THREE ESSAYS IN EMPIRICAL STUDIES ON DERIVATIVES

by

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Abstract

This thesis is a collection of three essays in empirical studies on derivatives. In the first chapter, I investigate whether credit default swap spreads are affected by how the total risk is decomposed into the systematic risk and the idiosyncratic risk for a given level of the total risk. The risk composition is measured by the systematic risk proportion, defined as the proportion of the systematic variance in the total variance. I find that a firm’s systematic risk proportion has a negative and significant effect on its CDS spreads. Moreover, this empirical finding is robust to various alternative specifications and estimations. Therefore, the composition of the total risk is an important determinant of CDS spreads.

In the second chapter, I estimate the illiquidity premium in the CDS spreads based on Jarrow’s illiquidity-modified Merton model using the transformed-data maximum likelihood estimation method. I find that the average model implied CDS illiquidity premium is about 15 basis points, accounting for 12% of the average level of the CDS
spread. I further investigate how this parameter is affected by CDS liquidity measures such as the percentage bid-ask spread and the number of daily CDS spreads available in one month. I find that both liquidity measures are significant determinants of the model implied CDS illiquidity premium. In terms of relative importance, the bid-ask spread is more important than the number of daily CDS spreads statistically and economically.

In the third chapter, I investigate the impact of the systematic risk on the volatility spread, i.e., the difference between the risk-neutral volatility and the physical volatility. I find that the systematic risk proportion of an underlying asset has a positive and significant impact on its volatility spread. The risk-neutral volatility in this study is measured with the increasingly popular approach known as the model-free risk-neutral volatility. The surprising positive systematic risk effect was first documented in Duan and Wei (2009) using the Black-Scholes implied volatility. I show that this effect is actually more prominent using the clearly better model-free risk-neutral volatility measure.
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# Table of Contents

Abstract ........................................................................................................................................ ii

Acknowledgements ................................................................................................................ iv

Table of Contents ...................................................................................................................... v

List of Tables ........................................................................................................................... viii

List of Figures .......................................................................................................................... ix

Chapter 1 Credit Default Swap Spreads and the Composition of the Total Risk ............... 1

1.1 Introduction ......................................................................................................................... 1

1.2 Data ..................................................................................................................................... 5

1.2.1 Credit Risk Measure .................................................................................................... 5

1.2.2 Risk Composition Measure ....................................................................................... 7

1.2.3 Total Risk Measure ..................................................................................................... 8

1.2.4 Other Control Variables ............................................................................................. 10

1.2.5 Merged Data and Summary Statistics ....................................................................... 10

1.3 Regression Analysis .......................................................................................................... 12

1.4 Robustness Checks ............................................................................................................ 15

1.4.1 Panel Regressions ....................................................................................................... 16

1.4.2 Systematic Risk Estimation Using Fama-French Factors ........................................ 16

1.4.3 GARCH Volatilities ..................................................................................................... 18

1.4.4 More Controls – Size and Liquidity ............................................................................ 21

1.4.5 Excluding Small Firms ............................................................................................... 23

1.5 Discussion .......................................................................................................................... 24
3.4 Conclusion .............................................................................................................. 72

Bibliography...................................................................................................................... 98
List of Tables

Table 1.1: Summary Statistics .......................................................... 74
Table 1.2: Regression Analysis............................................................ 75
Table 1.3: Robustness Checks ............................................................. 76
Table 1.4: Summary Statistics of NGARCH Estimates and NGARCH Volatilities .... 77
Table 1.5: Robustness Check Using NGARCH Volatilities...................... 78
Table 1.6: Robustness Check Using More Controls – Size and Liquidity .......... 79
Table 1.7: Robustness Check Excluding Small Firms............................... 80
Table 1.8: Correlation of CDS Spreads at Different SRP Levels ................. 81
Table 2.1: Summary Statistics of Sample Firms ...................................... 82
Table 2.2: Summary Statistics of Model Parameter Estimates ...................... 83
Table 2.3: Summary Statistics of Subgroups ......................................... 84
Table 2.4: Determinants of the Illiquidity Premium ................................. 85
Table 2.5: The Effect of the Risk Composition on the Illiquidity Premium .... 86
Table 3.1A: Summary Statistics of the Sample .................................... 87
Table 3.1B: Summary Statistics by Year .............................................. 88
Table 3.2: Regression Tests Using the Model-Free Risk-Neutral Volatility ....... 89
Table 3.3: Sub-Sample Regression Tests .............................................. 90
Table 3.4: Regression Tests at Different SRP Levels .............................. 91
List of Figures

Figure 2.1: Time-Series Plots of CDS Spreads and the Number of Firms Available....... 92
Figure 2.2: Time-Series Plots of Liquidity Measures.......................................................... 93
Figure 2.3: Time-Series Plots of the Illiquidity Premium...................................................... 94
Figure 2.4: Time-Series Plots of the Monthly Intercept ......................................................... 95
Figure 3.1: Time Series Plots of the Cross-Sectional Average of Volatilities, the Systematic Risk Proportion, and Volatility Spreads................................................................. 96
Figure 3.2: Time-Series Plots of the Coefficient of the Systematic Risk Proportion....... 97
Chapter 1

Credit Default Swap Spreads and the Composition of the Total Risk

1.1 Introduction

The purpose of this chapter is to examine whether the risk composition (i.e. systematic risk versus idiosyncratic risk) of the underlying firm has an impact on its credit default swap (CDS hereafter) spread. I find that a firm’s systematic risk has a negative and significant effect on its CDS spread for a given level of the total risk.

A major theoretical approach to price credit risk is the structural model framework initiated by Merton (1974). The structural models generally specify how firm value changes over time and derive default from the relationship between firm value and debt value, and, thus, are able to link the prices of credit sensitive securities to the economic determinants of default.\(^1\) Firm leverage, asset volatility, and the risk-free interest rate are three most important theoretical determinants of default risk. As asset volatility is unobservable, equity volatility is often used as a proxy in the literature.

As traditional structural models of default are built on the option-pricing theory of Black and Scholes (1973), prices of credit sensitive securities such as bonds and credit default swaps should be determined by the total risk of the underlying asset (i.e. firm), which leads to two implications. The total risk can be decomposed into the systematic

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risk and the idiosyncratic risk. Hence, the first implication is that both the systematic risk and the idiosyncratic risk of the underlying firm should have an impact on the price of its credit risk. The second implication is that credit spreads should not be determined by how much systematic risk is contained in the underlying asset as long as the total risk is fixed.

Many empirical studies support the first implication. They find that credit spreads can partly be explained by systematic risk factors and idiosyncratic risk factors. For example, Elton, Gruber, Agrawal, and Mann (2001) find that 85% of the part of corporate spot spreads that is not accounted for by taxes and expected default can be explained as a reward for bearing systematic risk. Delianedis and Geske (2001) find that corporate credit spreads are not primarily explained by default and recovery risk, but are mainly attributable to taxes, jumps, liquidity, and market risk factors. Campbell and Taksler (2003) find that idiosyncratic risk and S&P A-rated corporate bond yield spread are highly correlated with a correlation of 0.7. Moreover, idiosyncratic firm-level volatility is significantly and positively related to corporate bond yield spreads.

However, there is no empirical evidence for the second implication. We do not know empirically whether credit spreads are affected by how the total risk is decomposed into the systematic risk and the idiosyncratic risk for a given level of the total risk. This study fills this gap by investigating whether a firm’s risk composition has an impact on its CDS spread.

Using CDS spreads provided by GFI for the period of January 2000 to December 2004, I investigate the effects of the risk composition on CDS spreads for a given level of the total risk after controlling for other fundamental determinants of credit spreads that are commonly used in the literature, i.e. historical volatility, implied volatility level and
slope, leverage, and firm stock return. The variable used to measure the composition of the total risk is the systematic risk proportion, defined as the ratio of the systematic variance over the total variance.

I find that the systematic risk proportion has a negative and significant effect on the CDS spreads. More specifically, the systematic risk proportion has a negative impact on the CDS spreads in 57 months out of 60 months (95%). In terms of economic significance, given the sample standard deviation of 10.46% for the systematic risk proportion, a one standard deviation increase in the systematic risk proportion is associated with 8.68 basis points decrease in the CDS spreads.

I further investigate how robust this empirical finding is. Five robustness checks are presented. I find that the systematic risk proportion has a negative and significant effect on the CDS spreads when 1) using panel regressions, 2) using the systematic risk proportion estimated from three Fama-French factors, 3) using GARCH volatilities rather than historical volatilities, 4) including more control variables such as size and liquidity, and 5) excluding small firms. Hence, my empirical finding is robust to various alternative specifications and estimations. This result suggests that the composition of the total risk is an important determinant of CDS spreads, which does not support the second implication of traditional structural models of default.

Moreover, my finding has a meaning for CDS pricing and trading. Since current pricing models do not consider the effect of the risk composition on CDS spreads, dealers may need to adjust the model spreads for new CDS contracts to reflect the difference in the risk composition of the underlying firm. For instance, dealers may want to charge a premium on a firm that has a lower amount of systematic risk for a given level of total
risk relative to an otherwise identical firm. By the same token, it is also possible for investors to detect mispricing cases and trade accordingly.

One possible explanation based on transaction costs is provided to help understand the negative effect of the systematic risk proportion on the CDS spreads. I argue that a relatively higher price (i.e. spread) for CDS contracts with a lower systematic risk proportion is necessary to compensate for higher transaction or hedging costs of protection sellers. This explanation implies that the systematic risk has the same pricing impact on credit spreads as the idiosyncratic risk and, thus, the risk composition should not matter if there are no transaction costs.

To my best knowledge, this study is the first to identify the effect of the risk composition on the CDS spreads for a given level of the total risk. Duan and Wei (2009) also examine the pricing role of the risk composition for the derivatives. However, they focus on equity options, whereas I focus on credit default swaps. They find that systematic risk does matter for equity option pricing. Specifically, after controlling for the underlying asset’s total risk, a higher amount of systematic risk of the underlying equity leads to a higher level of implied volatility and a steeper slope of the implied volatility curve.

The remainder of this chapter is organized as follows. Section 1.2 describes the CDS data and the explanatory variables used in this study. Summary statistics of the data are also presented in this section. Section 1.3 reports the main empirical findings regarding the role of the risk composition in explaining CDS spreads. Various robustness checks are presented in Section 1.4. One possible explanation is discussed in Section 1.5. Section 1.6 concludes the chapter.
1.2 Data

The purpose of this chapter is to investigate whether CDS spreads are affected by how the total risk is decomposed into the systematic risk and the idiosyncratic risk for a given level of the total risk. Hence, the data used in this chapter include credit risk measure, risk composition measure, total risk (i.e. volatility) measure, and other control variables that are commonly used in the credit risk literature. The sources and methods to construct these variables are discussed as follows.

1.2.1 Credit Risk Measure

A credit derivative is a contingent claim that allows market participants to trade and manage pure credit risk. Due to this important function, in the past several years, the credit derivatives market has grown exponentially from a total notional amount of $180 billion in 1996 to $20 trillion in 2006.\(^2\) Banks, securities houses, insurance companies, and hedge funds constitute the majority of market participants. The most popular credit derivatives product is the credit default swap (CDS), which captures about a third of the market share in 2006. According to the International Swaps and Derivatives Association’s (ISDA) 2008 year-end market survey, the notional amount outstanding of credit default swaps was $38.6 trillion at year-end 2008, down 38 percent from $62.2 trillion at year-end 2007 as a result of the recent credit crunch. The CDS contract protects the buyer against a default by the underlying company or country, called the reference entity. The buyer makes periodic payments to the seller in exchange for the right to sell the bond issued by the reference entity to the seller for its face value if a default, known

\(^2\) See British Bankers’ Association (2006).
as a credit event, occurs. A credit event is typically defined as bankruptcy, failure to pay, or restructuring. The rate of payments made per year is known as the CDS spread and denoted in basis points.

Before the appearance of the credit derivatives market, corporate bond spreads are used to measure a firm’s credit risk. However, the rapid growing credit derivatives market makes CDS spreads a better measure of credit risk than corporate bond spreads due to the following reasons. First, corporate bond spreads are found to contain substantial tax premium due to the different tax treatments between corporate bonds and Treasury bonds (see Elton, Gruber, Agrawal, and Mann (2001) for example). Second, corporate bond markets are very illiquid. Edwards, Harris, and Piwowar (2007) find that the average number of trades per day is only 2.4. Third, the embedded options and the need to choose an appropriate reference for the risk-free rate make the calculation of bond spreads complicated. Fourth, transaction data of bonds are unavailable to the public before the introduction of the Transaction Reporting and Compliance Engine (TRACE) in July 2002.

This study uses CDS spreads to measure credit risk. My CDS spreads are provided by GFI, a broker specialized in credit derivatives trading. The data contains intra-day bid/ask quotes from January 1998 to December 2004. As in Predescu (2005) and Cao, Yu, and Zhong (2006), five-year CDS spreads are used in this analysis as they are the most common contracts in the CDS market. Only the quotes on senior debt are considered. Daily CDS spreads are generated from intra-day quotes using the following algorithm:
When there are pairs of bid and ask in a day, the daily CDS spread is the average of the last pair of bid and ask on that day. A pair of bid and ask means that a bid and an ask are provided at the same time.

When there are no pairs of bid and ask in a day, the last non-zero quote (bid or ask) is used to compute the other one (ask or bid) by assuming that the percentage bid-ask spread remains the same as the one on the previous most recent day. The CDS spread is then computed as the average of the last non-zero quote (bid or ask) and the computed counterpart (ask or bid).

### 1.2.2 Risk Composition Measure

This chapter is aimed at investigating the effect of the risk composition (i.e. systematic risk versus idiosyncratic risk) on CDS spreads for a given level of the total risk. The variable used to measure the composition of the total risk is the systematic risk proportion \( (srp) \), proposed by Duan and Wei (2009) and defined as the proportion of the systematic risk in the total risk. Specifically, I regress daily stock returns on S&P 500 index returns using a one-year rolling window of daily returns for each stock. The one-year window is rolled over by one day. Stock returns and index returns are retrieved from CRSP daily files. The regression equation is given below:

\[
R_{jt} = \alpha_j + \beta_j R_{mt} + \epsilon_{jt} \tag{1.1}
\]

The systematic risk and the total risk can be calculated as \( \beta_j^2 \sigma_m^2 \) and \( \sigma_j^2 \) for stock \( j \). The systematic risk proportion is simply \( b_j = \beta_j^2 \sigma_m^2 / \sigma_j^2 \) for a particular day.
1.2.3 Total Risk Measure

The relevant volatility in credit risk pricing is asset volatility. As a firm’s asset volatility is unobservable, equity volatility is often used as a proxy in the literature. For example, Ericsson, Jacobs, and Oviedo (2004) find that theoretical determinants of default risk such as firm leverage, equity volatility, and the risk-free interest rate explain around 60% of CDS spreads. Zhang, Zhou, and Zhu (2005) focus on the effects of equity volatility and jump risks on CDS spreads. They find that volatility risk alone predicts 50% of the variation in CDS spreads, while jump risk alone forecasts 19%.

While many researchers focus on the effects of historical volatility, a few other researchers also look at the effects of option-implied volatility. They argue that implied volatility is more relevant because it is a forward-looking measure of equity volatility while historical volatility is a historical measure. Benkert (2004) finds that option-implied volatility is a more important factor in explaining variation in CDS spreads than historical volatility. Cao, Yu, and Zhong (2006) provide further evidence that the information content of historical volatility is subsumed by option-implied volatility in explaining CDS spreads, suggesting that option-implied volatility contains additional information about the equity beyond historical volatility which captures only the total risk of the equity. In the corporate bond market, Cremers, Driessen, Maenhout, and Weinbaum (2004) find that the option-implied volatility and the implied volatility skew both matter for credit spreads. They provide further empirical support for the claim that individual options are relevant for understanding credit risk by showing the impact of option-market liquidity on the credit spreads of short-maturity bonds, and by documenting that option-implied volatilities anticipate downward credit rating migrations.
In this study, I use both historical volatility \((HV)\) and option-implied volatility \((IV)\). The daily historical volatility is the annualized standard deviation from the 252-day rolling window (annualization is done by multiplying \(\sqrt{252}\) to the daily volatilities). Option-implied volatilities are obtained from OptionMetrics. For each firm and on each day, I calculate the average of implied volatilities for out-of-the-money calls and puts with nonzero open interest to proxy for the level of the implied volatility curve.\(^3\) Level is just one measure of the implied volatility curve. To better capture the information in the implied volatility curve, I also estimate the slope of the implied volatility curve as in Bakshi, Kapadia, and Madan (2003).\(^4\) An advantage of this specification is its potential consistency with empirical implied volatility curves that are both decreasing and convex in moneyness. The regression equation is shown as follows:

\[
\ln(\sigma_{jk}^{imp}) = a_0 + a_{1j} \ln(y_{jk}) + a_{2j} \ln(T_{jk}) + \epsilon_{jk}, \quad k = 1, \cdots, N
\]

(1.2)

where \(y_{jk}\) is the moneyness of stock \(j\)’s \(k\)th option, \(T_{jk}\) is the time-to-maturity (in days) of stock \(j\)’s \(k\)th option, and \(N\) is the number of stock \(j\)’s options for a particular day. On each day, the regression coefficient \(a_{1j}\) is my measure of the slope of the implied volatility curve \((IVS)\) for stock \(j\).

\(^3\) In-the-money option prices are notoriously unreliable because in-the-money options are very infrequently traded relative to at-the-money and out-of-the-money options. The choice of nonzero open interest emphasizes the information content of options that are currently in use by market participants.

\(^4\) I also include time-to-maturity in the regression to account for the term structure of implied volatilities. For all regressions, I require that at least 10 options are available in order to compute the slope. In fact, the average number of implied volatilities is 32 per day in my data set. Therefore, the small sample problem is not a big issue.
1.2.4 Other Control Variables

Another key determinant of default risk suggested by structural models of default is firm leverage. Leverage \((lev)\) is defined as total liabilities divided by the sum of total liabilities and the market value of common stock. Equity prices and common shares outstanding are retrieved from CRSP daily files. Total liabilities are retrieved from Compustat quarterly files. To avoid any issues related to reporting delays, leverage is calculated using total liabilities reported in the most recent fiscal quarter, with the requirements that 90 days have elapsed from the end of the previous fiscal year end (i.e. the 4\(^{th}\) fiscal quarter) and 45 days from the end of each of the first three fiscal quarters. For example, total liabilities for the fourth quarter of 2003 are used on March 31, 2004 and total liabilities for the first quarter of 2004 are used on May 17, 2004. In case of missing values of total liabilities, I use the most recent available data.

