V converge.

When analyzing the trading exercise based on implied volatilities from equity options, we do not face the problem of changing leverage in a historical estimation window. Therefore, we solve the instantaneous relationship given by

$$S_t = f(V_t, \sigma_V, \theta) \tag{2.16}$$

$$\sigma_S = \frac{\partial S_t}{\partial V_t} \sigma_V \frac{V_t}{S_t} \tag{2.17}$$

numerically for the unknown asset value V_t and asset volatility σ_V.

Before conducting the trading exercise, we now use the bond-specific recovery rate R to align the model with the market spreads. This is possible since the default barrier is endogenously determined. For this purpose, again we use the first 10 CDS spreads in the sample for each firm. As noted in Yu (2006), the bond-specific recovery rate is also the free parameter used in practice by traders to fit the level of market spreads.

2.4.3 Model Calibration and Implied Parameters

Table 2.2 presents the summary statistics of implied parameters from CreditGrades and Leland & Toft (1996) using a rolling 250-day historical volatility (HV) and implied volatility (IV). The table also shows average calibration targets from the equity and equity options market together with asset payout rates. In CreditGrades implemented with a historical volatility in Panel A, the average market value of assets V is \$20,592 million with a median of \$14,839 million, while the average and median expected default barrier $\bar{L}D$ are \$8,556 million and \$3,846 million, respectively. The mean asset volatility σ_V is 22.8 percent with a median of 21.3 percent. Finally, the average and median mean global recovery rate $\bar{L}$ are 0.799 and 0.573, respectively. Similar implied parameters result on aggregate when implemented with the implied volatility in Panel B.

When implementing Leland & Toft (1996) in Panel C and D, several differences from CreditGrades are apparent. First, the asset values appear larger and asset volatilities lower. This is due to the observation that the relatively high endogenous default barrier V_B increases the theoretical equity volatility, ceteris paribus. Hence, the model implies a higher asset value and/or lower asset volatility in order to match the theoretical and observed equity volatility.

Second, the variation in implied bond recovery R across the two volatility measures is large. Based on the historical volatility, both the average and median implied bond recovery are highly negative, indicating that the model underestimates the level of market spreads in the beginning of the sample period.[15] Implied recoveries are more plausible when inferred from option-implied volatilities. Although the mean continues to be negative, the median is now 0.233. This is indicative of an implied volatility that varies stronger with changes in the CDS spread. Indeed, calculating the mean correlation between changes in CDS spreads and changes in volatility measures, the correlation is 1.8 and 9.9 percent based on historical and implied volatilities, respectively.

The variation in implied mean global recovery $\bar{L}$ in CreditGrades is much smaller across volatility measures. This is a manifestation of the difference in information used at various stages, when calibrating the two models. In CreditGrades the expected default barrier is exogenous, while it is endogenously determined in Leland & Toft (1996). As a result of the linear approximation in equation (2.11), asset values, the asset volatility and the expected default barrier are not nailed down and determined in CreditGrades until the mean global recovery rate is inferred from the initial CDS spreads. Subsequent to nailing down this key parameter, there is a one-to-one relationship between changes in equity and assets, $\frac{\partial S}{\partial V} = 1$.

The default mechanism in Leland & Toft (1996) implies a different use of market data. Here, the asset value and asset volatility are solely determined from the equity and equity options market. Together with the endogenous default barrier, this gives far less flexibility when fitting the final bond recovery from initial CDS spreads. The result is more extreme values for this parameter.[16] However, the subsequent relationship and wedge between equity and assets vary with the distance to default. When close to default, $\frac{\partial S}{\partial V}$ is very steep and below one. Although delta may go above one as the credit quality improves, the relationship approaches one-to-one when far from default. Hence, the variation in asset dynamics across the two models may be substantial for speculative grade obligors, with direct consequences for the arbitrageur.

[15] This should not be a problem for the current trading strategy, since subsequent movements in relative prices across equity and credit markets drive the arbitrageur, not absolute levels. The most extreme bond recovery of -1,858 results from an underestimation of only 50 bps. In this case, the market spread is close to 50 bps, while the model spread with a reasonable bond recovery is close to zero.

[16] If CreditGrades is implemented with a mean global recovery of 0.5 as suggested in Finger (2002), we qualitatively get the same results for the implied bond recovery as in Leland & Toft (1996).

Table 2.2: Descriptive Statistics of Implied Parameters

This table reports the central implied parameters from CreditGrades and Leland & Toft (1996), calibrated with a historical volatility HV and option-implied volatility IV. While the first measure is calculated from a 250-day rolling window of equity returns, the latter is implied from 30-day at-the-money put options. The descriptive statistics for the payout rate, global recovery and bond recovery are calculated across obligors. The remaining variables are first averaged over time, before the statistics are calculated across obligors. The equity value, asset value and default barrier are measured in millions of dollars. The upper three rows report the summary statistics of calibration targets from the equity and equity options market. The global recovery rate is the mean global recovery on all liabilities of the firm, while the bond recovery is the recovery rate on the specific debt issue underlying the CDS. Finally, the payout rate is calculated from historical dividend yields and relative interest expenses.

Variable	Mean	Median	Std. dev.	Min	Max
Equity value	20,592	9,479	33,425	919	238,995
HV	0.329	0.313	0.106	0.175	0.989
IV	0.318	0.302	0.090	0.135	0.717
Panel A. CreditGrades HV					
Asset value	29,895	14,839	46,655	1,360	337,381
Asset vol.	0.228	0.213	0.085	0.084	0.583
Default barrier	8,556	3,846	15,892	59	154,585
Global rec.	0.799	0.573	0.772	0.009	6.025
Panel B. CreditGrades IV					
Asset value	26,189	12,914	40,418	1111	294,685
Asset vol.	0.232	0.227	0.079	0.0843	0.552
Default barrier	4,901	2,199	9,071	14	93,838
Global rec.	0.549	0.285	0.719	0.0097	5.715
Panel C. Leland & Toft HV					
Asset value	34,837	18,100	53,727	2,008	417,807
Asset vol.	0.179	0.167	0.073	0.0382	0.446
Default barrier	12,445	5,939	32,871	591	374,849
Bond rec.	-17.410	-0.443	129.611	-1,858	0.919
Payout rate	0.020	0.020	0.011	0	0.059
Panel D. Leland & Toft IV					
Asset value	34,502	17,897	52,035	1972	373,672
Asset vol.	0.167	0.156	0.069	0.0077	0.413
Default barrier	12,762	6,105	33,360	593	364,376
Bond rec.	-3.554	0.233	18.256	-222.69	0.835
Payout rate	0.020	0.020	0.011	0	0.059

From the discussion in section 2.2, the chosen structural model plays a central role in all parts of capital structure arbitrage. In particular, the model underlies the term-structure of survival probabilities, equity-implied CDS spreads, hedge ratios, the valuation of open CDS positions and trading returns. As shown above, assumptions behind CreditGrades and Leland & Toft (1996), as well as practical implementation, vary substantially. How these differences in model choice and calibration manifest in profitability and strategy execution is analyzed next. Before turning to the general results across all obligors, some case studies are analyzed.

2.5 Case Studies

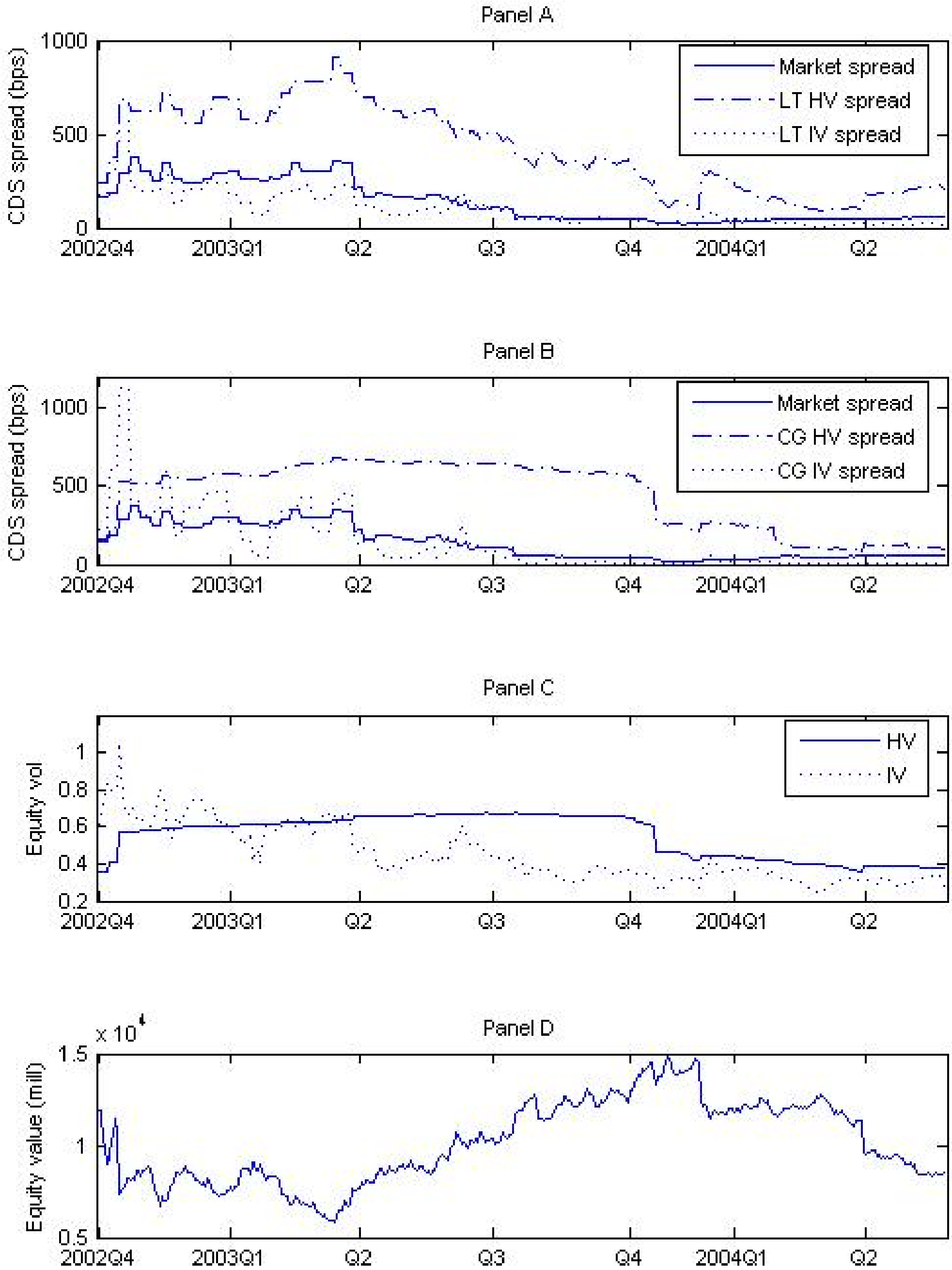
In this section, the two models calibrated with historical and option-implied volatilities are used to identify divergent views in equity and credit markets. The case studies illustrate that while model choice certainly matters in identifying relative value opportunities, the volatility input is of primary importance. In fact, the two volatility measures may result in opposite positions, with obvious consequences for the arbitrageur. The final study illustrates that the strategy is very risky at the level of individual obligors.

2.5.1 Sears, Roebuck and Company

Figure 2.1 illustrates the fundamentals of capital structure arbitrage for the large retailer Sears, Roebuck and Company rated A by S&P and Baa1 by Moody's. Panel A and B depict the equity-implied model spreads and CDS spreads observed in the market from September 2002 to June 2004 (excluding the initial 10 spreads reserved for calibration), while Panel C and D depict equity volatilities and the market value of equity, respectively.

Figure 2.1: Sears, Roebuck and Company

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.



The uncertainty in the markets increases substantially in the beginning of the period. Moody's changes their rating outlook to negative on October 18, 2002 due to increasing uncertainty in the credit card business and management changes. In this period equity prices tumble and CDS spreads reach 379 bps on October 24, 2002, a doubling in 2 weeks. While the markets begin to recover shortly thereafter, model spreads based on the sticky historical volatility continue far into 2003 to suggest the arbitrageur to buy protection and buy equity as a hedge. However, with only few exceptions the market spreads tighten in the succeeding period, and the market and model spreads never converge. Depending on the size of the trading trigger and the chosen model, many losing CDS positions are initiated although partially offset by an increasing equity price.

Panel C illustrates how the historical volatility severely lags the more timely implied volatility, sending the arbitrageur a false signal of relatively cheap protection in the aftermath of the crisis. In fact, spreads inferred from implied volatilities quickly tighten and may initiate the exact opposite strategy. Using this volatility, spreads in Leland & Toft (1996) indicate that protection is trading too expensive relative to equity from the end of 2002. Indeed, selling protection and selling equity as hedge result in trading returns of 5 to 15 percent on each daily position due to tightening market spreads and convergence on June 5, 2003. Subsequent to convergence, implied volatilities suggest the equity and credit markets to move in tandem and hold similar views on the credit outlooks.

As a final observation, model spreads in CreditGrades react stronger to changes in volatility than Leland & Toft (1996), widening to over 1,000 bps as the implied volatility from equity options peaks. This may be due to the endogenous default barrier in the latter model. Indeed, increasing the asset volatility causes equityholders to optimally default later in Leland & Toft (1996). This mitigates the effect on the spread.

2.5.2 Time Warner and Motorola

Simulating the trading strategy on Time Warner and Motorola supports the former insights. Figure 2.2 depicts the fundamentals behind Time Warner, rated BBB by S&P and Baa1 by Moody's. In August 2002 just prior to the beginning of the sample, Moody's changes their outlook to negative as the SEC investigates the accounting practices and internal controls. As markets recover in late 2002, CreditGrades with historical volatility indicates that protection is cheap relative to equity, while spreads in Leland & Toft (1996) are more neutral. Although equity prices increase throughout 2003, many losing trades are initiated as market spreads are more than cut by half within few months and Moody's changes their outlook back to stable.

Again, the historical volatility lags the market following the episode, while the implied volatility is more responsive. In October and November 2002, where market spreads have already tightened substantially, model spreads inferred from implied volatilities suggest that protection is expensive relative to equity and should tighten further. Selling protection at 339 bps and equity at $14.75 on October 31, 2002 result in convergence and 15 percent returns on December 12, where the CDS and equity are trading at 259 bps and $13.56, respectively. However, spreads inferred from implied volatilities are volatile, resulting in rather noisy estimates of credit outlooks and a frequent liquidation of positions as market spreads tighten. Operating with a very low trigger may reverse positions several times during this period, while a trigger of 0.5 results in only few positions.

In Figure 2.3, the key variables for Motorola rated BBB by S&P are depicted. Building on historical volatilities the arbitrageur initiates many trades and suffers losses, while implied volatilities suggest the two markets to move in tandem and hold similar views on the obligor. In the latter case, only few relative value opportunities are apparent.

Figure 2.2: Time Warner

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.

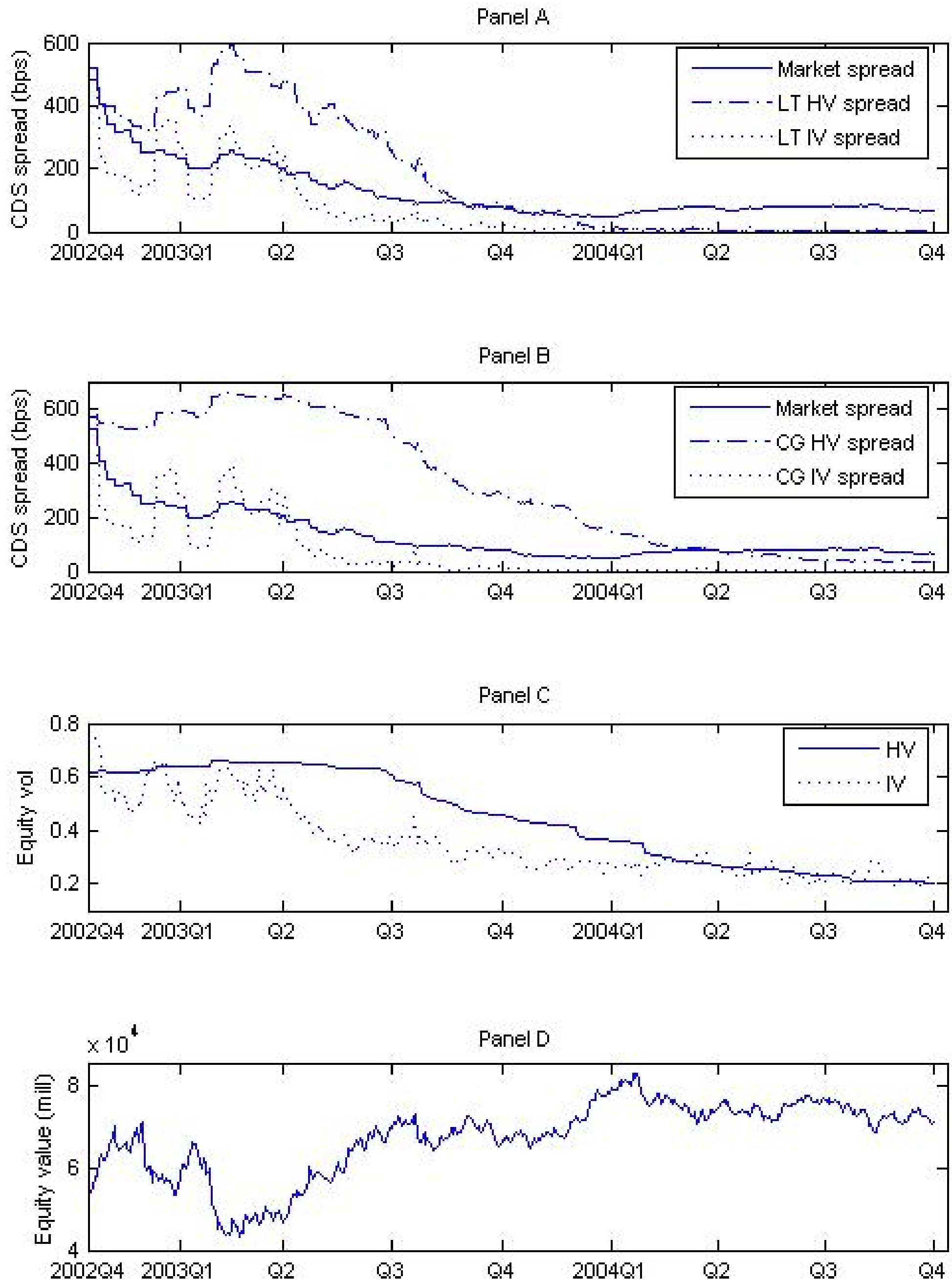
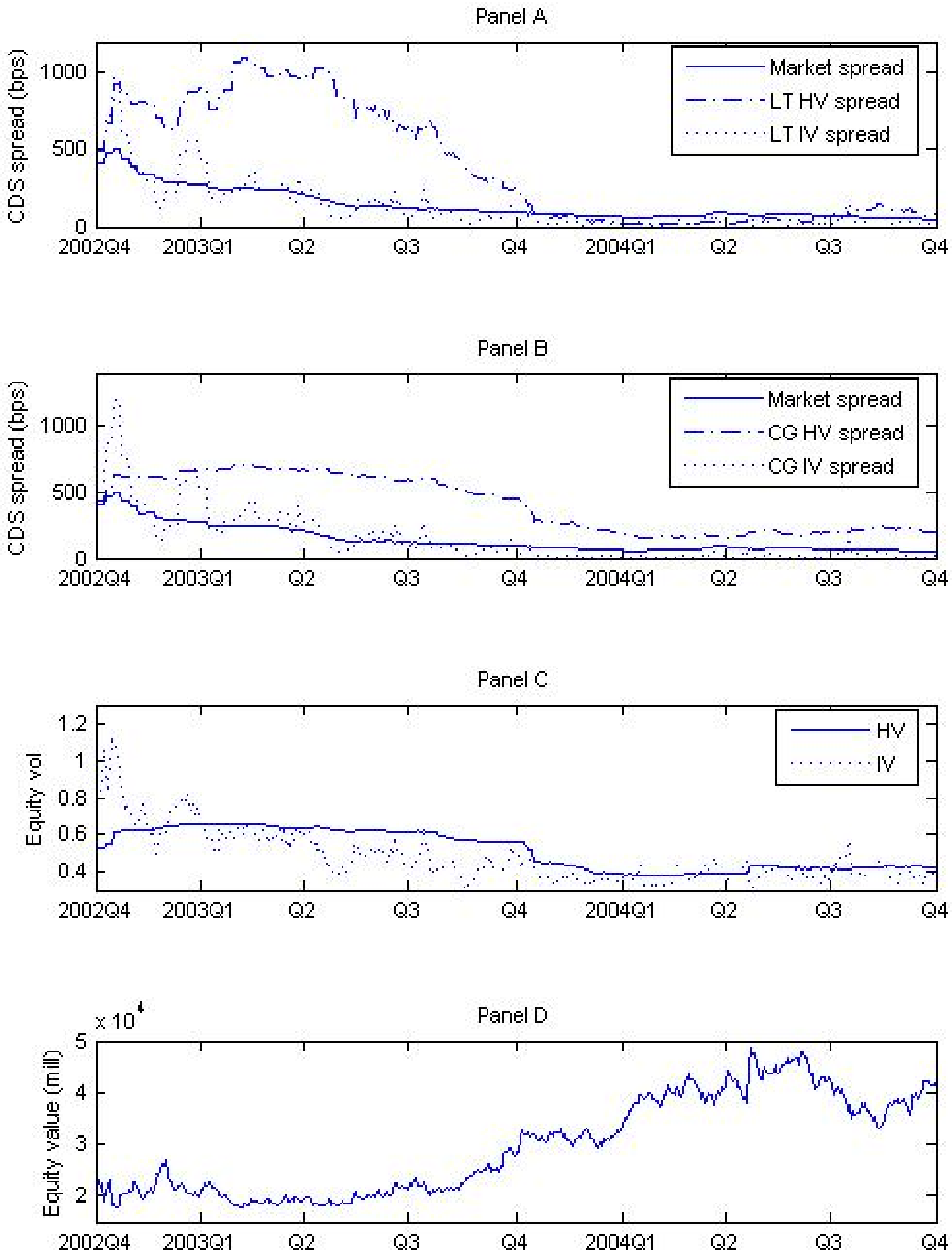


Figure 2.3: Motorola

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.



