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Essays on Credit Risk

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Essays on Credit Risk

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To My grandparents, Liwei Luo and Jinzhao Hu

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Essays on Credit Risk

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This dissertation examines the determinants of credit spreads. The purpose and contribution of this dissertation is to provide a more comprehensive and coherent view of credit risk valuation. Specifically, I examine the effects of previously overlooked factors (in addition to conventional factors such as market financing costs, firm leverage, and firm risk) on credit risk using credit default swap (CDS) rates that better reflect associated credit risk. I undertake this study through both theoretical exploration and empirical examination.

On the theoretical front, I present a structural credit risk model that explicitly considers both macro-economic conditions and firm fundamentals. I show that the model predicts more appropriate levels of credit spreads across all credit rating classes than the existing structural models and produces the empirically observed upward-sloping term structure of credit spreads for high-yield bonds that most other models fail to explain.

On the empirical front, I capitalize on the advantage of CDS spreads as a better measure of credit risk than other existing measures. Using this measure, I first test and verify some of our model's predictions, namely, both macro-economic conditions and firm characteristics have significant effects on credit spreads. The most notable finding is that

credit spreads increase with investor sentiment.

The second part of my empirical investigation examines the role of imperfect information in the CDS market. Using several proxies (especially analyst forecast dispersion) for transparency, I find that credit spreads decrease with transparency, but this effect is most pronounced for issuers with low disclosure costs. I also find significant liquidity effects and illiquidity spillover in the CDS market, contrary to the conventional wisdom.

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Chapter 1

Introduction

Credit risk refers to the possibility of loss due to a counterparty's failure to meet contractual debt obligations (e.g., loan, bond, trade credit, etc.).[1] Credit risk is determined by two components: probability of default (PD) and loss given default (LGD).

Debt is the most widely used financing vehicle. Valuation of risky debt is central to corporate financing choices and credit investors' portfolio management. Accurate measure of credit risk is critical to financial and banking stability. The rapid growth of credit derivatives market in the last decade reflects the demand for credit products. Concerning the lack of sufficient knowledge about those credit derivatives, Federal Reserve Board Chairman Greenspan urges that "market participants and policymakers must be aware of the risk-management challenges associated with the use of derivatives to transfer risk, . . . and they must take steps to ensure that those challenges are addressed."[2]

A good understanding of credit risk is essential to banking regulations. Basel Committee on Banking Supervision (BCBS) of the Bank for International Settlements (BIS) recently allowed banks to evaluate their own credit risk and capital requirement through internal credit scoring. This new rule, known as Basel II, puts a lot of faith upon banks' ability accurately model their credit risk exposure. The hot debate on Basel II is another demonstration that better understanding of credit risk is imperative and urgent.

Credit risk modeling was pioneered by Merton (1974) and Black and Scholes (1973).

[1] Credit risk is often used interchangeably with default risk even though credit risk is a more general term. Any fluctuation in credit quality is part of credit risk. Default is one of the (extreme) cases. Not all failure to meet debt obligations will trigger default.

[2] *Risk Transfer and Financial Stability*, Remarks by Chairman Alan Greenspan to the Federal Reserve Bank of Chicago's Forty-first Annual Conference on Bank Structure, May 5, 2005.

Since then substantial research has been done in this area. The last three decades have been very fruitful. At this point we have accumulated a lot evidence and knowledge, which also provides challenges for future research. In the rest of this chapter we will discuss extant literature and remaining issues on credit risk, as well as our contributions.

1.1 Existing Literature on Credit Risk

Credit risk models can be classified into three generations: the first generation of structural models, the second generation of reduced form models, and the current third generation of incomplete information models. Empirical studies have shifted from testing qualitative predictions to quantitative ones, from levels to shapes, and from aggregate behavior to cross-sectional differences.

1.1.1 Theoretic models

Based on the insight that debt can be seen as writing a call option on the firm's assets, Black and Scholes (1973) and Merton (1974) derived firm's default probability and debt value given firm's asset value process. In this *structural* approach, firm defaults when its asset value drops below a threshold for the first time. Therefore structural models are also called *first-passage* models. This model was subsequently extended by considering coupon bonds (Black and Cox (1976), Geske (1977)), adjustment costs (Fischer, Heinkel, and Zechner (1989)), cash flow (Kim, Ramaswamy, and Sundaresan (1993), Goldstein, Ju, and Leland (2001)), endogeneous default boundary (Leland (1994), Leland and Toft (1996), Leland (1998)), strategic default (Anderson and Sundaresan (1996), Mella-Baral and Perraudin (1997)), stochastic interest rate (Longstaff and Schwartz (1995)), jump in asset value (Zhou (2001)), capital structure rebalancing (Collin-Dufresne and Goldstein (2001)), bankruptcy procedures (François and Morellec (2004)), and endogeneous collateral value (Titman, Tompaidis, and Tsyplakov (2004)), among others.

The structural approach prices corporate bonds relative to equity value. A striking counterfactual result of structural models is that default time is perfectly predictable. If the purpose of the model is to find the optimal hedging strategies or price credit derivatives, it is not necessary to know the source of credit risk. Instead, default can be assumed to be controlled by some exogenous intensity process. In this *reduced form* approach, default time is totally inaccessible (unpredictable) and cause of default is irrelevant. This approach was initiated by Jarrow and Turnbull (1995) and extended by Jarrow, Lando, and Turnbull (1997), Duffie and Singleton (1999), Jarrow and Yu (2001), among others.

The fundamental difference between structural and reduced form models is driven by the information set available to the modeler. In structural models, the modeler has perfect information regarding the firm's asset value, while this restriction is not imposed on reduced form models. Structural models converge to reduced form models when this perfect information assumption is relaxed, as shown by Duffie and Lando (2001), Cetin, Jarrow, Protter, and Yildirim (2004), Guo, Jarrow, and Zeng (2005), and Giesecke (2005). The relationship between these two approaches is discussed in detail by Jarrow and Protter (2004). Which model to use depends on the problem at hand. The reduced form models have a better chance fitting the observed bond prices because they have fewer constraints. But it is unclear which approach has more forecasting power.

1.1.2 Empirical evidence

There is still no consensus on how well structural models explain observed corporate yield spreads. While Sarig and Warga (1989), Titman and Torous (1989), and Bohn (1999) find supportive evidence, Jones, Mason, and Rosefield (1984), Huang and Huang (2003), Eom, Helwege, and Huang (2004) find that the structural models cannot accurately predict the magnitude of yield spreads. Furthermore, Collin-Dufresne, Goldstein, and Martin (2001) and Elton, Gruber, Agrawal, and Mann (2001) find that factors other than those credit risk determinants suggested by structural models are important for yield spread dynamics.

Leland (2004) shows that structural models can predict default probability well. Therefore, the failure of structural models is very likely, at least in part, due to the measurement error in credit spreads (the portion of yield spreads attributable to credit risk). Indeed, Longstaff, Mithal, and Neis (2005) and Ericsson, Reneby, and Wang (2005) find that corporate yield spreads contain significant liquidity premium while credit default swap (CDS) spreads (presumably a better measure of credit spreads) do not. The failure of structural model may also be caused by omitted variables. Yu (2005) find that accounting transparency drives cross-sectional dispersion of yield spreads. Khurana and Raman (2003) find that earnings related fundamentals are important for corporate bond pricing. Other factors affecting corporate yield spreads include: idiosyncratic volatility (Campbell and Taksler (2003)), corporate governance (Bhojraj and Sengupta (2003), Anderson, Mansi, and Reeb (2004), Klock, Mansi, and Maxwell (2005), Ortiz-Molina (2005)), auditor quality (Mansi, Maxwell, and Miller (2004)), and analyst forecast (Mansi, Maxwell, and Miller (2005), Guntay and Hackbarth (2005)).

While reduced form models render modeling convenience, Arora, Bohn, and Zhu (2005) find that reduced form models do not outperform structural model when predicting the probability of default and the CDS spreads.

1.2 Stylized Facts and Open Questions

Three decades of studies have made significant progress on our understanding of credit risk. Nevertheless, several empirical puzzles challenge current theoretic models and remain to be resolved. Furthermore, some areas are yet to be explored both theoretically and empirically.

A caveat needs to be put in place first. Here we will mainly discuss the troubles with structural models. The reduced form model is designed such that it can fit the data well in a system of latent variables. There are two major criticisms to reduced form models: (1) the models lack economic intuition as to what causes default; (2) the models are internally inconsistent as each time the model parameters and state variables are recalculated.[3]

Although conceptually elegant, the structural models have had limited success in matching with empirical data. While there is qualitative evidence supporting the Merton-type models (see, for instance, Sarig and Warga (1989), Titman and Torous (1989), and Bohn (1999)), three empirical puzzles remain. First, the magnitude of credit spreads predicted by theoretical models is inconsistent with historical observations. Jones, Mason, and Rosenfeld (1984) and, more recently, Huang and Huang (2003) show that credit spreads predicted by the structural models are significantly below the observed levels, especially for high-grade bonds. In assessing empirical performance of several notable structural models, Eom, Helwege, and Huang (2004) find that these models to varying degrees tend to underestimate credit spreads for high quality bonds, but overestimate those for junk debt. Those empirical studies indicate that the accuracy of structural models is a major concern.

Second, the predicted shape of the credit yield spread curve for speculative-grade bonds is at odds with historical observations. Helwege and Turner (1999) document that the

[3]A minor problem with reduced form models is that default time is not completely unpredictable: defaults occur more often on coupon dates.

yield spread curves for high-yield corporate bonds are upward sloping. This finding contradicts the prediction of humped-shape high-yield credit spread curves from most Merton-type structural models, with the notable exception of Collin-Dufresne and Goldstein (2001) in which firms' leverage ratios are exogenously assumed to be mean-reverting.

Third, some fundamental determinants of credit spreads remain elusive. Collin-Dufresne, Goldstein and Martin (2001) show that "variables that should in theory determine credit spread changes have rather limited explanatory power." They also demonstrate that the unexplained changes are likely driven by a common factor. Duffie and Singleton (1997) observe that a substantial fraction of swap spreads variation is left unexplained by their model. Elton, Gruber, Agrawal and Mann (2001) illustrate that default risk factors "account for a surprisingly small fraction" of credit spreads. Meanwhile, although it is generally accepted that the correlation between interest rates and credit spreads is negative (see, e.g., Duffee (1998)), Alessandrini (1999) finds evidence for time-series and cross-sectional variations in this correlation.

The majority of structural models assume that default is triggered by low asset value. However, Davydenko (2005) shows that liquidity (capital shortage) is a more common reason for default, and a lot firms default even though their asset values are high. This finding indicates that modeling cash flow instead of asset value may be more appropriate.

All current credit risk models deal with a single issuer. This type of model cannot capture contagion effect in default, which is an important source of default (Das, Duffie, Kapadia, and Saita (2005), Zhang (2004)). Default correlation modeling is critical to portfolio credit risk studies. Currently, copula, as a pure mathematical tool first applied by Li (2000), is widely used to study default correlations.

Another component determining the severity of credit loss additional to default probability is recovery rate, which has been treated as constant for modeling convenience. Recovery rate specification can significantly affect a model's performance (Bakshi, Madan, and Zhang (2003)). Empirical evidence has shown that recovery rate varies with business cycles and across industries (Thorburn (2000), Gupton and Stein (2002), Altman, Brady, Resti, and Sironi (2002), and Acharya, Bharath, and Srinivasan (2003)) and recovery to face value is more realistic than other specifications (Guha (2003)). Those empirical findings have yet to be incorporated into a theoretic model.

1.3 Outline and Contributions of Current Study

This study attempts to advance our understanding of credit risk on both theoretic and empirical fronts.

I first derive a structural credit risk model with more realistic assumptions. I incorporate macroeconomic conditions in a cash flow based credit risk model. In the model, recovery rate is time-varying: higher recovery in economic expansions and lower recovery in recessions. This model employs a beta specification for firm growth rate therefore our modeling framework is easy to be adapted to portfolio credit risk modeling. The model successfully predicts upward sloping credit spread curves for speculative grade bonds. It also predicts reasonable level of credit spreads. This model makes several unique predictions that are empirically supported. Most interestingly, investor sentiment affects credit spreads.

I further study the cross-sectional determinants of credit spreads. I first construct a better measure of credit spreads using credit default swap (CDS) prices. CDS spreads are arguably the best measure of credit spreads to date because they are contract for trading pure default risk. In addition to conventional fundamental determinants of credit spreads, I examine how accounting transparency and market liquidity affect credit spreads. I find accounting transparency is an important explanatory variable for credit spreads, and this effect is non-linear: it is less severe for firms with a "technological edge." CDS market liquidity and liquidity spillover from other markets are also important determinants of credit spreads. But as the market develops, this effect weakens.

The purpose and contribution of this dissertation is to provide more *comprehensive* and *coherent* view of credit risk valuation. Specifically, I examine the effects of previously overlooked factors (in addition to conventional factors such as market financing costs, firm leverage, and firm risk) on credit risk using better measure of credit spreads. I argue that the aforementioned puzzling stylized facts can be much better explained and understood after considering those factors and using improved credit spread measure.

Chapter 2

Macroeconomic Conditions, Firm Characteristics, and Credit Spreads: Theoretical Modeling

The collective evidence discussed in previous chapter seems to suggest that structural models are misspecified as some systematic factors that affect default risk and credit spread dynamics are not properly incorporated. A number of authors have recognized the importance of macroeconomic conditions for assessing credit risk and credit spread dynamics. Jarrow and Turnbull (2000) propose that incorporating macroeconomic variables may improve a reduced-form model. Collin-Dufresne, Goldstein, and Martin (2001) point to "the need for further work on the interaction between market risk and credit risk — that is, general equilibrium models embedding default risk." Moreover, Duffie and Singleton (2003) conjecture that the effects of macroeconomic business cycles on spreads are one of the possible interpretations of the observed negative correlations between credit spreads and yields on Treasury bonds of comparable maturities. Surprisingly, little theoretical work has been done to examine the relation between credit spread dynamics and the state of the economy in an equilibrium setting.

In this chapter we explore the effects of macroeconomic conditions on credit spreads from a theoretical perspective. Specifically, we first solve for the equilibrium in a Lucas (1978) exchange economy, in which the growth rate of the economic output is mean-reverting and the representative investor has a constant relative risk aversion (CRRA) utility function. Within this economy, we study a firm whose cash flow growth has both systematic and firm-specific components, with its firm-specific component also following a mean-reverting process. The firm issues a bond with continuous coupons and a finite maturity and default occurs when the firm's cash flow fails to cover the interest payment. Consistent with empirical evidence, our model assumes a stochastic default recovery rate that is dependent on the macroeconomic condition at the moment of default. The risky bond is then valued using the contingent claim approach now standard in the literature (see, e.g., Longstaff and Schwartz (LS, 1995) and Collin-Dufresne and Goldstein (CDG, 2001)).

While many of the structural models do consider one macroeconomic variable, the risk-free interest rate, it is treated as an exogenous variable. In fact, it is endogenously determined by market equilibrium depending on fundamental macroeconomic variables such as GDP growth rates, aggregate market volatility, and investors' risk preferences that also affect credit spread dynamics. Therefore, treating the effect of macroeconomic variables, and particularly the risk-free rate, in a reduced form as done in the existing literature will mask true determinants of credit risk and the dynamics of credit spreads. We explicitly consider the equilibrium of the macroeconomy in which the pricing kernel and the risk-free rate are determined jointly and then used to price the equity and debt of a firm in a consistent manner.[1] Moreover, we model a firm's cash flow instead of its asset value because cash flow characteristics are more easily observable and liquidity constraints are a major cause for default. This approach also allows us to investigate differential sensitivity of asset value to shocks in cash flows and in the discount rate (Campbell and Vuolteenaho (2004)).

We calibrate our model to historical default frequencies and leverage ratios, similar to the approach in Huang and Huang (2003) and Leland (2004). Since our model focuses on default risk, its predicted yield spreads will inevitably deviate from empirical observations because of other known factors impounded in credit spreads such as liquidity and taxes not considered here. Nevertheless, the prediction of credit spreads from our model fares better than other well-known structural models. Our model generates higher yield spreads for high-grade bonds than other models which tend to underestimate the spreads for these bonds, yet for high yield bonds, our model produces smaller yield spreads than other models which are shown to over-predict credit spreads for very risky bonds (Eom, Helwege, and

[1] A similar approach has been used in pricing equity options (Bakshi and Chen (1997)) and in studying the effect of labor income on asset prices (Santos and Veronesi (2002)).

Huang (2004)). More strikingly, our model generates upward-sloping yield spread curves for speculative-grade bonds, which are consistent with recent empirical evidence and contrary to other structural models, except for the CDG model.

Our comparative static analysis yields results that manifest the significant impact of macroeconomic conditions on credit spread changes. First, credit spreads are counter-cyclical, widening during recessions and narrowing during economic expansions. Because there is a one-to-one relation between economy growth rate and risk-free interest rate, our model demonstrates the economic underpinning for the observed negative correlation between interest rate and credit spreads. Furthermore, our model illustrates cross-sectional variations in this negative correlation.

Second, credit spreads increase with volatility of the economic growth rate. This result is intuitively understandable as a firm is more likely to experience cash flow shortfalls in a more volatile economic environment, and hence more likely to default. Credit spreads also widen when investors are more risk averse. It is believed that investors become more risk averse during economic downturns, and this effect has been linked to the "flight to quality" phenomena. Although we do not explicitly model the endogenous change of investors' preferences, these comparative static analysis results provide a gauge of the sensitivity of credit spreads to changes in macroeconomic conditions.

Lastly, our model also has cross-sectional implications for credit spread dynamics and for the effect of the interaction between macroeconomic conditions and industry characteristics. We find that credit spreads decrease with the current firm-specific growth rate and increase with its volatility. The correlation between the firm-level cash flow and the aggregate output, which can be thought of as an industry characteristic, plays a significant role in determining credit spreads and their changes.

A few recent papers are related to our study. Hackbarth, Miao and Morellec (2004) study the effect of aggregate shocks on optimal capital structure choices and credit risk in a model with an exogenous and constant risk-free rate. On the other hand, David (2004) and Marsh and Yan (2002) investigate how learning about the state of the economy can affect default risk of a debt written on the aggregate output. David (2004) also considers the effect of inflation. Demchuk and Gibson (2005) derive a model in which stock market performance directly affect credit spreads. These papers, however, face the challenge of interpreting the resulting credit spreads associated with the aggregate output and their relevance to empirical observations. Moreover, Pesaran, Schuermann, Treutler, and Weiner (2003) provide a global perspective of the empirical evidence on macroeconomic dynamics and credit risk.

The rest of this chapter is organized as follows. Section 2.1 introduces our modeling framework. We first lay out the economic structure and derive the equilibrium of the macroeconomy, and then we describe the cash flow process of an individual firm and derive the valuation of its risky debt using the contingent claim approach. Section 2.2 examines the calibration of the model. The analysis of our model is in Section 2.3. We offer concluding remarks in Section 2.4. All technical details are provided in the Appendix A.

2.1 The Model

2.1.1 The Economy

We consider a Lucas (1978)-type exchange economy. In this economy, there could be many firms and multiple risk factors, such as the one studied by Bakshi and Chen (1997). Without loss of generality for our purpose here, we model the aggregate output directly. The total output of this economy, $D(t)$, is described by the following process

$$\frac{dD(t)}{D(t)} = \mu(t)dt + \sigma_D(t)dZ_D(t), \tag{2.1}$$

where $Z_D(t)$ is a standard Brownian motion. Unless explicitly specified, all processes are under the real probability measure $\mathbb{P}$ in the probability space $\mathbf{\Omega}$ with an information filtration $\mathcal{F}_t$, satisfying all regularity conditions. We assume that $D(t)$ has constant volatility, $\sigma_D(t) = \sigma_D$, and its growth rate is mean-reverting,

$$d\mu(t) = \kappa(\bar{\mu} - \mu(t))dt + \sigma_\mu dZ_D(t), \tag{2.2}$$

where κ is the speed of mean reversion, $\bar{\mu}$ the long-run mean, and σ_μ the (constant) growth rate volatility. Therefore the aggregate economy is characterized by a one-factor model.[2] There is a risk-free bond in the economy with zero net supply. The bond price $B(t)$ is

[2]The growth rate $\mu(t)$ may be unobservable and have its own shocks that are orthogonal to the shocks to $D(t)$. In this case, its filtering process based on the observations of $D(t)$ will make its inferred value follow the process in (2). See Detemple (1986), Dothan and Feldman (1986) and Gennotte (1986) for the separation principle in a partially observable economy.

defined by the following process,

$$dB(t) = r(t)B(t)dt. \tag{2.3}$$

The instantaneous risk-free interest rate $r(t)$ is endogenously determined as an equilibrium outcome. The economy specified here is similar to that discussed in Goldstein and Zapatero (1996).

We assume that there is a representative investor who has CRRA utility over consumption C_t with relative risk aversion coefficient γ and time discount factor δ,

$$U_t = \mathbf{E}_t \left[\int_0^\infty e^{-\delta s} \frac{C_{t+s}^{1-\gamma} - 1}{1-\gamma} ds \right]. \tag{2.4}$$

The investor chooses the optimal consumption-investment rule to maximize his expected lifetime utility. The first order condition yields the stochastic discount factor (SDF), or pricing kernel, $\pi(t)$ which prices all the assets and payoffs in this economy,

$$\pi(t) = e^{-\delta t} C_t^{-\gamma}. \tag{2.5}$$

Since in this endowment economy the output is perishable and the total consumption of the entire economy comes from the aggregate output, also known as the dividends, in equilibrium the price of a claim to the aggregate output will be adjusted such that the total consumption equals the dividends, $C_t = D_t$. Using this equilibrium condition and Itô's Lemma, we have

$$\frac{d\pi(t)}{\pi(t)} = -\left(\delta + \gamma\mu(t) - \frac{1}{2}\gamma(1+\gamma)\sigma_D^2 \right) dt - \gamma\sigma_D dZ_D(t). \tag{2.6}$$

Therefore the instantaneous riskfree rate is given by

$$r(t) = -\frac{1}{dt}\mathbf{E}_t \left(\frac{d\pi(t)}{\pi(t)} \right) = \delta + \gamma\mu(t) - \frac{1}{2}\gamma(1+\gamma)\sigma_D^2, \tag{2.7}$$

and the market price of risk is constant,

$$\theta = \gamma\sigma_D. \tag{2.8}$$

The following lemmas give the standard results for the prices of risk-free discount bonds and the risky asset.

LEMMA 1 *The time-t price of the risk-free discount bond which pays 1 with certainty at maturity time T is given by*

$$P(t,T,r(t)) = e^{A(t,T)-B_\kappa(t,T)r(t)}, \tag{2.9}$$

where

$$\begin{aligned} A(t,T) &= -\left[\bar{r} - \frac{1}{2}\gamma^2\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)\right](T-t) + \bar{r}B_\kappa(t,T) \\ &\quad -\frac{1}{2}\gamma^2\left[\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right)B_\kappa(t,T) - \frac{\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,T)\right], \\ B_\kappa(t,T) &= \frac{1-e^{-\kappa(T-t)}}{\kappa}. \end{aligned}$$

Proof: See Appendix A. ■

LEMMA 2 *The present value of the aggregate output $D(t)$ at time t is given by*

$$S(t) = D_t\int_t^\infty \exp(\psi(t,s;r(t)))ds, \tag{2.10}$$

where

$$\begin{aligned} \psi(t,s;r(t)) &= \left[-\frac{\delta}{\gamma} + \frac{1-\gamma}{\gamma}\bar{r} + \frac{\gamma(1-\gamma)}{2}\sigma_D^2 + \frac{1}{2}(1-\gamma)^2\left(\sigma_D^2 + \frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)\right](s-t) \\ &\quad +\left[\frac{1-\gamma}{\gamma}(r(t)-\bar{r}) - \frac{1}{2}(1-\gamma)^2\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right)\right]B_\kappa(t,s) \\ &\quad +\frac{1}{2}(1-\gamma)^2\frac{\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,T). \end{aligned}$$

Proof: See Appendix A. ■

The unlevered equity value formula (10) will help to establish the transversality condition for our model parameters. The risk-free discount bond price is affine and the risk-free rate process is the same as the seminal equilibrium model of Vasicek (1977). This economy is completely characterized by the pricing kernel $\pi(t)$. Below we study an individual firm in this economy.

2.1.2 The Firm

We examine a firm whose cash flow is a tiny portion of the aggregate output. The cash flow the firm generates, $K(t)$, has the following dynamics:

$$\frac{dK(t)}{K(t)} = (\beta\mu(t) + \xi(t))dt + \sigma_K \rho dZ_D(t) + \sigma_K\sqrt{1-\rho^2}dZ_K(t), \tag{2.11}$$

$$d\xi(t) = \lambda(\bar{\xi} - \xi(t))dt + \sigma_\xi dZ_K(t). \tag{2.12}$$

where $Z_K(t)$ is a standard Brownian motion independent of $Z_D(t)$, ρ is the correlation between the firm-level cash flow process and the aggregate output process, σ_K is the volatility of the firm's cash flow. The drift term, $m(t) = \beta\mu(t) + \xi(t)$, is the current firm-level cash flow growth rate, and $\xi(t)$ is the firm-specific growth rate which is independent of the growth rate of the aggregate output, $\mu(t)$, and assumed to follow a mean-reverting process, with mean-reverting speed λ, long-run mean $\bar{\xi}$ and volatility σ_ξ. The sensitivity of firm growth to economic growth,

$$\beta = \mathrm{Cov}\left(\frac{dK(t)}{K(t)}, \frac{dD(t)}{D(t)}\right) \Big/ \mathrm{Var}\left(\frac{dD(t)}{D(t)}\right) = \rho\frac{\sigma_K}{\sigma_D},$$

can be thought of as the cash flow beta as in Campbell and Vuolteenaho (2004).

The cash flow $K(t)$ is a part of the aggregate output of the economy, $D(t)$. We can think of $D(t)$ as a forest and $K(t)$ as an individual tree in this forest. We do not explicitly model the rest of the economy. Following the reasoning of Bakshi and Chen (1997), we assume that the rest of the economy $D(t) - K(t)$ follows a process such that $K(t)$ and $D(t) - K(t)$ will aggregate to $D(t)$. Therefore, we can use the pricing kernel of the economy to evaluate an all-equity firm whose cash flow is described by (11) and (12). The following lemma provides such valuation.

LEMMA 3 *The unlevered equity value of the firm with cash flow described by (11) and (12) is given by*

$$S_K(t) = K_t \int_t^\infty \exp(\psi_K(t, s; \mu(t), \xi(t)))ds, \tag{2.13}$$

where

$$
\begin{aligned}
& \psi_K(t,s;\mu(t),\xi(t)) \\
= & \left[-\delta + (\beta-\gamma)\bar{\mu} + \bar{\xi} + \frac{1}{2}\gamma\sigma_D^2 - \frac{1}{2}\sigma_K^2 + \frac{1}{2}(\rho\sigma_K - \gamma\sigma_D)^2 + \frac{1}{2}\sigma_K^2(1-\rho^2) \right. \\
& \left. +(\beta-\gamma)(\rho\sigma_K - \gamma\sigma_D)\frac{\sigma_\mu}{\kappa} + \sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda} + \frac{1}{2}\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2} + \frac{1}{2}\frac{\sigma_\xi^2}{\lambda^2}\right](s-t) \\
& +(\beta-\gamma)(\mu(t)-\bar{\mu})B_\kappa(t,s) + (\xi(t)-\bar{\xi})B_\lambda(t,s) \\
& -\left[(\beta-\gamma)(\rho\sigma_K - \gamma\sigma_D)\frac{\sigma_\mu}{\kappa} + \frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}\right]B_\kappa(t,s) \\
& -\left[\sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda} + \frac{\sigma_\xi^2}{\lambda^2}\right]B_\lambda(t,s) \\
& +\frac{1}{2}\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,s) + \frac{1}{2}\frac{\sigma_\xi^2}{\lambda^2}B_{2\lambda}(t,s)
\end{aligned}
$$

Proof: See Appendix A. ■

Our model does not explicitly examine the firm's investment opportunities and capital structure decisions. Following the literature, we assume that the Modigliani-Miller theorem holds, which means that the firm's financing decisions do not affect its enterprise value. Therefore, the firm's value will remain the same even if it alters its capital structure in the future. We may extend our model in the dimension along which capital structure matters for the total firm value and the firm chooses optimal capital structure to maximize the firm value.[3] This, however, will introduce more complexity before we have a better understanding of the pricing effect of macroeconomic conditions. Therefore, as an initial step towards a more comprehensive study, we maintain our current setting and apply the contingent claim approach to value a bond that uses the cash flow $K(t)$ as collateral.

Most other structural credit risk models in the literature start from the asset value process. However, an exogenously assumed asset value process may not be internally consistent with a pricing kernel that prices securities in a unified framework. In those models, default occurs when the firm value falls below some threshold. In reality this is rarely the case. Firm value falling below a threshold may precipitate some interest payments, but the

[3]See, among others, Fischer, Heinkel, and Zechner (1989), Leland (1994, 1998), Leland and Toft (1996), Goldstein, Ju, Leland (2001), and Titman, Tompaidis, and Tsyplakov (2004). Hackbarth, Miao and Morellec (2004) examine the effect of macroeconomic shocks to optimal capital structure decisions and credit spreads, but they use a partial equilibrium framework in which the risk-free rate is assumed to be constant.

fundamental reason for default is that the firm does not have enough cash for its interest payments.[4] Uhrig-Hombug (2005) explicitly models cash flow shortage as an endogenous bankruptcy reason in the presence of equity-issuance costs.[5]

Here we model the firm's cash flow as a primary process, and the firm defaults when it does not have enough cash to pay its dues. Other studies have also examined cash flow rather than firm value process. Kim, Ramaswamy, and Sundaresan (1993) argue that firm defaults when its cash flow is not sufficient for its coupon payments, but they specify the cash flow in such a way that the firm's asset value follows a geometric Brownian motion and still treat the firm value as the fundamental variable. Goldstein, Ju, and Leland (2001) model the firm-level cash flow directly in determining optimal dynamic capital structure choice. Titman, Tompaidis, and Tsyplakov (2004) consider endogenous cash flow processes with investment decisions and investigate the effect of investment flexibility on credit spreads. In addition, Marsh and Yan (2002) study credit spread dynamics for defaultable debt on the aggregate output.