Moreover, I also include variables that are often used to explain corporate bond spreads i.e. firm stock return. Firm stock return \((hret)\) is the 252-day average of firm stock returns.

1.2.5 Merged Data and Summary Statistics

The companies in the GFI database were first manually matched by company name with those in OptionMetrics and COMPUSTAT. Companies in the financial and government sectors are excluded because of the difficulty in interpreting their capital structure variables. As the systematic risk is the cross-sectional property and CDS quotes are not available daily for all companies in the sample, I choose to perform my analysis on a
monthly basis. Monthly observations are obtained by simply averaging daily observations within one month. Moreover, I require that there are at least 30 firms available in each month to perform regression analysis. This leaves me with a final sample of 236 companies (8040 firm-month observations) from January 2000 to December 2004 (60 months). On average, there are 134 firms available in each month.

Table 1.1 presents the cross-sectional summary statistics of the time-series means of the firm-level variables. The firms are quite large in my sample with the average firm size of about $34.33 billion. The average CDS spread is 125 basis points, which is much higher than the median CDS spread of 82 basis points, indicating that the distribution is positively skewed and there are firms with very high levels of CDS spreads in my sample. The average beta is about 0.88, the average systematic risk proportion is about 23.62%, and the average leverage is about 47.37%. Compared with S&P 500 index, the average firm has done quite well during the sample period with an annualized 252-day average return of 3.09%, while the annualized 252-day average return on the S&P 500 index is only -2.34% in the same period.

For the volatility measures, the implied volatility is higher than the historical volatility. At the firm level, the average implied volatility is 39.93%, around 1% higher than the average historical volatility of 38.58%. The average firm-level implied volatility slope in the moneyness dimension is -0.49.

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5 There are less than 30 firms available in each month prior to 2000 that have data in GFI, OptionMetrics, Compustat, and CRSP. The number of firms available in each month ranges from 2 to 11 in 1998 and from 10 to 28 in 1999.
1.3 Regression Analysis

The foundation of traditional Merton-type models is the option-pricing theory of Black and Scholes (1973). Hence, prices of credit sensitive securities such as bonds and credit default swaps should be determined by the total risk of the underlying asset (i.e. firm). One important implication is that credit spreads should not be determined by how the total risk is decomposed into the systematic risk and the idiosyncratic risk as long as the total risk is fixed. In other words, credit spreads should be the same when their underlying firms differ only in the composition of the total risk. Duan and Wei (2009) study equity options. They argue that option prices, represented by implied volatilities, should not be related to the proportion of systematic risk relative to the total risk according to the Black and Scholes (1973) option-pricing theory. Therefore, my null hypothesis is as follows:

• Hypothesis 1.1: A firm’s CDS spread is unrelated to its systematic risk proportion.

As the systematic risk is the cross-sectional property and CDS quotes are not available daily for all companies in the sample, I choose to perform the analysis on a monthly basis. To test the hypothesis that a firm’s CDS spread is not affected by its systematic risk proportion, I run the cross-sectional regression in each month. More specifically, I regress CDS spreads on the systematic risk proportion and five control variables. The five control variables are historical volatility, implied volatility level and slope, leverage, and stock return, all of which are suggested either by theories of default risk or by the extant empirical evidence. The market-level variables that are often used in the literature (e.g. market return and volatility, market-level credit risk, bond market
liquidity, and the risk-free interest rate) are excluded from the regression as the regression is performed cross-sectionally. The regression equation is shown as follows:

\[ CDS_j = \alpha + \beta_1 \text{srp}_j + \beta_2 \text{HV}_j + \beta_3 \text{IV}_j + \beta_4 \text{IVS}_j + \beta_5 \text{lev}_j + \beta_6 \text{hret}_j + \epsilon_j \]

in each month. \hspace{0.5cm} (1.3)

The time-averaged regression coefficients are used to determine whether a hypothesis is rejected or not. Specifically, the time-series of the regression coefficients, 60 in total, are averaged and the corresponding \(t\)-statistics are calculated using the Fama-MacBeth (1973) method, which is widely used in credit risk studies such as Collin-Dufresne, Goldstein and Martin (2001).

Table 1.2 reports the time-series averages of regression coefficients and their corresponding \(t\)-statistics. On average, the six firm-level variables collectively explain about 58% of the cross-sectional variation in the CDS spreads. Several interesting observations emerge immediately from Table 1.2. First of all, the systematic risk proportion is significantly and negatively related to CDS spreads, which rejects the null hypothesis that a firm’s CDS spread is unrelated to its systematic risk proportion. Specifically, the systematic risk proportion has a negative effect on the CDS spreads in 57 months out of 60 months (95%). Taking into consideration the statistical significance, the systematic risk proportion is significantly related to CDS spreads in 16 months at the significance level of 10%, all of which are with negative sign. From the statistical point of view, roughly speaking, I expect to see six months of significance at the level of 10%. Now I find that the systematic risk proportion has a negative and significant effect on the CDS spreads in 16 months, which is more than twice as large as six months. This also supports the rejection of the null hypothesis. In terms of economic significance, given the
sample standard deviation of 10.46% for the systematic risk proportion, a one standard deviation increase in the systematic risk proportion is associated with 8.68 (-0.8302*10.46) basis points decrease in the CDS spreads.

Second, I find that both historical volatility and implied volatility are positively and significantly related to CDS spreads. However, implied volatility is more important both economically (reflected by the size of coefficient) and statistically (reflected by \( t \)-statistic). This finding confirms Cao, Yu, and Zhong’s (2006) main result that the implied volatility dominates the historical volatility in its informativeness for CDS spreads. Third, leverage is also positively and significantly related to CDS spreads. The positive and significant coefficients on equity volatility and leverage confirm Ericsson, Jacobs, and Oviedo’s (2004) results that theory-suggested variables are important determinants of CDS spreads with estimated coefficients consistent with theory. Fourth, the slope of the implied volatility curve is negatively and significantly related to CDS spreads. Given that the slope is negative, it means that the steeper the implied volatility curve, the higher the firm’s jump risk and so the higher the CDS spreads. Cao, Yu, and Zhong (2006) find that the average coefficient on the firm implied volatility skew is positive. Given that the skew is positive, it means that the larger the skew, the higher the probability of default and the CDS spread. Fifth, the firm stock return is negatively and significantly related to CDS spreads. A higher stock return implies a higher growth in firm value and, thus, reduces the probability of default. This result is consistent with earlier empirical studies on credit risk. Campbell and Taksler (2003) find that 180-day historical return is

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6 The risk-free interest rate plays no role in interpreting the cross-sectional variation in CDS spreads, as its effect is subsumed in the intercept.
7 The implied volatility skew is thought to proxy for the risk-neutral skewness of the stock return distribution.
negatively and significantly related to corporate bond yield spreads. Zhang, Zhou, and Zhu (2005) find that one-year historical return is negatively and significantly related to CDS spreads.

1.4 Robustness Checks

I have shown that the systematic risk proportion has a negative and significant effect on the CDS spreads after including variables that are suggested by theories of default risk and the extant empirical evidence. In other words, the composition of the total risk does matter for CDS pricing. This section further investigates the robustness of this result. Five robustness checks are presented.\(^8\) That is, I would like to examine whether the systematic risk proportion still has a negative and significant effect on the CDS spreads when 1) using panel regressions, 2) using the systematic risk proportion estimated from three Fama-French factors, 3) using GARCH volatilities rather than historical volatilities, 4) including more control variables such as size and liquidity, and 5) excluding small firms.

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\(^8\) The underlying asset of CDS is firm asset not equity. In principle, one should work on the asset volatility and estimate the systematic risk of firm asset. However, this is not feasible without a structural pricing model. As a result, equity volatilities are often used to proxy for asset volatilities in the empirical studies, as the two variables are correlated. However, for curiosity, I apply a quick and rough way to convert equity volatility and equity systematic risk proportion to asset volatility and asset systematic risk proportion, and repeat the cross-sectional regressions. The unreported results show that the systematic risk proportion still has a negative and significant effect on the CDS spreads using firm’s volatility and systematic risk proportion, although the statistical significance weakens slightly.
1.4.1 Panel Regressions

In the benchmark regressions, I require that there are at least 30 firms available in each month. To address the concern of the insufficient observations available in each month, I run a panel regression with month dummies. The regression coefficients and their corresponding $t$-statistics are reported in Table 1.3.

Table 1.3 about here

I find that the regression result is much similar to the benchmark results. The systematic risk proportion still has a negative and significant effect on the CDS spreads. Compared with the benchmark regressions, the effect of the systematic risk proportion on CDS spreads rises both in size and in statistical significance. Both historical volatility and implied volatility are positively and significantly related to CDS spreads. Implied volatility again dominates historical volatility both economically and statistically. Leverage is positively and significantly related to CDS spreads. The slope of the implied volatility curve and the firm stock return are negatively and significantly related to CDS spreads. Except historical volatility, the statistical significance of all other variables increases relative to the benchmark regressions. These variables explain about 63% of the variation in the CDS spreads.

1.4.2 Systematic Risk Estimation Using Fama-French Factors

So far, all the tests use systematic risk estimates from a single factor model, the market model with the market return proxied by S&P 500 index returns. Two concerns arise naturally. First, is S&P 500 index a good proxy for the market portfolio? Second, is it
enough to consider only one systematic risk factor? To address the first concern only, I
replace the S&P 500 index returns with CRSP value-weighted returns in the market
model and re-estimate the systematic risk. The unreported regression results show that the
systematic risk proportion still has a negative and significant effect on the CDS spreads.
Moreover, the average difference between the two systematic risk proportions is 0.12%.

To address both concerns, following Duan and Wei (2009), I re-estimate the
systematic risk using three Fama-French factors, i.e. the market factor proxied by CRSP
value-weighted returns, SMB, and HML, and see if the finding of the negative relation
between the systematic risk proportion and the CDS spreads is robust to the multi-factor
model. The daily factors are downloaded from Kenneth French’s website. The average
difference between the original systematic risk proportion and the one estimated with
three Fama-French factors is 3.73%.

The month-by-month cross-sectional regressions are repeated using the newly
estimated systematic risk proportions. The time-series averages of regression coefficients
and their corresponding $t$-statistics are reported in Table 1.3. Compared with the
benchmark results in Table 1.2, I find that the results are virtually the same. The
systematic risk proportion still has a negative and significant effect on the CDS spreads.
The size of its coefficient and the statistical significance improve slightly. There are 56
months out of 60 months (93.33%) in which the systematic risk proportion has a negative
impact on the CDS spreads, almost the same as 57 months in the benchmark regressions.
Considering the statistical significance, the systematic risk proportion is significantly
related to CDS spreads in 20 months at the level of 10%, all of which are with negative
sign. The rate of significance, 20 months, is larger than that in the benchmark regressions

17
(i.e. 16 months). The size of coefficients and the statistical significance of all other variables are almost identical to those in the benchmark regressions. On average, the six regressors collectively explain about 58% of the cross-sectional variation in the CDS spreads, the same level as in the benchmark case.

1.4.3 GARCH Volatilities

Historical volatility is by nature a volatility estimate that is slow reacting to market new conditions and, thus, cannot adequately capture time-varying volatility. For this reason, I assume that stock volatility follow NGARCH (1,1) specification of Engle and Ng (1993) and replace the smoothing historical volatility with NGARCH volatility. The objective is to investigate whether the systematic risk proportion is still significant in explaining CDS spreads when volatility is better measured by NGARCH specification.

Stock volatility is assumed to follow the NGARCH (1,1) process:

\[
\sigma_{jt}^2 = b_0 + b_1 \sigma_{jt-1}^2 + b_2 \sigma_{jt-1}^2 (\varepsilon_{jt-1} - \theta_j)^2
\]

for each stock \(j\) (1.4)

where \(\varepsilon_{jt}\) is a standard normal random variable conditional on the time \(t-1\) information. A positive value for parameter \(\theta\) leads to an asymmetric volatility response to the return innovation, an empirical phenomenon commonly known as leverage effect.

There are five parameters in this pricing model: \(b_0, b_1, b_2, \theta,\) and \(\mu\). Maximum likelihood estimation is performed using a five-year rolling window of daily returns for each firm. The log-likelihood function is

\[
l = -0.5 \sum_{t=1}^{N} \left( \log(\sigma_{jt}^2) + \varepsilon_{jt}^2 \right)
\]

where \(N\) is the
number of five-year daily returns for each firm. The first conditional variance $\sigma^2_0$ is set to be the unconditional variance of the window sample.

The estimated NGARCH parameters are then used to produce one-day ahead out-of-sample NGARCH (1,1) conditional variances. To alleviate computation load, NGARCH parameters are updated annually. More specifically, for each firm, the NGARCH parameters estimated using daily returns from 1 January 1995 to 31 December 1999 are employed to calculate one-day ahead NGARCH conditional variances for year 2000 from 1 January 2000 to 31 December 2000. Then the NGARCH parameters are re-estimated using daily returns from 1 January 1996 to 31 December 2000. And the estimated parameters are then used to compute one-day ahead NGARCH conditional variances for year 2001 from 1 January 2001 to 31 December 2001. The same procedure is repeated until the one-day ahead NGARCH conditional variances for year 2004 are computed. The annualized NGARCH volatilities are calculated using $\hat{\sigma}_{\mu t} = \sqrt{\hat{\sigma}_t^2 \times 252}$, assuming 252 trading days per year.

Table 1.4 about here

The cross-sectional summary statistics of NGARCH estimates and NGARCH volatilities are presented in Table 1.4. Panel A reports the cross-sectional summary statistics of the time-series means of each firm’s NGARCH estimates. An average firm has the following NGARCH parameters: $b_0 = 0.00005391$, $b_1 = 0.80280870$, $b_2 = 0.08826840$, $\theta = 0.94586220$, and $\mu = 0.00023622$. Panel B reports the cross-sectional summary statistics of the time-series means and standard deviations of each firm’s annualized daily NGARCH volatilities and historical volatilities for the period of 2000 to 2004. The average NGARCH volatility is about 38.72%, slightly higher than the average
historical volatility of 38.47%. On average, the NGARCH volatilities are more volatile than the historical volatilities as expected. The mean standard deviation of NGARCH volatilities is about 11.63%, about 40% higher than the mean standard deviation of historical volatilities (8.29%).

The benchmark regressions and the previous two robustness checks are all performed on a monthly basis. Naturally, one would expect to perform the robustness check with NGARCH volatilities on a monthly basis as well. However, NGARCH volatilities are in nature stochastic and, thus, may vary a lot over one day. The monthly average of daily NGARCH volatilities smoothes out a lot of daily variations in stock volatility and, thus, behaves more like historical volatility, as both are now smoothed variables. Therefore, it makes more sense to run the cross-sectional regressions on a daily basis when NGARCH volatilities are used. As in monthly regressions, I also require that there are at least 30 firms available on each day to perform regression analysis. This leaves me with a final sample of 232 firms (46586 firm-day observations) on 894 days. On average, there are 52 firms available on each day, less than half of the average number (134) of firms available in each month.

Table 1.5 about here

I then repeat the cross-sectional regression specified in equation (1.3) but replace historical volatility with NGARCH volatility on each day. The time-series averages of regression coefficients and their corresponding $t$-statistics are reported in Table 1.5. I observe that the systematic risk proportion still has a negative and significant effect on the CDS spreads when NGARCH volatility is used to replace historical volatility and on a daily basis. There are 733 days out of 894 days (81.99%) on which the systematic risk
proportion has a negative impact on the CDS spreads. Considering the statistical significance, the systematic risk proportion is significantly related to CDS spreads on 257 days at the level of 10%, 252 of which (98.05%) are with negative sign. The rate of negative significance, 252 days, is more than twice as large as 90 days, which is the rate of occurrence expected under the 10% test when a firm’s CDS spread is unrelated to its systematic risk proportion. This also supports the rejection of the null hypothesis.

All other variables have the same sign as in the benchmark regressions. NGARCH volatilities and implied volatilities are positively and significantly related to CDS spreads. The slope of the implied volatility curve is negatively and significantly related to CDS spreads. Leverage is positively and significantly related to CDS spreads. The firm stock return is negatively and significantly related to CDS spreads. On average, these six variables collectively explain about 60% of the cross-sectional variation in the daily CDS spreads.

Moreover, this test can also be taken as a robustness check for data frequency. That is, the systematic risk proportion has a negative and significant effect on the CDS spreads in both monthly and daily data. In addition, the benchmark regressions performed in the daily data also suggest that the systematic risk proportion has a negative and significant impact on the CDS spreads. The results are omitted for brevity.

1.4.4 More Controls – Size and Liquidity

It is generally believed that larger firms are more difficult to fail, so firm size is often used to predict the probability of bankruptcy. A number of empirical studies such as Shumway (2001), Chava and Jarrow (2004), and Campbell, Hilscher, and Szilagyi (2005)
find that firm size is an important predictor of default probability and larger firms are associated with lower default probability. For this reason, I add firm size to the benchmark regressions as an additional control variable and see if the negative effect of the systematic risk proportion on the CDS spreads persists. Firm size is proxied by the natural logarithm of a firm’s market value, which is calculated as the sum of the market value of common stock and the book value of total debt.

The extant literature generally believes that CDS spreads capture only credit risk. However, a recent study by Tang and Yan (2006) find that liquidity concern cannot be ignored in the CDS market. They estimate an illiquidity premium of 9.3 basis points in CDS spreads, which is comparable to the five-year Treasury bond illiquidity premium and the average size of the nondefault component of corporate bond spreads. For robustness check, I also add liquidity to the benchmark regressions and see if the systematic risk proportion still has a negative and significant effect on the CDS spreads. My liquidity proxy is percentage bid-ask spread, which is bid-ask spread divided by CDS spreads. High bid-ask spread corresponds to low liquidity.

Table 1.6 about here

I then repeat the month-by-month cross-sectional regressions with these two additional control variables, and report the time-series averages of regression coefficients and their corresponding $t$-statistics in Table 1.6. I observe that the systematic risk proportion still has a negative and significant effect on the CDS spreads after controlling for size and liquidity. There are 48 months out of 60 months (80%) in which the systematic risk proportion has a negative impact on the CDS spreads. Considering the statistical significance, the systematic risk proportion is significantly related to CDS
spreads in 13 months at the level of 10%, 12 of which (92.31%) are with negative sign. The rate of negative significance, 12 months, is just twice as large as six months, which is the rate of occurrence expected under the 10% test when a firm’s CDS spread is unrelated to its systematic risk proportion. This also supports the rejection of the null hypothesis.

