Essex Finance Centre
Working Paper Series

Working Paper No 63: 11-2020

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October 22, 2020

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Keywords: Credit Default Swap (CDS), CDS Systematic Factors.

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Abstract

This study examines the statistical significance of systematic and firm-specific determinants of Credit Default Swap (CDS) price variations. We cast doubt on the firm-specific determinants showed in prior research to be statistical significance to CDS price variations. In this paper, two research questions are studied: (1) "Which and to what extent systematic factors can explain the individual CDS price variations?" and (2) "Which and to what extent the firm-specific factors can predict CDS spread variations that are not explained by systematic factors?". We find that systematic factors account for the majority changes of the CDS spreads ($R^2 = 35\%$). Merely 4 of 28 firm-specific factors are statistically significant predictors for CDS changes that are not explained by the systematic factors and they have little explanatory power ($R^2 = 8\%$). We document that individual CDS variations can be more related to the systematic factors than to firm-specific factors.

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1 Introduction

Credit default swap (CDS) is a financial product, serving as an insurance to protect contract buyers against a loss due to firm's default. Because of its simple product structure[1], CDS becomes the most popular tool for managing individual firm's default risk among institutional investors such as banks. The structure of the CDS contract implies that the price, or CDS spread, should reflect only individual firm's default probability. Before the Great Financial Crisis, CDS studies were centered on the modeling of firm's credit or default risk (see, e.g., Duffie and Singleton, 1999; Jarrow et al., 1997; Merton, 1974, among the seminal papers).

Although these models work reasonably well in pricing the CDS spreads, the models fail to explain the changes of the CDS spreads.[2] In the last decade, identifying the determinants for CDS spreads changes has been a central question in CDS studies, and many studies have provided insights on the CDS spread changes (e.g. Das and Hanouna (2009) and Pereira et al. (2018) studied accounting- and market-based information effect on individual CDS changes; Tang and Yan (2007) and Coró et al. (2013) studied the non-credit effect on CDS spread changes).

The studies on CDS determinants mostly focused on firm-specific factors, while very few looked at how systematic information can influence CDS price dynamics. Regardless, there are growing evidence of the systematic dynamic of the CDS spread (e.g. Anderson, 2017). To illustrate our argument, Table 1 lists the literature on CDS determinants chronically from 2005 to 2019[3] from 21 journal articles. Although unlikely exhausting, our list illustrates the firm-

[1] In a CDS contract, protection seller compensates protection buyer the amount lost due to a credit event (e.g. default) of a firm. In return, protection buyer pays periodic premium, or CDS spread, to protection seller during the protection periods until the credit event. CDS spread is the quoted price traded in CDS markets; higher spread indicates more likeliness of firm's default; hence CDS spread can measure firm's default in a given future period. In the following, the terms CDS spread and CDS price are used interchangeably.

[2] Houweling and Vorst (2005) compared the model prices and the market prices of the CDS spread and conclude that the theoretical pricing models were in general working fine. But Lin et al. (2019) document that the CreditGrade model, a CDS pricing model based on Merton (1974), only captures 9% of the monthly variation of the CDS spreads.

[3] Here we briefly explain the inclusion of the list: we base on the literature review in Augustin et al. (2014) and extend the list of publications that we found up to 2019. Due to the sheer amount of CDS literature and the result credibility, we include only journal publications of empirical studies on CDS determinants. In addition, we exclude sovereign CDS studies. We also exclude studies in CDS indexes or portfolios for the same reason; however, we also note here that CDS studies on systematic factors sometimes use CDS index or CDS portfolio to investigate the systematic factors. The discussion in this strand is provided in latter section. For the short-listed studies on individual CDS, we first read the article abstract and decide subjectively whether or not this article fits in our inclusion criteria. If the article of interest is related to CDS determinants, then we further read the article's empirical results and categorize the article into one of three groups–Systematic, Firm-specific or Both, depending on what factors the article used in the empirical results. Our search begins with 2005 because we find that the CDS literature focused on the CDS pricing model, no publication studies empirical test on determinants.

specific determinants being dominated in CDS literature. Although 12 articles (or just under 60% of our list) included systematic factors as a subset of their variables, many of these studies did not study these factors carefully and they were only included as control variables in the regressions.[4] Hence, the importance of CDS systematic factors has seemingly been overlooked in the CDS literature.

