Macroeconomic Conditions and

Credit Default Swap Spread Changes

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Abstract

We investigate the importance of the business cycle in explaining credit default swap spread changes by utilizing *ex ante* proxy. Through portfolio regression, we find that the structural variables, including the business cycle, explain approximately 65% of the spread differences. Furthermore, the business cycle variable enhances explanatory power to a greater extent during the pre-crisis and post-crisis periods than during the crisis period and shows larger improvement for investment-grade firms than for non-investment-grade firms. These results suggest that macroeconomic conditions play a critical role when the underlying asset value is likely to have a longer distance to the default barrier.

JEL classification: G12.

Keywords: CDS; business cycle; default barrier; structural model, portfolio regression.

1. Introduction

The credit spread puzzle that "observed corporate spreads are much larger than what would be predicted by historical rates of default and recovery rates" (Amato and Remolona (2003), p. 1) has led to a series of investigations of the factors impacting the credit spread that cannot be explained by theoretical variables (e.g., Elton, Gruber, Agrawal, and Mann (2001); Amato and Remolona (2003); Chen, Collin-Dufresne, and Goldstein (2009); Chen (2010)). The determinants of credit spreads have been explored by regressing corporate bond credit spreads on the proxies for structural variables. The representative study by Collin-Dufresne, Goldstein, and Martin (2001) finds that the theoretical variables of structural models have limited explanatory power for credit spread changes. In addition, the authors' principal component analysis (PCA) of the regression residuals suggests that monthly credit spread changes are mostly driven by a single common risk factor—one that cannot be explained by their macroeconomic and financial variables.

Recent studies of corporate credit risk tend to investigate the determinants of credit default swap (CDS) spreads rather than corporate bond spreads (e.g., Benkert (2004); Greatrex (2009); Ericsson, Jacobs, and Oviedo-Helfenberger (2009); Zhang, Zhou, and Zhu (2009); Cao, Yu, and Zhong (2010); Cesare and Guazzarotti (2010); Tang and Yan (2010); Galil, Shapir, Amiram, and Ben-Zion (2014)), for the following well-known reasons. First, the CDS market has expanded rapidly during the past decade, resulting in a rich platform for the study of credit risk. Second, unlike corporate bond spreads, CDS spreads are less susceptible to extraneous factors such as risk-free benchmark yields, tax treatments, and bond-specific contract conditions such as seniority, call or put provisions, and guarantees. Finally, as pointed out by Zhang et al. (2009), there are virtually no limits to CDS market positions, and CDS spreads, therefore, tend to respond quickly to changes in credit conditions.

A body of the literature had confirmed that structural variables inspired by theory are important determinants of the variation in CDS spreads. Ericsson et al. (2009) show that the leverage ratio, volatility, and the risk-free rate explain about 60% of CDS spread levels. Zhang et al. (2009) find that the realized volatility from high-frequency equity prices predicts around 50% of the variations in CDS premia, while jump risk characteristics such as jump intensity, jump mean, jump volatility, and jump size forecast 19%. Cao et al. (2010) also provide evidence that credit-related firm-specific and macro variables, including option-implied volatility, explain approximately 84% of CDS spread variations.

Even with the high explanatory power for CDS premium levels shown in the above-mentioned studies, changes in CDS premia are not well explained by theoretical variables, consistent with the previous finding of Collin-Dufresne et al. (2001) for bond credit spread changes. Zhang et al. (2009) find that the explanatory power of structural factors in CDS spread changes is around 5%, whereas Greatrex (2009) and Ericsson et al. (2009) find that the variables suggested by structural models explain approximately 30% of the variation in CDS spread changes. Han and Zhou (2015) also report that structural variables explain only 10% of the differences in premia through panel regression.

In addition, the results determining the existence of a common risk factor in CDS premium changes are mixed. By utilizing a dataset of 107 firms' CDS spreads from CreditTrade over the period 1999–2002, Ericsson et al. (2009) show that the PCA of the three factors' (the leverage ratio, equity volatility, and the risk-free rate) regression residuals presents only weak evidence of the existence of a common factor. On the contrary, by using a dataset of 167 firms' CDS spreads from January 2002 to March 2009 obtained from Bloomberg, Cesare and Guazzarotti (2010) report that a common risk factor drove CDS spread changes during the crisis period and that proxies for economic activity, uncertainty, and risk aversion cannot explain this systematic risk factor.

In this study, motivated by the empirically insufficient usefulness of structural models in addition to the mixed findings for CDS spread changes, we focus on the sources of the low explanatory power of the structural variables for changes in CDS spreads and conjecture that both the usage of inappropriate proxies for macroeconomic conditions and the pricing errors of the structural variables can be culprits.

To resolve the first source, we utilize the "continuous and *ex ante"* proxies for the business cycle. The background is Petkova and Zhang's (2005) investigation into the relation between time-varying market risks and value firms' portfolio returns. The authors insist that *ex post* realized market returns or GDP growth can be a noisy measure for marginal utility or the business cycle and that the *ex ante* expected market risk premium should be used to capture business states. Thus, by using the *ex ante* proxy instead of real economic variables, we investigate whether the business cycle is an important determinant of CDS spread changes and hypothesize that the business cycle variable is related to a common or systematic risk factor of changes in CDS spreads.

This research hypothesis is based on recent theoretical studies of the relation between credit spreads and the business cycle. Chen (2010) insists it is necessary to endogenously consider a cyclical market price of risk that increases with the default probability or default loss in structural models to explain the observed corporate credit spreads. In addition, the author states that these co-movements require higher credit risk premia for investment-grade firms, which may explain the credit spread puzzle where the proportion of theoretically estimated credit spreads to observed spreads tends to be much smaller for investment-grade firms than for non-investment-grade firms. Kim and Kim (2005) derive the estimate equation for the default probability depending on the business cycle, as an extension of Merton's (1974) model, reflecting the assumption that expected asset returns will be higher in a bullish market if instantaneous asset returns are proportional to the production growth rate. Tang and Yan (2006) construct a theoretical model that explicitly incorporates equilibrium macroeconomic dynamics into a firm's cash flow process. They find that firm characteristics such as cash flow volatility, the current firm-specific growth rate, and cash flow beta have significant effects on credit spreads and that these effects change depending on the economic conditions.

To settle the second source, that is pricing errors, we conduct portfolio-level regressions. Eom, Helwege, and Huang (2004) document that the pricing errors of structural models are systematically relevant to several firm characteristics such as the leverage ratio and asset volatility. Further, the authors insist that the leverage ratio has the most significant effect on pricing errors. Therefore, we construct portfolios grouped by the leverage ratio and equity volatility ranges to eliminate the errors generated from idiosyncratic risks.

Our main empirical results are summarized as follows. First, contrary to the results of Ericsson et al. (2009) showing weak evidence of the three factors' regression residual common factor, we find that the coefficients of the business cycle variables orthogonal to the three factors are strongly significant and robust. We also discover that the business cycle variables explain a greater part of the variation in CDS spread changes for investment-grade firms than for non-investment-grade firms.

Second, through portfolio-level regressions, we find that our structural model variables explain approximately 65% of spread changes, which is almost twice the explanatory power of the variable sets of Ericsson et al. (2009). In addition, even after the removal of idiosyncratic risks, the coefficients of our business cycle variables are substantially significant.

Finally, we find that the business cycle variables—the expected market risk premium, financial conditions index, and industrial price index—are strongly significant, increasing explanatory power considerably for the pre-crisis period (e.g., approximately 3.4%, 9.7%, and 8.4%, respectively) and the post-crisis period (e.g., approximately 10%, 11.2%, and 4.6%, respectively). Further, they are robust over the full sample as well as for the pre-crisis and post-crisis periods independent of the number of portfolios. However, it should be noted that during the crisis period, the three factors of Merton's (1974) model explain 67% of the differences in CDS spreads, while the coefficients of the market risk premium, financial conditions index, and industrial price index show relatively weak significance levels and their incremental explanatory power is also slight (about 0.5%, -0.1%, and 2.1%, respectively).

Taken together with these results, if we consider CDS as a kind of put option[1] on the asset value, it is inferred that the main factors affecting CDS price depend on its current moneyness, which is a mapping to the distance between the current underlying asset value and default barrier. In particular, the crisis period is when the distance becomes severely narrow and investment-grade firms tend to have a relatively long distance to default. Therefore, we conclude that the factor representing macroeconomic conditions may play a critical role in pricing CDS when the underlying asset value of CDS is likely to be farther from the default barrier, whereas the three factors of Merton's (1974) model fair well only when the distance to default is very short.

Most empirical studies of the impacts of macroeconomic conditions on CDS spreads have used real economic variables. For instance, Baum and Wan (2010) find that macroeconomic uncertainties such as the predicted conditional volatilities of the GDP growth rate, the index of industrial

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[1] Carr and Wu (2011) and Kim, Park and Noh (2013) demonstrate the strong linkage between the CDS and deep-out-of-money put options based on the cash flow replication concept.

production, and Standard & Poor's (S&P) index returns have greater explanatory power for CDS spreads than traditional macroeconomic factors such as the risk-free rate and term spread. Tang and Yan (2010) find that the average credit spread increases with a declining GDP growth rate, but decreases with an increase in its volatility. In addition, firms with higher cash flow beta exhibit lower credit spreads than firms with lower cash flow beta, but this tendency disappears during recessions.

The previous studies mentioned above examine the associations between macroeconomic conditions and CDS spread levels, not CDS spread changes, and generally use GDP growth, GDP volatility, and investor sentiment as proxies for macroeconomic conditions. However, other earlier research using data before the financial crisis generally failed to detect any associations between changes in macroeconomic factors and CDS spreads. For example, Galil et al. (2014) report that only changes in the default premium among Chen, Roll, and Ross' (1986) five factors as macroeconomic variables significantly contribute to CDS spread changes but their significance disappears after controlling for firm-specific variables.

This paper continues along this line of research by focusing on the effects of macroeconomic conditions on credit spread; however, it makes the following additional contributions to the literature. First, in contrast to prior research using real economic variables, we estimate the expected market risk premium as a continuous and *ex ante* proxy for the business cycle and provide strong evidence of the significant impact of macroeconomic conditions on CDS spread changes even after controlling for firm-specific variables. In addition, we confirm the robustness by utilizing price indexes such as the industrial price index and financial conditions index.

Our second contribution is that we perform portfolio-level regressions. Since illiquid CDSs tend to have difficulties in discovering fair prices and firm-specific explanatory variables may contain some noise in discovering true prices, the construction of portfolios grouped by the leverage ratio and equity volatility ranges can eliminate any errors generated from the above limits or idiosyncratic risks. This approach thus helps us demonstrate that a substantial proportion of CDS spread changes are well explained under the framework of structural models.

Third, to the best of our knowledge, this study is novel in the literature on CDS spreads in that we empirically examine whether macroeconomic variables play different roles in pricing CDSs depending on the level of the default barrier, utilizing a comprehensive and recent dataset that includes the pre-crisis, crisis, and post-crisis periods.

The remainder of this paper is organized as follows. Section 2 describes the data used in the CDS spreads and other explanatory variables. Section 3 explains the analytical framework and Section 4 presents the empirical results. Section 5 summarizes the results and presents our concluding remarks.

2. Data

2.1. CDS spread

The CDS spread data for senior unsecured USD-denominated debt with five years of maturity and a modified restructure clause are obtained from Markit. Firms from the utility and financial sectors are excluded, as are firms with unknown ratings. After merging stock price data from the Center for Research in Security Prices (CRSP), accounting data from Compustat and the equity-option implied volatility data from Bloomberg, we have 641 firms. We then produce the monthly averaged time series of CDS spread for each firm and exclude the averaged data with quotes of less than 9 trading days for each month. Finally, we select 384 firms, each with at least 58 monthly change observations over the sample period from September 2004 to March 2012.

Table 1 presents the structural model variables expected to explain the CDS spread changes and describes their notation, the specific data used to estimate them, and their data sources. The last column shows the expected signs of the regression coefficients. Since we intend to compare the importance of the business cycle variables with that of the other proxies of structural determinants used in literature, most additional variables follow the base regressors of Collin-Dufresne et al. (2001). Here, we describe the various proxies for the business cycle in section 2.2 and discuss in detail the data used to estimate the additional explanatory variables in section 2.3.