Firm size is negatively and significantly related to CDS spreads, consistent with previous studies that larger firms are associated with lower default probability and, thus, lower CDS spreads. Bid-ask spread is positively but insignificantly related to CDS spreads. Credit default swaps with higher bid-ask spreads have lower liquidity and, thus, require a larger illiquidity premium which raises their CDS spreads. All other variables are significant and with the expected signs. On average, these eight variables collectively explain around 60% of the cross-sectional variation in the CDS spreads.

1.4.5 Excluding Small Firms

The summary statistics in Table 1.1 indicate that the sample is skewed towards large firms and also towards high CDS spreads. Normally high CDS spreads are associated with small firms. Therefore, it is highly likely that there are only a few small firms in the sample. In this section, I examine whether the main results still hold after excluding the outliers. To this end, I exclude the small firms in the lowest decile and repeat the analysis. The cutoff point is 5.6 billion, which is the 10th percentile of firm size. This screening rule leaves me with a sample of 212 companies (7445 firm-month observations).

The time-series averages of regression coefficients and their corresponding t-statistics are reported in Table 1.7. Compared with the benchmark results in Table 1.2, I
find that the results are slightly stronger. The systematic risk proportion still has a negative and significant effect on the CDS spreads. The size of its coefficient and the statistical significance improve slightly. All other variables have the same sign as in the benchmark regressions. Therefore, the main results hold after excluding the outliers.

1.5 Discussion

CDS contracts are purchased to obtain protection against a default by the underlying company. The counterparty, i.e. the seller of CDS contracts, collects CDS spreads to compensate the default risk they undertake. According to the structural models of default, credit spreads are determined by the total risk of the underlying firm and have nothing to do with the risk composition. However, this chapter finds that empirically the risk composition does matter for credit risk pricing. In particular, I find that the systematic risk proportion has a negative and significant effect on the CDS spreads after controlling for economic factors that are suggested by theories of default risk and the extant empirical evidence. Moreover, this empirical finding is robust to various alternative specifications and estimations. Given this robust empirical finding, people may naturally ask why a firm’s CDS spread is negatively affected by its systematic risk for a given level of the total risk. One possible explanation is provided in this section.

1.5.1 A Transaction-Cost-Based Explanation

Credit default swaps can be a great tool for diversifying or hedging one’s portfolio. CDS buyers (i.e. protection buyers) eliminate credit risk, while CDS sellers (i.e. protection
sellers) take on credit risk. By selling CDS, investors can diversify their portfolio by adding desired credits. As a result, CDS sellers can access additional asset classes they may not otherwise have and/or enhance investment yields. In fact, according to Greenwich Associates 2003 Credit Derivative Survey, three most important reasons that market participants use CDS are to achieve incremental returns (50%), to invest in an asset class (48%), and to hedge credit risk of bonds (34%).

A higher systematic risk proportion means that the underlying firm has a higher systematic risk for a given level of the total risk. As the firm value moves more closely to the market, it is easier for the seller of the CDS contract to hedge the systematic risk of this firm because the seller can use instruments written on firms that have a higher correlation with this firm or the indices. Hence, the seller may charge a lower CDS spread due to the lower hedging cost, leading to a negative relation between a firm’s systematic risk proportion and its CDS spread. In fact, for firms with higher systematic risk proportion, the asset values of these firms are more correlated, and so it is with their CDS spreads. As a consequence, hedging becomes easier and cheaper, resulting in a relatively lower CDS spread. To see the relation between the systematic risk proportion and the correlation among CDS spreads, I sort firms equally into three subgroups by the systematic risk proportion in each month and then compare to what extent CDS spreads are correlated in each of the three subgroups.

Two variables are used to measure the degree of correlation of CDS spreads. The first variable is the average correlation coefficient. To avoid calculating all pairwise correlations, I follow the simplified procedure suggested by Aneja, Chandra, and Gunay.
The formula to compute the average correlation coefficient ($\bar{c}$) is shown as follows:

$$\bar{c} = \frac{s^2_x - N}{N(N - 1)}$$

where $s^2_x$ is the sample variance of the portfolio $y_t$ \( y_t = \sum_{i=1}^{N} \frac{r_{t}}{s_i} ; \ t=1, \ldots, T \); $r_{t}$ is the return on security $i$ at $t$; $s_{i}$ is the standard deviation of security $i$, so the investment in security $i$ in the portfolio is $1/s_{i}$; and $N$ is the number of securities in the portfolio. Given that the number of firms available in each month is different, as a rough calculation, I use two different $N$s in the calculation of the average correlation coefficient: the maximum number of firms available in one month ($N_{\text{max}}$), and the average number of firms available in one month ($N_{\text{mean}}$). The average correlation coefficients using two different $N$s for each of the three subgroups are reported in Table 1.8.

Table 1.8 about here

The second variable is the cross-sectional CDS spread dispersion. Low dispersion implies that all CDS contracts in the subgroup (or portfolio) behave similarly, and, thus, in essence is equivalent to high correlation among the CDS contracts. In each month, I calculate the standard deviation of the CDS spreads and then report the time-series average and median of the standard deviations for each of the three subgroups in Table 1.8.

Table 1.8 shows that the average correlation coefficient increases with the systematic risk proportion. As the average systematic risk proportion increases from 10.83% to 38.82%, the average correlation coefficient increases from 0.3325 to 0.6359 using $N_{\text{max}}$ and increases from 0.4873 to 0.9299 using $N_{\text{mean}}$. Cross-sectional CDS
spread dispersion decreases with the systematic risk proportion, indicating the same pattern as the one when correlation is measured by the average correlation coefficient since low dispersion is equivalent to high correlation among CDS contracts. As the average systematic risk proportion increases from 10.83% to 38.82%, the average dispersion decreases from 130.36 basis points to 109.23 basis points and the median dispersion decreases from 112.62 basis points to 92.01 basis points. Hence, both correlation proxies suggest that CDS contracts are more correlated in the group with a higher systematic risk proportion.

Moreover, this transaction-cost-based explanation implies that the systematic risk has the same pricing impact on credit spreads as the idiosyncratic risk and, thus, the risk composition should not matter if there are no transaction costs. This explanation is consistent with structural models of default.

1.6 Conclusion

A key variable in the structural models of default, pioneered by Merton (1974), is asset volatility, which measures the total risk of the underlying firm asset. A direct implication is that prices of credit sensitive securities are determined by the total risk and have nothing to do with how the total risk is decomposed into systematic and non-systematic risks as long as the total risk is fixed. However, there is no empirical evidence for this implication. We do not know empirically the effect of the risk composition on credit spreads.

This chapter fills this gap by investigating whether a firm’s risk composition has an impact on its CDS spread for a given level of total risk. The risk composition measure
is the systematic risk proportion, which is defined as the ratio of the systematic variance over the total variance. Using CDS spreads to measure credit risk for the period of January 2000 to December 2004, I find that the systematic risk proportion has a negative and significant effect on the CDS spreads. In terms of economic significance, given the sample standard deviation of 10.46% for the systematic risk proportion, a one standard deviation increase in the systematic risk proportion is associated with 8.68 basis points decrease in the CDS spreads. Moreover, this empirical finding is robust to various alternative specifications and estimations. Therefore, I conclude that the composition of the total risk is an important determinant of CDS spreads. Finally, one possible explanation, i.e. the transaction-cost-based explanation, is provided to help understand the negative effect of the systematic risk proportion on the CDS spreads.
Chapter 2

The Illiquidity Premium in the Credit Default Swap Spreads

2.1 Introduction

A credit derivative is a contingent claim that allows market participants to trade and manage pure credit risk. Due to this important function, in the past several years, the credit derivatives market has grown exponentially from a total notional amount of $180 billion in 1996 to $20 trillion in 2006. Banks, securities houses, insurance companies, and hedge funds constitute the majority of market participants. The most popular credit derivatives product is the credit default swap (CDS), which captures about a third of the market share in 2006. According to the International Swaps and Derivatives Association’s (ISDA) 2008 year-end market survey, the notional amount outstanding of credit default swaps was $38.6 trillion at year-end 2008, down 38 percent from $62.2 trillion at year-end 2007 as a result of the recent credit crunch. The CDS contract protects the buyer against a default by the underlying company or country, called the reference entity. The buyer makes periodic payments to the seller in exchange for the right to sell the bond issued by the reference entity to the seller for its face value if a default, known as a credit event, occurs. A credit event is typically defined as bankruptcy, failure to pay, or restructuring. The rate of payments made per year is known as the CDS spread and denoted in basis points.

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9 See British Bankers’ Association (2006).
A credit default swap could be thought of an insurance contract against corporate
default. Roughly speaking, buying a corporate bond and the corresponding CDS as
default protection is equivalent to buying a default-free corporate bond.\textsuperscript{10} Hence, it is
widely believed that CDS spreads capture pure credit risk. For example, Longstaff,
Mithal, and Neis (2005) use CDS spreads as a measure of pure credit risk to compute the
default and non-default components in corporate bond spreads.

However, the actual quotes in the market suggest that liquidity concern may not
be ignored in the CDS market. In fact, using a dataset provided by GFI, a broker
specialized in credit derivatives trading, I find that the average bid-ask spread is about
22\% of the mid quote between bid and ask. Compared to the equity markets where the
average percentage bid-ask spread is far less than 5\%,\textsuperscript{11} liquidity may play a crucial role
in the pricing of CDS contracts. Moreover, liquidity in the credit market has dried up
substantially since the subprime crisis of summer 2007, which calls for more research on
the impact of liquidity on the credit derivatives.

This chapter investigates the pricing effect of liquidity on CDS spreads. As a
derivative contract, the credit default swap is in zero net supply. As argued by Brenner,
Eldor and Hauser (2001), for an asset in zero net supply, both the buyer and the seller are
cconcerned about illiquidity, pushing the prices in the opposite directions. More
specificially, to compensate for the illiquidity, the buyer demands a reduction in price,
while the seller demands an increase in price. Therefore, the net effect of the illiquidity
on the CDS spread could be positive or negative, depending on which effect dominates.

\textsuperscript{10} Hull, Predescu and White (2004) show that the CDS spread should be very close to the credit spread of a
par yield bond over the par yield risk-free rate using a no arbitrage argument.
\textsuperscript{11} Lin, Sanger, and Booth (1995) find that the average relative bid-ask spread is 1.24\% for a representative
sample of NYSE stocks.
To incorporate the effect of liquidity into the modeling of credit risk, I augment the Merton’s (1974) model with a simple model of an illiquidity premium proposed by Jarrow (2001). Transformed-data maximum likelihood estimation (MLE) method developed by Duan (1994, 2000) is then used to estimate the model implied CDS illiquidity premium. Next, panel regressions are performed to examine the relation between the model implied CDS illiquidity premium and CDS liquidity measures.

I find that the average model implied CDS illiquidity premium is about 15 basis points, accounting for 12% of the average level of the CDS spread. The positive value indicates that on average there is a shortage of the CDS contract. Investors cannot readily buy the CDS contract and sellers have the pricing power. Moreover, liquidity conditions are highly variable across firms, as reflected by the large standard deviation of the illiquidity premium.

I further investigate how the model implied CDS illiquidity premium is affected by liquidity measures of the CDS market. Given the data available, two liquidity measures related to the CDS market are constructed. The first measure is the percentage bid-ask spread, which is defined as bid-ask spread divided by CDS spreads. The second measure is the number of daily CDS spreads available in one month.

Using panel regressions with monthly dummies and issuer-clustering adjusted $t$-values, I find that both liquidity measures are significant determinants of the model implied CDS illiquidity premium, suggesting that this parameter does capture liquidity’s effect on CDS spreads. In terms of relative importance, the bid-ask spread is more important than the number of daily CDS spreads statistically and economically. In more detail, a one standard deviation increase in the percentage bid-ask spread is associated
with 17.3 basis points increase in the illiquidity premium, while a one standard deviation increase in the number of daily CDS spreads available in one month is associated with 9.9 basis points decrease in the illiquidity premium. The average of these two estimates of illiquidity premium is 13.6 basis points.

In terms of the monthly intercept, which is calculated as the sum of the regression constant and the corresponding monthly dummy, 32 months out of 48 months (66.67%) have a negative intercept. And there is an upward trend in the intercept over time. As monthly dummies capture the effects of macroeconomic variables that are common to all CDS contracts in a particular month, a possible explanation to this negative intercept could be the neglect of the possibility of double default by the seller of the CDS contract at the market level. The double default discount is the compensation for bearing this risk. With the development of the CDS market and the increased competition in the market, the market-level double default discount may decrease over time as a result of the decreased risk of doubt default, yielding an upward trend in the intercept.

Several recent papers have explored the effect of liquidity on CDS spreads. For example, Tang and Yan (2008) use panel regressions to investigate the pricing effects of liquidity and liquidity risk on CDS spreads. Bongaerts, de Jong, and Driessen (2008) derive a theoretical asset-pricing model for derivative contracts that allows for expected liquidity and liquidity risk and test the model using CDS portfolios. Chen, Fabozzi, and Sverdlove (2008) estimate the liquidity premium in CDS quotes using a two-factor reduced form model. Despite the differences in methodologies and datasets, these papers agree that liquidity plays an important role in the pricing of CDS contracts.
This chapter differs from these studies in that 1) I use an illiquidity-augmented structural model of default to estimate the effect of liquidity after properly controlling for the effects of credit risk factors such as leverage, asset volatility, and the risk-free rate; and 2) I use the transformed-data MLE method to estimate model parameters from daily equity values and sparse CDS spreads without the requirement that both equity and CDS data are concurrent.

The remainder of this chapter is organized as follows. Section 2.2 reviews the Merton model and describes how the Merton model is augmented with an illiquidity premium. Section 2.3 explains the estimation methodology. Section 2.4 describes the CDS data and other data used in the model estimation. Summary statistics of the data are also presented in this section. Section 2.5 reports the empirical results. Section 2.6 concludes the chapter.

### 2.2 The Model

A major theoretical approach to price credit risk is the structural model framework initiated by Merton (1974). The structural models generally specify how firm value changes over time and derive default from the relationship between firm value and debt value, and, thus, are able to link the prices of credit sensitive securities to the economic determinants of default.\(^\text{12}\) Firm leverage, asset volatility, and the risk-free interest rate are three most important theoretical determinants of default risk. In this section, I describe

how equity and credit spreads are priced in the Merton model and how I can augment the Merton model with an illiquidity premium.

2.2.1 The Merton Model

In Merton’s model, the value of the firm at time $t$, $V_t$, is assumed to follow a geometric Brownian motion with constant drift $\mu_v$ and volatility $\sigma_v$; that is,

$$\frac{dV_t}{V_t} = \mu_v dt + \sigma_v dz$$

(2.1)

where $z$ is a Wiener process. The risk-free rate $r$ is assumed to be constant. The firm is assumed to have a simple capital structure: non-dividend paying equity and a zero-coupon bond with face value $D$ and maturity $T$.

When the bond matures at time $T$, equity holders repay the debt and keep the balance if the firm’s value is greater than the promised payment. Otherwise, the firm defaults. The bondholders receive the value of the firm and the equity holders get nothing. Hence, the payoff structure for the bondholders at time $T$ is:

$$B_T = \min(V_T, D)$$

(2.2)

and the payoff structure for the equity holders at time $T$ is:

$$E_T = \max(V_T - D, 0)$$

(2.3)

The payoff structure for the equity holders implies that the stock can be viewed as a call option written on the firm value with a strike price equal to the debt principal. Using the standard Black-Scholes option pricing model, the stock value at time $t$ is therefore:
\[ E_t = V_t N(d_1) - D e^{-r(T-t)} N(d_2) \]  

(2.4)

where \( d_1 = \frac{\ln \left( \frac{V_t}{D e^{-r(T-t)}} \right) + \frac{1}{2} \sigma \sqrt{T-t}}{\sigma \sqrt{T-t}} \), \( d_2 = d_1 - \sigma \sqrt{T-t} \), and \( N(\cdot) \) is the standard normal distribution function.

As Merton’s model assumes that the firm has only two classes of claims – equity and a zero-coupon bond, the value of the bond at time \( t \) is therefore the difference of the firm value and the equity value:

\[ B_t = V_t - E_t = V_t N(-d_1) + D e^{-r(T-t)} N(d_2) \]  

(2.5)

The credit spread \( s \) is defined as the difference between the yield-to-maturity of a corporate bond and the yield-to-maturity of a riskless bond with the same maturity, where the yield to maturity \( y \) is implicitly defined from the bond value as follows:

\[ B_t = D e^{-y(T-t)} \]  

(2.6)

Hence, the credit spread implied from Merton’s model can be calculated using the following formula:

\[ s = y - r = -\frac{1}{T-t} \ln \left[ \left( \frac{V_t}{D e^{-r(T-t)}} \right) N(-d_1) + N(d_2) \right] \]  

(2.7)

Under Merton’s framework, the model implied CDS spread is assumed to be equal to the credit spread defined in equation (2.7).
2.2.2 The Illiquidity Premium

The liquidity effects for traditional securities such as stocks and bonds have been studied extensively in the literature.\textsuperscript{13} The stylized fact is that illiquidity affects prices adversely. That is, stocks (bonds) with lower liquidity have lower prices and command higher expected returns (yields). This is because stocks and bonds are in positive net supply and the marginal investors typically hold a long position, thereby demanding compensation for the lack of immediacy they face if they wish to sell the asset.

Derivatives are different from traditional securities. They are generally in zero net supply. Therefore, it is not obvious whether the marginal investor in derivatives holds a long or a short position. As argued by Brenner, Eldor and Hauser (2001), for an asset in zero net supply, both the buyer and the seller are concerned about illiquidity, pushing the prices in the opposite directions. More specifically, to compensate for the illiquidity, the buyer demands a reduction in price, while the seller demands an increase in price. Therefore, the net effect of the illiquidity could be positive or negative, depending on which effect dominates. For instance, Brenner, Eldor and Hauser (2001) find a significant illiquidity discount in the prices of non-tradable currency options compared to their exchange-traded counterparts, while Deuskar, Gupta, and Subrahmanyam (2007) find a significant illiquidity premium in the prices of euro interest rate caps and floors.

A credit default swap is a credit derivative that allows market participants to trade and manage pure credit risk. As a derivative contract, the credit default swap is also in zero net supply. Hence, the net effect of the illiquidity on the CDS spread could be

\textsuperscript{13} See Amihud, Mendelson, and Pedersen (2005) for an excellent review.
positive or negative, depending on whether the buyer-effect or the seller-effect dominates. To incorporate the effect of liquidity into the modeling of credit risk, I consider a simple model of an illiquidity premium proposed by Jarrow (2001).