2.1.3 Bond Valuation

Given the firm's cash flow process, we can value any contingent claims written on this cash flow. We assume that the firm has a bond at time 0 and focus on the pricing of such a contingent claim.

The risky debt has a face value F, coupon payment rate c, and maturity T. This risky bond is pledged on the firm cash flow $K(t)$. During each period, Δt, the firm will pay the bondholders a fixed coupon, $c\Delta t$, before the bond matures. The firm defaults when its cash flow is not enough to cover the coupon payment, $K < c$. In that event, either reorganization or liquidation is imposed and the bondholders recover a fraction $w(\cdot)$ of the face value F. This recovery of face value at default (RFV) assumption is shown to be most consistent with empirical evidence among alternative default recovery assumptions (Guha (2003)). The payoff stream of this defaultable bond is

$$g(t) = c \cdot \mathbf{1}(t \leq T) \cdot \mathbf{1}(t < \tau) + F \cdot \delta(t - T) \cdot \mathbf{1}(t < \tau) + w(\cdot)F \cdot \delta(t - \tau) \cdot \mathbf{1}(t \leq T), \quad (2.14)$$

[4]See Wruck (1990) for the information problem in financial distress and the difference between cash flow triggered default and asset value triggered default.

[5]Here we exclude the possibility of strategic default because the firm value will never fall below zero. For studies on strategic debt services, see Anderson and Sundaresan (1996, 2000), Mella-Barral and Perraudin (1997), Mella-Barral (1999), Fan and Sundaresan (2000), and John, Lynch, and Puri (2003).

where $\tau = \inf\{t : K(t) < c\}$ is the first passage time which represents the time of default, and $\delta(t - \tau)$ is the Kronecker delta.

Extant studies on bond valuation in the literature assume constant default recovery rate. Beyond tractability reasons, this assumption is not supported by empirical evidence. For example, in a comprehensive investigation of all defaulted bonds, Altman and Kishore (1996) find that recovery rates are time varying. Further, Collin-Dufresne, Goldstein, and Martin (2001) argue that "even if the probability of default remains constant for a firm, changes in credit spreads can occur due to changes in the expected recovery rate. The expected recovery rate in turn should be a function of the overall business climate."

Here we assume that the recovery rate $w(\mu_t)$ depends on the current growth rate of the economy, which is consistent with recent empirical findings of Thorburn (2000), Gupton and Stein (2002), Altman, Brady, Resti, and Sironi (2002), and Acharya, Bharath, and Srinivasan (2003), who collectively show that macroeconomic and industry conditions at the time of default are important and robust determinants of the recovery rate. The intuition for this is also found in Shleifer and Vishny (1992) who show, in an industry equilibrium setting, that a firm's liquidation value is lower when its competitors are experiencing cash flow problems. We capture this relation in a parsimonious way by assuming

$$w(\mu_t) = a + b\mu_t, \tag{2.15}$$

where $b \geq 0$. Although such a linear specification for the recovery rate would allow it to go beyond the $[0, 1]$ range, in our model the volatility of μ_t, σ_μ, is so low that the actual recovery rate in our investigation should stay in the $[0, 1]$ range.

Moreover, Acharya, Bharath, and Srinivasan (2003) show that the factors affecting default risk are only weakly dependent on the factors affecting recovery rate. Therefore, for analytical tractability, we assume that default risk and recovery rate risk are independent, that is,

$$\mathbf{E}[w(\mu_t)\delta(t - \tau)] = \mathbf{E}[w(\mu_t)]\mathbf{E}[\delta(t - \tau)].$$

Note that since the empirical correlation is marginally positive, our simplification will decrease expected loss, thereby bias downward credit spreads in our calculation.

With these assumptions, we arrive at the following Proposition.

PROPOSITION 1 *The value of the risky debt at $t = 0$ is given by*

$$
\begin{aligned}
DV &= \mathbf{E}^{\mathbb{Q}}\left[\int_0^T e^{-\int_0^t r(s)ds} g(t)dt\right] && (2.16)\\
&= FV - EL,
\end{aligned}
$$

where

$$FV = c\int_0^T P(0,t,r(0))dt + F\cdot P(0,T,r(0)) \qquad (2.17)$$

is the value of a default risk-free bond with an identical payment structure, and

$$
\begin{aligned}
EL &= c\int_0^T P(0,t,r(0))\Gamma(t)dt + (1-a-b\mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mu(t)])F\cdot P(0,T,r(0))\cdot\Gamma(T) \qquad (2.18)\\
&\quad +F\int_0^T\left(P_t(0,t,r(0))(a+b\mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mu(t)]) + P(0,t,r(0))b\frac{\partial\mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mu(t)]}{\partial t}\right)\Gamma(t)dt
\end{aligned}
$$

is the expected loss of the risky bond, where $\Gamma(t) \equiv \mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mathbf{1}(\tau\le t)]$ is the cumulative distribution function of τ in the T-forward risk neutral measure, which represents the probability that default occurs before time t, and its density function is $f(t) \equiv \mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\delta(t-\tau)]$, $P_t(0,t,r(0)) = \partial P(0,t,r(0))/\partial t$, the expressions for $\mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mu(t)]$ and $\frac{\partial\mathbf{E}_0^{\mathbb{F}_\mathbb{T}}[\mu(t)]}{\partial t}$ are given in the Appendix A.

Proof: See Appendix A. ■

The valuation formula for the risky bond is very intuitive. The expected loss given default (LGD) consists of three components: the present value of the sum of all remaining coupon payments, the present value of the loss on the principal, and the present value of the reinvestment on the recovered principal. The yield to maturity of this risky bond Y is implicitly defined by

$$DV = \frac{c}{Y} + \left(F - \frac{c}{Y}\right)e^{-YT}. \qquad (2.19)$$

Similarly, the yield to maturity of a risk-free bond with the same payment structure, R, is given by

$$FV = \frac{c}{R} + \left(F - \frac{c}{R}\right)e^{-RT}. \qquad (2.20)$$

Following the extant literature such as LS and CDG, the credit yield spread is defined as $Y - R$.

A key ingredient of the bond valuation formula is the default probability $\Gamma(t)$. In our model, conditioning on the current growth rate, the firm's cash flow is normally distributed and has a two-factor structure. Therefore we can directly apply the flows of probability approach to find the probability distribution function for τ. This approach was first used by LS and subsequently modified by CGD and Huang and Huang (2003). We adopt the formulation of the cumulative default probability from Huang and Huang (2003) as stated in the following Lemma.

LEMMA 4 *The probability of default before time t under the risk-neutral forward measure is given by:*

$$\Gamma(t) = \lim_{n\to\infty} \sum_{i=1}^{n} q(t_{i-\frac{1}{2}}), \quad i = 1, 2, \ldots, n, \tag{2.21}$$

where

$$\begin{aligned} t_i &= i\frac{T}{n}, \\ q(t_{i-\frac{1}{2}}) &= \frac{N(a(t_i)) - \sum_{j=1}^{i-1} q(t_{j-\frac{1}{2}}) N(b(t_i; t_{j-\frac{1}{2}}))}{N(b(t_i; t_{i-\frac{1}{2}}))}, \\ a(t_i) &= -\frac{M(t_i, T|X_0, m_0)}{\sqrt{W(t_i|X_0, m_0)}}, \\ b(t_i; t_j) &= -\frac{M(t_i, T|X_{t_j})}{\sqrt{W(t_i|X_{t_j})}}, \end{aligned}$$

where

$$\begin{aligned} M(t_i, T|X_0, m_0) &\equiv \mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}], \\ W(t_i|X_0, m_0) &\equiv \mathbf{Var}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}], \\ M(t_i, T|X_{t_j}) &= M(t_i, T|X_0, m_0) - M(t_j, T|X_0, m_0)\frac{\mathbf{Cov}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}, X_{t_j}]}{W(t_j|X_0, m_0)}, \\ W(t_i|X_{t_j}) &= W(t_i|X_0, m_0) - \frac{\left(\mathbf{Cov}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}, X_{t_j}]\right)^2}{W(t_j|X_0, m_0)}, \end{aligned}$$

where $X_0 = \log(K_0/c)$ is current firm coverage ratio, $m_0 = \beta\mu_0 + \xi_0$ is current firm growth rate. The expressions for $\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}]$, $\mathbf{Var}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}]$, and $\mathbf{Cov}_0^{\mathbb{F}_{\mathbb{T}}}[X_{t_i}, X_{t_j}]$ are given in the Appendix A.

Proof: See Appendix A. ■

The default probability formula is completely characterized by the conditional and unconditional first two moments of the current firm coverage ratio X_0 (i.e., how well the firm's cash flow can cover its interest payments). The series in its expression converges very rapidly. The default probability has the same form under the real measure, with only the expressions for the first moment being modified, as given in the Appendix A.

2.2 Calibration of the Model

Similar to Huang and Huang (2003), we choose the parameters by jointly matching the historical leverage ratios and realized default frequencies. However, we do not strictly follow the procedure in Huang and Huang (2003). After fixing other free parameters for various models, Huang and Huang (2003) choose initial firm value, asset risk premium, asset volatility, and recovery rate to match initial leverage ratio, equity premium, cumulative default probability, and recovery rate. Therefore, for each credit rating over a given horizon, the calibration yields a distinctive value of asset volatility. This approach may be inherently inconsistent, as for the same firm, there can be different asset volatilities calibrated to bonds of different horizons. Instead, we follow the approach in Leland (2004) by choosing initial cash flow, initial firm-specific growth rate, and volatility of firm growth rate to jointly match leverage ratio and default probabilities at one, four and ten year horizons. While we will not exactly match all default probabilities due to the over-identification problem (four constraints with only three free parameters), we choose those parameters to minimize the difference between predicted and historical default probabilities.

The resulting parameter values are reported in Table 2.1. The calibration of macroeconomic variables follows the existing evidence in the literature as summarized in Huang and Huang (2003). The risk aversion (γ)is taken to be 2, which is the typical value used in the literature (e.g., Campbell and Cochrane, 1999).[6] We choose the time discount factor (δ) to be 0.05, which in the range of values used in the literature, and the average growth rate of economic output ($\bar{\mu}$) to be 3% per annum. The volatility of the economic output is set at 10% per annum. This choice of variables allows us to set the long-run mean of the risk-free rate at 8% per annum as indicated in Huang and Huang (2003). Because of the power utility for the representative agent in our model, the equity premium may be lower than the historical average, but it is roughly on par with ex ante estimates (e.g., Claus and

[6] Chen, Collin-Dufresne and Goldstein (2005) use instead $\gamma = 4$. To avoid an unrealistically high volatility for the risk-free rate in our model, we stick with $\gamma = 2$.

Table 2.1: Baseline Parameters Used in the Calibration

This table summarizes the baseline parameters used in our calibration exercise and comparative static analysis.

Parameter	Symbol	Value
Preference:		
Risk aversion	γ	2
Time discount factor	δ	0.05
Macroeconomic condition:		
Standard deviation of economy growth	σ_D	10%
Mean reversion of economy growth rate	κ	1.5
Long-run mean of economy growth rate	$\bar{\mu}$	3%
Long-run mean of risk-free rate	$\bar{r} = \delta + \gamma\bar{\mu} - \frac{1}{2}\gamma(1+\gamma)\sigma_D^2$	8%
Standard deviation of growth rate	σ_μ	2%
Current economy growth rate	μ_0	4%
Firm characteristics:		
Std of firm cash flow growth	σ_K	12%
Correlation between firm and economy	ρ	0.6
Cash-flow beta	$\beta = \rho\sigma_K/\sigma_D$	0.72
Mean reversion of firm-specific growth rate	λ	1
Long-run mean of firm-specific growth rate	$\bar{\xi}$	2%
Std of firm-specific growth rate	σ_ξ	2%
Current cash flow	K_0	16
Current firm-specific growth rate	ξ_0	2%
Current firm growth rate	$m_0 = \beta\mu_0 + \xi_0$	4.88%
Bond feature:		
Face value	F	100
Coupon rate	c	8%
Recovery rate constant	a	42.5%
Recovery rate amplifier	b	2.5
Recovery rate mean	$\bar{w} = a + b\bar{\mu}$	50%

Thomas (2001)). In addition, we set the mean-reversion parameter, κ, to be 1.5, on par with the value used in Longstaff and Schwartz (1995).

On the firm level, there is a wide range of values we could choose for various parameters, depending on the firm characteristics we want to focus on. In our calibration, we define leverage ratio as book debt divided by the market value of the firm,

$$\text{Leverage Ratio} = \frac{F}{S_K(0)}.$$

We obtain different firm leverage ratios by changing current earnings K_0 and, consequently, the current coverage ratio $X_0 = \log(K_0/c)$. Although many of the other parameters will be varied in our sensitivity analysis, as a benchmark case, we set the standard deviation of the firm's cash flow at 12% per annum, the correlation between the firm's cash flow and macro-economic output at 0.6, resulting the firm's cash flow beta to be 0.72. The long-run mean of firm-specific growth rate is set at 2% per annum, with a 2% standard deviation and a mean-reversion parameter of 1. For bonds issued by the firm, we use a 8% coupon rate and assume an average recovery rate at 50%, on par with the number used in Huang and Huang (2003). With the stochastic recovery with the same mean, we set $a = 42.5$, and $b = 2.5$.

For this set of parameters, a firm with a leverage ratio 30.58% (with an approximate A rating) has a predicted default probability of 1% if its bond maturity is four years, and 6.39% if its bond maturity is ten years. The historical data from Standard & Poor's and Moody's, as documented by Huang and Huang (2003), show that for A-rated bonds with an average leverage ratio of 31.98%, the corresponding default frequencies are 0.35% and 1.55%, respectively. To further demonstrate qualitatively the fit of our predicted default probability curve with respect to the historical experience, we plot in Figure 1 three cumulative default probabilities for three credit rating classes, following the approach in Leland (2004).[7]

In our model, both macroeconomic and firm-specific variables jointly determine yield spreads and yield spread changes. The macroeconomic condition variables we will focus on are risk aversion, current growth rate, and volatility of economic growth. Firm-specific variables include current leverage ratio, volatility of the growth rate of cash flow, current firm-specific growth rate, and correlation between economy-wide and firm-level growth which links market risk and credit risk. In addition, the default recovery rate is dependent on the current economic conditions. In the following we use the calibrated parameters to generate predictions for credit yield spreads and carry out a series of comparative static analysis.

[7]Duffie, Saita and Wang (2005) find that incorporating macro-economic variables helps improve corporate default predictions. Due to data limitation, we are not able to make comparisons between their approach and our model in this paper.

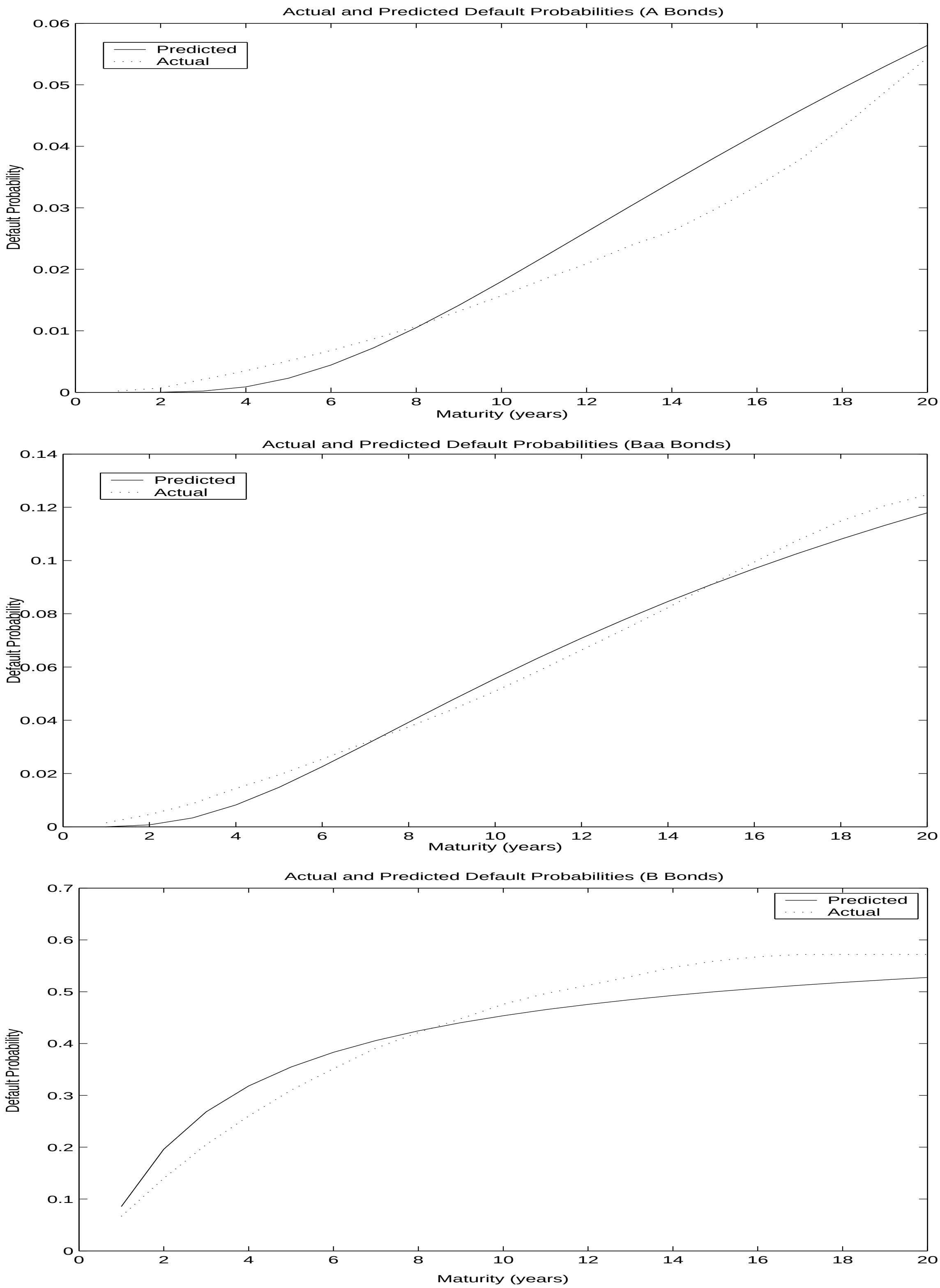

Figure 2.1: Term structure of cumulative default probability. Three panels, from top to bottom, are for A-rated, Baa-rated, and B-rated bonds, respectively. The historical default frequencies are from Moody's Investors Service (2002). The parameters used are provided in Table 2.1.

2.3 Analysis of Results

In this section, we first discuss the level and the shape of credit yield spread curves generated by our model using the calibrated parameters. We then conduct a comparative static analysis to gauge the effects of macroeconomic conditions, firm characteristics, and the interaction between market risk and credit risk on credit yield spread changes. We note that our analysis is done to assess qualitative properties of credit spreads, in the same spirit of Huang and Huang (2003), instead of a more quantitative prediction on a day-to-day basis.

2.3.1 Level and Shape of Yield Spread Curves

Our model compares favorably to some well-known structural models such as LS and CDG, in predicting the magnitude of credit yield spreads for both investment-grade and speculative grade corporate bonds. Table 2.2 reports predicted credit spreads from our model for three credit rating classes (A, Baa and B) and two horizons (4 and 10 years). It also lists comparable numbers from other models, including the Longstaff and Schwartz (1995) model (LS), the Leland and Toft (1998) model (LT) and the Collin-Dufresne and Goldstein (2001) model (CDG), based on the estimates in Huang and Huang (2003). The table shows that for high-grade bonds (with A and Baa ratings), our predicted values are substantially larger than other models. While the predicted values are still significantly below the historical averages as expected, due to tax and liquidity issues addressed in the literature, the results indicate our predicted values are about 50% higher for four-year bonds, and more than double in the yield spread for 10-year bonds.

More notable is the fact that for lower grade bonds, such as ones with a B rating, our predicted significantly lower spreads than other models. This is, in our view, an advantage, because tax and liquidity issues should be of concern for high grade bonds as much as, if not more, for low grade bonds. Other models tend to predict much higher credit spreads for low grade bonds which would result in a relatively smaller portion of the spread attributable to these non-default related components. Eom, Helwege and Huang (2004) discuss this concern of over-fitting for low grade bonds by other models. Our predicted values for low grade bonds seem more reasonable and consistent in light of this concern. The reason our model seems to perform better than these other models is because, in our model, there are

Table 2.2: Comparison of Model Predictions of Credit Spreads

This table reports predicted credit spreads from our model using calibrated parameters and other models from Huang and Huang (2003). LS refers to the Longstaff and Schwartz (1995) model with stochastic interest rate. LT refers to the Leland and Toft (1998) model. CDG refers to the Collin-Dufresne and Goldstein (2001) model.

Horizon and rating	Historical	Our Model	LS	LT	CDG
4-year A	96	13.2	7.5	–	9.9
4-year Baa	158	56.6	25.4	–	31.1
4-year B	470	240.5	406.0	–	435.3
10-year A	123	48.1	14.5	38.5	22.5
10-year Baa	194	109.6	38.6	59.5	52.3
10-year B	470	318.5	341.9	408.4	371.6

two distinct uncertainties in the growth rate which follow mean-reverting processes. The combined effect of two uncertainties increases yields for safer bonds; at the same time it drives down the yield spreads for very risky bonds.

Just as important, our model obtains a qualitatively accurate prediction for the shape of the yield spread curve. Our model predicts upward-sloping yield spread curves for speculative grade bonds, as shown in Figure 2.2, which is consistent with recent empirical evidence documented by Helwege and Turner (1999). The finding of Helwege and Turner is considered to be one of the most serious challenges to Merton-type bond pricing models because most of other structural models, with the notable exception of CDG, generate hump-shaped or downward-sloping yield spread curves for junk bonds. In Merton-type models, the drift term of the asset value process is always positive, therefore conditioning on that the firm does not default in the short run, the long-run survival probability for the firm is very high. This is not the case in our model, the growth rate can go negative due to the two mean-reverting components therefore the default probability always increases with maturity. Incidentally, in CDG the default probability increases with maturity because the firm maintains a stationary leverage ratio.

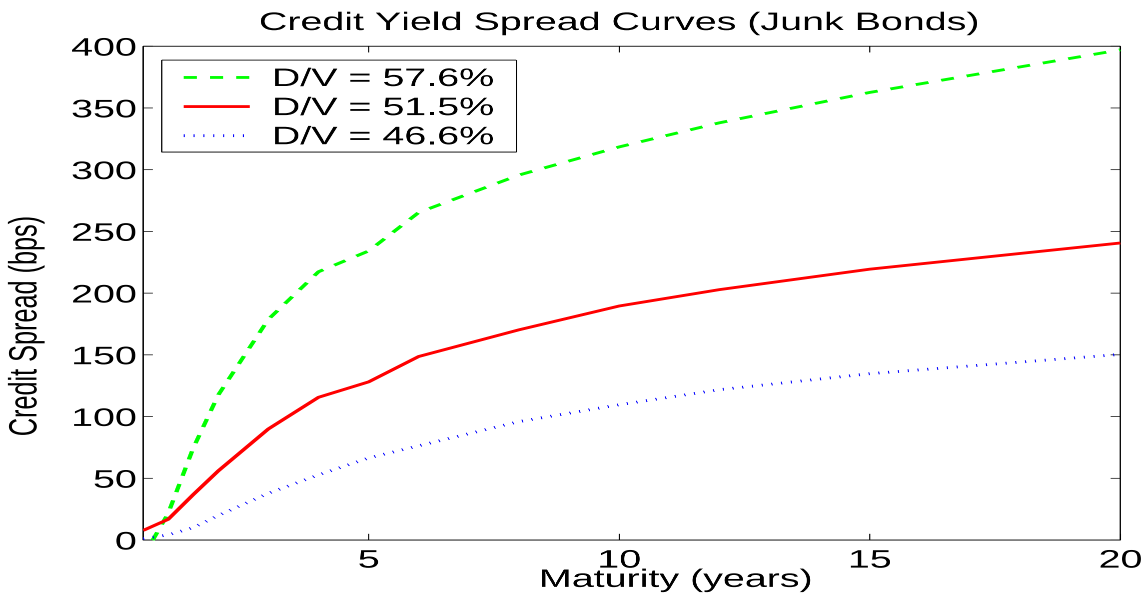

Figure 2.2: Speculative-grade credit spreads. The parameters used are provided in Table 2.1. Three leverage ratios are considered, corresponding to rating classes around "Ba" and "B".

2.3.2 Macroeconomic Conditions and Yield Spreads

Current Aggregate Growth Rate

Our model predicts that credit spreads widen during economic downturns. Figure 2.3 shows the yield spread curves for three different values of current economic growth rate $\mu_0 = -1\%, 4\%, 7\%$. Yield spreads decrease significantly when the current growth rate moves from -1% to 7%. For example, for a ten-year maturity Baa bond, yield spread declines to 48.7 basis points from 57.2 basis points as current economic growth rate increases from -1% to 7%. This finding is qualitatively consistent with empirical evidence documented by Fama and French (1989) who show that credit yield spreads display a business cycle pattern: yield spread narrows when economic conditions are strong and widens when conditions are weak. Similar empirical evidence is also found in a number of other studies.

Because, *ceteris paribus*, there is a one-to-one relation between economic growth rate and real risk-free interest rate, as in

$$r(t) = \delta + \gamma\mu(t) - \frac{1}{2}\gamma(1+\gamma)\sigma_D^2,$$

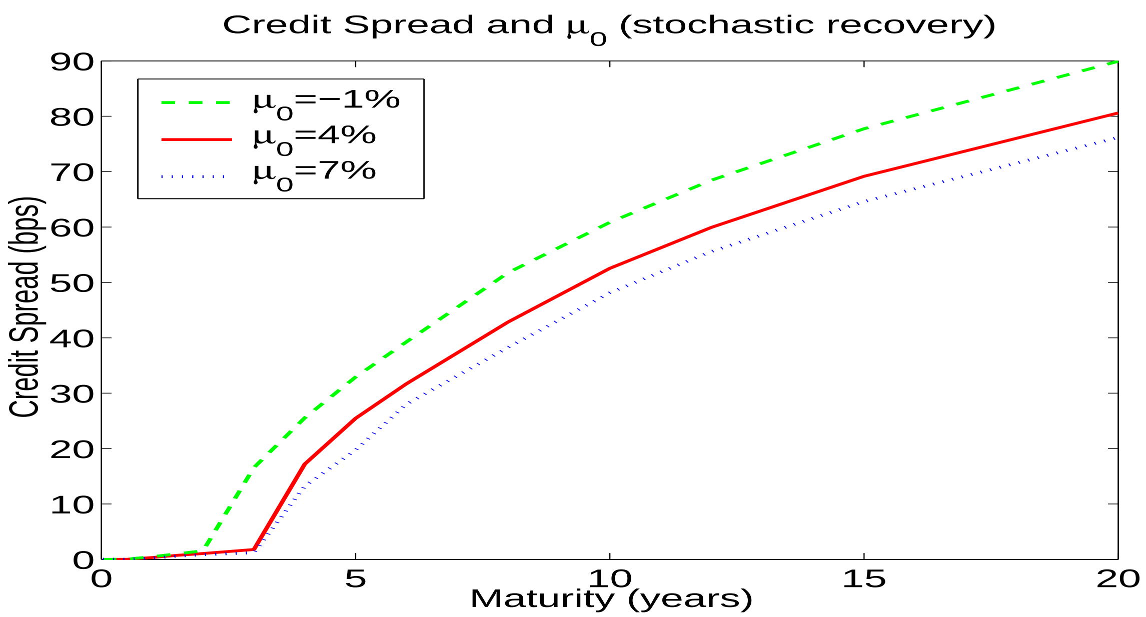

Figure 2.3: Credit spreads for different values of the current economy growth rate μ_0. The parameters used are provided in Table 2.1.

yield spreads should be negatively correlated with the risk-free rate. This prediction is consistent with the finding in Duffee (1998) and confirms the conjecture by Duffie and Singleton (2003) that this negative correlation could be due to macroeconomic factors. The intuition for the negative correlation is as follows. The drift of the firm's cash flow process is positively related to economy growth rate (with a positive cash flow beta). An increase in economic growth rate will increase the drift, and therefore decrease the default probability and credit spreads.