[Table 1 goes here]

2.2. Proxies of the business cycle

1) *Expected market risk premium (EMKT)*

Petkova and Zhang (2005) suggest that since the *ex post* realized market return or GDP growth is a noisy measure for marginal utility or the business cycle, the expected market risk premium may be a more precise measure of aggregate economic conditions. Thus we construct a proxy for the business cycle by estimating the expected market risk premium. This measure is estimated by regressing the realized market return from t to $t+1$ on macroeconomic variables known at t, as in equation (1), and obtaining the expected market risk premium estimates with the fitted value of regression as in equation (2):

$$R_{t+1}^{M} = \alpha_0 + \alpha_1 DIV_t + \alpha_2 DEF_t + \alpha_3 TERM_t + \alpha_4 TB_t + \varepsilon_{t+1}^{M} \tag{1}$$

$$E_t[R_{t+1}^{M}] = \hat{\alpha}_0 + \hat{\alpha}_1 DIV_t + \hat{\alpha}_2 DEF_t + \hat{\alpha}_3 TERM_t + \hat{\alpha}_4 TB_t \tag{2}$$

where *DIV* is the aggregate dividend yield, *DEF* denotes the default premium, *TERM* is the term spread, and *TB* is the risk-free rate. In more detail, the default spread is the difference between the yields of a long-term corporate Baa bond and a long-term government bond, the risk-free rate is the three-month T-bill yield, the term spread is the difference between the yields of a 10-year and a one-year government bond, and the aggregate dividend yield is the dividend yield of the CRSP value-weighted portfolio, computed as the sum of dividends over the last 12 months, divided by the level of the index. The monthly data on bond yields are from the FRED (Federal Reserve Economic Data) database of the Federal Reserve Bank of St. Louis.

The left in Figure 1 graph shows the estimated monthly market risk premium as a proxy for the business cycle. It illustrates the in-sample fitted estimates of the expected market risk premium from January 1954 to December 2000. The right graph depicts the out-of-sample time series estimates of the monthly expected market risk premium between September 2004 and March 2012, based on in-sample parameters. It is conspicuous that the expected market risk premium increased enormously during the subprime mortgage crisis, surging to around 7%, a level never reached between 1954 and 2007. In addition, we can confirm that the cross-sectional average CDS spread grows as the economic state deteriorates from the right graph. This also supports the intuition that there is strong co-movement between CDS spreads and the continuous and *ex ante* business cycle proxy.

[Figure 1 goes here]

2) *Volatility index (VIX)*

The *VIX* is a measure of implied volatility extracted from S&P 500 stock index option prices with 30-day maturity. We select the *VIX* as a macroeconomic variable since the *VIX* is referred as a measure of the investor's risk appetite or market uncertainty (Pan and Singleton (2008), Eichengreen, Mody, Nedeljkovic, and Sarno (2009) and Kim, Park and Noh (2013)). The *VIX* is expected to show the positive sign since the investor's risk aversion affects positively on credit spreads. The *VIX* is obtained from Chicago Board Options Exchange (CBOE).

3) *Goldman Sachs financial conditions index (FCI)*

The *FCI* is the weighted sum of a short-term bond yield, a long-term corporate yield, the exchange rate, and a stock market variable. The weights are computed from the Federal Reserve Board's macroeconomic model added by Goldman Sachs modeling. The index starts from 100 at Oct. 2003 and use the levels of financial variables, differently from the other index reflecting the changes or spreads of them. Tightening of financial conditions is suggested by an increase in the FCI and easing of them is suggested by the decline of the *FCI*. Therefore, we expect the positive relationship between the *FCI* and the CDS spreads.

4) *JOC-ECRI industrial price index (IPI)*

The *IPI* is developed by the Economic Cycle Research Institute (ECRI) and collected from Bloomberg. It is an indicator of inflation based on a broad assortment of raw materials used in industrial production. As Galil et al. (2014) pointed out, the relationship between inflation and CDS spread is unclear. High inflation renders economies growing which can lead to a decrease in the CDS spreads, while difference between nominal and real interest rates requires its compensation and thus pushes up CDS spreads.

5) *Ted spread (TED)*

The ted spread is the difference between 3 month LIBOR rate and 3 month U.S. T-bill rate. Eichengreen, Mody, Nedeljkovic, and Sarno (2009) interpret that ted spread is decomposed into banking sector credit risk part coming from "LIBOR - OIS(Overnight Index Swap)" and liquidity or flight-to-quality premium coming from "OIS - T-bill rate". The authors show that ted spread enormously rose after the post-Lehman crisis period and it can be a proxy for rollover risk in the short-term funding. Thus we consider the *TED* as a proxy for the business cycle and expect the positive sign of the coefficient as the explanatory variable for the CDS spreads.

6) *Dollar index spot (DIS)*

The *DIS* measures the value of U.S. dollar relative to a static basket of major foreign currencies such as Euro, Japanese Yen, Canadian Dollar, Pound Sterling and so on. It can be an indicator of the U.S. macroeconomic conditions and thus we expect the negative association between the *DIS* and the CDS spreads.

2.3. Additional explanatory variables

1) *Leverage ratio (LEV)*

The leverage ratio is computed as follows, where the market value of firm equity is obtained from the CRSP and the quarterly book value of firm debt and preferred stock are downloaded from Compustat for each firm:

$$LEV = \frac{book\ value(debt + preferred\ stock)}{[\ book\ value(debt + preferred\ stock) + market\ value\ (equity)]}$$

Since an increase in firm leverage ratio means an increasing probability of triggering the default boundary on the structural framework, CDS spreads are predicted to increase with the increase of the leverage ratio.

2) *Stock return volatility (VOL)*

Cao, Yu, and Zhong (2010) show that the implied volatility dominates historical volatility in explaining the time-series variation of CDS spreads and thus we use the option-implied volatility as a proxy for stock return volatility. The three-month implied volatility extracted from a weighted average price of the two put options closest to the at-the-money strikes is obtained from Bloomberg. Unobservable firm value volatility is usually replaced by stock return volatility because many studies document a strong linkage between corporate bond spreads and stock return realized volatility or stock option implied volatility through empirical analysis (e.g., Delianedis and Geske (2001); Campbell and Taksler (2003); Cremers, Driessen, and Maenhout (2008a); Cremers, Driessen, Maenhout, and Weinbaum (2008b)). Therefore, we expect that an increase in stock return volatility will raise the probability of firm value reaching the default boundary and lead to an increase in CDS spreads.

3) *Risk-free rate* (R^f)

To match with the maturity of the CDS spreads, we collect the 5-year maturity Treasury bond yield time series for R^f from the FRED dataset. The risk-free rate is known to increase the risk-neutral drift of the firm value process and decrease the probability of default and credit spread.

4) *Square of the risk-free rate* ($(R^f)^2$)

The square of the risk-free rate is included to consider the nonlinear effects deriving from the convexity of the risk-free rate. We predict that the more convex the risk-free rate, the more the probability of default decreases with reducing credit spread levels.

5) *Term spread (TERM)*

We estimate the term spread or the slope of the yield curve as the 10-year maturity Treasury yield minus the two-year maturity Treasury yield. As Collin-Dufresne et al. (2001) describe, a decrease in yield curve slope implies usually related to an economic recession and it may reduce the expected recovery rate and enlarge credit spreads. We therefore expect a negative relation between the CDS spread and term spread. On the other hand, we should consider the possibility that the number of expected projects available to a company can be reduced by an increase in expected future interest rates as the yield curve slope increases, which causes an increase in credit spreads (Cesare et al. (2010)). Therefore, there are two facets to interpreting the sign of the term spread affecting the

CDS spreads.

6) *Return on the S&P 500 index (R^{sp})*

We use S&P 500 returns obtained from the CRSP as a proxy for business climate following Collin-Dufresne et al. (2001). An overall boom of the equity market is associated with a good economic environment and improves the expected recovery rates of companies, thus decreasing CDS spreads.

7) *Slope of the smirk (SMIRK)*

We use the SKEW Index collected from CBOE as a proxy for a jump in firm value. The SKEW Index is generated from the price of a tradable portfolio of out-of-the-money S&P 500 options. It is a global, strike independent measure of the slope of the implied volatility curve that increases as this curve tends to steepen. Collin-Dufresne et al. (2001, p.2183) state that "if large negative jumps in firm value are highly correlated with market crashes, slope of smirk can reflect systematic changes in the market's expectation of such events." Therefore, we expect that the slope of the smirk will be steeper during the crisis period and lead to an increase in credit spreads.

Monthly averaged data computed from daily data are used for all variables, but monthly data are used for estimating the *EMKT*.

Figure 2 shows the scatter plots of the average CDS spread with five-year maturity versus firm-specific variables for 384 different companies. The upper graph shows the scatter plot of the time series average rating number and the time series average CDS spread. The rating numbers range from 1(AAA) to 9(C). As credit quality declines, the average of the CDS spread increases in general, even though some outliers are found in the ratings CCC and C.

The lower left graph shows the scatter plots of the time series average leverage ratio and the time series average CDS spread, and the lower right graph shows the scatter plots of the time series average volatility and the time series average CDS spread. The relation between the average leverage ratio and average CDS spread is positive but not linear. In addition, the relation between average volatility and the CDS spread is nearly positive, while average CDS spreads tend to increase exponentially with the increase of the average volatility.

[Figure 2 goes here]

Panel A of Table 2 reports summary statistics for all the regression variables. The first and second rows in Panel A show the cross-sectional average and cross-sectional standard deviation of the time-series mean of the CDS spreads, the leverage ratios, and the stock return volatilities for investment-grade, non–investment-grade, and total firms, respectively. The magnitudes of the CDS spread, leverage ratio, and volatility for non–investment-grade firms are higher than those for investment-grade firms, as expected. In particular, the cross-sectional average of the mean of the CDS spread for non–investment-grade firms is about five times that for investment-grade firms. The last column shows that the number of investment-grade firms selected in our sample is 98, which is about 26% of total sample firms.

Panel B to D of Table 2 show summary statistics for each subsample period - the pre-crisis period (August 2004 to July 2007), the crisis period (August 2007 to June 2009), and the post-crisis period (July 2009 to March 2012)[2]. The cross-sectional average of CDS spread during the crisis period is 2.67%, which is much higher than 0.91% during the pre-crisis period and slightly higher than 2.05% during the post-crisis period. Some explanatory variables have similar pattern and thus their strong time series associations with the CDS spread is confirmed. However, the other variables show the different behaviors. The term spread and industrial price index have the highest mean during the post-crisis period while the risk-free rate and the ted spread have the lowest mean during the post-crisis period. In addition, it is the opposite of our expectation that the slope of smirk has the lowest mean during the crisis period. Thus we predict that each independent variable may have different effects, depending on the economic state.

[Table 2 goes here]

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2 We divide the pre-crisis, the crisis and the post-crisis periods following Galil et al. (2014).

Panel E of Table 2 reports the correlation coefficients between the time series changes in all the regression variables. It is interesting that the cross-sectional average of the time series correlation between the change in CDS spread and the change in the expected market risk premium is 0.26, which is higher compared with those for the leverage ratio and volatility. The change in the expected market risk premium exhibits the highest correlation with the change in CDS spread among the various business cycle proxies. In addition, the change in the market risk premium is also highly correlated with S&P returns, exhibiting correlation coefficient of -0.59. However, since S&P returns and the market risk premium are not perfectly correlated, this business cycle proxy may have other information in explaining CDS spread variations.

3. Analysis Framework

3.1. Individual firm-level regressions

Ericsson et al. (2009) state that differences in CDS spreads are harder to explain than CDS spread levels. In addition, Greatrex (2009) points out that CDS spreads have unit roots in time series analysis and thus there is a possibility of spurious regression when we perform the regression of CDS spread levels. Therefore, this research focuses on finding the determinants of CDS spread differences.

According to the base regressions of Ericsson et al. (2009), we implement the following regression equations:

$$\Delta CDS_t^i = c^i + \beta_1^i \Delta LEV_t^i + \beta_2^i \Delta VOL_t^i + \beta_3^i \Delta R_t^f + \varepsilon_t^i, \; i = 1,2,3...384 \qquad (3)$$

We perform the regression of CDS spread on the three factors suggested by theory—the leverage ratio, volatility, and the risk-free rate—for each individual firm *i,* as represented in the equation (3), and average the 384 coefficients. The t-statistics are generated the same way as those of Collin-Dufresne et al. (2001), showing the cross-sectional variation in the time series regression coefficient estimates.

Since this research investigates whether the business cycle is an important risk factor in CDS spreads, our base regressions are related to the following regression equations where *BC* implies the proxy of the business cycle:

$$\Delta CDS_t^i = c^i + \beta_4^i \Delta LEV_t^i + \beta_5^i \Delta VOL_t^i + \beta_6^i \Delta R_t^f + \beta_7^i \varepsilon_t^{BC} + \varepsilon_t^i$$
$$\text{where } \Delta BC_t = c^i + \beta_8^i \Delta LEV_t^i + \beta_9^i \Delta VOL_t^i + \beta_{10}^i \Delta R_t^f + \varepsilon_t^{BC} \tag{4}$$

Then, we perform regression equation (5), where the four independent variables consist of the three main factors of Merton's (1974) model and the business cycle—which is orthogonal to the leverage ratio, volatility, and the risk-free rate—to explore the impact of additional information of the business cycle independent of the three factors.