In an illiquid and incomplete market, Jarrow (2001) shows that there exists a process $\gamma(t,T)$ such that

$$P_I(t,T) = e^{-\gamma(t,T)}P(t,T)$$

(2.8)

where $P(t,T)$ is the price of a risky bond at time $t$ maturing at time $T$, and $P_I(t,T)$ is the price of an otherwise identical risky bond trading in an illiquid market. The subscript “I” indicates the bond’s price in an illiquid market. This specification implies an illiquidity premium of $\gamma(t,T)/(T-t)$ in the credit spread on a zero-coupon bond in an illiquid market.

The process $\gamma(t,T)$ can be interpreted as a convenience yield for holding the illiquid risky debt and, thus, could be positive or negative, depending on market conditions. When there is a shortage, investors cannot buy the risky bond at reasonable prices, leading to a negative $\gamma(t,T)$. The function $-\gamma(t,T) > 0$ can be interpreted as being a positive convenience yield obtained from holding the illiquid bond. This case is just like the storage of commodities used in production such as oil. When there is an oversupply, investors cannot sell the risky bond at reasonable prices, leading to a positive $\gamma(t,T)$. The function $-\gamma(t,T) < 0$ can be interpreted as being a negative convenience yield obtained from holding the illiquid bond. This case is just like the storage of spoilable commodities.

This argument can also be applied to the CDS contract written on the same firm. The CDS contract is used to eliminate the default risk of the risky bond. Hence, buying
CDS contracts is equivalent to selling risky bonds, as default risk is transferred away in both cases. When there is a shortage of the CDS contract (equivalent to an oversupply of the risky bond), investors cannot readily buy the CDS contract, leading to a higher CDS spread and a positive $\gamma(t, T)$. When there is a glut of the CDS contract (equivalent to a shortage of the risky bond), investors cannot readily sell the CDS contract, leading to a lower CDS spread and a negative $\gamma(t, T)$. Therefore, in this setup, the liquidity effect on the CDS spread could go either way.

Several studies implement Jarrow (2001)’s illiquidity-premium model using corporate bond prices. Janosi, Jarrow, and Yildirim (2003) estimate a reduced-form credit risk model with liquidity risk modeled as a convenience yield. The illiquidity premium $\gamma(t, T)$ is assumed to be an affine function of three market-wide variables: the 5-day average spot rate, the volatility of an equity market index, and the 5-day average return on the equity market index. They find a non-zero illiquidity premium and the best performing illiquidity-premium model appears to be firm specific and not dependent on market-wide variables, reflecting idiosyncratic and not systematic risk. Willemann (2004) calibrates a structural credit risk model with liquidity risk modeled as a convenience yield. The illiquidity premium $\gamma(t, T)$ is assumed to be a function of the time to maturity $(T-t)$. He finds a positive illiquidity premium for all firms and the average illiquidity spread $\gamma(t, T)/(T-t)$ is around 40 bps.

The purpose of this chapter is to estimate the illiquidity premium in the CDS spreads. Five-year CDS spreads are used in this chapter. This is because five-year CDS contracts are the most liquid and standard contracts in the market and for this reason they are commonly used in the literature. As the maturity is fixed to be five years, there is no
need to consider the maturity dependence of the illiquidity premium. Therefore, the illiquidity premium $\gamma(t, T)$ is simply:

$$\gamma(t, T) = \gamma(T - t).$$

(2.9)

This specification implies an illiquidity premium of $\gamma$ in the credit spread on a zero-coupon bond with a maturity of five years in an illiquid market.

### 2.3 Estimation Methodology

As pointed out in Jarrow and Turnbull (2000), the major difficulty in implementing structural models of default is that firm values are not directly observable and the model parameters are unknown.

At least four methods have been developed to solve this unobservability issue in the literature. The first method uses a firm value proxy which is defined as the sum of the market value of the firm’s equity and the book value of total liabilities (see Brockman and Turtle (2003), Eom, Helwege, and Huang (2004), for example). The second method is to solve a system of two equations linking the unknown firm value and firm volatility to the equity value and equity volatility (see Jones, Mason, and Rosenfeld (1984), Ronn and Verma (1986), for example). The third method is Moody’s KMV method which is an iterative algorithm inferring the unobserved firm values and unknown model parameters from equity prices (see Vassalou and Xing (2004) for example). The fourth method is the transformed-data maximum likelihood estimation (MLE) method developed by Duan (1994, 2000). This method views the observed equity prices as a transformed dataset to compute the MLE parameter estimates for the unobserved firm value process with the
theoretical equity pricing formula serving as the transformation. Predescu (2005) extends this method to include CDS spreads in addition to equity values in the transformed dataset.

Following Predescu (2005), in this study, I also use the transformed-data MLE method to estimate unknown parameters for the illiquidity-Merton’s model using both equity values and CDS spreads. To apply the transformed-data method, CDS spreads are assumed to contain some measurement errors. Duan and Fulop (2009) find measurement errors in stock prices and measurement errors are lower for more liquid firms. As measurement errors decrease with liquidity and stocks are more liquid than credit default swaps,\textsuperscript{14} it is reasonable to assume that measurement errors in stock prices are negligible. I can assume that both stock prices and CDS spreads contain measurement errors, but then I need to use more complicated nonlinear filtering methods to estimate the parameters.

The transformed-data formulation of the illiquidity-Merton’s model includes the transition dynamic for the unobserved firm value and two equations linking the firm value to two observed variables with the CDS being observed with error. This econometric formulation is sensible because equity market is much more liquid and should thus be subject to negligible measurement errors:

\[ \ln V_t = \ln V_{t-1} + (\mu_r - 0.5\sigma_r^2)\Delta t + \sigma_r\sqrt{\Delta t}\varepsilon_t \]  \hspace{1cm} (2.10)

\[ E_t = V_t N(d_1) - De^{-r(T-t)}N(d_2) \]  \hspace{1cm} (2.11)

\textsuperscript{14} This is because the average percentage bid-ask spread is about 2\% in the stock market (See Lin, Sanger, and Booth (1995) for example) but about 22\% in the CDS market and lower bid-ask spread corresponds to higher liquidity.
\[ s_i = \gamma - \frac{1}{T - t_i} \ln \left[ \frac{V_i}{De^{-r(T-t_i)}} \right] N(-d_1) + N(d_2) + \sigma_i \epsilon_i \]  

(2.12)

where \( E_{ti} \) denotes the market equity value at \( t_i \), \( s_i \) denotes the market CDS spread at \( t_i \), and \( \epsilon_i, \eta_i \) are independent standard normal variables. The set of parameters \( \Theta \) that needs to be estimated includes \( \sigma, \mu, \gamma, \sigma_x \).

The log-likelihood function of the observed equity values and CDS spreads equals:

\[ LL_{E,s}(E_{t_1}, \ldots, E_{t_n}, s_{t_1}, \ldots, s_{t_n} ; \Theta) = LL_{\epsilon, \eta}(s_{t_1}, \ldots, s_{t_n} | E_{t_1}, \ldots, E_{t_n} ; \Theta) + LL_E(E_{t_1}, \ldots, E_{t_n} ; \Theta) \]  

(2.13)

The first term is the conditional log-likelihood function of the CDS spreads given the equity values. As equity values are one-to-one related to asset values, conditioning on the equity values is equivalent to conditioning on the implied asset values for a given set of parameters. Hence, the first term can be rewritten as:

\[ LL_{\epsilon, \eta}(s_{t_1}, \ldots, s_{t_n} | E_{t_1}, \ldots, E_{t_n} ; \Theta) = LL_{\hat{V}, \hat{V}}(s_{t_1}, \ldots, s_{t_n} | \hat{V}_{t_1}, \ldots, \hat{V}_{t_n} ; \Theta) \]

\[ = - \frac{m}{2} \ln(2\pi) - \frac{m}{2} \ln(\sigma_i^2) - \frac{1}{2\sigma_i^2} \sum_{i=1}^{n} \left( s_i - s(\hat{V}_{t_i} ; \Theta) \right)^2 \]  

(2.14)

where \( \hat{V}_{t_i} \) is the implied asset value from \( E_{ti} \) using equation (2.11) and \( s(\hat{V}_{t_i} ; \Theta) \) is the mean of equation (2.12).

The second term in equation (2.13) is the log-likelihood function of equity values. Duan (1994) derives it and gets the following equation:

\[ LL_E(E_{t_1}, \ldots, E_{t_n} ; \Theta) = LL_{\hat{V}, \hat{V}}(\hat{V}_{t_1}, \ldots, \hat{V}_{t_n} ; \Theta) - \sum_{i=2}^{n} \ln \left| \frac{\partial E(\hat{V}_{t_i} ; \sigma_i)}{\partial \hat{V}_{t_i}} \right| \]  

(2.15)
where $\partial E(\cdot)/\partial V$ equals $N(d_1)$ in Merton’s model and $LL_t(\hat{V}_t, \cdots, \hat{V}_{t_i}; \Theta)$ is the log-likelihood function of firm values and equals:

$$LL_t(\hat{V}_t, \cdots, \hat{V}_{t_i}; \Theta) = -\frac{n-1}{2} \ln(2\pi) - \frac{n-1}{2} \ln(\sigma_t^2 \Delta t)$$

$$- \frac{1}{2\sigma_t^2 \Delta t} \sum_{i=2}^{n} \left( \ln(\hat{V}_t / \hat{V}_{t-i}) - (\mu_t - 0.5\sigma_t^2) \Delta t \right)^2 - \sum_{i=2}^{n} \ln \hat{V}_t$$

(2.16)

The parameters $\sigma_v, \mu_v, \gamma, \sigma_s$ are estimated using a one-year rolling window of daily equity values for each firm, rolling forward by one month. As CDS spreads are not available everyday, I require that there are at least 20 spreads available in each window to perform the MLE estimation.

### 2.4 Data

This chapter is to estimate the illiquidity premium in the CDS spreads. To perform the transformed-data MLE estimation, I need equity values, CDS spreads, debt values, and risk-free rates. The sources and methods to construct these variables are discussed as follows.

#### 2.4.1 CDS Spreads

The CDS spreads used in this chapter are provided by GFI, a broker specialized in credit derivatives trading. The data contains intra-day bid/ask quotes from January 1998 to December 2004. As in Predescu (2005) and Cao, Yu, and Zhong (2006), five-year CDS spreads are used in this analysis as they are the most common contracts in the CDS
market. Only the quotes on senior debt are considered. Daily CDS spreads are generated from intra-day quotes using the following algorithm:

- When there are pairs of bid and ask in a day, the daily CDS spread is the average of the last pair of bid and ask on that day. A pair of bid and ask means that a bid and an ask are provided at the same time.
- When there are no pairs of bid and ask in a day, the last non-zero quote (bid or ask) is used to compute the other one (ask or bid) by assuming that the percentage bid-ask spread remains the same as the one on the previous most recent day. The CDS spread is then computed as the average of the last non-zero quote (bid or ask) and the computed counterpart (ask or bid).

### 2.4.2 Other Data Used in the Estimation

Daily equity prices and common shares outstanding are retrieved from CRSP daily files. Total liabilities are retrieved from Compustat quarterly files. To avoid any issues related to reporting delays, I use total liabilities reported in the most recent fiscal quarter, with the requirements that 90 days have elapsed from the end of the previous fiscal year end (i.e. the 4th fiscal quarter) and 45 days from the end of each of the first three fiscal quarters. For example, total liabilities for the fourth quarter of 2003 are used on March 31, 2004 and total liabilities for the first quarter of 2004 are used on May 17, 2004. In case of missing values of total liabilities, the most recent available data are used. Daily one-year Treasury rates are retrieved from Federal Reserve Banks. As five-year CDS spreads are used in this analysis, maturity is set to be five years in the parameter estimation.
2.4.3 Merged Data and Summary Statistics

The companies in the GFI database were first manually matched by company name with those in COMPUSTAT. Companies in the financial and government sectors are excluded because of the difficulty in interpreting their capital structure variables. The model parameters are estimated using a one-year rolling window of daily equity values for each firm, rolling forward by one month. As CDS spreads are not available everyday, I require that there are at least 20 spreads available in each window to perform the transformed-data MLE estimation. The final sample includes 229 companies ranging from 2001 to 2004.

Table 2.1 presents the cross-sectional summary statistics of the time-series means of the firm-level variables. The firms are quite large in my sample with the average firm size of about $33.6 billion. The average CDS spread is 125 basis points, which is much higher than the median CDS spread of 80 basis points, indicating that the distribution is positively skewed and there are firms with very high levels of CDS spreads in my sample. The average leverage is about 47.12% and the average historical volatility is 37.57%.

For the liquidity measures, the average percentage bid-ask spread is 22.43%, which is far higher than that in the equity market, suggesting that liquidity may play a crucial role in the pricing of CDS contracts. Moreover, on average, there are about 71 daily CDS spreads available in the one-year window and about 7 daily CDS spreads available in one month, indicating that CDS markets are quite illiquid.
The number of firms available in each month and the month-by-month cross-sectional average CDS spread are plotted in Figure 2.1. The number of firms available in each month increases steadily from 60 in January 2001 to 171 in October 2002 and gradually decreases to 114 in December 2004. CDS spreads peaked in October 2002 and decreased significantly in 2003. In 2004, CDS spreads were quite stable, staying at the level of about 90 basis points.

Figure 2.2 about here

Two liquidity measures are plotted in Figure 2.2. The month-by-month cross-sectional average CDS percentage bid-ask spread has dropped significantly from about 30% in 2001 to less than 15% in 2004, indicating the substantial improvement in the liquidity of the CDS market. However, there is no significant trend in the number of daily CDS spreads available in one month.

2.5 Empirical Results

In this section, I discuss the estimated model parameters. To better understand the model implied CDS illiquidity premium, I investigate how this parameter is affected by various liquidity measures.

2.5.1 Model Parameter Estimates

As discussed in Section 2.3, the illiquidity-Merton’s model specified in equations (2.10) to (2.12) is estimated using the transformed-data MLE estimation. The model parameters $\sigma_v, \mu_v, \gamma, \sigma_y$ are estimated firm by firm. For each firm, the estimation is performed every
month using a rolling window of one year, which yields parameter estimates for 6147 firm-months.

Table 2.2 about here

Table 2.2 presents the cross-sectional summary statistics of the time-series means of each firm’s model parameter estimates. The average asset volatility $\sigma_v$ is about 24.6%. The average asset drift $\mu_v$ is about 7.9%. The average CDS measurement error $\sigma_s$ is about 33 basis points.

The average illiquidity premium $\gamma$ is about 15 basis points with a $t$-statistic of 1.9, statistically significant at the 10% level. Given the average level of the CDS spread at around 125 basis points, the illiquidity premium accounts for a substantial portion of the CDS spread (12%). The positive value of $\gamma$ indicates that on average there is a shortage of the CDS contract. Investors cannot readily buy the CDS contract and sellers have the pricing power. The large standard deviation of the illiquidity premium indicates that liquidity conditions are highly variable across firms.

The finding of a positive average illiquidity premium is not surprising for the CDS market after considering the motivations of the two parties for engaging in the transaction. The buyers of credit default swap contracts use them to hedge the default risk of the risky bonds. They are usually not concerned about the liquidity of the CDS contracts as they typically hold them to maturity. Whereas, the sellers are concerned about hedging the risks of the CDS contracts they sell, and hence concerned about the liquidity of these contracts. Therefore, the seller-effect dominates, giving rise to an illiquidity premium (or liquidity discount). Using a different method and a different dataset, Tang and Yan (2008) also find that sellers are charging a premium for faster
matching when the demand of a particular contract exceeds its supply because they provide not only insurance against credit risk but also liquidity service in the market.

**Figure 2.3 about here**

Figure 2.3 plots the time-series mean of illiquidity premium for each firm. Most of the sample firms have a positive average illiquidity premium. However, about 20% of sample firms (i.e. 46 firms out of 229 firms) have a negative average illiquidity premium. For these firms, the estimated illiquidity premium $\gamma$ is not always negative. It is positive in some months and negative in other months. The negative average illiquidity premium suggests that on average there is an oversupply of the CDS contract for these firms. Investors cannot readily sell the CDS contract and buyers have the pricing power. Therefore, the buyer-effect dominates, giving rise to an illiquidity discount (or liquidity premium). Tang and Yan (2008) also find that sellers are offering a discount for a better matching intensity when the supply of a particular contract exceeds its demand. The time series of the cross-sectional average of illiquidity premium is also plotted in Figure 2.3. It appears that there is an oversupply in the CDS market in the early months of 2001 and a shortage in the CDS market in the first half of 2002 and in 2004.

Empirical studies such as Eom, Helwege, and Huang (2004) have shown that the Merton model on average underestimates credit spreads, especially for investment-grade firms. To see how the nonlinear relationship between the degree of the underestimation and the credit quality affects $\gamma$, I sort firms equally into three subgroups ascending in the estimated Merton spread, i.e. the second term in equation (2.12), in each month and report the statistics of each group in Table 2.3.

**Table 2.3 about here**
Panel A of Table 2.3 presents the cross-sectional summary statistics of the time-series means of the firm-level variables. It shows that firms in the high-Merton-spread group tend to be smaller, riskier, and have higher levels of interest in credit protection, which helps to increase liquidity and reduce the bid-ask spread. Panel B presents the cross-sectional summary statistics of the time-series means of each firm’s model parameter estimates. It shows that firms in the high-Merton-spread group have higher levels of asset volatility and CDS measurement error. And the illiquidity premium parameter is on average negative. These findings are not surprising because the Merton model has been found to underestimate the credit spreads of investment-grade bonds and overestimate the credit spreads of junk bonds.

2.5.2 Determinants of the Model Implied CDS Illiquidity Premium

The estimated CDS illiquidity premium parameter measures the overall effect of liquidity on CDS spreads. To better understand this parameter, in this section, I investigate how this parameter is affected by liquidity measures of the CDS market.

Given the data available, two liquidity measures related to the CDS market are constructed. The first measure is the percentage bid-ask spread, which is defined as bid-ask spread divided by CDS spreads. Monthly observations are obtained by simply averaging daily observations within one month. Bid-ask spread is a commonly used measure of liquidity in the literature. A larger bid-ask spread corresponds to lower liquidity. Therefore, a positive relation between the model implied illiquidity premium and the bid-ask spread is expected.
The second measure is the number of daily CDS spreads available in one month. A higher number corresponds to higher liquidity. Therefore, a negative relation between the model implied illiquidity premium and the number of daily CDS spreads is expected.