2.5.3 Mandalay Resort Group

Capital structure arbitrage is very risky when based on individual obligors, and the arbitrageur may end up in severe problems irrespective of model choice and calibration. Figure 2.4 presents the fundamental variables behind Mandalay Resort Group, rated BB by S&P. Throughout the coverage, spreads in Leland & Toft (1996) based on historical volatilities diverge from market spreads in a smooth manner, while spreads in CreditGrades diverge more slowly. In both cases the arbitrageur sells protection and equity as hedge, but suffers losses as positions are liquidated after the maximum holding period.

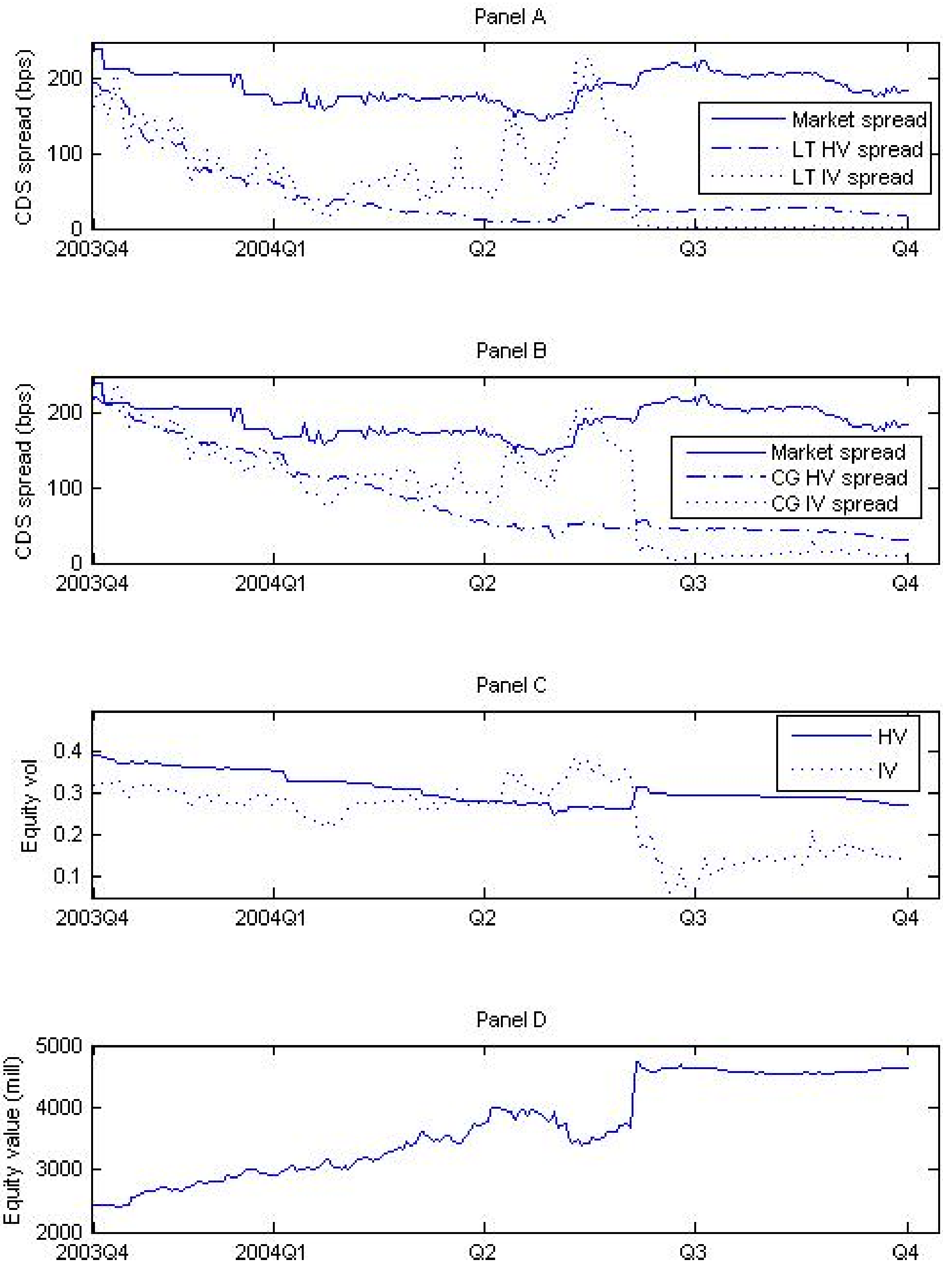
Based on implied volatilities, May and June 2004 are particularly painful as model spreads plunge and stay tight throughout the coverage. On June 4, 2004 the competitor MGM Mirage announces a bid to acquire Mandalay Resort Group for $68 per share plus assumption of Mandalay's existing debt. Moody's places the rating on review for a possible downgrade due to a high level of uncertainty regarding the level of debt employed to finance the takeover. As a result, the equity price increases from $54 to $69 over a short period, the implied volatility plunges and the CDS spread widens from 188 bps to 227 bps.[17] On June 15, 2004 a revised offer of $71 per share is approved, and the transaction is completed on April 26, 2005.

This opposite reaction in equity and credit gives the arbitrageur short in both markets a painful one-two punch similar to the one experienced by hedge funds in May 2005, where General Motors is downgraded while the equity price soars.[18] Luckily, not many trades are open during the takeover bid as model and market spreads recently converged. However, the short positions initiated in May 2004, where credit seems expensive relative to equity, suffer large losses on both legs.

[17] Implied volatilities from at-the-money calls plunge as well.
[18] This case study is discussed in Duarte et al. (2005).

Figure 2.4: Mandalay Resort Group

This figure illustrates the fundamentals behind capial structure arbitrage. In panel A, we depict market CDS spreads together with model spreads in Leland & Toft (1996) LT inferred from historical HV and option-implied volatilities IV. In panel B, the corresponding spreads are depicted based on CreditGrades CG. Panel C depicts the historical and option-implied volatility, where the first is calculated from a rolling 250-day window of equity returns and the latter is inferred from 30-day at-the-money puts. Finally, panel D illustrates the total market value of equity in millions of dollars.



2.6 General Results

In this section, we simulate the trading strategy for all 221 obligors. Following Yu (2006), we assume an initial capital of \$0.5 for each trade and \$1 notional in the CDS. The strategy is implemented for trading triggers α of 0.5 and 2, and maximum holding periods of 30 and 180 days.

Naturally, absolute trading returns will vary with the above characteristics, as well as the particular period studied and how to account for vanishing liquidity. However, these characteristics are all fixed when studying the relative risk and return across models and calibration methods. Therefore, a scaling of returns with the amount of initial capital is unlikely to influence our conclusions.[19] Indeed, although based on a different dataset, the benchmark results for CreditGrades with a historical volatility are similar to the findings in Yu (2006).

Table 2.3 and 2.4 present the summary statistics of holding period returns based on CreditGrades and Leland & Toft (1996), respectively. A longer maximum holding period leads to more converging trades, fewer trades with negative returns and higher average returns. This fundamental result underlies both models and volatility measures. Consistent with Yu (2006), although the distribution of returns becomes less dispersed, a higher trading trigger does not necessarily lead to higher mean returns.

When identifying relative value opportunities from implied not historical volatilities, the number of initiated trades rises for investment grade obligors and falls for speculative grade obligors. This results from both models, although the absolute number of trades is larger in Leland & Toft (1996). This is consistent with findings in Finger & Stamicar (2005*a*) and Cao et al. (2006), where the advantage of implied volatility in tracking market spreads with CreditGrades is concentrated among speculative grade obligors. We find this measure to identify fewer relative value opportunities on obligors with larger variations in spreads.

The results clearly show a difference in risk and return across models and volatility input. Identifying relative value opportunities on speculative grade

[19] Yu (2006) also conducts his analysis with an initial capital of \$0.1. The resulting returns are scaled up accordingly. Unreported results with this initial capital and other trading triggers leave our conclusions unchanged.

obligors in CreditGrades with a historical volatility, a maximum holding period of 180 days and a trading trigger of 2 yields a mean holding period return of 2.64 percent. However, simulating the trading strategy with option-implied volatilities increases the return to 4.61 percent.[20] The corresponding numbers based on Leland & Toft (1996) are 3.14 and 5.47 percent. The gain from implied volatilities across trading triggers and maximum holding periods is also apparent from the number of trades ending in convergence and the fraction of trades with negative returns. However, the incremental return is much smaller for investment grade obligors.

On top of this, the mean holding period return and dispersion are both higher on speculative grade obligors compared to the investment grade sample. This supports the similar result in Yu (2006) and happens irrespective of model choice and volatility measure. Although more likely to suffer from vanishing liquidity and default, this supports his observation that the aggregate success of the strategy depends on the availability of large variations in spreads. For such obligors, the more timely implied volatility results in incremental trading returns from superior entry and exit decisions.

The holding period returns are more favorable when Leland & Toft (1996) is used to identify relative value opportunities. However, in practice it is hard to discern exactly where the difference arises, as the models differ in many respects and enter in all parts of the strategy. While model choice does matter, it seems second to properly measured key inputs.

[20] While the average profitability increases when identifying relative value opportunities from implied volatilities, so does the volatility of returns. As the mean holding period return consists of many overlapping holding periods, the statistical significance of trading returns is analyzed from a return index below.

Table 2.3: Holding Period Returns Based on CreditGrades

This table shows the holding period returns resulting from CreditGrades CG with a historical volatility HV and option-implied volatility IV. The maximum holding period HP is either 30 or 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. N is the number of trades, N_{conv} the number of trades ending in convergence, and Neg is the percentage of trades ending in negative return. The mean and median returns are in percentages.

Model	HP	Trigger	Rating	N	N_{conv}	Neg.	Mean	Median	Std.dev.	Min	Max
Panel A. CreditGrades Holding Period Returns (30 Days)											
CG HV	30	0.5	Inv	45,190	789	0.45	0.01	0.04	1.16	-24.39	25.42
		0.5	Spec	1,860	0	0.47	0.28	0.08	3.38	-11.07	16.66
CG IV	30	0.5	Inv	53,559	2,787	0.32	0.33	0.13	1.75	-23.22	66.22
		0.5	Spec	1,598	231	0.27	2.46	0.74	10.20	-28.57	90.18
CG HV	30	2	Inv	27,212	46	0.41	0.05	0.06	0.84	-9.09	25.42
		2	Spec	824	0	0.38	0.84	0.47	2.76	-6.63	12.41
CG IV	30	2	Inv	46,179	727	0.32	0.28	0.13	1.38	-17.80	38.64
		2	Spec	380	19	0.11	2.06	1.36	4.96	-3.31	89.76
Panel B. CreditGrades Holding Period Returns (180 Days)											
CG HV	180	0.5	Inv	45,190	7,088	0.40	-0.08	0.15	3.10	-36.25	35.88
		0.5	Spec	1,860	3	0.43	0.17	0.38	5.50	-24.02	15.18
CG IV	180	0.5	Inv	53,559	6,231	0.27	1.13	0.39	3.58	-25.18	89.74
		0.5	Spec	1,598	665	0.18	6.58	2.08	16.83	-28.46	124.99
CG HV	180	2	Inv	27,212	1,488	0.30	0.26	0.26	2.00	-26.99	14.84
		2	Spec	824	0	0.16	2.64	1.48	3.76	-6.42	15.18
CG IV	180	2	Inv	46,179	2,504	0.27	0.95	0.38	3.14	-12.87	58.71
		2	Spec	380	103	0.08	4.61	2.61	8.12	-0.63	100.52

Table 2.4: Holding Period Returns Based on Leland & Toft

This table shows the holding period returns resulting from Leland & Toft (1996) LT with a historical volatility HV and option-implied volatility IV. The maximum holding period HP is either 30 or 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. N is the number of trades, N_{conv} the number of trades ending in convergence, and Neg is the percentage of trades ending in negative return. The mean and median returns are in percentages.

Model	HP	Trigger	Rating	N	N_{conv}	Neg.	Mean	Median	Std.dev.	Min	Max
Panel A. Leland & Toft Holding Period Returns (30 Days)											
LT HV	30	0.5	Inv	50,196	1,857	0.41	0.15	0.07	1.39	-19.05	38.39
		0.5	Spec	2,496	81	0.33	0.99	0.61	4.35	-40.44	94.04
LT IV	30	0.5	Inv	54,708	3,305	0.32	0.31	0.13	1.64	-31.46	65.21
		0.5	Spec	2,438	337	0.27	2.48	0.88	10.04	-37.16	106.59
LT HV	30	2	Inv	36,673	260	0.38	0.13	0.08	0.99	-16.06	17.05
		2	Spec	1,598	4	0.31	0.86	0.59	2.37	-14.00	13.59
LT IV	30	2	Inv	45,139	1,239	0.32	0.24	0.12	1.22	-21.61	21.55
		2	Spec	1,370	101	0.21	2.76	0.88	11.17	-16.73	106.59
Panel B. Leland & Toft Holding Period Returns (180 Days)											
LT HV	180	0.5	Inv	50,196	7,964	0.35	0.49	0.22	3.01	-86.92	55.60
		0.5	Spec	2,496	226	0.21	2.90	1.67	5.96	-20.39	94.04
LT IV	180	0.5	Inv	54,708	7,966	0.28	1.07	0.37	3.62	-47.01	89.32
		0.5	Spec	2,438	673	0.13	7.02	2.41	17.20	-39.32	147.05
LT HV	180	2	Inv	36,673	2,428	0.31	0.42	0.25	2.02	-86.92	42.43
		2	Spec	1,598	11	0.16	3.14	1.67	4.16	-14.00	16.22
LT IV	180	2	Inv	45,139	3,921	0.28	0.82	0.34	2.94	-39.70	49.71
		2	Spec	1,370	194	0.09	5.47	2.26	12.66	-2.94	117.00

2.6.1 Capital Structure Arbitrage Index Returns

As illustrated in the previous sections, capital structure arbitrage is very risky at the level of individual trades. The hedge may be ineffective and the markets may continue to diverge, resulting in losses and potential early liquidations. However, when initiated on the cross-section of obligors, the strategy may be profitable on average depending on the particular implementation. Having established this finding, the next step is to understand the sources of the profits, i.e. whether the returns are correlated with priced systematic risk factors. Hence, we construct a monthly capital structure arbitrage excess return index from all individual trades, following Duarte et al. (2005) and Yu (2006).

Specifically, we compute daily excess returns for all individual trades over the entire holding period. On a given day, thousands of trades may be open. By essentially assuming that the arbitrageur is always invested in an equally-weighted portfolio of hedge funds, where each fund consists of one trade, we calculate an equally-weighted average of the excess returns on a daily basis. These average daily excess returns are then compounded into a monthly frequency.

Table 2.5 presents the summary statistics of monthly excess returns based on a maximum holding period of 180 days, covering 24 months in 2002-2004. However, some strategies result in months with no trades. In this case, a zero excess return is assumed.

Again, although also present in the investment grade segment, the benefit of option-implied volatilities is concentrated among speculative grade obligors. Additionally, timely inputs are relatively more important than the exact structural model underlying the strategy. In particular, when based on CreditGrades with option-implied volatilities and a trading trigger of 2, the mean excess return is 0.44 percent on investment grade and 1.33 percent on speculative grade obligors. These numbers are highly significant after correcting for serial correlation. The corresponding numbers when Leland & Toft (1996) is used to identify relative value opportunities are 0.27 and 2.39 percent, respectively, both highly significant.

The excess returns resulting from a historical volatility are much smaller and most often insignificant. Indeed, the mean excess return from this measure may turn negative and significant at a lower trading trigger of 0.5, while it continues to be positive and significant based on implied volatilities.

Table 2.5: Monthly Excess Returns

This table shows the summary statistics of monthly capital structure arbitrage excess returns resulting from CreditGrades CG and Leland & Toft (1996) LT, calibrated with a historical HV and option-implied volatility IV. The maximum holding period HP is 180 days. Trigger denotes the minimum threshold between the market and model spread before positions are initiated. Rating denotes whether the strategy is implemented on investment grade or speculative grade obligors. In case of a month with no trades, a zero excess return is assumed, and N denotes the number of months with non-zero returns. Neg is the fraction of months with negative excess return. The mean and median returns are in percentages, and the t-statistics for the means are corrected for a first-order serial correlation. Sharpe denotes the annualized Sharpe ratio. The coverage is 24 months from October 2002 to September 2004.

Model	HP	Trigger	Rating	N	Neg.	Mean	t-Stat.	Median	Min	Max	Skew.	Kurt.	Corr.	Sharpe
Panel A. CreditGrades Monthly Excess Returns														
CG HV	180	0.5	Inv	24	0.83	-0.25	-2.13	-0.19	-1.33	0.51	-0.61	1.36	0.36	-2.15
		0.5	Spec	22	0.58	-0.34	-0.76	-0.14	-4.06	2.59	-0.29	0.45	0.37	-0.78
CG IV	180	0.5	Inv	24	0.29	0.41	3.72	0.50	-0.37	1.75	0.68	0.52	0.29	2.63
		0.5	Spec	24	0.25	2.82	2.13	1.22	-6.47	22.06	1.86	3.40	0.02	1.51
CG HV	180	2	Inv	24	0.75	-0.18	-1.52	-0.11	-1.33	0.49	-1.24	2.87	0.43	-1.65
		2	Spec	22	0.21	0.93	2.31	1.04	-3.98	5.75	0.03	1.55	-0.04	1.63
CG IV	180	2	Inv	24	0.25	0.44	2.26	0.42	-0.37	3.22	2.48	8.65	0.27	2.07
		2	Spec	18	0.13	1.33	2.23	0.52	-1.74	13.43	3.38	13.60	-0.05	1.57
Panel B. Leland & Toft Monthly Excess Returns														
LT HV	180	0.5	Inv	24	0.58	0.01	0.06	-0.05	-1.02	1.20	0.41	2.26	0.26	0.04
		0.5	Spec	23	0.21	1.99	2.86	1.32	-2.64	12.50	1.78	3.57	0.06	2.02
LT IV	180	0.5	Inv	24	0.25	0.45	3.41	0.40	-0.37	2.16	1.08	1.00	0.32	2.41
		0.5	Spec	23	0.16	3.04	2.62	1.43	-3.51	18.39	1.97	3.24	-0.02	1.85
LT HV	180	2	Inv	24	0.63	-0.06	-0.82	-0.11	-0.82	0.61	0.05	0.71	0.06	-0.58
		2	Spec	18	0.13	-0.09	-0.10	0.51	-18.07	2.56	-4.20	19.24	0.06	-0.07
LT IV	180	2	Inv	24	0.25	0.27	3.64	0.25	-0.31	1.09	0.27	-0.04	0.28	2.56
		2	Spec	23	0.08	2.39	3.65	1.32	-1.17	12.50	1.85	3.43	0.13	2.57

Addressing whether fixed income arbitrage is comparable to picking up nickels in front of a steamroller, Duarte et al. (2005) find that most of the strategies result in monthly excess returns that are positively skewed. While our results are mixed when relative value positions are identified from historical volatilities, the skewness is always positive when based on the implied measure. Thus, while producing large negative returns from time to time, this strategy tends to generate even larger offsetting positive returns.