To test the robustness of our base regression, we also add the expected premium for the risk variable to the base regression of Collin-Dufresne et al. (2001), as follows:

$$\begin{aligned}\Delta CDS_t^i = c^i &+ \beta_{11}^i \Delta LEV_t^i + \beta_{12}^i \Delta VOL_t^i + \beta_{13}^i \Delta R_t^f + \beta_{14}^i \varepsilon_t^{BC} \\ &+ \beta_{15}^i \varepsilon_t^{R2} + \beta_{16}^i \varepsilon_t^{TERM} + \beta_{17}^i \varepsilon_t^{SP} + \beta_{18}^i \varepsilon_t^{SMIRK} + \varepsilon_t^i\end{aligned}$$
$$\text{where } \begin{bmatrix} (\Delta R_t^f)^2 \\ \Delta TERM_t \\ R_t^{SP} \\ \Delta SMIRK_t \end{bmatrix} = C + \delta'^i \begin{bmatrix} \Delta LEV_t^i \\ \Delta VOL_t^i \\ \Delta R_t^f \\ \Delta BC_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{R2} \\ \varepsilon_t^{TERM} \\ \varepsilon_t^{SP} \\ \varepsilon_t^{SMIRK} \end{bmatrix} \tag{5}$$

The additional explanatory variables—which consist of the square of the risk-free rate, the term spread, the slope of the smirk, and the return on the S&P 500 index—are orthogonalized to the leverage ratio, volatility, the risk-free rate, and the business cycle to check that these variables contain additional information independent of the four factors.

3.2. Portfolio-level regressions

Since the estimates of the individual firm-level regressions can be biased by idiosyncratic risks from a large number of individual firms, we design the portfolio regression as follows. First, we select data for 219 individual firms with the complete 89 monthly CDS spread quotes from November 2004 to March 2012. Second, we calculate the time series average of the leverage ratio for each firm and divide these into five groups according to the magnitude of the leverage ratio. Third, within a leverage group, we calculate the time series average of the volatility for each firm and divide these into five groups according to the magnitude of the volatility. Then, we assign each of the 219 firms to one of the 25 portfolios, grouped by five leverage and five volatility ranges, so that each portfolio has 8 or 9 firms. For each portfolio, we compute the cross-sectional averages of the CDS spread, leverage ratio, and volatility and finally obtain the time series of each variable for the 25 different portfolios.

The following portfolio-level regression equations are the same as equations (6), (7), and (8) for individual firm-level regression, except that we replace the individual *i* by the portfolio *p*:

$$\Delta CDS_t^p = c^p + \beta_1^p \Delta LEV_t^p + \beta_2^p \Delta VOL_t^p + \beta_3^p \Delta R_t^f + \varepsilon_t^p,\ p = 1,2,\ ....25 \tag{6}$$

$$\begin{aligned} &\Delta CDS_t^p = c^p + \beta_4^p \Delta LEV_t^p + \beta_5^p \Delta VOL_t^p + \beta_6^p \Delta R_t^f + \beta_7^p \varepsilon_t^{BC} + \varepsilon_t^p \\ &where\ \Delta BC_t = c^p + \beta_8^p \Delta LEV_t^p + \beta_9^p \Delta VOL_t^p + \beta_{10}^p \Delta R_t^f + \varepsilon_t^{BC} \end{aligned} \tag{7}$$

$$\begin{aligned} \Delta CDS_t^p = c^p + \beta_{11}^p \Delta LEV_t^p + \beta_{12}^p \Delta VOL_t^p + \beta_{13}^p \Delta R_t^f + \beta_{14}^p \varepsilon_t^{BC} \\ \beta_{15}^p \varepsilon_t^{R2} + \beta_{16}^p \varepsilon_t^{TERM} + \beta_{17}^p \varepsilon_t^{SP} + \beta_{18}^p \varepsilon_t^{SMIRK} + \varepsilon_t^p \end{aligned}$$

$$\text{where} \begin{bmatrix} (\Delta R_t^f)^2 \\ \Delta TERM_t \\ R_t^{SP} \\ \Delta SMIRK_t \end{bmatrix} = C + \delta'^p \begin{bmatrix} \Delta LEV_t^p \\ \Delta VOL_t^p \\ \Delta R_t^f \\ \Delta BC_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{R2} \\ \varepsilon_t^{TERM} \\ \varepsilon_t^{SP} \\ \varepsilon_t^{SMIRK} \end{bmatrix} \tag{8}$$

In equations (7) and (8), the business cycle is orthogonalized to the leverage ratio, volatility, and the risk-free rate at the portfolio level. In addition, in equation (8), the additional explanatory variables—which consist of the square of the risk-free rate, the term spread, the slope of the smirk, and S&P 500 index returns—are orthogonalized to the leverage ratio, volatility, the risk-free rate, and the business cycle variable at the portfolio level.

4. Empirical Results

4.1. Regression results for individual firms

Before we examine the regression models defined in the analysis framework, we conduct the various linear regressions without the orthogonality to check the importance of each business cycle variable in explaining the CDS spread variations. Table 3 reports the linear regression results for each CDS i of 384 individual firms, each with at least 58 monthly CDS spread change observations from September 2004 to March 2012.

[Table 3 goes here]

First, we find that the leverage ratio, volatility, and risk-free rate, as the three important theoretical determinants of the base regression of Ericsson et al. (2009), are strongly significant and explain approximately 32.7% of the difference in CDS spreads in M1.

In M2, we use the VIX instead of volatility in M1. The background is that the VIX is utilized as a substitute for firm's volatility in Collin Dufresne et al. (2001). As a result, the coefficient of the VIX is positively significant but the size of it and the adjusted R-square of the regression are smaller than that of volatility. In addition, in M3, when we perform the regression with the three factors and the VIX simultaneously, the coefficient sign of VIX is flipped to minus which is opposite to the expectation whereas that coefficient of volatility keeps its size and significance. From this result, it is inferred that the effect of the VIX on the CDS spread variation is subsumed by the information of volatility. Therefore, we will not include the VIX as a proxy of business cycle in below regressions, even though we consider the VIX as a candidate following the previous literature in Section 2.

Second, according to the base regression of Collin Dufresne et al. (2001), we perform the linear regression such as M4 and we find that all variables except the slope of smirk are significant and they explain 36.5% of the variations in the CDS spreads. This result is consistent with Galil et al.'s (2014) result that market variables have explanatory power after controlling for firm-specific variables contrary to Ericsson et al. (2009). In M5, we conduct regression with only market variables and macroeconomic variables. As a result, we find that they explain about 38% of the differences in CDS spreads and most variables are significant. However, the coefficients of ted spread and dollar index spot show the opposite sign of the expected and the multi-collinearity problem can be concerned.

Next, we add candidate business cycle variable one by one to the regression model, M4 in order to discover the good proxy for explaining the CDS spread changes well. From M6 to M9, we find that the expected market risk premium, financial conditions index, and industrial price index are substantially significant and increases explanatory power by about 5.7%, 3.1%, and 2.5%, respectively. On the other hand, ted spread, which is not reported in Table 3, and dollar index spot do not raise much. Thus we choose the expected market risk premium, financial conditions index, and industrial price index as the appropriate proxies for the business cycle. Then we perform regressions with both the base regressors of Collin Dufresne et al. (2001) and these three business cycle proxies and find the coefficients of expected market risk premium and industrial price index are strongly significant in M10.

4.2. Subsample regression results for individual firms

With the chosen appropriate proxies for the business cycle, we conduct the subsample regressions following the analysis framework in the section 3.1. Panels A and B of Table 4 present the regression results for each CDS i for investment-grade and non–investment-grade firms, respectively. The magnitudes of all the regression coefficients for non-investment-grade firms are greater than those for investment-grade firms, consistent with Greatrex's (2009) results, where the magnitude of the coefficients of volatility and equity returns increases considerably as credit quality declines. In addition, the average adjusted R-squared value of the three factor regression for non-investment-grade firms is higher than that for investment-grade firms.

[Table 4 goes here]

However, the average adjusted R-squared values of the four factors regressions for investment-grade firms (e.g., 38.9%, 35.3%, and 36.1%) are similar to those for non–investment-grade firms (e.g., 37.1%, 36.9%, and 36.8%). This finding is contrary to the literature that has documented that a structural model is more appropriate for low-grade firms instead of high-grade firms, such as Greatrex's (2009) result that as credit quality increases, the explanatory power of four variables—equity return, volatility, credit rating index, and the risk-free rate—declines, with adjusted R-squared values ranging from 22.5% for AAA/AA-rated firms to 37.8% for non–investment-grade companies.

The reason of inconsistency is supported by the following analysis. The business cycle variables—the expected market risk premium, financial condition index, and industrial price index—being orthogonal to the three factors increase the explanatory power for investment-grade firms by about 7%, 3.4%, and 4.2% and those for non–investment-grade firms by about 2.7%, 2.5%, and 2.4%. The business cycle can explain more of the variation of credit spreads for investment-grade firms than for non–investment-grade firms. Therefore, these results can be interpreted to mean that some portion of the observed credit spread of high-grade firms, which is unexplained by such structural variables as the three factors, can be well explained by the business cycle variable, and thus the gap disappears.

In addition, the coefficient of slop of smirk is significantly positive and robust for investment-grade firms whereas it is not for non-investment grade firms. This result suggest that CDS spread changes for investment-grade firms are more sensitive to jumps in firm value or systematic changes in the market's expectation of negative events than those for non-investment-grade firms.

Panels C to E of Table 4 present the regression results for CDS i during the pre-crisis and crisis, and post-crisis periods, respectively. During the pre-crisis period, our set of structural variables including the business cycle explains just up to 21.6% of the CDS spread changes. However, the coefficients of the expected market risk premium, financial condition index, and industrial price index are strongly significant, improving explanatory power by about 3.3%, 6.7% and 2.4%, respectively.

On the other hand, during the crisis period, our structural variables explain about 52% of CDS spread changes, similar to the findings of Cesare et al. (2010). However, unlike the results of Cesare et al. (2010), the coefficients of the additional variables—such as the square of the risk-free rate, term spread and S&P returns, as well as the four factors—are significant and robust. In addition, the authors point out that the short-term estimate of volatility, inferred from the equity option, is not significant because it reflects a large fluctuation during the turmoil period and may thus be an inaccurate proxy for long-term firm value volatility. However, in our study, the coefficient of the volatility is economically and statistically significant over all the subsample periods. Besides, the negative coefficient of the term spread is a result supporting the theoretical prediction that a decline in yield curve slope is related to a weakening economy and higher credit spreads.

Furthermore, it is a noticeable result that the increases of explanatory power by the market risk premium, financial condition index, and industrial price index are relatively small (e.g., 1.8%, 0.8%, and 2.7%, respectively) compared with the following results during the post-crisis period. The market risk premium, financial condition index, and industrial price index enhance considerably explanatory power (e.g., 8.8%, 8.4%, and 5.3%, respectively) even though our structural variables explains up to 34% of the CDS spread changes during the post-crisis period. Specially, the coefficient of the risk-free rate shows the weak significance and thus these results can be interpreted as that macroeconomic condition strongly impacts on the CDS spread changes, reducing the role of the risk-free rate during the post-crisis period.

4.3. Liquidity bin analysis

Even though we confirm the importance of the business cycle in addition to those of Merton's (1974) three factors in explaining the variations in CDS spread changes, serious doubt about which factor is related to the remaining unexplained part remains. Thus, we construct liquidity bins to examine the liquidity effects, considering Coro, Dufour, and Varotto's (2013) result showing that firm-specific credit risks are less critical than liquidity risk in explaining CDS spread changes independent of market conditions. Here, liquidity is measured by the depth of the five-year CDS spread, which is defined as the total quoted number by brokers. We average the depths over the sample period for each firm and then allocate all sample firms to four CDS liquidity level bins. Table 5 reports the linear regression results for *CDS i* contained in each liquidity bin.

[Table 5 goes here]

Our structural model variables have greater explanatory power for firms in the second, third, and highest liquidity bins, while they have much less explanatory power for firms in the lowest liquidity bin compared with the result for the full sample. In particular, explanatory power is increased by about 8% for firms in the third liquidity bin. Therefore, this finding suggests that the unexplainable part of the CDS spread variations may be related to the illiquidity of CDS contracts.

