THE DETERMINANTS OF CDS SPREADS

Koresh Galil, Offer Moshe Shapir,
Dan Amiram and Uri Ben-Zion

Discussion Paper No. 13-18

December 2013

Monaster Center for
Economic Research
Ben-Gurion University of the Negev
P.O. Box 653
Beer Sheva, Israel

Fax: 972-8-6472941
Tel: 972-8-6472286

The determinants of CDS spreads

Koresh Galil*

Offer Moshe Shapir*, **

Dan Amiram*

Uri Ben-Zion*

November 30, 2013

Abstract

This study proposes models that can be used as shorthand analysis tools for CDS spreads and CDS spread changes. For this purpose we examine the determinants of CDS spreads and spread changes on a broad database of 718 US firms during the period from early 2002 to early 2013. Contrary to previous studies, we discover that market variables still have explanatory power after controlling for firm-specific variables inspired by structural models. Three explanatory variables appear to overshadow the other variables examined in this paper: Stock Return, ΔVolatility (the change in stock return volatility) and ΔMRI (change in the median CDS spread in the rating class). We also discover that models used in the event study literature to explain spread changes can be improved by using additional market variables. Further, we show that ratings explain cross-section variation in CDS spreads even after controlling for structural model variables.

Keywords: Credit Default Swap; CDS; Credit spread; Corporate bond; Structural model

JEL classifications: G12, G13

---

* Koresh Galil (galilk@bgu.ac.il) and Offer Moshe Shapir (offers@bgu.ac.il) are from the Economics Department at Ben-Gurion University of the Negev. Dan Amiram is from Columbia Business School (da2477@columbia.edu) and Uri Ben-Zion is from Western Galilee College. We would like to thank Suleiman Abu-Bader, Zvika Afik, Ilan Cooper, Marti Subrahmanyam and the seminar participants at Ben-Gurion University and the 2012 annual meeting of MFS in Krakow for their helpful comments and suggestions. All remaining errors are ours.

** Corresponding author.

Introduction

The growth of the CDS market over the last decade has increased the use of this market in finance literature. Several studies, among them Blanco et al. (2005) and Zhu (2006), have explored the relationship between bond credit spreads (yield difference between corporate bonds and treasuries) and CDS spreads. Other studies have explored the relation between CDS spreads and credit ratings (Hull, Predescu and White 2004, Norden and Weber 2004, Galil and Soffer, 2011). These studies used the market model as a proxy for expected change in CDS spreads. Adjusted change in CDS spread during a specific time interval was calculated as the CDS spread change minus the spread change in a CDS index. This simplistic adjustment method was used merely because of a lack of validated models that explain CDS spread changes.

The aim of this study is to propose models that can be used as shorthand analysis tools for CDS spreads and CDS spread changes. For this purpose we analyze the determinants of changes in CDS spreads on a broad database of US firms, from January 2002 to February 2013. We evaluate the ability of firm-specific data inspired by structural models and market risk factors to explain changes in CDS spreads. We find that firm-specific variables substantially explain CDS spread changes. However, contrary to Avramov et al. (2007) and Ericsson et al. (2009), we discover that market variables still have explanatory power after controlling for firm-specific variables. In addition, we find that models used in event study literature (e.g., Norden and Weber, 2004 and Galil and Soffer, 2011) to explain spread changes can be improved by using additional market variables, such as ΔSpot, ΔSlope, ΔVIX, MP, and ΔUTS.

In the study, we present four sets of variables, each of which is applicable depending upon availability of data. One set of variables is suggested for cases in which a firm's stock returns are observable. Another set is suggested for cases in which a firm's stock return and credit rating are observable. A third set is suggested for cases in which neither the firm's stock return nor its credit rating is observable, and a fourth set is for cases in which only the credit rating is observable. The ability to propose these alternative models relies on the structural model rationale. Since according to these models the value of equity and the volatility of equity returns are inputs in pricing corporate bonds, they can be replaced by factors that explain these variables (e.g., market return and VIX).

Three explanatory variables appear to overshadow the other variables examined in this paper: Stock Return, ΔVolatility (change in stock return volatility) and ΔMRI (change in median CDS spread in the rating class). These three variables are able to explain changes in CDS spreads even after controlling for the information embedded in all other explanatory variables. Interestingly, two of these are firm-specific variables (Stock Return and ΔVolatility), while the third is a market factor (ΔMRI).

Our results also suggest that the Global Financial Crisis (GFC) was responsible for a structural change in pricing of CDS spreads, especially among investment-graded firms. While the coefficient estimates of the various models changed during the crisis, they did not reverse that much at the end of the crisis. More interestingly, during and after the GFC, the explanatory power of the model for investment-graded firms was higher than for speculative-graded firms. This result differs from previous findings in the literature which found the opposite.

We then use a cross-section analysis to search for the determinants of CDS spreads before, during and after the GFC. Fundamental variables such as historical stock returns, historical stock volatility and leverage explain CDS spreads after controlling for ratings. Nevertheless, we also discover that ratings explain cross-section variations in CDS spreads after controlling for fundamental variables. This finding suggests that using a linear combination of these fundamental variables is not effective from the informational perspective. Finally, we show that during the GFC fundamental variables maintained their explanatory power, while the explanatory power of ratings decreased to almost zero.

The remainder of the paper is organized in the following way: Section 1 describes the sample data and the methodology. Section 2 presents the explanatory variables and their theoretical relation to CDS spread changes. In Section 3 we provide a time-series analysis. Cross-section analysis is provided in Section 4, and Section 5 concludes.

1. Data and methodology

In this section we describe the methodology and data we use for explaining CDS spread changes.

1.1 Methodology

We use a framework similar to that used in Collin-Dufresne et al. (2001), Avramov et al. (2007) and Ericsson et al. (2009) to explain the determinants of credit spreads. First, we use a time-series analysis to investigate the ability of various factors to explain CDS spread changes: firm-specific variables (stock return, ΔVolatility and ΔLeverage), common factors (ΔSpot rate, ΔTerm-structure slope, ΔVIX), F&F factors (HML, SML and MKT), stock liquidity factor (innovations in aggregate liquidity (IAL) from Pastor and Stambaugh, 2003) and five Chen, Roll and Ross (1986) macro-variables - CRR factors (MP, UI, DEI, ΔUTS, ΔUPR). We offer four sets of variables, each of which is useful in explaining CDS spread changes, depending on availability of data.

For measuring the ability of the four sets of variables to explain CDS spread changes we use time-series analysis. We run individual regressions for each CDS and then average the estimated coefficients across all CDS. The t-statistics are computed from the cross-section of the individual regression coefficients, as in Collin-Dufresne et al. (2001), Avramov et al. (2007) and Ericsson et al. (2009).

In addition, we conduct a cross-section analysis to examine the ability of ratings and firm-specific variables (stock return, stock volatility and leverage) to explain CDS spreads (level-analysis). We address this issue using two methods: First, we run cross-section regressions on four different time periods (prior to the GFC - May 2007; the peak of the GFC – September 2008; and a year after the peak of the GFC - July 2009; and after the GFC – July 2011). Doing so allows us to explore the ability of ratings and common factors to explain CDS spreads. Second, we use the methodology of Fama and MacBeth (1973) to explain CDS prices over time. We run a cross-section regression for each month and then report the average estimate coefficients separating the results into four time periods (data period from January 2002 to February 2013; before GFC - January 2002 to June 2007; during GFC - July 2007 to June 2009; and after GFC- July 2009 to February 2013).

1.2 Data

The initial sample includes all US dollar nominated 5-year CDS data in the Markit database for the period from January 2002 to February 2013. We were able to obtain equity returns for 764 firms from the Center for Research in Security Prices (CRSP). In line with Collin-Dufresne et al. (2001) and Avramov et al. (2007), we omit firms with less than 25 monthly quotes of CDS prices and equity return. This leaves us with 695 rated firms and 23 unrated firms traded on the US stock market. For each firm we calculate the CDS spread change as follows:

$$(1)\quad \Delta CDS_{i,t} = CDS_{i,t} - CDS_{i,t-1}\ .$$

where $CDS_{i,t}$ is the CDS spread of firm i in month t.