As a final exercise, in Table 2.6, we explore whether the excess returns represent compensation for exposure to systematic market factors.[21] In particular, we use the excess return on the S&P Industrial Index (S&PINDS) to proxy for equity market risk. To proxy for investment grade and speculative grade bond market risk, the excess returns on the Lehman Brothers Baa and Ba Intermediate Index (LHIBAAI) and (LHHYBBI) are used. These variables are obtained from Datastream. As argued by Duarte et al. (2005), such market factors are also likely to be sensitive to major financial events such as a sudden flight-to-quality or flight-to-liquidity. As this risk would be compensated in the excess returns from these portfolios, we may be able to control for the component of returns that is compensation for bearing the risk of major, but not yet realized, financial events.

As the CDS market was rather illiquid before mid-2002, the regressions consist of no more than 24 monthly excess returns. Hence, the results must be interpreted with caution. Yu (2006) finds no relationship between capital structure arbitrage monthly excess returns and any of the factors, and the factors cannot bid away the alphas (regression intercepts) of the strategy. Our R^2 ranges from 8 to 35 percent, but the market factors are either insignificant or only weakly significant. Surprisingly, the occasional weak significance is not related to the size and significance of excess returns, nor rating category. Hence, the evidence does not indicate that the excess returns represent compensation for exposure to factors proxying equity and bond market risk.

As we only have 24 monthly excess returns, there is little chance of detecting significant alphas after controlling for the market risk. However, the structure of excess returns after a risk-adjustment is similar to the structure of raw excess returns in Table 2.5. Indeed, the largest difference in alphas across the historical

[21] For brevity, only regressions with a trading trigger of 2 are reported. Similar results are obtained at a lower threshold of 0.5.

and option-implied volatility is in the speculative grade segment. While three of four intercepts are negative based on the investment grade obligors, it is always positive on speculative grade obligors.

Table 2.6: Regression Results

This table reports the results from regressing capital structure arbitrage monthly percentage excess returns on the excess returns of equity and bond market portfolios. The models underlying the strategy are CreditGrades CG and Leland & Toft (1996) LT, calibrated with a historical HV and option-implied volatility IV. The strategy is implemented separately on investment grade and speculative grade obligors. $S\&PINDS$ is the excess return on the S&P Industrial Index. $LHIBAAI$ and $LHHYBBI$ are the excess returns on the Lehman Brothers Baa and Ba Intermediate Index, respectively. The coverage is 24 months beginning October 2002 and ending September 2004. Standard errors are shown in parantheses, and ***, ** and * denote significance at 1, 5 and 10 percent, respectively.

Strategy	Intercept	S&PINDS	LHIBAAI	LHHYBBI	R^2
CG HV Inv	-0.57*	0.09	7.29	-14.40*	0.21
	(0.28)	(2.27)	(7.06)	(7.80)	
CG HV Spec	1.96	-2.61	-53.73	77.25*	0.17
	(1.48)	(12.02)	(37.30)	(41.19)	
CG IV Inv	-0.15	6.13	-26.18**	12.77	0.35
	(0.49)	(3.96)	(12.29)	(13.58)	
CG IV Spec	3.76	9.11	-45.06	81.11	0.16
	(2.21)	(18.00)	(55.87)	(61.70)	
LT HV Inv	-0.59**	1.51	-1.86	-8.44	0.32
	(0.21)	(1.74)	(5.41)	(5.98)	
LT HV Spec	1.76	33.36	39.03	-40.44	0.08
	(3.18)	(25.91)	(80.41)	(88.80)	
LT IV Inv	0.27	2.34	-13.22*	12.13*	0.32
	(0.24)	(1.98)	(6.78)	(6.14)	
LT IV Spec	7.04***	-22.35	-21.91	121.69*	0.30
	(2.22)	(18.04)	(55.98)	(61.82)	

2.7 Conclusion

This paper conducts a comprehensive analysis of the risk and return of capital structure arbitrage using alternative structural credit risk models and volatility measures. Studying 221 North American industrial obligors in 2002 to 2004, a divergence between equity and credit markets initiates a convergence-based market-neutral trading strategy. However, an observed difference in market and equity-implied model CDS spread may be driven by model misspecification and key inputs may be mismeasured, sending a false signal of mispricing in the market. These caveats constitute the focal point in the study.

As the arbitrageur feeds on large variations in equity and credit markets and the asset volatility is a key input to the pricing of credit, a timely volatility measure is desirable. In such markets, the historical volatility may severely lag the market, suggesting the arbitrageur to enter into unfortunate positions and face large losses.

Using an option-implied volatility results in superior strategy execution and may initiate the opposite positions of the historical measure. The result is more positions ending in convergence, more positions with positive holding-period returns and highly significant excess returns. The gain in returns is largest for the speculative grade obligors, and cannot be explained by well-known equity and bond market factors. At a low threshold for strategy initiation, the excess return may turn negative and significant based on the historical measure, while it continues to be positive and significant based on implied volatilities.

Duarte et al. (2005) and Yu (2006) conduct the first analysis of the strategy by implementing the industry benchmark CreditGrades with a historical volatility, as reputed used by most professionals. CreditGrades and the Leland & Toft (1996) model differ extensively in assumptions governing default and calibration method. However, while model choice certainly matters, the exact model underlying the strategy is of secondary importance.

While profitable on an aggregate level, individual trades can be very risky. Irrespective of model choice and volatility measure, the market and equity-implied model spread may continue to drift apart, and the equity hedge may be ineffective. This may force the arbitrageur to liquidate individual positions early, and suffer large losses.

A structural model allows for numerous implementations of capital structure arbitrage, as it links firm fundamentals with equities, equity options, corporate bonds and credit derivatives. As we often find the hedge in cash equities ineffective, a further improvement may lie in offsetting positions in equity options such as out-of-the-money puts. This non-linear product may also reduce the gamma risk of the strategy, which can cause losses in a fast moving market. As CDS data continues to expand, future research will shed light on many unexplored properties of relative value trading across equity and credit markets.

A Appendix

The appendix contains formulas for the risk-neutral survival probability $q_t(s)$, the CDS spread $c(0,T)$, the contract value $\pi(t,T)$ and the equity delta δ_t. Both models assume constant default-free interest rates, which allow us to concentrate on the relationship between the equity price and CDS spread, also exploited in the relative value strategy.

A.1 CreditGrades

The default barrier is given by

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2}, \tag{2.18}$$

where L is the random recovery rate given default, $\bar{L} = E(L)$, Z is a standard normal random variable and $\lambda^2 = Var(\ln L)$. Finger (2002) provides an approximate solution to the survival probability using a time-shifted Brownian motion, which yields the following result[22]

$$q(t) = \Phi\left(-\frac{A_t}{2} + \frac{\ln d}{A_t}\right) - d \cdot \Phi\left(-\frac{A_t}{2} - \frac{\ln d}{A_t}\right), \tag{2.19}$$

where $\Phi(\cdot)$ is the cumulative normal distribution function and

$$d = \frac{V_0}{\bar{L}D}e^{\lambda^2}, \tag{2.20}$$

$$A_t^2 = \sigma_V^2 t + \lambda^2. \tag{2.21}$$

The CDS Spread and Hedge Ratio

Assuming constant interest rates, the CDS spread for maturity T is found by inserting the survival probability (2.19) in equation (2.6), yielding

$$c(0,T) = r(1-R)\frac{1 - q(0) + H(T)}{q(0) - q(T)e^{-rT} - H(T)}, \tag{2.22}$$

[22] In essence, the uncertainty in the default barrier is shifted to the starting value of the Brownian motion. In particular, the approximation assumes that W_t starts at an earlier time than $t = 0$. As a result, the default probability is non-zero for even very small t, including $t = 0$. In other models such as Leland & Toft (1996), the survival probability $q(0) = 1$.

where

$$
\begin{aligned}
H(T) &= e^{r\xi}\left(G(T+\xi) - G(\xi)\right), && (2.23)\\
G(T) &= d^{z+1/2}\Phi\left(-\frac{\ln d}{\sigma_V\sqrt{T}} - z\sigma_V\sqrt{T}\right)\\
&\quad + d^{-z+1/2}\Phi\left(\frac{\ln d}{\sigma_V\sqrt{T}} + z\sigma_V\sqrt{T}\right), && (2.24)\\
\xi &= \frac{\lambda^2}{\sigma_V^2}, && (2.25)\\
z &= \sqrt{\frac{1}{4} + \frac{2r}{\sigma_V^2}}, && (2.26)
\end{aligned}
$$

and $G(T)$ is given in Reiner & Rubinstein (1991).

When determining the hedge ratio, we follow Yu (2006) and approximate the contract value in equation (2.7) by

$$
\begin{aligned}
\pi(0,T) &= (c(0,T) - c)\int_0^T e^{-rs} q(s)\, ds && (2.27)\\
&= \frac{c(0,T) - c}{r}\left(q(0) - q(T)e^{-rT} - H(T)\right),
\end{aligned}
$$

where $c(0,T)$ is a function of the value of equity S in equation (2.22), and c is the CDS spread at initiation.[23]

Using equation (2.8) and the product rule, the hedge ratio is found as

$$
\delta_0 = N * \frac{d\pi(0,T)}{dS} = \frac{N}{r}\frac{\partial c(0,T)}{\partial S}\left(q(0) - q(T)e^{-rT} - H(T)\right), \qquad (2.28)
$$

where N denotes the number of shares outstanding. The second term in the product rule is zero, since by definition c is numerically equal to $c(0,T)$, evaluated at the equity value S. Finally, $\frac{\partial c(0,T)}{\partial S}$ is found numerically.

[23] Yu (2006) interprets this equation in his appendix. Equation (2.27) represents the value of a contract entered into one instant ago at spread c, that now has a quoted spread of $c(0,T)$ due to a change in the value of equity.

A.2 Leland & Toft (1996)

Equation (2.14) may be written as

$$\upsilon(V_t) = V_t + \tau\frac{C}{r}\left(1-\left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B\left(\frac{V_t}{V_B}\right)^{-x}, \tag{2.29}$$

with the value of debt $D(V_t)$

$$D(V_t) = \frac{C}{r} + \left(P-\frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) + \left(\left(1-\alpha\right)V_B - \frac{C}{r}\right)J\left(\Upsilon\right), \tag{2.30}$$

and equity $S(V_t)$

$$\begin{aligned} S(V_t) = {} & V_t + \tau\frac{C}{r}\left(1-\left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B\left(\frac{V_t}{V_B}\right)^{-x} \\ & -\frac{C}{r} - \left(P-\frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) \\ & -\left(\left(1-\alpha\right)V_B - \frac{C}{r}\right)J\left(\Upsilon\right), \end{aligned} \tag{2.31}$$

and default barrier V_B

$$V_B = \frac{\frac{C}{r}\left(\frac{A}{r\Upsilon} - B\right) - \frac{AP}{r\Upsilon} - \frac{\tau C x}{r}}{1+\alpha x - \left(1-\alpha\right)B}. \tag{2.32}$$

The components of the above formulae are

$$\begin{aligned} A &= 2ae^{-r\Upsilon}\Phi\left(a\sigma_V\sqrt{\Upsilon}\right) - 2z\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) && (2.33) \\ &\quad -\frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \frac{2e^{-r\Upsilon}}{\sigma_V\sqrt{\Upsilon}}\phi\left(a\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right), \\ B &= -\left(2z + \frac{2}{z\sigma_V^2\Upsilon}\right)\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) && (2.34) \\ &\quad -\frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right) + \frac{1}{z\sigma_V^2\Upsilon}, \\ I\left(\Upsilon\right) &= \frac{1}{r\Upsilon}\left(K\left(\Upsilon\right) - e^{-r\Upsilon}F\left(\Upsilon\right)\right), && (2.35) \end{aligned}$$

$$K\left(\Upsilon\right) = \left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1\left(\Upsilon\right)\right) + \left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2\left(\Upsilon\right)\right), \tag{2.36}$$

$$F(\Upsilon) = \Phi(h_1(\Upsilon)) + \left(\frac{V}{V_B}\right)^{-2a} \Phi(h_2(\Upsilon)), \tag{2.37}$$

$$\begin{aligned} J(\Upsilon) &= \frac{1}{z\sigma_V\sqrt{\Upsilon}} \left(-\left(\frac{V}{V_B}\right)^{-a+z} \Phi(j_1(\Upsilon))\, j_1(\Upsilon) \right. \\ &\quad \left. + \left(\frac{V}{V_B}\right)^{-a-z} \Phi(j_2(\Upsilon))\, j_2(\Upsilon) \right), & (2.38) \\ j_1(\Upsilon) &= \frac{(-b - z\sigma_V^2\Upsilon)}{\sigma_V\sqrt{\Upsilon}};\; j_2(\Upsilon) = \frac{(-b + z\sigma_V^2\Upsilon)}{\sigma_V\sqrt{\Upsilon}}, & (2.39) \\ h_1(\Upsilon) &= \frac{(-b - a\sigma_V^2\Upsilon)}{\sigma_V\sqrt{\Upsilon}};\; h_2(\Upsilon) = \frac{(-b + a\sigma_V^2\Upsilon)}{\sigma_V\sqrt{\Upsilon}}, & (2.40) \\ a &= \frac{(r - \rho - (\sigma_V^2/2))}{\sigma_V^2}, & (2.41) \\ b &= \ln\left(\frac{V_t}{V_B}\right), & (2.42) \\ z &= \frac{\sqrt{\left((a\sigma_V^2)^2 + 2r\sigma_V^2\right)}}{\sigma_V^2}, & (2.43) \\ x &= a + z. & (2.44) \end{aligned}$$

$\phi(\cdot)$ and $\Phi(\cdot)$ denote the density of the standard normal distribution and the cumulative distribution function, respectively.

The CDS Spread and Hedge Ratio

Using equation (2.37), the risk-neutral survival probability at horizon t is

$$\begin{aligned} q(t) &= 1 - F(t) & (2.45) \\ &= 1 - \left(\Phi(h_1(t)) + \left(\frac{V}{V_B}\right)^{-2a} \Phi(h_2(t))\right). \end{aligned}$$

Assuming constant interest rates, the CDS spread for maturity T is found by inserting the survival probability (2.45) in equation (2.6), yielding

$$0 = c(0,T) \int_0^T e^{-rs} q(s) ds + (1 - R) \int_0^T e^{-rs} q'(s) ds. \tag{2.46}$$

Integrating the first term by parts, yields

$$0 = \frac{c(0,T)}{r}\left(1 - e^{-rT}q(T) + \int_0^T e^{-rs}q'(s)ds\right) + (1-R)\int_0^T e^{-rs}q'(s)ds, \quad (2.47)$$

where the integral $-\int_0^T e^{-rs}q'(s)ds$ is given by $K(T)$ in equation (2.36), following Reiner & Rubinstein (1991). Then,

$$0 = \frac{c(0,T)}{r}\left(1 - e^{-rT}q(T)\right) - \left(\frac{c(0,T)}{r} + (1-R)\right)K(T), \quad (2.48)$$

which allows us to obtain a closed-form solution for the CDS spread

$$c(0,T) = r\,(1-R)\,\frac{K(T)}{(1 - e^{-rT}q(T) - K\,(T))}. \quad (2.49)$$

When determining the hedge ratio, we again follow Yu (2006) and approximate the contract value in equation (2.7) by

$$\begin{aligned}\pi(0,T) &= (c\,(0,T) - c)\int_0^T e^{-rs}q\,(s)\,ds. \quad (2.50)\\ &= \frac{c\,(0,T) - c}{r}\left(1 - e^{-rT}q(T) - K\,(T)\right),\end{aligned}$$

where $c\,(0,T)$ is a function of the value of equity S, and c is the CDS spread at initiation.

Similar to CreditGrades, the hedge ratio is found using equation (2.8)

$$\delta_0 = \frac{N}{r}\frac{\partial c\,(0,T)}{\partial S}\left(1 - e^{-rT}q(T) - K\,(T)\right). \quad (2.51)$$

However, in Leland & Toft (1996) the CDS spread is not an explicit function of the equity value. Therefore, $\frac{\partial c(0,T)}{\partial S}$ is found numerically using

$$\frac{\partial c\,(0,T)}{\partial S} = \frac{\partial c\,(0,T)}{\partial V}\frac{\partial V}{\partial S} = \frac{\partial c\,(0,T)}{\partial V}\frac{1}{\frac{\partial S}{\partial V}}. \quad (2.52)$$

Chapter 3

Credit Risk Premia in the Market for Credit Default Swaps

Abstract[1]

This paper estimates the time-series behavior of credit risk premia in the market for Credit Default Swaps for the period 2001 to 2006. A structural model is used to back out objective default probabilities. The results indicate that risk premia might be incorrectly estimated, when expected losses are based on a historical equity volatility measure as opposed to implied volatility. This effect is largest following the peak in credit spreads and risk premia in the second half of 2002. Secondly, when default probabilities are based on implied volatility, the risk premia tend to be countercyclical in the sense that the risk premium is high when expected losses are high. Finally, using linear regressions, I find that augmenting the set of variables predicted by structural models with equity-implied credit risk premia significantly increases the explanatory power. This echoes the results found in Elkamhi & Ericsson (2007) and suggests the need for time varying risk premia in structural models.

[1] I thank MarkIt for access to credit default swap data. I am grateful to David Lando and Jesper Rangvid for useful comments. All remaining errors are my own.

3.1 Introduction

This paper estimates the time-series behavior of credit risk premia in the market for Credit Default Swaps (CDS) for the period 2001 until the end of 2006. More specifically the structural model by Leland & Toft (1996) is used to back out objective default probabilities from the equity market, and the market CDS spread is then decomposed into an expected loss component and a risk premium component.

Not much empirical work has been done on the time variation of risk premia in credit markets. Berndt, Douglas, Duffie, Ferguson & Schranz (2005) and Berndt, Lookman & Obreja (2006) use expected default frequencies (EDF) from Moody's KMV together with CDS spreads to extract historical and risk neutral default intensities respectively. The ratio of these is interpreted as a measure of the default risk premium observed in the marketplace. They document substantial time-series variation in risk premia for the period from 2000-2004 with a peak in the third quarter of 2002 and a subsequent dramatic drop. Elkamhi & Ericsson (2007) develop a methodology to study the linkages between equity and corporate bond risk premia and apply it to a panel of corporate bond transactions data for the period 1995 - 2005. They find a time-series behavior and degree of time variation in credit risk premia similar to Berndt et al. (2005), although their study is based on different data, a different financial instrument and a different methodology.

An obvious problem when estimating credit risk premia is the measurement of objective default probabilities and expected losses. Elkamhi & Ericsson (2007) base the default probabilities on a historical volatility measure, while Berndt et al. (2005) and Berndt, Lookman & Obreja (2006) use the EDF measure, and their estimated default probabilities are thus essentially also based on historical volatility[2]. I contribute to the existing literature by applying the methodology developed in Elkamhi & Ericsson (2007) to a large panel of CDS quotes, but contrary to them I also back out the default probabilities using option implied volatility. This should give a better view of the uncertainty in the market, especially when the uncertainty changes rapidly. According to Cremers et al. (2006) and Cao et al. (2006), the implied volatility contains important and timely in-

[2]See Crosbie & Bohn (2003) and Berndt et al. (2005) for a discussion of the EDF measure.

formation about credit risk different from the historical measure, while Finger & Stamicar (2005*a*) and Finger & Stamicar (2005*b*) show how model spreads based on historical volatilities lag the market when spreads increase, while overpredicting the market as spreads recover.

The computation of objective default probabilities is done as in Elkamhi & Ericsson (2007) by estimating firm specific equity risk premia using the Fama & MacBeth (1973) approach, and then the equity risk premia are "delevered" into asset value risk premia. The measure of the credit risk premium is then the part of the CDS spread in excess of the expected loss component.

Although a close relation exists between corporate bonds and CDS spreads (Duffie (1999)), the latter are preferable from several perspectives. The use of CDS spreads avoids any noise arising from a misspecified risk-free yield curve (Houweling & Vorst (2003)) and several recent studies find that CDS spreads are a purer measure of credit risk compared to corporate bond credit spreads[3]. Furthermore, while the corporate bonds used in Elkamhi & Ericsson (2007) are of different maturity and coupon, all of the CDS spreads in this paper have a 5-year maturity and are effectively new par-coupon credit spreads on the underlying firm. The results are also expected to be more robust compared to Elkamhi & Ericsson (2007) since the data in this paper are larger in the cross section, and the same firms are followed over time.