On the contrary, the coefficients of the business cycle variables are significant and robust for firms in the lowest, second, and third liquidity bins, whereas they are less significant and not robust for firms in the highest liquidity bin. This finding implies that only three factors explain the variations in CDS spreads when CDSs have the highest liquidity.

Motivated by the above inferences, we construct the portfolios of CDS spreads for two main reasons. First, illiquid CDSs tend to have difficulties discovering fair prices and have large pricing error bounds. Second, firm-specific explanatory variables may also contain some noise in discovering true prices. For example, the leverage ratio cannot be continuously observable in the market and should be estimated from the accounting data, while volatility tends to be inferred from relatively liquid short-term option-implied volatility instead of illiquid long-term option-implied volatility even though CDSs have the characteristic of long-term maturity in general. Hence, to reduce price discovery problems or diversify idiosyncratic risks, we construct portfolios of CDS spreads and examine whether our proxies for macroeconomic conditions still have a substantial impact on the changes in CDS spread.

4.4. Regression results for portfolios

Panel A of Table 6 reports the cross-sectional averages of the time series mean and the cross-sectional standard deviations of the mean of the CDS spread, the leverage ratio, and the volatility for the 25 different portfolios grouped by the five leverage ratio ranges and five volatility ranges. We find that the cross-sectional average of CDS spreads generally grows but that of leverage ratio does not as volatility increases within each leverage group. We also find that the cross-sectional average of CDS spreads increases but that of volatility does not as the leverage ratio moves from low to high within each volatility group. That is, CDS spreads grow up as volatility increases when leverage ratio is controlled as similar level, whereas CDS spreads grow down as leverage ratio declines when volatility is kept as equivalent level. In addition, panel A of Table 6 also shows the adjusted R-squared value of each portfolio regression for equation (8) using the *EMKT. Over 70% R*-squared values are mostly found at the high leverage group but about 81% *R*-squared value appears in the 3-leverage and high-volatility group. Thus it is hard to conclude any clear pattern.

[Table 6 goes here]

Panel B of Table 6 reports the correlation coefficients between the time series changes in all the regression variables for all 25 portfolios. The average correlation coefficient between the changes in CDS spreads and in leverage ratios is 0.64, and that between changes in CDS spreads and in S&P returns is -0.69, over twice those at the individual firm level. In addition, the correlation coefficient between the change in leverage ratio and S&P return is -0.82. This is a natural result, since monthly changes in leverage where idiosyncratic risks are eliminated tend to be affected by changes in the equity market.

Moreover, the cross-sectional average of the time series correlation between the change in CDS spreads and those in the expected market risk premium, financial condition index, and industrial price index are 0.56, 0.66, and -0.59, respectively. The latter business cycle proxies are also highly correlated with changes in leverage ratios, in volatility, and in S&P returns. In particular, the correlation coefficients between the changes in the three business cycle variables and the changes in leverage ratio and volatility rise after the portfolios are constructed. However, we use changes in the business cycle orthogonalized to the three factors and changes in S&P returns orthogonalized to the four factors and thus eliminate any multicollinearity problems between these variables in the multivariate framework.

Panel A in Table 7 presents the regression results for each portfolio *p* of the CDS spreads of the 25 portfolios. Our set of structural model determinants explains up to about 65% of the CDS spread changes, which is almost twice the explanatory power of the variable sets of Ericsson et al. (2009). In addition, the coefficients of the expected market risk premium, financial condition index, and industrial price index are substantially significant. This can then be interpreted as the cross-sectional CDS spreads, after the removal of idiosyncratic risks, having stronger co-movements with the structural model variables, including the proxy of the business cycle.

[Table 7 goes here]

Panels B to D of Table 7 present the regression results for each portfolio *p* of the CDS spreads of the 25 portfolios during the pre-crisis, crisis and post-crisis periods, respectively. During the pre-crisis period, the three factors are strongly significant but the adjusted *R*-squared value of regression by the three factors is 27.7%, which is very low when compared with 56.3% over the full sample period shown in Panel A in Table 7. In addition, our set of structural variables including the business cycle explains just up to 38% of the CDS spread changes. However, the coefficients of the expected market risk premium, financial condition index, and industrial price index are strongly significant, enhancing explanatory power by about 3.4%, 9.7% and 8.4%, respectively.

During the turmoil period, our set of structural variables explains approximately 70% of the CDS spread changes, a much greater explanatory power than that of Cesare et al. (2010). However, it is a surprising result that the coefficients of the market risk premium, financial condition index, and industrial price index show relatively weak significances and their magnitudes of explanatory power are also very slight appearing about 0.5%, -0.1%, and 2.1%, respectively. On the other hand, during the post-crisis period, structural variables including financial conditions index explains about 62% of the CDS spread changes and the coefficients of the market risk premium, financial conditions index, and industrial price index improve explanatory power by about 10%, 11.2%, and 4.6%, respectively. Further, the coefficient of the risk-free rate is most strongly significant during the crisis-period but it becomes not significant during the post-crisis period, similarly to the results of individual regressions.

Overall, business cycle's explanatory power is greater during the pre-crisis or the post-crisis period than during the crisis period. In detail, during the crisis period, the only three factors of Merton's (1974) model explains 67% of the variations in the CDS spread changes and the macroeconomic conditions factors have weak effects on them. This result can be interpreted as that if we assume that the CDS is a kind of put option on firm value, the main factors affecting on CDS price depend on its current moneyness which is relevant to the distance between the current underlying asset value and default barrier. Following this assumption, the CDSs for investment-grade firms are similar to deep-out-of-money put options and those for non-investment firms do to out-of-the-money put options. Specially, the crisis period is when this distance becomes severely narrow and investment-grade firms have the relatively longer distance to default. Therefore, we conclude that macroeconomic conditions factor plays an important role in pricing CDS when the underlying asset value of CDS is likely to be farther from default barrier, while the only three factors of Merton's (1974) model do enough when distance to default is extremely narrow.

4.5. Robust tests for portfolio regressions

To test the robustness of above portfolio regression result, we change the number of portfolios and repeat the regressions on the four factors, including the expected market risk premium or Industrial price index. Panels A to D of Table 8 report the linear regression results for each portfolio *p* of the CDS spreads of nine portfolios grouped by three leverage and three volatility ranges, and of 16 portfolios grouped by four leverage and four volatility ranges, respectively. Each panel shows the average coefficients and t-statistics from the sample over the full period (ALL), during the pre-crisis period (PRE), during the crisis period (CRISIS), and during the post-crisis period (POST), respectively.

[Table 8 goes here]

As expected, the coefficients of the expected market risk premium are significant and robust, independent of the number of portfolios except during the crisis period. The coefficients of the industrial price index exhibits the same pattern. These findings are consistent with the results from 25 portfolios grouped by five leverage and five volatility ranges. In addition, the average adjusted *R*-squared values of the regressions are higher for the nine portfolios grouped by three leverage ratios and three volatility ranges and the average adjusted *R*-squared value including industrial price index during crisis period is the highest as 72.8%.

Table 9 presents the regression results for each portfolio *p* of the CDS spreads of the 25 portfolios grouped by five stock price (*SP*) and five implied volatility (*VOL*) ranges. We substitute leverage ratio with stock price to test the robustness since leverage ratio can have some noise generated from the accounting data in price discovery. The multivariate regression shows the coefficients and t-statistics of the $\Delta E_t[R_{t+1}{}^M]$ *(or* ΔFCI *or* ΔIPI*)* variables orthogonal to SR_t^p, ΔVOL_t^p, and ΔR_t^f and those of the additional variables orthogonal to SR_t^p, ΔVOL_t^p, ΔR_t^f, and $\Delta E_t[R_{t+1}{}^M]$ *(or* ΔFCI *or* ΔIPI*)*.

Our set of structural model determinants explains up to about 67% of the CDS spread changes, which shows a little bit higher explanatory power than the original result. Thus we confirm that our results are robust.

[Table 9 goes here]

5. Conclusions

We investigate whether changes in CDS spreads depend on changes in macroeconomic conditions and hypothesize that the business cycle is an important determinant of the differences in CDS spreads. Petkova and Zhang (2005) state that the *ex post* realized market return or GDP growth is a noisy measure for marginal utility or the business cycle and that the *ex ante* expected market risk premium should be used to capture business states. Hence, we estimate the expected market risk premium as a proxy for the business cycle according to Petkova and Zhang (2005). In addition, we collect price indexes such as the volatility index, industrial price index, and financial conditions index to investigate whether a large proportion of CDS spread changes can be explained by the various proxies for macroeconomic conditions.

Contrary to the results of Ericsson et al. (2009) showing weak evidence of the three factors' regression residual common factor, we find that the coefficient of the business cycle variable orthogonal to the three factors is strongly significant and robust. We also discover that the business cycle variables explain more of the changes in CDS spreads for investment-grade firms than for non-investment-grade firms.

Furthermore, our structural model variables, including the proxy of the business cycle, explain approximately 65% of the changes in CDS spreads, almost twice the explanatory power of the variable sets of Ericsson et al. (2009). Moreover, the coefficients of our business cycle variables are substantially significant when we conduct regressions at the portfolio level to eliminate the errors generated from the limits to discovering fair prices in illiquid markets or to diversifying idiosyncratic risks.

Finally, through portfolio regressions, we find that our business cycle variables (expected market risk premium, financial conditions index, industrial price index) are strongly significant, increase explanatory power considerably for the pre-crisis and post-crisis periods, and are robust over the full sample as well as for the pre-crisis and post-crisis periods independent of the number of portfolios. However, interestingly, during the crisis period, only the three factors of Merton's (1974) model explain 67% of the variation in CDS spread changes, whereas the coefficients of the business cycle variables show relatively weak significance and their increment in explanatory power is also slight.

Taken together with these results, if we assume CDSs as a kind of put option on firm value, it is inferred that the main factors impacting on CDS price depend on its current moneyness, which is related to the distance between the current underlying asset value and default barrier. In particular, the crisis period is when the distance to default becomes severely tight and non-investment-grade firms tend to have a relatively short distance to default. Therefore, we conclude that macroeconomic conditions play a critical role in pricing CDSs, as the underlying asset value of CDSs is likely to be farther from the default barrier, whereas only the three factors of Merton's (1974) model are sufficient when distance to default is very tight.

This study makes the following contributions. First, previous studies using data before the financial crisis generally failed to detect the associations between changes in macroeconomic factors and CDS spreads. In contrast to prior research using real economic variables, we estimate the expected market risk premium as a continuous and *ex ante* proxy for the business cycle and provide strong evidence of the significant impact of macroeconomic conditions on CDS spread changes even after controlling for firm-specific variables. Second, we perform portfolio-level regressions and thus demonstrate that a substantial proportion of CDS spread changes are well explained under the framework of structural models. Third, we empirically examine whether macroeconomic variables play different roles in pricing CDSs depending on the level of the default barrier, utilizing a comprehensive and recent dataset that includes the pre-crisis, crisis, and post-crisis periods.

However, a part of the CDS spread changes is still unexplained. As inferred from our findings as well as the recent literature on the association between CDS price and liquidity (e.g., Bongaerts, de Jong, and Driessen (2011); Tang and Yan (2012, 2013); Qiu and Yu (2012); Coro et al. (2013)), we presume that the proxies for the structural model variables as well as CDS prices themselves may have pricing errors or limits to discovering fair prices because of market friction such as illiquidity. We speculate that these errors may be relevant to the unexplainable part and leave this subject to future works.

References

Amato, J. D., and E. M. Remolona. "The Credit Spread Puzzle." *BIS Quarterly Review,* December (2003), 51–63.

Baum, C. F., and C. Wan. "Macroeconomic Uncertainty and Credit Default Swap Spreads." *Applied Financial Economics,* 20 (2010), 1163–1171.

Benkert, C. "Explaining Credit Default Swap Premia." *Journal of Futures Markets*, 24: 1 (2004), 71-92.

Bongaerts, D., F. De Jong, and J. Driessen. "Derivative Pricing with Liquidity Risk: Theory and Evidence from the Credit Default Swap Market." *Journal of Finance*, 66 (2011), 203-240.

Campbell, J. Y., and G. B. Taksler. "Equity Volatility and Corporate Bond Yields." *Journal of Finance,* 63 (2003), 2321–2349.

Cao, C., F. Yu, and Z. Zhong. "The Information Content of Option-Implied Volatility for Credit Default Swap Valuation." *Journal of Financial Markets,* 13 (2010), 321-343.

Carr, P. and L. Wu. "A Simple Robust Link between American Puts and Credit Insurance." *Review of Financial Studies*, 24 (2011), 473-505.

Cesare, A. D., and G. Guazzarotti. "An Analysis of the Determinants of Credit Default Swap Spread Changes before and during the Subprime Financial Turmoil." Working paper, No. 749, Bank of Italy (2010).