In our time-series analysis we focus on the changes in CDS spreads rather than on the levels of CDS spreads. This method is justified because, as shown subsequently, changes are stationary while levels tend not to be stationary.

2. **Description of explanatory variables and their relation to CDS spread changes.**

In this section we describe the variables and their theoretical relation to CDS spread changes. We divide the variables into four groups (firm-specific variables, common factors, F&F and P&S factors, and CRR factors) and present the descriptive statistics for independent and dependent variables during the period from January 2002 to February 2013.

2.1 Firm-specific variables

Stock return: The Merton model suggests a negative connection between a firm's equity and its probability of defaulting. We use monthly stock returns obtained from CRSP as an indication of changes in a firm's equity. Higher stock returns increase a firm's value, which theoretically should decrease CDS spreads. Hence, a negative relation is expected between stock returns and CDS spreads.

Volatility (stock volatility): The Merton model views debt as a combination of a short put-option on a firm's assets and a risk-free loan. Therefore, we expect that higher stock volatility (reflecting higher asset volatility) will lead to a greater probability of default and a higher CDS spread. Firm-specific volatility is estimated separately for each firm as the annualized variance of the individual stock returns for the previous 250 trading days obtained from CRSP. Our approach resembles that of Campbell and Taksler (2003) and of Ericsson et al. (2009).[1]

Leverage: We calculate leverage as follows:

$$(2) \quad Leverage = \frac{Book\_Debt}{Book\_Debt + Equity\_Value}.$$

The book value of debt ($Book\_Debt$) is compiled from long-term debt and debt in current liabilities. The market value of equity ($Equity\_Value$) is the number of outstanding shares multiplied by the price per share. Since the data obtained from COMPUSTAT are quarterly, we use a linear interpolation (as in Collin-Dufresne et al., 2001 and Ericsson et al., 2009) for estimating monthly leverage to fill the gaps. According to Merton's approach, higher leverage indicates a shorter distance to the default barrier and hence a higher probability of default. Therefore, we expect a positive connection between leverage changes and CDS spread changes.

2.2 Common factors

Spot: To be consistent with the 5-year maturity of the CDS contracts, we measure the spot rate using the daily 5-year Treasury Constant Maturity Rate obtained from the St. Louis Federal Reserve (FRED). Longstaff and Schwartz (1995) argued that a higher reinvestment rate (higher spot rate) increases future value. Collin-Dufresne et al. (2001) noted that a higher spot

[1] In their base case regressions, Campbell and Taksler (2003) construct historical volatility based on 180 days of return.

rate reduces the probability of default. Both arguments support a negative connection between spot rate and credit spreads. Longstaff and Schwartz (1995) empirically confirmed the negative relationship.

Term-structure slope: We use the differences between the 10-year Treasury Constant Maturity Rate and the 2-year Treasury Constant Maturity Rate obtained from FRED as the term-structure slope. The expected relation between term-structure slope and credit spreads is unclear. On the one hand, Fama and French (1989) claimed that an increase in the yield-curve slope anticipates improved economic growth, thus improving recovery rates. Therefore, a negative relationship is expected between term-structure slope and credit spread. On the other hand, the same process of slope steepening may reduce the number of projects with a positive net present value available to firms. This effect leads to an increase in the probability of default and therefore to a positive relation between term-structure slope and credit spread.

Market condition: The overall business climate affects the probability of default and the expected recovery rate (Altman and Kishor, 1996). An improvement in market conditions reduces the probability of default and increases the expected recovery rate, which leads to lower credit spreads. For measuring market conditions we use the change in the Median Rated Index (ΔMRI) calculated as the median spread change of all the firms in the same rating group. We use four groups: 1) AAA/AAs; 2) As; 3) BBBs; and 4) BB+ or lower (speculative grades). We expect a positive relationship between market condition and spread change.

Market volatility (VIX): For measuring market volatility we follow Collin-Dufrense et al. (2001) and use the VIX index, which represents option-implied volatility based on S&P 500 index options obtained from the Chicago Board Options Exchange (CBOE). As with firm-specific volatility, we expect a positive relation between market volatility and CDS spreads.

2.3 Fama and French (F&F) factors and Pastor and Stambaugh (P&S) liquidity factor

We use three F&F factors: HML, SMB and MKT.[2] HML is the return on the portfolio of high book-to-market stocks minus the return on the portfolio of low book-to-market stocks. SMB is the return on a small capitalization portfolio minus the return on a big capitalization portfolio. MKT is the excess return on the market and is calculated as Rm-Rf. The market return (Rm) is the value weighted return of all NYSE, AMEX and NASDAQ stocks (from CRSP), and the risk-free return (Rf) is the one month treasury bill rate.

[2]Data obtained from Professor Kenneth French's website.

In the literature, the connection between F&F factors and the CDS spread was claimed to be negative. Higher factors indicate better economic conditions (higher assets value) and therefore lower credit spreads.

We also use innovations in the aggregate liquidity factor (hereafter, IAL) of Pastor and Stambaugh (2003).[3] The relation between this factor and changes in CDS spreads is not clear. On the one hand, based on structural models stock price liquidity premium is not relevant for bond pricing. The price and statistical features of stock prices are used in pricing corporate bonds simply because they enable extracting the value and statistical features of a firm's assets that constitute the underlying asset for the two derivatives - equity and debt. Yet stock illiquidity does not necessarily signal features of firm's assets. Therefore, based on this logic we should not find any relation between CDS spread changes and the IAL factor. On the other hand, innovations in the liquidity factor of stock markets may be correlated with innovations in the liquidity factor of the corporate bonds market. If so, we can expect a negative relation between CDS spread changes and P&S factor.

2.4 Chen, Roll and Ross (1986) factors

We use the same factors as in Liu and Zhang (2008) and Cooper and Pristley (2011). The five factors are as follow:

MP: MP is the growth rate of industrial production, calculated as $MP_t = Log(IP_t) - Log(IP_{t-1})$ where IP_t is the index of Industry Production at month t obtained from the FRED database. Chen, Roll, and Ross (1986) showed that MP is a priced risk factor. Johnson (2002) and Sagi and Seasholes (2007) argued that apparent momentum profits can reflect temporary increases in growth-related risk for winner-minus-loser portfolios. Liu and Zhang (2008) found that winners have temporarily higher MP loadings than do losers for short periods. Therefore, we expect a negative connection between MP and CDS spreads.

UI and DEI: The unexpected inflation (UI) and the change in expected inflation (DEI) are calculated as in Cooper and Priestley (2011). The unexpected inflation implies unexpected economic growth, and therefore a negative relation is expected between UI and CDS spread changes. The connection between DEI and the spread is unclear. On the one hand, high inflation suggests growing economics that can reduce the spreads. On the other hand, compensation may exist between nominal and real interest rates, which can lead to an increase in the spreads.

[3] Data obtained from Professor Lubos Pastor's website.

UTS: Term Structure (UTS) is the yield spread between the twenty-year (long-term) and the one-year treasury bonds obtained from FRED. We conjecture that the relation between UTS and CDS spreads is similar to the relation between the term-structure slope and the CDS spread (negative).

UPR: Risk Premium (UPR) is the default premium calculated as the yield spread between Moody's Baa and Aaa corporate bonds from FRED. It is reasonable to assume that a higher default premium, which indicates a riskier market, would lead to higher CDS spreads. UPR is another measure of market condition.

Table 1 summarizes the variables and the direction of their impact on CDS spread changes.

2.5 Descriptive statistics

Table 2 outlines the descriptive statistics of independent and dependent variables during the period from January 2002 to February 2013. Panel A describes the variables divided into five groups: spread variables, firm-specific variables, common factors, F&F and P&S factors, and CRR factors. The CDS spread mean is 196.02 basis points (BP), with a standard deviation of 187.59 BP. The monthly mean of spread changes is 3.07 BP, and the stock monthly change mean is 1.03%. The stock return ranges from -99% to 396%. This range is due to the unique situation during and after the GFC. For example, our dataset includes Washington Mutual Inc., which was the largest savings and loan association in the US until its collapse in 2008. Within a short period of time, its stock price decreased from approximately $50 to less than $0.04. Other companies in our sample that collapsed during the sample period include American International Group (AIG), Hartford Financial Services Group Inc. (HIG), Nova Chemicals Corp and others. The sample includes 20 companies (out of 718) that lost more than 70% of their stock value during a single month.