I find that the estimated credit risk premia appear more volatile when default probabilities and expected losses are based on the historical volatility measure compared to implied volatility. Similar to earlier results I find that the risk premia peak in the third quarter of 2002, but the subsequent drop in risk premia is not as dramatic, when expected losses are based on implied volatility. Furthermore there is a high degree of uncertainty in the option market in the second half of 2002 as measured by the implied volatility. This result is consistent across industries and ratings (investment grade and speculative grade), and suggests that it may be inappropriate to base expected losses on a historical volatility measure, when estimating credit risk premia.

Secondly, when expected losses are based on implied volatility, the credit risk premium is high in times of high default probabilities and low in times of low default probabilities. This suggests that the credit risk premium is countercycli-

[3] See e.g. Longstaff et al. (2005).

cal. Furthermore the expected loss ratio and the risk premium ratio behave quite differently from one another over time. Interestingly, when based on implied volatility, the expected loss ratio peaks in late 2002, when credit spreads soared and the credit risk premium peaked. The expected loss ratio is actually higher than 50% at certain points in this period. On the other hand the risk premium ratio tends to be high in times of low credit spreads and low default probabilities.

Thirdly I show that there is a close relation between VIX and expected losses, when the asset volatilities are based on implied volatility. Earlier papers such as Collin-Dufresne et al. (2001) and Schaefer & Strebulaev (2004) have showed that VIX is an important explanatory variable for changes in credit spreads, although they do not pin down an explanation for the role of VIX, while Berndt et al. (2005) find that VIX is related to the credit risk premium. The results of this paper suggest that VIX is indeed a measure of systematic volatility.

Finally I carry out a regression analysis similar to Ericsson et al. (2005), Collin-Dufresne et al. (2001) and Campbell & Taksler (2003). A benchmark regression is performed including standard variables implied from structural models. Augmenting the regressions with an equity implied measure of the credit risk premium improves the explanatory power for the levels of the credit spread, while the coefficient on this purely model implied risk premium is highly significant. With the historical volatility as part of the variables in the regressions the R-square is 49.4%, and it increases by 3% to 52.4%, when the risk premium is included, while the R-square increases by 5.5% from 57.4% to 62.9%, when the regressions are performed with implied volatility. The increase in the explanatory power is substantially higher, when the risk premium is included for the investment grade segment compared to the speculative grade segment. This suggests that investment grade firms have proportionally higher risk premia and that risk premia are more important for investment grade firms than for speculative grade firms. Similar results are found in Huang & Huang (2003) and Berndt et al. (2005).

The regression results echo results in Elkamhi & Ericsson (2007), and combined with the other results of the paper, it suggests that structural models should contain a time varying and countercyclical risk premium. The results also suggest a link between equity risk premia and credit spreads, when the equity risk premium is properly translated to the credit risk premium through a structural model. This is in line with Elton et al. (2001), who show that there is a nontrivial component of credit spreads, interpreted as a risk premium, which is correlated with factors explaining equity risk premia. Elkamhi & Ericsson (2007) also find that risk premia in the credit and equity markets are related. On the other hand Berndt, Lookman & Obreja (2006) extract a factor representing the part of default swap returns, implied by a reduced form credit risk model, that does not compensate for interest rate risk or expected default losses. They find that this factor is priced in the corporate bond market but that they cannot establish with the same confidence that it is a factor for equity returns. However, the expected losses in Berndt, Lookman & Obreja (2006) are based on the EDF measure.

The results of the paper suggest that much more research is needed is this area, to understand the link between risk premia in the two markets. Some work in this direction have recently been done by Chen, Collin-Dufresne & Goldstein (2006), Bhamra, Kuehn & Strebulaev (2007) and Chen (2007).

Furthermore the R-squares of the regressions are substantially higher when the implied volatility is included in the regressions, and the explanatory power is especially high for speculative grade spreads. This supports results in Cao et al. (2006), who also find the strongest link between option-implied volatilities and CDS spreads among firms with the lowest rating.

The paper is also related to Leland (2004), who looks at default probabilities in structural models, Saita (2006), who studies the risk and return of corporate bond portfolios, and Driessen (2005), who decomposes corporate bond yield spreads into tax, liquidity and default risk premia.

Section 3.2 describes how the credit risk premium can be measured, and also how the premium is measured in this paper. In section 3.3 the data are presented, while section 3.4 describes the empirical implementation. The results are presented in section 3.5, and finally section 3.6 concludes.

3.2 Measuring Credit Risk Premia (RPI) from Yield Spreads

We describe the basic intuition behind the credit risk premium and how it can be measured, and then the approach chosen in this paper is presented.

3.2.1 Yield Spread Components

There is a distinction between the credit risk premium and the yield spread. In order to make this distinction a simple numerical example from Elkamhi & Ericsson (2007) is used. We consider a unit zero discount bond with zero recovery in default issued by a firm that can only default at time T. The value of such a bond is

$$B_t = e^{-r(t,T)*T} E^Q \left[1_{(\tau > T)} \right] = e^{-r(t,T)*T} Q_t(\tau > T),$$

where $E^Q[\cdot]$ is the risk neutral expectation, $Q_t(\tau > T)$ the risk neutral survival probability and τ the default stopping time. The value of the bond is thus the present value of the risk adjusted survival probability. For now assume that default risk is not priced and that $P_t(\tau > T) = Q_t(\tau > T) = 80\%$, where P_t denotes the objective survival probability. Further assume that $r(t,T) = 10\%$ and $T = 10$. The price of the bond is then $B_t = e^{-0.1*10} * 0.8 = 0.2943$ and its continuously compounded yield is 12.23%. The bond thus pays a spread of 223 basis point, even though a risk premium is not present. In this case the spread is merely an actuarial fair compensation for expected losses.

We now assume that default risk is priced, which implies that $P_t(\tau > T) > Q_t(\tau > T)$. With the same parameters as above and now assuming that $Q_t(\tau > T) = 70\%$ and $P_t(\tau > T) = 80\%$ the bond price will be lower at $B_t = e^{-0.1*10} * 0.7 = 0.2575$ and the yield will be 0.1357. The spread has thus increased to 357 basis points. This increase in the spread of 134 basis points, denoted π, reflects the risk premium for bearing default risk. We can thus express the price of the bond in three different ways

$$B_t = e^{-r(t,T)*T} E^Q \left[1_{(\tau > T)} \right] = e^{-(r(t,T)+\pi)*T} E^P \left[1_{(\tau > T)} \right] = e^{-(r(t,T)+\pi+\gamma)*T} * 1,$$

where $E^P[\cdot]$ is the objective expectation and γ is a component which adjusts for the expected loss (in this case 223 basis points). The first is the standard valuation method, using the risk neutral expectation discounted at the risk-free rate. The second is the present value at the risk adjusted rate of the expected payment at maturity $E^P[\cdot]$. The third is the present value of the full face value discounted at the risk adjusted rate rate augmented by a component γ, which adjusts for the expected loss.

3.2.2 Measuring the Risk Premium from CDS Spreads

We now proceed to describe the methodology used to measure the risk premium π from CDS spreads. This is done by decomposing the CDS spread as Elkamhi & Ericsson (2007) do for corporate bond spreads. Since the accrued premium must also be paid if a credit event occurs between two payments dates, the payments in a CDS fit nicely into a continous-time framework. Given knowledge of the term structure of objective survival probabilities of the obligor, $\{P_t(\tau > s); s \in (t, \infty)\}$ one can obtain an estimate of the CDS spread that would prevail in a market without a risk premium (assuming a constant risk-free interest rate r and a constant recovery rate R)

$$c^{no\ risk}(0,T) = -\frac{(1-R)\int_0^T e^{-rs}P_0'(s)ds}{\int_0^T e^{-rs}P_0(s)ds}, \tag{3.1}$$

where $P_0(s)$ is the objective survival probability of the obligor at $t = 0$ and $P_0'(t) = dP_0(t)/dt$[4]. The spread in (3.1) only takes expected losses into account and the credit risk premium (RPI_t) is then measured as the difference between the CDS spread observed in the market c^{market} and $c_t^{no\ risk}$

$$RPI_t = c_t^{market} - c_t^{no\ risk}. \tag{3.2}$$

The CDS spread when a risk premium is present can be priced as in equation (3.1)

$$c^{risk}(0,T) = -\frac{(1-R)\int_0^T e^{-rs}Q_0'(s)ds}{\int_0^T e^{-rs}Q_0(s)ds}, \tag{3.3}$$

where $Q_0(s)$ is the risk neutral survival probability of the obligor at $t = 0$ and $Q_0'(t) = dQ(t)/dt$. A purely model-implied measure of the credit risk premium is then defined as[5]

$$RPI_t^{equity} = c_t^{risk} - c_t^{no\ risk}. \tag{3.4}$$

To obtain an estimate of the CDS spreads in equation (3.1) and (3.3) we need the recovery rate and survival probabilities for different horizons. The recovery rate R is set equal to 40%, roughly consistent with the average observed recovery

[4] $-dP_0(t)/dt$ is then the first hitting time density.

[5] This purly model implied measure of the risk premium is denoted RPI_t^{equity} since it will be based on the risk premium in the equity market.

rate between 1982-2006[6]. The recovery rate is kept constant through out the period, and it is assumed that there is no risk premium associated with the recovery rate. The size and possible time-series behavior of the expected recovery rate could be of importance though. We will get back to this in section 3.5.

To get the term structures of survival probabilities, the structural model by Leland & Toft (1996) is calibrated to the equity market using information from each firm's balance sheet. Together with estimates of the asset value risk premium it is then possible to also obtain objective survival probabilities. This is similar to Leland (2004) and Huang & Huang (2003), but the focus in this paper is on the time-series behavior of the risk premium, and thus it is not assumed, that current conditional default probabilities are equal to historical average default probabilities by credit rating.

A different structural could have been used, but Leland (2004) shows that the model by Leland & Toft (1996) does a reasonable job of predicting observed default rates, although short term default rates tend to be underestimated, while Ericsson et al. (2006) find that the model performs very well when predicting CDS spreads[7]. The empirical implementation is further described in section 3.4 and the model by Leland & Toft (1996) is described in appendix A, which also presents the model-implied survival probabilities and CDS spreads in closed form.

The risk premia described above is based on the contingent claims approach, while other empirical studies such as Driessen (2005), Berndt et al. (2005) and Berndt, Lookman & Obreja (2006) rely on intensity based models. A discussion of risk premia in these models can be found in Lando (2004).

[6]According to Moody's (Hamilton, OU, Kim & Cantor (2007)) the average recovery rate on senior unsecured bonds for the period 1982-2006 was 38.4% : The choice of recovery rate is also in accordance with Elkamhi & Ericsson (2007).

[7]The model by Leland & Toft (1996) is also the one used in Elkamhi & Ericsson (2007). Secondly Huang & Huang (2003) shows that different structural models predict fairly similar credit spreads under empirically reasonable parameters.

3.3 Data

5-year credit default swap spreads with modified restructuring (MR) for U.S.-dollar denominated senior unsecured debt are used[8]. The credit default swap data is provided by MarkIt, who receives data from more than 50 global banks. These data are aggregated into composite numbers after filtering out outliers and stale data, and a price is only published if at least three contributors provide data[9]. Several filters are then applied to obtain the final dataset.

First, the CDS data are merged with quarterly balance sheet data from Compustat and daily stock market data from CRSP. The quarterly balance sheet data are lagged one month from the end of the quarter to avoid any look-ahead bias in using data not yet available to the market. Firms from the financial and utility sector are then excluded since their capital structure is very different from other corporates.

Secondly, the dataset is merged with daily data on the 30-day at-the-money put-implied volatility obtained from OptionMetrics. OptionMetrics is a comprehensive database of daily information on exchange-listed equity options in the U.S. dating back to 1996. OptionMetrics generates the 30-day at-the-money put-implied volatility by interpolation.

Thirdly, 1250 days of equity returns[10] are needed prior to each CDS quote to estimate daily equity risk premia (see section 3.4 for details).

Finally to minimize market microstructure effects, I only use weekly (Wednesday) observations on the CDS quotes, and to ensure that the analysis is based on reasonably liquid CDS's I exclude firms which have less than 150 weekly quotes. The final dataset consists of 33401 weekly quotes distributed across 142 unique firms, dating back to May 2001 and onwards to the end of October 2006.

[8]The 5-year maturity is the most liquid point on the credit curve (see e.g. Blanco et al. (2005)).

[9]MarkIt data is also used in e.g. Berndt, Lookman & Obreja (2006) and Huang & Zhou (2007).

[10]Corresponding to 5 years.

In Figure 3.1 the average market CDS spread is plotted over time. The average market spread varies considerably through the sample period, peaking during the credit crunch in the second half of 2002 and beginning of 2003. Following the peak in 2002 the average credit spread falls until the end of 2006. The time-series behavior of the average spread is very similar to the behavior of the median spread in Berndt, Lookman & Obreja (2006).

In Table 3.1 summary statistics are shown across the senior unsecured credit rating from Standard & Poors. The presented variables are averages across the number of quotes in each rating category. The majority of the quotes are A or BBB rated, and the vast majority of the quotes are also within the investment grade segment. A better rating is associated with a lower spread and lower leverage and volatility. This is in line with the predictions of structural models. A better rating is also associated with a larger firm size.

Figure 3.1: Average Market CDS Spread over Time

The figure illustrates the average market CDS spread over time. The mean is calculated as averages over the cross section of weekly spreads.

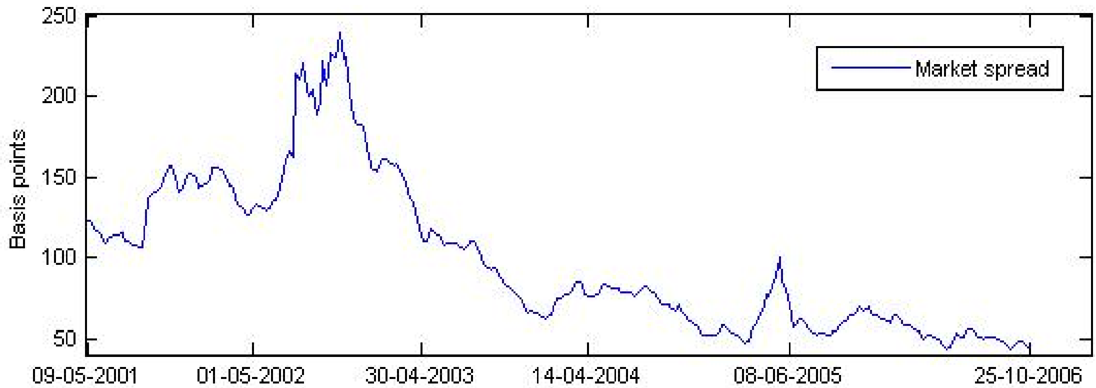


Table 3.1: Sample Characteristics

This table reports sample characteristics for the 142 obligors. The sample characteristics are averages over the number of quotes. The statistics are presented across the senior unsecured credit rating from Standard & Poor's. N is the number of quotes and *spread* is the avererage 5-year CDS quote. While the historical equity volatility HV is calculated from a 250-day rolling window of equity returns, the implied equity volatility IV is inferred from 30-day at-the-money put options. The leverage ratio *Lev* is total liabilities divided by the sum of total liabilities and equity market capitalization, and *size* is the sum of total liabilities and equity market capitalization in billions of dollars. *Equity prem.* is the estimated equity premium.

Rating	N	Spread	HV	IV	Lev.	Size	Equity prem.
AAA	956	21	0.284	0.261	0.274	375.086	0.067
AA	2580	26	0.289	0.273	0.211	98.894	0.074
A	11671	49	0.315	0.302	0.346	44.080	0.075
BBB	15505	120	0.349	0.331	0.508	29.403	0.076
BB	2069	321	0.454	0.422	0.559	19.094	0.100
B	620	522	0.629	0.507	0.706	25.701	0.106

3.4 Empirical Implementation

The structural model by Leland & Toft (1996) is used to obtain risk neutral and objective survival probabilities. In Leland & Toft (1996), firm assets V are assumed to follow a geometric Brownian motion under the risk-neutral measure

$$dV_t = (r - \rho)V_t dt + \sigma_V V_t dW_t, \tag{3.5}$$

with

$$dV_t = u_V V_t dt + \sigma_V V_t dW_t \tag{3.6}$$

under the objective measure[11]. r is the risk free interest rate, ρ is the payout ratio and σ_V is the asset volatility. The firm defaults when the asset value hits the endogenously derived default barrier V_B. To obtain the survival probabilities the unobserved asset value V_t, and asset volatility σ_V are needed, and to get the objective survival probabilities estimates of the expected asset return u_V is needed as well. In the next two sections I describe how these unobserved parameters are

[11] In this case μ_V includes the payout ratio ρ.

inferred. A more detailed description of the model by Leland & Toft (1996) is given in appendix A.

3.4.1 Calibrating the Leland & Toft (1996)-Model

To infer the unobserved asset value V_t, and asset volatility σ_V the model is calibrated to equity market data in two ways. Firstly using a 250-day historical volatility and secondly using an implied volatility from equity options. According to Cremers et al. (2006) and Cao et al. (2006), the implied volatility contains important and timely information about credit risk different from the historical measure.

To implement the model, we follow Ericsson et al. (2006) in setting the realized bankruptcy cost fraction $\alpha = 0.15$, the tax rate $\tau = 0.20$ and the average debt maturity $\frac{\Upsilon}{2} = 3.38$.[12] Furthermore P is the total liabilities from quarterly balance sheet data, S is the market value of equity and r is the 5-year constant maturity treasury yield. We also follow Ericsson et al. (2006) in assuming that the average coupon paid out to all debtholders equals the risk-free interest rate, $C = rP$.[13] The asset payout rate ρ is calculated as a time-series mean of the weighted average historical dividend yield and relative interest expense from balance sheet data

$$\rho = \left(\frac{Interest\ expenses}{Total\ liabilities}\right) \times L \ + (Dividend\ yield) \times (1 - L) \tag{3.7}$$
$$L = \frac{Total\ liabilities}{Total\ liabilities + Market\ equity}.$$

The iterative algorithm of Moody's KMV outlined in Crosbie & Bohn (2003) and Vassalou & Xing (2004) is used to infer the unobserved time-series of asset values and asset volatility. This iterative scheme goes as follows. The value of equity S_t is a function of the asset value V_t, asset volatility σ_V and a set of parameters θ (see equation (3.17) in appendix A), i.e. $S_t = f(V_t, \sigma_V, \theta)$. A 250-

[12] The choice of 15 percent bankruptcy costs lies well within the range estimated by Andrade & Kaplan (1998). 20 percent as an effective tax rate is below the corporate tax rate to reflect the personal tax rate advantage of equity returns. Stohs & Mauer (1996) find an average debt maturity of 3.38 years using a panel of 328 industrial firms with detailed debt information in Moody's Industrial Manuals in 1980-1989.

[13] A firm's debt consists of more than market bonds, and usually a substantial fraction of total debt is non-interest bearing such as accrued taxes and supplier credits. Furthermore, corporate bonds may be issued below par, which also opens up for this approximation.

day window of historical equity values is used to obtain an estimate of the equity volatility σ_S, by viewing the value of equity as a geometric Brownian motion. Given this initial estimate of the asset volatility σ_V and quarterly balance sheet data, the value of the default barrier can be calculated. Using the daily market values of equity and the equity pricing formula we then back out an implied time-series of asset values $V_t(\sigma_V) = f^{-1}(S_t, \sigma_V, \theta)$. Next, since the daily asset values follow a geometric Brownian motion we obtain an improved estimate of the asset volatility σ_V, which is used in the next iteration. This procedure is repeated until the values of σ_V converge.

When using implied volatilities from equity options, the instantaneous relationship given by

$$S_t = f(V_t, \sigma_V, \theta) \tag{3.8}$$

$$\sigma_S = \frac{\partial S_t}{\partial V_t}\sigma_V \frac{V_t}{S_t} \tag{3.9}$$

is solved numerically for the unknown asset value V_t and asset volatility σ_V, where (3.9) follows from Ito's lemma on S_t.

Table 3.2 gives summary statistics for the calibrated parameters. For each rating category the average calibrated parameters look reasonably similar across the two calibration methods, but as we will see later, they will behave differently over time. At first sight it may seem surprising that the average calibrated asset volatilities are smallest for the lower ratings, which is consistent for both calibration methods. The reason is that these firms have very large leverage ratios as seen in Table 3.1. So even though these firms have higher equity volatilities they end up with lower calibrated asset volatilities due to the high leverage. If we look at the average distance to default measure DD, calculated as $\frac{V-V_B}{\sigma_V V}$, we also see that the better rated firms have a larger distance to default, and thus a smaller risk of defaulting.