Chen, H. “Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure.” *Journal of Finance,* 65 (2010), 2171–2212.

Chen, L., P. Collin-Dufresne, and R. S. Goldstein. “On the Relation between the Credit Spread Puzzle and the Equity Premium Puzzle.” *Review of Financial Studies,* 22: 9 (2009), 3367–3409.

Chen, N., R. Roll, and S. A. Ross. "Economic Forces and the Stock Market." *Journal of business,* (1986), 383-403.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin. “The Determinants of Credit Spread Changes.” *Journal of Finance,* 56 (2001), 2177–2207.

Coro, F., A., Dufour, and S. Varotto. “Credit and liquidity components of corporate CDS spreads.” *Journal of Banking and Finance,* 37 (2013), 5511–5525.

Cremers, M., J. Driessen, and P. J. Maenhout. “Explaining the Level of Credit Spreads: Option-Implied Jump Risk Premia in a Firm Value Model.” *Review of Financial Studies,* 21: 5 (2008a), 2209–2242.

Cremers, M., J. Driessen, P. J. Maenhout, and D. Weinbaum. “Individual Stock Options and Credit Spreads.” *Journal of Banking and Finance,* 32 (2008b), 2706–2715.

Delianedis, G., and R. Geske. “The Components of Corporate Credit Spreads: Default, Recovery, Tax, Jumps, Liquidity, and Market Factors.” Working paper, the University of California at Los Angeles (2001).

Elton, E. J., M. J. Gruber, D. Agrawal, and C. Mann. “Explaining the Rate Spread of Corporate Bonds.” *Journal of Finance,* 56 (2001), 247–277.

Eom, Y. H., J. Helwege, and J. Huang. "Structural Models of Corporate Bond Pricing: An Empirical Analysis." *Review of Financial Studies,* 17.2 (2004), 499-544.

Ericsson, J., K. Jacobs, and R. Oviedo-Helfenberger. “The Determinants of Credit Default Swap Premia.” *Journal of Financial and Quantitative Analysis,* 44 (2009), 109–132.

Galil, K., O. M. Shapir, D. Amiram, and U. Ben-Zion. “The Determinants of CDS Spreads.” *Journal of Banking and Finance* 41 (2014), 271–82.

Greatrex, C. A. “Credit Default Swap Market Determinants.” *Journal of Fixed Income,* 18 (2009), 18-32.

Han, B. and Y. Zhou. “Understanding the Term Structure of Credit Default Swap Spreads.” *Journal of Empirical Finance* 31 (2015), pp. 18-35.

Kim, T. S., and M. A. Kim. “Default Correlation Dynamics with Business Cycle and Credit Quality Changes.” *Journal of Derivatives,* 13: 1 (2005), 8–2.

Kim, T. S., Y. J., Park, and J. Noh. “The Linkage between the Options and Credit Default Swap Markets during the Subprime Mortgage Crisis.” *Journal of Futures Markets,* 33: 6 (2013), 518–554.

Merton, R. C. “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates.” *Journal of Finance,* 29 (1974), 449–470.

Pan, J. and K. J. Singleton. “Default and Recovery Implicit in the Term Structure of Sovereign CDS Spreads.” *The Journal of Finance,* 63 (2008): 2345–84.

Petkova, R., and L. Zhang. "Is Value Riskier than Growth?" *Journal of Financial Economics,* 78 (2005), 187–202.

Qiu, J. and F. Yu. "Endogeneous liquidity in credit derivatives." *Journal of Financial Economics,* 103 (2012), 611-631.

Tang, D. Y., and H. Yan. "Macroeconomic Conditions, Firm Characteristics, and Credit Spreads." *Journal of Financial Services Research,* 29: 3 (2006), 177–210.

Tang, D. Y., and H. Yan. "Market Conditions, Default Risk and Credit Spreads." *Journal of Banking and Finance,* 34 (2010), 743–753.

Tang, D. Y., and H. Yan. "Liquidity and Credit Default Swap Spreads" Working paper, the University of South Carolina and Shanghai Advanced Institute of Finance (2012).

Zhang, B., H. Zhou, and H. Zhu. "Explaining Credit Default Swap Spreads with the Equity Volatility and Jump Risks of Individual Firms." *Review of Financial Studies,* 22: 15 (2009), 5099–5131.

Table 1. Description of structural model variables and predicted signs of the regression coefficients.
This table lists the structural model variables expected to explain the CDS spread changes and describes their notation, the specific data used in their estimation, and data source. The last column shows the expected signs of the regression coefficients.

Variables	Description	Data Source	Expected Sign
ΔLEV_t^i	Change in firm leverage ratio	COMPUSTAT/CRSP	+
ΔVOL_t^i	Change in three-month implied volatility computed from a weighted average of the two put options closest to the at-the-money strikes	Bloomberg	+
ΔR_t^f	Change in yield on 5-year Treasury	FRED	-
$(\Delta R_t^f)^2$	Square of change in yield on 5-year Treasury	FRED	+
$\Delta TERM_t$	Change in 10-year minus 2-year Treasury yields	FRED	+/-
R_t^{SP}	Return on S&P 500 Index	CRSP	-
$\Delta SMIRK_t$	Change in CBOE Skew index, a strike-independent measure of the slope of the implied volatility curve	CBOE	+
ΔVIX_t	Change in CBOE VIX index	CBOE	+
$\Delta E_t[R_{t+1}{}^M]$	Change in expected market risk premium (EMKT)	CRSP/FRED	+
ΔFCI_t	Change in Goldman Sacks Financial Condition Index	Bloomberg	+
ΔIPI_t	Change in JoC-ECRI Industrial Price Index	Bloomberg	+/-
ΔTED_t	Change in TED spread	FRED	+
ΔDIS_t	Change in Dollar Index Spot	Bloomberg	-

Table 2. Summary statistics and correlation coefficients.

The first to third rows in Panel A show the cross-sectional average and cross-sectional standard deviation (Stdev) of the time-series mean, and also the minimum, median and maximum levels of the CDS spreads, the leverage ratios, and the stock return volatilities for investment-grade, non–investment-grade, and total firms, respectively. The last rows in Panel A show the time series statistics of the other explanatory variables. Panel B to D show summary statistics for each subsample period - the pre-crisis period (August 2004 to July 2007), the crisis period (August 2007 to June 2009), and the post-crisis period (July 2009 to March 2012). Panel E reports the correlation coefficients between the time series changes in all the regression variables. Num. of firms implies the number of firms collected. Monthly averaged data computed from daily data are used for all variables, except that monthly data are used for the EMKT variable.

	Variables	Mean (%)	Stdev (%)	Min (%)	Median (%)	Max (%)	Num. of Firms	Mean (%)	Stdev (%)	Min (%)	Median (%)	Max (%)
		Panel A : Full Sample						**Panel B : Pre-Crisis Period**				
[Individual variables]												
Investment Grade	CS_t^i	0.50	0.19	0.23	0.44	1.30		0.22	0.12	0.06	0.20	0.85
	LEV_t^i	29.66	13.67	7.54	25.95	70.11		26.41	13.79	5.38	24.86	64.95
	VOL_t^i	28.72	6.37	17.35	28.47	42.40	98	22.76	5.48	13.91	22.14	39.67
Non-Investment Grade	CS_t^i	2.28	2.55	0.41	1.27	16.61		1.15	1.57	0.19	0.60	13.50
	LEV_t^i	50.00	15.92	7.50	48.96	90.70		44.65	16.58	4.89	43.14	94.04
	VOL_t^i	39.16	13.68	17.50	37.19	114.70	286	28.50	9.14	13.71	26.59	71.01
Total	CS_t^i	1.83	2.33	0.23	0.99	16.61		0.91	1.42	0.06	0.44	13.50
	LEV_t^i	44.81	17.74	7.50	44.38	90.70		40.00	17.78	4.89	38.28	94.04
	VOL_t^i	36.49	13.05	17.35	34.03	114.70	384	27.04	8.72	13.71	25.25	71.01
[Market variables]												
	R_t^f	3.03	1.29	0.83	2.87	5.06		4.35	0.51	3.32	4.48	5.06
	$TERM_t$	1.37	1.02	-0.15	1.60	2.83		0.31	0.49	-0.15	0.13	1.59
	R_t^{SP}	0.33	4.25	-20.52	1.32	11.89		0.93	1.94	-2.80	1.28	4.66
	$SMIRK_t$	119.67	4.13	110.94	119.68	128.89		120.74	3.24	112.46	120.70	126.90
[Macroeconomic variables]												
	VIX_t	21.54	10.69	10.82	19.15	62.73		13.08	1.70	10.82	12.92	17.27
	$E_t[R_{t+1}^M]$	2.13	1.80	0.07	2.24	7.44		0.52	0.37	0.07	0.37	1.37
	FCI_t*100	99.75	0.90	98.82	99.50	102.71		99.10	0.17	98.82	99.07	99.58
	IPI_t*100	107.04	20.22	65.39	109.57	146.56		96.16	10.72	81.66	95.05	116.73
	TED_t	0.58	0.56	0.13	0.36	3.39		0.36	0.10	0.21	0.34	0.64
	DIS_t*100	81.51	4.94	72.10	81.71	91.46		85.88	2.94	80.78	85.61	91.46

	Variables	Mean (%)	Stdev (%)	Min (%)	Median (%)	Max (%)	Mean (%)	Stdev (%)	Min (%)	Median (%)	Max (%)
		Panel C : Crisis-Period					**Panel D : Post-Crisis Period**				
[Individual variables]											
Investment Grade	CS_t^i	0.73	0.40	0.27	0.62	2.61	0.62	0.23	0.36	0.57	1.66
	LEV_t^i	31.05	14.51	6.86	28.97	72.79	32.12	14.31	9.66	29.12	77.64
	VOL_t^i	38.64	9.01	22.09	38.11	63.80	27.56	6.34	15.88	27.87	42.48
Non-Investment Grade	CS_t^i	3.34	4.36	0.38	1.79	26.74	2.54	2.74	0.35	1.58	21.26
	LEV_t^i	53.53	16.85	8.73	53.08	95.55	52.51	16.78	9.53	51.57	94.42
	VOL_t^i	53.18	20.21	23.59	49.76	137.80	38.68	16.27	15.58	36.14	179.04
Total	CS_t^i	2.67	3.94	0.27	1.30	26.74	2.05	2.51	0.35	1.13	21.26
	LEV_t^i	47.80	19.00	6.86	47.91	95.55	47.31	18.46	9.53	47.14	94.42
	VOL_t^i	49.47	19.10	22.09	45.68	137.80	35.84	15.19	15.58	33.26	179.04
[Market variables]											
	R_t^f	2.84	0.84	1.51	2.83	4.44	1.75	0.60	0.83	1.90	2.56
	$TERM_t$	1.54	0.59	0.36	1.62	2.54	2.38	0.38	1.69	2.48	2.83
	R_t^{SP}	-1.92	6.45	-20.52	-1.78	11.89	1.29	3.58	-10.64	1.99	7.82
	$SMIRK_t$	115.22	3.08	110.94	114.73	119.99	121.62	3.29	115.00	120.90	128.89
[Macroeconomic variables]											
	VIX_t	32.20	13.40	18.27	25.81	62.73	23.08	5.71	16.36	21.28	36.53
	$E_t[R_{t+1}^M]$	3.68	2.37	0.40	2.84	7.44	2.75	0.41	2.06	2.72	3.96
	FCI_t*100	100.47	1.37	98.92	99.68	102.71	99.93	0.29	99.44	99.95	100.84
	IPI_t*100	103.57	25.42	65.39	114.95	133.85	121.00	15.62	85.07	122.12	146.56
	TED_t	1.36	0.62	0.46	1.16	3.39	0.27	0.12	0.13	0.22	0.56
	DIS_t*100	78.99	4.93	72.10	78.27	86.55	78.62	2.98	74.26	78.39	86.58