Panel B shows the descriptive statistics for the data, divided into investment-graded firms (554) and speculative-graded firms (141). The other 23 firms were not rated and are not included in these results. The means of CDS and ΔCDS are 143.25 and 2.42 BP, respectively, in the investment-graded group and are lower than in the speculative-graded group (433.31 BP and 4.81 BP, respectively). The standard deviation in the investment-graded group is lower than in the speculative-graded group (146.79 and 58.68 BP for CDS and ΔCDS vs. 317.15 and 142.50 in the speculative-graded group). These results are consistent with the higher probabilities to default among the speculative-graded group.

Table 3 shows the results of two unit-root tests (Augmented Dickey-Fuller test and Philip-Perron test) for CDS spreads and the main explanatory variables. These tests are conducted both on levels and first differences (stock returns in the case of stock prices). The firm-specific variables are tested for each firm separately. Therefore, panel A shows the number of firms for which unit-root is not rejected (non-stationary) vs. firms for which unit-root is rejected (stationary). The results of both tests lead to the conclusion that for the majority of firms, CDS spreads, stock prices, leverage and stock volatility are non-stationary in levels but stationary in first difference. Unit root in the first difference of CDS spreads is rejected for 14 firms according to the Augmented Dickey-Fuller test and for six firms according to the Phillips-Perron test. Panel B also shows that the main common variables (VIX, Spot, Slope, MRI) are stationary in first differences. These results justify the time-series of first differences because these appear to be stationary while levels tend not to be stationary.

3. Results – time-series analysis

In this section we explore the ability of different factors to explain changes in the CDS spreads. First, we explore the ability of firm-specific variables (stock return, ΔVolatility and ΔLeverage), common factors (ΔSlope, ΔSpot and ΔVIX), F&F and P&S factors (F&F: MKT, SMB and HML; P&S: IAL) and CRR factors (MP, UI, DEI, ΔUTS, ΔUPR) using both univariate (results are not reported) and multivariate regressions.[4] Table 4 presents the results of the following multivariate regressions:

(3) M1: $\Delta CDS_{i,t} = \alpha_0 + \beta_1 \cdot Stock\,Return_{i,t} + \beta_2 \cdot \Delta Volatility_{i,t} + \beta_3 \cdot \Delta Leverage_{i,t} + \varepsilon_{i,t}$

(4) M2: $\Delta CDS_{i,t} = \alpha_0 + \beta_1 \cdot HML_t + \beta_2 \cdot SMB_t + \beta_3 \cdot MKT_t + \varepsilon_{i,t}$

(5) M3: $\Delta CDS_{i,t} = \alpha_0 + \beta_1 \cdot HML_t + \beta_2 \cdot SMB_t + \beta_3 \cdot MKT_t + \beta_4 \cdot IAL_t + \varepsilon_{i,t}$

(6) M4: $\Delta CDS_{i,t} = \alpha_0 + \beta_1 \cdot MP_t + \beta_2 \cdot UI_t + \beta_3 \cdot DEI_t + \beta_4 \cdot \Delta UTS_t + \beta_5 \cdot \Delta UPR_t + \varepsilon_{i,t}$

M1 checks the ability of structural model-induced firm-specific variables to explain changes in CDS spreads. We find that ΔLeverage is not statistically significant. This result may reflect the high correlation between ΔLeverage and stock return (-0.73). In addition, we find that this model can explain 16.23% of CDS spread changes, compared to 23% explained by Ericsson et al. (2009). This difference in explanatory power may be attributed to the sample differences.

Next we explore the ability of F&F factors to explain changes in CDS spreads (M2). To the best of our knowledge, this is the first study to examine these factors using CDS data.

---

[4] Woolridge test statistics for serial correlation in panel data for these four regressions are 2.753, 2.630, 2.632 and 2.522 respectively, and therefore the absence of serial correlation in the data is not rejected at the 5% level.

Avramov et al. (2007) used bonds data to show that F&F factors explain approximately 26% of the variation in credit spread changes. They also found that all three factors are statistically significant and have the expected coefficient sign according to theory. Using CDS data, we find that F&F factors together can explain 16.03% of the changes in CDS spreads (Table 4). The factors' coefficients have the expected sign and all are statistically significant at the 5% level. Next (for M3) we add the Pastor and Stambaugh (2003) innovations in the aggregate liquidity factor to the F&F factors. We find that the stock liquidity factor (IAL) is not statistically significant (t=-0.74) and fails to increase the explanatory power of the model (16.98% VS 16.03% without IAL factor).

We continue by examining five CRR factors (M4).[5] We find that this regression can explain only 10.39% of the CDS spread changes. All the factors (except ΔUTS) are statistically significant at the level of 1% (MP and ΔUPR), 5% (UI) and 10% (DEI) and have the expected sign. In a univariate regression we find that ΔUPR alone explains 9.97% of the spread changes (not reported). This means that ΔUPR is the most important factor of the five. The other four factors make a very limited contribution to the explanatory power of the model (0.42%). Overall, the CRR model underperforms all previous empirical models, which were able to explain approximately 16%-17% of the time-series variation in CDS spreads.

Next, we describe the results of time-series analysis using 695 rated firms with firm-specific variables, common factors, F&F and CRR factors.[6,7] We suggest four basic sets, each of which is useful conditional upon the availability of data. Model A is useful when a firm's stock returns are observable, model B is useful when a firm's stock returns and credit rating are observable, model C is useful when both the stock returns and the credit ratings are not observable, and model D is useful when only credit rating is observable. The ability to propose these alternative models relies on the structural model rationale. Since according to these models the value of equity and the volatility of equity returns are inputs in pricing corporate bonds, they can be replaced by factors that explain these variables (e.g., market return and VIX).

---

[5] Industrial production figures for month t are first observed in month t+1; therefore we use the growth rate of month t-1 (lag MP) in the regressions.

[6] Our rating-based CDS indices (ΔMRI) may be used only on rated firms. We also explore two additional CDS indices: Average Spread Change Index (ASCI) and Reduced Average Spread Change Index (RASCI). The ASCI is the monthly average spread change of all 718 firms in the sample. The RASCI is the same, except for the number of firms. For each case we calculate RASCI from the participating firms. For example, our sample contains 141 speculative-grade firms, so when analyzing only the speculative-graded firms we use the index compiled from speculative-graded firms only. We also use ASCI instead of ΔMRI in measuring the effect of market condition, and the qualitative results remain the same. The results with ASCI are omitted for space considerations and are available upon request.

[7] We do not use stock liquidity factor (IAL) because in the previous section this factor was found not to be significant when combined with other factors.

Table 5 displays the results of five sets of variables.[8] In the first set we use all factors that can explain CDS spread changes. These variables explain more than 38% of spread changes. Models A-D explain between 20.35% and 31.76% of the CDS spread changes. All variables in these models (A-D) are statistically significant, and their coefficients have the expected signs.

In model A we use the stock return, ΔVolatility, ΔSpot, HML, MKT, UI and DEI variables. The variables stock return, ΔSpot, ΔVolatility are considered solid determinants in explaining credit spread changes (e.g., Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Avramov et al., 2007; and Ericsson et al., 2009). The term-structure slope factors (ΔSlope and ΔUTS) are limited in their ability to explain the credit spread changes. Therefore we do not use these factors when stock return is observable. We use the CRR factors – UI and DEI – because their information is not captured by the other factors in our model. This model explains almost 25% of the CDS spread changes.

In model B we use only four variables – stock return, Δ Volatility, HML and Δ MRI – which manage to explain 31.76% of the CDS spread changes. Adding more variables to the model (as in model A) increases the explanatory power of the model but reduces the significance of the explanatory factors. In models C and D we use the same six variables – ΔSpot, ΔSlope, ΔVIX, MP, ΔUTS – but one (model C) also uses ΔUPR and the other (model D) uses Δ MRI instead. Adding the macro variables ΔUTS, ΔSlope and the ΔVIX variables compensates for the lack of stock data. Thus, although we do not have information on stock prices, these models are able to explain 20.35% (C) and 28.84% (D) of the CDS spread changes.