Note that this negative correlation was generated by the positive correlation between firm cash flow growth and economic growth. This is the case in our calibrated parameters because an average firm, which is a part of the aggregate economy, is positively correlated with the economy. Since some firms may be counter-cyclical (negative beta firms), a positive correlation between interest rate and credit spreads can arise for these firms. Because most empirical tests use portfolios and the aggregate cash flow beta in a portfolio beta tend to be positive, as most firms are more pro-cyclical than counter-cyclical, so measured correlations will be negative. But the magnitude of this correlation may not be very large. While Longstaff and Schwartz (1995) find a significantly negative correlation, Duffee (1998) and Jacoby (2002) show that optionality in the callable bonds used in that analysis may account

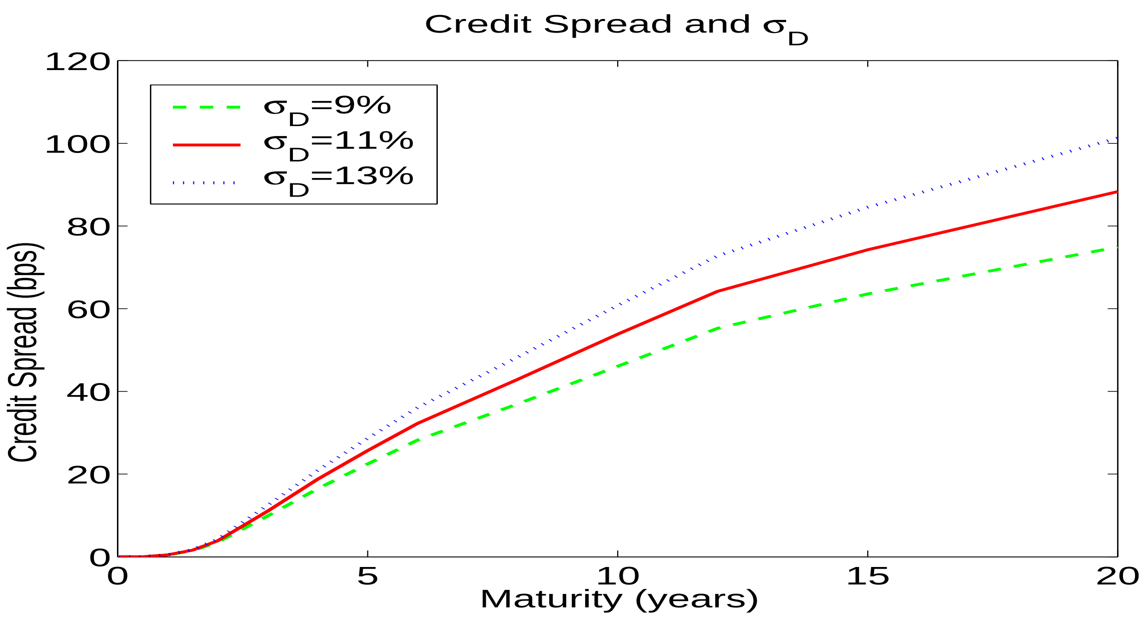

Figure 2.4: Credit spreads for different values of the standard deviation of economy growth σ_D. The parameters used are provided in Table 2.1.

for a significant amount of the negative correlation they found.[8] Duffee (1998) uses straight bonds and finds negative correlations at a much smaller level. The relatively small changes in credit spreads in Figure 2.3 in response to the large change in the economic growth rate seems consistent with that result.

Volatility of Aggregate Economic Growth

Firms are more likely to default in a volatile market because there is a greater chance for a firm to experience dramatically negative growth and therefore realize a low level of cash flow. Figure 2.4 graphs the term structure of credit spreads for three different values of aggregate growth volatility: $\sigma_D = 9\%$, 11%, 13%. As expected, yield spreads monotonically increase with σ_D. Yield spreads are substantially larger during volatile markets. As σ_D increases from 9% to 13%, yield spread widens by 14.7 basis points (from 46.1 to 60.8 basis points) for ten-year bonds and 26.4 basis points (from 74.9 to 101.3 basis points) for twenty-year bonds. Note this effect is stronger for longer term bonds.

There are two reinforcing effects contributing to the sensitivity of yield spreads to aggregate growth volatility. On one hand, a higher σ_D leads to a lower risk-free interest

[8]Because when the market interest rate increases, the value of the call options will decrease, consequently the price of the bond will increase resulting in a drop in yields and yield spreads.

rate r_t, due to the precautionary savings motive. Hence, the price of a risk-free bond will be higher and its yield will be lower. On the other hand, the market risk premium $\theta = \gamma\sigma_D$ increases with σ_D, a higher risk premium will push down the price of the risky bond resulting in a higher yield. These two effects reinforce each other, and subsequently the yield spreads rise with σ_D. In volatile markets, investors tend to prefer safe securities. Therefore this effect may be associated with the "flight-to-quality" phenomenon.

Risk Aversion

Some have argued that changing economic conditions can be characterized by changes in investor's risk aversion, and investors are more risk averse during economic recessions (see, e.g., Campbell and Cochrane (1999)). We plot yield spread curves for three different values of investor risk aversion parameter $\gamma = 0.5$, 2, 3.5 in Figure 2.5. Yield spreads increase significantly with risk aversion. The mechanism for γ to influence yield spreads is similar to the mechanism for σ_D, and this effect is also more pronounced for longer maturity bonds. Yield spreads increase by 40 basis points (from 32.9 to 72.9 basis points) for ten-year bonds and 69 basis points (from 52.5 to 121.5 basis points) for twenty-year bonds. Moreover, there is convexity in this relationship: The same amount of change in risk aversion affects credit spreads more at a higher level of risk aversion. When investors are more risk averse, they invest in safer securities; yield spreads will have to widen more to attract investors. This relation between yield spreads and risk aversion is also consistent with the "flight-to-quality" phenomenon.

2.3.3 Firm Characteristics and Yield Spreads

Cash Flow Volatility

For an individual firm, the more volatile its cash flow is, the more likely it will encounter a shortfall in covering the interest payment, and hence is more likely to default. This reasoning indicates that the cost of capital, or credit spread in this context, should increase with the cash-flow volatility. As shown in Figure 2.6, our model predicts that credit spreads rise dramatically (from 25.7 basis points to 72.2 basis points) for ten-year maturity when a firm's cash-flow volatility increases from 10% to 14%. This finding is empirically supported by Minton and Schrand (1999).

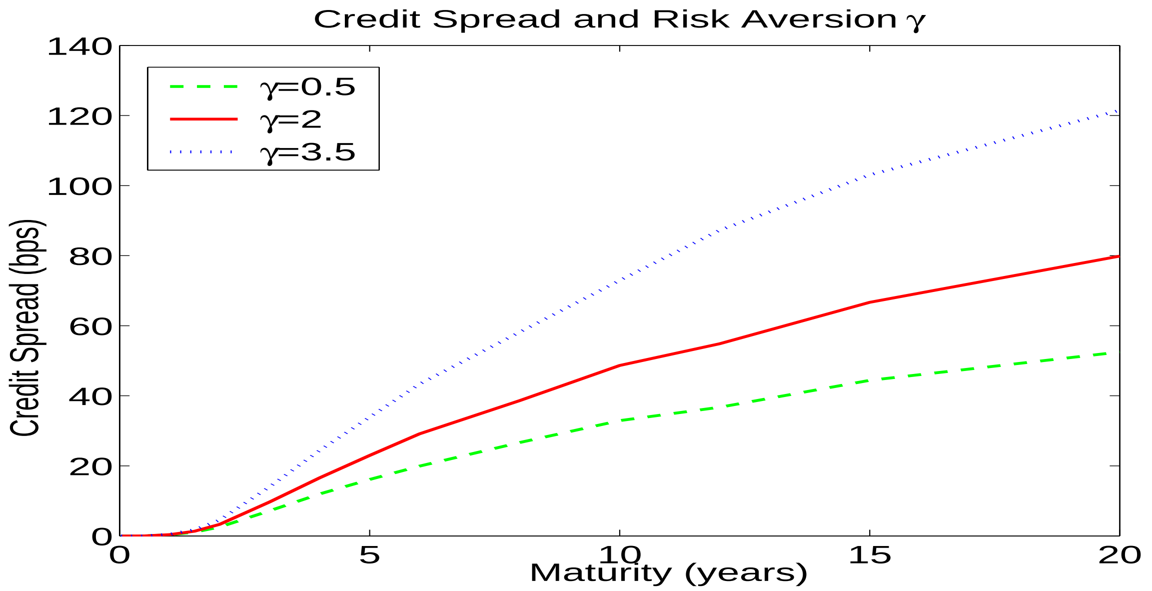

Figure 2.5: Credit spread and risk aversion. The parameters used are provided in Table 2.1.

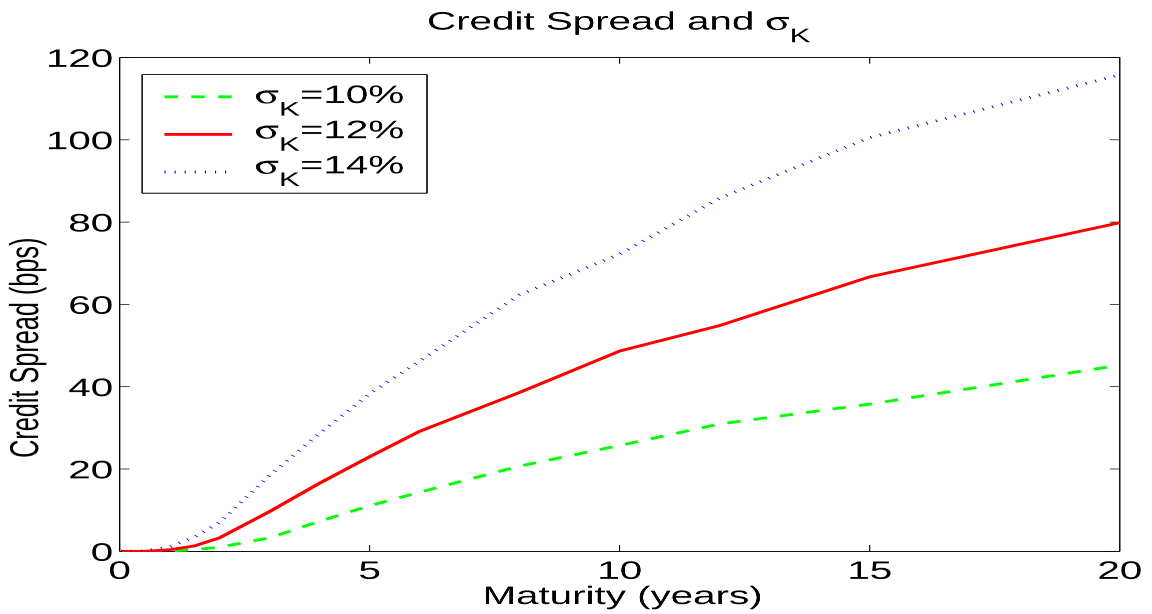

Figure 2.6: Credit spreads for different values of the standard deviation of firm growth σ_K. The parameters used are provided in Table 2.1.

Comparing Figure 2.4 and Figure 2.6, we observe that cash flow volatility seems to have a larger impact on credit spreads than the volatility of aggregate output. To the extent that cash flow volatility relates to firm-specific risk, this is consistent with the empirical evidence provided by Campbell and Taksler (2003) who show that the increase in corporate bond yields in the late 1990s can be largely explained by the increase in idiosyncratic firm-level volatility and the explanatory power of idiosyncratic volatility is as good as credit ratings. In addition, empirical evidence has also shown that a firm's total equity volatility significantly influences yield spreads (Collin-Dufresne, Goldstein, and Martin (2001) and Cremers, Driessen, Maenhout and Weinbaum (2004)).

Current Firm-Specific Growth Rate

In our model, firm-level growth rate consists of two components: the market or systematic component and the firm-specific or idiosyncratic component:

$$m_t = \beta\mu_t + \xi_t.$$

It is therefore clear that firm-specific growth rate will have similar effects on credit yield spreads as economic growth rate: yield spreads decrease as growth rate increases. This observation is confirmed by Figure 2.7. The difference in yield spreads between two firms having the same cash flow beta, one with 2% firm-specific growth rate and another with -2%, is 11 basis points (between 59.7 and 48.7 basis points) for ten-year bonds. While we are not aware of any empirical studies examining this issue, our model provides a refutable empirical prediction.

Cash Flow Beta

One innovative aspect of our model is that we incorporate a beta specification in a firm's cash flow growth. Therefore the correlation between the growth rate of the firm and the growth rate of the economy, ρ, or equivalently, the firm's cash flow beta, plays an important role in determining credit yield spreads. This correlation may be used to characterize different industries. For example, the utility industry may be modestly correlated with aggregate economy, while the financial sector is more correlated with the aggregate economy than the consumer product sector.

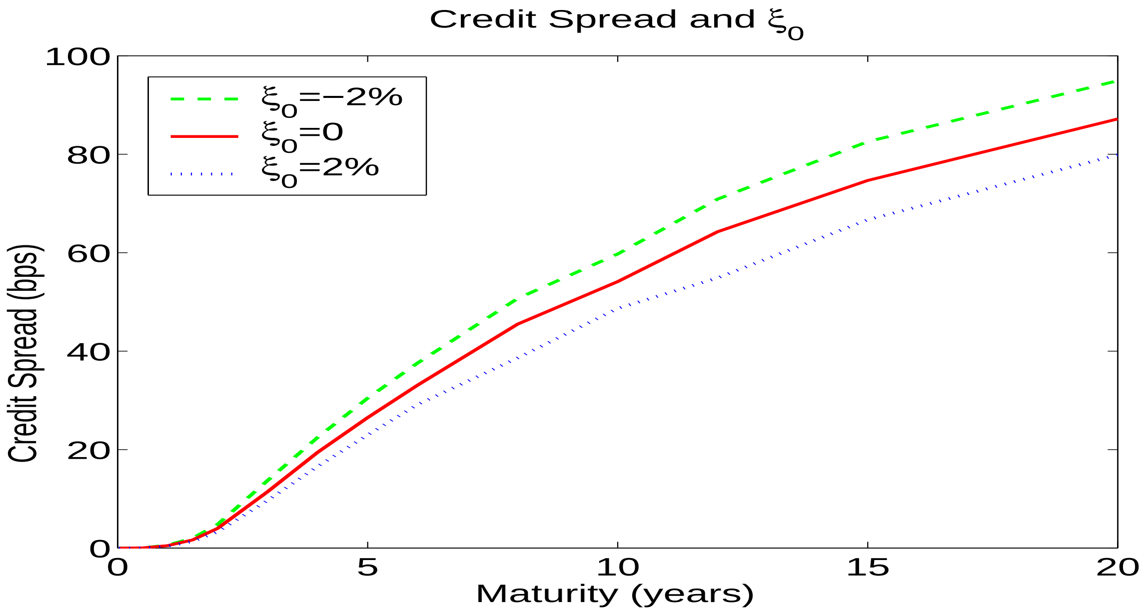

Figure 2.7: Credit spreads for different values of the current firm-specific growth rate ξ_0. The parameters used are provided in Table 2.1.

Figure 2.8 graphs the term structure of yield spreads for different values of ρ in different states of the economy. The results are consistent with empirical evidence that yield spreads for investment-grade bonds vary across sectors, albeit the magnitude of this effect may be modest. Moreover, the relation between credit spreads and firm cash flow beta depends on the current state of the economy, as shown in the figure. During economic downturns, firms highly correlated with the economy will more likely experience low growth than less correlated firms. Consequently yield spreads will be larger for more economy-sensitive firms. The opposite is true during economic expansions. These predictions provide good refutable hypotheses for empirical tests.

2.4 Summary and Discussions

We have theoretically explored the effects of macroeconomic conditions on credit spread dynamics in an equilibrium framework. Our modeling of fundamental processes (cash flow or EBIT) ensures the internal consistency of our valuation system. Our model is easy to implement and requires very simple inputs: aggregate economic output (i.e., GDP) and firm-level cash flow variables. We contribute to the risky debt valuation literature by exploring the important link between market risk and credit risk.

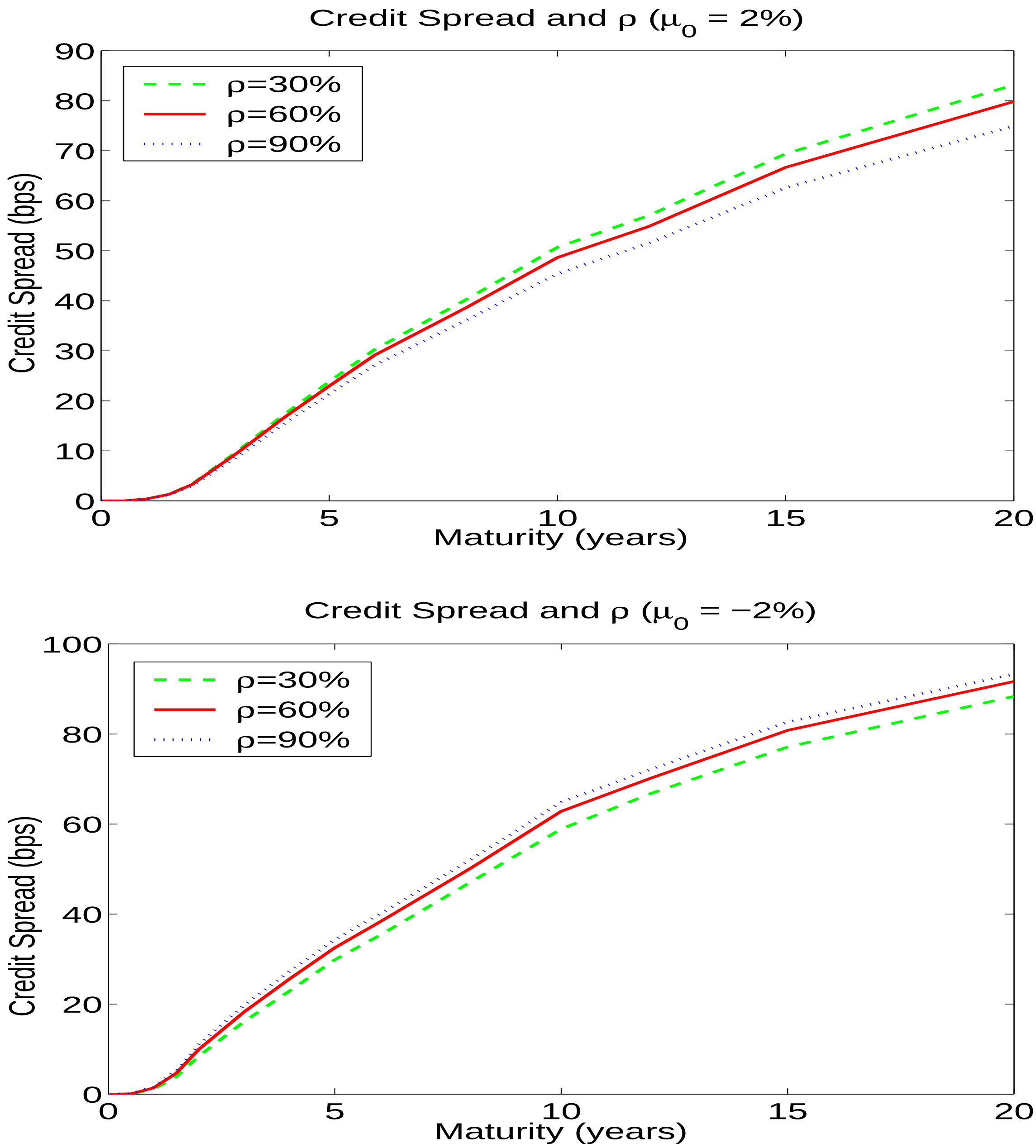

Figure 2.8: Credit spreads for different values of correlation between the economy and firm growth ρ. The top panel depicts an economic expansion, and the bottom panel describes an economic downturn. The parameters used are provided in Table 2.1.

We calibrate the model by jointly matching historical leverage ratios and default frequencies, similar to the approach proposed by Huang and Huang (2003) and Leland (2004). Our model compares favorably with other well-known structural defaultable bond pricing models in matching the magnitude of credit spreads for both investment-grade and speculative-grade bonds. Our model also generates upward-sloping yield spread curves for speculative-grade bonds, an empirical feature that most other structural models fail to explain. The success of our model is attributable to the intrinsic link between shocks to aggregate output and firm-level cash flows that we explicitly model in this paper.

Through comparative static analysis, we show that macroeconomic variables are important in explaining a substantial portion of yield spread changes. Industry and firm-level characteristics determine the cross-sectional differences in the level of credit spreads as well as the response of yield spreads to the change in macro-economic conditions. Our analysis yields results that are either consistent with existing evidence or amenable to further empirical tests.

Our beta specification for firm-level cash flow growth makes our model feasible for credit portfolio risk management. Similar to the portfolio theory in investment, this approach allows us to value each bond individually and then combining them with all correlations taken care of by cash flow betas. Therefore, we may deal with the issue involving correlated defaults.[9] Further exploration of this issue is left for future research.

2.4.1 Source of Success of Our Model

If we follow the approach of Huang and Huang (2003) by matching the historical default probabilities, how could our model outperform the ones considered by Huang and Huang (2003) who argue that their findings are robust to the model employed? To answer this question, we need to analyze the link between default probabilities and credit spreads.

The Huang and Huang (2003) approach matches the historical average *terminal* default probabilities to the model. While we follow their approach, our *interim* default probabilities are higher due to the extra uncertainties regarding macroeconomic conditions. Therefore, our model generates wider credit spreads.

[9] Our focus on macroeconomic conditions also grants us a unique advantage in reconciling related empirical anomalies. For example, Covitz and Downing (2002) find that "the correlation between many firms' short-term and long-term yield spreads are negative, typically during periods characterized by credit market disruptions." While we do not yet explore this point in our current study, our model clearly has the potential to examine this anomaly.

It is intriguing that our model yields significant improvements in terms of predicting the level of credit spreads over the existing structural models. This advantage comes from two potential sources. One is the correlation between aggregate output and firm-level cash flow. This additional systematic exposure that we consider adds to the risk premium contained in credit spreads. Another source may be due to our assumption that firms will default when their cash flow is not enough to service their debt. This liquidity-induce default precludes the possibility of issuing new equity to deal with cash flow shortage and may be more applicable to firms facing high equity-issuance costs. However, as pointed out by Uhrig-Homburg (2005), such a constraint may lead to a different choice of capital structure and therefore affect credit spreads through additional channels. This suggests some interesting cross-sectional studies to better understand the implication of cash flow constraints for bond pricing and represents a promising venue for further investigation.

2.4.2 Advantages of Modeling Cashflow

In our model, we choose firm cashflow rather than asset value as the primitive process because macroeconomic condition has the most direct impact on cash flow. Asset value includes other components investors may factor in.

Modeling cash flow may also be more realistic. Davydenko (2005) shows that liquidity default is very common in practice. Asset value default is difficult to enforce and uncommon.

Finally, while our study contributes to the literature by modeling credit risk and market risk jointly in an equilibrium framework, it is a first step towards a comprehensive understanding of the issue. Alternative equilibrium frameworks have been explored in Alvarez and Jermann (2000) and Chang and Sundaresan (2002). However, it is difficult to provide quantitative characterization of credit dynamics in these frameworks. Recent work by Chen, Collin-Dufresne and Goldstein (2005) is another attempt in this direction. More effort is needed to have a truly integrated approach that both endogenizes default risk and characterizes credit spread dynamics in an equilibrium.

Chapter 3

A New Database for Empirical Credit Risk Studies

Data quality is critical to any empirical finance studies. Unlike stock market for U.S., which has comprehensive and user-friendly databases such as the daily stock transaction data provided by Center for Research in Security Prices (CRSP) of University of Chicago and intraday trade and quote data provided by The Institute for the Study of Security Markets (ISSM) at the University of Memphis, The Trade and Quote (TAQ) database, and The NASdaq TRade And Quote (NASTRAQ) database, data collection for bond market is rather *ad hoc*. This chapter discusses issues with current bond databases and introduces a new database.

3.1 Existing Databases and Data Issues

The most often-used bond database for academic research is the Fixed Income Securities Database (FISD) (also called Warga (2000)),[1] which replaces the Lehman Brothers Fixed Income (or Warga (1998)) database. Some researchers also use Datastream bond data (e.g., Chen, Lesmond, and Wei (2005)), Merrill Lynch master bond database (e.g., Covitz and Downing (2005)) and Bloomberg corproate bond database (Cremers, Driessen, Maenhout, and Weinbaum (2005)).[2]

[1]This database is a product of the joint effort of the Fixed Income Research Program at the University of Houston (led by Arthur Warga) with LJS Global Information Services, Inc. and the National Association of Insurance Commissioners (NAIC).

[2]Reuters recently started to offer bond data for academic use.

Because the bond market is relatively thin and not every bond is traded every day, dealers fill in non-traded bonds with matrix prices (from reference of a matrix of similar bonds). Sarig and Warga (1989) have shown that matrix prices are problematic when making inferences from the data. Corporate bond yields contain a substantial liquidity (Longstaff, Mithal, and Neis (2005) and Covitz and Downing (2005)) and tax premia (Elton, Gruber, Agrawal, and Mann (2001)) due to the thinness of corporate bond market and different tax treatments between corporate bonds and Treasury bonds. Many corporate bonds have embedded options. Credit spreads without properly adjusting the optionality will cause mis-measurement problem. (But this problem can be attenuated by carefully handling the data.) Factors other than default risk make model testing more difficult.

Another data problem is that we do not directly observe yield spreads. In order to calculate yield spreads from bond prices, we need to choose a reference risk-free yield curve.[3] Schönbucher (2003) has shown that conclusions can be sensitive to the reference yield curve employed when pricing credit derivatives or hedging credit portfolios.

Below we introduce a clean measure of credit spread from an innovation in the credit derivative market.

3.2 Credit Derivative Market

Credit risk is not the only risk imbedded in most credit risky assets (e.g., corporate bonds, bank loans, etc.). Other risks such as market risk and liquidity risk are often inherently bundled with credit risk. A credit derivative is an agreement between two parties on transactions contingent on stipulated credit events regarding a reference entity (or portfolio). Credit derivatives facilitate the separation of credit risk from other risk factors and make credit risk transfer (CRT) feasible. Investors can trade the credit risk inherent to a credit risky asset without transferring the ownership of the underlying asset. Credit derivatives are essential to credit portfolio diversification. Below are the milestones for the development of credit derivatives market:

- 1992 - Credit derivatives emerge. ISDA first uses the term "credit derivatives" to describe a new, exotic type of over-the-counter contract.

[3] Longstaff (2004), Liu, Longstaff, and Mandell (2005), Collin-Dufresne, Goldstein, and Jones (2005), and Houweling and Vorst (2005) discuss different candidate risk-free yield curves.

- 1993 -KMV introduces the first version of its Portfolio Manager model, the first credit portfolio model.
- 1994 - Credit derivatives market begins to evolve.
- September 1996 - The first CLO of UK's National Westminster Bank.
- April 1997 - J P Morgan launches CreditMetrics
- October 1997 - Credit Suisse launches CreditRisk+
- December 1997 - The first synthetic securitization, JP Morgan's Bistro deal.
- July 1999 - Credit derivative definitions issued by ISDA.

Credit derivatives market has been growing rapidly. The global market in credit derivatives increased from $180 billion in 1997 to $5 trillion in 2004 and is expected to rise to $8.2 trillion by the end of 2006 according to a new report (a survey based on 30 market leaders) published by the British Bankers' Association (BBA).[4] Banks, securities houses and insurance companies constitute the majority of market participants. Recently, hedge funds have emerged to be an important player in both the buy and the sell side of the market.

Increased market liquidity, improved standardization within the market and a greater understanding by clients have all been instrumental in the rapid growth of the global market in credit derivatives. Most credit derivatives are unfunded, i.e., they do not require capital investment up front. The reference entity for a credit derivative can be both a single issuer of a portfolio of issuers. The major types of credit derivatives are:

- Credit default swaps (CDS): CDS is the most important instrument in the credit derivative market. It counts for about one half of the market size. CDS is an insurance contract between a buyer and a seller against default loss. More details will be discussed in the next subsection.

[4] As shown by the International Swaps and Derivatives Association (ISDA) 2005 Mid-Year Market Survey, the notional amount of credit default swaps grew by almost 48% during the first six months of the year to $12.43 trillion from $8.42 trillion. This represents a year-on-year growth rate of 128% from $5.44 trillion at mid-year 2004.???
CDS market is the fastest growing market in the last few years. As shown by the International Swaps and Derivatives Assocation (ISDA) Market Survy, the notional amount outstanding for CDS contracts globally is $5.4 trillion in the first half of 2004, a near tenfold increase from $0.6 trillion in the first half of 2001. The CDS market is larger than the equity derivatives market which has notional amount outstanding of $3.8 trillion the the first half of 2004.

- Synthetic collateralized debt obligations (CDO): In a CDO, bonds or loans are pooled together and the proceeds are separated into different tranches according to their risk profiles. The most risky tranch will take the first losses of the pool but is sold at a cheaper price. The safest tranch or equity tranch will take loss at the last. A synthetic CDO does not directly trade the tranches, rather it sells protection on those tranches.

- Credit linked notes (CLN): In CDS contract, protection buyers is exposed to counterparty default risk because protection seller does not put funds up front. In CLN, Investors buy securities from a trust that pays a fixed or floating coupon during the life of the note. At maturity, the investors receive par unless the referenced credit defaults or declares bankruptcy, in which case they receive an amount equal to the recovery rate. The trust enters into a default swap with a deal arranger. In case of default, the trust pays the dealer par minus the recovery rate in exchange for an annual fee which is passed on to the investors in the form of a higher yield on the notes.

- Total return swaps: Any swap in which the non-floating rate side is based on the total return of an equity or fixed income instrument with a life longer than the swap.

- Equity default swaps: As with a credit default swap, an equity default swap is a vehicle for one party to provide another protection against some possible event relating to some reference asset. With a credit default swap, the reference asset is a debt instrument, and protection is provided against a possible default or other credit event. With an equity default swap, the reference asset is some company's stock, and protection is provided against a dramatic decline in the price of that stock. For example, the equity default swap might provide protection against a 70% decline in the stock price from its value when the equity default swap was initiated. The event being protected against is called the trigger event or knock-in event.

3.3 Credit Default Swap (CDS)

CDS's are over-the-counter contracts for credit protection. CDS contracts were developed by banks in order to reduce their risk exposure and better satisfy regulatory requirements. The major participants of CDS market additional to banks now include insurance companies, hedge funds, and securities houses. In a CDS contract, the two parties, protection buyer and seller, agree to swap the credit risk of a bond issuer or loan debtor ("reference entity"). Credit protection buyer pays a periodic fee (CDS premium or spread) to the protection seller until the contract matures or a credit event occurs, in which case the protection buyer delivers defaulted bonds or loans ("reference issue") to the seller in exchange for the face value of the issue in cash ("physical settlement"), or the protection seller directly pays the difference between market value and face value of the reference issue to the protection buyer ("cash settlement"). Credit event and deliverable obligations are specified in the contract. Credit events generally include bankruptcy, failure to pay, and restructuring. Along the development of the CDS market, ISDA has given definitions to four types of restructuring: full restructuring, modified restructuring (only bonds with maturity shorter than 30 months can be delivered), modified-modified restructuring (restructured obligations with maturity shorter than 60 months and other obligations with maturity shorter than 30 months can be delivered), and no restructuring.