As described in the introduction the difference in calibration method could give rise to different implied credit risk premia, and less volatile risk premia are expected, when the survival probabilities and expected losses are based on the model implemented with the option implied volatility. Suppose e.g. that the uncertainty in the market suddenly increases. This implies both a higher option implied volatility and a higher realized equity volatility. The difference is that a change in uncertainty is immediately captured in the implied volatility but only slowly in the historical volatility. This leads to differences in the calibrated asset volatility σ_V, and thus in expected losses. Since a change in uncertainty is also immediately captured in the market CDS spread c_t^{market}, the use of default probabilities based on historical volatility, when calculating $c^{no\ risk}(0,T)$ from equation (3.1) might give rise to credit risk premia that are mismeasured. Expected losses in both Berndt et al. (2005), Berndt, Lookman & Obreja (2006) and Elkamhi & Ericsson (2007) are based on historical volatilities. I will therefore check if the use of implied volatility when calculating expected losses leads to better measured and less volatile risk premia.

Table 3.2: Descriptive Statistics of Implied Parameters

This table reports the central implied parameters from Leland & Toft (1996), calibrated with a historical volatility HV in panel A and option-implied volatility IV in panel B. While the first measure is calculated from a 250-day rolling window of equity returns, the latter is implied from 30-day at-the-money put options. The descriptive statistics are averaged over the number of quotes. The *asset value* and default barrier (*barrier*) are measured in billions of dollars. *Asset vol.* is the implied asset volatility and DD is the measure of distance to default calculated as $(V - V_B)/(\sigma_V V)$.

Variable	Asset value	Asset vol.	Barrier	DD
	Panel A. Leland & Toft HV			
AAA	357.000	0.209	121.274	4.064
AA	95.754	0.234	15.304	4.021
A	41.933	0.209	12.604	3.924
BBB	27.857	0.171	15.282	3.753
BB	17.981	0.189	8.112	3.203
B	24.002	0.171	15.350	2.562
	Panel B. Leland & Toft IV			
AAA	354.573	0.190	124.643	4.431
AA	95.627	0.218	15.579	4.197
A	41.789	0.200	12.844	3.961
BBB	27.962	0.161	15.929	3.854
BB	18.018	0.179	8.247	3.272
B	24.366	0.146	16.359	2.858

Having found the asset value V and asset volatility σ_V we can calculate risk neutral survival probabilities. We now go on to estimate the expected return on assets u_V in equation (3.6) to be able to calculate objective probabilities and price the CDS in a market without risk premia $c^{no\ risk}(0,T)$.

3.4.2 Estimating the Asset Value Risk Premia

The expected asset return u_V is found as in Elkamhi & Ericsson (2007). More specifically we link the risk premium on assets to the risk premium on equity[14]

$$u_V - r = (R_V(t) - r) = \Delta S \left(R_S(t) - r\right), \tag{3.10}$$

where $(R_S(t) - r)$ is the estimated equity risk premium,

$$R_S(t)dt = E^P[\frac{dS_t(V_t)}{S_t(V_t)}].$$

$$R_V(t)dt = E^P[\frac{dV_t}{V_t}]$$

is the expected asset return u_V, and

$$\Delta S = \left(\frac{\frac{\partial S_t(V_t)}{\partial V_t}V_t}{S_t(V)}\right)^{-1} \tag{3.11}$$

is found numerically using the structural model by Leland & Toft (1996) and depending on, whether the model parameters (V & σ_v) are calibrated with the historical volatility or option implied volatility.

The equity premium $(R_S(t) - r)$ is estimated for each CDS quote in the dataset. The approach by Fama & MacBeth (1973) is used together with the Fama & French (1993) market factor[15]. Using a history of 1250 daily stock returns betas are estimated for each CDS quote. A cross sectional regression of the individual stock returns on the betas is then run each day, which yields a daily market risk premium. A moving average over 1250 days is then used as the factor risk premium on the given day[16].

[14] The proof of equation (3.10) can be found in Campello, Chen & Zhang (2008).

[15] This factor can be found on Kenneth French's website.

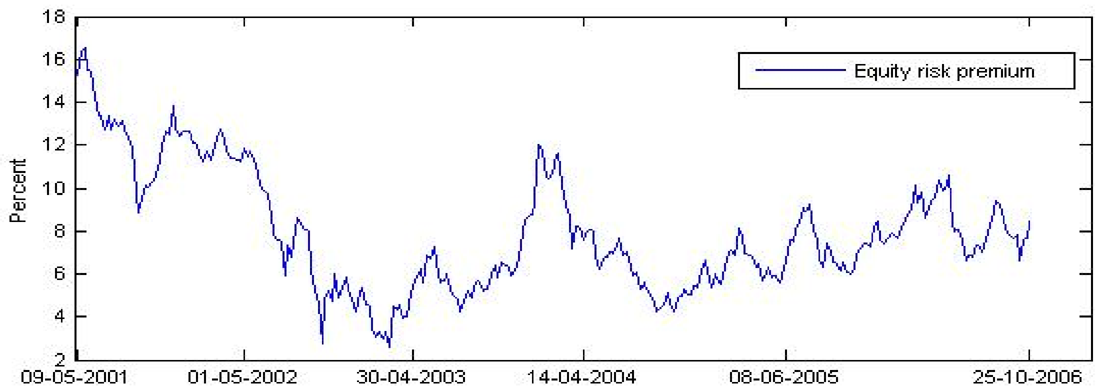
[16] Running monthly cross sectional regressions instead, followed by averages over 60 month

For each stock on each day the equity premium is then found as the beta multiplied by the market risk premium, and the expected asset return u_V is then found using equation (3.10).

In the last column of Table 3.1 the average equity premia are given across rating and the average equity premium over time is given in Figure 3.2. The average risk premium across all observations is 7.76% and we see from Table 3.1 that better rated firms have a lower average risk premium. This is similar to the average equity risk premia across ratings in Huang & Huang (2003), although the average estimated risk premia in this paper generally are a bit higher.

Figure 3.2: Equity Risk Premium

The figure illustrates the average equity risk premium over time calculated as averages over the cross section of weekly risk premia. The risk premia are measured using the Fama & MacBeth (1973) methodology.



does not change the estimated risk premia significantly. Nor did the risk premia change significantly, when all three Fama & French (1993) factors where used, but the factor risk premia on the SMB and HML where insignificant in a large part of the cross sectional regressions.

3.5 Empirical Results

With all estimated parameters in place we are able to calculate both objective and risk neutral default probabilities. Furthermore CDS spreads can be calculated both with and without the risk premium included, which allows us to decompose the spread. Before we decompose the CDS spreads and calculate the credit risk premium, a comparison of the estimated objective default probabilities with actual default rates is in place. We thus start out by comparing the objective default probabilities across rating categories and horizon with the historical default rates from Moody's (Hamilton et al. (2007)). Although the sample periods are different it will give us an indication of whether the estimated objective default probabilities are reasonable.

Table 3.3 shows the estimated objective default probabilities together with the average Moody's default rates for the period 1920-2006[17]. The historical default rates are generally higher than the model implied default probabilities and the model implied default probabilities based on implied volatility are generally lower than the default probabilities based on historical volatility. If we look at the five year horizon, which is the maturity of the CDS spreads in the sample, the implied default probabilities match the historical default rates quite well, although the default rates are underestimated for the speculative grade segment. Looking at the A and BBB ratings, which constitutes the majority of the quotes in the sample, the default rates are also not that dissimilar.

Earlier work by Berndt et al. (2005) and Berndt, Lookman & Obreja (2006) have relied on KMV expected default frequencies (EDF) as measures of objective default probabilities. KMV also uses a structural model to estimate a distance to default measure, which is then mapped into the EDF measure using historical default rates[18]. Since the applied methodology in this paper is the same as in Elkamhi & Ericsson (2007) and given the reasonable size of the estimated objective default probabilities it is expected that the results of this paper can be compared to the three mentioned papers.

[17] The Moody's ratings are transferred to the S&P ratings with $Aaa = AAA$, $Aa = AA$ and so forth.

[18] See Crosbie & Bohn (2003).

Table 3.3: Historical and Model Implied Default Probabilities

This table reports the historical and model implied default probabilities by rating category and horizon. *HV* is based on the historical volatility while *IV* is based on option-implied volatility. The model implied default probabilities are averaged over the number of quotes, while the historical default probabilities (*Actual*) represents Moody's cumulative default rates for the period 1920-2006.

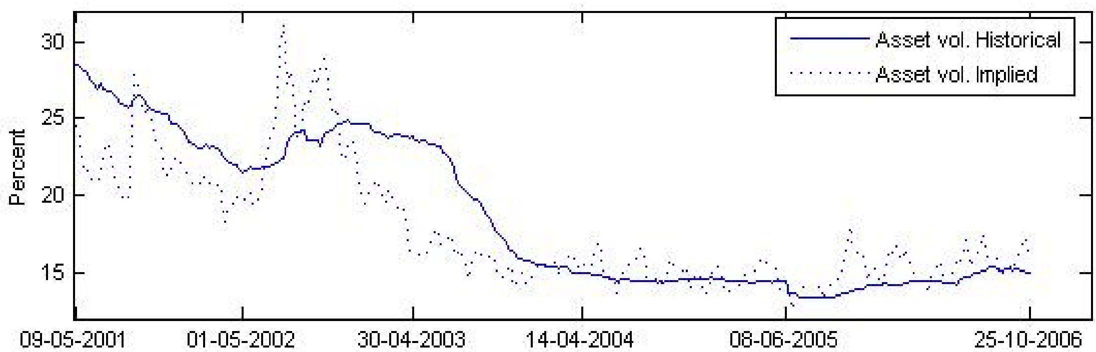
Rating/Horizon	1	3	5	7	10	15	20
AAA (Actual)	0.00	0.02	0.16	0.37	0.89	1.44	1.82
AAA (HV)	0.00	0.08	0.33	0.73	1.50	2.96	4.42
AAA (IV)	0.00	0.07	0.29	0.59	1.15	2.14	3.11
AA (Actual)	0.06	0.29	0.72	1.34	2.31	4.29	5.3
AA (HV)	0.00	0.08	0.34	0.75	1.48	2.77	3.96
AA (IV)	0.00	0.05	0.25	0.55	1.13	2.19	3.21
A (Actual)	0.07	0.51	1.13	1.80	2.9	4.91	6.39
A (HV)	0.05	0.59	1.41	2.32	3.63	5.53	7.06
A (IV)	0.01	0.24	0.79	1.49	2.58	4.24	5.61
BBB (Actual)	0.3	1.61	3.26	4.85	7.29	10.87	13.45
BBB (HV)	0.24	1.66	3.26	4.72	6.57	8.88	10.53
BBB (IV)	0.06	0.70	1.68	2.72	4.13	6.00	7.39
BB (Actual)	1.38	5.47	9.83	13.64	18.79	25.81	30.81
BB (HV)	0.58	3.41	5.98	8.03	10.36	13.00	14.75
BB (IV)	0.27	2.22	4.20	5.87	7.82	10.06	11.55
B (Actual)	4.32	14.23	22.45	28.58	34.86	42.11	46.09
B (HV)	2.42	8.51	12.75	15.76	18.91	22.18	24.20
B (IV)	0.56	3.52	6.28	8.45	10.84	13.42	15.05

One of the main drivers of the default probabilities and expected losses is the volatility of the firm's assets σ_v. To understand what drives the differences in the time-series behavior of the estimated credit risk premia later on, we also take a look at the average time-series behavior of the calibrated asset volatilities from section 3.4.

In Figure 3.3 the average calibrated asset volatilities are shown over time, when based on historical and implied volatility respectively. It is clear, that the calibrated volatilities do not move together and that the asset volatility based on historical volatility is much smoother than the one based on implied volatility. In the second half of 2002 the asset volatility based on implied volatility rises substantially, while this rise in uncertainty is only partly captured by the asset volatility based on historical volatility. Subsequently the asset volatility based on implied equity volatility falls faster than the more rigid asset volatility based on historical equity volatility.

Figure 3.3: Asset Volatilities

The figure illustrates the average calibrated asset volatilities over time based on historical and option implied equity volatilities respectively. The means are calculated as averages over the cross section of weekly volatilities.



As we will see in the next section this different behavior of the calibrated asset volatilities has implications for the way the expected loss component behaves over time and thus for the time-series behavior of the estimated credit risk premium. From the beginning of 2004 we see that the two calibrated volatilities move together. We now go on to decompose the CDS spread into an expected loss component and a risk premium component.

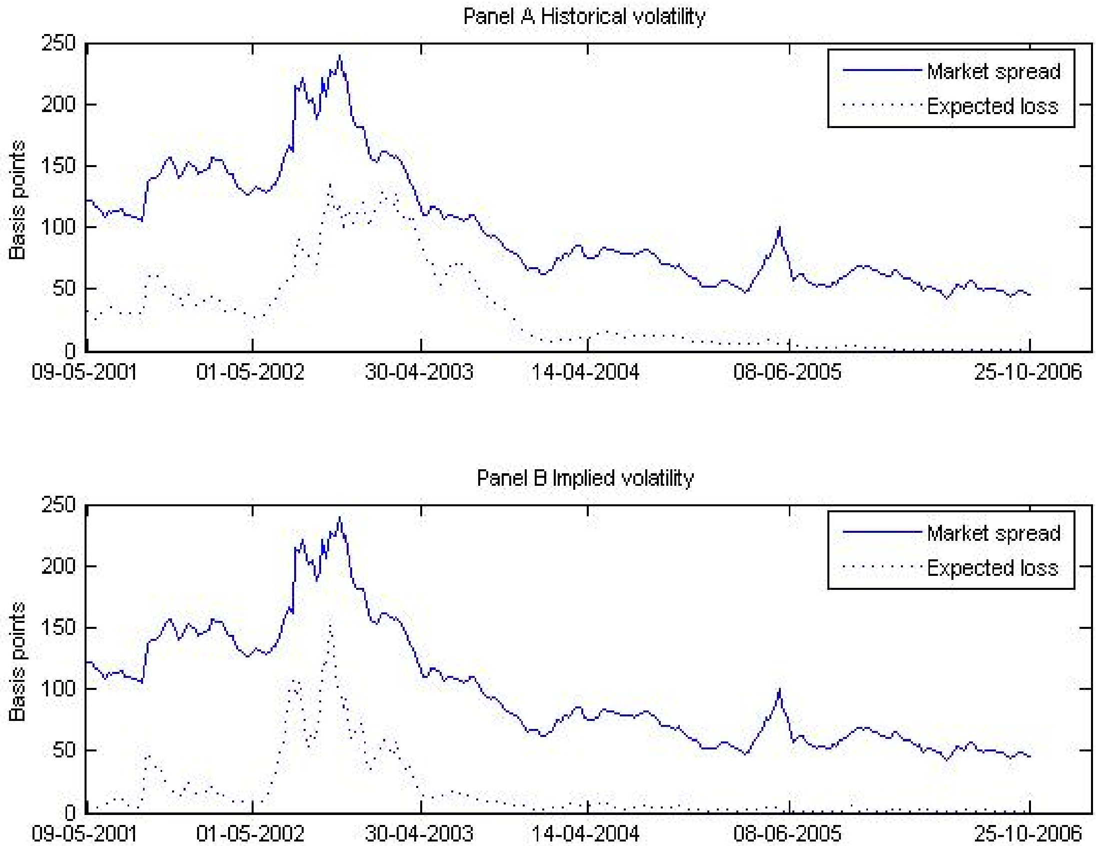
3.5.1 Decomposing the Credit Spread

To decompose the CDS spread and examine the time-series behavior of the credit risk premium an estimate of the expected loss component is needed.

In Figure 3.4 the average expected loss component $c_t^{no\ risk}$ calculated in equation (3.1) is plotted over time together with the average market CDS spread c_t^{market} from Figure 3.1. In panel A of Figure 3.4 the expected loss component is calculated with asset volatilities based on historical equity volatility, while the expected loss component is calculated with asset volatilities based on implied equity volatility in panel B.

Similar to the market spreads, the expected loss components vary considerably through the sample period, and when based on implied equity volatility the component peaks around the same time as the market spread, although there is a tendency for the peaks in the expected loss component to appear a little earlier than in the spread. The expected loss component peaks somewhat later, when based on historical equity volatility. When the spreads start to fall the expected loss component based on implied volatility falls as well, while this happens with a lag for the expected loss component based on historical volatility. From a comparison with Figure 3.3 we see that the different behavior of the asset volatilities in Figure 3.3 to a large degree is reflected in the movement of the respective expected losses in Figure 3.4.

Figure 3.4: Average Market Spread and Expected Loss Component
The figure illustrates the average market CDS spread and the expected loss component over time. The means are calculated as averages over the cross section of weekly spreads. In Panel A the expected loss component is based on historical volatility and in Panel B it is based on implied volatility.



The credit risk premium RPI_t is the difference between the market CDS spread c_t^{market} and the expected loss component $c_t^{no\ risk}$ as calculated in equation (3.2). Figure 3.5 plots the resulting cross sectional averages of the credit risk premia over time. To illustrate the difference, Figure 3.5 includes both the average risk premium based on the historical equity volatility and the average risk premium based on implied equity volatility. The level of the average risk premia are very similar to the level found in Elkamhi & Ericsson (2007) and the risk premia also peak in the second half of 2002 as found in earlier studies, but we see a clear difference in the time-series behavior of the two estimated risk premia. This difference is especially pronounced in the second half of 2002 and until the beginning of 2004.

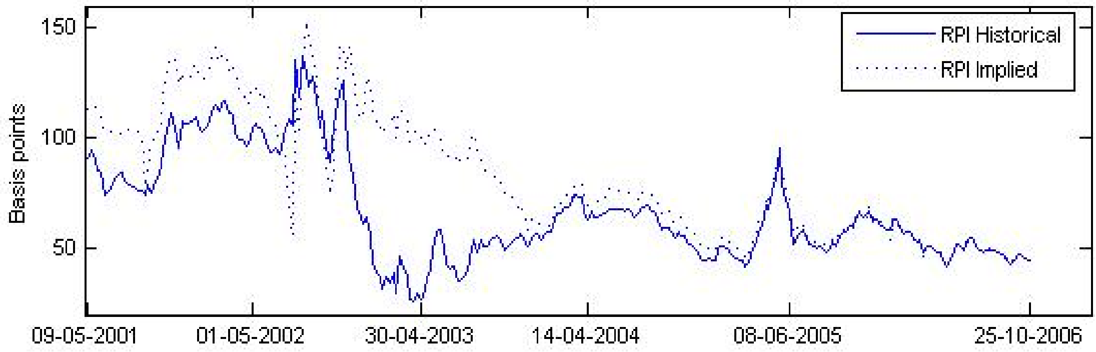
After the peak in late 2002 the risk premia starts to fall, and they basically keep falling until the end of 2006. The initial fall is much more dramatic though, when the risk premia are based on historical volatility, compared to the fall in risk premia, when they are based on implied volatility. The reason for this different behavior is of course to be found in the fact, that the rise in uncertainty towards the end of 2002 stays in the historical equity volatility for some time following the events.

As we saw in Figure 3.3 and Figure 3.4 this leads to asset volatilities and expected losses that are too high compared to the expected losses based on implied volatility, which immediately falls when the uncertainty disappears from the market. From the beginning of 2004 and onwards the two estimated risk premia move together, just as the asset volatilities in Figure 3.3.

When the expected losses are based on implied volatility there seems to be a high degree of variation in the risk premia around the peak in late 2002. This is because the expected loss component and the market CDS spreads do not peak at the exact same time as seen in Figure 3.4. It is interesting to note that Cao et al. (2006) find that the options market tend to lead the CDS market. From Figure 3.4 we see that this could be the case, and thus the reason for this high variation in risk premia, since the expected loss component based on implied volatility peaks earlier than the CDS spread.

Figure 3.5: Average Credit Risk Premium

The figure illustrates the average credit risk premia over time based on historical volatility and implied volatility respectively. The means are calculated as averages over the cross section of weekly spreads.



To show that the different behavior of the credit risk premia in Figure 3.5 is consistent across ratings and industries we split up the sample into investment grade firms and speculative grade firms, and also into five different industries.

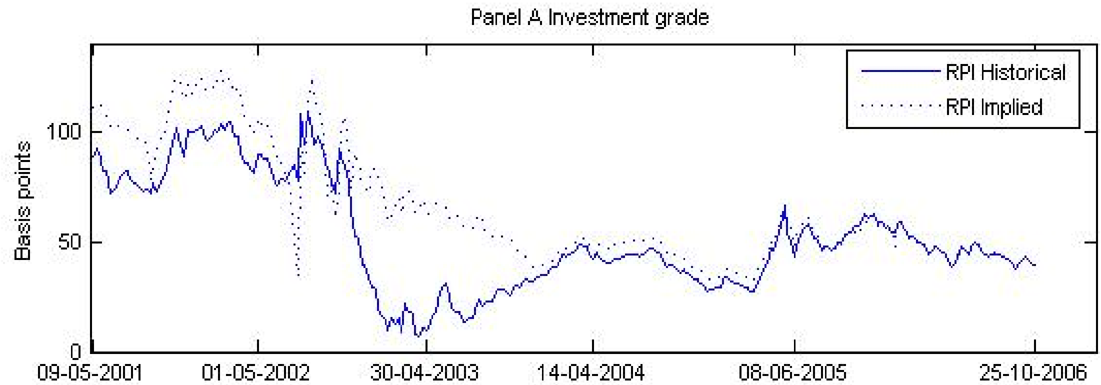
In Figure 3.6 the average estimated risk premia are plotted for the investment grade segment in panel A and for the speculative segment in panel B. The same pattern as in Figure 3.5 emerges. Following the events in 2002 the fall in risk premia are much more dramatic, when expected losses are based on historical volatility.