A comparison between the model with all regressors (M1) and the models with subsets of explanatory variables (models A-D) reveals the collinearity among the explanatory variables. We find that ΔLeverage, ΔSpot, ΔSlope, ΔVIX, HML, SMB, MKT, MP, UI, DEI, ΔUTS, ΔUPR are not statistically significant (at 5% level). However, all of them are statistically significant in other regressions with subsets of explanatory variables. This finding indicates that all these variables are conditionally correlated. Interestingly, the variables that remain statistically significant in the M1 model are the firm-specific variables: stock return, ΔVolatility and the market factor ΔMRI. This finding indicates that both firm-specific variables and market factors are needed to explain changes in CDS spreads. In contrast to structural model predictions, firm-specific variables (stock return, ΔVolatility) alone are not able to explain spreads, and market factors such as ΔMRI still have explanatory power. This finding differs from findings by

[8] Woolridge test statistics for serial correlation in panel data for these five regressions are 2.784, 2.746, 2.738, 2.625 and 2.668 respectively, and therefore absence of serial correlation in the data is not rejected at the 5% level.

Avramov et al. (2007) and Ericsson et al. (2009), which concluded that firm-specific variables inspired by structural models capture most of the systematic variation in credit-spread changes.

We can also conclude that these variables (stock return, ΔVolatility and ΔMRI) are the strongest explanatory variables of changes in CDS spreads in the sense that they incorporate information not reflected in the other common explanatory variables. Therefore, not surprisingly model B has the highest adjusted R-squared. This model outperforms the other models even though it is based on four variables only.

The estimation of Model D reveals that market factors such as ΔSpot, ΔSlope, ΔVIX, MP, and ΔUTS are statistically significant in explaining spread changes after controlling for the market factor ΔMRI. This finding suggests that event studies such as Norden and Weber (2004) and Galil and Soffer (2011) could improve their spreads-changes model by adding these variables in addition to the ΔMRI they used. It is worth mentioning that using a model that incorporates firm-specific information (model A and model B) would not be appropriate in such event studies because stock returns and stock volatility may themselves be directly affected by the event (rating announcements in the case of these two studies).

These results show that even in the absence of stock prices, the ability to explain CDS spread changes is relatively steady. The drop in explanatory power due to the absence of stock prices is compensated by the use of market factors. Therefore, overall structural variables do not significantly improve the explanation of CDS spread changes.

3.4 Consistency across rating classes and throughout the business cycle

Next we examine the strength of the four models under different conditions. We choose to divide our sample into four time periods and three rating groups (4X3 options) The time periods are: (1) February 2002 to February 2013 (133 months); (2) prior to the GFC (February 2002 to June 2007, 65 months); (3) during the GFC (July 2007 to June 2009, 24 months); (4) after the GFC (July 2009 to February 2013, 44 months). We also divide the firms into: (1) all-rated firms; (2) speculative-graded firms; and (3) investment-graded firms.[9] Panel A in Table 6 shows the Adj. R^2 of the models, and panel B shows the results of Chow tests for structural changes between two subsequent sub-periods.

[9] We also examine the models for 718 unrated and rated firms using the ASCI (Average Spread Change Index) instead of ΔMRI. The results are similar and are omitted due to space considerations. We also compare three different indices to calculate the market condition - ASCI, RASCI and ΔMRI - during four different time periods (before/during/after GFC and all periods) and three categories (rated firms, investment-graded firms, and speculative-graded firms). We find that all three methods have approximately the same ability to explain changes in CDS spread. The variable coefficients for the most part maintain their signs and statistical significance. Due to space considerations, we only present the ΔMRI results in this paper; the results using other indices are available upon request.

We find that in many cases the differences in the ability of the four models to explain the CDS spread changes are small and the variables have the correct sign, though some of them are not significant. We find that during and after the GFC, the four models better explain the investment-graded firms than the speculative-graded firms, while before the GFC, the comparison is inconclusive. This result diverges from the results of Avramov et al. (2007) and Ericsson et al. (2009), which show the higher explanatory power of structural variables among speculative-graded firms (compared to investment-graded firms).[10]

We also find that Model B has the highest explanatory power among all models for almost all sub-periods and groups (speculative-grade firms and investment-graded firms). This result is interesting since Model B uses the lowest number of explanatory variables (Stock return, ΔVolatility, ΔMRI and HML). It also conforms to the finding that the first three variables are statistically significant after being conditioned upon all other explanatory variables (Model 1).

Consistent with Annaert et al. (2010), we find that the Adj R^2 of the models is higher during the GFC (ranging from 18.48% to 43.69%) than before the GFC (from 9.32% to 22.57%). We also discover that stock information is for the most part critical when credit ratings are not observable. The difference between model B (firm's stock return and credit rating are observable) and model D (only credit rating is observable) is always smaller than the difference between model A (stock return are observable, credit rating are not) and model C (neither the stock return nor the credit rating are observable).

The Chow tests for structural changes (Panel B in Table 6) reveal statistically significant changes in the coefficient estimates for a large group of firms in the sample. Interestingly, the greater regime change appeared during the GFC rather than during the exit from the GFC (e.g. 48.6% vs. 19.1% in model A) and among investment-graded firms rather than among speculative-graded firms (53.7% vs. 27.7% in model A). The overall variation in the coefficient estimate over time is not surprising and conforms to the vast literature on instability of coefficient estimates in stock returns models. Such instability in coefficients may result from the estimation process (see for example Scott and Brown, 1980, and Fabozzi and

[10] Avramov et al. (2007) and Ericsson et al. (2009) found that variables are better at explaining speculative-graded firms than investment-graded firms and that the adjusted R^2 monotonically increases with credit risk. Avramov et al. (2007) used bonds data (different dependent variable) from 1990-2003 (different period) and did not use bond ratings to form the groups because many bonds were not rated by any agency. They divided the groups on the basis of the bonds' credit spread levels. Ericsson et al. (2009) used limited data from 4,813 bid and 5,436 offer quotes of CDS spread over 94 companies during the limited period of 1999-2002 (different period). They found that Adj. R^2 for the lower ratings are always a bit higher than those for the higher ratings. More recently, Annaert et al. (2010) used CDS spread change data for 31 listed euro area banks and did not find a monotonic link between the model's explanatory ability and credit risk.

Francis, 1978) and/or the instability of systematic risk in asset returns (see for example Kon and Jrn, 1978).

4 Results - cross-section analysis

We explore the cross-sectional ability of annual stock return, annual stock volatility, leverage and credit ratings by Standard & Poor's (S&P) to explain CDS spreads using the following regressions:

(7) $$CDS_{i,t} = \alpha_0 + \beta_0 \cdot Stock\,\mathrm{Re}\,turn_{i,t} + \beta_1 \cdot Volatility_{i,t} + \beta_2 \cdot Leverage_{i,t} + \varepsilon_{i,t}$$

(8) $$CDS_{i,t} = \alpha_0 + \beta_0 \cdot D_{0,i} + \beta_1 \cdot D_{1,i} + \beta_2 \cdot D_{2,i} + \beta_3 \cdot D_{3,i} + \varepsilon_{i,t}$$

(9) $$\begin{aligned} CDS_{i,t} &= \alpha_0 + \beta_0 \cdot Stock\,\mathrm{Re}\,turn_{i,t} + \beta_1 \cdot Volatility_{i,t} + \beta_2 \cdot Leverage_{i,t} + \\ &\beta_3 \cdot D_{0,i} + \beta_4 \cdot D_{1,i} + \beta_5 \cdot D_{2,i} + \beta_6 \cdot D_{3,i} + \varepsilon_{i,t} \end{aligned}$$

Consistent with the Merton (1974) model (stock return, volatility and leverage), Equation (7) shows the ability of structural variables to explain CDS spreads. It should be noted that the risk-free interest rate, which is also used in the Merton (1974) model, must be omitted in a cross-section analysis. Equation (8) shows the ability of credit ratings to explain CDS spreads.[11] Equation (9) shows CDS as a function of all variables.