The typical maturity of a CDS contract is five years. The typical notional amount is \$10-20 million for investment grade credits and \$2-5 millions for high yield credits. CDS trading is concentrated in London and New York, each accounts about 40% of the total market. Most transactions (86%) use physical settlement. (British Bankers' Association – Credit Derivatives Report 2003/2004).

3.4 CDS Data

CDS data are from a major CDS broker. The dataset spans from June 1997 to April 2005. It is the largest CDS database so far. It has information on all the intraday quotes and trades, including transaction time, reference entity (bond issuer), seniority of the reference issue, maturity, notional amount and currency denomination of the CDS contract, restructuring code, and the quote or trade price. In this study, we only use CDS prices for non-Sovereign U.S. bond issuers denominated in U.S. dollar with reference issue ranked senior and CDS maturity between 4.5 and 5.5 years. Monthly data are obtained by averaging over the month. There are 10697 issuer-month CDS spread observations.

Average CDS spreads are plotted in Figure 3.1. There is significant time-series variation in market CDS spreads. CDS spreads peaked in the second half of year 2002 due

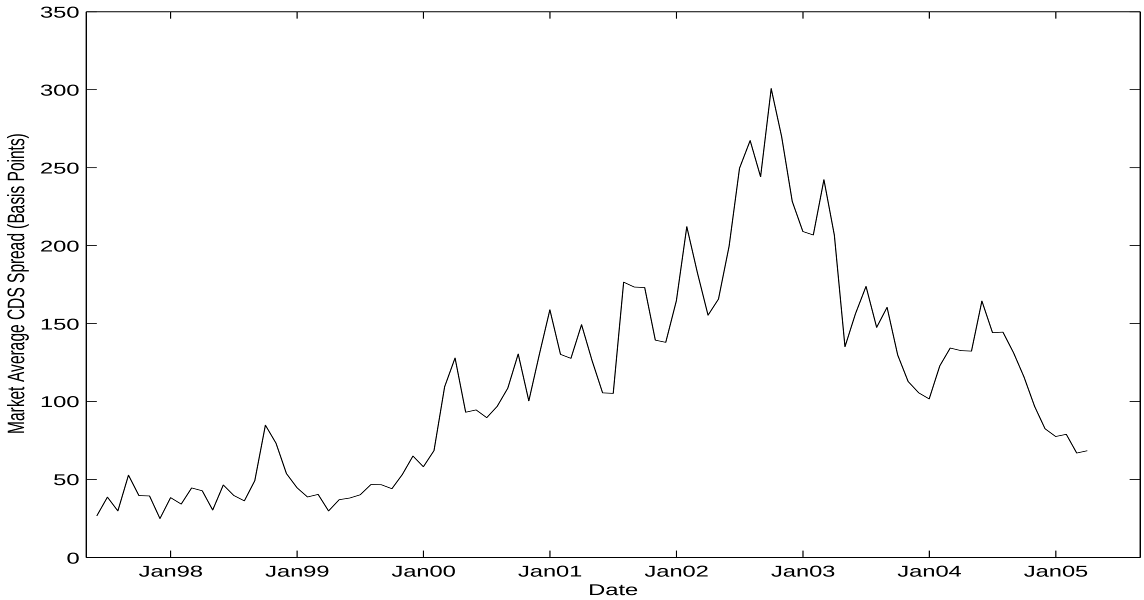

Figure 3.1: Market average CDS spreads.
The sample includes only U.S. dollar denominated contracts for U.S. corporations with reference issues being senior unsecured bonds, from one CDS broker.

to credit market turbulence. CDS spreads subsequently declines afterwards possibly due to (1) macroeconomic conditions improved so that the average market credit risk fell; (2) the market were more dominated by high quality issuers; (3) market became more competitive so that CDS sellers cannot overprice the CDS contracts.

Figure 3.2 draws the monthly number of quotes and trades in the sample from this broker. It can be seen there was little trading prior to 1999. Trading activity from this broker is shrinking since 2003, which largely reflects the increasing competition for service providing in this industry. This broker is one of the handful of earliest market participants. Now a new player emerges every several months. It is conceivable that the market is much more competitive and liquid than the early stage of the market.

Table 3.1 provides the year by year summary statistics for the sample. One observation from the summary table is that CDS spreads for AAA bonds are not always smaller than CDS spreads for AA bonds, which indicates the CDS spreads may not be pure characterization for credit risk. Other factors such as liquidity may also at work. Alternatively,

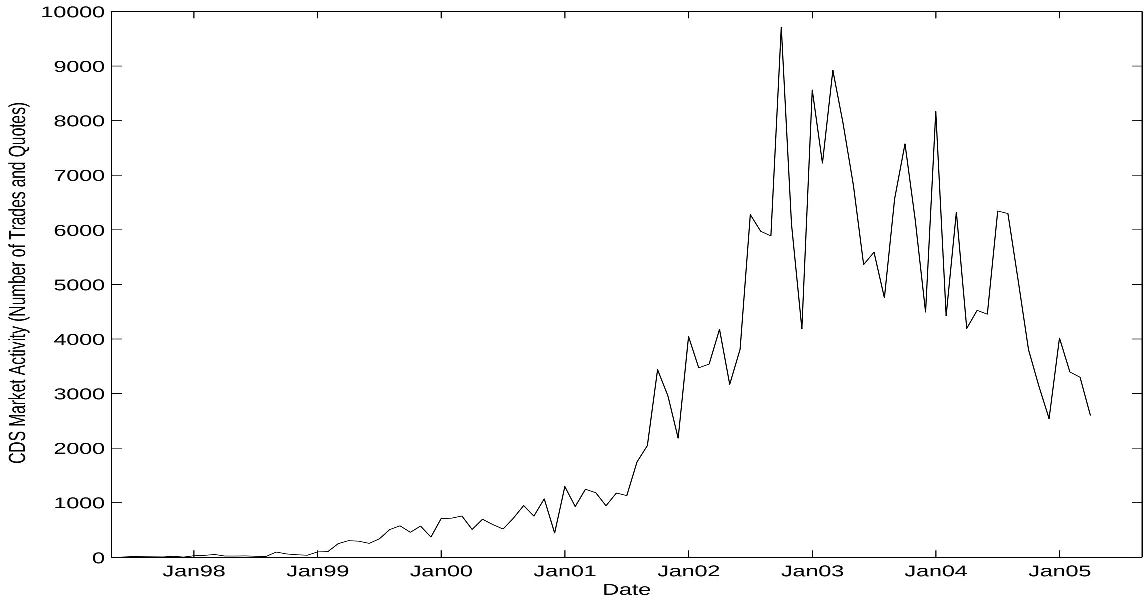

Figure 3.2: Total number of quotes and trades in the sample.
The sample includes only U.S. dollar denominated contracts for U.S. corporations with reference issues being senior unsecured bonds, from one CDS broker.

CDS spreads may react to news more promptly than credit ratings. For AAA bonds, the only possible rating change is downgrade. Therefore, market could incorporate information before rating agencies adjust the ratings.

In our sample, there was little trading prior to 1999. CDS spreads peaked in the second half of year 2002 due to credit market turbulence. The average CDS spread over the entire sample is 125.73 basis points. The majority of the CDS contracts are for A and BBB bonds. Trading activity from this broker is shrinking since 2003, which largely reflects the increasing competition for service providing in this industry. This broker is one of the handful of earliest market participants. Now a new player emerges every several months. It is conceivable that the market is much more competitive and liquid than the early stage of the market.

Two observations from the summary table are noteworthy. First, The average spreads for AAA bonds is about 35 basis points, which is still much higher than predicted value by most structural models. Second, CDS spreads for AAA bonds are not always smaller than CDS spreads for AA bonds. Both indicate the CDS spreads may not be pure characterization for credit risk. Other factors such as liquidity may also at work.

Table 3.1: CDS Data Summary Statistics

This table reports pooled time-series and cross-sectional year-by-year summary statistics of monthly average CDS prices in basis points from CreditTrade from June 1997 to April 2005.

		Rating Groups						
		AAA	AA	A	BBB	BB	B	NR
1997	N	4	6	20	13	5	1	–
	Mean	23.50	24.00	40.17	37.50	71.00	120.00	–
	Stdev	10.79	18.53	41.68	11.69	38.79	–	–
1998	N	6	39	119	49	11	–	6
	Mean	38.44	38.35	33.84	54.52	73.41	–	44.11
	Stdev	25.63	32.56	18.66	40.75	47.03	–	14.89
1999	N	9	73	238	139	12	–	17
	Mean	38.95	30.15	34.64	70.99	59.82	–	49.08
	Stdev	23.54	15.67	17.30	44.79	18.06	–	28.06
2000	N	15	83	326	377	56	15	14
	Mean	57.27	42.26	55.28	130.60	220.07	388.27	166.59
	Stdev	31.13	30.25	38.98	109.80	125.95	125.36	171.75
2001	N	24	139	523	625	116	28	16
	Mean	42.68	53.78	84.42	172.40	376.51	596.90	216.47
	Stdev	27.47	37.61	49.93	106.72	151.04	243.97	151.63
2002	N	39	151	808	1106	176	20	33
	Mean	67.82	67.88	101.83	213.63	481.41	642.20	250.38
	Stdev	51.95	58.34	77.13	172.56	236.02	322.55	254.37
2003	N	58	82	776	1220	220	75	15
	Mean	35.08	30.15	59.06	126.62	362.32	573.91	129.83
	Stdev	33.45	25.19	56.24	104.33	183.34	293.44	87.59
2004	N	51	98	491	965	245	61	211
	Mean	15.19	24.97	40.79	73.32	182.46	329.81	116.33
	Stdev	9.14	8.91	38.84	47.14	111.57	170.76	116.10
2005	N	8	18	98	285	91	19	185
	Mean	11.82	18.90	30.07	48.16	102.15	236.40	79.04
	Stdev	3.80	7.37	46.53	38.56	55.14	92.62	80.32

3.5 Default Probability and Expected Default Frequency (EDF)

Credit risk consists of two components: default probability (DP) and loss given default (LGD) or recovery rate. Current single-issuer credit risk models assume constant recovery rate, leaving default probability as the primary concern and a one-to-one mapping from DP to credit spreads. In later chapters we also conduct empirical analysis on DP, therefore we introduce our data on DP in this section.

While every credit risk model makes predictions about default probabilities, defaults are rare events (See Campbell, Hilscher, and Szilagyi (2005) and Saretto (2005)). Rating agencies (Standard and Poors, Moody's, Fitch etc.) use letter ratings to specify firms' credit quality. Currently, there are two major databases on historical defaults. Standard and Poors' CreditPro database contains a large sample of default and rating transition experience since 1981. Moody's Default Risk Service database covers bond rating time series of corporate bond issuers rated by Moodys.

Credit ratings are rough measures of credit risk. For risk management and sophisticated trading, more accurate measures of credit risk is needed. Altman (1968) proposed Z-score to measure default probabilities using multivariate discriminate analysis. Ohlson (1980) proposed O-score using logit models. Shumay (2000) use a multi-period hazard model to predict default. One problem with above models is that model inputs are arbitrary due to their empirical nature. Hillegeist, Keating, Cram, and Lundstedt (2004) advocate Merton approach to O-score and Z-score. KMV (now Moody's KMV) uses Merton model to estimate Expected Default Frequency (EDF) using stock market and balance sheet information. The KMV-Merton model is a structural model so firm default probability is determined by firm fundamentals. Back testing has shown that EDFs have performed well historically.[5] The key input to the KMV-Merton approach is Distance to Default (DD). KMV uses a proprietary empirical distribution to map DD to obtain EDF. Appendix B explains the KMV approach with more details.

The time series of market average five-year EDF is plotted in Figure 3.3 along with market average CDS spreads. It can be seen that the correlation between these two series are pretty high, but they started to diverge at the end of year 2000. It will be interesting to find out what causes this phenomenon.

[5]Bharath and Shumway (2004) challenge the KMV approach. But because they do not exactly replicate the KMV approach, no verdict can be reached yet.

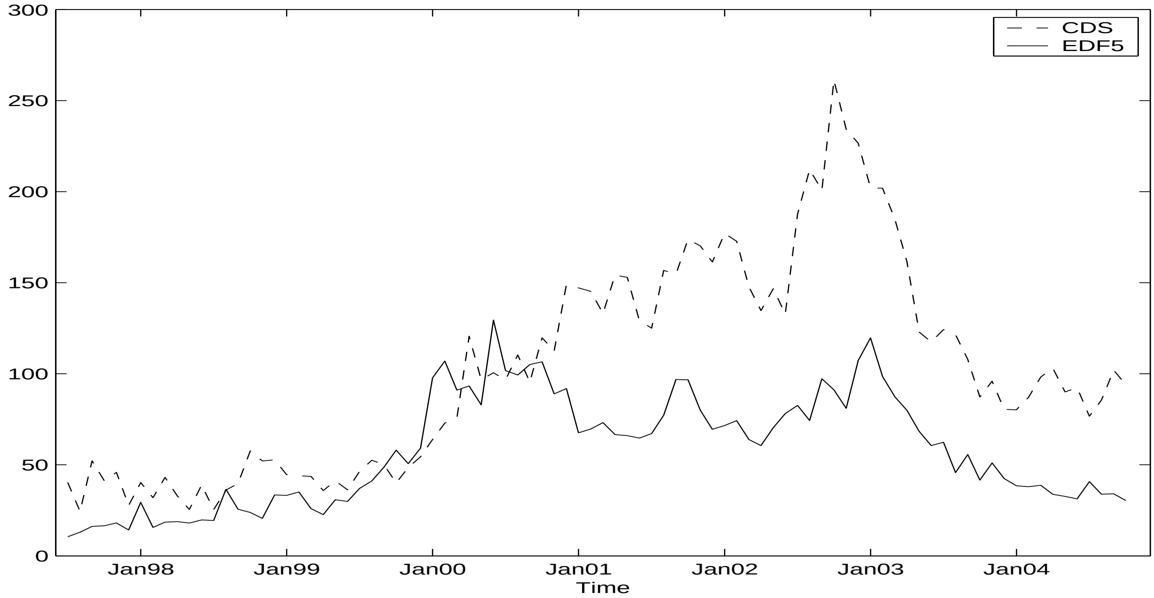

Figure 3.3: Market average EDF5 in the sample across time. The unit for both CDS spread and EDF5 is basis point.

Chapter 4

Macroeconomic Conditions, Firm Characteristics, and Credit Risk: Empirical Investigation

A model is useless unless it provides refutable predictions. This chapter empirically examines some of the predictions from the model in Chapter 2.[1] We will focus more on the predictions which have not been tested in the literature. We first conduct time-series analysis on the effects of macroeconomic conditions on credit spreads. We show that average market risk aversion (proxied by investor sentiment) affects credit spreads. We then examine some cross-sectional predictions on firm characteristics and credit spreads. We find that firm specific growth rate is negatively associated with credit spreads.

One caveat regarding our time-series tests is that our CDS data mostly only covers a relatively short time span. We basically have about three years (2001-2004) of data for most issuers. Within these three years, economic conditions have been relatively stable. This data limitation may weaken the power of our empirical tests. Another data related issue is that we may not be able to test our theoretical predictions directly. We will need to

[1]Some of our model predictions have been empirically confirmed. For example, our model predicts that credit spreads (or default probabilities) decrease with economic growth rate. Duffie, Saita, and Wang (2005) find that industrial production growth is negatively associated with default probabilities. Ample evidence has shown that risk free rates are negatively correlated with credit spreads. This finding is consistent with our model prediciton if we recall that there is a positive linear relation between economic growth rate and risk free rate. Observing that cash shortage rather than asset value is more likely to cause default, we model cash flow as the primitive process. Therefore, our model has several predictions on cash flow and credit spreads. Minton and Schrand (1999) have shown that credit spreads increase with cash flow volatility.

find proxies for some unobservable variables. Any measurement error will also affect testing results.

4.1 Time-Series Results: Macroeconomic Conditions and Credit Spreads

4.1.1 Existing Evidence

Empirical evidence shows that both default probabilities and recovery rates vary with business cycles. Consequently, credit spreads should depend on macroeconomic conditions. It is well known that interest rates and corporate bond yield spreads fluctuate over business cycles. Aggregate and firm-level outputs critically depend on the state of the economy. Therefore, macroeconomic fundamentals such as economic growth rate should play an important role in determining credit spread dynamics. A growing body of empirical studies has shown that macroeconomic conditions affect yield spreads. Jaffee (1975) finds substantial explanatory power in macroeconomic variables for the cyclical variations in corporate bond yields. Altman (1983) finds that, among other economic variables, real economic growth can predict aggregate business failures. Fama and French (1989) find that credit spreads widen when economic conditions are weak. Wilson (1997a, b) and Duffie, Saita and Wang (2005) find that macroeconomic variables can help explain a significant portion of default rates or yield spread changes. Bakshi, Madan and Zhang (2004) and Elton, Gruber, Agrawal and Mann (2001) show that a substantial portion of corporate bond credit spreads may be explained by factors that we commonly use to model risk premiums for common stocks. Altman, Brady, Resti, and Sironi (2003) demonstrate the impact of business cycles on the correlation between default and recovery. Huang and Kong (2003) show that Conference Board economic indicators can explain credit spreads. Furthermore, Korajczyk and Levy (2003) document that macroeconomic conditions account for 12% to 51% of the time-series variation in firms' leverage between 1984 and 1998, and leverage has been shown to have significant explanatory power for yield spread levels and changes (Collin-Dufresne, Goldstein and Martin (2001) and Elton, Gruber, Agrawal and Mann (2001)).

Although lacking in theoretical modeling of academic research, industrial practice has already incorporated the effect of macroeconomic variables on default probabilities (e.g., McKinsey's CreditPortfolioView and Algorithmic's Mark to Future).

4.1.2 New Predictions and Results

Our model is a structural model in a general equilibrium framework. In the model firm fundamentals are linked to macroeconomic conditions. We first discuss several testable time-series predictions unique to our model. We then use data to empirically test our predictions.

We apply a beta specification for cash flow process. High economic growth rate implies high total firm growth rate. A firm is less likely to default when it grows fasters.

PREDICTION 1 *Credit spreads decrease with economic growth rate.*

The most intuitive proxy for economic growth rate is the real GDP growth rate. Real GDP data is obtained from Federal Reserve Economic Database (FRED).[2] GDP numbers are only available at quarterly frequency. We interpolate quarterly GDP numbers to obtain monthly growth rate. Our results are not affected by this interpolation.

In our model, economic growth rate has constant volatility, therefore the market price of risk is constant. But we do model mean-reverting growth rate. In a more volatile environment, firms are less likely to meet their payment schedule.

PREDICTION 2 *Credit spreads increase with volatility of economic growth rate.*

In order to have monthly measure of volatility, we need to have daily observation of raw data. However, we do not observe daily economic growth rate. Therefore, we use monthly average implied volatility of at-the-money S&P 500 index option from OptionMetrics to proxy for the volatility of economic growth rate. This measure of volatility is forward-looking as it contains investors' expectation about future market volatility.

When investors are more risk averse, they require a higher discount rate and avoid risky assets. The following prediction is novel to our model and we will focus more on it.

PREDICTION 3 *Credit spreads increase with investor risk aversion.*

We do not directly observe the level of investor risk aversion, we need to find a good proxy for it. A common approach to estimate risk aversion is to estimate risk premium using option prices (See Jackwerth (2000) and Bliss and Panigirtzoglou (2004)). This aproach generates one risk aversion for each option. Certain type of aggregation will then be needed

[2]http://research.stlouisfed.org/fred2/

to obtain market risk aversion. We opt to use simpler proxy. Considering our short time series for CDS spreads, we need a relatively high frequency proxy. Investor sentiment is a straightforward proxy for investor risk aversion.[3] Among several available measures of investor sentiment, only Conference Board Consumer Confidence Index and University of Michigan Consumer Sentiment are updated monthly.[4] Qiu and Welch (2004) show that survey based sentiment measure is superior to other constructed measures.[5] We use monthly Conference Board Consumer Confidence Index as our sentiment measure. Similar results can be obtained using Michigan Consumer Confidence Index.

It has long been recognized among practitioners that investor sentiment affects bond yields. Based on the belief that investor sentiment affects bond yields, *Barron's* constructs its investor confidence index by dividing the average yield on high-grade bonds by the average yield on intermediate-grade bonds. The discrepancy between the yields is indicative of investor confidence. A rising ratio indicates investors are demanding a lower premium in yield for increased risk and so are showing confidence in the economy. The theory is that if investors are optimistic they are more likely to invest in the more speculative grade of bonds, driving yields downwards and the confidence index upwards. The opposite is true if investors are pessimistic.

Figure 4.1 plots the time series of those economic series. It is rather clear that credit spread is negatively correlated with investor sentiment but positively correlated with economic growth volatility. Table 4.1 provides the descriptive statistics of those macroeconomic series. The correlations among those series are rather low. Therefore the concern of multi-collinearity is minimal.

Next we conduct regression analysis in order to get more conclusive results. We use three approaches to ensure robust results. Because we are interested in the relation

[3]We recognize the important distinction between investor sentiment and risk aversion. Sentiment reflects investors' belief about future market movement. Risk aversion measures investors' taste of risky assets over riskfree assets. Nevertheless, these two can be highly correlated. When investor sentiment is low, investors may save more in preparation for upcoming bad times. Similar behavior can be observed in a market with highly risk averse investors. We thank Lorenzo Garlappi for pointing out the distinction between investor sentiment and risk aversion.

[4]Other sentiment proxies include Barron's weekly investor confidence index, Investor Intelligence Index, State Street Investor Confidence Index, Hulbert Nasdaq Newsletter Sentiment Index, etc.

[5]Baker and Wurgler (2005) constructed a sentiment measure but it is only available at annual base. Kaniel, Saar, and Titman (2005) construct an individual investor sentiment measure (on daily basis) but their data is not readily available.

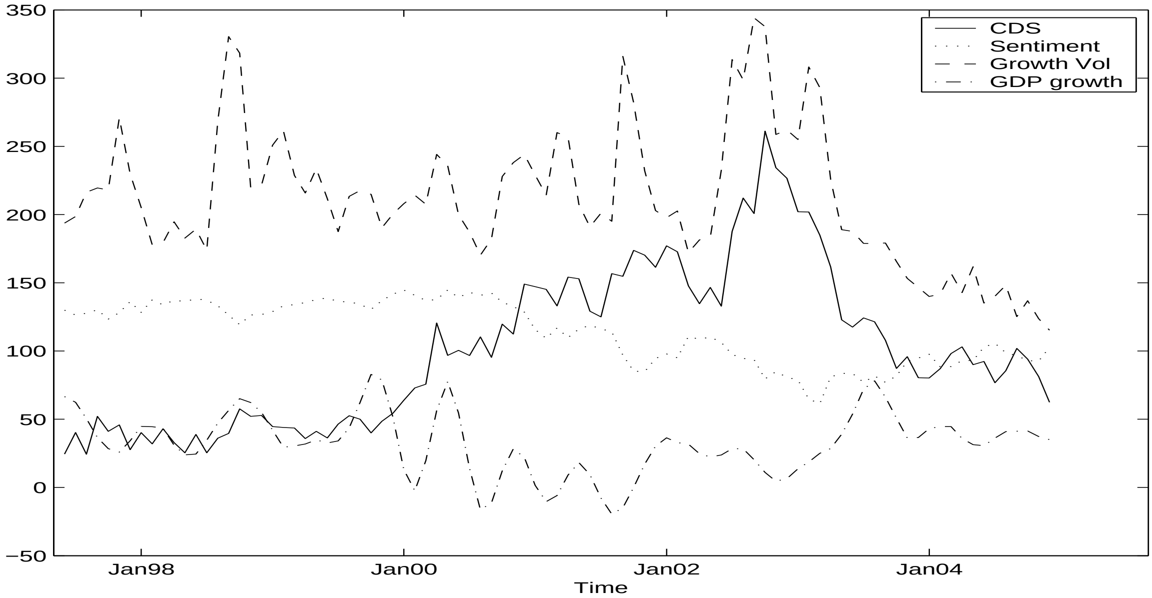

Figure 4.1: CDS and macroeconomic variables.

This figure plots the three monthly macroeconomic series: GDP growth rate, implied volatility and investor sentiment. GDP growth rate is interpolated from quarterly observations to monthly observations. IV is monthly average implied volatility of at-the-money S&P 500 index option. Sentiment is the Conference Board consumer confidence index. GDP growth and growth volatility are enlarged by 1000.

Table 4.1: Descriptive statistics for macroeconomic variables

This table presents descriptive statistics of the three monthly macroeconomic series: GDP growth rate, implied volatility and investor sentiment. GDP growth rate is interpolated from quarterly observations to monthly observations. IV is monthly average implied volatility of at-the-money S&P 500 index option. Sentiment is the Conference Board consumer confidence index.

						Correlation	
Variable	Obs	Mean	Std.	Min	Max	GDP	IV
GDP Growth	85	3.12%	2.26%	−1.96%	8.28%		
IV	85	0.22	0.05	0.14	0.34	-0.185	
Sentiment	85	113.89	22.88	61.42	144.71	0.054	-0.087

between macroeconomic condition and credit spreads in the time series, not cross-sectional variations, we first regress market average CDS spreads on those three economic series. This approach assumes that firm characteristics that affects credit spreads are not correlated with macroeconomic conditions and the level of market average CDS spreads is solely determined by macroeconomic conditions.

Adimttedly, the assumption that firm characteristics that may also affect credit spreads are not related to macroeconomic conditions is rather strong. For example, Korajczyk and Levy (2003) show that firm leverage is largely determined by macroeconomic conditions. In order to relax this assumption, we regress CDS spreads on macroeconomic variables for each firm. We keep firms with at least 16 monthly observations. We have 176 such time series regressions. We then calculate the cross sectional mean and standard errors of those coefficient estimates. The standard errors are adjusted by the number of firms in the cross-section. This approach implicitly assumes that firms are independent in order to make justification to the standard errors. This approach is taken by Collin-Dufresne, Goldstein, and Martin (2001).

Relaxing both implicit assumptions that firm characteristics are not related to macroeconomic conditions and firms are independent, we use a two-stage approach, following Titman, Tompaidis, and Tsyplakov (2005). In the first stage, we regress CDS spreads on cross sectional fundamental determinants (discussed in Chapter 5) of credit spreads with issuer fixed effects and monthly dummies. The coefficients for the monthly dummies can be attributed to any time-series effects unexplained by cross-sectional variables. In the second stage, we regress the coefficient estimates for monthly dummies from the cross-section regressions on macroeconomic variables.[6]

The results are in Table 4.2. Our predictions 1, 2, 3 are strongly supported using all three approaches, although the parameter estimates vary across specifications. On average, one percent increase in GDP growth lowers credit spreads by 2-9 basis points. If we assume the difference between GDP growth rate in expansion and recession is 7%, then the credit spread difference will be in the range of 14-63 basis points. This estimate seems plausible. Growth volatility is positively related to credit spreads. A one percent increase in growth volatility raises credit spreads by 3-6 basis points.

[6]We use the coefficient estimates as dependent variable. There does not exist the error-in-variable problem because any measurement error in the coefficient estimate goes into the residuals.

Table 4.2: Macroeconomic Conditions and Credit Spreads

For the "Average" regression, market average CDS spread is the dependent variable. The firm-by-firm regression regresses firm CDS spreads on macroeconomic variables then parameters are averaged across all issuers. Standard errors were adjusted by the number of issuers. In the "Residuals" regression, firm CDS spreads are first regressed in a panel regression with monthly time dummies. The coefficient estimates for those dummies are then regressed on macro variables. First order autocorrelation is corrected for "Average" and "Residuals" specifications.

	Average		Firm-by-firm		Residuals	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Intercept	250.71	10.34	95.17	3.05	79.43	3.55
GDP Growth	-943.32	-6.22	-213.91	-1.96	-323.21	-2.58
Growth Volatility	318.80	4.52	581.77	9.06	283.78	4.83
Sentiment	-1.65	-11.89	-0.73	-3.15	-1.08	-8.81
N	91		176		86	
R^2	0.715		0.513		0.635	

Investor sentiment is significantly negatively associated with credit spreads. It is actually the strongest explanatory variable among these three macroeconomic variables in two of the three specifications. A one standard deviation move in investor sentiment is associated with CDS spread change of 16-40 basis points. The R^2s are considerably high. More than 71% of market average CDS spreads is explained by these macroeconomic series.

4.2 Cross-Sectional Results: Firm Characteristics and Credit Spreads

In our theoretical model, the market is equivalent to the aggregation of all the individual firms within the market. Therefore, any cash flow predictions hold in the time series should also hold in the cross section. However, it is important to distinguish between our time-series and cross-sectional predictions. First of all, cross-sectional predictions can be more accurately tested because we have time series data for each firm. Unlike for the market, we do not have high frequency data to construct growth volatility. Second, the aggregation process may not be perfect. It has been shown that individual behavior could deviate from aggregate behavior in other contexts (See Yan (2004), Kothari, Lewellen, and Warner (2005), and Lamont and Stein (2004)).

4.2.1 Existing Evidence

The effect of cash flow variables on credit spreads has not been extensively examined in the empirical credit risk literature. We are aware of only a couple of studies, Minton and Schrand (1999) and Molina (2005), which analyzes the effect of cash flow volatility on corporate bond yield spreads. Although several other studies also model cash flows (Kim, Ramaswamy, and Sundaresan (1993), and Goldstein, Ju, and Leland (2003)), we are the first to make explicit predictions on cash flow and credit spreads. In this section, we focus on cash flow variables relevant to our model prediction and delay the discussion of other firm fundamental determinants of credit spreads to Chapter 5.