Panel E : Correlation Coefficients

	ΔCDS_t^i	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	ΔVIX_t	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	ΔTED_t	ΔDIS_t
ΔCDS_t^i	1.00	0.21	0.21	-0.30	0.07	-0.26	-0.09	0.19	0.26	0.23	-0.16	0.05	0.07
ΔLEV_t^i	0.21	1.00	0.54	-0.23	0.13	-0.44	-0.15	0.33	0.51	0.49	-0.37	0.19	0.14
ΔVOL_t^i	0.21	0.54	1.00	-0.17	0.03	-0.59	-0.11	0.64	0.48	0.62	-0.31	0.28	0.21
ΔR_t^f	-0.30	-0.23	-0.17	1.00	0.01	0.34	0.11	-0.24	-0.51	-0.26	0.37	-0.22	0.08
$\Delta TERM_t$	0.07	0.13	0.03	0.01	1.00	-0.16	0.06	0.23	0.24	0.25	0.15	0.26	-0.08
R_t^{SP}	-0.26	-0.44	-0.59	0.34	-0.16	1.00	0.08	-0.80	-0.59	-0.81	0.40	-0.31	-0.29
$\Delta SMIRK_t$	-0.09	-0.15	-0.11	0.11	0.06	0.08	1.00	0.03	-0.06	-0.10	0.07	-0.03	-0.04
ΔVIX_t	0.19	0.33	0.64	-0.24	0.23	-0.80	0.03	1.00	0.50	0.71	-0.25	0.48	0.18
$\Delta E_t[R_{t+1}^M]$	0.26	0.51	0.48	-0.51	0.24	-0.59	-0.06	0.50	1.00	0.74	-0.58	0.48	0.31
ΔFCI_t	0.23	0.49	0.62	-0.26	0.25	-0.81	-0.10	0.71	0.74	1.00	-0.53	0.53	0.46
ΔIPI_t	-0.16	-0.37	-0.31	0.37	0.15	0.40	0.07	-0.25	-0.58	-0.53	1.00	-0.16	-0.48
ΔTED_t	0.05	0.19	0.28	-0.22	0.26	-0.31	-0.03	0.48	0.48	0.53	-0.16	1.00	0.10
ΔDIS_t	0.07	0.14	0.21	0.08	-0.08	-0.29	-0.04	0.18	0.31	0.46	-0.48	0.10	1.00

Table 3. Results from the regression of CDS spread changes on structural model determinants. This table presents the linear regression results for each *CDS i* of the 384 individual firms, each with at least 58 monthly CDS spread change observations from September 2004 to March 2012. The reported coefficients are the average coefficients from the time series regressions of CDS spread changes on structural model determinants. The t-statistics reported in parentheses are calculated according to the time series regression coefficients, as in Collin-Dufresne et al. (2001). The final rows show the average *R*-squared (R^2) and adjusted *R*-squared (Adj. R^2) values of the regression.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.966)	(-1.443)	(-1.316)	(-1.931)	(-1.01)	(-3.194)	(-5.155)	(-0.04)	(-3.04)	(-1.446)
ΔLEV_t^i	0.039	0.070	0.042	0.024		0.024	0.024	0.023	0.024	0.022
	(6.351)	(7.897)	(6.517)	(5.045)		(5.004)	(5.141)	(5.131)	(5.096)	(5.09)
ΔVOL_t^i	0.021		0.026	0.018		0.014	0.014	0.016	0.018	0.013
	(10.429)		(10.591)	(8.964)		(6.974)	(7.036)	(8.553)	(8.941)	(6.944)
ΔR_t^f	-0.003	-0.003	-0.003	-0.002	-0.001	-0.001	-0.002	-0.001	-0.002	-0.001
	(-11.541)	(-10.926)	(-11.722)	(-8.041)	(-2.424)	(-4.491)	(-8.002)	(-5.072)	(-8.33)	(-4.133)
$(\Delta R_t^f)^2$				0.003	0.003	0.004	0.005	0.003	0.004	0.003
				(3.805)	(4.174)	(4.679)	(6.208)	(3.556)	(4.986)	(4.347)
$\Delta TERM_t$				-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002
				(-4.225)	(-3.589)	(-4.987)	(-4.695)	(-2.555)	(-3.761)	(-3.35)
R_t^{SP}				-0.018	-0.012	-0.012	-0.001	-0.011	-0.014	-0.009
				(-4.015)	(-2.638)	(-2.583)	(-0.298)	(-2.719)	(-3.19)	(-2.518)
$\Delta SMIRK_t$				-0.001	-0.001	-0.002	0.000	-0.001	-0.001	-0.002
				(-0.54)	(-0.294)	(-1.163)	(0.14)	(-0.633)	(-0.636)	(-0.943)
ΔVIX_t		0.011	-0.010							
		(5.818)	(-3.834)							
$\Delta E_t[R_{t+1}^M]$					0.001	0.002				0.001
					(2.417)	(6.493)				(2.844)
ΔFCI_t					0.006		0.004			0.000
					(4.137)		(7.121)			(0.314)
ΔIPI_t					-0.009			-0.016		-0.011
					(-3.674)			(-7.331)		(-4.093)
ΔTED_t					0.000					
					(-4.966)					
ΔDIS_t					-0.020				0.013	
					(-4.539)				(4.164)	
R^2	35.21%	31.87%	37.40%	42.07%	45.86%	47.95%	45.65%	45.14%	43.13%	49.99%
adj. R^2	32.68%	29.21%	34.09%	36.50%	38.13%	42.15%	39.60%	39.02%	36.79%	42.83%

Table 4. Subsample Results from the regression of CDS spread changes on structural model determinants

Panels A and B present the linear regression results for each *CDS i* for investment-grade and non–investment-grade firms, respectively. Panel C to E presents the linear regression results during the pre-crisis, crisis and post-crisis periods, respectively. The pre-crisis period is from August 2004 to July 2007, the crisis period is from August 2007 to June 2009, and the post-crisis period is from July 2009 to March 2012. The multivariate regression shows the coefficients and t-statistics of the $\Delta E_t[R_{t+1}^M]$ *(or* ΔFCI_t *or* ΔIPI_t*)* variables orthogonal to ΔLEV_t^i, ΔVOL_t^i, and ΔR_t^f and those of the additional variables orthogonal to ΔLEV_t^i, ΔVOL_t^i, ΔR_t^f, and $\Delta E_t[R_{t+1}^M]$ *(or* ΔFCI_t *or* ΔIPI_t*)*. The reported coefficients are the average coefficients from the time series regressions of CDS spread changes on structural model determinants. The t-statistics are calculated according to the time series regression coefficients, as in Collin-Dufresne et al. (2001). The right-hand entries show the average *R*-squared (R^2) and adjusted *R*-squared (Adj. R^2) values of the regression.

Panel A: Regression of CDS Spread Changes on Structural Model Determinants for Investment Grade Firms

	C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.017	0.012	-0.002								34.4%	31.9%
	0.000	0.017	0.012	-0.002	0.001							41.9%	38.9%
	0.000	0.017	0.012	-0.002		0.002						38.5%	35.3%
Coefficients	0.000	0.017	0.012	-0.002			-0.009					39.2%	36.1%
	0.000	0.017	0.012	-0.002	0.001			0.003	-0.001	-0.001	0.002	48.2%	42.5%
	0.000	0.017	0.012	-0.002		0.002		0.003	-0.001	0.005	0.003	45.3%	39.3%
	0.000	0.017	0.012	-0.002			-0.009	0.002	0.000	-0.002	0.002	44.6%	38.6%
	-0.734	9.493	14.822	-14.451									
	-0.734	9.493	14.822	-14.451	13.791								
	-0.734	9.493	14.822	-14.451		10.100							
t-stats	-0.734	9.493	14.822	-14.451			-10.812						
	-0.734	9.493	14.822	-14.451	13.791			6.021	-6.198	-1.487	3.419		
	-0.734	9.493	14.822	-14.451		10.100		7.456	-5.514	5.233	5.972		
	-0.734	9.493	14.822	-14.451			-10.812	5.011	-2.006	-2.220	4.711		

Panel B: Regression of CDS Spread Changes on Structural Model Determinants for Non-Investment Grade Firms

	C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
Coefficients	0.000	0.088	0.043	-0.005								36.9%	34.4%
	0.000	0.088	0.043	-0.005	0.004							40.4%	37.1%
	0.000	0.088	0.043	-0.005		0.007						40.2%	36.9%
	0.000	0.088	0.043	-0.005			-0.047					40.1%	36.8%
	0.000	0.088	0.043	-0.005	0.004			0.006	-0.005	-0.035	-0.010	47.4%	41.3%
	0.000	0.088	0.043	-0.005		0.007		0.009	-0.005	-0.016	-0.006	46.5%	40.4%
	0.000	0.088	0.043	-0.005			-0.047	0.005	-0.003	-0.030	-0.008	46.2%	40.1%
t-stats	-0.838	4.738	7.290	-6.799									
	-0.838	4.738	7.290	-6.799	4.231								
	-0.838	4.738	7.290	-6.799		3.911							
	-0.838	4.738	7.290	-6.799			-5.381						
	-0.838	4.738	7.290	-6.799	4.231			2.702	-3.809	-2.438	-1.877		
	-0.838	4.738	7.290	-6.799		3.911		3.669	-3.664	-1.164	-1.217		
	-0.838	4.738	7.290	-6.799			-5.381	1.989	-2.244	-2.416	-1.643		

Panel C: Regression of CDS Spread Changes during the Pre-Crisis Period

	C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
Coefficients	0.000	0.024	0.012	-0.002								22.8%	14.1%
	0.000	0.024	0.012	-0.002	0.003							28.6%	17.4%
	0.000	0.024	0.012	-0.002		0.004						31.5%	20.8%
	0.000	0.024	0.012	-0.002			-0.007					27.8%	16.5%
	0.000	0.024	0.012	-0.002	0.003			0.003	0.000	-0.003	0.000	39.6%	17.4%
	0.000	0.024	0.012	-0.002		0.004		0.006	-0.001	0.010	0.001	42.7%	21.6%
	0.000	0.024	0.012	-0.002			-0.007	0.004	0.001	-0.008	0.001	39.8%	17.6%
t-stats	5.735	6.709	10.068	-10.980									
	5.735	6.709	10.068	-10.980	8.408								
	5.735	6.709	10.068	-10.980		9.205							
	5.735	6.709	10.068	-10.980			-8.846						
	5.735	6.709	10.068	-10.980	8.408			3.109	-1.522	-1.790	0.692		
	5.735	6.709	10.068	-10.980		9.205		6.080	-5.320	4.778	1.079		
	5.735	6.709	10.068	-10.980			-8.846	3.951	3.535	-4.119	1.215		

Panel D: Regression of CDS Spread Changes during the Crisis Period

	C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.062	0.021	-0.005								49.9%	41.9%
	0.000	0.062	0.021	-0.005	0.001							54.0%	43.6%
	0.000	0.062	0.021	-0.005		0.002						53.3%	42.7%
Coefficients	0.000	0.062	0.021	-0.005			-0.028					54.8%	44.6%
	0.000	0.062	0.021	-0.005	0.001			0.006	-0.004	-0.036	-0.010	69.8%	52.3%
	0.000	0.062	0.021	-0.005		0.002		0.006	-0.004	-0.033	-0.009	68.0%	49.4%
	0.000	0.062	0.021	-0.005			-0.028	0.006	-0.002	-0.030	-0.022	68.6%	50.4%
	-1.343	2.519	8.788	-9.471									
	-1.343	2.519	8.788	-9.471	3.089								
	-1.343	2.519	8.788	-9.471		3.077							
t-stats	-1.343	2.519	8.788	-9.471			-5.750						
	-1.343	2.519	8.788	-9.471	3.089			3.349	-3.975	-4.074	-1.261		
	-1.343	2.519	8.788	-9.471		3.077		3.466	-4.628	-3.920	-1.081		
	-1.343	2.519	8.788	-9.471			-5.750	3.274	-2.333	-3.977	-2.809		

Panel E: Regression of CDS Spread Changes during the Post-Crisis Period

	C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.055	0.018	-0.001								32.0%	24.6%
	0.000	0.055	0.018	-0.001	0.003							42.1%	33.4%
	0.000	0.055	0.018	-0.001		0.004						41.8%	33.0%
Coefficients	0.000	0.055	0.018	-0.001			-0.014					39.1%	29.9%
	0.000	0.055	0.018	-0.001	0.003			0.000	0.003	-0.008	0.001	51.2%	33.8%
	0.000	0.055	0.018	-0.001		0.004		0.001	0.002	0.004	0.007	51.6%	34.3%
	0.000	0.055	0.018	-0.001			-0.014	-0.002	0.002	-0.018	0.006	49.6%	31.6%
	-1.116	6.284	10.973	-1.748									
	-1.116	6.284	10.973	-1.748	8.753								
	-1.116	6.284	10.973	-1.748		9.146							
t-stats	-1.116	6.284	10.973	-1.748			-5.568						
	-1.116	6.284	10.973	-1.748	8.753			-0.469	1.450	-2.277	0.390		
	-1.116	6.284	10.973	-1.748		9.146		0.611	1.290	1.011	1.701		
	-1.116	6.284	10.973	-1.748			-5.568	-2.053	1.146	-5.458	1.774		

Table 5. Liquidity Bin Analysis from the regression of CDS spread changes.