The intercept in equations (8) and (9) represents firms with high ratings (AAA-AAs), and the independents variables $D_{0,t}$, $D_{1,t}$, $D_{2,t}$, $D_{3,t}$ are binary dummy variables indicating credit ratings at time i. $D_{0,t}$ gets 1 if the rating is As, and 0 otherwise. Similarly, $D_{1,t}$ equals 1 if the rating is BBBs, $D_{2,t}$ gets 1 for speculative-graded firms only and $D_{3,t}$ gets 1 for unrated firms only.

In Table 7 we present the results of the cross-section analysis using the above three regressions (equations 7-9) during four period times: May 2007, September 2008, July 2009 and July 2011. May 2007 is selected as being several months prior to the beginning of the GFC (the fall of two hedge funds associated with Bear Stearns in July 2007). September 2008 is selected as the peak of the GFC, when Merrill Lynch was purchased by Bank of America, Lehman Brothers filed for bankruptcy and AIG was bailed out. July 2009 is one year after the peak of the GFC. Finally, July 2011 represents the period after the GFC.

The results show that the model using structural and credit rating variables maintained its ability to explain CDS spreads during our four sample periods (Adj R^2 of 58.88%, 43.54%,

[11] We also analyze the results in equations (8, 9) using 10 rating dummy variables, one for each rating group (AAA down to BBB-) and two additional dummy variables for speculative and unrated firms. These results are not reported and are available upon request.

39.32% and 50.84%). When dividing the variables into structural-model variables and credit rating variables we find that the ability of structural-model variables to explain CDS spreads remains relatively steady over time (40.48%, 40.01%, 36.62% and 42.01%), while the ability of credit rating variables is substantially lower for the period during and after the GFC (Adj. R^2 of 15.48%, 19.80% and 7.94%) than in the period prior to GFC (Adj. R^2: 36.94%). We find that the ratings were less able to predict CDS spreads during the crisis, but the structural factors continued to predict the spreads relatively well.

The coefficient estimates for volatility have the hypothesized sign and are statistically significant in all estimations. The high correlation coefficient between stock return and leverage causes the coefficient of stock return to become not statistically significant in some regressions and the coefficient of leverage to flip signs in the regression of July 2011. In the credit-rating model, we find that all dummy variable coefficients are positive and increase monotonically. However, only the coefficients for unrated firms and speculative-graded firms are statistically significant (different from AAA-AAs graded firms).

F-tests for equation (9) reveal that structural variables are informative after controlling for rating information (Panel B in Table 7). This finding is not surprising and conforms with event studies such as Norden and Weber (2004) and Galil and Soffer (2011) that documented the delay in rating changes after new information already arrived at the CDS market. More interestingly, the tests also show that except for July 2009, rating information had explanatory power after controlling for the information embedded in the structural variables. This finding may indicate that ratings embed information not reflected in the structural variables and that a linear combination of structural variables is not a sufficient statistic in explaining CDS spreads. [12]

Next we apply the Fama MacBeth procedure twelve times, for three models in four different time periods. The three models are: (1) structural variables, (2) credit-rating variables and (3) both structural and credit variables. The four different time periods are: (1) the entire sample period, January 2002 to February 2013; (2) before the GFC, January 2002 to June 2007; (3) during the GFC, July 2007 to June 2009; and (4) after the GFC, July 2009 to February 2013. We use an implementation of the Fama and MacBeth (1973) two-step procedure: first, for each month we run a cross-section regression and find the coefficient estimated by the regression. Second, we average the coefficient estimated in the first step. Newey-West estimator (one lag)

[12] We also conduct F-tests for examining the explanatory power of ratings with notches (e.g. ‘A+’, ‘A’, ‘A-‘instead of ‘As’ only) together with the structural model factors. All tests reveal that in all four periods, the structural model variables are informative after controlling for rating information and vice versa (except for July 2009). These results are omitted due to space considerations and are available upon request.

is used to correct coefficients standard errors. The R-square reported is the average R-squared provided by the first step.

Table 8 shows the results. We find that all factor coefficients have the expected sign and are statistically significant at the 1% level, except for stock return in Panels B and C and D0 (As rated firms) in Panel D model M3. Panel A describes the results during the entire sample period (January 2002 to February 2013). We find that the structural variables and credit-rating variables explain on average 41.45% and 30.01% of the CDS spreads, respectively. When the ratings are combined with the structural variables, their explanatory ability increases to 51.29% on average. Panel B describes the results during the pre-GFC period (January 2002 to June 2007). We find that the ratings model and the structural variables model have almost the same explanatory power (41.17% and 38.82%, respectively). The combination adds 14% to the explanatory power of the model (55.08%). Panel C describes the results for the GFC period (July 2007 to June 2009) and Panel D for the period after the GFC (July 2009 to February 2013). We find that the ability of ratings to explain CDS spreads drops from 38.82% to 17.99% during the GFC and 23.35% after the GFC, but the structural model retains its ability during and after the GFC (47.37% and 47.74%).

Figure 1 shows the ability (Adj R^2) of the three models M1-M3 (eq. 7-9) to explain the CDS prices for each month in our sample period. We find that during the GFC the ratings' ability to explain the CDS spreads practically disappeared (almost 0% in March 2009), while the ability of the structural variables dropped more moderately and for a shorter period of time (the lowest explanatory power was 13% in May 2009 but remained at around 30% throughout most of the GFC period). The sharp drop in the explanatory power of ratings in August 2011 may be attributed to the European sovereign debt crisis during that month. Fears that the crisis would spread to Spain and Italy and of a possible drop in France’s AAA rating resulted in a sharp drop in stock exchanges and a rise in volatility of stock markets. We here document that this crisis also severely affected the CDS market.

5. Conclusions

This paper investigates the determinants of credit spread changes using a broad dataset of 718 US firms during the period from January 2002 to February 2013. We find that firm-specific variables consistent with structural models substantially explain spread changes. Yet, unlike Avramov et al. (2007), we find that, after controlling for firm-specific variables, market factors can add to the models' explanatory power in explaining CDS spread changes. Overall, our results suggest that structural-model variables have limited explanatory ability after ratings and common market variables are controlled for.

We present four different sets of models that can be used to explain the spread changes upon availability of data. We find that three variables – stock return, ΔVolatility (the change in stock return volatility), and ΔMRI (the change in the median CDS spread in the rating class) – are the strongest explanatory variables of changes in CDS spreads. However, in the absence of these variables, other factors may be used to explain the CDS changes, such as the change in spot rates, the change in the slope of the term structure of the interest rates, the change in VIX, MP and the change in UTS.

We also discover that several market factors are statistically significant in explaining spread changes after controlling for the market factor ΔMRI. This finding suggests that event studies such as Norden and Weber (2004) and Galil and Soffer (2011) can improve their spread-changes model by adding these variables in addition to the ΔMRI they used.

We find that our models better explains the GFC period (July 2007 to June 2009) and the period after the GFC (July 2009 to February 2013) than the period prior to the GFC (February 2002 to June 2007). In addition, the models are better able to explain investment-graded firms than speculative-graded firms. This result is in contrast to Avramov et al. (2007), who found that the structural model better explains credit spreads of lower-rated bonds. This difference in results may be due to the difference in sample periods (1990-2003 vs. 2002-2013) or due to the source of spread data (bonds vs. CDS).

Our results also suggest that the GFC was responsible for a structural change in pricing of CDS spreads, especially among investment-graded firms. The coefficient estimates of the various models changed during the crisis, but they were not reversed to the same extent at the end of the crisis. More interestingly, during and after the GFCs, the explanatory power of the model for investment-graded firms was higher than for speculative-graded firms. This result contrasts previous findings in literature indicating the opposite. Furthermore, the flip in explanatory power also continued after the end of the GFC.

We also explore the cross-sectional ability of structural model variables and S&P credit ratings to explain CDS spreads. We find that the ratings and the structural model variables both have explanatory power after controlling for each other. The finding that ratings substantially improve the explanation of CDS spreads indicates that a linear combination of the structural model variables is not statistically sufficient in explaining CDS spreads. Nevertheless, it also appears that the ability of ratings to predict CDS spreads was severely damaged by the crisis and diminished almost to zero, while the ability of structural-model variables only mildly deteriorated and for a shorter period of time.