4.2.2 New Predictions and Results

Our model makes cross-sectional predictions on the effects of interaction between firm characteristics and macroeconomic conditions on credit spreads. When a firm's cash flow is more volatile, it is more likely that it will have a cash shortfall.

PREDICTION 4 *Credit spreads increase with cash flow volatility.*

This prediction has already been verified by Minton and Schrand (1999) and Molina (2005). We re-evaluate this prediction, along with other preditions, using different credit spread measure and different econometric method.

Prediction 4 is the counterpart of Prediction 2 in the cross section at individual firm level. We use option implied volatility to proxy for market economic growth volatility when testing Prediction 2 because we do not have high frequency data. We have time series for each firm therefore we can directly construct cash flow volatility directly. Furthermore, firm cash flow volatility can be decomposed into systematic or market volatility and idiosyncratic or firm specific volatility. Prediction 4 implies that idiosyncratic cash flow volatility also affects credit spreads.

We measure quarterly operating cash flow (OCF) as operating income before depreciation (Compustat data item 21) adjusted for working capital accruals (Dechow (1994)).[7]

[7]Minton and Schrand (1999) argue that debtholders can only claim the firm value after investments. They adjust this operating cash flow number for investment expenditures that are expensed as part of operating income by adding back quarterly research and development and advertising expenses, estimated as the annual research and development or advertising expense from Compustat divided by four. Our results are not qualitatively affected by this adjustment. We do not make such adjustment because it significantly reduces the available number of observations.

Cash flow volatility is measured as the coefficient of variation in a firm's quarterly operating cash flows over the past six year period:

$$\text{CVCF} = 100 \times \frac{\text{standard deviation of OCF}}{|\text{mean of OCF}|}. \tag{4.1}$$

A minimum of twelve quarterly observations is required to calculate CVCF. W use a six-year rolling window to calculate CVCF in order to obtain more accurate measures, similar windows were chosen by Minton and Schrand (1999) and Molina (2005),

Some firms thrive even during economic downturns. Firm specific growth rate is another dimension for total firm growth rate. Firms with high firm specific growth rates are easier to survive.

PREDICTION 5 *Credit spreads decrease with firm specific growth rate.*

We run the following regression for each firm i using data from the previous six years to obtain firm specific growth rates α^i for each month:

$$\xi_t^i = \alpha^i + \beta^i \mu_t + \epsilon_t^i, \tag{4.2}$$

where ξ_t^i is firm's total cash flow growth rate, μ_t is GDP growth rate, and ϵ_t^i is random noise.

Lastly, our comparative statics in Section 2.3.3 show that the effects of cash flow beta on credit spreads vary with macroeconomic conditions. Firms highly correlated with the market in an up market are more likely to perform well. While in a down market, high correlation with the market is less desirable. Our model has the following prediction on the interaction between firm characteristics and macroeconomic conditions:

PREDICTION 6 *Credit spreads increase with firm cash flow beta during economic downturns, while decrease with firm cash flow beta during economic expansions.*

Campbell and Vuolteenaho (2004) distinguish cash flow beta from discount rate beta. They argue that cash flow beta should have higher price of risk, which may be consistent with our prediction. We need to measure cash flow beta first. Campbell and Vuolteenaho (2004) use a VAR system to decompose stock returns into components due to cash flow news and discount rate news then calculate corresponding betas. We use a more straightforward measure of cash flow beta: β^i from above regression (4.2).

Table 4.3: Descriptive statistics for cash flow data

CVCF is the coefficient of variation in quarterly operating cash flow, a measure of cash flow volatility. CF beta is cash flow beta, obtained from regression (4.2), along with firm-specific growth rate.

						Correlation	
Variable	Obs	Mean	Std.	Min	Max	(1)	(2)
CVCF (1)	9476	68.34	435.98	0.30	15070.33	1.000	
Firm Growth (2)	8898	0.35	4.31	-43.89	39.85	0.055	1.000
Cash Flow Beta (3)	8898	2.34	84.75	-788.65	888.69	-0.019	-0.481

In order to test Prediction 6, we first need to have different economic conditions. In our data sample period, there are three quarters with negative GDP growth: 2001Q3 (-1.41%, annualized), 2001Q1 (-0.49%), 2000Q3 (-0.46%). The fastest growth is witnessed in 2003Q3 (7.21%), 1999Q4 (7.11%), 2000Q2 (6.28%). We regress credit spreads on cash flow betas for each of these sample periods and examine whether the signs are different during different economic conditions.

Cash flow data is summarized in Table 4.3. The cross sectional variations for all three variables are dramatic.[8] The arithmetic average of firm cash flow beta is 2.34, which is much greater than the unconditional expectation of 1. This indicates positive skewness in cash flow beta. Firms with higher firm specific growth have more volatile cash flows and lower cash flow betas, as shown in the correlation matrix.

We regress monthly average CDS spreads on cash flow variables and other commonly used explanatory variables in a pooled time-series and cross-sectional data. Table 4.4 displays regression results. All regressions include monthly time dummies. The coefficient estimates on those monthly dummies are not shown to preserve space. Issuer clustering, cross correlation, and heteroskadasticity are adjusted to obtain robust t-statistics. Petersen (2005) has shown that this approach is the best (compared to Fama-MacBeth and firm fixed effect) to handle panel data. (The econometric methodology is discussed with more details in Chapter 5.) We find cash flow volatility to be significant explanatory variable for CDS spreads, consistent with Minton and Schrand (1999) and Molina (2005). Note that our predictions are conditional, the relation between cash flow volatility or firm specific

[8]When we calculate cash flow volatility, firm specific growth and cash flow beta, we have limited the minimum number of quarterly observations to be 12 (three years). Hence, the wide variation in all cash flow variables is not due to idiosyncratic reasons. Results are not changed much after we throw out the top and bottom 10% of the data.

Table 4.4: Credit spreads and cash flow characteristics

The table reports regression results for the effects of cash flow variables on credit spreads. The dependent variable is monthly average CDS price from CreditTrade. CVCF is the coefficient of variation of operating cash flow. FSG is firm-specific growth rate. CF beta is cash flow beta. Leverage is book value of debt over the sum of book value of debt and market value of equity. IV is implied volatility from at-the-money options. Jump is the slope of the volatility curve from option prices. All regressions include monthly time dummies (not shown). Issuer-clustering, cross-correlation, and heteroskedacity are adjusted to obtain robust t-statistics.

	(1)		(2)		(3)		(4)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Intercept	26.92	6.22	22.36	4.37	21.40	2.52	-284.95	-6.02
CVCF	0.03	3.00					0.01	1.99
FSG			-1.12	-0.65			-2.83	-3.82
CF Beta					0.12	2.00	-0.09	-2.14
Leverage							109.07	4.02
IV							682.58	17.41
Jump							1065.03	5.61
N	9476		8898		8898		8074	
Clusters	528		496		496		462	
Adj. R^2	0.142		0.138		0.141		0.499	
F	8.23		8.37		8.47		21.50	

growth rate and credit spreads are conditional on holding everything else fixed. In this sense, we find support for both our Predictions 4 and 5, although firm specific growth alone is insignificant.

Interestingly, cash flow beta is positively related to credit spreads without controlling for other factors. Controlling for other factors, cash flow beta is negatively associated with credit spreads, consistent with our prediction 6 because our sample covers mostly positive economic growth period. The sign flip for cash flow beta deserves more discussion. In our model, the relation between cash flow beta and credit spread depends on macroeconomic conditions. The negative unconditional relation between cash flow betas and credit spreads can be understood from two directions: (1) cash flow beta is positively related to default probability; (2) cash flow beta is negatively related to recovery rate. Given that our model does not relate cash flow beta to default probability, the second scenario is more plausible. The significance of this sign flip is downplayed by the limited explanatory power of cash flow beta (monthly dummies explain 13%, cash flow beta only explains 1%).

We use regression estimates (firm specific growth rate and cash flow beta) as independent variables. There could potentially exist an error-in-variable problem. Shanken (1992) shows that, in the presence of error-in-variable problem, the two-pass Fama-MacBeth approach (estimating risk premium) could result in biased coefficient estimates and incorrect standard errors.[9] If estimation errors within the same cluster are highly correlated, our clustering adjusted panel data regression may be able to alleviate this concern because cluster level correlation is controlled. We are not aware of any formal procedure handling error-in-variable problem in panel regressions.

Prediction 6 is more difficult to test because it involves both macroeconomic conditions and firm characteristics. We first attempt to add an interaction term (cash flow beta with negative growth dummy) to the regression model. The interaction term is insignificant. This result is not surprising because the prediction is on cross-sectional relation between credit spreads and cash flow betas and there are only three negative growth quarters, adding a time dummy interaction term would not be able to distinguish difference economic states. In order to more formally test our Prediction 6, we run cross-sectional regressions for each of the six quarters with relatively extreme economic growth. Results are reported in Table 4.5. We find some supportive evidence for our prediction 6. The evidence is mainly from positive growth period. Four of the six signs are consistent with our prediction, although the relation from negative growth periods is insignificant. Indirect evidence is from comparing all positive growth periods and overall sample. The t value and absolute value of coefficient estimate are all greater in the regression using only positive growth quarters than the regression using the full sample including the three negative growth quarters.

4.3 Discussions

In this chapter we empirically test some of our model's predictions. The overall evidence to a large extent supports our model predictions. Although the evidence is less strong for our cross-sectional predictions, it is reasonable to expect so because of error in variable problem and relatively flat economic condition during this period. Moreover, out test power is limited because we have short time series for most firms and our cross-section sample is small as well.

[9]There is a renewed interest in the empirical methods estimating beta-pricing models. See, for example, Shanken and Zhou (2005).

Table 4.5: Credit spreads and cashflow beta in different economic states

The table sub-sample regression results for the effects of cash flow beta on credit spreads. The dependent variable is monthly average CDS price from CreditTrade. The indepdent variables include CVCF, FSG, CF Beta, Leverage, IV, and Jump. Only the coefficient estimates and t-statistics of cash flow beta are reported. All regressions include monthly time dummies (not shown). Issuer-clustering, cross-correlation, and heteroskedacity are adjusted to obtain robust t-statistics.

Time Period	GDP growth	Predicted sign	Coef.	t-stat	N	Clusters
		Panel A: Negative Growth				
2001Q3	-1.41%	+	-0.24	-0.51	276	142
2001Q1	-0.49%	+	0.22	0.71	282	130
2000Q3	-0.46%	+	0.41	0.83	172	89
All three	-0.79%	+	0.14	0.39	730	211
		Panel B: Positive Growth				
2003Q3	7.21%	–	-0.18	-2.80	471	219
1999Q4	7.11%	–	-0.07	-0.48	110	50
2000Q2	6.28%	–	0.58	5.16	160	79
All three	6.87%	–	-0.10	-1.49	741	254
All Positive Growth	3.63%	–	-0.10	-2.36	7344	456
		Panel C: Full Sample				
Overall	3.16%	–	-0.09	-2.14	8074	462

Our time-series findings strongly support our model, especially on the effect of investor sentiment. Investor sentiment may affect credit spreads more than it affects default probabilities. Firm default probabilities are associated with investor sentiment because investor sentiment changes the required returns. Credit spreads are determined by secondary market trading which is affected by investor sentiment as well. This point can be further studied in the future.

Chapter 5

Effects of Transparency and Liquidity on Credit Spreads

Empirical studies suggest that a limited portion of corporate bond yield spread variations is explained by existing financial and economic variables. For example, Gebhardt, Hvidkjaer, and Swaminathan (2005) show that corporate bond returns are affected by systematic risk factors, but after controlling both systematic factors and firm characteristics, only 44% of the variation is explained. (See Turnbull (2005) for a recent review.) As we discussed earlier, this limited explanatory power could be due to two factors. The first is measurement error in credit spreads (credit spreads measured as the difference between corporate bond yields and Treasury yields contain liquidity and tax premiums). This problem is mitigated in our study by using CDS spreads. The second is omitted variables. In Chapter 4, we have investigated the role of macroeconomic variables and firm cash flow variables suggested by our model. In this chapter we examine two factors, accounting transparency and liquidity, resulting from imperfect information.

Information quality, the portion of information about the firm accurately provided to the investing public, is important for firm valuation. First, investors may be ambiguity averse and tend to use the worse case scenario. They treat firms with lower information quality as less valuable firms. Titman and Trueman (1986), in a model of auditor and underwriter selection for new issues, show that high quality firms choose more prestigious auditors who provides high quality information about the firm, subsequently the firm is valued more by investors. Secondly, high quality information improves coordination between firm managers and investors on firm investment decisions. Better aligned interests for managers and investors reduces agency costs and increases firm value.

Information imperfection (incomplete information and asymmetric information) has not been investigated in either theoretical or empirical credit risk literature, with few exceptions. Nevertheless, CDS market, as in any markets, is contaminated by information imperfection. Acharya and Johnson (2005) find evidence of insider trading in the credit derivatives market. The recently gained popularity of capital structure arbitrage reflects the presence of sophisticated investors (presumably with superior information) in this market. Therefore, it is meaningful to study the effects of information imperfection on CDS spreads.

We study incomplete information in the form of accounting transparency and asymmetric information in the form of (il)liquidity separately. These two may seem similar but the distinction should be recognized. In a market with low accounting transparency, every investor in the market observes the same information set, insiders know more than others but they do not trade on their informational advantage (for reasons outside of our consideration). In the case of asymmetric information, insiders know more and they can trade on their private information. It should be noted that these two scenarios are not exclusive of each other, they may coexist in the same market.

Accounting transparency is hard to quantify. Higher disclosure quality delivers better accounting transparency. Three approaches have been used to quantify accounting transparency. The first is to survey financial experts who are qualified to evaluate the firm's accounting transparency. One example is the disclosure ranking from Association for Investment Management and Research (AIMR).[1] The second approach is to thoroughly investigate the firm's reports, announcements, and briefings. Disclosure quality is judged based on how much information the firm discloses to the market compared to how much information the firm could have disclosed. S&P and Audit Integrity produces disclosure scores following this approach. The third approach is market-based. Disclosure quality may be estimated from market trading activity or opinions revealed by financial analysts. We will elaborate this approach further in the next section. We use several proxies from above three approaches to ensure that our results are not driven by any single measure of transparency. We find evidence that more transparent firms have lower CDS spreads.

[1] AIMR was renamed to CFA Institute in May, 2004.

If transparency always reduces costs of debt, there must exist some economic forces preventing firms from disclose every piece of information to the market. There is a large accounting literature on discretionary disclosure and how firms should disclose optimally. Some firms may be better off being more secretive (less transparent) and investors may value this strategic action. We conjecture that firms with higher research and development expenses, more selling costs, and lower capital intensity may have higher proprietary costs associated with disclosure. We investigate the non-linearity in transparency effect by separating firms with valuable intangible information or high proprietary costs from others and find supportive evidence for optimal disclosure.

The major advantage of CDS spread over corporate bond yield spread is reduced liquidity premium. But CDS market is not perfectly liquid. Investors with private information may consider first trade in the CDS market. Blanco, Brennan, and Marsh (2005) show that the price discovery process of CDS market leads that of corporate bond market. They also show that imperfect CDS contract specification affects CDS prices. CDS trading is sparse. On average, each issuer has about one trade or quote per trading day. The market is by and large speculative. Around 15% of market trading activity is contributed by hedge funds, according to British Bankers' Association 2003/2004 Credit Derivatives Survey. Above evidence indicates that liquidity plays a nontrivial role in CDS market. In an integrated market environment, investors are not restricted from trading in only one market. Hence, illiquidity could spill over from other markets such as stock, bond, and option markets. We find evidence of both liquidity and liquidity spillover effects in the CDS market.

Empirical studies in the credit risk literature have different focus. Collin-Dufresene, Goldstein, and Martin (2001) examine the determinants of time variations in credit spread changes. Campbell and Taskler (2003) explain the cross-sectional and time-series variation in credit spread level with idiosyncratic volatility. We study the effects of transparency and liquidity on the *level* rather than change of credit spreads for several reasons. First, we are mostly interested in the cross-sectional relation. Credit spread changes may be more suitable for time-series studies. Second, we are not aware of any evidence for unit roots in credit spreads. Differencing a stationary process is unnecessary and problematic. Third, taking first difference produces auto-correlations in the data. Autocorrelations make statistical inference more difficult in panel data analysis. Lastly, our data is generated from transactions. A lot of issuers do not have complete continuous time series of data. Taking the changes of credit spreads significantly reduces our sample size.

In the reminder of this chapter, we first discuss fundamental determinants of credit spreads, which serve as our control variables in later analysis. We then demonstrate the explanatory power of transparency and liquidity for CDS spreads, with a focus on the non-linear effect of transparency and time-varying effects of liquidity.

5.1 Fundamental Determinants

5.1.1 Explanatory Variables and Data

We identify the set of credit risk factors that are commonly studied in the literature (see, among others, Collin-Dufresne, Goldstein, and Martin (2001), Campbell and Taskler (2003), Eom, Helwege, and Huang (2004)). Those factors affect credit spreads either through default probabilities or through expected recovery rates. Although most theoretic models assume constant recovery rate, empirical evidence has shown that recovery rate varies across industries and with time. It is necessary to control for those factors in order to show that our transparency and liquidity effects are not due to correlation with existing factors that are left out.

Merton (1974) model suggests leverage ratio and asset volatility as the only cross-sectional determinants of default probabilities (DP). Leland (2004) argues that in order to better match historical default probabilities, a jump component is needed for the asset value process. Driessen (2005) estimates a reduced form model and uncovers significant jump risk premium. Therefore, our first set of credit risk factors include leverage, asset volatility, and jump component in asset value. In theory, credit spreads should increase with leverage, asset volatility, and jump magnitude.

We measure leverage using book value of debt and market value of equity, as following:

$$\text{Leverage} = \frac{\text{Book Value of Debt}}{\text{Market Value of Equity} + \text{Book Value of Debt}}. \tag{5.1}$$

Market value of equity is calculated as stock price multiplied by number of shares outstanding. Book value of debt is the sum of short-term debt (Compustat quarterly file data item 45) and long-term debt (item 51). Debt level is only available at quarterly frequency. Following Collin-Dufresne, Goldstein, and Martin (2001), we use linear interpolation to obtain monthly debt levels from quarterly debt level.[2] When this interpolation results in negative debt level, we keep previous debt level.

Asset volatility is not directly observable. We use the data provided by KMV. KMV backs out asset value and asset volatility from stock price and stock volatility using a recursive algorithm (discussed in Appendix B). In a simplified framework, asset volatility should be proportional to stock volatility. We also use average monthly at-the-money stock option implied volatility from OptionMetrics. Option implied volatility measures total equity volatility, including idiosyncratic volatility. Campbell and Taskler (2003) show that idiosyncratic volatility can explain as much cross-sectional variation in credit spreads as can credit ratings. Cremers, Driessen, Maenhout, and Weinbaum (2005) argue that option prices contain information for credit spreads.

Asset value jump size is proxied by the monthly average slope of option implied volatility curve. Specifically, it is the difference between the implied volatilities at 0.9 strike-to-spot ratio and implied volatility at the money. The idea is that the skewness of the volatility curve is mainly caused by jump component. Similar measure of jump size is used by Collin-Dufresne, Goldstein, and Martin (2001), and Cremers, Driessen, Maenhout, and Weinbaum (2005).

Although credit rating does not directly enter into any structural credit risk model, we include credit rating for two reasons. First, credit rating has been shown to affect credit spreads even after controlling for leverage, volatility, and other factors. Second, Molina (2005) shows that, when leverage ratio is endogenized, the effect of leverage on credit risk is much larger than the case of exogeneous leverage choice. Leverage ratio could be chosen to target certain credit rating (Kisgen (2005)). Therefore, credit rating could have explanatory power above rating per se. Credit rating is included in our CDS database. Missing values were filled in using data in Compustat and the Fixed Income Securities Database (FISD). Letter ratings are converted into numerical values as 37 minus the numerical number in Compustat, with AAA corresponding to 35, AA+ to 33, and D to 10. etc.

In our theoretical model in Chapter 2, cash shortage is the primary default cause. Profitability, measured as the ratio of operating cash flow to total assets, is related to the

[2] All of our results are not affected by this interpolation. Using quarterly leverage produces almost identical results.

Table 5.1: Descriptive statistics of fundamental determinants of credit spreads

This table summarizes the set of fundamental determinants of credit spreads. IV is at-the-money option implied volatility. Jump is the slope of implied volatility curve. Both are provided by OptionMetrics. KMV AV is asset volatility estimated by KMV. Credit rating is converted into numerical numbers, with AAA assigned a number 35. EDF5 is KMV's five-year EDF. Leverage is market leverage. CVCF is the coefficient of variation on quarterly cash flow. Profitability is the operating cash flow to total asset ratio. B/M is the book-to-market ratio. Market cap is firm's stock price multiplied by shares outstanding. Leverage, CVCF, Profitability, B/M, and Market cap are obtained from CRSP and Compustat merged data file. The data spans from July 1997 to December 2004 (October 2004 for KMV AV, April 2005 for Credit Rating). Panel A reports the pooled summary statistics. Panel B reports pairwise Pearson correlations.

Panel A: Summary Statistics

Variable	Obs	Mean	Std.	Min	Max
IV	9737	0.38	0.15	0.03	1.43
Jump ($\times$ 100)	9737	0.21	0.87	-8.86	14.01
KMV AV	7442	0.21	0.11	0.04	1.20
Credit Rating	10604	27.20	2.63	10.00	35.00
EDF5 (%)	7352	0.79	1.12	0.02	19.29
Leverage	9137	0.37	0.23	0.00	0.99
CVCF	9476	68.34	435.98	0.30	15070.33
Profitability	8648	0.03	0.05	0.00	0.20
B/M	9312	15.91	1485.60	0.00	143358.90
Market Cap ($ Billion)	9866	29.59	50.13	0.00	581.10

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IV (1)	1.000								
Jump ($\times$ 100) (2)	0.016	1.000							
KMV AV (3)	0.387	-0.009	1.000						
Credit Rating (4)	-0.264	-0.099	-0.088	1.000					
EDF5 (%) (5)	0.623	0.063	0.307	-0.412	1.000				
Leverage (6)	0.211	0.067	-0.482	-0.146	0.410	1.000			
CVCF (7)	0.076	0.008	0.102	-0.113	0.114	-0.018	1.000		
Profitability (8)	-0.056	-0.018	-0.284	0.029	-0.091	-0.130	-0.026	1.000	
B/M (9)	0.024	-0.003	-0.004	-0.002	0.009	0.000	0.001	-0.005	1.000
Market Cap ($ Billion) (10)	-0.123	-0.051	0.096	0.522	-0.200	-0.199	-0.015	0.035	-0.005

firm's financial health and default probability. Moreover, we have shown that cash flow volatility is related to credit risk. We also include book-to-market ratio, firm size, and KMV's five-year EDF. Book-to-market has long been argued to be associated with firm distress. Campbell, Hilscher, and Szilagyi (2005) show that book-to-market ratio and firm size are strong predictors of default probability, especially for long run predictions. EDF5 is a direct measure of default probability.

Table 5.1 provides the descriptive statistics for our fundamental explanatory variables. The average option implied volatility is 0.38, which is slightly higher than predicted by an asset volatility of 0.21 with a leverage ratio of 0.37, if we assume bond volatility is negligible. The sample contains mostly large and high quality firms. The average firm has a equity size of around \$30 billion, with A rated bonds, and a five year default probability of 0.79%. Most of the firms are profitable value firms with an average book-to-market ratio of 16. Most of the variables are not highly correlated. We observe that credit rating is negatively correlated with implied volatility, EDF5, and positively correlated with size. Appendix C provides a bigger correlation matrix, including other variables used in other parts of this chapter. Credit rating is also negatively correlated with PIN, stock illiquidity, stock trading costs and analysts forecast dispersion, consistent with Odders-White and Ready (2005) that stock market liquidity affects credit rating. Credit rating is positively correlated with average bond maturity and positively correlated with coupon rate, which suggests that high quality firms issue longer term bonds with lower coupon rate.

5.1.2 Econometric Issues and Results

We conduct regression analysis to examine the effects of fundamental determinants on CDS spreads. We are primarily interested in the cross-sectional relation. Our dataset is a pooled time-series and cross-section unbalanced panel. Extra care needs to be exerted when analyzing such a panel data. Fama and French (2002) have expressed their concern on obtaining robust econometric inference from panel data by stating that "the most serious problem in the empirical leverage literature is understated standard errors that cloud inferences." Two types of correlations need to be considered in panel data: Observations from the same issuer cannot be treated as independent to each other, therefore we need to control for issuer effect; firms in the aggregate may be affected by the same macroeconomic condition, therefore we need to control for time effect. Petersen (2005) provides a detailed analysis on

Table 5.2: Fundamental determinants of credit spreads

The dependent variable is monthly average CDS price from CreditTrade. Data starts at June 1997 and ends at December 2004 (April 2005 for CDS price and credit ratings, October 2004 for KMV AV and EDF5). Variable definitions are in Appendix C. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedacity are adjusted to obtain robust t-statistics (in parenthesis).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	27.67	-239.69	963.91	19.91	25.14	8.19	422.83	-23.78	447.43
	(6.18)	(-7.71)	(15.07)	(13.40)	(5.44)	(1.13)	(8.06)	(-1.15)	(5.26)
IV		697.68					410.90		389.44
		(18.83)					(9.70)		(8.21)
Jump					1469.45		987.05		789.12
					(4.64)		(5.31)		(4.02)
KMV AV						200.06	-177.56		-39.51
						(3.14)	(-3.81)		(-0.47)
Credit Rating			-31.02				-20.29		-21.00
			(-14.85)				(-10.10)		(-9.29)
EDF5				78.12			32.25		27.74
				(7.46)			(3.18)		(2.71)
Leverage								136.88	107.73
								(3.97)	(2.98)
CVCF								0.05	0.00
								(1.39)	(0.10)
Profitability								-94.83	-35.96
								(-0.74)	(-0.71)
B/M								-0.38	-1.20
								(-3.78)	(-9.46)
Market Cap								-0.47	0.46
								(-2.53)	(4.49)
N	10884	9737	10604	7352	9737	7442	7087	8022	6232
Clusters	583	530	566	435	530	440	409	496	383
Adj. R^2	0.140	0.456	0.441	0.447	0.142	0.151	0.611	0.216	0.624
F	7.87	13.47	9.95	6.96	8.46	14.65	118.13	23.02	103.87

the performance of various approaches in this setting. He shows that when firm effect exists, adjusting for firm clustering is the preferred approach,[3] while when time effect exists, Fama-MacBeth should be applied, when both firm and time effects are present, one may consider controlling time effect parametrically (using time dummies) with firm clustering.

Petersen (2005) states that "when the standard errors clustered by firm are much larger than the White standard errors (three to four times larger), this indicates the presence of a firm effect in the data. When the standard errors clustered by time are much larger than the White standard errors, this indicates the presence of a time effect in the data." Using this diagnosis, we find both firm and (relatively weaker) time effects in our panel data. Hence, we follow Petersen's suggestion when conduct our empirical analysis by adjusting for issuer clustering and controlling time effect by adding time dummies. We do not include any macroeconomic variable. Any time-series effect is controlled by monthly time dummies.[4] Table 5.2 reports the regression results. The dependent variable is average monthly CDS price. We adjust all standard errors to obtain robust t statistics.

Column (1) shows the regression results with monthly dummies and a constant. Monthly time dummies can explain 14% (adjusted R^2) of the overall variations in credit spreads. Financial and accounting variables are included, in addition to monthly dummies, in column (8). Financial and accounting variables explain only 7.6% (the R^2 difference between column (8) and column (1)) of the variations in CDS spreads. This finding provides indirect supporting evidence and confirms our finding in Chapter 4 that macroeconomic conditions affect credit spreads.

Option implied volatility has strong explanatory power. Because option implied volatility measuring total volatility including market volatility and idiosyncratic volatility, this result is consistent with the findings in Campbell and Taskler (2003) that idiosyncratic volatility affects credit spreads and almost has as strong explanatory power as credit ratings. Credit rating is highly significant. Better rated firms have lower credit spreads. Option implied volatility has more explanatory power (higher R^2) than credit ratings and KMV's

[3]Petersen (2005) verifies that the bootstrapping method employed by Kayhan and Titman (2004) performed equally well.

[4]We have also entertained other approaches to obtain robust cross-sectional results. We first consider firm fixed effect rather than issuer clustering. For the second alternative approach we first calculate the time-series average for each issuer then we run one cross-sectional regression. In this way we suppress any time-series variations. Lastly we run cross-sectional regression for each month. The average coefficient and t values are then calculated by aggregating over all the months. This is the Fama-MacBeth approach which provides the most conservative results. All results are consistent with our issuer clustering adjusted results.

five-year EDF.

Our finding reinforces Leland's (2004) proposition that jump should be included in the asset dynamics process to better explain default probabilities and credit spreads. The magnitude of jump effect is also significant. A one standard deviation shock in jump magnitude affects credit spreads by 10 basis points. KMV's asset volatility is positively associated with credit spreads when we do not include option implied volatility. After controlling option-implied volatility, credit spreads are *negatively* associated with asset volatility. (Asset volatility is insignificant when accounting and financial variables are included.) At first the negative relation between credit spreads and asset volatility may seem puzzling. When two firms have the same equity volatility and leverage ratio, the one with higher asset volatility will have higher bond volatility. Our result hints that bond yields are negatively associated with bond volatility.[5] A plausible explanation is that higher bond volatility is associated with higher recovery rate. This finding deserves further investigation.

Leverage has been a strong explanatory variable for credit spreads and default probabilities. But we find its explanatory power significantly weaker than that of credit ratings, which is consistent with the conjecture that firms may target certain credit ratings. (All financial and accounting variables explain 21.6% of CDS spreads, in contrast to 44.1% for credit rating.) Although we have the right signs for cash flow volatility and profitability, they are insignificant. Consistent with Campbell, Hilscher, and Szilagyi (2005), we find book-to-market ratio is significantly related to credit risk.