The sample consists of 229 firms and 6147 firm-month observations ranging from 2001 to 2004 (a total of 48 months). Panel regressions are performed with the dependent variable being the monthly illiquidity premium $\gamma$. As observations from the same firm cannot be treated as independent of each other, the issuer effect needs to be controlled for. Moreover, the time effect also needs to be controlled for as firms may be affected by the same macroeconomic conditions. Petersen (2009) suggests that when both firm and time effects are present, the preferred approach is to control for the time effect using time dummies with firm clustering. Hence, I include monthly dummies in the regressions and adjust for issuer-clustering to obtain robust $t$-values. Because of the use of time dummies, I do not include any other macroeconomic variables in the analysis.

Table 2.4 about here

Table 2.4 presents the regression results. Model (1) is regressing the illiquidity premium on the percentage bid-ask spread and a constant. As expected, the bid-ask spread is positively and significantly related to the model implied illiquidity premium, suggesting that the parameter $\gamma$ does capture liquidity’s effect on CDS spreads. In terms of intercept, there is a large variation across months. 41 months out of 48 months (85.42%) have a negative intercept.

Model (2) is regressing the illiquidity premium on the number of daily CDS spreads available in one month and a constant. As expected, the number of daily CDS spreads is negatively and significantly related to the model implied illiquidity premium,
suggesting again that the parameter $\gamma$ does capture liquidity’s effect on CDS spreads. In terms of intercept, 7 months out of 48 months (14.58%) have a negative intercept.

As both liquidity measures are proved to be significant determinants of the model implied CDS illiquidity premium, model (3) includes both variables in the panel regression. The regression result remains virtually same. Both variables are significant and have the expected signs. In terms of relative importance, the bid-ask spread is more important than the number of daily CDS spreads statistically and economically. In terms of intercept, 32 months out of 48 months (66.67%) have a negative intercept.

To compare the illiquidity premium associated with the two liquidity measures, I multiply the coefficient estimate by the standard deviation of the corresponding liquidity measure. In more detail, a one standard deviation increase in the percentage bid-ask spread is associated with 17.3 (0.0164*0.1054) basis points increase in the illiquidity premium, while a one standard deviation increase in the number of daily CDS spreads available in one month is associated with 9.9 (-0.0003*3.31) basis points decrease in the illiquidity premium. The average of these two estimates of illiquidity premium is 13.6 basis points.

Tang and Yan (2008) estimate an illiquidity premium of 13.2 basis points with a different method and different liquidity proxies. They perform a panel regression, regressing the monthly average CDS spreads on liquidity proxies, credit risk proxies, and some control variables. The common liquidity proxy in their paper and this study is the percentage bid-ask spread. In contrast to the approach in this chapter, their study does not use any theoretical pricing model as the basic premise. The illiquidity premium
associated with the bid-ask spread in Tang and Yan’s paper is 2.4 basis points, much lower than my estimate of 17.3 basis points.

Figure 2.4 about here

Figure 2.4 plots the monthly intercept from the regression of the model implied CDS illiquidity premium on the percentage bid-ask spread and the number of daily CDS spreads available in one month. The monthly intercept is calculated as the sum of the regression constant and the corresponding monthly dummy. This variable provides information about how market conditions vary over time, as monthly dummies capture the effects of macroeconomic variables that are common to all CDS contracts in a particular month. Figure 2.4 shows that the monthly intercept is negative before 2004 and stays positive after March 2004. Moreover, there is an upward trend in the intercept over time.

Larger stocks are generally more liquid. Consequently, firm size as measured by the market capitalization of equity is also frequently used as a measure of stock liquidity (see Kluger and Stephan (1997) for example). For this reason, I also investigate whether firm size is an important determinant of the model implied CDS illiquidity premium. A larger firm size corresponds to higher liquidity. Therefore, a negative relation between the model implied illiquidity premium and firm size is expected.

Model (4) is regressing the illiquidity premium on firm size and a constant. As expected, firm size is negatively related to the model implied illiquidity premium, though insignificantly. As a result, firm size is not an important determinant of the model implied CDS illiquidity premium. In terms of intercept, 13 months out of 48 months (27.08%) have a negative intercept.
To complete the investigation, model (5) includes all of the three liquidity measures. The regression results are almost same as those from Model (3). Two CDS market liquidity measures are significantly related to the model implied CDS illiquidity premium and have the expected sign. Firm size is still insignificant. In terms of intercept, 29 months out of 48 months (60.42%) have a negative intercept.

The significance of two liquidity measures indicates that the estimated parameter $\gamma$ does capture the effect of liquidity on the CDS spreads. However, the R-squares in the regressions are low (about 3%). One possible reason is that the parameter $\gamma$ actually serves as a catch-all variable for anything not captured by the Merton model such as stochastic volatility and possible jumps in asset value. Although the illiquidity premium parameter $\gamma$ defined in equation (2.12) appears a relatively clean measure since measurement errors are captured by the term $\sigma \eta$, it is too naïve to believe that this parameter captures only the effect of liquidity. In the estimation, the model is required to price stocks exactly and meanwhile minimize the credit spread errors. Therefore, in reality, the average CDS pricing errors are generally not zero. As a consequence, $\gamma$ has the effect of absorbing the expected structural pricing errors of CDS spreads. The fact that $\gamma$ may be the catch-all variable leads me to actually relate $\gamma$ to the CDS liquidity variables and estimate an illiquidity premium based on these liquidity variables, which is 13.6 basis points. Yet, I still refer to this parameter as the generic term “liquidity”.

Another possible reason for the low R-squares is the missing liquidity variables. Since liquidity cannot be described by a sufficient statistic, Tang and Yan (2008) construct four liquidity proxies from their CDS data i.e. the volatility-to-volume ratio, the number of contracts outstanding, the trade-to-quote ratio, and the bid-ask spread, all of
which are found to be significant in explaining CDS spreads. However, trade data are unavailable in my dataset. As a consequence, I cannot include the first three variables in my analysis. Moreover, the illiquidity in the underlying stock and bond markets can affect sellers’ hedging capability and hence increase the premium embedded in CDS spreads. However, I do not have such information in my dataset.

The risk composition of the underlying firm has been shown to be an important determinant of its CDS spreads in the first chapter. Although this measure has not been used in the existing literature, studies such as Stoll (1978) have investigated the effects of firms’ systematic risks and specific risks on bid-ask spreads. Therefore, the risk composition may be a missing explanatory factor of the model implied illiquidity premium. To see whether the risk composition helps to explain the illiquidity premium, I include the systematic risk proportion defined in Section 1.2.2 in the panel regression.

Table 2.5 presents the regression results. Model (6) is regressing the illiquidity premium on the systematic risk proportion and a constant. Model (7) includes the percentage bid-ask spread and the number of daily CDS spreads available in one month as well. It appears that firms with higher idiosyncratic risk have higher levels of interest in credit protection, which in turn helps reduce the illiquidity premium. The effects of the two CDS liquidity measures remain virtually same as in Model (3). Moreover, the inclusion of the risk composition variable increases the R-square by nearly 50%. I also calculate the illiquidity premium associated with the three variables by multiplying the coefficient estimate by the standard deviation of the corresponding variable. The average illiquidity premium based on the three variables is 15.7 basis points.
2.5.3 The Evolution of the Market Conditions over Time

Section 2.5.2 has shown that the model implied CDS illiquidity premium can be explained partly by two CDS liquidity variables and, thus, liquidity does play an important role in the pricing of CDS contracts. The monthly intercept from the regression captures the effects of macroeconomic variables that are common to all CDS contracts in a particular month. Hence, this variable can be regarded as a proxy for the macroeconomic conditions. It is shown in Figure 2.4 that the monthly intercept is negative in about 70% of the sample period and there is an upward trend in the intercept over time. If the intercept captures the market liquidity, I would expect a downward trend over time. This is because the liquidity of the CDS market has improved significantly since January 2001, as indicated by the cross-sectional average CDS bid-ask spread plotted in Figure 2.2.

A possible explanation to this negative intercept could be the neglect of the possibility of double default by the seller of the CDS contract. When there is a possibility of double default, the buyer of the CDS contract will get a compensation for bearing this risk by paying a lower spread. As the illiquidity-Merton’s model does not consider the pricing effect of the double default, this double default discount is subsumed in the illiquidity premium $\gamma$. To estimate the double default discount, one must know the information about the seller of the CDS contract. However, this information is unavailable. As an alternative, one may consider the market-level double default, which is subsumed in the monthly regression intercept. With the development of the CDS market and the increased competition in the market, the market-level double default
discount may decrease over time as a result of the decreased risk of doubt default, yielding an upward trend in the intercept.

2.6 Conclusion

It is widely believed that CDS spreads capture pure credit risk. However, the actual quotes in the market suggest that liquidity concern may not be ignored in the CDS market. This chapter investigates the pricing effect of liquidity on CDS spreads. More specifically, I estimate an illiquidity premium from the illiquidity-Merton’s model using the transformed-data MLE method. How the model implied CDS illiquidity premium is affected by CDS liquidity measures is then investigated using panel regressions.

I find that the average model implied CDS illiquidity premium is about 15 basis points, accounting for 12% of the average level of the CDS spread. Moreover, liquidity conditions are highly variable across firms. To better understand the model implied CDS illiquidity premium, two liquidity measures related to the CDS market are constructed, i.e. the percentage bid-ask spread and the number of daily CDS spreads available in one month.

Using panel regressions with monthly dummies and issuer-clustering adjusted \( t \)-values, I find that both liquidity measures are significant determinants of the model implied CDS illiquidity premium, suggesting that this parameter does capture liquidity’s effect on CDS spreads. In terms of relative importance, the bid-ask spread is more important than the number of daily CDS spreads statistically and economically. The average of these two estimates of illiquidity premium is 13.6 basis points. The monthly intercept is negative in about 70% of the sample period. And there is an upward trend in
the intercept over time. A possible explanation to this negative intercept could be the neglect of the possibility of double default by the seller of the CDS contract at the market level.
Chapter 3

The Effect of Systematic Risk on the Volatility Spread

3.1 Introduction

An important general principle in option pricing is risk-neutral valuation, which assumes that the world is risk neutral and the expected return on all securities is the risk-free interest rate. As a result, the return distribution implied from option prices is risk neutral.

One important characteristic of the return distribution is the volatility. Most of the existing studies on the risk-neutral volatility focus on the Black-Scholes implied volatility, and its forecasting ability and information content (see, for example, Canina and Figlewski, 1993; and Fleming, 1998 among others). The Black-Scholes implied volatilities have a well-known drawback. That is, it displays a smile/skew pattern across moneyness.

To address the issue of volatility smile/skew, several recent studies have derived an alternative implied volatility measure that is independent of option pricing models and unrelated to the moneyness (e.g., Britten-Jones and Neuberger, 2000; and Bakshi, Kapadia and Madan, 2003). Subsequent studies using the model-free risk-neutral volatility measure continue to focus on its forecasting ability and information content. For instance, Jiang and Tian (2005) find that the model-free implied volatility estimated from the S&P’s 500 index options subsumes all information contained in the Black-Scholes implied volatility and is a more efficient forecast for future realized volatility.
In this chapter I study the difference between the risk-neutral return volatility and the physical return volatility, termed volatility spread. More specifically, I investigate how the systematic risk of the underlying stock affects the volatility spread. The focus on the systematic risk is motivated by the fact that the risk-neutral return distribution differs from the physical return distribution by a risk premium term. The risk-neutral volatility in this study is measured with the increasingly popular approach known as the model-free risk-neutral volatility, a volatility measure superior to the Black-Scholes implied volatility in that it incorporates information across all strike prices and does not require the specification of an option pricing model. To control for the difference in the level of the volatility across different underlying stocks, the systematic risk is scaled by the total risk. More specifically, the systematic risk measure is the systematic risk proportion, defined as the ratio of the systematic variance over the total variance.

Using individual option prices on firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index options over a period of ten years from 1997 to 2006, I investigate how the volatility spread is affected by the systematic risk of its underlying stock. I find that the systematic risk proportion of an underlying stock has a positive and significant impact on its volatility spread. On average, this positive effect exists in about 76% of the sample period. Across maturities, this positive effect is stronger for long-term options (121 – 180 days) and becomes weaker as the maturity gets shorter. Across time, I find that the systematic risk proportion has a large negative effect on the volatility spread in the period from 2001 to 2002 when the dot-com bubble burst. Further investigation shows that the negative effect of the systematic risk is
mainly for small firms and the effect of the systematic risk remains positive for large firms even in the crisis periods.

The positive systematic risk effect was first documented in Duan and Wei (2009) using the Black-Scholes implied volatility. For comparison, I also repeat the analysis using the Black-Scholes implied volatilities in my sample. I find that the coefficient of the systematic risk proportion is still positive but now insignificant for the whole moneyness. More specifically, I find that the systematic risk proportion has a stronger effect on the volatility spread using the model-free risk-neutral volatilities than on the volatility spread using the Black-Scholes implied volatilities in all aspects (i.e. the magnitude and t-value of the regression coefficient \( \gamma_1 \) and the percentage of positive entries). Hence, the positive effect of the systematic risk on the volatility spread is actually more prominent using the clearly better model-free risk-neutral volatility measure. This result is completely expected because the model-free risk-neutral volatility is superior to the traditional Black-Scholes implied volatility and it is the right measure to use in the studies involving risk-neutral volatilities. Moreover, the sub-sample results suggest that this positive effect is stronger in the first half of the sample period when the overall total risk is high.

Several recent papers have explored the effect of the systematic risk on the risk-neutral distribution implied from option prices. For instance, Dennis and Mayhew (2002) investigate the relative importance of various firm characteristics (e.g. implied volatility, firm size, trading volume, leverage, and beta) in explaining the risk-neutral skewness. They find that the risk-neutral skewness tends to be more negative for stocks with larger betas, suggesting the importance of market risk in option pricing. Engle and Mistry (2007)
examine both physical and risk-neutral measures of skewness. They find that stocks with higher systematic risk exhibit more negative skews using both measures. Duan and Wei (2009) study implied volatility smiles and find that after controlling for the underlying equity’s total risk, a higher amount of systematic risk of the underlying equity leads to a higher level of Black-Scholes implied volatility and a steeper slope of the implied volatility curve. Despite the differences in the research questions and methodologies, these papers agree that the systematic risk affects the risk-neutral return distribution.

This chapter differs from previous literature in the following. First, I examine the role of the systematic risk in explaining the structural difference between the risk-neutral volatility and the physical volatility. Second, the risk-neutral volatility measure employed in this study is the model-free risk-neutral volatility, which is a better volatility measure than the Black-Scholes implied volatility in that the former utilizes information across all strike prices and is independent of option pricing models. Third, I study the volatility spread using a larger universe of firms in a longer and more recent period. Duan and Wei (2009) is the most related work to this chapter. They use options on the S&P 100 index and its 30 largest component stocks from 1991 to 1995. My sample comprises individual option prices on firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index options over a period of ten years from 1997 to 2006. The broader sample offers me further insight into the cross-sectional variation of the volatility spread.

Another related paper is Bakshi and Madan (2006). They theoretically link the volatility spread to the higher-order physical return moments and the parameters of the pricing kernel process. Using S&P 100 index returns and options, they find that the risk-
neutral volatility is higher than its physical counterpart when investors are risk-averse and when the physical index distribution is negatively skewed and leptokurtic. This chapter differs from their study in that 1) I focus on the effect of the systematic risk on the volatility spread and 2) I study the volatility spread of individual stocks. Moreover, my findings of the impact of the risk-neutral higher-order moments on the volatility spread also complement their study.

The remainder of this chapter is organized as follows. Section 3.2 discusses the data used in this study. Summary statistics of the data are also presented in this section. Section 3.3 presents the effect of the systematic risk on the volatility spread using the model-free risk-neutral volatility. The comparison with the effect of the systematic risk on the volatility spread using the Black-Scholes implied volatility is also reported in this section. Section 3.4 concludes the chapter.

### 3.2 Data

My sample comprises individual option prices on firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index options over a period of ten years from January 1997 to December 2006. Option observations are deleted if the bid price is lower than or equal to $0.125, or the bid price is higher than the ask price, or the moneyness is outside the range [0.5, 2.0]. As in Duan and Wei (2009), only out-of-the-money call and put options are retained.\(^\text{15}\) Moreover, option observations are deleted if option prices violate the arbitrage conditions (i.e. the option price must be smaller than

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\(^{15}\) In-the-money option prices are notoriously unreliable because in-the-money options are very infrequently traded relative to at-the-money and out-of-the-money options.
the stock price, but larger than the stock price minus the present value of the exercise price and the dividends), or the time-to-maturity is outside the range $[20, 180]$ days.\footnote{This is because very short and very long maturity option quotes may not be active.}
Option prices are obtained by averaging the bid and ask prices.

The volatility spread is defined as the difference between the risk-neutral volatility and the physical volatility. The risk-neutral volatility measure used in this chapter is the model-free risk-neutral volatility proposed by Bakshi, Kapadia and Madan (2003).\footnote{The risk-neutral skewness and kurtosis in the regression are calculated following Bakshi, Kapadia and Madan (2003). For consistency, the same approach is used to calculate the risk-neutral volatility. Bakshi and Madan (2006) also use this measure to study the volatility spread.}

Theorem 1 of Bakshi, Kapadia and Madan (2003) gives the formulae to calculate the $\tau$-period risk-neutral variance, skewness and kurtosis. The risk-neutral volatility is the square root of the annualized risk-neutral variance.