This table presents the linear regression results for *CDS i* contained in each bins. We divide the sample into 4 CDS liquidity level bins. The reported coefficients are the average coefficients from the time series regressions of CDS spread changes on structural model determinants. The multivariate regression shows the coefficients and t-statistics of the $\Delta E_t[R_{t+1}^M]$ *(or* ΔFCI_t *or* ΔIPI_t*)* variables orthogonal to ΔLEV_t^i, ΔVOL_t^i, and ΔR_t^f and those of the additional variables orthogonal to ΔLEV_t^i, ΔVOL_t^i, ΔR_t^f, and $\Delta E_t[R_{t+1}^M]$ *(or* ΔFCI_t *or* ΔIPI_t*)*. The t-statistics are calculated according to the time series regression coefficients, as in Collin-Dufresne et al. (2001). The right-hand entries show the average R-squared (R^2) and adjusted R-squared (Adj. R^2) values of the regression.

		C	ΔLEV_t^i	ΔVOL_t^i	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
Lowest-Liquidity	Coefficients	0.000	0.020	0.006	-0.002	0.002			0.004	-0.001	-0.016	0.001	34.0%	26.0%
		0.000	0.020	0.006	-0.002		0.004		0.005	-0.001	-0.005	0.003	31.5%	23.2%
		0.000	0.020	0.006	-0.002			-0.019	0.003	0.000	-0.014	0.002	31.0%	22.6%
	t-stats	0.132	3.100	3.578	-5.447	5.152			3.739	-2.261	-1.394	0.583		
		0.132	3.100	3.578	-5.447		2.583		4.318	-1.898	-0.510	1.372		
		0.132	3.100	3.578	-5.447			-2.794	3.141	-0.756	-1.508	1.033		
2-Liquidity	Coefficients	0.000	0.059	0.037	-0.005	0.004			0.007	-0.005	-0.018	-0.009	52.1%	46.9%
		0.000	0.059	0.037	-0.005		0.005		0.009	-0.005	-0.002	-0.005	49.4%	43.9%
		0.000	0.059	0.037	-0.005			-0.035	0.006	-0.003	-0.020	-0.007	48.5%	42.8%
	t-stats	-1.802	3.776	6.554	-6.172	4.005			2.647	-3.324	-1.726	-2.191		
		-1.802	3.776	6.554	-6.172		3.562		3.503	-3.194	-0.196	-1.224		
		-1.802	3.776	6.554	-6.172			-5.353	2.085	-2.167	-2.028	-1.745		
3-Liquidity	Coefficients	0.000	0.020	0.019	-0.003	0.002			0.002	-0.002	-0.003	-0.003	56.3%	51.6%
		0.000	0.020	0.019	-0.003		0.003		0.004	-0.002	0.010	0.000	53.5%	48.5%
		0.000	0.020	0.019	-0.003			-0.014	0.001	-0.001	-0.003	-0.002	52.5%	47.3%
	t-stats	-0.538	2.361	6.415	-10.083	5.582			5.228	-3.782	-0.885	-1.272		
		-0.538	2.361	6.415	-10.083		4.978		8.731	-3.688	2.285	-0.174		
		-0.538	2.361	6.415	-10.083			-4.725	2.409	-2.634	-1.272	-0.930		
Highest-Liquidity	Coefficients	0.000	0.056	0.023	-0.002	0.001			0.002	-0.001	-0.011	0.003	49.2%	44.0%
		0.000	0.056	0.023	-0.002		0.002		0.002	-0.001	-0.008	0.003	48.1%	42.7%
		0.000	0.056	0.023	-0.002			-0.015	0.001	0.000	-0.006	0.002	48.5%	43.1%
	t-stats	0.838	3.698	5.298	-4.466	2.031			1.402	-1.360	-1.173	0.676		
		0.838	3.698	5.298	-4.466		1.445		1.589	-1.293	-0.884	0.755		
		0.838	3.698	5.298	-4.466			-2.545	0.995	0.317	-0.761	0.569		

Table 6. Summary statistics and correlation coefficients for 25 portfolios.

Panel A presents the cross-sectional average of the time series mean and the cross-sectional standard deviations of the mean of the CDS spreads, leverage ratios, and volatilities assigned to each of the 25 portfolios grouped by five leverage ratio ranges and five volatility ranges. The last columns of Panel A show Adj. R^2 for portfolio regression equation (8) using the expected market risk premium and the number of firms assigned to each portfolio. The last row of Panel A shows these statistics for all 219 firms. Panel B reports the correlation coefficients between the time series changes in all the regression variables for all 25 portfolios.

Panel A: Summary Statistics for 25 Portfolios

		CDS spread (%)		Leverage (%)		Volatility (%)		Adj.	N. of
Leverage	**Volatility**	**Mean**	**St Dev**	**Mean**	**St Dev**	**Mean**	**St Dev**	R^2 **(%)**	**firms**
Low	Low	0.381	0.221	21.29	3.28	21.02	6.15	51.55	9
Low	2	0.385	0.243	22.60	3.19	25.50	7.72	52.16	9
Low	3	0.530	0.264	19.20	2.25	29.24	8.74	54.21	8
Low	4	0.668	0.397	20.84	4.59	34.32	10.82	60.92	9
Low	High	0.716	0.338	20.10	3.99	39.24	10.68	47.63	9
2	Low	0.445	0.245	31.82	2.91	21.06	6.30	49.76	9
2	2	0.548	0.251	31.70	3.99	27.71	8.26	57.12	9
2	3	0.749	0.350	30.75	4.45	31.51	8.47	60.55	8
2	4	0.895	0.472	34.30	4.40	35.52	11.57	59.99	9
2	High	1.410	0.644	34.02	7.82	44.59	14.49	62.66	9
3	Low	0.592	0.268	42.01	3.57	22.01	6.52	50.28	9
3	2	0.714	0.423	44.00	5.86	28.15	9.19	47.24	8
3	3	0.736	0.429	43.31	5.64	31.80	10.49	62.16	9
3	4	0.896	0.508	41.88	7.02	35.60	11.57	63.63	8
3	High	1.931	0.918	44.40	7.19	43.58	13.29	80.91	9
4	Low	0.856	0.464	52.22	4.12	25.75	8.19	62.98	9
4	2	1.244	0.685	54.03	7.14	32.56	11.16	61.63	9
4	3	1.084	0.580	52.19	5.21	37.04	12.15	57.24	8
4	4	2.367	1.681	51.96	7.86	42.32	16.01	59.84	9
4	High	3.610	2.819	53.78	12.05	54.50	22.71	78.94	9
High	Low	0.762	0.449	65.10	2.77	20.69	6.81	59.84	9
High	2	1.158	0.764	67.47	4.22	27.63	10.34	78.83	9
High	3	2.403	1.122	70.16	5.19	38.87	14.50	73.72	8
High	4	5.301	4.136	72.79	5.62	51.69	22.83	70.11	9
High	High	8.488	6.434	70.68	10.33	68.87	29.41	63.98	9
Total		1.55	1.83	43.70	17.06	34.83	11.58	64.58	219

Panel B: Correlation Coefficients for 25 Portfolios

	ΔCDS_t^p	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$
ΔCDS_t^p	1.000	0.640	0.609	-0.319	0.555	0.659	-0.587	0.032	-0.685	-0.136
ΔLEV_t^p	0.640	1.000	0.757	-0.341	0.566	0.729	-0.542	0.034	-0.820	-0.187
ΔVOL_t^p	0.609	0.757	1.000	-0.318	0.716	0.808	-0.579	0.163	-0.759	-0.072
ΔR_t^f	-0.319	-0.341	-0.318	1.000	-0.471	-0.312	0.442	0.177	0.393	0.233
$\Delta E_t[R_{t+1}^M]$	0.555	0.566	0.716	-0.471	1.000	0.827	-0.714	0.135	-0.652	-0.072
ΔFCI_t	0.659	0.729	0.808	-0.312	0.827	1.000	-0.692	0.189	-0.854	-0.123
ΔIPI_t	-0.587	-0.542	-0.579	0.442	-0.714	-0.692	1.000	0.123	0.602	0.124
$\Delta TERM_t$	0.032	0.034	0.163	0.177	0.135	0.189	0.123	1.000	-0.119	0.171
R_t^{SP}	-0.685	-0.820	-0.759	0.393	-0.652	-0.854	0.602	-0.119	1.000	0.151
$\Delta SMIRK_t$	-0.136	-0.187	-0.072	0.233	-0.072	-0.123	0.124	0.171	0.151	1.000

Table 7. Results from the portfolio regression of CDS spread changes on structural model determinants.

Panel A presents the linear regression results for each portfolio *p* of the CDS spreads of the 25 portfolios from November 2004 to March 2013. The reported coefficients are the average coefficients from the time series regressions of credit spread changes on structural model determinants. Panel B to D presents the linear regression results during the pre-crisis, crisis and post-crisis periods, respectively. The pre-crisis period is from November 2004 to July 2007, the crisis period is from August 2007 to June 2009, and the post-crisis period is from July 2009 to March 2012. The reported coefficients are the average coefficients from the time series regressions of CDS spread changes on structural model determinants. This table shows the coefficients and t-statistics of the $\Delta E_t[R_{t+1}^M]$ (or ΔFCI_t or ΔIPI_t) variable orthogonal to ΔLEV_t^p, ΔVOL_t^p, and ΔR_t^f and those of the additional variables orthogonal to ΔLEV_t^p, ΔVOL_t^p, ΔR_t^f, and $\Delta E_t[R_{t+1}^M]$ (or ΔFCI_t or ΔIPI_t). The t-statistics are calculated according to the time series regression coefficients, as in Collin-Dufresne et al. (2001). The right-hand entries show the average *R*-squared (R^2) and adjusted *R*-squared (Adj. R^2) values of the regression.

Panel A: Portfolio Regression of CDS Spread Changes

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.065	0.018	-0.002								57.8%	56.3%
	0.000	0.065	0.018	-0.002	0.002							63.9%	62.2%
	0.000	0.065	0.018	-0.002		0.004						60.8%	58.9%
Coefficients	0.000	0.065	0.018	-0.002			-0.019					61.9%	60.0%
	0.000	0.065	0.018	-0.002	0.002			0.002	-0.001	-0.021	-0.001	67.8%	64.6%
	0.000	0.065	0.018	-0.002		0.004		0.002	-0.001	-0.028	0.004	68.2%	64.6%
	0.000	0.065	0.018	-0.002			-0.019	0.002	0.000	-0.018	0.000	64.6%	61.0%
	-0.559	2.774	5.289	-7.619									
	-0.559	2.774	5.289	-7.619	4.347								
	-0.559	2.774	5.289	-7.619		2.628							
t-stats	-0.559	2.774	5.289	-7.619			-2.817						
	-0.559	2.774	5.289	-7.619	4.347			3.266	-3.513	-1.820	-0.224		
	-0.559	2.774	5.289	-7.619		2.628		2.634	-3.065	-1.564	1.967		
	-0.559	2.774	5.289	-7.619			-2.817	2.218	-1.039	-1.851	-0.112		

Panel B: Portfolio Regression of CDS Spread Changes during the Pre-Crisis Period

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.022	0.020	-0.001								34.7%	27.7%
	0.000	0.022	0.020	-0.001	0.001							40.1%	31.2%
Coefficients	0.000	0.022	0.020	-0.001		0.003						45.5%	37.5%
	0.000	0.022	0.020	-0.001			-0.009					44.3%	36.1%
	0.000	0.022	0.020	-0.001	0.001			0.003	-0.002	0.005	0.001	46.9%	28.5%
	0.000	0.022	0.020	-0.001		0.003		0.005	-0.003	0.019	0.001	55.9%	37.9%
	0.000	0.022	0.020	-0.001			-0.009	0.003	0.000	0.001	0.002	50.2%	32.8%
	3.042	4.521	3.733	-4.327									
	3.042	4.521	3.733	-4.327	5.045								
t-stats	3.042	4.521	3.733	-4.327		4.922							
	3.042	4.521	3.733	-4.327			-4.117						
	3.042	4.521	3.733	-4.327	5.045			1.340	-2.380	1.544	1.534		
	3.042	4.521	3.733	-4.327		4.922		1.974	-3.270	3.408	1.108		
	3.042	4.521	3.733	-4.327			-4.117	1.244	-0.788	0.327	1.699		