The largest difference in the behavior is seen for the investment grade segment in panel A. The behavior is very similar to the behavior in Figure 3.5, which is because the main part of the sample is investment grade firms. The difference is not as pronounced for the speculative grade segment in panel B.

In Figure 3.7 the firms in the sample have been split up into the five Fama & French industries: *Consumer, Manufacturing, Hitec, Health* and *Other*[19]. Again the same pattern appears. Looking e.g. at the behavior of the average risk premium in the Health sector in panel D the effect of using default probabilities based on implied volatility is clear. We see a much smoother risk premium, while the risk premium based on historical volatility takes a sharp fall in 2003. Subsequently the estimated risk premia move together from the beginning of 2004.

[19] See the website of Kenneth French.

Figure 3.6: Credit Risk Premia for Investment and Speculative Grade The figure illustrates credit risk premia over time for the investment grade segment and the speculative grade segment. In panel A the average risk premium is depicted for the investment grade segment, while the average risk premium for the speculative grade segment is depicted in panel B. The means are calculated as averages over the cross section of weekly spreads.



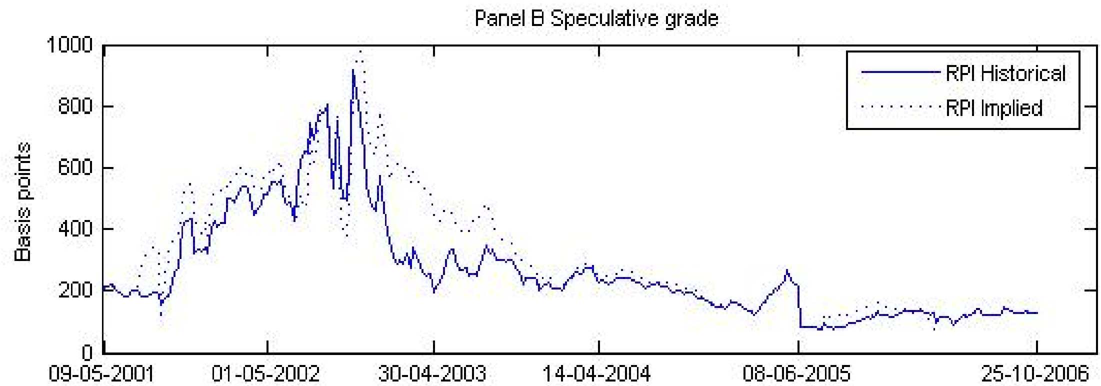
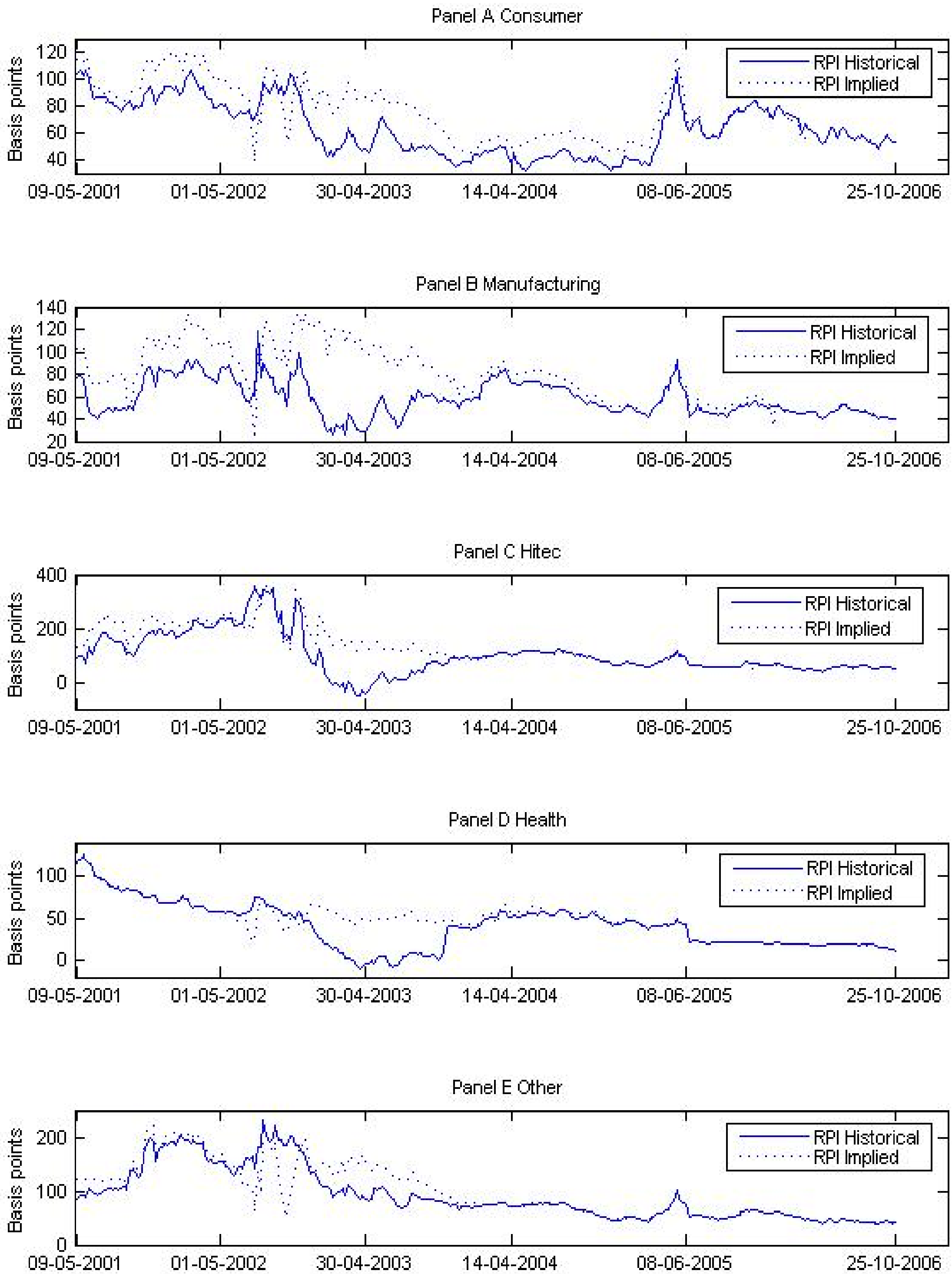


Figure 3.7: Credit Risk Premia Across Industries

The figure illustrates the credit risk premia over time for the five Fama & French industries, *Consumer* in panel A, *Manufacturing* in panel B, *Hitec* in panel C, *Health* in panel D and *Other* in panel E. The means are calculated as averages over the cross section of weekly spreads



The decomposition of the CDS spread into a risk premium component and an expected loss component allows us to study the relative importance of these components for the CDS spread over time.

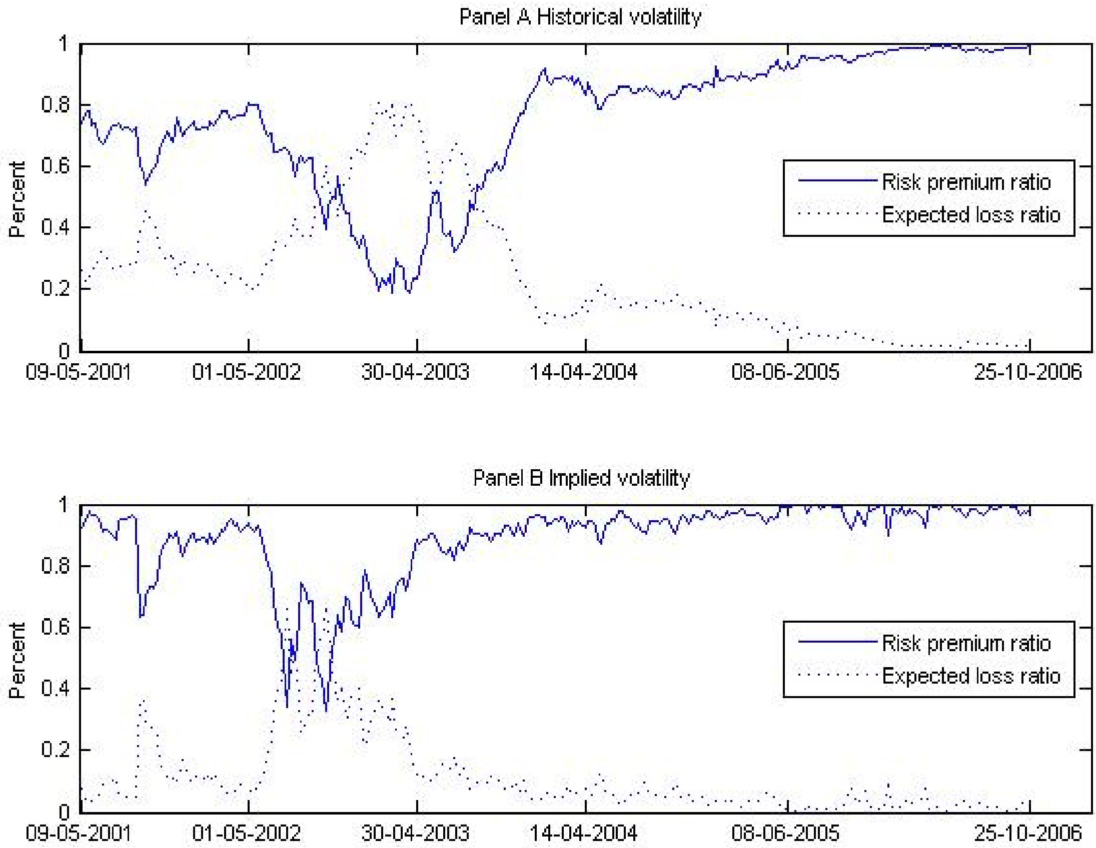
Figure 3.8 plots the respective percentage of the total market spread explained by risk premia ($\frac{RPI_t}{c_t^{market}}$) and expected losses ($\frac{c_t^{no\ risk}}{c_t^{market}}$). In Panel A the ratios are plotted, with expected losses based on historical volatility. More interestingly panel B studies the behavior of the two ratios when expected losses are based on implied volatility. We see that the expected loss ratio is largest in the second half of 2002, the period when spreads soared and the credit risk premium peaks. The expected loss ratio is actually higher than 50% at certain points in this period. In periods of tight credit spreads and low risk premia, we see that the risk premium component dominates.

It is natural to combine this result with the results on expected losses and the credit risk premium, when based on implied volatility in Figure 3.4 and Figure 3.5. What we see is that in times of high default probabilities and high expected losses the credit risk premium is high and in times of low default probabilities the credit risk premium is low. On the other hand the relative importance of the credit risk premium is highest in times of low default probabilities and low spreads. This suggests a countercyclical risk premium, something we look more into in section 3.5.2.

Unreported results show that the pattern is the same for the speculative grade and investment grade segment, although the expected loss ratio seems to play a larger part for the speculative grade segment. I will also get back to this in section 3.5.2. In panel A of Figure 3.8, where expected losses are based on historical volatility the lagging behavior shows up clearly again, and the expected loss ratio seems to be of most importance during 2003, with a peak in the middle of 2003.

Figure 3.8: Expected Loss and Risk Premium Ratios

The figure illustrates the expected loss ratio and the risk premium ratio over time. In Panel A the expected loss component is based on historical volatility and in Panel B it is based on implied volatility.



Berndt et al. (2005) offer possible explanations for the time variation in the risk premia, which I will relate to the findings in this paper. One explanation is that the variation in risk premia is partly caused by sluggish movement in risk capital across sectors. Berndt et al. (2005) argue that variations of the supply and demand for risk bearing are exacerbated by limited mobility of capital across different classes of asset markets, implying that risk premia would tend to adjust so as to match the demand for capital with the supply of capital that is available to the sector. Proxying for market volatility they find that VIX[20] adds significantly to the explanation of CDS spreads after the EDF measure has been accounted for, and they suggest that credit risk premia strongly depend on market volatility/VIX. If the market volatility goes up, a given level of capital available to bear risk represents less and less capital per unit of risk to be borne. If replacement capital does not move into the corporate debt sector immediately, the supply and demand for risk capital will match at a higher price per unit of risk.

In Figure 3.9 the average calibrated asset volatilities from Figure 3.3 are plotted together with VIX. In panel A the average calibrated asset volatilities are based on the historical volatility, while panel B plots the average asset volatilities based on the implied volatility together with VIX. Looking at panel A we see that VIX is much more volatile than the asset volatility based on historical volatility, and VIX also spikes in late 2002 just as the market CDS spreads in Figure 3.1. It is a different story in panel B. We see that the average calibrated asset volatilities based on implied volatility and the VIX move very closely together throughout the entire period, suggesting that the asset volatilities and expected losses based on implied volatility and VIX are related. In theory the average calibrated asset volatilities should contain both systematic volatility and idiosyncratic volatility, and the systematic volatility should explain part of the expected losses but also the credit risk premia[21]. What the results of Figure 3.9 suggest is that VIX is indeed a measure of systematic volatility and also an important driver of expected losses, when these are measured with implied volatility[22][23]. This also suggests

[20]VIX is an index of option implied volatility on the S&P 500.

[21]Elkamhi & Ericsson (2007) also includes a discussion of this topic, and relate their results to Campbell & Taksler (2003).

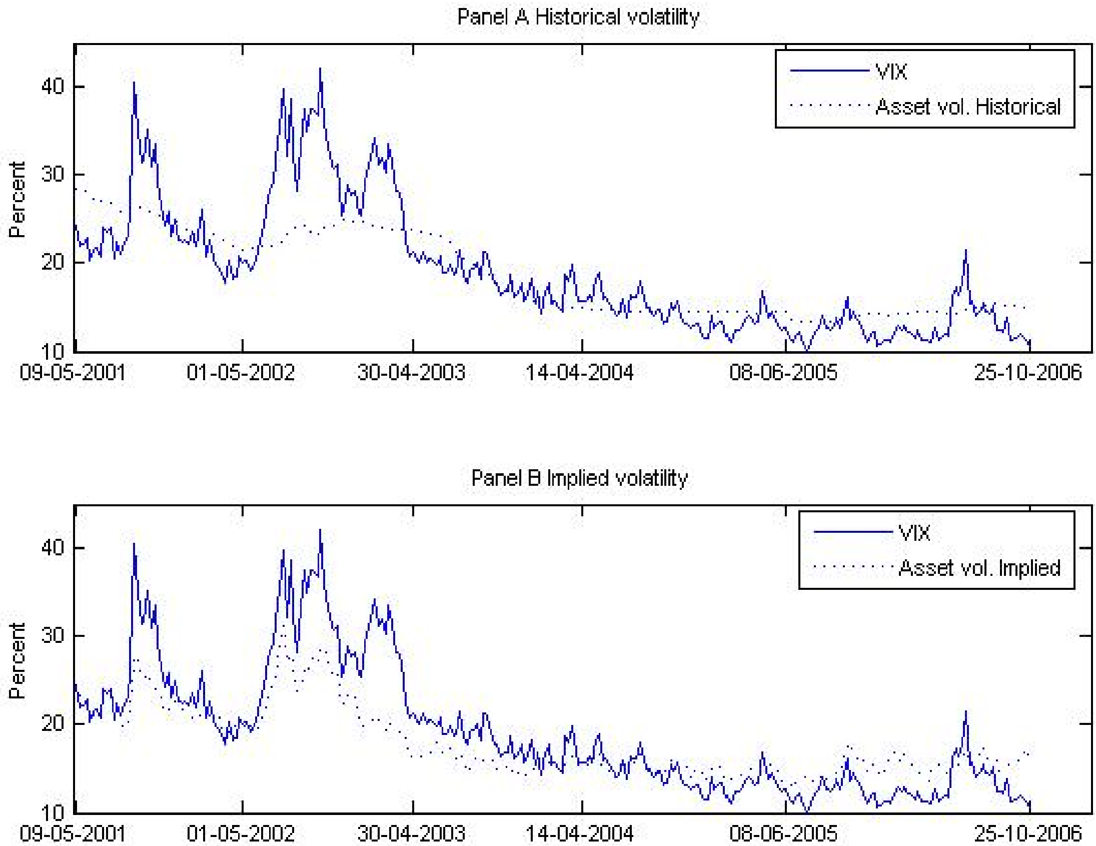
[22]Unreported results also show that VIX adds explanatory power to the credit spreads when both leverage and volatility have been accounted for.

[23]In panel B the asset volatilities are "delevered", while the VIX volatility is not, and the

that the EDF measure and expected losses based on historical volatility do not adequately capture the probability of default implied by the market. Earlier papers such as Collin-Dufresne et al. (2001) and Schaefer & Strebulaev (2004) have shown that VIX is an important explanatory variable for changes in credit spreads, although they did not pin down an explanation for the role of VIX.

Figure 3.9: Asset Volatilities and VIX Volatility

The figure illustrates the average asset volatilities and the VIX volatility over time. In panel A the VIX volatility is depicted together with the asset volatility based on historical equity volatility, and in Panel B the VIX volatility is depicted together with the asset volatility based on implied volatility.



VIX volatility is thus higher than the average asset volatilities during the main part of the sample period. Interestingly, the average asset volatilities are higher than VIX towards the end of 2005 and the beginning of 2006, suggesting a lot of idiosyncratic volatility in this period.

We have not yet discussed the assumption of a constant expected recovery rate R of 40%. In Figure 3.10, where the average model spread and the average market spread are plotted, we see that the structural model underestimates the market spreads during large parts of the sample period[24]. This suggests that the assumed recovery rate could be too large. Lowering the recovery rate would raise the spreads, but from equation (3.1) we see that loss given default (LGD) is multiplied onto the part of the calculated spread that is determined by the default probabilities. A lower recovery rate would thus have a small effect on the size of the calculated spreads in times of low default probabilities, and it is in exactly these periods that the model underestimates the spreads. Consequently, as long as the recovery rate is within a reasonable range the results of the paper would not change[25].

As discussed in Berndt et al. (2005), there could also be correlation between loss given default/recovery rates and the probability of default and in fact Moody's (Hamilton et al. (2007)) estimate a negative correlation between annual corporate default rates and recovery rates. The possibility of a negative correlation between default probabilities and the expected recovery rate could lower the time variation in the estimated risk premia, when the default probabilities are based on implied volatility. If we look at Figure 3.4 and 3.5 again, a negative correlation between the recovery rate and the default probabilities based on implied volatility would increase the expected loss component in late 2002, and make it even smaller in 2003 leading to less variation in the resulting average risk premium. But this would also imply a larger underestimation by the structural model of the average market spread in times of low spreads as seen in Figure 3.10[26].

Based on the above discussion and decomposition of the CDS spreads I conclude that the risk premia estimated in earlier papers such as Berndt et al. (2005) and Elkamhi & Ericsson (2007) might be inappropriate since these risk premia are based on historical volatility, and one should be careful when drawing conclusions on risk premia based on expected losses estimated with a historical volatility.

[24] Elkamhi & Ericsson (2007) find similar results for the same period.