References

Altman, E. I., and V. M. Kishore. (1996). Almost everything you wanted to know about recoveries on defaulted bonds, Financial Analysts Journal, 52:6, 57–64.

Annaert, J., M. De Ceuster, P. Van Roy, and C. Vespro. (2010). What Determines Euro Area Bank CDS Spreads?. Working Paper Research Series, No. 190, National Bank of Belgium.

Avramov D., G. Jostova, and A. Philipov. (2007). Understanding changes in corporate credit spreads, Financial Analysts Journal, 63 (2), 90-105.

Blanco, R., S. Brennan, and I.W. Marsh. (2005). An empirical analysis of the dynamic relationship between investment-grade bonds and credit default swaps. Journal of Finance, 60 (5), 2255-2281.

Campbell, J. T., and G. B. Taksler. (2003). Equity Volatility and Corporate Bond Yields. Journal of Finance, 58, 2321–2349.

Chen, N., R. Roll., and S. A. Ross.(1986). Economic forces and the stock market, Journal of Business 56, 383-403.

Collin-Dufresne, P., R. Goldstein, and J. S. Martin. (2001). The Determinants of Credit Spread Changes, Journal of Finance 56, 2177-2208.

Cooper, I., and R. Priestley. (2011). Real Investment and Risk Dynamics, Journal of Financial Economics, 101, 182-205.

Ericsson, J., K. Jacobs, and R. Oviedo. (2009). The Determinants of credit default swap premia. Journal of Financial and Quantitative Analysis, 44 (1), 109-132.

Fabozzi, F., and J.C. Francis. (1978). Beta as a random coefficient. Journal of Financial and Quantitative Analysis 13, 101–116.

Fama, Eugene F., and J. D. MacBeth. (1973). Risk, Return, and Equilibrium: Empirical tests, Journal of Political Economy 81, 607-636.

Fama, E., K. R. French. (1989). Business conditions and expected returns on stocks and bonds, Journal of Financial Economics 25, 23-49.

Galil, K., and G. Soffer. (2011). Good News, Bad News and Rating Announcements: An Empirical Investigation. Journal of Banking and Finance.

Hull, J., M. Predescu., and A. White. (2004). The relationship between credit default swap spreads, bond yields and credit rating announcements, Journal of Banking and Finance 28, 2789-2811.

Johnson, T. C. (2002). “Rational Momentum Effects," Journal of Finance 57, 585-608.

Kon, S. J., and F. C. Jen. (1978). Estimation of time-varying systematic risk and performance for mutual fund portfolios: an application of switching regression. Journal of Finance 33, 457–475.

Liu, L. X., and L. Zhang. (2008). Momentum Profits, Factor Pricing, and Macroeconomic Risk. Review of Financial Studies 21: 2417–2448.

Longstaff, F. A., and E. S. Schwartz. (1995). A simple approach to valuing risky fixed and floating rate debt. Journal of Finance 50 (3): 789–819.

Merton, Robert C. (1974). On the Pricing of Corporate Debt: The Risk Structure of Interest Rates. Journal of Finance 29 (2): 449-470.

Norden, L., and M. Weber. (2004). Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements, Journal of Banking and Finance 28, 2813-2843

Pastor, L., and R.F. Stambaugh. (2003). Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Sagi, J., and M.S. Seasholes. (2007). Firm-specific attributes and the Cross-section of Momentum. Journal of Financial Economics. Vol. 84, PP. 389-434.

Scott, E., and S. Brown, (1980). Biased estimators and unstable betas. Journal of Finance 35, 49–55.

Zhu, H. (2006). An empirical comparison of credit spreads between the bond market and the credit default swap market. Journal of Financial Services Research 29, 211-235.

Table 1: Definition of variables explaining CDS spread changes

This table describes the variables used in the time series regressions explaining CDS spread changes and their predicted sign. CRSP database is Center for Research in Security Prices. FRED is Federal Reserve Economic Data. CBOE is Chicago Board Options Exchange. The F&F factors, HML, SML and MKT, are taken from the Kenneth French site. MRI is Median Rated Index. IAL is Innovations in Aggregate Liquidity from Pastor and Stambaugh (2003).

Variable	**Description**	**Data Source**	**Predicted sign**
	Firm-specific variables		
Stock return	Monthly stock return	CRSP	-
ΔVolatility	250 days variance of individual stock return	CRSP	+
ΔLeverage	Book value of debt divided by the sum of book value of debt and the market value of equity	COMPUSTAT	+
	Common factors		
ΔSpot	5-year treasury rate	FRED	-
ΔSlope	Difference between 10-year Treasury Constant Maturity Rate and 2-year Treasury Constant Maturity Rate	FRED	?
ΔVIX	CBOE volatility index	CBOE	+
Market condition (ΔMRI)	Median spread change of all the firms in the same rating group (AAA/AAs, As, BBBs and lower ratings)	Inside calculation	+
	Fama & French and Pastor & Stambaugh (2003) factors		
HML	High book-to-market portfolio minus low book-to-market portfolio return	Kenneth French website	-
SML	Small capitalization portfolio minus big capitalization portfolio return	Kenneth French website	-
MKT	Market excess return	Kenneth French website	-
IAL	Innovation in aggregate liquidity factor (stock market)	Lumbos Pastor website	?
	Five Chen, Roll and Ross (1986) factors		
MP	Growth rate of industrial production	FRED	-
UI	Unexpected inflation	Labor Bureau of Statistic	-
DEI	Change in expected inflation	Labor Bureau of Statistic	?
ΔUTS	Term premium	FRED	?
ΔUPR	The default premium	FRED	+

Table 2 : Descriptive statistics of the data set

This table presents the descriptive statistics of the dataset for the period from January 2002 to February 2013. Panel A describes the variables divided into five groups: spread variables, firm-specific variables, common factors, F&F factors and Pastor-Stambaugh factors, and CRR factors. The spread and firm-specific variables are calculated using data from 695 rated and 23 unrated firms. Panel B describes the firm-specific variables using 695 rated firms divided into investment-graded firms (AAA to BBB- ratings) and speculative-graded firms (BB+ or lower). ΔVolatility is the change in volatility of the annualized daily stock returns. Leverage is the book value of debt divided by the sum of book value of debt plus the market value of equity. Spot is the 5-year treasury rate, and term-structure slope (marked as Slope) is the difference between the 10-year and the 2-year treasury constant maturity rate. Change in Median Rated Index (ΔMRI) is calculated from the mean spread change of all the firms in the same rating groups of: 1) AAA-AA's, 2) A's, 3) BBB's and 4) BB+ or lower). IAL is innovations in aggregate liquidity factor by Pastor and Stambaugh (2003). The CRR macro factors are: MP – growth rate industrial production; UI – unexpected inflation; DEI – change in the expected inflation; UTS – term premium. UPR is the default premium.

Panel A

Statistic	Mean	Median	Min	Max	St. Dev.
			Spread variables		
CDS (bp)	196.02	80.18	1	27,914	187.59
ΔCDS (bp)	3.07	-0.10	-8,044	22,778	78.94
			Firm-specific variables		
Stock Ret (%)	1.03	1.05	-99.11	396.32	10.28
ΔVolatility (%)	1.98	0.21	-2483	2478	11.16
ΔLeverage	0.01	-0.03	-68.53	73.13	2.14
			Common factors		
ΔSpot	-0.03	-0.04	-0.87	0.92	0.30
ΔSlope	0.00	-0.02	-0.52	0.60	0.20
ΔVIX	-0.04	-0.43	-16.09	20.50	4.83
			Fama-French and Pastor-Stambaugh factors		
MKT (%)	0.38	0.86	-17.15	11.34	4.62
SMB (%)	0.37	0.20	-5.32	10.64	2.52
HML (%)	0.23	0.01	-8.75	19.72	3.39
IAL *100	-0.13	0.25	-22.15	12.64	6.04
			Five Chen, Roll and Ross factors		
MP (%)*100	8.23	19.24	-421.28	155.56	79.12
UI (%)*100	1.64	4.55	-172.97	97.07	36.18
DEI (%)*100	0.22	0.53	-40.95	20.55	8.83
ΔUTS *100	-0.95	-3.00	-63.00	80.00	23.05
ΔUPR *100	0.05	-1.00	-63.00	94.00	15.00