Panel C: Portfolio Regression of CDS Spread Changes during the Crisis Period

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	-0.001	0.119	0.007	-0.004								71.2%	66.6%
	-0.001	0.119	0.007	-0.004	0.002							73.1%	67.1%
Coefficients	-0.001	0.119	0.007	-0.004		0.003						72.6%	66.5%
	-0.001	0.119	0.007	-0.004			-0.024					74.4%	68.8%
	-0.001	0.119	0.007	-0.004	0.002			0.004	-0.003	-0.040	-0.006	80.9%	70.1%
	-0.001	0.119	0.007	-0.004		0.003		0.011	0.003	-0.030	-0.001	82.8%	70.8%
	-0.001	0.119	0.007	-0.004			-0.024	0.004	0.000	-0.031	-0.015	80.1%	68.7%
	-3.324	2.731	2.702	-7.699									
	-3.324	2.731	2.702	-7.699	2.425								
t-stats	-3.324	2.731	2.702	-7.699		1.343							
	-3.324	2.731	2.702	-7.699			-2.444						
	-3.324	2.731	2.702	-7.699	2.425			3.493	-1.805	-1.999	-0.782		
	-3.324	2.731	2.702	-7.699		1.343		3.178	1.851	-2.263	-0.113		
	-3.324	2.731	2.702	-7.699			-2.444	3.229	-0.537	-2.098	-1.441		

Panel D: Portfolio Regression of CDS Spread Changes during the Post-Crisis Period

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
	0.000	0.069	0.018	0.000								52.7%	47.8%
	0.000	0.069	0.018	0.000	0.002							63.0%	57.7%
Coefficients	0.000	0.069	0.018	0.000		0.005						64.1%	59.0%
	0.000	0.069	0.018	0.000			-0.013					58.3%	52.3%
	0.000	0.069	0.018	0.000	0.002			-0.002	0.006	-0.013	-0.003	68.6%	58.2%
	0.000	0.069	0.018	0.000		0.005		0.001	0.005	-0.022	0.007	72.4%	61.6%
	0.000	0.069	0.018	0.000			-0.013	-0.003	0.005	-0.021	0.001	65.6%	54.2%
	3.242	2.629	4.486	-0.549									
	3.242	2.629	4.486	-0.549	2.882								
t-stats	3.242	2.629	4.486	-0.549		3.590							
	3.242	2.629	4.486	-0.549			-2.422						
	3.242	2.629	4.486	-0.549	2.882			-2.674	1.207	-3.872	-0.637		
	3.242	2.629	4.486	-0.549		3.590		0.723	1.268	-1.566	3.994		
	3.242	2.629	4.486	-0.549			-2.422	-2.570	1.121	-3.927	0.402		

Table 8. Robust tests for portfolio regression.

Panel A and B report the linear regression results using EMKT for each portfolio *p* of the CDS spreads of nine portfolios grouped by three leverage and three volatility ranges, and 16 portfolios grouped by four leverage and four volatility ranges, respectively. Panel C and D report the same linear regression results using IPI. Each panel shows the average coefficients and t-statistics (in parentheses) from the sample for the full period (ALL), the pre-crisis period (PRE), the crisis period (CRISIS) and the post-crisis period (POST). The right-hand entries show the average R-squared (R^2) and adjusted R-squared (Adj. R^2) values.

Panel A : 3 Leverage X 3 Volatility Portfolio Regression using EMKT

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	R^2	adj. R^2
ALL	0.000	0.089	0.013	-0.002	0.002	68.51%	66.99%
	(-0.838)	(1.861)	(6.098)	(-6.247)	(2.523)		
PRE	0.000	0.026	0.022	-0.002	0.001	44.76%	36.58%
	(2.151)	(3.238)	(2.494)	(-2.707)	(3.821)		
CRISIS	-0.001	0.148	0.000	-0.004	0.002	76.29%	71.02%
	(-1.895)	(1.919)	(0.043)	(-4.826)	(1.789)		
POST	0.000	0.095	0.011	0.000	0.003	68.45%	63.94%
	(2.16)	(1.659)	(6.612)	(0.663)	(2.428)		

Panel B : 4 Leverage X 4 Volatility Portfolio Regression using EMKT

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}^M]$	R^2	adj. R^2
ALL	0.000	0.074	0.016	-0.002	0.002	66.17%	64.54%
	(-0.741)	(2.413)	(4.853)	(-7.588)	(4)		
PRE	0.000	0.026	0.022	-0.001	0.001	42.43%	33.90%
	(2.606)	(3.469)	(3.025)	(-3.565)	(4.275)		
CRISIS	-0.001	0.136	0.003	-0.004	0.001	74.27%	68.56%
	(-2.565)	(2.4)	(0.671)	(-7.135)	(2.004)		
POST	0.000	0.076	0.016	0.000	0.002	66.66%	61.90%
	(3.89)	(2.183)	(5.485)	(0.308)	(3.403)		

Panel C : 3 Leverage X 3 Volatility Portfolio Regression using IPI

	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	ΔIPI_t	R^2	adj. R^2
ALL	0.000	0.089	0.013	-0.002	-0.020	66.30%	64.67%
	(-0.838)	(1.861)	(6.098)	(-6.247)	(-1.74)		
PRE	0.000	0.026	0.022	-0.002	-0.010	50.55%	43.22%
	(2.151)	(3.238)	(2.494)	(-2.707)	(-2.442)		
CRISIS	-0.001	0.148	0.000	-0.004	-0.026	77.72%	72.77%
	(-1.895)	(1.919)	(0.043)	(-4.826)	(-1.483)		
POST	0.000	0.095	0.011	0.000	-0.014	62.71%	57.39%
	(2.16)	(1.659)	(6.612)	(0.663)	(-1.986)		

Panel D : 4 Leverage X 4 Volatility Portfolio Regression using IPI

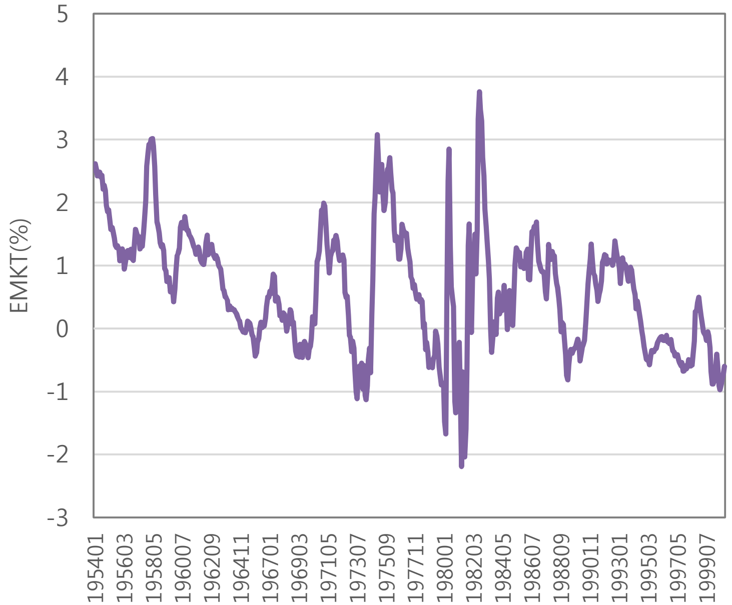
	C	ΔLEV_t^p	ΔVOL_t^p	ΔR_t^f	ΔIPI_t	R^2	adj. R^2
ALL	0.000	0.074	0.016	-0.002	-0.018	63.83%	62.09%
	(-0.741)	(2.413)	(4.853)	(-7.588)	(-2.438)		
PRE	0.000	0.026	0.022	-0.001	-0.009	47.79%	40.05%
	(2.606)	(3.469)	(3.025)	(-3.565)	(-3.43)		
CRISIS	-0.001	0.136	0.003	-0.004	-0.023	75.48%	70.03%
	(-2.565)	(2.4)	(0.671)	(-7.135)	(-2.072)		
POST	0.000	0.076	0.016	0.000	-0.014	60.67%	55.06%
	(3.89)	(2.183)	(5.485)	(0.308)	(-2.558)		

Table 9. Robust tests for portfolio regression with stock return variable.

This table presents the linear regression results for each portfolio *p* of the CDS spreads of the 25 portfolios grouped by five stock price (*SP*) and five implied volatility (*VOL*) ranges from November 2004 to March 2013. The reported coefficients are the average coefficients from the time series regressions of credit spread changes on structural model determinants. The multivariate regression shows the coefficients and t-statistics of the $\Delta E_t[R_{t+1}{}^M]$ (or ΔFCI_t or ΔIPI_t) variables orthogonal to SR_t^p, ΔVOL_t^p, and ΔR_t^f and those of the additional variables orthogonal to SR_t^p, ΔVOL_t^p, ΔR_t^f, and $\Delta E_t[R_{t+1}{}^M]$ (or ΔFCI_t or ΔIPI_t). The t-statistics are calculated according to the time series regression coefficients, as in Collin-Dufresne et al. (2001). The right-hand entries show the average *R*-squared (R^2) and adjusted *R*-squared (Adj. R^2) values of the regression.

	C	SR_t^p	ΔVOL_t^p	ΔR_t^f	$\Delta E_t[R_{t+1}{}^M]$	ΔFCI_t	ΔIPI_t	$(\Delta R_t^f)^2$	$\Delta TERM_t$	R_t^{SP}	$\Delta SMIRK_t$	R^2	adj. R^2
Coefficients	0.000	-0.020	0.012	-0.002								60.5%	59.1%
	0.000	-0.020	0.012	-0.002	0.002							66.8%	65.2%
	0.000	-0.020	0.012	-0.002		0.002						63.4%	61.7%
	0.000	-0.020	0.012	-0.002			-0.012					64.4%	62.6%
	0.000	-0.020	0.012	-0.002	0.002			0.003	0.000	0.002	0.001	70.1%	67.1%
	0.000	-0.020	0.012	-0.002		0.002		0.004	0.000	0.010	0.003	67.6%	64.4%
	0.000	-0.020	0.012	-0.002			-0.012	0.002	0.001	0.002	0.002	66.9%	63.6%
t-stats	3.075	-3.084	5.919	-6.878									
	3.075	-3.084	5.919	-6.878	7.287								
	3.075	-3.084	5.919	-6.878		2.237							
	3.075	-3.084	5.919	-6.878			-4.345						
	3.075	-3.084	5.919	-6.878	7.287			4.043	-0.489	0.391	0.609		
	3.075	-3.084	5.919	-6.878		2.237		5.721	-0.381	2.133	1.323		
	3.075	-3.084	5.919	-6.878			-4.345	3.416	0.695	0.311	0.684		

Figure 1. Time series of the expected market risk premium and average CDS spreads.
The left graph shows the estimated monthly market risk premium as a proxy for the business cycle. It illustrates the in-sample fitted estimates of the expected market risk premium from January 1954 to December 2000. The graph labeled EMKT in the right chart depicts the out-of-sample time series estimates of the monthly expected market risk premium between September 2004 and March 2012, based on in-sample parameters. The graph labeled CDS is the time series of the cross-sectional average CDS spreads for 384 firms for each of the reference dates between September 2004 and March 2012.



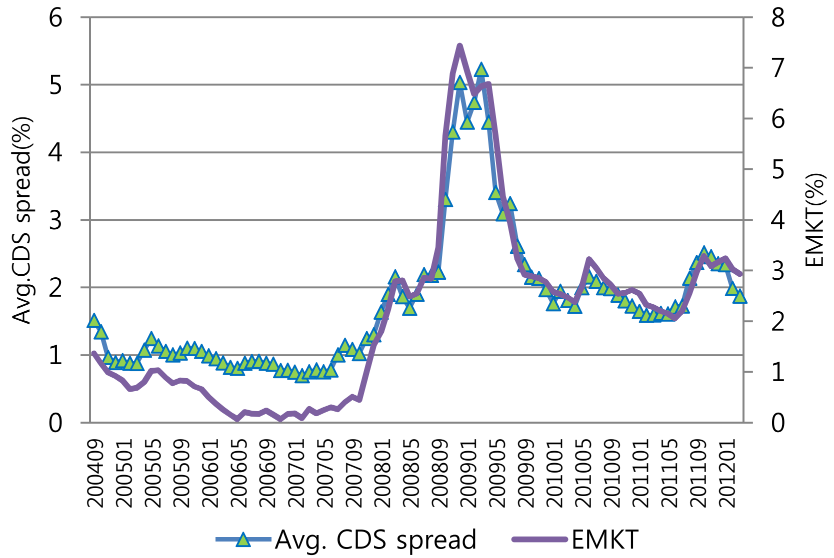


Figure 2. Scatter plots of the time series average of CDS spreads versus average rating, average leverage ratio, and average volatility.

These graphs show the scatter plots of the average CDS spread for five-year maturity versus firm-specific variables for 384 different companies. The upper graph shows the scatter plot of the time series average rating number and the time series average CDS spread. The rating numbers range from 1(AAA) to 9(C). The lower left graph shows the scatter plot of the time series average leverage ratio and the time series average CDS spread, and the lower right graph shows the scatter plot of the time series average volatility and the time series average CDS spread.