One interesting result is on firm size. Size is negatively associated with credit spreads without controlling for direct measures of default probabilities such as credit rating and EDF5. After controlling for credit rating and EDF5, larger firms have *larger* credit spreads. This counter-intuitive finding can be understood using the argument of shareholders' advantages studied by Garlappi, Shu, and Yan (2005). Size is a proxy for bargaining power. When two firms have the same default probability, the larger firm's shareholders will have more bargaining power during Chapter 11 reorganization. Moreover, larger firms may have lower recovery rates during Chapter 7 liquidation simply because it is more difficult to liquidate a larger company.

CDS spreads are better explained by fundamental determinants than corporate bond

[5] This finding is coincidentally consistent with the historical fact on Merrill Lynch's MOVE bond volatility index which is negatively correlated with bond yields.

yield spreads. The R^2 from the overall regression is 0.624, which is much higher than comparable studies using corporate bond yield spreads (R^2's in Campbell and Taskler (2003) range from 0.25 to 0.40. Considering that they use firm fixed effects which essentially add firm dummies, the difference is even more significant), which provides indirect evidence that CDS spreads are cleaner measure of credit spreads.

Credit ratings are ordinal observations. In order to better estimate the economic significance of credit ratings on CDS spreads, we regress CDS spreads on credit rating dummies instead of numerical credit ratings. The results are presented in Table 5.3. Column (1) shows that, without controlling for other factors, CDS spreads of investment grade bonds (BBB or better) are 184 basis points lower than CDS spreads of junk bonds (BB or worse). CDS spreads of AAA, AA, and A bonds are 75 basis points lower than CDS spreads of BBB bonds. CDS spreads of AAA and AA bonds are 24 basis points lower than A bonds. After controlling for other factors in Column (2), the magnitude of those changes becomes smaller.

Because credit rating dummies are less accurate measures of credit rating than numerical credit rating, several other interesting findings emerge from Table 5.3. First, cash flow volatility and profitability become more significant. This finding indicates that credit rating agencies indeed take account of cash flow variability. Second, firm size becomes insignificant. This finding further provide evidence that firm size may proxy for shareholder's bargaining power at default. This effect is most evident after controlling for default probabilities.

5.2 Accounting Transparency

A deficiency in structural credit risk models is their prediction that credit spreads are zero at zero maturity. This result is driven by the assumption of continuous asset process and perfect information for investors. That is, firm managers disclose every piece of information to the market. In actuality, voluntary disclosure is limited and discrete. The market does not observe the complete information. This problem is analyzed in a seminal model by Duffie and Lando (2001). In their model, bond investors only have access to periodic and imperfect accounting reports. Equity holders observe the true value of the firm. They decide when to liquidate the firm but they cannot trade on the secondary market. Under this imperfect

Table 5.3: Credit spreads and credit rating

This table shows the effects of credit ratings on credit spreads. The dependent variable is monthly average CDS price from CreditTrade. *AA or better* is a dummy variable, it takes a value of one if credit rating is AA or better. Similarly for A and BBB. See Appendix C for variable definitions. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedacity are adjusted to obtain robust t-statistics.

	(1)		(2)	
	Coef.	t-stat	Coef.	t-stat
Constant	290.56	16.86	6.32	0.23
IV			392.64	8.55
Jump			677.03	3.54
KMV AV			-35.62	-0.49
AA or better	-23.67	-4.93	5.40	0.62
A or better	-75.11	-12.18	-40.26	-5.55
BBB or better	-184.56	-13.41	-132.56	-9.79
EDF5			25.62	2.77
Leverage			119.26	3.76
CVCF			0.01	2.55
Profitability			-57.66	-1.56
B/M			-1.27	-10.49
Market Cap			0.11	1.36
N	10906		6274	
Clusters	583		387	
Adj. R^2	0.447		0.650	
F	15.08		114.50	

information environment, default probability inferred by bond investors is always positive even for very short maturity bonds. Yu (2005) finds empirical evidence consistent with Duffie and Lando's (2001) prediction. Yu (2005) uses AIMR's annual disclosure ranking and finds that firms with higher ranking have lower spreads. Moreover, he finds that this transparency effect is more pronounced for short-term bonds.

There are two major concerns with Yu's (2005) study. First, His conclusions critically rely on the accuracy of AIMR's rankings. It is worthwhile to examine the robustness of his finding using different disclosure proxies. In this study, we use four different proxies for accounting transparency: probability of informed trading (PIN) in equity market, S&P's disclosure and transparency score, AuditIntegrity's accounting disclosure and governance score, and analyst forecast dispersion. Second, Yu examines corporate bond yield spreads.

Although Yu has controlled for liquidity for some of his analyses, it is still possible that his disclosure measure is correlated with bond liquidity. The liquidity concern is significantly alleviated in this study because we use CDS spreads. Furthermore, we control for liquidity and liquidity spillover for robustness check. In this section, we provide a more comprehensive view of the effect of accounting transparency on credit spreads.

More important contribution of our study is to examine the effect of firm's strategic disclosure decision on credit spreads (which will be elaborated more later) from the discretionary disclosure literature. That is, every firm has an optimal level of transparency. Some firms should be less transparent than other firms. Firms do not disclose sufficiently because there is a cost of doing so. Investors value that consideration which should be reflected in credit spreads as well. To the best of our knowledge, we are the first to examine the effect of optimal disclosure on credit spreads or cost of debt.

5.2.1 Measuring Accounting Transparency

We use four different proxies for transparency in order to show that our results do not depend on the specific proxy we use. Although we recognize that it is difficult to completely distinguish accounting transparency from information asymmetry, difference of opinion, etc., we argue that our proxies are easily justified by findings in previous literature.[6]

Our first proxy is the probability of informed trading (PIN) constructed by Easley, O'Hara, and Hvidkjaer (2002) using intraday trade and quote data. PIN is derived from a microstructure model of strategic trading by informed traders in a market with Bayesian learning. As shown by Brown and Hillegeist (2005), less transparent firms are more likely to have higher PIN. The idea is rather simple. Investors are less likely to private information if the firm disclose every piece of information to the market. The PIN data is obtained from Soeren Hvidkjaer's website. It covers only NYSE/Amex firms from 1983 to 2001 at annual frequency.

Our second proxy is S&P's Transparency and Disclosure score, which is computed by comparing the the amount of information disclosed by the firm (through annual report, quarterly announcements, etc.) to the amount of information the firm could have disclosed.

[6] We by no means argue that our proxies are exhaustive or best. We recently became aware of a working paper by Garfinkel (2005), he argues that unexplained trading volume around earnings announcements best measures investors' opinion divergence.

See Patel and Dallas (2002) for the construction and results of the data.[7] S&P has two sets of transparency scores: one based on annual report disclosure and another based on overall disclosure (all filing or announcements including annual reports). This data is generously provided by Ian Byrne of Standard and Poors. The data is only available for year 2001 at annual frequency.

Our third proxy is Audit Integrity's Accounting and Governance Rankings.[8] Audit Integrity analyzes company financial and litigation information, with a focus on the firm's accounting aggresiveness and governance quality. The approach is similar to S&P's overall score. This data is generously provided by Ophir Gottlieb of Audit Integrity. This data is available quarterly since 1989.

Our fourth proxy is analyst forecast dispersion. The idea behind this measure is that the degree of consensus among information users increases with the precision of disclosed information (Barron, Kim, Lim, and Stevens (1998)). Empirical evidence shows a negative relation between quality of disclosure and analyst forecast dispersion (Hope (2003)). Zhang (2005) validates the use of analyst forecast dispersion as a measure of disclosure quality. Dispersion is measured as follows:

$$\text{dispersion} = \frac{\text{standard deviation of forecast}}{|\text{mean forecast}|}, \tag{5.2}$$

where forecast is annual EPS from I/B/E/S summary file. We require at least five forecast to calculate the standard deviation. Scaling is necessary to avoid misleading inference, as argued by Qu, Starks, and Yan (2003). Scaling by stock prices produces similar results. Recency (distance from forecast date to report date) is an issue for analyst forecast as more recent forecasts are more accurate. We verify that our results holds after controlling recency. The data is available at monthly frequency.

Table 5.4 reports summary statistics of our transparency proxies. On average, our sample firms have lower level of PIN with an average of 0.10 (the sample average for Easley, O'Hara, and Hvidkjaer (2002) is 0.19). According to S&P, a substantial portion of accounting information is disclosed via channels other than annual reports (annual reports disclose 44% of relevant information but the aggregate disclosure level is 72%). The average disclosure level for the AuditIntegrity sample is lower (66%) than S&P (72%) because S&P only

[7] See http://www.governance.standardandpoors.com for more details.
[8] See http://www.auditintegirty.com for more details.

Table 5.4: Descriptive statistics of transparency proxies

This table provides descriptive statistics for our transparency proxies. PIN is the probability of informed trading in equity market, available at annual frequency for NYSE firms from 1997 to 2001. S&P scores are S&P's disclosure scores for year 2001. Audit Integrity AGR is Audit Integrity's accounting and governance ranking, available quarterly from 1997 to 2004. Analyst forecast dispersion is the standard deviation to absolute mean ratio for firs year EPS from I/B/E/S summary file.

Panel A: Summary Statistics

	N	Mean	Std	Minimum	Maximum
PIN	2316	0.10	0.03	0.00	0.24
S&P Annual Report Score	1111	44.18	9.58	10.31	75.53
S&P Overall Score	1111	71.88	3.82	58.16	81.44
Audit Integrity AGR	9645	65.91	12.39	8.00	90.00
Analyst Forecast Dispersion	7180	0.05	0.05	0.01	0.30

Panel B: Pairwise Pearson Correlations

	PIN	Annual	Overall	AGR	Disp.
PIN	1.000				
S&P Annual Report Score	-0.090	1.000			
S&P Overall Score	-0.055	0.361	1.000		
Audit Integrity AGR	0.006	0.035	-0.037	1.000	
Analyst Forecast Dispersion	0.040	0.060	0.014	-0.021	1.000

covers S&P 500 firms. There is substantial cross-sectional variation in forecast dispersion. The range for S&P's overall score is very narrow, which provides some clue on its limited explanatory power.

Above proxies measure different aspects of accounting transparency or disclosure quality. Those proxies are not highly correlated, as shown by the correlations in Table 5.4. PIN is a measure based on stock market trading. It reflects transparency relative to public information. S&P and Audit Integrity provide rankings, but their approaches through which they derive the rankings are unknown and could be subjective. Analyst forecast dispersion may well be the most suitable measure of disclosure quality for several reasons. First, Lang and Lundholm (1996) provide evidence that firms with more informative disclosure policies, measured by AIMR disclosure ranking, have less analyst forecast dispersion. Second, it is perceivable that analysts, especially star analysts, should have access to all sorts of information the company can disclose. Third, analysts are prohibited from trading on their information advantage. Lastly, analyst forecast dispersion reflects the views from multiple

Table 5.5: Credit spreads and transparency

This table demonstrates the effect of transparency on credit spreads. The dependent variable is monthly average CDS price from CreditTrade. Transparency proxies are: probability of informed trade (PIN) in equity market; S&P's disclosure scores (Annual Report and All Reports); Audit Integrity's accounting and governance ranking; and I/B/E/S analyst forecast dispersion for first year EPS. See Appendix C for variable definitions. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedasticity are adjusted to obtain robust t-statistics.

	Transparency Proxies									
	PIN		Annual Report		All Reports		Audit Integrity		Forecast Dispersion	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	392.02	4.80	503.49	4.42	450.38	2.03	462.29	5.42	437.67	5.98
IV	116.26	2.92	115.32	2.07	118.66	2.15	393.87	8.26	352.15	6.97
Jump	640.52	1.25	1105.33	1.53	988.45	1.32	793.47	4.04	686.71	2.60
KMV AV	48.87	0.40	11.44	0.08	9.87	0.07	-39.70	-0.47	-50.23	-0.53
Credit Rating	-16.81	-7.07	-16.83	-5.29	-17.57	-5.16	-20.99	-9.38	-21.84	-9.29
EDF5	63.91	5.15	82.89	4.59	83.98	4.48	27.03	2.65	34.43	2.54
Leverage	30.02	0.77	18.30	0.33	8.12	0.15	108.19	3.02	84.12	2.10
CVCF	-0.02	-0.92	0.00	0.03	0.08	0.68	0.00	-0.20	-0.02	-0.87
Profitability	-27.32	-0.13	164.57	0.65	135.95	0.54	-33.04	-0.64	-51.39	-1.06
B/M	-0.91	-5.19	745.41	0.03	4824.90	0.16	-1.21	-9.48	-1.16	-7.84
Market Cap	0.28	2.23	0.11	1.02	0.15	1.47	0.46	4.43	0.42	3.94
Transparency	377.37	2.46	-1.18	-1.68	0.25	0.11	-0.22	-0.97	117.29	1.83
N	1535		696		696		6174		4769	
Clusters	207		143		143		378		351	
Adj. R^2	0.632		0.654		0.646		0.626		0.628	
F	39.44		17.60		17.32		102.67		80.35	

sources, rather than a single subjective ranking.

5.2.2 Basic Results

We examine the effects of transparency on credit spreads on all four transparency proxies (five if we count two from S&P). We control all the fundamental determinants discussed in the previous section. We also control for issuer clustering and include monthly time dummies. We would like to point out that we are unable to directly compare our findings with Yu's (2005) because the AIMR disclosure rankings cover the time period of 1979–1996 while our CDS data begins in 1997. The results are reported in Table 5.5. First to notice is that adding transparency in the regression does not affect our conclusion on the effect of fundamental determinants, except in a few cases the significance levels are reduced due to smaller sample size. Particularly noteworthy is the reduced significance of leverage. This result seems to be consistent with the idea that transparency is related to capital structure (Almazan, Suarez, and Titman (2004)).

The overall evidence is consistent with transparency as a significant explanatory variable for CDS spreads, but its explanatory power (marginal increase in R^2) is limited. Using PIN as a proxy for accounting transparency, we find credit spreads are positively significantly associated with PIN. One standard deviation shock in PIN moves credit spreads by about 10 basis points. Note that PIN also proxy for information risk and liquidity in the stock market. This result also indicates that stock market information is important for CDS price formation.

Our result on S&P's annual report score is also reasonably strong, although at 10% significance level. Note that higher S&P score means better disclosure and more transparency. A one standard deviation move in S&P's annual report score is accompanied by 10 basis point reduction in credit spreads. We might presume that as a better measure of disclosure, S&P's overall score may even produce stronger result than annual report score. To the contrary, overall score is insignificant in explaining credit spreads. Our interpretation is that investors focus more on salient, attention-grabbing information, an established phenomenon in the mutual fund industry (Barber, Odean, and Zheng (2002)). This finding is confirmed using Audit Integrity's Accounting and Governance Ranking, which is constructed using similar approach.

Finally, we analyze the effect of analyst forecast dispersion. Forecast dispersion is

Table 5.6: Credit ratings and transparency

This table demonstrates the effect of transparency on credit ratings. Both OLS and ordered probit results are presented. The dependent variable is firm monthly credit rating. Transparency is proxied by I/B/E/S analyst forecast dispersion for first year EPS. See Appendix C for variable definitions. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedasticity are adjusted to obtain robust t-statistics.

	OLS		Ordered Probit	
	Coef.	t-stat	Coef.	z-value
Constant	28.24	60.57		
IV	-1.00	-1.18	-0.72	-1.39
Jump	-1.93	-0.31	-1.11	-0.28
KMV AV	-6.31	-3.44	-4.08	-3.55
EDF5	-0.11	-0.67	-0.04	-0.40
Leverage	-3.44	-3.54	-2.23	-3.66
CVCF	-1.83	-2.72	-1.08	-2.68
Profitability	-2.75	-2.22	-1.69	-2.11
B/M	-0.50	-1.69	-0.35	-1.87
Market Cap	0.03	5.27	0.02	4.98
Transparency	-2.59	-2.20	-1.56	-2.06
N	4710		4710	
Clusters	345		345	
Adj./Pseudo R^2	0.446		0.138	
F/χ^2	38.31		2775.65	

positively associated with credit spreads (at 10% significance level). A one deviation move in forecast dispersion changes credit spreads by about 6 basis points. Because we have the largest sample for analyst forecast dispersion, we will use it as proxy for transparency in the following analysis.

Credit ratings are widely used as measure of credit risk. We further demonstrate the effect of transparency on credit risk using credit rating as dependent variable and analyst forecast dispersion as explanatory variable. Results are presented in Table 5.6. We find less transparent firms (with higher forecast dispersion) have lower credit ratings. Considering that credit ratings are ordinal observations, we use ordered probit instead of OLS and obtain similar results that less transparent firms are less likely to have high credit ratings.[9]

Transparency has the strongest effect for the short term, as all information is even-

[9]Other notable results from Table 5.6 including: Credit rating is not related to implied volatility, jump, and EDF5. Larger firms have better credit rating. Cash flow volatility is negatively associated with credit rating. Interestingly, after controlling other factors, more profitable firms have worse credit rating.

tually revealed to the market. This term structure of transparency effect is predicted by Duffie and Lando (2001) and verified by Yu (2005). Due to our data constraint (our sample concentrates on five-year maturity), we are unable to analyze this effect. Nevertheless, below we will show that there is cross-sectional difference for the transparency effect.

5.2.3 Interaction Effects

Public disclosure of (valuable) firm-specific information can be costly, especially in the presence of competitors who are also able to observe publicly disclosed firm information. For example, suppose a firm is raising capital for an investment that involves a new technology or marketing strategy, the value of which would be reduced if competitors learn of it prior to its introduction. A firm's disclosure decision is a function of its cost-benefit trade-off. Extant theory points to the existence of an interior optimal level of disclosure (Verrechia (1983)).[10]

In a model with human capital and costly external financing, Almazan, Suarez, and Titman (2004) show that, when the costs of bad news outweigh the benefits of good news or when transparency diminishes firm value, managers may have incentive to reduce firm's transparency. As shown by Zhang (2005), disclosure quality or transparency is determined by firm's proprietary costs. If transparency is universally beneficial to all firms, we would see all firms disclose information maximally. Therefore, the asymmetric effect of transparency makes firms to choose different level of transparency. This transparency consideration may be most evident for firms with a "leading edge," as suggested by Almazan, Suarez, and Titman (2004).

Even though transparency reduces credit spreads. Transparency premium (or opacity premium to be more precise) may be smaller for firms in which confidentiality of information is valued more if investors value managers' firm value maximizing effort. We use three proxies for the proprietary cost of firm's accounting transparency or disclosure quality: R&D intensity (measured as quarterly R&D expenses divided by quarterly sales, or RD/S), selling difficulty (measured as quarterly selling expenses over sales, or SE/S), and capital intensity (measured as total plant, property, and equipment divide by total assets,

[10] A similar argument has been made in agency problem: more transparency may increase the misalignment between principal and agent's interests. Prat (2005), in a model of career concerns, shows that, while transparency about the consequences of the agent's action is beneficial to the principal, transparency about the agent's action may have detrimental effects. Morris and Shin (2002) shows that, when market participants have access to private information, increased public disclosure may not always improve social welfare.

or PPE/TA) . Titman and Wessels (1988) argue that R&D intensity and SE/S are good measures of firm's uniqueness. It is conceivable that more unique firms have more valuable intangible information and are more concerned with disclosure quality. Higher PPE/TA represents higher entry barrier for new product market competitors. We characterize firms with higher RD/S and SE/S and lower PPE/TA as firms which have higher cost of transparency. According to the discretionary disclosure theory, for two firms with the same level of transparency, the firm with high proprietary cost will have lower credit spreads. High R&D intensity is defined as the top half of the firms having some R&D activity. Same categorization is used for SE/S and 1−PPE/TA.[11]

We empirically examine the effect of optimal disclosure on credit spreads by adding an interaction term between transparency and high proprietary cost dummy when regressing CDS spreads to transparency and other control variables. We focus on analyst forecast dispersion as the proxy for transparency for aforementioned reasons. If investors value firms' strategic disclosure decision, we expect firms with good reasons to disclose less to have a smaller transparency premium and a negative sign for the interaction term.

The regression results are reported in Table 5.7. We find supportive evidence for the optimal disclosure theory. Transparency effect is significantly reduced for high R&D firms. The magnitude of transparency effect on high R&D firms is about half of that of low R&D firms. A one standard deviation change in transparency for low R&D firms is associated with a change of 6 basis points in CDS spreads, while for high R&D firms the change is only 3 basis points. This result is consistent with the idea that investors require lower transparency premium for firms with higher R&D intensity. Using SE/S as a proxy for proprietary costs shows insignificant results. This finding is not surprising because 1-SE/S also measures firm's gross margin. Firms with higher gross margin may face more potential competition in the product market therefore have less incentive to disclose accurate information. We also find significant (at 10% significance level) interaction effect using 1-PPE/TA as proxy for proprietary costs. The magnitude of transparency premium reduction is even greater. (Transparency premium is only 1 basis point for less capital intensive firms.) The reduced significance level and enhanced transparency premium reduction can be understood as follows. On one hand, PPE/TA measures proprietary cost only with respect

[11] This approach categorizes observations with RD/S, SE/S, and 1−PPE/TA into the low cohort. Adding a dummy for missing values does not affect our results and the dummy variable is insignificant in our regressions.

Table 5.7: Credit spreads and transparency: Interaction effect

This table shows the interaction effects of transparency on credit spreads. Transparency is proxied by analyst forecast dispersion. RD/S is the ratio of research and development expenditures to sales. SE/S is selling expenses to sales. PPE/TA is total plant, property and equipment over total assets. All three variables are constructed from CRSP/Compustate merged quarterly data file. See Appendix C for variable definitions. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedasticity are adjusted to obtain robust t-statistics.

	Proprietary Cost (P.C.) Proxies					
	RD/S		SE/S		1−PPE/TA	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	434.44	5.96	470.70	6.01	470.91	6.06
IV	352.82	7.07	356.34	7.02	360.61	7.27
Jump	686.07	2.60	636.17	2.36	639.66	2.38
KMV AV	-45.05	-0.47	-44.90	-0.44	-47.97	-0.48
Credit Rating	-21.75	-9.23	-21.72	-9.38	-21.77	-9.50
EDF5	34.54	2.54	33.24	2.41	32.98	2.40
Leverage	84.40	2.11	79.96	1.88	79.95	1.89
CVCF	-0.02	-0.89	-0.02	-0.85	-0.02	-0.90
Profitability	-49.68	-1.02	-41.75	-0.92	-46.99	-1.03
B/M	-1.17	-7.86	-1.08	-7.69	-1.14	-7.73
Market Cap	0.42	3.94	0.42	3.73	0.43	3.82
Transparency	123.44	1.90	112.11	1.96	119.66	1.88
Transparency×High P.C.	-61.52	-2.33	-24.48	-1.24	-96.02	-1.89
N	4769		4710		4710	
Clusters	351		345		345	
Adj. R^2	0.628		0.628		0.628	
F	95.16		78.56		78.68	

to entrant product market competitors, but firms may as well concern other incumbent competitors in the product market. On the other hand, capital intensity is a very effective entry barrier (Schmalensee (1989)). Therefore, transparency consideration is even more important for less capital intensive firms. Our results are robust to liquidity factors, as we will show in the next section.

In summary, our analysis in this section shows that transparency affects credit spreads and the transparency effect is most pronounced for firms with low proprietary disclosure costs (or firms that does not have a good reason to provide low disclosure quality).[12]

[12]Our conclusion that discretionary disclosure is priced in CDS spreads is based on the premise that RD/S, SE/S, ad PPE/TA are good proxies for disclosure costs. Alternatively, we can use a hazard model

5.3 Liquidity and Liquidity Spillover

The contractual nature of CDS makes liquidity or convenience yield a much less serious concern. As argued by Longstaff, Mithal, and Neis (2005), CDS provides researchers "a near-ideal way of directly measuring the size of the default component in corporate spread." However, like in any other markets, CDS market participants are not symmetrically informed. Liquidity costs induced by information asymmetry may affect CDS spreads. Furthermore, CDS is often traded jointly with other securities. It is likely that liquidity or illiquidity of other market could spill over to CDS market. Before we can conclusively argue that liquidity is not an important factor for CDS spreads, it is necessary that we empirically estimate the liquidity and liquidity spillover effects.

CDS contracts are used for two purposes: hedging and speculation. Corporate bondholders averse to default risk may want to buy CDS if selling the bonds is too costly due to corporate bond market illiquidity.[13] If CDS market is imperfectly competitive and liquid (which is generally the case in the development stage of a market), CDS sellers may want to share part of the benefit (corporate bond liquidity premium saved) with the CDS buyers. Note that the difference between CDS contract and an insurance contract is that the protection buyer does not have to hold the underlying bonds. This fact may weaken the link between CDS market and corporate bond market.

In order to implement their speculative strategies, credit traders often trade CDS simultaneously with other securities. The price formation of CDS market depends on liquidity of other markets. For example, if an investor wants to build a portfolio with both stocks and CDS contracts because she has some information, she may not trade CDS at all if her stock position is too costly to build. Consequently, information will not be impounded into CDS price. CDS's are being increasingly used by credit traders such as hedge funds to speculate. The most popular hedge fund strategy nowadays is capital structure arbitrage. Such strategy involves trading CDS contracts and stocks (or bonds) simultaneously. Obviously the success of capital structure arbitrage depends on the liquidity of the equity or

to predict the disclosure level for individual firms and examine the effect of abnormal disclosure on CDS spreads. Another approach is to extract principal component from common disclosure determinants instead of relying on one single determinant.

[13]There are other reasons that bondholders cannot sell the bonds. For example, a bond underwriter may agree to hold the bond they underwrite for certain period. Holders of convertible bonds will not want to sell the bonds because they like the convertibility portion of the security. Nevertheless, this will have similar effect on CDS spreads.

bond market, in addition to CDS market liquidity.

We are not aware of any study on illiquidity and illiquidity spillover in CDS market, although illiquidity and illiquidity spillover have been extensively studied in corporate bond market. Ericsson and Renault (2005), Chen, Lesmond, and Wei (2005) has analyzed liquidity effect in corporate bond yield spread. Illiquidity spillover has been shown in Euro Telecom industry by Newman and Rierson (2004). Odders-White and Ready (2005) show that credit ratings are related to equity market liquidity.

5.3.1 Liquidity Proxies

Liquidity is an elusive concept. Often times liquidity has several distinctive dimensions. It is difficult to find a single superior measure for liquidity. Therefore, our objective is to find multiple proxies for liquidity to ensure the robustness of our findings.

CDS's are contracts. Protection buyers and sellers agree on the terms of the contract. They do no pay the bid-ask spread to market makers. Bid-ask spread could still be the cost a trader needs to pay if she wants to unwind a position. We argue bid-ask spread can also measure the degree divergence of opinion or information asymmetry of the market. We use percentage bid-ask spread (bid-ask spread divided by mid quote or trade price) to get a unitless measure. High bid-ask spread is associated with low liquidity. Another relevant measure of CDS market liquidity is from market trading activity, which is the number of quotes and trades within a given month. Because we cannot identify the trade direction or calculate order imbalance, it is hard to tell whether high trading activity reflects more liquidity or the reverse. Because CDS contracts protects against default, which is a downside event, it is arguable that demand for protection may be particularly high when a firm's financial condition deteriorates. Therefore, active trading may be linked to high order imbalance and less liquidity.

Edwards, Harris, and Piwowar (2004) argue that age, maturity, and amount outstanding are good measures of bond liquidity. Amount outstanding measures the availability of the bond. Recently issued or new bonds may be more liquid because they attract more of investors' attention. Bonds with shorter maturity may be more liquid because investors for long bonds may prefer the cash flow therefore not trade the bonds. For similar reason, bonds with high coupon may be less liquid.

Table 5.8: Descriptive statistics of liquidity proxies

This table presents descriptive statistics of liquidity measure from CDS, bond, stock, and option markets. CDS market liquidity is measured by the percentage bid-ask spread and number of trades and quotes per month. Bond liquidity proxies are average bond coupon, maturity, age, and total amount outstanding for all the bonds issued the same issuer in the Fixed Income Securities Database. Stock illiquidity is the Amihud measure, and stock trading cost is Hasbrouck's Gibbs Sampler measure. Option market liquidity is proxied by bid-ask spread, trading volume, and open interest. Data covers the period between June 1997 and December 2004, except CDS B/A spread (June 1997 to March 2003) and stock trading cost (June 1997 to December 2003).

Panel A: Summary Statistics

	N	Mean	Std	Minimum	Maximum
CDS B/A Spread	7726	0.23	0.16	0.00	2.00
CDS NQT	10884	25.89	58.11	1.00	1098.00
Average Coupon	8280	6.10	2.09	0.00	10.25
Average Maturity	8280	11.16	6.84	0.17	54.07
Average Age	8280	3.18	2.17	0.08	23.58
Bond Outstanding	8422	6.29	17.00	0.00	211.00
Stock Illiquidity	9765	0.02	0.03	0.00	1.52
Stock Trading Costs	7501	0.00	0.00	0.00	0.03
Option B/A Spread	9562	0.19	0.09	0.00	1.17
Option Volume	9563	5.47	10.75	0.00	192.16
Option Open Interest	9563	182.70	312.84	0.00	2550.35

Panel B: Pairwise Pearson Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
CDS B/A Spread (1)	1.000										
CDS NQT (2)	-0.251	1.000									
Average Coupon (3)	-0.010	-0.066	1.000								
Average Maturity (4)	0.044	-0.010	-0.140	1.000							
Average Age (5)	0.008	-0.056	0.388	0.097	1.000						
Bond Outstanding (6)	-0.072	0.030	-0.371	-0.163	-0.108	1.000					
Stock Illiquidity (7)	0.039	-0.065	0.232	-0.022	0.035	-0.152	1.000				
Stock Trading Costs (8)	-0.078	0.009	0.065	0.053	0.000	0.010	0.247	1.000			
Option B/A Spread (9)	0.182	-0.204	0.180	0.064	0.098	-0.114	0.183	0.005	1.000		
Option Volume (10)	-0.067	0.154	-0.308	-0.051	-0.085	0.424	-0.274	0.048	-0.240	1.000	
Option Open Interest (11)	-0.152	0.208	-0.281	-0.029	-0.063	0.381	-0.292	0.044	-0.341	0.806	1.000

Firm i's stock liquidity in month m is proxied by the Amihud measure as monthly average absolute return over volume:

$$\text{Illiquidity}_{im} = \frac{1}{D_{im}} \sum_{d=1}^{D_{im}} \frac{|r_{id}|}{\text{Volume}_{id}}, \tag{5.3}$$

where D_{im} is the number of days in month m for firm i, r_{id} is day d's return, and Volume_{id} is day d's volume. This measure actually measures illiquidity rather than liquidity. We also use Hasbrouck's Gibbs sampler measure of stock trading costs (Roll's measure). Hasbrouck (2005) argues that these two measures are the best liquidity proxies that can be constructed from low frequency data and are highly correlated with proxies constructed using transaction data.