Panel B

Statistic	Investment graded firms				Speculate-graded firms			
	Mean	Min	Max	Stdev	Mean	Min	Max	Stdev
CDS (bp)	143.25	1	23,131	146.79	433.31	15.36	27,914	317.15
Δ CDS (bp)	2.42	-8,044	13,821	58.68	4.81	-7,901	22,778	142.50
Stock Ret (%)	1.01	-98.66	396.32	8.21	1.04	-99.11	384.89	16.43
Δ Volatility(%)	1.92	-236	1,875	7.84	2.12	-2,483	2,478	25.75
Δ MRI (bp)	0.07	-33.86	60.68	8.59	0.41	-69.5	91.5	15.38
Num of firms	554				141			

Table 3: Dickey Fuller and Phillips Perron Tests

Stationarity is determined based on Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Stationarity Tests using 1 lag and a single mean. Panel A summarizes the results of 718 individual firm-level variables using both ADF and PP tests. The reported numbers are of firms for which the tests failed to reject the null hypothesis (non-stationary) and the number of firms for which the tests rejected the hypothesis (stationary). Panel B provides the test statistics and associated p-values for the common time-series explanatory variables..

Panel A: Summary Results for Firm-Specific Variables

		CDS	Stock Price	Leverage	Volatility
ADF Test Results					
Levels	Non-Stationary	538	666	610	690
	Stationary	180	52	108	28
First Differences	Non-Stationary	14	2	16	46
	Stationary	704	716	702	672
PP Test Results					
Levels	Non-Stationary	581	665	622	690
	Stationary	137	53	96	28
First Differences	Non-Stationary	6	0	4	12
	Stationary	712	718	714	706

Panel B: Summary Results for Common Variables

		VIX	SPOT	SLOPE	MRI AAA/AA	MRI A	MRI BBB	MRI <BBB
ADF Test Results								
Levels	Z	-3.374	-1.167	-1.392	-1.750	-1.872	-2.170	-1.762
	P-value	(0.012)	(0.688)	(0.586)	(0.406)	(0.345)	(0.217)	(0.400)
First Differences	Z	-9.639	-8.710	-9.051	-7.593	-7.540	-7.490	-7.291
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP Test Results								
Levels	Z-Rho	-20.21	-3.142	-3.323	-5.150	-5.229	-6.143	-9.511
	P-value	(0.017)	(0.697)	(0.632)	(0.483)	(0.489)	(0.398)	(0.152)
First Differences	Z-Rho	-125.27	-122.68	-118.22	-93.97	-94.33	-95.44	-106.44
	P-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4 : Spread changes explanatory power of firm-specific variables, common factors, F&F and P&S factors and CRR factors

This table shows the results of the regressions for CDS spread change and the various factors. The data refer to 718 firms during the period from February 2002 to February 2013. IAL is innovations in aggregate liquidity factor. The CRR factors are MP – growth rate industrial production; UI – unexpected inflation; DEI – change in expected inflation; ΔUTS – term premium; and ΔUPR – default premium. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

	M1- Firm-Specific variables	M2- Fama-French Factors	M3 -F&F and P&S factors	M4 – five CRR factors
intercept	2.78***	5.44***	5.31***	2.90***
	(4.39)	(6.31)	(6.20)	(3.53)
Stock return	-1.28***			
	(-4.55)			
ΔVolatility	31.37***			
	(8.10)			
ΔLeverage	2.04			
	(1.55)			
HML		-2.19***	-2.16***	
		(-5.30)	(-5.27)	
SMB		-1.26**	-1.24**	
		(-2.42)	(-2.28)	
MKT		-3.65***	-3.63***	
		(-7.34)	(-6.91)	
IAL			-12.10	
			(-0.74)	
MP				-4.07***
				(-3.99)
UI				11.14**
				(2.08)
DEI				-44.52*
				(-1.93)
ΔUTS				4.84
				(1.02)
ΔUPR				90.06***
				(6.88)
R2 (%)	20.47	18.53	20.39	15.23
Adj R2 (%)	16.23	16.03	16.98	10.39

Table 5 : Suggested models for spread changes

This table describes the ability of four models (A-D) to explain CDS spread changes using data from 695 rated-firms during the period from Feb 2002 through Feb 2013. Model A is useful when a firm's stock returns are observable. Model B is useful when a firm's stock returns and credit rating are observable. Model C is useful when neither the firm's stock returns nor its credit rating are observable. Model D is useful when credit rating only is observable. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

	M1- all info	Model A: Stock return is observable	Model B: stock return and ratings are both observable	Model C: neither stock return nor ratings are observable	Model D: only credit rating is observable
Stock return	-0.87*** (-3.03)	-1.21*** (-8.06)	-1.08*** (-7.25)		
ΔVolatility	13.83*** (3.75)	26.72*** (7.13)	21.22*** (5.84)		
Δ Leverage	2.54* (1.81)				
ΔSpot	-6.20* (-1.67)	-12.43** (-3.17)		-24.44*** (-7.08)	-7.25** (-2.15)
ΔSlope	-11.40 (-1.15)			-36.46*** (-3.59)	-27.19** (-2.72)
ΔVIX	-0.11 (-0.23)			2.37*** (5.56)	0.59*** (2.87)
HML	-0.52 (-1.38)	-1.62*** (-5.02)	-0.75** (-2.03)		
SMB	0.05 (0.16)				
MKT	0.55 (0.95)	-1.21*** (-3.26)			
MP	-0.19 (-0.15)			-4.23*** (-3.72)	-3.00*** (-2.60)
UI	-1.52 (-0.26)	-9.06*** (-3.07)			
DEI	1.60 (0.07)	7.37 (0.58)			
ΔUTS	6.43 (0.73)			33.68*** (4.13)	18.92** (2.49)
ΔUPR	4.97 (0.35)			59.87*** (4.33)	
ΔMRI	1.64*** (9.45)		1.42*** (10.96)		2.06*** (12.57)
Adj R^2	38.07	24.82	31.76	20.35	28.84

Table 6: The Adjusted R^2 for various models and periods and Chow tests for structural changes.

This table shows the Adj. R^2 of all the models used in this paper (Panel A) and Chow tests for structural changes before, during and after the GFC (panel B). We divide the sample into twelve categories: four time categories – the sample period (February 2002- February 2013), before the GFC (February 2002- June 2007), during the GFC (July 2007 - June 2009) and after the GFC (July 2009 – February 2013) – and three ratings categories – rated firms, speculative-graded firms and investment-graded firms. The five models in this table are the same as those in Table 4.

Panel A : Adjusted R^2 for various models and periods

	M1- all info	Model A: Stock return is observable	Model B: both stock returns and ratings are observable	Model C: neither stock returns nor ratings are observable	Model D: only credit rating is observable
Entire sample period (Feb 2002 – Feb 2013)					
Rated firms	38.07	24.82	31.76	20.35	28.84
Investment-graded	40.93	26.06	34.19	22.14	31.75
Speculative-graded	26.85	19.98	22.21	13.31	17.39
Before GFC (Feb 2002 – June 2007)					
Rated firms	29.43	14.49	22.14	9.35	19.90
Investment-graded	28.44	13.97	22.57	9.32	20.17
Speculative-graded	33.89	16.70	20.32	9.49	18.76
During GFC (July 2007 – June 2009)					
Rated firms	50.66	36.27	39.39	29.64	37.57
Investment-graded	55.46	38.81	43.69	32.41	41.73
Speculative-graded	30.46	25.64	21.79	18.48	20.75
After GFC (July 2009 – Feb 2013)					
Rated firms	40.67	27.22	36.92	17.06	32.73
Investment-graded	43.74	27.76	39.00	18.06	36.22
Speculative-graded	25.86	24.94	27.91	12.64	17.24

Panel B : Results of Chow Tests for structural changes (5% significance level)