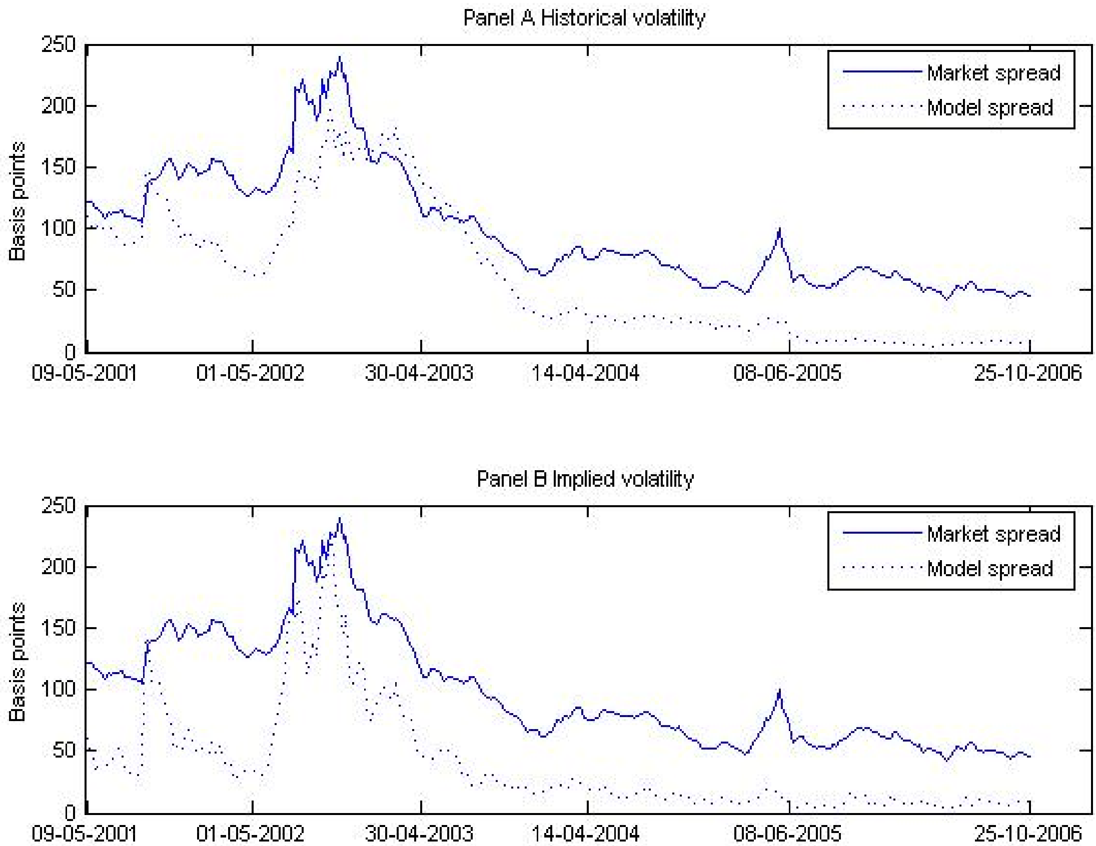
[25] If anything, a lower recovery rate would enhance the difference in the estimated risk premia based on historical and implied volatility, since a lower recovery rate would raise the expected loss component in times of high default probabilities.

[26] Assuming that the correlation is of similar size under P and Q. Introducing a time varying recovery rate would also imply a risk premium on the recovery rate.

This is especially important in times of high uncertainty. More specifically the expected losses based on historical volatility tend to be to smooth and there tends to be an overprediction of expected losses in 2003 following the period of high uncertainty in late 2002. Actually Bohn, Arora & Korablev (2005) report that the EDF's predicted too many defaults in 2003 consistent with the results in this paper. In the next section this conclusion is supported by a regression analysis showing that option implied equity volatility does a better job in explaining CDS spreads compared to the 250-day historical equity volatility. We will also discuss the possibility of adding a time varying risk premium to structural models.

Figure 3.10: Market Spreads and Model Spreads

The figure illustrates the average market spread and model spread over time. In panel A the model is calibrated with the historical volatility, and in Panel B the model is calibrated with implied volatility. The means are calculated as averages over the cross section of weekly spreads.



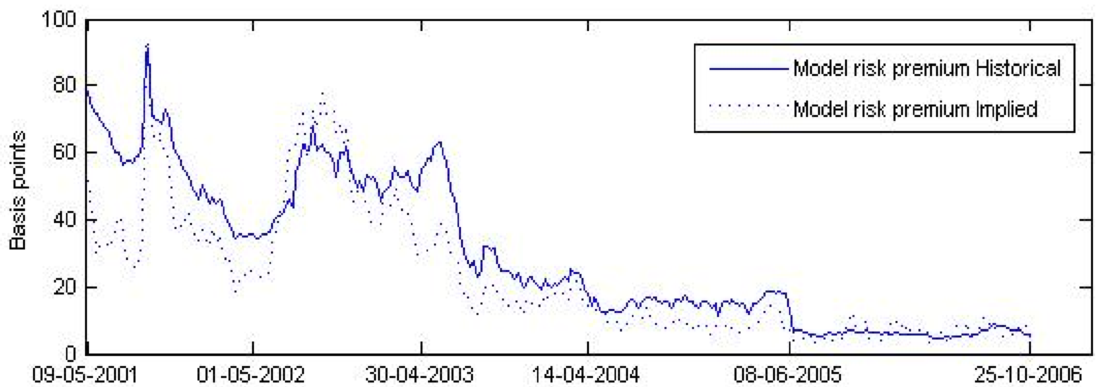
3.5.2 Modeling CDS Spreads

The typical structural model predicts, that the level of credit spreads mainly depends on asset volatilities and leverage, while most models are silent on risk premia. Notable exceptions are Chen et al. (2006), Bhamra et al. (2007) and Chen (2007). Chen et al. (2006) e.g. consider whether existing asset pricing models that have proven successful in explaining equity returns can explain the level and volatilities of credit spreads. They have some success with models that exhibit time varying risk premia. Leland (2004) and Huang & Huang (2003) have also studied risk premia in the context of structural models, but they do not consider their dynamics.

Figure 3.11 plots the average model implied credit risk premia (RPI^{equity}) over time calculated in equation (3.4). These model implied risk premia stem from the equity market through the translation of the equity risk premium via the structural model. The figure shows the risk premia when the structural model is calibrated with the historical volatility and the implied volatility respectively. The two risk premia do not move in exactly the same way, which follows from the differences in the calibration of the structural model, but there are large similarities.

Figure 3.11: Model Implied Risk Premia

The figure illustrates the average model implied credit risk premia over time, when the structural model is calibrated with the historical and implied equity volatility respectively. The means are calculated as averages over the cross section of weekly spreads.



A simple comparison of the two average estimated risk premia in Figure 3.11 with the average market CDS spread from Figure 3.1 suggest a link between the CDS spreads and these model implied risk premia. To see if a time varying risk premium can help structural models to explain credit spreads I follow Elkamhi & Ericsson (2007) and consider the following panel regression for the level of the CDS spreads[27]

$$CDS_{it} = \alpha + \beta_1 Lev_{i,t} + \beta_2 Evol_{i,t} + \beta_3 Eret_{i,t} + \beta_4 Slope_t + \beta_5 r_t + \beta_6 RPI^{equity}_{i,t} + \varepsilon_{i,t}, \tag{3.12}$$

where *Lev* denotes the firm's leverage, *Evol* is either the firm's 250 day historical volatility or it's 30-day option implied volatility, *Eret* is the daily equity return of the firm, *Slope* is the difference between the 10- and 2-year constant maturity rate and r is the 5-year constant maturity rate corresponding to the maturity of the CDS spreads. RPI^{equity} is the equity implied measure of the credit risk premium calculated in equation (3.4), and it is thus purely based on the equity market and the structural model. The regression in (3.12) is run both with and without the model implied risk premium in order to gauge the gain in explanatory power by including this variable. The results are shown in Table 3.4, when the regressions are run on the full sample[28]. Panel A of Table 3.4 tabulates the results with the historical volatility included in the regression, while the results with implied equity volatility are reported in panel B.

We see that including the equity implied risk premium increases the explanatory power of the regressions and the coefficients on the risk premium are all strongly significant[29]. When the risk premium is included in the regression with the historical volatility the R-square increases by 3% from 49.4% to 52.4%, while the R-square increases by 5.5% from 57.4% to 62.9% when the regressions are run with the implied volatility.

[27]The regresion in Elkamhi & Ericsson (2007) is performed on corporate bond spreads.

[28]The same variables are included in all of the regressions, although some of the variables may be insignificant at times.

[29]This is consistent both when the standard errors are clustered by time and by firm. The OLS standard errors on the risk premium coefficients are very similar to the standard errors when clustering by time, while standard errors are substantially larger when clustering by firm. This indicates a firm effect in the data (see Petersen (2007)). The results are also robust if a weekly time dummy is included, while clustering by firm. In this case the slope and the interest rate are left out of the regression since they capture a time effect.

Table 3.4: Importance of Risk Premium for CDS Spreads

This table reports the results of the panel regression $CDS_{it} = \alpha + \beta_1 Lev_{it} + \beta_2 Evol_{it} + \beta_3 Eret_{it} + \beta_4 Slope_t + \beta_5 r_t + \beta_6 RPI_{it} + \varepsilon_{it}$. T-statistics are reported in parentheses. *Evol* is either the historical equity volatility, calculated using 250 days of historical equity returns, or the implied volatility on 30-day at-the-money put options. Leverage (*lev*) is total liabilities divided by the sum of total liabilities and equity market capitalization. *Eret* is the daily equity return, *slope* is the slope of the yield curve and r is the level of the interest rate. *RPI* is the equity implied model risk premium. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A Historical volatility				Panel B Implied volatility			
Intercept	-191.83***	-127.96***	-191.83***	-127.96***	-252.2***	-142.97***	-252.2***	-142.97***
	(-9.51)	(-6.53)	(-7.38)	(-5.17)	(-13.3)	(-7.94)	(-8.79)	(-3.88)
Lev	2.81***	1.90***	2.81***	1.90***	2.67***	1.46***	2.67***	1.46***
	(39.40)	(32.04)	(6.95)	(5.08)	(43.24)	(20.97)	(7.29)	(4.08)
Evol.	5.84***	4.61***	5.84***	4.61***	7.82***	4.55***	7.82***	4.55***
	(24.97)	(20.39)	(7.96)	(5.33)	(35.81)	(15.99)	(7.93)	(3.25)
Eret	0.80	0.99	0.80	0.99*	1.95	2.12*	1.95***	2.12***
	(0.66)	(0.85)	(1.48)	(1.80)	(1.64)	(1.84)	(3.89)	(3.61)
Slope	-14.18***	-12.85***	-14.18***	-12.85***	-8.52***	-5.03**	-8.52**	-5.03
	(-4.49)	(-4.19)	(-3.10)	(-2.65)	(-3.08)	(-2.00)	(-2.07)	(-1.26)
r	-0.43	-1.68	-0.43	-1.68	0.85	3.53	0.85	3.53
	(-0.09)	(-0.34)	(-0.1)	(-0.41)	(0.25)	(1.15)	(0.21)	(1.08)
RPI^{equity}	-	0.60***	-	0.60***	-	1.32***	-	1.32***
	-	(22.19)	-	(2.71)	-	(21.37)	-	(3.45)
R^2	0.494	0.524	0.494	0.524	0.574	0.629	0.574	0.629
N	33401	33401	33401	33401	33401	33401	33401	33401
Cluster	Date	Date	Firm	Firm	Date	Date	Firm	Firm

The results are in line with Elton et al. (2001), who show that there is a nontrivial component of credit spreads, interpreted as a risk premium, which is correlated with factors explaining equity risk premia. Elkamhi & Ericsson (2007) also find that risk premia in credit and equity market are closely related, and emphasizes that the nonlinear relationship implied by the structural model plays an important role in establishing the link between the equity premium, the model implied credit risk premium and the credit spread.

On the other hand Berndt, Lookman & Obreja (2006) extract a factor representing the part of default swap returns, implied by a reduced form credit risk model, that does not compensate for interest rate risk or expected default losses. They find that this factor is priced in the corporate bond market but that they cannot establish with the same confidence that it is a factor for equity returns. Their estimate of credit risk premia is based on EDF's though, which we have seen might give rise to mismeasured credit risk premia.

In Table 3.5 the regressions are run for the investment grade segment. Again the coefficients are highly significant on the risk premium and now the R-square increases by 5.3% from 44.4% to 59.7% with the historical volatility included, while the R-square increases by 8.2% from 52.6% to 60.8% when the regressions are run with the implied volatility.

In Table 3.6 the regressions are run for the speculative grade segment. Now there is only a marginal increase in the R-square, which increases by 2.5% from 53.8% to 56.3% with the historical volatility included, while there is no increase in the R-square, which stays at 74.7%, when the regressions are run with the implied volatility. Furthermore the coefficient on the risk premium is insignificant when implied volatility is included. Combined with the regression results for the investment grade segment, this suggest that the risk premium is more important for investment grade firms than for speculative grade firms, and also that investment grade firms have proportionally higher risk premia. This supports results found in e.g. Elkamhi & Ericsson (2007), Berndt et al. (2005) and Huang & Huang (2003).

Table 3.5: Importance of Risk Premium for Investment Grade CDS Spreads

This table reports the results of the panel regression $CDS_{it} = \alpha + \beta_1 Lev_{it} + \beta_2 Evol_{it} + \beta_3 Eret_{it} + \beta_4 Slope_t + \beta_5 r_t + \beta_6 RPI_{it} + \varepsilon_{it}$. The regression is run for the investment grade quotes in the sample. T-statistics are reported in parentheses. *Evol* is either the historical equity volatility, calculated using 250 days of historical equity returns, or the implied volatility on 30-day at-the-money put options. Leverage (*lev*) is total liabilities divided by the sum of total liabilities and equity market capitalization.*Eret* is the daily equity return, *slope* is the slope of the yield curve and *r* is the level of the interest rate. *RPI* is the equity implied model risk premium. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A Historical volatility				Panel B Implied volatility			
Intercept	-167.99***	-110.49***	-167.99***	-110.49***	-215.28***	-114.21***	-215.28***	-114.21***
	(-11.48)	(-7.57)	(-7.99)	(-6.19)	(-16.78)	(-9.71)	(-8.98)	(-4.27)
Lev	2.04***	1.20***	2.04***	1.20***	1.96***	0.91***	1.96***	0.91***
	(32.74)	(25.15)	(7.91)	(4.80)	(36.04)	(20.55)	(7.94)	(3.37)
Evol.	4.54***	3.37***	4.54***	3.37***	5.87***	2.86***	5.87***	2.86***
	(18.72)	(15.37)	(6.59)	(5.18)	(27.14)	(12.95)	(7.88)	(3.43)
Eret	0.52	0.70	0.52	0.70	1.40*	1.44*	1.40**	1.44**
	(0.53)	(0.76)	(0.76)	(1.08)	(1.73)	(1.90)	(2.18)	(2.22)
Slope	-8.23***	-6.58**	-8.23*	-6.58	-2.87	0.41	-2.87	0.41
	(-2.96)	(-2.48)	(-1.74)	(-1.45)	(-1.47)	(0.24)	(-0.79)	(0.14)
r	7.76*	7.06*	7.76*	7.06*	9.95***	11.25***	9.95***	11.25***
	(1.94)	(1.79)	(1.86)	(1.88)	(4.48)	(5.38)	(2.77)	(3.92)
RPI^{equity}	-	0.57***	-	0.57***	-	1.28***	-	1.28***
	-	(23.99)	-	(3.85)	-	(20.54)	-	(3.48)
R^2	0.444	0.497	0.444	0.497	0.526	0.608	0.526	0.608
N	30712	30712	30712	30712	30712	30712	30712	30712
Cluster	Date	Date	Firm	Firm	Date	Date	Firm	Firm

Table 3.6: Importance of Risk Premium for Speculative Grade CDS Spreads

This table reports the results of the panel regression $CDS_{it} = \alpha + \beta_1 Lev_{it} + \beta_2 Evol_{it} + \beta_3 Eret_{it} + \beta_4 Slope_t + \beta_5 r_t + \beta_6 RPI_{it} + \varepsilon_{it}$. The regression is run for the speculative grade quotes in the sample. T-statistics are reported in parentheses. *Evol* is either the historical equity volatility, calculated using 250 days of historical equity returns, or the implied volatility on 30-day at-the-money put options. Leverage (*lev*) is total liabilities divided by the sum of total liabilities and equity market capitalization. *Eret* is the daily equity return, *slope* is the slope of the yield curve and r is the level of the interest rate. *RPI* is the equity implied model risk premium. *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

	Panel A Historical volatility				Panel B Implied volatility			
Intercept	-617.11***	-387.66***	-617.11***	-387.66*	-699.56***	-674.35***	-699.56***	-674.35***
	(-9.31)	(-5.99)	(-3.32)	(-1.82)	(-15.21)	(-13.97)	(-5.87)	(-3.56)
Lev	6.61***	4.20***	6.61***	4.20**	5.33***	4.99***	5.33***	4.99***
	(26.24)	(12.15)	(4.44)	(2.40)	(31.30)	(20.79)	(5.91)	(3.61)
Evol.	6.44***	4.02***	6.44***	4.02	12.64***	12.13***	12.64***	12.13***
	(12.66)	(6.09)	(3.65)	(1.67)	(30.06)	(19.63)	(6.00)	(3.27)
Eret	3.05	3.10	3.05	3.10	4.35*	4.47*	4.35*	4.47**
	(0.71)	(0.72)	(1.33)	(1.34)	(1.79)	(1.85)	(1.99)	(2.36)
Slope	63.31***	62.50***	63.31**	62.50***	37.29***	37.26***	37.29**	37.26**
	(4.91)	(5.18)	(2.74)	(2.91)	(4.38)	(4.39)	(2.64)	(2.62)
r	49.33***	33.29**	49.33	33.29	37.61***	38.70***	37.61*	38.70**
	(3.23)	(2.32)	(1.55)	(1.31)	(4.01)	(4.20)	(2.00)	(2.42)
RPI^{equity}	-	1.14***	-	1.14**	-	0.19*	-	0.19
	-	(9.20)	-	(2.32)	-	(1.84)	-	(0.30)
R^2	0.538	0.563	0.538	0.563	0.747	0.747	0.747	0.747
N	2689	2689	2689	2689	2689	2689	2689	2689
Cluster	Date	Date	Firm	Firm	Date	Date	Firm	Firm

In all of the regressions performed in Tables 3.4, 3.5 and 3.6 the R-squares are higher when implied volatility is included instead of the historical volatility and this is especially striking for the speculative grade segment, where the R-squares without the risk premium included are 53.8% and 74.7% respectively. This confirms that option implied volatility has a higher explanatory power for credit spreads, and suggest that when measuring the time variation in the risk premia one should use the information contained in option implied volatilities to back out default probabilities. Furthermore the results are also in line with Cao et al. (2006), who find the strongest link between option-implied volatilities and CDS spreads among firms with the lowest rating.

3.6 Conclusion

To estimate the time-series behavior of credit risk premia objective default probabilities and expected losses need to be measured correctly. Motivated by recent findings in Cao et al. (2006) this paper backs out default probabilities using option implied volatility through the structural model by Leland & Toft (1996).

Similar to earlier results I find that the risk premium peaks in the third quarter of 2002, but the subsequent drop in the risk premium is not as dramatic when expected losses are based on implied volatility instead of a historical volatility measure. The risk premia appear less volatile when based on implied volatility and this result is consistent across industries and ratings (investment grade and speculative grade), and suggests that it may be inappropriate to base expected losses on a historical volatility measure, when estimating risk premia.

Secondly, the credit risk premium tends to be countercyclical when expected losses are based on implied volatility. More specifically, the credit risk premium is high in times of high default probabilities and high expected losses and low in times of low default probabilities. Furthermore, the expected loss ratio and the risk premium ratio behave quite differently from one another over time. When based on implied volatility the expected loss ratio peaked in late 2002, when credit spreads soared and the credit risk premium peaked.

Finally, I carried out a panel regression analysis of the CDS market spreads. Augmenting the regressions with an equity implied measure of the credit risk premium improved the explanatory power for the levels of the credit spread, while the coefficient on this model implied risk premium was highly significant. These regression results echo results in Elkamhi & Ericsson (2007), and in combination with the other results of the paper, they suggest that structural models should contain a time varying and countercyclical risk premium.

The results also suggest a link between equity risk premia and credit spreads, when the equity risk premium is properly delevered through a structural model. Elton et al. (2001) show that there is a nontrivial component of credit spreads, interpreted as a risk premium, which is correlated with factors explaining equity risk premia and Elkamhi & Ericsson (2007) also find that risk premia in credit and equity market are closely related. On the other hand Berndt, Lookman & Obreja (2006) extract a factor representing the part of default swap returns, implied by a reduced form credit risk model, that does not compensate for interest rate risk or expected default losses. They find that this factor is priced in the corporate bond market but that they cannot establish with the same confidence that it is a factor for equity returns. However, the expected losses in Berndt, Lookman & Obreja (2006) are based on the EDF measure, and thus the estimation of the credit risk premium might be inappropriate. It is clear from the different results though that much more research is needed on the time variation of credit risk premia in credit markets, and also on the relation between the equity risk premium and credit risk premium. Interesting work in this direction has recently been done in Chen (2007) and Bhamra et al. (2007).

A Leland & Toft (1996)

The model by Leland & Toft (1996) assumes that the decision to default is made by a manager, who acts to maximize the value of equity. At each moment, the manager must address the question if meeting promised debt service payments is optimal for the equityholders, thereby keeping their call option alive. If the asset value exceeds the endogenously derived default barrier V_B, the firm will optimally continue to service the debt - even if the asset value is below the principal value or if cash flow available for payout is insufficient to finance the net debt service, requiring additional equity contributions.