Let $R(t, \tau) \equiv \ln \frac{S(t + \tau)}{S(t)}$ denote the $\tau$-period stock return. Let $V(t, \tau), W(t, \tau)$ and $X(t, \tau)$ represent the fair value of payoffs $R(t, \tau)^2, R(t, \tau)^3$ and $R(t, \tau)^4$ respectively. According to Theorem 1 of Bakshi, Kapadia and Madan (2003), the $\tau$-period risk-neutral variance, skewness and kurtosis can be expressed as

$$RNVar(t, \tau) = e^{\tau \mu} V(t, \tau) - \mu(t, \tau)^2$$ \hspace{1cm} (3.1)

$$Skew(t, \tau) = \frac{e^{\tau W(t, \tau)} - 3 \mu(t, \tau)e^{\tau V(t, \tau)} + 2 \mu(t, \tau)^3}{[e^{\tau V(t, \tau)} - \mu(t, \tau)^2]^{3/2}}$$ \hspace{1cm} (3.2)

$$Kurt(t, \tau) = \frac{e^{\tau X(t, \tau)} - 4 \mu(t, \tau)e^{\tau W(t, \tau)} + 6 \mu(t, \tau)^2 e^{\tau V(t, \tau)} - 3 \mu(t, \tau)^4}{[e^{\tau V(t, \tau)} - \mu(t, \tau)^2]^2}$$ \hspace{1cm} (3.3)

where

$$\mu(t, \tau) = e^{\tau} - 1 - \frac{e^{\tau}}{2} V(t, \tau) - \frac{e^{\tau}}{6} W(t, \tau) - \frac{e^{\tau}}{24} X(t, \tau),$$ \hspace{1cm} (3.4)
\[ V(t, \tau) = \int_{S(t)}^{\infty} \left( 2 \left( 1 - \ln \frac{K}{S(t)} \right) \frac{K^2}{2} \right) C(t, \tau, K) dK + \int_{0}^{S(t)} \left( 2 \left( 1 + \ln \frac{S(t)}{K} \right) \frac{K^2}{2} \right) P(t, \tau, K) dK, \quad (3.5) \]

\[ W(t, \tau) = \int_{S(t)}^{\infty} \frac{6 \ln \frac{K}{S(t)} - 3 \left( \ln \frac{K}{S(t)} \right)^2}{K^2} C(t, \tau, K) dK , \quad (3.6) \]

\[ - \int_{0}^{S(t)} \frac{6 \ln \frac{S(t)}{K} + 3 \left( \ln \frac{S(t)}{K} \right)^2}{K^2} P(t, \tau, K) dK \]

\[ X(t, \tau) = \int_{S(t)}^{\infty} \frac{12 \left( \ln \frac{K}{S(t)} \right)^2 - 4 \left( \ln \frac{K}{S(t)} \right)^3}{K^2} C(t, \tau, K) dK \]

\[ + \int_{0}^{S(t)} \frac{12 \left( \ln \frac{S(t)}{K} \right)^2 + 4 \left( \ln \frac{S(t)}{K} \right)^3}{K^2} P(t, \tau, K) dK \quad (3.7) \]

In the above equations, \( C(t, \tau, K) \) is the call option price with time-to-maturity \( \tau \) and exercise price \( K \), and \( P(t, \tau, K) \) is the corresponding put option price. \( \mu(t, \tau) \) is the risk-neutral expected value of the \( \tau \)-period stock return \( R(t, \tau) \). Note that \( e^{\mu(\tau)}V(t, \tau) \) is in effect the risk-neutral second moment of \( R(t, \tau) \).

One-month Treasury bill rate, one of the Fama-French factors downloaded from Kenneth French’s website, is used as the risk-free rate to calculate the risk-neutral volatility, skewness and kurtosis for a given day. As in Dennis and Mayhew (2002) and Duan and Wei (2009), the integrals are estimated using the trapezoidal approximation. Moreover, I require that there are at least two calls and two puts available for each maturity to compute the risk-neutral moments. The estimation of the integrals requires a continuum of option prices. However, the strike price interval is discrete in the actual data. Since most of the data have a strike price interval of $5 or $2.5, the bias introduced
by the discreteness of the strike price interval is roughly the same for all firms in the sample. Therefore, one should still be able to discern cross-sectional differences in the data.

The physical volatility is proxied by the commonly-used historical volatility. The daily historical volatility is the annualized standard deviation from the one-year rolling window (annualization is done by multiplying $\sqrt{250}$ to the daily volatilities). The choice of the historical volatility is to make sure that only the available information is used in the analysis. Daily stock prices are available in OptionMetrics.

As in Duan and Wei (2009), I use the S&P 500 index as a proxy for the market portfolio to calculate the systematic risk proportion, which is defined as the proportion of the systematic risk in the total risk of the underlying equity. Specifically, I regress daily stock returns on S&P 500 index returns using a one-year rolling window of daily returns for each stock. The one-year window is rolled over by one day. The regression equation is given below:

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}$$ (3.8)

The systematic risk and the total risk can be calculated as $\beta_j^2 \sigma_m^2$ and $\sigma_j^2$ for stock $j$. The systematic risk proportion is simply $b_j = \beta_j^2 \sigma_m^2 / \sigma_j^2$ for a particular day. The analysis is performed on a monthly basis. Monthly observations are obtained by simply averaging daily observations within one month.

Table 3.1A about here
Table 3.1A reports the cross-sectional summary statistics of the time-series means of the firm-level variables. The average Black-Scholes implied volatility is 45.7%, one percent lower than the average historical volatility. The average systematic risk proportion is 26.6%. The average risk-neutral volatility, skewness and kurtosis are 41.7%, -0.40, and 2.54 respectively. Compared to the Black-Scholes implied volatility, the model-free risk-neutral volatility is relatively low. The underestimation of the risk-neutral volatility results from the truncation error in the integration of $V(t, \tau)$, i.e. the fair value of the payoff $R(t, \tau)^2$, in equation (3.5).\footnote{Implied volatilities are downloaded from OptionMetrics. For European options, the implied volatility is estimated using the Black-Scholes model. For American options, the implied volatility is estimated using the industry-standard Cox-Ross-Rubinstein (CRR) binomial tree model.}

Table 3.1B about here

Figure 3.1 about here

Table 3.1B reports the cross-sectional means and medians of the time-series means of the firm-level variables by year. Stock volatility experienced a steady increase in the late 90’s, and peaked in 2000 for the Black-Scholes implied volatility and in 2001 for the model-free risk-neutral volatility and the historical volatility. Since then, stock volatility has been in a steady decline. In contrast, the systematic risk proportion was relatively low in 2000 and 2001, suggesting that the increase in the firm’s total risk is mainly due to the increase in its idiosyncratic risk. I also plot the month-by-month cross-sectional average of different volatilities, the systematic risk proportion, and volatility spreads from January 1997 to December 2006 in Figure 3.1. It is clearly shown that $V(t, \tau)$ is calculated using formula 7 in Bakshi, Kapadia and Madan (2003). For out-of-the-money calls and puts, the option prices are normally small. However, the weights of put options are big when the strike price goes to 0. As the moneyness is required to be within [0.5, 2] (In fact, options in the market rarely have moneyness close to 0), the part of the integration from 0 to 0.5 is lost. And this missing portion could be large, leading to the underestimation of the risk-neutral volatility.\footnote{$V(t, \tau)$ is calculated using formula 7 in Bakshi, Kapadia and Madan (2003). For out-of-the-money calls and puts, the option prices are normally small. However, the weights of put options are big when the strike price goes to 0. As the moneyness is required to be within [0.5, 2] (In fact, options in the market rarely have moneyness close to 0), the part of the integration from 0 to 0.5 is lost. And this missing portion could be large, leading to the underestimation of the risk-neutral volatility.}
firms’ total risks peaked in 2001 when the dot-com bubble burst, but the systematic risk proportion was relatively low in the same period.

### 3.3 Empirical Analyses

The risk-neutral return distribution differs from the physical return distribution by a risk premium term. Several recent papers have explored the effect of the systematic risk on the risk-neutral distribution implied from option prices. They find that the systematic risk of the underlying stock is an important determinant of the risk-neutral skewness (see Dennis and Mayhew, 2002; and Engle and Mistry, 2007 for example) and the risk-neutral volatility (see Duan and Wei, 2009 for example). I am interested in whether the systematic risk of the underlying stock affects the volatility spread, which is defined as the difference between the risk-neutral volatility and the physical volatility. Therefore, my null hypothesis is as follows:

- **Hypothesis 3.1:** The volatility spread between the risk-neutral return distribution and the physical return distribution of a firm is unrelated to its systematic risk.

Before proceeding to the empirical analyses, I have to first decide the choice of the risk-neutral volatility measure. Although the Black-Scholes implied volatility is a very popular measure of the risk-neutral volatility, it has a well-known drawback. That is, it displays a smile pattern across moneyness. As a consequence, studies using the Black-Scholes volatility often look at narrower moneyness ranges to separate potentially different effects. For instance, Duan and Wei (2009) perform the regressions in four moneyness subgroups i.e. 

- $[0.90, 0.95)$,
- $[0.95, 1.00)$,
- $[1.00, 1.05)$,
- $[1.05, 1.10]$,

where moneyness is defined as the strike price over the stock price.
The recently-developed model-free risk-neutral volatility overcomes the problem of volatility smile (e.g., Britten-Jones and Neuberger, 2000; and Bakshi, Kapadia and Madan, 2003). It is not based on any specific option pricing model and calculated using a complete set of option prices, thus unrelated to moneyness. Because this model-free volatility measure incorporates information across all strike prices and is not subject to model misspecification errors, it has become increasingly popular in the volatility literature since its development. In this study, I use the model-free risk-neutral volatility proposed by Bakshi, Kapadia and Madan (2003) to test the null hypothesis. As the model-free risk-neutral volatility is unrelated to the moneyness, my analyses are performed for the whole moneyness.

The physical return volatility is measured by the one-year historical volatility. To control for the difference in the level of the volatility across different underlying stocks, the systematic risk is scaled by the total risk as in Duan and Wei (2009). More specifically, the systematic risk measure is the systematic risk proportion, defined as the ratio of the systematic variance over the total variance.

To test the null hypothesis, for each stock in each month, I first calculate the average difference between the model-free risk-neutral volatility and the historical volatility. Then I run the following cross-sectional regression for 120 times (one for each month of ten years):

\[ VolSpread_j = \gamma_0 + \gamma_1 b_j + \gamma_2 skew^{(m)}_j + \gamma_3 kurt^{(m)}_j + e_j, \quad j = 1, 2, \ldots, up to 101 \]  

(3.9)

where the dependent variable is the average volatility spread and three independent variables are the systematic risk proportion, the risk-neutral skewness and kurtosis. The inclusion of the risk-neutral skewness and kurtosis in the regression is based on the
empirical results that higher-order moments of the risk-neutral return distribution help to explain the implied volatilities (see Bakshi, Kapadia and Madan, 2003; Duan and Wei, 2009; and Rompolis and Tzavalis, 2009 for example). The time-series of the regression coefficients, 120 in total, are then averaged and its corresponding $t$-statistics is calculated using the Newey-West standard error with four lags.

The model-free risk-neutral volatility is unrelated to the moneyness, but it still corresponds to a certain maturity. Hence, following Duan and Wei (2009), I examine three maturity ranges to see how the effect of the systematic risk on the volatility spread changes with maturities. The three maturity ranges are short-term, 20-70 days; medium-term, 71-120 days; and long-term, 121-180 days.

Table 3.2 about here

Table 3.2 reports the time-series averages of regression coefficients and their corresponding $t$-statistics. To conserve space, I do not report the intercepts from the regressions. I find that the systematic risk proportion of an underlying stock has a positive and significant impact on its volatility spread. On average, this positive effect exists in about 76% of the sample period.

Across maturities, the positive effect of the systematic risk proportion is stronger for long-term options (121 – 180 days) and it becomes weaker as the maturity gets shorter. This pattern is not surprising because the systematic risk proportion is calculated using one-year’s data, closer to the long-term’s maturity. Moreover, short-term volatilities are more volatile than long-term volatilities. Hence, it is more difficult for the smoother

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The positive effect of the systematic risk was first documented in Duan and Wei (2009). Readers are referred to their paper for the discussions on the possible reasons for the positive effect.
systematic risk proportion to explain the variation in the short-term volatilities than in the long-term volatilities.

For comparison, I also repeat the cross-sectional regressions using the Black-Scholes implied volatility for the whole moneyness. I find that the coefficient of the systematic risk proportion is still positive but now insignificant. This is not surprising because the Black-Scholes implied volatility is related to moneyness and displays a volatility smile. Hence, it is important to look at narrower moneyness ranges when using the Black-Scholes implied volatility. Across maturities, this positive effect keeps the same pattern. That is, the positive effect of the systematic risk proportion is stronger and significant for long-term options (121 – 180 days), and it becomes weaker and insignificant as the maturity gets shorter.

Moreover, I find that the systematic risk proportion has a stronger effect on the volatility spread using the model-free risk-neutral volatility than on the volatility spread using the Black-Scholes implied volatility in all aspects (i.e. the magnitude and $t$-value of the regression coefficient $\gamma_1$ and the percentage of positive entries). Hence, the positive effect of the systematic risk on the volatility spread is actually more prominent using the clearly better model-free risk-neutral volatility measure. This result is completely expected because the model-free risk-neutral volatility is superior to the traditional Black-Scholes implied volatility and it is the right measure to use in the studies involving risk-neutral volatilities.

Figure 3.2 about here

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21 I also perform the regressions in the four moneyness subgroups as in Duan and Wei (2009). The subgroup results confirm Duan and Wei’s (2009) findings that the systematic risk proportion of an underlying stock has a positive and significant effect on its volatility spread. The results are omitted for brevity.
I also plot the time-series of the regression coefficient on the systematic risk proportion from January 1997 to December 2006 in Figure 3.2. Figure 3.2 shows that the systematic risk proportion has a positive effect on the volatility spread most of the time in the 10-year sample period. However, there are two periods during which the effect is negative, i.e. from April 2001 to July 2002 and from October 2005 to May 2006. And the negative effect is very large in the period from 2001 to 2002 when the dot-com bubble burst. A possible explanation for this opposite effect is provided in Section 3.3.2.

Other observations from Table 3.2 include the effects of the risk-neutral skewness and kurtosis on the volatility spread. I find that 1) the risk-neutral skewness has a negative and significant impact on the volatility spread; and 2) the risk-neutral kurtosis has a positive and significant impact on the volatility spread. These findings imply that the volatility spread is larger for more negatively-skewed and/or fatter-tailed firms. Bakshi and Madan (2006) find positive volatility spreads when the physical index distribution is negatively skewed and leptokurtic. My findings complement theirs to show that the risk-neutral higher-order moments affect the volatility spread in the same way as the physical counterparts for individual stocks as well as the index.

### 3.3.1 Sub-Sample Results

It is shown in Figure 3.1 that stock volatility is generally higher in the first half of the sample period than in the second half. In this section, I examine whether the positive effect of the systematic risk holds up in different time periods and whether the general level of volatility matters. Therefore, I repeat the cross-sectional regressions in the two

Table 3.3 reports the time-series averages of regression coefficients and their corresponding \( t \)-statistics for the whole sample and three sub-samples. I find that the positive effect of the systematic risk on the volatility spread is more prominent in the first half than in the second half both statistically and economically. Given the observations that the first half period has a relatively higher volatility, the sub-sample results imply that the effect of the systematic risk on the volatility spread is stronger when the overall total risk is high. Moreover, the exclusion of year 2001 makes the positive effect of the systematic risk even more significant.

3.3.2 The Negative Systematic Risk Effect in Crisis Periods

Figure 3.2 shows that the systematic risk proportion has a negative effect on the volatility spread in two periods i.e. from April 2001 to July 2002 and from October 2005 to May 2006. These two periods are crisis periods. During the period of 2001 to 2002, there were bursting of dot-com bubble, corporate accounting scandals, and September-11 event. During the period of 2005 to 2006, there was energy crisis and oil prices experienced a huge increase. In this section, I am providing a possible explanation for the negative effect of the systematic risk.

As the systematic risk proportion is the key variable in the whole analysis, I sort firms equally into three subgroups ascending in the systematic risk proportion in each month of the two crisis periods (a total of 24 months), and repeat the cross-sectional...
regressions in each subgroup. The dependent variable is the average of the difference between the model-free risk-neutral volatility and the historical volatility. The maturity group is 20 to 180 days.

Table 3.4 reports the time-series averages of regression coefficients on the systematic risk proportion and their corresponding $t$-statistics for the whole sample as well as three subgroups. I find that the effect of the systematic risk proportion remains negative and significant in the low- and medium-SRP groups. However, the effect of the systematic risk proportion turns positive and significant in the high-SRP group. The percentage of the positive coefficient on the systematic risk proportion also increases from 25% in the low-SRP group to 67% in the high-SRP group. High systematic risk proportion is normally associated with large firm size. And Duan and Wei’s (2009) results are also based on 30 big firms. Hence, the systematic risk proportion has a positive effect on the volatility spread for large firms. However, this effect is reversed for small firms in the crisis periods.

3.4 Conclusion

The risk-neutral and physical return distributions are linked through the risk premium of the systematic risk factors. Several recent papers have explored the effect of the systematic risk on the risk-neutral volatility and skewness. This chapter studies whether the systematic risk of the underlying stock affects the difference between the risk-neutral volatility and the physical volatility, termed volatility spread. The risk-neutral volatility in
this study is measured by the model-free risk-neutral volatility, which is independent of option pricing models and unrelated to moneyness.