Option liquidity is measured by bid-ask spread, trading volume, and open interest. Options are standard securities. Bid-ask spread measures the trading costs compensating the market makers. Trading volume measures the activeness of the market. Open interest provides key information regarding the liquidity of an option. If there is no open interest for an option, there is no secondary market for that option. When options have large open interest, it means they have a large number of buyers and sellers, and an active secondary market will increase the odds of getting option orders filled at good prices. So, all other things being equal, the bigger the open interest, the easier it will be to trade that option at a reasonable spread between the bid and ask.

Table 5.6 presents the summary statistics of our liquidity proxies. The average percentage bid-ask spread for CDS is 23%, which is significantly higher than bid-ask spread in other markets. Trading is thin in CDS market. On average, about one trade or quote occurs per day. These CDS issuers issue relatively longer maturity (11 years) and lower coupon (6%) bonds.

The correlation matrix in Table 5.6 reveals the first evidence of illiquidity in the CDS market. CDS trading activity (number of trades and quotes per month) is negatively correlated with CDS bid-ask spread. This result indicates that, in the aggregate, CDS trading costs reduce CDS trading. CDS bid-ask spread is also positively correlated with stock illiquidity, bond maturity, and option bid-ask spread and negatively correlated with bond amount outstanding, option trading volume and option open interest, which is consistent with illiquidity spillover from stock, bond, and option markets to CDS market. Interestingly, CDS bid-ask spread is negatively correlated with stock trading cost. This result is consistent with the idea that, when trading stocks is more costly, investors may choose to trade in the CDS market instead and improve CDS market liquidity.

5.3.2 Basic Results

We regress CDS spreads on liquidity proxies, after controlling for fundamental determinants and transparency proxied by forecast dispersion, Table 5.8 provides the results. In order to better observe individual effect, we first examine liquidity measures from each of the four markets separately. Our conclusions hold after pooling all liquidity proxies together.

We uncover significant liquidity effect in CDS market. Although insignificant, bid-ask spread is positively associated with CDS spread. Trading activity is positively associated with CDS spreads. A one standard deviation change in trading activity is associated with 7 basis points change in CDS spreads. In order to formally verify the conjecture that CDS trading activity could be a measure for order imbalance, we use the Lee and Ready (1991) algorithm to assign trade direction.[14] The correlation between number of quotes and trades and order imbalance is 0.57. We repeat the regression using order imbalance and obtain nearly identical results.[15]

We find little evidence that bond market liquidity affect CDS spreads. The most significant effect comes from average bond age. CDS spreads are negatively associated the average age of bonds issued by the same issuer. Note that bond age usually proxies for bond illiquidity. This is consistent with the scenario that, when trading the bonds is more expense, investors choose to trade in the CDS market. This synchronization of trading improves CDS market liquidity. Anecdotal evidence indicates that credit traders trade more CDS from established firms which have older bonds, therefore CDS liquidity is better for those issuers. Consequently, the CDS prices are lower for those issuers.

We find illiquidity spillover from stock market to CDS market. When the issuer's stocks are less liquid, CDS spreads are wider. This finding on illiquidity spillover from stock market to CDS market is consistent with the fact that investors, especially capital structure

[14] The Lee and Ready algorithm classifies a trade as buyer initiated if the trade price is above mid bid and ask price and seller initiated if trade price is above the mid price. Random direction is assigned if trade occurs at mid price.

[15] Alternatively, this may indicate that CDS contracts are traded more actively after negative news. Subsequently, active trading is accompanied by higher CDS spread. But we have controlled EDF and credit rating in the regression. Therefore, our order imbalance story is more plausible.

Table 5.9: Credit spreads and liquidity

The dependent variable is monthly average CDS price. See Appendix C for variable definitions. Monthly time dummies (not shown) are included in all regressions. Issuer-clustering, cross-correlation, and heteroskedasticity are adjusted to obtain robust t-statistics.

	Markets									
	CDS		Bond		Stock		Option		All	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	512.59	5.62	422.86	5.25	440.00	5.39	403.52	5.16	543.86	5.22
IV	356.60	6.93	386.55	7.15	374.58	7.13	366.49	7.07	397.12	6.32
Jump	737.69	2.56	541.87	1.79	606.41	2.12	729.15	2.77	704.12	2.18
KMV AV	17.90	0.17	4.30	0.04	-34.21	-0.32	-33.54	-0.35	73.89	0.62
Credit Rating	-23.11	-9.01	-19.48	-8.28	-22.55	-8.57	-21.54	-9.15	-23.35	-7.95
EDF5	26.70	1.75	29.31	2.06	28.82	2.04	33.65	2.47	15.74	1.02
Leverage	107.74	2.37	94.22	2.24	86.31	1.98	87.66	2.09	119.02	2.37
CVCF	-0.03	-1.24	-0.02	-0.91	-0.01	-0.55	-0.03	-0.97	-0.02	-1.15
Profitability	-9.09	-0.13	-36.05	-0.70	-70.16	-1.09	-43.34	-0.90	-22.71	-0.33
B/M	11.54	0.71	1.04	0.00	-1.29	-7.87	-1.16	-7.74	-7.32	-0.31
Market Cap	0.49	3.61	0.40	3.47	0.51	4.19	0.55	3.77	0.58	2.72
Transparency	167.92	1.95	119.31	1.62	143.39	2.00	123.80	1.94	183.61	1.87
Transparency×High R&D	-201.18	-1.85	-100.60	-1.51	-4.52	-0.03	-46.49	-1.26	-241.33	-1.26
CDS B/A Spread	20.89	1.50							4.14	0.24
CDS NQT	0.12	2.84							0.11	2.28
Average Coupon			0.30	0.16					-0.43	-0.17
Average Maturity			0.03	0.06					-0.11	-0.13
Average Age			-2.86	-1.72					-3.64	-1.77
Bond Outstanding			-0.02	-0.91					-0.23	-0.98
Stock Illiquidity					0.85	2.60			1.09	2.22
Stock Trading Costs					-1.93	-1.16			-3.30	-1.61
Option B/A Spread							46.24	1.23	-43.54	-0.83
Option Volume							-1.19	-2.70	-1.57	-2.42
Option Open Interest							0.02	1.48	0.07	1.37
N	3437		4182		3900		4769		2420	
Clusters	313		290		320		351		241	
Adj. R^2	0.638		0.624		0.638		0.630		0.639	
F	26.57		65.64		73.85		77.82		37.14	

arbitrageurs, often trade simultaneously stocks and CDS's. When it is too expensive to build the stock position, those investors will not trade CDS's. Hence, stock illiquidity reduces CDS liquidity.[16]

More option trading volume is associated with lower CDS spreads. This finding is consistent with illiquidity spillover from option market to CDS market. One may concern the high correlation between option trading volume and open interests. In unreported results, we obtain similar resulting when we exclude option open interest from the regression.

5.3.3 Time-Variation in Liquidity Effect

CDS market is still at its early stage. Given its rapid growth, we may be able to observe some time variation in liquidity effects as the market develops into a more mature market. We expect the market to be more and more liquid. The market will be more integrated with other markets at recent time compared to earlier time.

Our first evidence of improving liquidity in the CDS market is from CDS market trading costs. As shown in Figure 5.1, market average bid-ask spread has decreased significantly, from the high of around 50 basis points before year 2003 to around 10 basis points at a more recent time. (The low bid-ask spread at the very beginning of the period may be driven by higher quality of issuers. It is conceivable that only high quality issuers are selected to be traded at the experimental stage of a market.) Because the set of issuers change over time, we also plot the percentage bid-ask spread (bid-ask spread divided by mid quote) in Figure 5.2, we still observe some evidence that percentage bid-ask spread has declined, although there is a sharp increase in year 2005.

We investigate the time variation in the explanatory power of liquidity to CDS spreads. For each month, we regress CDS spreads on liquidity proxies only. We do not include other determinants of CDS spreads in order to capture the pure explanatory power from liquidity proxies. We expect the explanatory power of liquidity (both own market liquidity and other market liquidity) to decrease as the market develops.

Figure 5.3 plots the time-series of R^2s from the regression of CDS spreads on all liquidity proxies (except stock trading costs in order to have long time series). The overall

[16] We also find weak evidence (insignificant t-statistics) that stock trading costs (not reported) and option trading costs (bid-ask spread) are associated with lower CDS spreads. One explanation for this seemingly puzzling finding is that when stocks and options are more expensive to trade, investors may choose to trade in CDS market which makes CDS market more liquid and lowers CDS spreads.

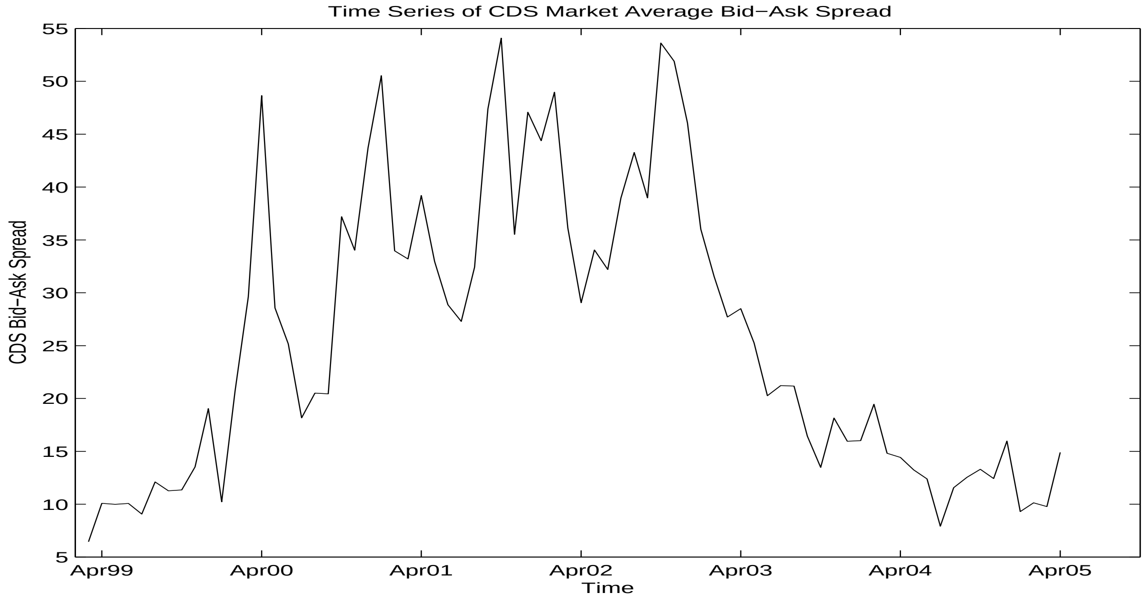

Figure 5.1: Time-series plot of CDS market average bid-ask spread.

evidence is clear. The explanatory power of liquidity has decreased since the beginning of year 2000. Admittedly, it is difficult to judge the statistical significance of the magnitude of this decrease without formal testing. On average, liquidity explains around 40% of the cross-sectional variations in CDS spreads.

We expect CDS market liquidity to have less impact on CDS price as the market environment improves. Figure 5.4 plots the time series of R^2 from regressing CDS price to CDS liquidity proxies (bid-ask spread and number of quotes and trades). At the beginning of the market, liquidity explains around 25 percent of the cross-sectional variations in CDS price. The R^2's has been reduced to 10 percent level before it increased to 15 percent level recently.

Stock market may have special linkage to CDS market due to recent capital structure arbitrage activities. Figure 5.6 plots the time-series of R^2s from the regression of CDS spreads on stock illiquidity (Amihud measure). There seems to exist a regime shift. Prior to 2000, stock illiquidity has more explanatory power than after 2000. One reason is that there are more observations in recent regressions. Overall, it shows that stock illiquidity explains a significant portion of the variations in CDS spreads. The Explanatory power has trended down. We see some evidence that stock liquidity is more associated with CDS spreads at the end of year 2003, which is coincident with the acceleration of capital structure

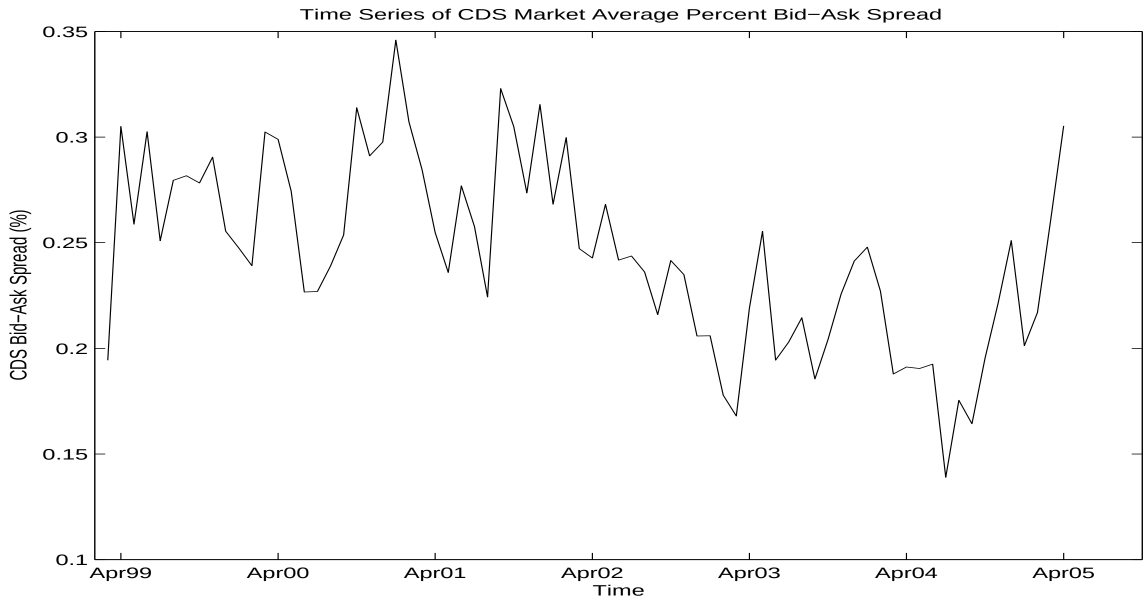

Figure 5.2: Time-series plot CDS market average percentage bid-ask spread.

arbitrage activities around that time. Without rigorous statistical evidence, these are pure speculations.

5.4 Summary and Discussions

Information is key to price formation. Incomplete information and asymmetric information are universal phenomena. In this chapter we show that these factors are significant predictors for CDS spreads. Using various proxies for transparency, we find that more transparent firms have lower credit spreads. Moreover, this effect is most pronounced among low R&D firm or firms with which transparency is less costly. We find both CDS market liquidity and liquidity from stock and option markets explain a substantial portion of credit spreads. Liquidity proxies alone explain around 40% of the cross-sectional variations in credit spreads. We find some evidence that the effect of liquidity on CDS spreads varies over time. It has less explanatory power in more recent time.

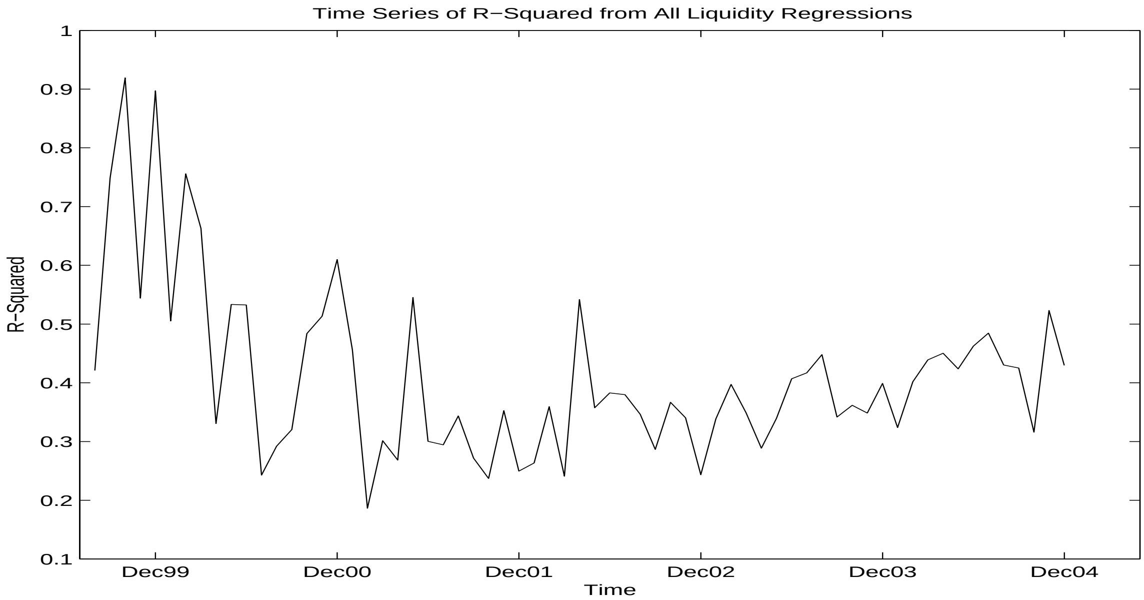

Figure 5.3: Time-series plot of R^2 from regressing CDS spreads on all liquidity proxies.

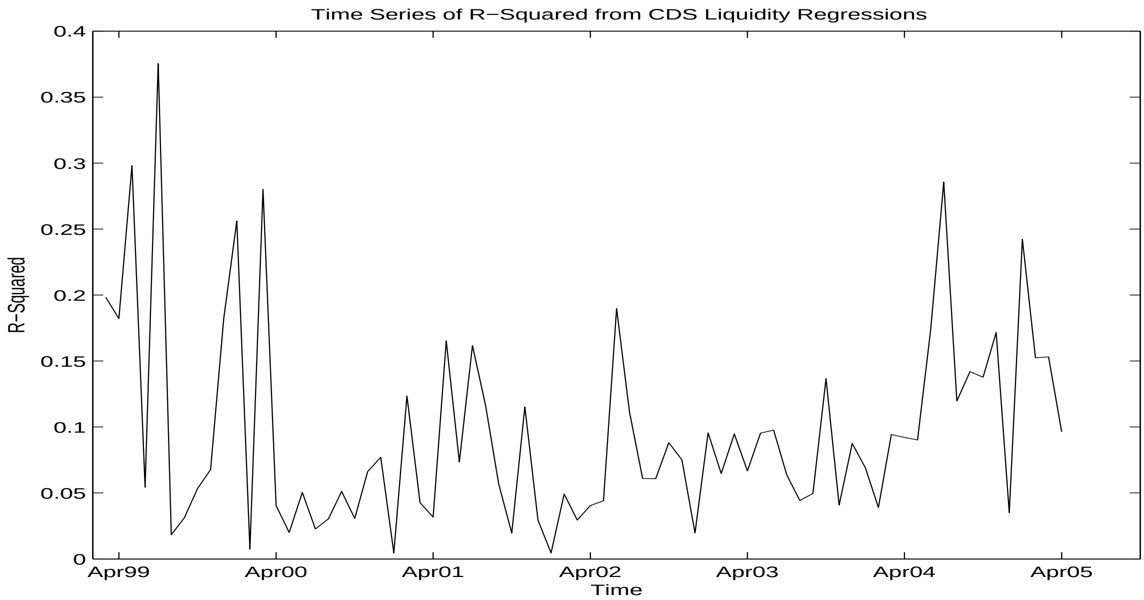

Figure 5.4: Time-series plot of R^2 from regressing CDS spreads on CDS market liquidity proxies (bid-ask spread and number of trades and quotes).

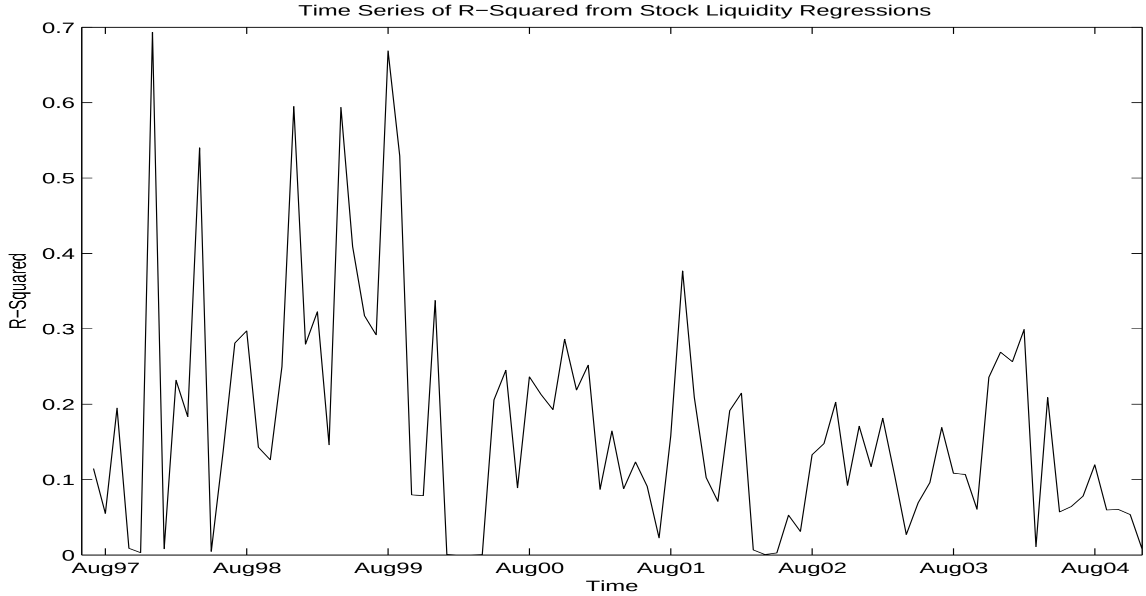

Figure 5.5: Time-series plot of R^2 from regressing CDS spreads on stock liquidity (Amihud measure).

Appendix A

Proofs

A.1 Proof of Lemma 1

From (2.2) we have

$$\mu(s) \quad = \quad \bar{\mu} + (\mu(t) - \bar{\mu})e^{-\kappa(s-t)} + e^{-\kappa s}\sigma_\mu \int_t^s e^{\kappa\tau} dZ_D(\tau) \tag{A.1}$$

and

$$\int_t^s \mu(u)du \quad = \quad \bar{\mu}(s-t) + (\mu(t) - \bar{\mu})B_\kappa(t,s) + \sigma_\mu \int_t^s B_\kappa(\tau, s) dZ_D(\tau) \tag{A.2}$$

For notational convenience, define

$$B_\kappa(t,s) = \frac{1 - e^{-\kappa(s-t)}}{\kappa}, \tag{A.3}$$

so we have

$$\begin{aligned} \int_t^s B_\kappa(t,u)du &= \frac{1}{\kappa}\left[(s-t) - B_\kappa(t,s)\right] \\ \int_t^s B_\kappa(t,u)^2 du &= \frac{1}{\kappa^2}\left[(s-t) - 2B_\kappa(t,s) + B_{2\kappa}(t,s)\right] \end{aligned}$$

The time-t price of the risk-free discount bond maturing at time T is given by the discounted payoff under risk-neutral measure $\mathbb{Q}$.

$$\begin{aligned} P(t,T,r(t)) &= \mathbf{E}_t^{\mathbb{Q}}\left[e^{-\int_t^T r(u)du}\right] = \mathbf{E}_t\left[e^{-\int_t^T \frac{1}{2}\theta^2 du - \int_t^T \theta dZ_D(u) - \int_t^T r(u)du}\right] \\ &= \mathbf{E}_t\left[\frac{\pi(T)}{\pi(t)}\right] = \mathbf{E}_t\left[e^{-\delta(T-t)}\left(\frac{D_T}{D_t}\right)^{-\gamma}\right] \\ &= D_t^\gamma e^{-\delta(T-t)}\mathbf{E}_t\left[D_T^{-\gamma}\right] \end{aligned} \tag{A.4}$$

Using Itô's Lemma, from (1) we have

$$d \ln D_s^{-\gamma} = -\gamma \left[\mu(s) - \frac{1}{2}\sigma_D^2\right] ds - \gamma\sigma_D dZ_D(s) \tag{A.5}$$

and

$$\begin{aligned}
\mathbf{E}_t\left[\ln D_T^{-\gamma}\right] &= \ln D_t^{-\gamma} - \left(\bar{r} - \delta + \frac{1}{2}\gamma^2\sigma_D^2\right)(T-t) - (r(t) - \bar{r})B_\kappa(t,T) &\text{(A.6)}\\
\mathbf{Var}_t\left[\ln D_T^{-\gamma}\right] &= \gamma^2 \int_t^T (\sigma_D + \sigma_\mu B_\kappa(\tau,T))^2 d\tau\\
&= \gamma^2 \left[\left(\sigma_D^2 + \frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)(T-t)\right.\\
&\quad \left. - \left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right)B_\kappa(t,T) + \frac{\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,T)\right]. &\text{(A.7)}
\end{aligned}$$

Because $\ln D_s^{-\gamma}$ is normally distributed, we have

$$P(t,T,r(t)) = D_t^{\gamma} e^{-\delta(T-t)} \exp\left\{\mathbf{E}_t\left[\ln D_T^{-\gamma}\right] + \frac{1}{2}\mathbf{Var}_t\left[\ln D_T^{-\gamma}\right]\right\} = e^{A(t,T) - B_\kappa(t,T)r(t)}, \tag{A.8}$$

where

$$\begin{aligned}
A(t,T) &= -\left[\bar{r} - \frac{1}{2}\gamma^2\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)\right](T-t) + \bar{r}B_\kappa(t,T)\\
&\quad -\frac{1}{2}\gamma^2\left[\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right)B_\kappa(t,T) - \frac{\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,T)\right].
\end{aligned}$$

The first order derivative is given by

$$\frac{\partial P(t,T,r(t))}{\partial T} = \left(\frac{\partial A(t,T)}{\partial T} - \frac{\partial B_\kappa(t,T)}{\partial T}r(t)\right)P(t,T,r(t)), \tag{A.9}$$

where

$$\begin{aligned}
\frac{\partial A(t,T)}{\partial T} &= \left(\gamma^2\sigma_D\sigma_\mu - \kappa\bar{r}\right)B_\kappa(t,T) + \frac{1}{2}\gamma^2\sigma_\mu^2 B_\kappa^2(t,T),\\
\frac{\partial B_\kappa(t,T)}{\partial T} &= e^{-\kappa(T-t)}.
\end{aligned}$$

Q.E.D.

A.2 Proof of Lemma 2

The price of this dividend stream is given by

$$\begin{aligned}
S(t) &= \mathbf{E}_t\left[\int_t^\infty \frac{\pi(s)}{\pi(t)} D_s ds\right] \quad \left(= \mathbf{E}_t^{\mathbb{Q}}\left[\int_t^\infty e^{-\int_t^s r(u)du} D(s)ds\right]\right) && \text{(A.10)}\\
&= \mathbf{E}_t\left[\int_t^\infty e^{-\delta(s-t)}\left(\frac{D_s}{D_t}\right)^{-\gamma} D_s ds\right] && \text{(A.11)}\\
&= D_t^\gamma \int_t^\infty e^{-\delta(s-t)} \mathbf{E}_t\left[D_s^{1-\gamma}\right] ds && \text{(A.12)}
\end{aligned}$$

From Ito's lemma, we have

$$dD_s^{1-\gamma} = (1-\gamma)D_s^{1-\gamma}\left[\mu(s) - \frac{1}{2}\gamma\sigma_D^2\right] ds + (1-\gamma)D_s^{1-\gamma}\sigma_D dZ_D \tag{A.13}$$

Therefore

$$d\ln D_s^{1-\gamma} = (1-\gamma)\left[\mu(s) - \frac{1}{2}\sigma_D^2\right] ds + (1-\gamma)\sigma_D dZ_D(s) \tag{A.14}$$

Therefore

$$\begin{aligned}
\mathbf{E}_t\left[\ln D_s^{1-\gamma}\right] &= \ln D_t^{1-\gamma} + (1-\gamma)\left[\left(\bar{\mu} - \frac{1}{2}\sigma_D^2\right)(s-t) + (\mu(t) - \bar{\mu}) B_\kappa(t,s)\right] && \text{(A.15)}\\
\mathbf{Var}_t\left[\ln D_s^{1-\gamma}\right] &= (1-\gamma)^2 \int_t^s (\sigma_D + \sigma_\mu B_\kappa(\tau,s))^2 d\tau \\
&= (1-\gamma)^2 \left[\left(\sigma_D^2 + \frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)(s-t)\right.\\
&\qquad \left. - \left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right) B_\kappa(t,s) + \frac{\sigma_\mu^2}{\kappa^2} B_{2\kappa}(t,T)\right] && \text{(A.16)}
\end{aligned}$$

Since $\ln D_s^{1-\gamma}$ is conditionally normal, we have

$$\begin{aligned}
S(t) &= D_t^\gamma \int_t^\infty e^{-\delta(s-t)} \exp\left\{\mathbf{E}_t\left[\ln D_s^{1-\gamma}\right] + \frac{1}{2}\mathbf{Var}_t\left[\ln D_s^{1-\gamma}\right]\right\} ds && \text{(A.17)}\\
&= D_t \int_t^\infty \exp(\psi(t,s;r(t)))ds && \text{(A.18)}
\end{aligned}$$

where

$$\begin{aligned}
\psi(t,s;r(t)) &= \left[-\frac{\delta}{\gamma} + \frac{1-\gamma}{\gamma}\bar{r} + \frac{\gamma(1-\gamma)}{2}\sigma_D^2 + \frac{1}{2}(1-\gamma)^2\left(\sigma_D^2 + \frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{\sigma_\mu^2}{\kappa^2}\right)\right](s-t)\\
&\quad + \left[\frac{1-\gamma}{\gamma}(r(t) - \bar{r}) - \frac{1}{2}(1-\gamma)^2\left(\frac{2\sigma_D\sigma_\mu}{\kappa} + \frac{2\sigma_\mu^2}{\kappa^2}\right)\right] B_\kappa(t,s)\\
&\quad + \frac{1}{2}(1-\gamma)^2 \frac{\sigma_\mu^2}{\kappa^2} B_{2\kappa}(t,T)
\end{aligned}$$

Q.E.D.