		Model A		Model B		Model C		Model D	
		Num	%	Num	%	Num	%	Num	%
Before / During GFC									
All Firms	Regime change	293	48.6%	207	34.4%	226	34.8%	230	35.1%
	Total	603	100.0%	601	100.0%	650	100.0%	656	100.0%
Investment-graded Firms	Regime change	260	53.7%	177	36.6%	197	37.6%	195	37.2%
	Total	484	100.0%	483	100.0%	524	100.0%	525	100.0%
Speculative - graded Firms	Regime change	33	27.7%	30	25.4%	29	23.0%	35	26.7%
	Total	119	100.0%	118	100.0%	126	100.0%	131	100.0%
Panel B. During / After GFC									
All Firms	Regime change	104	19.1%	119	21.8%	99	15.7%	118	18.7%
	Total	544	100.0%	545	100.0%	630	100.0%	630	100.0%
Investment-graded Firms	Regime change	91	20.7%	102	23.2%	84	16.4%	103	20.1%
	Total	439	100.0%	440	100.0%	512	100.0%	512	100.0%
Speculative - graded Firms	Regime change	13	12.4%	17	16.2%	15	12.7%	15	12.7%
	Total	105	100.0%	105	100.0%	118	100.0%	118	100.0%

Table 7: Cross-Section regression for CDS spreads before/during and after the GFC

This table shows the results of cross-section regression of three models over four periods for explaining CDS spread levels. Model M1 uses structural variables (annualized stock return, annualized volatility of daily stock return and leverage). Model M2 uses Moody's rating to explain CDS spreads. D0 is a dummy variable for As-rated firms, D1 for BBBs-rated firms, D2 for speculative-graded firms and D3 for unrated firms. The intercept is AAA-AAs rated firms. The last model (M3) uses both structural variables and credit ratings to explain the CDS spreads. Panel A shows the regression results and panel B the results of F tests for significance of variables in the M3 model. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

Panel A - Regression results

	Intercept	**Stock return**	**Volatility**	**Leverage**	**D0**	**D1**	**D2**	**D3**	R^2	**Adj**	**OBS**
05/2007	-65.10***	-0.62	60.32***	2.64***					40.77	40.48	611
M1	(-7.25)	(-0.11)	(11.69)	(12.38)							
05/2007	10.63				11.98	34.76**	219.40***	107.43***	37.32	36.94	662
M2	(0.67)				(0.67)	(2.01)	(12.02)	(5.16)			
05/2007	-61.69***	-0.61	35.68***	1.70***	13.82	32.33**	164.47***	80.38***	59.35	58.88	611
M3	(-4.59)	(-1.31)	(7.84)	(9.07)	(1.02)	(2.45)	(11.24)	(4.10)			
09/2008	-399.72***	-4.65***	122.17***	9.17***					40.33	40.01	560
M1	(-7.15)	(-3.19)	(7.26)	(8.19)							
09/2008	97.86				111.19	174.95	832.61***	459.57***	16.01	15.48	645
M2	(0.95)				(0.96)	(1.57)	(7.08)	(3.52)			
09/2008	-503.38***	-3.77***	120.59***	6.80***	82.65	160.72*	448.26***	147.42	44.24	43.54	560
M3	(-5.50)	(-2.64)	(7.35)	(5.86)	(0.93)	(1.87)	(4.74)	(1.09)			
07/2009	-314.98***	-0.03	68.18***	11.65***					36.98	36.62	534
M1	(-6.03)	(-0.02)	(5.45)	(9.21)							
07/2009	58.27				43.00	100.75	836.06***	149.99	20.32	19.80	621
M2	(0.52)				(0.35)	(0.85)	(6.79)	(1.12)			
07/2009	-337.12***	-0.32	61.07***	8.79***	30.94	70.21	371.06***	108.59	40.11	39.32	534
M3	(-3.33)	(-0.31)	(4.96)	(6.46)	(0.30)	(0.72)	(3.41)	(0.70)			
07/2011	-50.18.92***	-6.82***	55.36***	-0.55***					42.39	42.01	464
M1	(-2.79)	(-5.38)	(5.78)	(5.78)							
07/2011	67.87				17.19	60.79	383.88***	266.89**	8.62	7.94	540
M2	(0.76)				(0.18)	(0.64)	(3.85)	(2.49)			
07/2011	-53.91	-6.55***	37.23***	4.19***	6.08	42.27	228.08***	76.79	51.59	50.84	464
M3	(-1.51)	(-5.60)	(4.12)	(8.14)	(0.17)	(1.20)	(5.81)	(1.08)			

Panel B - F tests for the combined rating and structural variables model (M3)

Date	F-test: Stock Return= Volatility=leverage=0		F-test: D0=D1=D2=D3=0	
	F	**Prob**	**F**	**Prob**
05/2007	58.84	0.0000	30.66	0.0000
09/2008	77.07	0.0000	5.97	0.0149
07/2009	47.62	0.0000	2.13	0.1453
07/2011	53.07	0.0000	5.54	0.0190

Table 8: Fama MacBeth regression results:

This table presents Fama MacBeth regression results for three models in four time periods. The Fama MacBeth procedure follows two steps: (1) running a cross-section regression for each month in the sample period and (2) averaging the results from the first step. The R^2 is the average of R^2 from the first step. D0, D1, D2 and D3 are dummy variables. D0 gets 1 for As-rated firms, D1 gets 1 for BBBs-rated firms, D2 gets 1 for speculative-rated firms and D3 gets 1 for unrated firms. Standard errors are corrected for serial correlation using Newey-West estimator with one lag. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

	Intercept	Stock return	Volatility	Leverage	D0	D1	D2	D3	Ave. R^2	OBS
Panel A : Jan 2002 – Feb 2013										
M1	-181.26***	-1.21***	100.75***	5.40***					41.45	66,785
	(-13.37)	(-2.83)	(18.46)	(18.93)						
M2	45.77***				25.90***	79.10***	489.03***	179.07***	30.01	74,691
	(16.71)				(11.64)	(18.19)	(23.16)	(17.81)		
M3	-174.45***	-1.50***	78.32***	3.93***	13.5***	47.57***	262.59***	75.21***	51.29	66,784
	(-12.37)	(-3.62)	(14.21)	(16.21)	(3.63)	(10.19)	(22.40)	(10.82)		
Panel B : Jan 2002 – June 2007										
M1	-152.65***	-0.33	91.32***	3.85***					41.17	32,699
	(-11.10)	(-0.87)	(15.19)	(32.72)						
M2	19.08***				20.43***	70.98***	429.22***	146.24***	38.82	34,470
	(15.67)				(12.85)	(12.25)	(17.10)	(25.29)		
M3	-124.17***	-0.66*	61.18***	2.59***	5.68***	40.00***	270.81***	79.41***	55.08	32,698
	(-12.01)	(-1.85)	(12.61)	(22.92)	(5.04)	(13.51)	(19.02)	(12.15)		
Panel C: July 2007 – June 2009										
M1	-283.91***	-2.00	106.2***	9.10***					41.16	13,542
	(-6.73)	(-1.62)	(10.88)	(7.54)						
M2	81.93***				41.84***	101.96***	673.95***	290.35***	17.99	15,611
	(12.50)				(3.78)	(5.79)	(8.34)	(6.68)		
M3	-322.96***	-2.26*	92.82***	7.03***	38.65***	81.68***	342.44***	90.28***	47.37	13,542
	(-6.14)	(-1.80)	(8.73)	(6.89)	(3.20)	(5.07)	(9.09)	(5.91)		
Panel D : July 2009 – Feb 2013										
M1	-168.17***	-2.09**	111.92***	5.71***					42.03	20,544
	(-6.77)	(-2.23)	(8.72)	(25.53)						
M2	66.08***				25.41***	78.81***	477.87***	167.62***	23.35	24,610
	(34.21)				(27.41)	(48.22)	(27.49)	(14.85)		
M3	-168.88***	-2.35**	96.15***	4.26***	11.57	40.32***	206.71***	60.72***	47.74	20,544
	(-7.89)	(-2.59)	(7.18)	(22.77)	(1.34)	(4.21)	(12.70)	(3.61)		

Figure 1 : Evolution of the explanatory power of various types of variables

This figure shows the adjusted R^2 of three models: a model using rating information only, a model using structural variables only, and a model that combines them all. The sample covers the period from January 2002 through February 2013 (134 months).