Using individual option prices on firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index options over a period of ten years from 1997 to 2006, I find that the systematic risk proportion of an underlying stock has a positive and significant impact on its volatility spread. This positive effect was first documented in Duan and Wei (2009) using the Black-Scholes implied volatility. I show that this effect is actually more prominent using the clearly better model-free risk-neutral volatility measure. Moreover, the sub-sample results suggest that this positive effect is stronger in the first half of the sample period when the overall total risk is high.
Table 1.1: Summary Statistics

This table presents the cross-sectional summary statistics of the time-series means of the firm-level variables. CDS spread is five-year CDS spreads. Implied volatility is the average of implied volatilities for out-of-the-money calls and puts with nonzero open interest. Implied volatility slope is the regression coefficient on the moneyness calculated from equation (1.2). Historical volatility is the annualized historical volatility calculated from the 252-day rolling window. Firm stock return is the 252-day average of firm stock returns. Systematic risk proportion is defined as the ratio of the systematic variance over the total variance. Leverage is defined as total liabilities divided by the sum of total liabilities and the market value of common stock. Size is the sum of total liabilities and the market value of common stock. The sample contains 236 companies (8040 firm-month observations) from January 2000 to December 2004.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS spread (basis point)</td>
<td>124.93</td>
<td>53.95</td>
<td>82.14</td>
<td>168.50</td>
<td>101.31</td>
</tr>
<tr>
<td>Implied volatility (%)</td>
<td>39.93</td>
<td>34.17</td>
<td>38.50</td>
<td>44.34</td>
<td>8.67</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-0.49</td>
<td>-0.63</td>
<td>-0.45</td>
<td>-0.31</td>
<td>0.31</td>
</tr>
<tr>
<td>Historical volatility (%)</td>
<td>38.58</td>
<td>31.57</td>
<td>36.43</td>
<td>43.40</td>
<td>11.02</td>
</tr>
<tr>
<td>Firm stock return (%)</td>
<td>3.09</td>
<td>-3.78</td>
<td>5.29</td>
<td>13.49</td>
<td>16.85</td>
</tr>
<tr>
<td>Beta</td>
<td>0.88</td>
<td>0.62</td>
<td>0.87</td>
<td>1.07</td>
<td>0.34</td>
</tr>
<tr>
<td>Systematic risk proportion (%)</td>
<td>23.62</td>
<td>14.83</td>
<td>23.60</td>
<td>31.04</td>
<td>10.46</td>
</tr>
<tr>
<td>Leverage (%)</td>
<td>47.37</td>
<td>33.68</td>
<td>47.45</td>
<td>60.49</td>
<td>18.50</td>
</tr>
<tr>
<td>Equity ($billion)</td>
<td>18.88</td>
<td>4.31</td>
<td>9.68</td>
<td>18.24</td>
<td>28.51</td>
</tr>
<tr>
<td>Debt ($billion)</td>
<td>15.45</td>
<td>4.48</td>
<td>8.23</td>
<td>16.36</td>
<td>31.85</td>
</tr>
<tr>
<td>Size ($billion)</td>
<td>34.33</td>
<td>10.17</td>
<td>19.46</td>
<td>37.92</td>
<td>48.28</td>
</tr>
</tbody>
</table>
Table 1.2: Regression Analysis

This table reports the time-series averages of regression coefficients and their corresponding $t$-statistics. $t$-statistics are computed based on the time-series regression coefficients as in Collin-Dufresne, Goldstein and Martin (2001). The entry for $srp<0$ is the percentage of the monthly coefficient on the systematic risk proportion that is negative. The entry for $srp$ significant at 10% is the percentage of the monthly coefficient on the systematic risk proportion that is statistically significant at the level of 10%. The entry for $srp<0$ and significant is the percentage of the negative significance out of the total significance at the level of 10%. The sample contains 236 companies (8040 firm-month observations) from January 2000 to December 2004 (60 months). The $t$-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-310.7830</td>
<td>-26.11</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>-0.8302</td>
<td>-8.69</td>
</tr>
<tr>
<td>Historical volatility</td>
<td>0.4393</td>
<td>2.10</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>7.8446</td>
<td>20.66</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-16.0432</td>
<td>-4.01</td>
</tr>
<tr>
<td>Leverage</td>
<td>2.1392</td>
<td>25.47</td>
</tr>
<tr>
<td>Firm stock return</td>
<td>-0.3946</td>
<td>-5.65</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.5756</td>
<td></td>
</tr>
</tbody>
</table>

$srp<0$  57/60  (95%)
$srp$ significant at 10%: 16/60 (26.67%)
$srp<0$ and significant 16/16 (100%)
Table 1.3: Robustness Checks

This table reports the time-series averages of regression coefficients and their corresponding t-statistics for two robustness checks: 1) using panel regressions and 2) using the systematic risk proportion estimated from three Fama-French factors. The sample contains 236 companies (8040 firm-month observations) from January 2000 to December 2004 (60 months). The t-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled regression + month dummy</th>
<th>FF 3-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>t</td>
</tr>
<tr>
<td>Intercept</td>
<td>-299.7118</td>
<td>-32.64</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>-0.8609</td>
<td>-10.65</td>
</tr>
<tr>
<td>Historical volatility</td>
<td>0.2510</td>
<td>1.76</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>8.8807</td>
<td>49.48</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-19.3677</td>
<td>-7.49</td>
</tr>
<tr>
<td>Leverage</td>
<td>2.2506</td>
<td>41.00</td>
</tr>
<tr>
<td>Firm stock return</td>
<td>-0.4662</td>
<td>-14.62</td>
</tr>
<tr>
<td>Adj. R^2</td>
<td>0.6297</td>
<td></td>
</tr>
<tr>
<td>srp&lt;0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>srp significant at 10%:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>srp&lt;0 and significant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1.4: Summary Statistics of NGARCH Estimates and NGARCH Volatilities

This table presents the cross-sectional summary statistics of NGARCH estimates and NGARCH volatilities. Panel A reports the cross-sectional summary statistics of the time-series means of each firm’s NGARCH estimates. Panel B reports the cross-sectional summary statistics of the time-series means and standard deviations of each firm’s annualized daily NGARCH volatilities and historical volatilities for the period of 2000 to 2004. Stock volatility is assumed to follow the NGARCH(1,1) specification of Engle and Ng (1993):

\[
\begin{align*}
    r_{jt} &= \mu_j + \sigma_j \varepsilon_{jt} \\
    \sigma_{jt}^2 &= b_0 + b_1 \sigma_{jt-1}^2 + b_2 \sigma_{jt-1}^2 (\varepsilon_{jt-1} - \theta_j)^2 \quad \text{for each stock } j
\end{align*}
\]

where \( \varepsilon_{jt} \) is a standard normal random variable conditional on the time \( t-1 \) information. Maximum likelihood estimation is performed using a five-year rolling window of daily returns for each firm. The estimated NGARCH parameters are then used to produce one-step ahead out-of-sample NGARCH(1,1) conditional variance forecasts. To alleviate computation load, NGARCH parameters are updated annually.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: NGARCH estimates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>b0</td>
<td>0.00005391</td>
<td>0.00000814</td>
<td>0.00001648</td>
<td>0.00003854</td>
<td>0.00013919</td>
</tr>
<tr>
<td>b1</td>
<td>0.80280870</td>
<td>0.78767660</td>
<td>0.86477720</td>
<td>0.91130000</td>
<td>0.19303730</td>
</tr>
<tr>
<td>b2</td>
<td>0.08826840</td>
<td>0.04004340</td>
<td>0.06778370</td>
<td>0.11196800</td>
<td>0.07519330</td>
</tr>
<tr>
<td>theta</td>
<td>0.94586220</td>
<td>0.28339630</td>
<td>0.55755970</td>
<td>0.91763340</td>
<td>2.19991160</td>
</tr>
<tr>
<td>mu</td>
<td>0.00023622</td>
<td>0.00002768</td>
<td>0.00024133</td>
<td>0.00046183</td>
<td>0.00048801</td>
</tr>
<tr>
<td>Panel B: Volatilities (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ngarchvolA_mean</td>
<td>38.72</td>
<td>31.52</td>
<td>36.41</td>
<td>43.03</td>
<td>11.16</td>
</tr>
<tr>
<td>historicalvol_mean</td>
<td>38.47</td>
<td>31.37</td>
<td>36.95</td>
<td>42.51</td>
<td>10.95</td>
</tr>
<tr>
<td>ngarchvolA_StdDev</td>
<td>11.63</td>
<td>7.52</td>
<td>9.62</td>
<td>12.79</td>
<td>7.57</td>
</tr>
<tr>
<td>historicalvol_StdDev</td>
<td>8.29</td>
<td>5.21</td>
<td>7.10</td>
<td>9.70</td>
<td>5.05</td>
</tr>
</tbody>
</table>
Table 1.5: Robustness Check Using NGARCH Volatilities

This table reports the time-series averages of regression coefficients and their corresponding *t*-statistics using NGARCH volatilities rather than historical volatilities. This robustness check is performed on a daily basis. As in monthly regressions, I also require that there are at least 30 firms available on each day to perform regression analysis. This leaves me with a final sample of 232 firms (46,586 firm-day observations) on 894 days. The *t*-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th><em>t</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-276.4337</td>
<td>-68.79</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>-0.9674</td>
<td>-24.39</td>
</tr>
<tr>
<td>NGARCH volatility</td>
<td>0.1851</td>
<td>2.58</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>7.6633</td>
<td>74.08</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-18.9456</td>
<td>-14.75</td>
</tr>
<tr>
<td>Leverage</td>
<td>2.1917</td>
<td>79.17</td>
</tr>
<tr>
<td>Firm stock return</td>
<td>-0.4310</td>
<td>-20.54</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.5948</td>
<td></td>
</tr>
</tbody>
</table>

srp<0                                   | 733/894 (81.99%) |
srp significant at 10%:                  | 257/894 (28.75%) |
   srp<0 and significant                 | 252/257 (98.05%) |
Table 1.6: Robustness Check Using More Controls – Size and Liquidity

This table reports the time-series averages of regression coefficients and their corresponding t-statistics when additional control variables such as size and liquidity are included. Firm size is proxied by the natural logarithm of a firm’s market value, which is calculated as the sum of the market value of common stock and the book value of total debt. The liquidity proxy is percentage bid-ask spread, which is bid-ask spread divided by CDS spreads. The sample contains 236 companies (8040 firm-month observations) from January 2000 to December 2004 (60 months). The t-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-282.0325</td>
<td>-17.40</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>-0.4003</td>
<td>-3.52</td>
</tr>
<tr>
<td>Historical volatility</td>
<td>0.5764</td>
<td>2.69</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>7.5670</td>
<td>17.95</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-20.5697</td>
<td>-5.13</td>
</tr>
<tr>
<td>Leverage</td>
<td>2.0742</td>
<td>23.24</td>
</tr>
<tr>
<td>Firm stock return</td>
<td>-0.4291</td>
<td>-5.85</td>
</tr>
<tr>
<td>logsize</td>
<td>-7.9379</td>
<td>-4.16</td>
</tr>
<tr>
<td>baspread</td>
<td>4.9452</td>
<td>0.58</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.5924</td>
<td></td>
</tr>
<tr>
<td>srp&lt;0</td>
<td>48/60</td>
<td>(80%)</td>
</tr>
<tr>
<td>srp significant at 10%:</td>
<td>13/60</td>
<td>(21.67%)</td>
</tr>
<tr>
<td>srp&lt;0 and significant</td>
<td>12/13</td>
<td>(92.31%)</td>
</tr>
</tbody>
</table>
Table 1.7: Robustness Check Excluding Small Firms

This table reports the time-series averages of regression coefficients and their corresponding $t$-statistics after excluding small firms. The cutoff point is 5.6 billion, which is the 10th percentile of firm size. This screening rule leaves me with a sample of 212 companies (7445 firm-month observations) from April 2000 to December 2004 (57 months). The $t$-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-323.6885</td>
<td>-28.85</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>-0.8934</td>
<td>-8.8</td>
</tr>
<tr>
<td>Historical volatility</td>
<td>0.1246</td>
<td>0.55</td>
</tr>
<tr>
<td>Implied volatility</td>
<td>8.6561</td>
<td>21.96</td>
</tr>
<tr>
<td>Implied volatility slope</td>
<td>-20.8624</td>
<td>-6.06</td>
</tr>
<tr>
<td>Leverage</td>
<td>2.1236</td>
<td>27.27</td>
</tr>
<tr>
<td>Firm stock return</td>
<td>-0.4774</td>
<td>-7.08</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>0.5997</td>
<td></td>
</tr>
</tbody>
</table>

| srp<0                             | 54/57 (94.74%) |
| srp significant at 10%:           | 18/57 (31.58%) |
| srp<0 and significant             | 18/18 (100%)   |
Table 1.8: Correlation of CDS Spreads at Different SRP Levels

This table reports how CDS spreads are correlated at different systematic risk proportion levels. Firms are sorted equally into three subgroups by the systematic risk proportion in each month. The degree of correlation of CDS spreads in each subgroup is measured by two variables: the average correlation coefficient and the cross-sectional CDS spread dispersion. The average correlation coefficient is calculated using the simplified procedure suggested by Aneja, Chandra, and Gunay (1989). Given that the number of firms available in each month is different, as a rough calculation, I use two different Ns in the calculation: the maximum number of firms available in one month (N_max), and the average number of firms available in one month (N_mean). For the cross-sectional CDS spread dispersion, I calculate the standard deviation of the CDS spreads in each month and report the time-series average and median of the standard deviations for each of the three subgroups.

<table>
<thead>
<tr>
<th>Group</th>
<th>Average SRP (%)</th>
<th>Average Correlation (N_max)</th>
<th>Average Correlation (N_mean)</th>
<th>Cross-sectional Dispersion (Mean) (basis point)</th>
<th>Cross-sectional Dispersion (Median) (basis point)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10.83</td>
<td>0.3325</td>
<td>0.4873</td>
<td>130.36</td>
<td>112.62</td>
</tr>
<tr>
<td>2</td>
<td>24.20</td>
<td>0.4212</td>
<td>0.6261</td>
<td>131.76</td>
<td>110.55</td>
</tr>
<tr>
<td>3</td>
<td>38.82</td>
<td>0.6359</td>
<td>0.9299</td>
<td>109.23</td>
<td>92.01</td>
</tr>
</tbody>
</table>
Table 2.1: Summary Statistics of Sample Firms

This table presents the cross-sectional summary statistics of the time-series means of the firm-level variables. CDS spread is five-year CDS spreads. Size is the sum of total liabilities and the market value of common stock. Leverage is defined as total liabilities divided by the sum of total liabilities and the market value of common stock. Historical volatility is the annualized historical volatility calculated from the 252-day rolling window. Percentage bid-ask spread is bid-ask spread divided by CDS spreads. Nbcds_1month is the number of daily CDS spreads available in one month. Nbcds_1year is the number of daily CDS spreads available in the one-year window. The sample contains 229 companies from 2001 to 2004.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>CDS spread (basis point)</td>
<td>124.80</td>
<td>52.48</td>
<td>80.12</td>
<td>165.12</td>
<td>105.76</td>
</tr>
<tr>
<td>Equity ($billion)</td>
<td>18.22</td>
<td>4.48</td>
<td>10.04</td>
<td>18.56</td>
<td>27.69</td>
</tr>
<tr>
<td>Debt ($billion)</td>
<td>15.38</td>
<td>4.55</td>
<td>8.54</td>
<td>16.44</td>
<td>32.96</td>
</tr>
<tr>
<td>Size ($billion)</td>
<td>33.60</td>
<td>10.66</td>
<td>18.96</td>
<td>36.47</td>
<td>48.21</td>
</tr>
<tr>
<td>Leverage (%)</td>
<td>47.12</td>
<td>34.36</td>
<td>47.90</td>
<td>60.67</td>
<td>18.23</td>
</tr>
<tr>
<td>Historical volatility (%)</td>
<td>37.57</td>
<td>31.02</td>
<td>35.68</td>
<td>41.75</td>
<td>10.83</td>
</tr>
<tr>
<td>Percentage bid-ask spread (%)</td>
<td>22.43</td>
<td>15.40</td>
<td>20.03</td>
<td>26.67</td>
<td>10.54</td>
</tr>
<tr>
<td>Nbcds_1month</td>
<td>6.84</td>
<td>4.64</td>
<td>5.77</td>
<td>8.45</td>
<td>3.31</td>
</tr>
<tr>
<td>Nbcds_1year</td>
<td>70.83</td>
<td>42.00</td>
<td>60.92</td>
<td>90.50</td>
<td>37.88</td>
</tr>
</tbody>
</table>
Table 2.2: Summary Statistics of Model Parameter Estimates

This table presents the cross-sectional summary statistics of the time-series means of each firm’s model parameter estimates. The illiquidity-Merton’s model specified in equations (2.10) to (2.12) is estimated using the transformed-data MLE estimation firm by firm. For each firm, the estimation is performed every month using a one-year rolling window of daily equity values. As CDS spreads are not available everyday, I require that there are at least 20 spreads available in each window to perform the MLE estimation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asset volatility ( \sigma_y ) (%)</td>
<td>24.58</td>
<td>18.35</td>
<td>23.01</td>
<td>29.52</td>
<td>9.26</td>
</tr>
<tr>
<td>Asset drift ( \mu_y ) (%)</td>
<td>7.87</td>
<td>1.96</td>
<td>8.04</td>
<td>15.26</td>
<td>14.85</td>
</tr>
<tr>
<td>Illiquidity premium ( \gamma ) (basis point)</td>
<td>15.22</td>
<td>13.59</td>
<td>35.78</td>
<td>62.01</td>
<td>121.30</td>
</tr>
<tr>
<td>CDS measurement error ( \sigma_x ) (bp)</td>
<td>33.42</td>
<td>13.11</td>
<td>23.27</td>
<td>46.39</td>
<td>27.61</td>
</tr>
</tbody>
</table>
Table 2.3: Summary Statistics of Subgroups

This table presents the summary statistics of the three subgroups. Firms are sorted equally into three subgroups ascending in the estimated Merton spread, i.e. the second term in equation (2.12), in each month. Panel A reports the cross-sectional summary statistics of the time-series means of the firm-level variables. Panel B reports the cross-sectional summary statistics of the time-series means of each firm’s model parameter estimates.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Low Mean</th>
<th>Low Median</th>
<th>Medium Mean</th>
<th>Medium Median</th>
<th>High Mean</th>
<th>High Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Firm-level variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDS spread (basis point)</td>
<td>64.54</td>
<td>51.81</td>
<td>103.59</td>
<td>79.92</td>
<td>179.66</td>
<td>138.25</td>
</tr>
<tr>
<td>Size ($billion)</td>
<td>37.90</td>
<td>22.04</td>
<td>32.33</td>
<td>18.89</td>
<td>31.32</td>
<td>17.46</td>
</tr>
<tr>
<td>Leverage (%)</td>
<td>39.53</td>
<td>39.08</td>
<td>46.87</td>
<td>46.01</td>
<td>53.14</td>
<td>54.35</td>
</tr>
<tr>
<td>Historical volatility (%)</td>
<td>31.02</td>
<td>30.51</td>
<td>37.38</td>
<td>36.23</td>
<td>44.54</td>
<td>43.17</td>
</tr>
<tr>
<td>Percentage bid-ask spread (%)</td>
<td>25.30</td>
<td>23.45</td>
<td>20.90</td>
<td>19.65</td>
<td>18.71</td>
<td>15.99</td>
</tr>
<tr>
<td>nbcds_1month</td>
<td>6.15</td>
<td>5.00</td>
<td>7.24</td>
<td>6.76</td>
<td>8.18</td>
<td>7.69</td>
</tr>
<tr>
<td>nbcds_1year</td>
<td>63.21</td>
<td>52.06</td>
<td>74.96</td>
<td>66.89</td>
<td>82.15</td>
<td>71.13</td>
</tr>
<tr>
<td>Panel B: Parameter estimates</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asset volatility (%)</td>
<td>19.73</td>
<td>19.05</td>
<td>23.03</td>
<td>21.39</td>
<td>32.32</td>
<td>30.97</td>
</tr>
<tr>
<td>Asset drift (%)</td>
<td>7.58</td>
<td>7.76</td>
<td>5.58</td>
<td>7.26</td>
<td>10.64</td>
<td>9.83</td>
</tr>
<tr>
<td>Illiquidity premium (basis point)</td>
<td>62.27</td>
<td>53.72</td>
<td>69.15</td>
<td>57.72</td>
<td>-69.17</td>
<td>-13.05</td>
</tr>
<tr>
<td>CDS measurement error (basis point)</td>
<td>14.41</td>
<td>12.20</td>
<td>25.28</td>
<td>20.40</td>
<td>53.09</td>
<td>45.34</td>
</tr>
</tbody>
</table>
Table 2.4: Determinants of the Illiquidity Premium