A.3 Proofs of Lemma 3

Easy calculation shows

$$\xi(s) = \bar{\xi} + (\xi(t) - \bar{\xi})e^{-\lambda(s-t)} + e^{-\lambda s}\sigma_\xi \int_t^s e^{\lambda\tau} dZ_K(\tau)$$

and

$$\int_t^s \xi(u)du = \bar{\xi}(s-t) + (\xi(t) - \bar{\xi})B_\lambda(t,s) + \sigma_\xi \int_t^s B_\lambda(\tau, s)dZ_K(\tau)$$

where

$$B_\lambda(t,s) = \frac{1 - e^{-\lambda(s-t)}}{\lambda}. \tag{A.19}$$

The present value (or unlevered equity price) is given by

$$\begin{aligned}
S_K(t) &= \mathbf{E}_t^{\mathbb{Q}}\left[\int_t^\infty e^{-\int_t^s r(u)du} K(s)ds\right] && \text{(A.20)}\\
&= \mathbf{E}_t\left[\int_t^\infty \frac{\pi(s)}{\pi(t)} K(s)ds\right] && \text{(A.21)}\\
&= \mathbf{E}_t\left[\int_t^\infty e^{-\delta(s-t)} \left(\frac{D_s}{D_t}\right)^{-\gamma} K_s ds\right] && \text{(A.22)}\\
&= D_t^\gamma \int_t^\infty e^{-\delta(s-t)} \mathbf{E}_t\left[D_s^{-\gamma} K_s\right] ds && \text{(A.23)}
\end{aligned}$$

Using Ito's lemma, we have

$$\begin{aligned}
d\ln\left(D_s^{-\gamma} K_s\right) &= \left[(\beta - \gamma)\mu(t) + \xi(s) + \frac{1}{2}\gamma\sigma_D^2 - \frac{1}{2}\sigma_K^2\right] ds && \text{(A.24)}\\
&\quad + (\rho\sigma_K - \gamma\sigma_D)dZ_D(s) + \sigma_K\sqrt{1-\rho^2}dZ_K(s)
\end{aligned}$$

Therefore

$$\begin{aligned}
\mathbf{E}_t\left[\ln\left(D_s^{-\gamma}K_s\right)\right] &= \ln\left(D_t^{-\gamma}K_t\right)+\left[(\beta-\gamma)\bar{\mu}+\bar{\xi}+\frac{1}{2}\gamma\sigma_D^2-\frac{1}{2}\sigma_K^2\right](s-t)\\
&\quad+(\beta-\gamma)(\mu(t)-\bar{\mu})B_\kappa(t,s)+(\xi(t)-\bar{\xi})B_\lambda(t,s)\\
\mathbf{Var}_t\left[\ln\left(D_s^{-\gamma}K_s\right)\right] &= \int_t^s\Big(\left[(\beta-\gamma)\sigma_\mu B_\kappa(\tau,s)+\rho\sigma_K-\gamma\sigma_D\right]^2\\
&\qquad+\left[\sigma_K\sqrt{1-\rho^2}+\sigma_\xi B_\lambda(\tau,s)\right]^2\Big)d\tau\\
&= \Bigg[(\rho\sigma_K-\gamma\sigma_D)^2+\sigma_K^2(1-\rho^2)+2(\beta-\gamma)(\rho\sigma_K-\gamma\sigma_D)\frac{\sigma_\mu}{\kappa}\\
&\qquad+2\sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda}+\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}+\frac{\sigma_\xi^2}{\lambda^2}\Bigg](s-t)\\
&\quad-2\left[(\beta-\gamma)(\rho\sigma_K-\gamma\sigma_D)\frac{\sigma_\mu}{\kappa}+\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}\right]B_\kappa(t,s)\\
&\quad-2\left[\sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda}+\frac{\sigma_\xi^2}{\lambda^2}\right]B_\lambda(t,s)\\
&\quad+\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,s)+\frac{\sigma_\xi^2}{\lambda^2}B_{2\lambda}(t,s)
\end{aligned}$$

Because $\ln\left(D_s^{-\gamma}K_s\right)$ is conditionally normal, we have

$$S_K(t) = D_t^{\gamma}\int_t^\infty e^{-\delta(s-t)}\exp\left\{\mathbf{E}_t\left[\ln\left(D_s^{-\gamma}K_s\right)\right]+\frac{1}{2}\mathbf{Var}_t\left[\ln\left(D_s^{-\gamma}K_s\right)\right]\right\}ds \tag{A.25}$$

$$= K_t\int_t^\infty \exp(\psi_K(t,s;\mu(t),\xi(t)))ds \tag{A.26}$$

where

$$\begin{aligned}
&\psi_K(t,s;\mu(t),\xi(t))\\
&= \Bigg[-\delta+(\beta-\gamma)\bar{\mu}+\bar{\xi}+\frac{1}{2}\gamma\sigma_D^2-\frac{1}{2}\sigma_K^2+\frac{1}{2}(\rho\sigma_K-\gamma\sigma_D)^2+\frac{1}{2}\sigma_K^2(1-\rho^2)\\
&\qquad+(\beta-\gamma)(\rho\sigma_K-\gamma\sigma_D)\frac{\sigma_\mu}{\kappa}+\sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda}+\frac{1}{2}\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}+\frac{1}{2}\frac{\sigma_\xi^2}{\lambda^2}\Bigg](s-t)\\
&\quad+(\beta-\gamma)(\mu(t)-\bar{\mu})B_\kappa(t,s)+(\xi(t)-\bar{\xi})B_\lambda(t,s)\\
&\quad-\left[(\beta-\gamma)(\rho\sigma_K-\gamma\sigma_D)\frac{\sigma_\mu}{\kappa}+\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}\right]B_\kappa(t,s)\\
&\quad-\left[\sqrt{1-\rho^2}\frac{\sigma_K\sigma_\xi}{\lambda}+\frac{\sigma_\xi^2}{\lambda^2}\right]B_\lambda(t,s)\\
&\quad+\frac{1}{2}\frac{(\beta-\gamma)^2\sigma_\mu^2}{\kappa^2}B_{2\kappa}(t,s)+\frac{1}{2}\frac{\sigma_\xi^2}{\lambda^2}B_{2\lambda}(t,s)
\end{aligned}$$

Q.E.D.

A.4 Proof of Lemma 4

Under the risk-neutral measure $\mathbb{Q}$ the cash flow dynamics is

$$\begin{aligned} \frac{dK(t)}{K(t)} &= (\beta\mu(t) + \xi(t) - \gamma\rho\sigma_D\sigma_K)dt + \sigma_K\rho dZ_D^{\mathbb{Q}}(t) + \sigma_K\sqrt{1-\rho^2}dZ_K^{\mathbb{Q}}(t), && \text{(A.27)} \\ d\xi(t) &= \lambda(\bar{\xi} - \xi(t))dt + \sigma_\xi dZ_K^{\mathbb{Q}}(t), && \text{(A.28)} \end{aligned}$$

where $dZ_K^{\mathbb{Q}}(t) = dZ_K(t)$ because $dZ_K(t)$ is independent of $dZ_D(t)$. Using change of numerair:

$$E^{\mathbb{F}_\mathbb{T}}\left[1_{\{A\}}\right] = \mathbf{E}^{\mathbb{Q}}\left[\frac{e^{-\int_0^T r(t)dt}}{P(T,r)}1_{\{A\}}\right], \tag{A.29}$$

we have

$$dZ_D^{\mathbb{Q}}(t) = dZ_D^{\mathbb{F}_\mathbb{T}}(t) + \beta(t)dt \tag{A.30}$$

where

$$\beta(t) = \frac{\gamma\sigma_\mu P_r(t,T,r(t))}{P(t,T,r(t))} = -\gamma\sigma_\mu B_\kappa(t,T). \tag{A.31}$$

Therefore under the forward risk-neutral measure $\mathbb{F}_\mathbb{T}$, the cash flow dynamics is

$$\begin{aligned} \frac{dK(t)}{K(t)} &= (\beta\mu(t) + \xi(t) - \gamma\rho\sigma_D\sigma_K - \gamma\rho\sigma_\mu\sigma_K B_\kappa(t,T))dt && \text{(A.32)} \\ &\quad +\sigma_K\rho dZ_D^{\mathbb{F}_\mathbb{T}}(t) + \sigma_K\sqrt{1-\rho^2}dZ_K^{\mathbb{F}_\mathbb{T}}(t), && \text{(A.33)} \\ d\xi(t) &= \lambda(\bar{\xi} - \xi(t))dt + \sigma_\xi dZ_K^{\mathbb{F}_\mathbb{T}}(t). && \text{(A.34)} \end{aligned}$$

Let $X(t) = \ln(K(t)/c)$, we have

$$\begin{aligned} dX(t) &= \Big(\beta\mu(t) + \xi(t) - \frac{1}{2}\sigma_K^2 - \gamma\rho\sigma_D\sigma_K - \gamma\rho\sigma_\mu\sigma_K B_\kappa(t,T)\Big)dt \\ &\quad +\sigma_K\rho dZ_D^{\mathbb{F}_\mathbb{T}}(t) + \sigma_K\sqrt{1-\rho^2}dZ_K^{\mathbb{F}_\mathbb{T}}(t). \end{aligned}$$

Therefore

$$\begin{aligned} X(s) &= X(t) + \beta\int_t^s \mu(u)du + \int_t^s \xi(u)du - \left(\frac{1}{2}\sigma_K^2 + \gamma\rho\sigma_D\sigma_K\right)(s-t) \\ &\quad -\frac{\gamma\rho\sigma_\mu\sigma_K}{\kappa}\left[(s-t) - e^{-\kappa(T-s)}B_\kappa(t,s)\right] \\ &\quad +\sigma_K\left[\int_t^s \rho dZ_D^{\mathbb{F}_\mathbb{T}}(u) + \sqrt{1-\rho^2}\int_t^s dZ_K^{\mathbb{F}_\mathbb{T}}(u)\right]. \end{aligned}$$

Recall

$$\begin{aligned}
\mu(s) &= \bar{\mu} + (\mu(t) - \bar{\mu})e^{-\kappa(s-t)} - \gamma\sigma_D\sigma_\mu B_\kappa(t,s) \\
&\quad -\frac{\gamma\sigma_\mu^2}{\kappa}\Big[B_\kappa(t,s) - e^{-\kappa(T-s)}B_{2\kappa}(t,s)\Big] + e^{-\kappa s}\sigma_\mu \int_t^s e^{\kappa\tau} dZ_D^{\mathbb{F}_\mathbb{T}}(\tau),
\end{aligned}$$

therefore

$$\begin{aligned}
\int_t^s \mu(u)du &= \bar{\mu}(s-t) + (\mu(t) - \bar{\mu})B_\kappa(t,s) - \frac{\gamma\sigma_D\sigma_\mu}{\kappa}\Big[(s-t) - B_\kappa(t,s)\Big] \\
&\quad -\frac{\gamma\sigma_\mu^2}{\kappa}\left[\frac{1}{\kappa}\Big((s-t) - B_\kappa(t,s)\Big) - \frac{1}{2}e^{-\kappa(T-s)}B_\kappa^2(t,s)\right] \\
&\quad +\sigma_\mu \int_t^s B_\kappa(u,s) dZ_D^{\mathbb{F}_\mathbb{T}}(u)
\end{aligned}$$

We also have

$$\int_t^s \xi(u)du = \bar{\xi}(s-t) + (\xi(t) - \bar{\xi})B_\lambda(t,s) + \sigma_\xi \int_t^s B_\lambda(\tau,s)dZ_K(\tau).$$

Therefore we have the conditional mean

$$\begin{aligned}
\mathbf{E}_t^{\mathbb{F}_\mathbb{T}}[X_s] &= X(t) + \left[\beta\bar{\mu} + \bar{\xi} - \beta\frac{\gamma\sigma_D\sigma_\mu}{\kappa} - \beta\frac{\gamma\sigma_\mu^2}{\kappa^2} - \frac{\gamma\rho\sigma_\mu\sigma_K}{\kappa} - \frac{1}{2}\sigma_K^2 - \gamma\rho\sigma_D\sigma_K\right](s-t) \\
&\quad +\beta(\mu(t) - \bar{\mu})B_\kappa(t,s) + (\xi(t) - \bar{\xi})B_\lambda(t,s) + \beta\frac{\gamma\sigma_D\sigma_\mu}{\kappa}B_\kappa(t,s) + \beta\frac{\gamma\sigma_\mu^2}{\kappa^2}B_\kappa(t,s) \\
&\quad +\frac{\gamma\rho\sigma_\mu\sigma_K}{\kappa}e^{-\kappa(T-s)}B_\kappa(t,s) + \beta\frac{\gamma\sigma_\mu^2}{2\kappa}e^{-\kappa(T-s)}B_\kappa^2(t,s)
\end{aligned}$$

and conditional covariance, where $s_1 < s_2$,

$$
\begin{aligned}
\mathbf{Cov}_t^{\mathbb{F}_{\mathbb{T}}}[X_{s_1}, X_{s_2}] &= \int_t^{s_1} \Big[\big(\rho\sigma_K + \beta\sigma_\mu B_\kappa(\tau, s_1)\big)\big(\rho\sigma_K + \beta\sigma_\mu B_\kappa(\tau, s_2)\big) \\
&\qquad + \big(\sigma_K\sqrt{1-\rho^2} + \sigma_\xi B_\lambda(\tau, s_1)\big)\big(\sigma_K\sqrt{1-\rho^2} + \sigma_\xi B_\lambda(\tau, s_2)\big)\Big] d\tau \\
&= \int_t^{s_1} \Big[\sigma_K^2 + \beta\rho\sigma_K\sigma_\mu\big(B_\kappa(\tau, s_1) + B_\kappa(\tau, s_2)\big) + \beta^2\sigma_\mu^2 B_\kappa(\tau, s_1)B_\kappa(\tau, s_2) \\
&\qquad + \sigma_K\sigma_\xi\sqrt{1-\rho^2}\big(B_\lambda(\tau, s_1) + B_\lambda(\tau, s_2)\big) + \sigma_\xi^2 B_\lambda(\tau, s_1)B_\lambda(\tau, s_2)\Big] d\tau \\
&= \left[\sigma_K^2 + \frac{2\beta\rho\sigma_K\sigma_\mu}{\kappa} + \frac{\beta^2\sigma_\mu^2}{\kappa^2} + \frac{2\sigma_K\sigma_\xi\sqrt{1-\rho^2}}{\lambda} + \frac{\sigma_\xi^2}{\lambda^2}\right](s_1 - t) \\
&\quad - \left(1 + e^{-\kappa(s_2 - s_1)}\right)\left[\frac{\beta\rho\sigma_K\sigma_\mu}{\kappa} + \frac{\beta^2\sigma_\mu^2}{\kappa^2}\right] B_\kappa(t, s_1) \\
&\quad - \left(1 + e^{-\lambda(s_2 - s_1)}\right)\left[\frac{\sigma_K\sigma_\xi\sqrt{1-\rho^2}}{\lambda} + \frac{\sigma_\xi^2}{\lambda^2}\right] B_\lambda(t, s_1) \\
&\quad + e^{-\kappa(s_2 - s_1)}\frac{\beta^2\sigma_\mu^2}{\kappa^2} B_{2\kappa}(t, s_1) + e^{-\lambda(s_2 - s_1)}\frac{\sigma_\xi^2}{\lambda^2} B_{2\lambda}(t, s_1)
\end{aligned}
$$

Under the physical measure $\mathbb{P}$, the expected mean is

$$
\begin{aligned}
E_t^{\mathbb{P}}[X_s] &= X(t) + \Big[\beta\bar{\mu} + \bar{\xi} - \frac{1}{2}\sigma_K^2 - \gamma\rho\sigma_D\sigma_K\Big](s - t) \\
&\quad + \beta(\mu(t) - \bar{\mu})B_\kappa(t, s) + (\xi(t) - \bar{\xi})B_\lambda(t, s)
\end{aligned}
$$

Expected variances and covariances are the same as in the risk-neutral T-forward measure. **Q.E.D.**

A.5 Proof of Proposition 1

The expected payoff stream of this coupon bond is

$$g(t) = c \cdot \mathbf{1}(t \le T) \cdot \mathbf{1}(t < \tau) + F \cdot \delta(t - T) \cdot \mathbf{1}(t < \tau) + w(\mu_t)F \cdot \delta(t - \tau) \cdot \mathbf{1}(t \le T). \quad \text{(A.35)}$$

Assume the recovery rate is proportional to economy growth rate,

$$w(\mu_t) = a + b\mu_t, \quad \text{(A.36)}$$

where $b \ge 0$.

$$\begin{aligned}
DV &= \mathbf{E}^{\mathbb{Q}}\left[\int_0^T e^{-\int_0^t r(s)ds} g(t)dt\right] \\
&= c\int_0^T \mathbf{E}^{\mathbb{Q}}\left[e^{-\int_0^t r(s)ds}\mathbf{1}(t<\tau)\right]dt + F\cdot \mathbf{E}^{\mathbb{Q}}\left[e^{-\int_0^T r(s)ds}\mathbf{1}(T<\tau)\right] \\
&\quad + F\int_0^T \mathbf{E}^{\mathbb{Q}}\left[e^{-\int_0^t r(s)ds} w(\mu_t)\delta(t-\tau)\right]dt \\
&= c\int_0^T P(0,t,r(0))\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}\left[\mathbf{1}(t<\tau)\right]dt + F\cdot P(0,T,r(0))\cdot \mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}\left[\mathbf{1}(T<\tau)\right] \\
&\quad + F\int_0^T P(0,t,r(0))\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}\left[w(\mu_t)\right]\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}\left[\delta(t-\tau)\right]dt \\
&= FV - EL
\end{aligned}$$

where

$$FV = c\int_0^T P(0,t,r(0))dt + F\cdot P(0,T,r(0)),$$

is the value of a default risk-free bond with identical payment structure, and

$$\begin{aligned}
EL &= c\int_0^T P(0,t,r(0))\Gamma(t)dt + (1-a-b\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[\mu(t)])F\cdot P(0,T,r(0))\cdot\Gamma(T) \\
&\quad + F\int_0^T \left(P_t(0,t,r(0))(a+b\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[\mu(t)]) + P(0,t,r(0))b\frac{\partial \mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[\mu(t)]}{\partial t}\right)\Gamma(t)dt
\end{aligned}$$

is the expected loss of the risky bond, where $\Gamma(t) \equiv \mathbf{E}^{\mathbb{F}_{\mathbb{T}}}\left[\mathbf{1}(\tau \le t)\right]$ is the cumulative distribution function of τ in the risk neutral T-forward measure (which represetns the probability that the firm will default before time t), its density function is $f(t) \equiv \mathbf{E}^{\mathbb{F}_{\mathbb{T}}}\left[\delta(t-\tau)\right]$, and $P_t(0,t,r(0)) = \partial P_t(0,t,r(0))/\partial t$.

From (2.2) we have

$$\begin{aligned}
\mu(s) &= \bar{\mu} + (\mu(t)-\bar{\mu})e^{-\kappa(s-t)} - \gamma\sigma_D\sigma_\mu B_\kappa(t,s) \\
&\quad -\frac{\gamma\sigma_\mu^2}{\kappa}\left[B_\kappa(t,s) - e^{-\kappa(T-s)}B_{2\kappa}(t,s)\right] + e^{-\kappa s}\sigma_\mu\int_t^s e^{\kappa\tau}dZ_D^{\mathbb{F}_{\mathbb{T}}}(\tau)
\end{aligned}$$

Therefore

$$\begin{aligned}
\mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[\mu(t)] &= \bar{\mu} + (\mu(0)-\bar{\mu})e^{-\kappa t} - \gamma\sigma_D\sigma_\mu B_\kappa(0,t) \\
&\quad -\frac{\gamma\sigma_\mu^2}{\kappa}\left[B_\kappa(0,t) - e^{-\kappa(T-t)}B_{2\kappa}(0,t)\right] \\
\frac{\partial \mathbf{E}_0^{\mathbb{F}_{\mathbb{T}}}[\mu(t)]}{\partial t} &= -\left[\kappa(\mu(0)-\bar{\mu}) + \gamma\sigma_D\sigma_\mu + \frac{\gamma\sigma_\mu^2}{\kappa}\right]e^{-\kappa t} \\
&\quad +\gamma\sigma_\mu^2 e^{-\kappa(T-t)}\frac{1+e^{-2\kappa t}}{2\kappa}
\end{aligned}$$

Q.E.D.

Appendix B

Moody's KMV's Algorithm

KMV applies Merton's model to estimate firm's monthly EDF. KMV does not directly use Merton's (1974) model. It uses a variant of it derived by Vasicek. The difficulty for the Merton model lies in backing out asset value and asset volatility using stock price, stock volatility, and debt level. A recursive approach is used. See Vassalou and Xing (2003) and Bharath and Shumway (2004) for more details.

B.1 Calculating Asset Volatility and Asset Value

Assume standard geometric Brownian motion for firm's asset value process:

$$\frac{dV}{V} = \mu dt + \sigma_V dW. \tag{B.1}$$

The firm has debt X outstanding with maturity T. Using Black and Scholes (1973) formula, we find the firm's equity value is:

$$S = VN(d_1) - Xe^{-rT}N(d_2), \tag{B.2}$$

where

$$d_1 = \frac{\ln(V/X) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}, \quad d_2 = d_1 - \sigma_A\sqrt{T}. \tag{B.3}$$

For each month, equity volatility is used as the root. Together with stock price, asset value can be calculated. Using volatility of asset value for the repetition until convergence is reached.

B.2 Obtaining EDF Measures

After obtaining asset value and asset volatility, distance to default is easily computed:

$$DD = \frac{\ln(V/X) + (\mu - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}. \tag{B.4}$$

KMV uses a comprehensive proprietary historical default database to map distance to default to EDF.

Appendix C

Variable Definitions and Correlation Matrix

IV: At-the-money option implied volatility from OptionMetrics.

Jump: Slope of implied volatility curve from OptionMetics.

KMV AV: Asset volatility estimated by KMV.

Credit rating: Numerical rating converted from letter ratings, with AAA assigned a number 35.

EDF5: KMV's five-year EDF.

Leverage: Market leverage.

CVCF: Coefficient of variation on quarterly cash flow.

Profitability: Operating cash flow to total asset ratio.

B/M: Book-to-market ratio.

Market cap: Firm's stock price multiplied by shares outstanding.

PIN: Probability of informed trading.

ARScore: S&P disclosure score based on annual reports.

OverallScore: S&P disclosure score based on all reports.

AGR: Audit Integrity accounting and governance ranking.

Forecast Dispersion: I/B/E/S first year EPS forecast standard deviation over forecast mean.

CDS B/A Spread: CDS bid-ask spread over mid quote.

CDS NQT: CDS number of quotes and trades per month.

Average Coupon: Average coupon per issuer for all bonds in FISD database.

Average Maturity: Average maturity per issuer for all bonds in FISD database.

Average Age: Average age per issuer for all bonds in FISD database.

Bond Outstanding: Total bond amount outstanding per issuer for all bonds in FISD databse.

Stock Illiquidity: Amihud measure of stock illiquidity, measured as monthly average absolute return over volume.

Stock Trading Costs: Hasbrouck's Gibbs Sampler measure of trading costs.

Option B/A spread: Monthly average bid-ask spread for options in OptionMetrics.

Option Volume: Monthly average trading volume for options in OptionMetrics.

Option open interest: Monthly average total open interest for options in OptionMetics.

Table C.1: Overall Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
IV (1)	1.00												
Jump (× 100) (2)	0.02	1.00											
KMV AV (3)	0.39	-0.01	1.00										
Credit Rating (4)	-0.26	-0.10	-0.09	1.00									
EDF5 (%) (5)	0.62	0.06	0.31	-0.41	1.00								
Leverage (6)	0.21	0.07	-0.48	-0.15	0.41	1.00							
CVCF (7)	0.08	0.01	0.10	-0.11	0.11	-0.02	1.00						
Profitability (8)	-0.06	-0.02	-0.28	0.03	-0.09	-0.13	-0.03	1.00					
B/M (9)	0.02	0.00	0.00	0.00	0.01	0.00	0.00	-0.01	1.00				
Market Cap ($ Billion) (10)	-0.12	-0.05	0.10	0.52	-0.20	-0.20	-0.01	0.04	-0.01	1.00			
PIN (11)	0.14	0.07	0.11	-0.32	0.20	0.09	0.04	-0.01	0.04	-0.32	1.00		
ARScore (12)	-0.05	0.00	-0.13	0.14	-0.05	0.04	-0.04	0.06	0.01	0.04	-0.09	1.00	
OverallScore (13)	0.01	0.00	-0.06	-0.07	0.04	0.15	0.03	-0.02	-0.02	-0.15	-0.06	0.36	1.00
AGR (14)	-0.02	-0.01	-0.06	0.06	-0.06	0.02	-0.05	0.01	0.00	-0.02	0.01	0.04	-0.04
Forecast Dispersion (15)	0.21	0.03	0.08	-0.24	0.23	0.14	0.10	-0.05	-0.01	-0.14	0.04	0.06	0.01
CDS B/A Spread (16)	-0.05	-0.02	0.06	0.22	-0.13	-0.25	-0.04	0.05	-0.17	0.05	0.05	0.00	-0.05
CDS NQT (17)	0.03	0.01	0.03	-0.05	0.06	-0.01	0.12	0.01	0.00	0.01	-0.06	0.00	0.05
Average Coupon (18)	0.12	0.04	-0.09	-0.31	0.11	0.04	-0.04	-0.02	0.14	-0.31	0.14	0.12	0.09
Average Maturity (18)	-0.06	0.02	-0.05	0.11	-0.10	-0.09	-0.03	-0.08	-0.04	-0.05	-0.03	0.03	0.13
Average Age (19)	-0.04	0.01	-0.15	-0.02	-0.05	-0.03	-0.06	0.06	-0.02	-0.15	0.03	0.11	0.05
Bond Outstanding (20)	-0.04	-0.01	-0.08	0.21	-0.06	0.19	-0.01	-0.01	-0.05	0.38	-0.19	-0.03	-0.10
Stock Illiquidity (21)	0.31	0.15	0.03	-0.24	0.38	0.15	-0.01	-0.03	0.01	-0.21	0.37	-0.05	0.03
Stock Trading Costs (22)	0.42	0.00	0.16	-0.15	0.26	0.09	0.02	-0.03	0.00	-0.03	-0.03	-0.02	0.02
Option B/A Spread (23)	0.02	0.01	-0.14	-0.03	-0.12	0.06	-0.07	0.00	-0.01	-0.13	-0.01	-0.05	0.02
Option Volume (24)	0.11	0.00	0.24	0.23	-0.01	-0.09	0.04	0.01	-0.01	0.56	-0.24	0.03	-0.09
Option Open Interest (25)	0.07	-0.02	0.26	0.18	0.07	-0.07	0.06	0.00	-0.01	0.54	-0.31	0.05	-0.04

Table C.1: Overall Correlation Matrix (Continued)

	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
IV (1)													
Jump (× 100) (2)													
KMV AV (3)													
Credit Rating (4)													
EDF5 (%) (5)													
Leverage (6)													
CVCF (7)													
Profitability (8)													
B/M (9)													
Market Cap ($ Billion) (10)													
PIN (11)													
ARScore (12)													
OverallScore (13)													
AGR (14)	1.00												
Forecast Dispersion (15)	-0.02	1.00											
CDS B/A Spread (16)	0.07	-0.12	1.00										
CDS NQT (17)	-0.06	0.07	-0.25	1.00									
Average Coupon (18)	0.06	0.08	-0.01	-0.07	1.00								
Average Maturity (18)	0.02	0.01	0.04	-0.01	-0.14	1.00							
Average Age (19)	0.07	0.01	0.01	-0.06	0.39	0.10	1.00						
Bond Outstanding (20)	0.04	-0.02	-0.07	0.03	-0.37	-0.16	-0.11	1.00					
Stock Illiquidity (21)	0.06	0.16	0.04	-0.06	0.23	-0.02	0.03	-0.15	1.00				
Stock Trading Costs (22)	-0.03	0.10	-0.08	0.01	0.06	0.05	0.00	0.01	0.25	1.00			
Option B/A Spread (23)	0.14	-0.05	0.18	-0.20	0.18	0.06	0.10	-0.11	0.18	0.00	1.00		
Option Volume (24)	-0.10	-0.02	-0.07	0.15	-0.31	-0.05	-0.09	0.42	-0.27	0.05	-0.24	1.00	
Option Open Interest (25)	-0.13	0.02	-0.15	0.21	-0.28	-0.03	-0.06	0.38	-0.29	0.04	-0.34	0.81	1.00

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