In particular, firm assets V are assumed to follow a geometric Brownian motion under the risk-neutral measure

$$dV_t = (r - \rho)V_t dt + \sigma_V V_t dW_t, \tag{3.13}$$

where r is the constant risk-free interest rate, ρ is the fraction of asset value paid out to security holders, σ_V is the asset volatility and W_t is a standard Brownian motion. Debt of constant maturity Υ is continuously rolled over, implying that at any time s the total outstanding debt principal P will have a uniform distribution over maturities in the interval $(s, s + \Upsilon)$. Each debt contract in the multi-layered structure is serviced by a continuous coupon. The resulting total coupon payments C are tax deductible at a rate τ, and the realized costs of financial distress amount to a fraction α of the value of assets in default V_B. Rolling over finite maturity debt in the way prescribed implies a stationary capital structure, where the total outstanding principal P, total coupon C, average maturity $\frac{\Upsilon}{2}$ and default barrier V_B remain constant through time.

To determine the total value of the levered firm $\upsilon(V_t)$, the model follows Leland (1994) in valuing bankruptcy costs $BC(V_t)$ and tax benefits resulting from debt issuance $TB(V_t)$ as time-independent securities. It follows, that

$$\begin{aligned} \upsilon(V_t) &= V_t + TB(V_t) - BC(V_t) \\ &= S(V_t) + D(V_t), \end{aligned} \tag{3.14}$$

where $S(V_t)$ is the market value of equity and $D(V_t)$ the market value of total debt. Equation (3.14) may be written as

$$\upsilon(V_t) = V_t + \tau\frac{C}{r}\left(1 - \left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B \left(\frac{V_t}{V_B}\right)^{-x}, \tag{3.15}$$

with the value of debt

$$D(V_t) = \frac{C}{r} + \left(P - \frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) + \left(\left(1-\alpha\right)V_B - \frac{C}{r}\right)J\left(\Upsilon\right), \tag{3.16}$$

equity $S(V_t) = \upsilon(V_t) - D(V_t)$

$$\begin{aligned} S(V_t) = {} & V_t + \tau\frac{C}{r}\left(1 - \left(\frac{V_t}{V_B}\right)^{-x}\right) - \alpha V_B \left(\frac{V_t}{V_B}\right)^{-x} \\ & - \frac{C}{r} - \left(P - \frac{C}{r}\right)\left(\frac{1-e^{r\Upsilon}}{r\Upsilon} - I\left(\Upsilon\right)\right) \\ & - \left(\left(1-\alpha\right)V_B - \frac{C}{r}\right)J\left(\Upsilon\right), \end{aligned} \tag{3.17}$$

and default barrier V_B

$$V_B = \frac{\frac{C}{r}\left(\frac{A}{r\Upsilon} - B\right) - \frac{AP}{r\Upsilon} - \frac{\tau C x}{r}}{1 + \alpha x - \left(1-\alpha\right)B}. \tag{3.18}$$

The components of the above formulae are

$$\begin{aligned} A &= 2ae^{-r\Upsilon}\Phi\left(a\sigma_V\sqrt{\Upsilon}\right) - 2z\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) \\ &\quad - \frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \frac{2e^{-r\Upsilon}}{\sigma_V\sqrt{\Upsilon}}\phi\left(a\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right), \end{aligned} \tag{3.19}$$

$$\begin{aligned} B &= -\left(2z + \frac{2}{z\sigma_V^2\Upsilon}\right)\Phi\left(z\sigma_V\sqrt{\Upsilon}\right) \\ &\quad - \frac{2}{\sigma_V\sqrt{\Upsilon}}\phi\left(z\sigma_V\sqrt{\Upsilon}\right) + \left(z-a\right) + \frac{1}{z\sigma_V^2\Upsilon}, \end{aligned} \tag{3.20}$$

$$I\left(\Upsilon\right) = \frac{1}{r\Upsilon}\left(K\left(\Upsilon\right) - e^{-r\Upsilon}F\left(\Upsilon\right)\right), \tag{3.21}$$

$$K\left(\Upsilon\right) = \left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1\left(\Upsilon\right)\right) + \left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2\left(\Upsilon\right)\right), \tag{3.22}$$

$$F\left(\Upsilon\right) = \Phi\left(h_1\left(\Upsilon\right)\right) + \left(\frac{V}{V_B}\right)^{-2a}\Phi\left(h_2\left(\Upsilon\right)\right), \tag{3.23}$$

$$\begin{aligned}
J\left(\Upsilon\right) &= \frac{1}{z\sigma_V\sqrt{\Upsilon}}\left(-\left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1\left(\Upsilon\right)\right)j_1\left(\Upsilon\right)\right. \\
&\quad \left. + \left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2\left(\Upsilon\right)\right)j_2\left(\Upsilon\right)\right), && (3.24) \\
j_1\left(\Upsilon\right) &= \frac{\left(-b - z\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}};\ j_2\left(\Upsilon\right) = \frac{\left(-b + z\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}}, && (3.25) \\
h_1\left(\Upsilon\right) &= \frac{\left(-b - a\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}};\ h_2\left(\Upsilon\right) = \frac{\left(-b + a\sigma_V^2\Upsilon\right)}{\sigma_V\sqrt{\Upsilon}}, && (3.26) \\
a &= \frac{\left(r - \rho - \left(\sigma_V^2/2\right)\right)}{\sigma_V^2}, && (3.27) \\
b &= \ln\left(\frac{V_t}{V_B}\right), && (3.28) \\
z &= \frac{\sqrt{\left(\left(a\sigma_V^2\right)^2 + 2r\sigma_V^2\right)}}{\sigma_V^2}, && (3.29) \\
x &= a + z. && (3.30)
\end{aligned}$$

$\phi\left(\cdot\right)$ and $\Phi\left(\cdot\right)$ denote the density of the standard normal distribution and the cumulative distribution function, respectively.

A.1 Survival Probabilities

The risk-neutral survival probability in the model at horizon t is given as

$$\begin{aligned}
Q\left(t\right) &= 1 - F\left(t\right) && (3.31) \\
&= 1 - \left(\Phi\left(h_1\left(t\right)\right) + \left(\frac{V}{V_B}\right)^{-2a}\Phi\left(h_2\left(t\right)\right)\right),
\end{aligned}$$

where $h_1\left(t\right)$ and $h_2\left(t\right)$ are given above. The objective survival probability is given as

$$P(t) = 1 - \left(\Phi\left(d_1\left(t\right)\right) + \left(\frac{V}{V_B}\right)^{-2c}\Phi\left(d_2\left(t\right)\right)\right), \tag{3.32}$$

where

$$c = \frac{(u_V - (\sigma_V^2/2))}{\sigma_V^2}$$

$$d_1(t) = \frac{(-b - c\sigma_V^2 t)}{\sigma_V \sqrt{t}};\ d_2(t) = \frac{(-b + c\sigma_V^2 t)}{\sigma_V \sqrt{t}}$$

and μ_V is the realized mean of the time series of V_t from equation (3.6) The term structure of default probabilities is needed to price the credit default swap.

A.2 Pricing the Credit Default Swap without a Risk Premium

The CDS can be priced both with and without a risk premium in the Leland & Toft (1996) model, when the default probabilities are known. The CDS price of a contract initiated at time 0 with maturity date T, when there is no risk premium, is given as

$$c^{no\ risk}(0,T) = -\frac{(1-R)\int_0^T e^{-rs} P_0'(s)ds}{\int_0^T e^{-rs} P_0(s)ds},$$

where r is the constant risk-free interest rate, R is the recovery rate, $P_0(s)$ is the objective survival probability of the obligor at $t = 0$ and $-P_0'(t) = -dP_0(t)/dt$ is the first hitting time density. Rearranging we get

$$0 = c^{no\ risk}(0,T)\int_0^T e^{-rs} P(s)ds + (1-R)\int_0^T e^{-rs} P'(s)ds, \tag{3.33}$$

and Integrating the first term by parts, yields

$$0 = \frac{c^{no\ risk}(0,T)}{r}\left(1 - e^{-rT}P(T) + \int_0^T e^{-rs}P'(s)ds\right) + (1-R)\int_0^T e^{-rs}P'(s)ds. \tag{3.34}$$

following Reiner & Rubinstein (1991) the integral $-\int_0^T e^{-rs}P'(s)ds$ is given as

$$G(T) = \left(\frac{V}{V_B}\right)^{-c+y}\Phi\left(g_1(T)\right) + \left(\frac{V}{V_B}\right)^{-c-y}\Phi\left(g_2(T)\right), \tag{3.35}$$

where

$$c = \frac{(u_V - (\sigma_V^2/2))}{\sigma_V^2},$$

$$y=\frac{\sqrt{\left(\left(c\sigma_V^2\right)^2+2r\sigma_V^2\right)}}{\sigma_V^2}$$

and

$$g_1\left(t\right)=\frac{\left(-b-y\sigma_V^2t\right)}{\sigma_V\sqrt{t}};\;g_2\left(t\right)=\frac{\left(-b+y\sigma_V^2t\right)}{\sigma_V\sqrt{t}}.$$

Then,

$$0=\frac{c^{no\ risk}(0,T)}{r}\left(1-e^{-rT}P(T)\right)-\left(\frac{c^{no\ risk}(0,T)}{r}+(1-R)\right)G(T),\qquad(3.36)$$

which allows us to obtain a closed-form solution for the CDS spread, when there is no risk premium

$$c^{no\ risk}(0,T)=r\left(1-R\right)\frac{G(T)}{\left(1-e^{-rT}P(T)-G\left(T\right)\right)}\qquad(3.37)$$

where $G(T)$ is given above and

A.3 Pricing the Credit Default Swap with a Risk Premium Included

The formula for the CDS spread when there is a risk premium present is analogous to the price without a risk premium

$$c^{risk}(0,T)=r\left(1-R\right)\frac{K(T)}{\left(1-e^{-rT}Q(T)-K\left(T\right)\right)},\qquad(3.38)$$

where

$$K\left(T\right)=\left(\frac{V}{V_B}\right)^{-a+z}\Phi\left(j_1\left(T\right)\right)+\left(\frac{V}{V_B}\right)^{-a-z}\Phi\left(j_2\left(T\right)\right)$$

$$\begin{aligned}a&=\frac{\left(r-\rho-\left(\sigma_V^2/2\right)\right)}{\sigma_V^2},\\ b&=\ln\left(\frac{V_t}{V_B}\right),\\ z&=\frac{\sqrt{\left(\left(a\sigma_V^2\right)^2+2r\sigma_V^2\right)}}{\sigma_V^2},\end{aligned}$$

$$j_1\left(T\right)=\frac{\left(-b-z\sigma_V^2T\right)}{\sigma_V\sqrt{T}};\ j_2\left(T\right)=\frac{\left(-b+z\sigma_V^2T\right)}{\sigma_V\sqrt{T}}$$

and $Q(T)$ is given is equation (3.31).

Summary

English summary

Chapter 1: Accounting Transparency and the Term Structure of Credit Default Swap Spreads

This chapter is the first contribution in the literature to estimate the component of the term structure of CDS spreads associated with accounting transparency. To this end, CDS spreads at the 1, 3, 5, 7 and 10-year maturity for a large cross-section of firms are used together with a newly developed measure of accounting transparency by Berger et al. (2006). Estimating the gap between the high and low transparency credit curves, the transparency spread is estimated around 20 bps at the 1-year maturity. At longer maturities, the transparency spread narrows and is estimated at 14, 8, 7 and 5 bps at the 3, 5, 7 and 10-year maturity, respectively. While highly significant in the short end, the impact of accounting transparency is not robust and most often insignificantly estimated for maturities exceeding 5 years. Finally, the effect of accounting transparency on the term structure of CDS spreads is largest for the most risky firms. These results are strongly supportive of the model by Duffie & Lando (2001), and add an explanation to the underprediction of short-term credit spreads by traditional structural credit risk models.

Chapter 2: Capital Structure Arbitrage: Model Choice and Volatility Calibration

This chapter analyzes the use of CDSs in a convergence-type trading strategy popular among hedge funds and proprietary trading desks. This strategy, termed capital structure arbitrage, takes advantage of a lack of synchronicity between equity and credit markets and is related to recent studies on the lead-lag relationship between bond, equity and CDS markets. In particular, a structural model that links fundamentals with different security classes is used to identify CDSs that either offer a discount against equities or trade at a very high level. If a relative value opportunity is identified, the arbitrageur takes an appropriate market-neutral position and hopes for market convergence. However, the arbitrageur faces two major problems, namely positions based on model misspecification and mismeasured inputs. The chapter contributes with an analysis of the risk and return of capital structure arbitrage addressing both of these concerns. In particular, we implement the industry benchmark model CreditGrades and Leland & Toft (1996). The models are calibrated with a traditional 250-day volatility from historical equity returns and an implied volatility from equity options. In spite of differences in assumptions governing default and calibration, we find the exact structural model linking the markets second to timely key inputs. Studying an equally-weighted portfolio of all relative value positions, the excess returns are insignificant when based on the historical volatility. However, as the arbitrageur feeds on large variations in equity and credit markets and the asset volatility is a key input to the pricing of credit, a timely volatility measure is desirable. Indeed, using an option-implied volatility results in superior strategy execution and may initiate the opposite positions of the historical measure. The result is more positions ending in convergence, more positions with positive holding-period returns and highly significant excess returns. The gain is largest in the speculative grade segment and cannot be explained from systematic market risk factors. Although the strategy may seem attractive at an aggregate level, positions on individual obligors can be very risky.

Chapter 3: Credit Risk Premia in the Market for Credit Default Swaps

This chapter estimates the time-series behavior of credit risk premia in the market for Credit Default Swaps for the period 2001 to 2006. The structural model by Leland & Toft (1996) is used to back out objective default probabilities. To estimate the time-series behavior of credit risk premia objective default probabilities and expected losses need to be measured correctly. Motivated by recent findings in Cao et al. (2006) this paper backs out the default probabilities using option implied volatility through the structural model.

Similar to earlier results I find that the risk premium peaks in the third quarter of 2002, but the subsequent drop in the risk premium is not as dramatic, when expected losses are based on implied volatility instead of a historical volatility measure. The risk premia appear less volatile when based on implied volatility and this result is consistent across industries and ratings (investment grade and speculative grade), and suggests that it may be inappropriate to base expected losses on a historical volatility measure, when estimating risk premia.

Secondly, the credit risk premium tends to be countercyclical when expected losses are based on implied volatility. More specifically the credit risk premium is high in times of high default probabilities and high expected losses and low in times of low default probabilities. Furthermore the expected loss ratio and the risk premium ratio behave quite differently from one another over time. When based on implied volatility the expected loss ratio peaked in late 2002, when credit spreads soared and the credit risk premium peaked.

Finally I carried out a panel regression analysis of the CDS market spreads. Augmenting the regressions with an equity implied measure of the credit risk premium improved the explanatory power for the levels of the credit spread, while the coefficient on this model implied risk premium was highly significant. These regression results echo results in Elkamhi & Ericsson (2007), and suggest that structural models should contain a time varying risk premium. Together with the other results of the paper a risk premium that is countercyclical seems to be desirable. The results also suggests a link between equity risk premia and credit spreads, when the equity risk premium is properly delevered through a structural model.

Dansk resumé

Kapitel 1: Regnskabstransparens og strukturen af CDS kurven

Dettte kapitel er det første bidrag i litteraturen, som estimerer komponenten i kurven af CDS spænd, som skyldes støjfyldte observationer af værdien af aktiver. Til dette formål anvendes CDS spænd med løbetider på 1, 3, 5, 7 og 10 år for et bredt tværsnit af virksomheder, sammen med et nyudviklet mål for regnskabstransparens af Berger et al. (2006). Ved en estimation af spændet mellem kreditspændskurverne for virksomheder med høj og lav transparens, estimeres transparensspændet til 20 bps ved en løbetid på 1 år. Dette transparensspænd indsnævres ved længere løbetider, og estimeres til 14, 8, 7 og 5 bps ved en løbetid på henholdsvis 3, 5, 7 og 10 år. Transparensspændet er stærkt signifikant i den korte ende, men ej robust og ofte insignifikant ved løbetider over 5 år. Endelig findes effekten af regnskabstransparens på kurven af CDS spænd at være størst for de mest risikable virksomheder. Disse resultater støtter klart modellen af Duffie & Lando (2001), og tilføjer en forklaring til undervurderingen af korte kreditspænd af traditionelle strukturelle kreditrisikomodeller.

Kapitel 2: Kapitalstruktur arbitrage: Modelvalg og valg af volatilitet

Kapitel to analyserer anvendelsen af CDS'er i en konvergensbaseret handelsstrategi, som er populær i hedge fonde og kvantitative handelsafdelinger. Denne strategi, kaldet kapitalstruktur arbitrage, udnytter en begrænset synkronicitet mellem aktie- og kreditmarkeder, og er relateret til nyere studier om hastigheden, hvormed ny information indregnes i forskellige markeder. En strukturel model som relaterer virksomhedens fundamentale variable til prisen på forskellige aktivklasser anvendes til at identificere CDS'er, som handles for dyrt eller billigt relativt til aktien. Hvis en relativ prismulighed kan identificeres, tager arbitragøren en passende markedsneutral position, og håber på konvergens mellem markederne. Arbitragøren står dog overfor to væsentlige problemer, nemlig positioner initieret af en misspecificeret model eller fejlbedømte inputs. Dette kapitel bidrager med en analyse af risiko og afkast ved kapitalstruktur arbitrage, og adresserer begge ovenstående bekymringer. I særdeleshed implementeres den i praksis ofte benyttede CreditGrades model samt modellen af Leland & Toft (1996). Modellerne kalibreres med en traditionel 250-dages volatilitet fra historiske aktieafkast samt en implicit volatilitet fra aktieoptioner. På trods af forskelle i antagelser bag fallit og kalibrering finder vi, at den præcise model som relaterer markederne, er mindre væsentlig end rettidige inputs. Studeres en ligevægtet portefølje af alle relative positioner, er merafkastet insignifikant baseret på den historisk volatilitet. Men da arbitragøren igangsættes af store variationer i aktie- og kreditmarkeder, og aktivvolatiliteten er en nøglevariabel i prisfastsættelsen af kredit, er et rettidigt volatilitetsmål ønskværdigt. Anvendelsen af en implicit volatilitet fra aktieoptioner resulterer i en bedre afvikling af strategien, og kan initiere de modsatte positioner af det historiske mål. Resultatet er flere positioner, som ender i konvergens, flere positioner med positivt afkast samt et stærkt signifikant merafkast. Gevinsten er størst blandt virksomheder med lavere kreditvurdering, og kan ikke forklares af systematiske markedsfaktorer. Selvom strategien synes attraktiv på aggregeret niveau, kan relative positioner på individuelle virksomheder være meget risikable.

Kapitel 3: Kredit risikopræmier i CDS markedet

Kapitel 3 undersøger, hvorledes risikopræmierne i markedet for Credit Default Swaps (CDS) opførte sig i perioden fra 2001 til 2006. Den strukturelle kreditrisiko model af Leland & Toft (1996) kalibreres til aktiemarkedet, hvorved både risikoneutrale -og objektive fallitsandsynligheder kan estimeres, og motiveret af resultater i Cao et al. (2006) bliver implicit volatilitet fra aktieoptioner brugt til at kalibrere modellen. Resultaterne viser, at risikopræmierne toppede i slutningen af 2002, hvilket også er fundet i tidligere studier. Det efterfølgende fald i risikopræmierne er dog ikke så dramatisk, når de objektive fallitsandsynligheder er baseret på volatilitet fra optionsmarkedet. Risikopræmierne synes således at være mindre volatile, når de objektive fallitsandsynligheder er baseret på implicit volatilitet. Dette resultat er konsistent, både på tværs af ratings og på tværs af industrier, og indikerer at risikopræmier, som er estimeret på baggrund af historisk volatilitet måske ikke er valide.

Derudover er risikopræmierne mod-cykliske, når de objektive fallitsandsynligheder er baseret på implicit volatilitet. Det vil sige, at der er en tendens til at risikopræmierne er høje når fallitsandsynlighederne er høje.

Til sidst blev der foretaget en regressionsanalyse, hvor risikopræmier impliceret fra den strukturelle model blev inkluderet i regressionen sammen med standard variable, som forklarer CDS spændene. Tilføjelsen af risikopræmien fra modellen øgede forklaringsgraden, og koefficienten på risikopræmien var signifikant. Resultaterne indikerer at en tidsvariende og mod-cyklisk risikopræmie bør tilstræbes i strukturelle modeller for kreditrisiko.

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