This table shows how liquidity measures of the CDS market affect the model implied illiquidity premium. Shown in the table are panel regression results. The dependent variable is monthly illiquidity premium. Percentage bid-ask spread is bid-ask spread divided by CDS spreads. Nbcds_1month is the number of daily CDS spreads available in one month. logME is the natural logarithm of the market equity capitalization. Monthly dummies (not shown) are also included in the regressions. Intercept<0 represents the percentage of the negative monthly intercept. Issuer-clustering is adjusted to obtain robust $t$-values. The sample includes 6147 firm-month observations ranging from 2001 to 2004 (a total of 48 months). The number of clusters (i.e. firms) is 229. The $t$-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.0030</td>
<td>0.0077</td>
<td>0.0052</td>
<td>0.0060</td>
<td>0.0061</td>
</tr>
<tr>
<td></td>
<td>2.11</td>
<td>4.43</td>
<td>3.13</td>
<td>3.09</td>
<td>2.59</td>
</tr>
<tr>
<td>bid-ask spread</td>
<td>0.0201</td>
<td>0.0164</td>
<td>0.0164</td>
<td>0.0166</td>
<td>0.0166</td>
</tr>
<tr>
<td></td>
<td>3.72</td>
<td>3.89</td>
<td>3.92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>nbcds_1month</td>
<td>-0.0004</td>
<td>-0.0003</td>
<td>-0.0003</td>
<td>-0.0002</td>
<td>-1.66</td>
</tr>
<tr>
<td></td>
<td>-2.26</td>
<td>-1.65</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>logME</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.0004</td>
<td>-0.65</td>
</tr>
<tr>
<td></td>
<td>-0.67</td>
<td>-0.65</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>2.79%</td>
<td>2.40%</td>
<td>3.13%</td>
<td>1.61%</td>
<td>3.17%</td>
</tr>
<tr>
<td>Intercept&lt;0</td>
<td>85.42%</td>
<td>14.58%</td>
<td>66.67%</td>
<td>27.08%</td>
<td>60.42%</td>
</tr>
</tbody>
</table>
Table 2.5: The Effect of the Risk Composition on the Illiquidity Premium

This table shows how the risk composition of the underlying firm affects the model implied illiquidity premium. Shown in the table are panel regression results. The dependent variable is monthly illiquidity premium. Percentage bid-ask spread is bid-ask spread divided by CDS spreads. Nbcds_1month is the number of daily CDS spreads available in one month. Systematic risk proportion is defined as the ratio of the systematic variance over the total variance. Monthly dummies (not shown) are also included in the regressions. Issuer-clustering is adjusted to obtain robust $t$-values. The sample includes 6147 firm-month observations ranging from 2001 to 2004 (a total of 48 months). The number of clusters (i.e. firms) is 229. The $t$-statistics in bold type are significant at the 10% level or higher.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(6)</td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0003</td>
</tr>
<tr>
<td>bid-ask spread</td>
<td></td>
</tr>
<tr>
<td>nbcds_1month</td>
<td>-0.0003</td>
</tr>
<tr>
<td>Systematic risk proportion (srp)</td>
<td>0.0002</td>
</tr>
<tr>
<td>$R^2$</td>
<td>2.99%</td>
</tr>
</tbody>
</table>
Table 3.1A: Summary Statistics of the Sample

This table reports the cross-sectional summary statistics of the time-series means of the firm-level variables. The BS implied volatility is the Black-Scholes implied volatility downloaded from OptionMetrics. Systematic risk proportion is defined as the ratio of the systematic variance over the total variance. The risk-neutral volatility, skewness, and kurtosis are estimated using the model-free approach of Bakshi, Kapadia and Madan (2003). Historical volatility is the annualized historical volatility calculated from the one-year rolling window. The sample includes 100 firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index over a period of ten years from 1997 to 2006.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>25th percentile</th>
<th>Median</th>
<th>75th percentile</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>BS implied volatility</td>
<td>0.4567</td>
<td>0.3292</td>
<td>0.4157</td>
<td>0.5546</td>
<td>0.1556</td>
</tr>
<tr>
<td>Systematic risk proportion</td>
<td>0.2657</td>
<td>0.1859</td>
<td>0.2578</td>
<td>0.3110</td>
<td>0.1310</td>
</tr>
<tr>
<td>Risk-neutral volatility</td>
<td>0.4173</td>
<td>0.3024</td>
<td>0.3824</td>
<td>0.5125</td>
<td>0.1409</td>
</tr>
<tr>
<td>Risk-neutral skewness</td>
<td>-0.3973</td>
<td>-0.5871</td>
<td>-0.3665</td>
<td>-0.2252</td>
<td>0.2666</td>
</tr>
<tr>
<td>Risk-neutral kurtosis</td>
<td>2.5360</td>
<td>2.2161</td>
<td>2.4546</td>
<td>2.7081</td>
<td>0.4544</td>
</tr>
<tr>
<td>Historical volatility</td>
<td>0.4683</td>
<td>0.3255</td>
<td>0.4217</td>
<td>0.6015</td>
<td>0.1844</td>
</tr>
</tbody>
</table>
Table 3.1B: Summary Statistics by Year

This table reports the cross-sectional means and medians of the time-series means of the firm-level variables by year. BSvol stands for the Black-Scholes implied volatility downloaded from OptionMetrics. RNvol stands for the model-free risk-neutral volatility estimated using the model-free approach of Bakshi, Kapadia and Madan (2003). HV stands for the annualized historical volatility calculated from the one-year rolling window. SRP stands for the systematic risk proportion, which is defined as the ratio of the systematic variance over the total variance. BSvol-HV stands for the volatility spread using the Black-Scholes implied volatility. RNvol-HV stands for the volatility spread using the model-free risk-neutral volatility. The sample includes 100 firms whose total option volume ranks among the top 100 in OptionMetrics and the S&P 100 index over a period of ten years from 1997 to 2006.

| Year | BSvol Mean | BSvol Median | RNvol Mean | RNvol Median | HV Mean | HV Median | SRP Mean | SRP Median | BSvol-HV Mean | BSvol-HV Median | RNvol-HV Mean | RNvol-HV Median |
|------|------------|--------------|------------|--------------|---------|-----------|----------|-----------|---------------|----------------|---------------|----------------|----------------|
| 1997 | 0.3845     | 0.3383       | 0.3377     | 0.2902       | 0.3687  | 0.3165    | 0.2443   | 0.1904    | 0.0159        | 0.0261         | -0.0310       | -0.0151        |
| 1998 | 0.4498     | 0.3829       | 0.3960     | 0.3452       | 0.4431  | 0.3820    | 0.2984   | 0.2616    | 0.0067        | 0.0070         | -0.0471       | -0.0365        |
| 1999 | 0.4884     | 0.4421       | 0.4353     | 0.3997       | 0.5115  | 0.4538    | 0.2630   | 0.2385    | -0.0231       | -0.0116        | -0.0762       | -0.0610        |
| 2000 | 0.5922     | 0.5494       | 0.5410     | 0.5104       | 0.5888  | 0.5483    | 0.1926   | 0.1700    | 0.0033        | 0.0141         | -0.0478       | -0.0349        |
| 2001 | 0.5818     | 0.5031       | 0.5423     | 0.4746       | 0.6539  | 0.5295    | 0.2440   | 0.2369    | -0.0718       | -0.0498        | -0.1116       | -0.0752        |
| 2002 | 0.5539     | 0.4914       | 0.5146     | 0.4714       | 0.5626  | 0.4585    | 0.3221   | 0.3139    | -0.0084       | 0.0219         | -0.0480       | -0.0138        |
| 2003 | 0.4262     | 0.3980       | 0.3931     | 0.3750       | 0.4969  | 0.4284    | 0.3743   | 0.3555    | -0.0707       | -0.0513        | -0.1038       | -0.0795        |
| 2004 | 0.3531     | 0.3201       | 0.3214     | 0.2957       | 0.3328  | 0.3013    | 0.2861   | 0.2771    | 0.0203        | 0.0219         | -0.0114       | -0.0026        |
| 2005 | 0.3061     | 0.2729       | 0.2822     | 0.2459       | 0.2907  | 0.2562    | 0.2504   | 0.2409    | 0.0156        | 0.0249         | -0.0085       | 0.0045         |
| 2006 | 0.3176     | 0.2857       | 0.2918     | 0.2651       | 0.2873  | 0.2632    | 0.2286   | 0.2013    | 0.0303        | 0.0272         | 0.0045        | 0.0051         |
Table 3.2: Regression Tests Using the Model-Free Risk-Neutral Volatility

This table reports the time-series averages of regression coefficients and their corresponding $t$-statistics. The $t$-statistics are calculated using the Newey-West standard error with four lags. The dependent variable is the average of the difference between the risk-neutral volatility and the historical volatility. RNvol-HV stands for the average of the difference between the model-free risk-neutral volatility and the historical volatility. BSvol-HV stands for the average of the difference between the Black-Scholes implied volatility and the historical volatility. The entries under $>0$ (%) are the percentages of the monthly coefficient on the systematic risk proportion that are positive.

<table>
<thead>
<tr>
<th>Moneyness</th>
<th>$\gamma_1$ (bj)</th>
<th>$\gamma_2$ (skew)</th>
<th>$\gamma_3$ (kurt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>$t$</td>
<td>$&gt;0$ (%)</td>
</tr>
<tr>
<td>K/S - all</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RNvol-HV</td>
<td>[20,180]</td>
<td>0.047</td>
<td>2.281</td>
</tr>
<tr>
<td></td>
<td>[20,70]</td>
<td>0.040</td>
<td>1.923</td>
</tr>
<tr>
<td></td>
<td>[71,120]</td>
<td>0.042</td>
<td>2.114</td>
</tr>
<tr>
<td></td>
<td>[121,180]</td>
<td>0.056</td>
<td>2.767</td>
</tr>
<tr>
<td>BSvol-HV</td>
<td>[20,180]</td>
<td>0.025</td>
<td>1.278</td>
</tr>
<tr>
<td></td>
<td>[20,70]</td>
<td>0.016</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>[71,120]</td>
<td>0.021</td>
<td>1.114</td>
</tr>
<tr>
<td></td>
<td>[121,180]</td>
<td>0.034</td>
<td>1.719</td>
</tr>
</tbody>
</table>
Table 3.3: Sub-Sample Regression Tests

This table reports the time-series averages of regression coefficients and their corresponding $t$-statistics for the whole sample (1997-2006) as well as three sub-samples: (1997-2001), (2002-2006), and (1997-2000). The $t$-statistics are calculated using the Newey-West standard error with four lags for the whole sample and three lags for the three sub-samples. The dependent variable is the average of the difference between the model-free risk-neutral volatility and the historical volatility. The entries under $>0$ (%) are the percentages of the monthly coefficient on the systematic risk proportion that are positive.

<table>
<thead>
<tr>
<th>Maturity</th>
<th>$\gamma_1$ (bj)</th>
<th>$\gamma_2$ (skew)</th>
<th>$\gamma_3$ (kurt)</th>
<th>Coef.</th>
<th>Coef.</th>
<th>Coef.</th>
<th>t</th>
<th>t</th>
<th>t</th>
<th>R$^2$</th>
<th>Adj. R$^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>[20,180]</td>
<td>1997 2006</td>
<td>0.047</td>
<td>2.281</td>
<td>77.5</td>
<td>-0.050</td>
<td>-4.568</td>
<td>0.005</td>
<td>1.518</td>
<td>0.189</td>
<td>0.160</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2001</td>
<td>0.065</td>
<td>2.042</td>
<td>85.0</td>
<td>-0.034</td>
<td>-2.516</td>
<td>0.011</td>
<td>2.636</td>
<td>0.187</td>
<td>0.158</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2002 2006</td>
<td>0.028</td>
<td>1.832</td>
<td>70.0</td>
<td>-0.066</td>
<td>-5.097</td>
<td>-0.001</td>
<td>-0.325</td>
<td>0.191</td>
<td>0.162</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2000</td>
<td>0.124</td>
<td>14.535</td>
<td>100.0</td>
<td>-0.009</td>
<td>-1.851</td>
<td>0.013</td>
<td>2.804</td>
<td>0.148</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td>[20,70]</td>
<td>1997 2006</td>
<td>0.040</td>
<td>1.923</td>
<td>75.8</td>
<td>-0.037</td>
<td>-3.832</td>
<td>0.007</td>
<td>2.190</td>
<td>0.150</td>
<td>0.112</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2001</td>
<td>0.067</td>
<td>2.203</td>
<td>83.3</td>
<td>-0.027</td>
<td>-2.410</td>
<td>0.006</td>
<td>2.025</td>
<td>0.145</td>
<td>0.112</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2002 2006</td>
<td>0.014</td>
<td>0.714</td>
<td>68.3</td>
<td>-0.047</td>
<td>-3.616</td>
<td>0.007</td>
<td>1.461</td>
<td>0.154</td>
<td>0.112</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2000</td>
<td>0.118</td>
<td>8.994</td>
<td>95.8</td>
<td>-0.007</td>
<td>-1.464</td>
<td>0.007</td>
<td>2.661</td>
<td>0.123</td>
<td>0.088</td>
<td></td>
</tr>
<tr>
<td>[71,120]</td>
<td>1997 2006</td>
<td>0.042</td>
<td>2.114</td>
<td>74.2</td>
<td>-0.045</td>
<td>-4.491</td>
<td>0.006</td>
<td>1.876</td>
<td>0.185</td>
<td>0.152</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2001</td>
<td>0.065</td>
<td>2.083</td>
<td>81.7</td>
<td>-0.032</td>
<td>-2.563</td>
<td>0.012</td>
<td>2.925</td>
<td>0.193</td>
<td>0.162</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2002 2006</td>
<td>0.019</td>
<td>1.363</td>
<td>66.7</td>
<td>-0.057</td>
<td>-4.810</td>
<td>0.000</td>
<td>0.054</td>
<td>0.176</td>
<td>0.142</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2000</td>
<td>0.123</td>
<td>13.769</td>
<td>100.0</td>
<td>-0.009</td>
<td>-1.951</td>
<td>0.013</td>
<td>2.969</td>
<td>0.150</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td>[121,180]</td>
<td>1997 2006</td>
<td>0.056</td>
<td>2.767</td>
<td>76.7</td>
<td>-0.056</td>
<td>-5.102</td>
<td>0.010</td>
<td>2.413</td>
<td>0.242</td>
<td>0.213</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2001</td>
<td>0.070</td>
<td>2.129</td>
<td>80.0</td>
<td>-0.045</td>
<td>-3.103</td>
<td>0.025</td>
<td>5.572</td>
<td>0.267</td>
<td>0.239</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2002 2006</td>
<td>0.042</td>
<td>3.218</td>
<td>73.3</td>
<td>-0.066</td>
<td>-5.417</td>
<td>-0.004</td>
<td>-1.003</td>
<td>0.216</td>
<td>0.188</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1997 2000</td>
<td>0.134</td>
<td>15.766</td>
<td>100.0</td>
<td>-0.019</td>
<td>-3.572</td>
<td>0.025</td>
<td>5.315</td>
<td>0.216</td>
<td>0.185</td>
<td></td>
</tr>
</tbody>
</table>
Table 3.4: Regression Tests at Different SRP Levels

This table reports the time-series averages of regression coefficients on the systematic risk proportion and their corresponding $t$-statistics for the whole sample as well as three subgroups. Firms are sorted equally into three subgroups ascending in the systematic risk proportion in each month of the two crisis periods i.e. from April 2001 to July 2002 and from October 2005 to May 2006, a total of 24 months. The dependent variable is the average of the difference between the model-free risk-neutral volatility and the historical volatility. The maturity group is 20 to 180 days. The entries beside $>0$ (%) are the percentages of the monthly coefficient on the systematic risk proportion that are positive.

<table>
<thead>
<tr>
<th>$\gamma_1$</th>
<th>All</th>
<th>Low SRP</th>
<th>Medium SRP</th>
<th>High SRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coef.</td>
<td>-0.1304</td>
<td>-0.2383</td>
<td>-0.1361</td>
<td>0.0902</td>
</tr>
<tr>
<td>$t$</td>
<td>-5.88</td>
<td>-2.38</td>
<td>-1.71</td>
<td>4.27</td>
</tr>
<tr>
<td>$&gt;0$ (%)</td>
<td>0</td>
<td>25%</td>
<td>42%</td>
<td>67%</td>
</tr>
</tbody>
</table>
This figure reports the number of firms available in each month and the month-by-month cross-sectional average CDS spread. The sample contains 229 companies from 2001 to 2004.
Figure 2.2: Time-Series Plots of Liquidity Measures

This figure reports the month-by-month cross-sectional average CDS percentage bid-ask spread and the number of daily CDS spreads available in each month. Percentage bid-ask spread is bid-ask spread divided by CDS spreads. The sample contains 229 companies from 2001 to 2004.
Figure 2.3: Time-Series Plots of the Illiquidity Premium

This figure reports the time-series mean of illiquidity premium for each firm and the cross-sectional average of illiquidity premium for each month. The illiquidity premium is estimated using the transformed-data MLE estimation from equations (2.10) to (2.12) for each firm. The estimation is performed every month using a one-year rolling window of daily equity values. As CDS spreads are not available everyday, I require that there are at least 20 spreads available in each window to perform the MLE estimation. The sample contains 229 companies from 2001 to 2004.
Figure 2.4: Time-Series Plots of the Monthly Intercept

This figure reports the monthly intercept from the regression of illiquidity premium on the percentage bid-ask spread and the number of daily CDS spreads available in one month. The monthly intercept is calculated as the sum of the regression constant and the corresponding monthly dummy. The sample includes 6147 firm-month observations ranging from 2001 to 2004 (a total of 48 months). The number of clusters (i.e. firms) is 229.
Figure 3.1 plots the time-series of the cross-sectional average of volatilities, the systematic risk proportion, and volatility spreads from January 1997 to December 2006. The Black-Scholes implied volatilities and the model-free risk-neutral volatilities are calculated from the maturity group of 20 to 180 days.
Figure 3.2: Time-Series Plots of the Coefficient of the Systematic Risk Proportion

Figure 3.2 plots the time-series of the regression coefficient on the systematic risk proportion from January 1997 to December 2006 for the maturity group of 20 to 180 days. RNvol-HV stands for the volatility spread between the model-free risk-neutral volatility and the historical volatility. \( \gamma_1 \) represents the average coefficient on the systematic risk proportion.
Bibliography


Tang, D., and H. Yan, 2008, Liquidity and Credit Default Swap Spreads, Working paper, University of Hong Kong.