[Table 1 is around here.]

In this study, we highlight the importance of the systematic factors to the individual CDS spread. Since each firm has different risk exposure to systematic factors, traditional analysis on CDS spread (which usually put all systematic and firm-specific variables together in one regression) potentially underestimates the impact from systematic side, as such method overlooks the cross-sectional effect imposed by the systematic factors. Different from prior studies, we allow the systematic effect to be different at firm level. Thus, we study firm-specific determinants' impact that cannot be explained by the systematic factors (i.e. idiosyncratic changes of the CDS spreads). Using idiosyncratic values of a variable when studying firm-specific effect is not new to many financial studies (e.g. stock), but this is not yet seen in CDS studies. Hence, we analyze the systematic and firm-specific impact separately. The separation of CDS spread changes into systematic and firm-specific impacts is motivated by Green et al. (2017), in which the authors find that only a few firm characteristics can explain the monthly stock return, after controlling for well-known stock systematic factors. Inspired by their study, we cast doubt on the importance of the firm-specific determinants showed in prior research to be statistical significance to CDS price variations.

Two research questions are studied in this paper: (1) "Which and to what extent systematic factors can explain the individual CDS spread variations?" and (2) "Which and to what extent the firm-specific factors can predict CDS spread variations that are not explained by systematic factors?" For the first question, we start by identifying a list of exogenous and endogenous CDS systematic factors that were mentioned or showed to influence individual CDS spreads. We then run individual time-series regressions of CDS spreads on the list of systematic factors for each CDS underlying firms to determine the systematic factors that are statistically significant.

For the second question, we regress the unexplained part taken from the first-step regressions on a set of CDS firm-specific factors identified in literature; we then investigate whether these firm-specific variables are still significant predictors or determinants of CDS price. While prior

[4]While all the articles used firm-specific or mixed CDS determinants, we further note with an asterisk if the study uses systematic variables only as control variables.

studies put all the variables of interest together in one regression, the novelty of our two-step procedure can provide an insight on the importance of systematic and firm-specific factors separately. We argue that many of the CDS firm-specific factors, identified by prior studies, may just covariate with the systematic information; therefore, the "idiosyncratic component" of these factors actually carries very little information about CDS price variations and are not as important as previously documented. To our best knowledge, we are the first CDS study on identifying the *separate* effects of systematic and firm-specific variables.

We investigate the 5-year CDS spreads of U.S. non-financial firms over the sample period of January 2001 to June 2018 and document the impact of systematic factors on the CDS spreads. Eight systematic factors we proposed in this study – default spread (defined as the difference between Moody's BAA and AAA), term spread (defined as the difference between 10-year and 3-month U.S. Treasury yields), VIX, S&P500 index, 5-year U.S. Treasury yield, and three CDS spread averages (overall, rating, and sector) – account for, on average, 35% of the monthly CDS spread variations of 259 firms. Furthermore, we find evidence that endogenous systematic factors are stronger in explaining contemporaneous CDS variations while exogenous systematic factors are stronger in explaining predictive CDS variations. These results are also robust in our sub-sample analyses. The results for systematic factors provide several new insights on understanding the monthly changes of the individual CDS spreads. First of all, we highlight the systematic risk embedded in the CDS spreads, consistent with prior literature on the common pricing factors in CDS spreads (e.g., Anderson, 2017; Blanco et al., 2005, among others). Further to these studies, in which usually CDS index or portfolios are used, we show that the systematic factors also have pronounced explanatory power at entity level.

We show the exogenous source of the systematic risks. Our factors are constructed from stock, bond, and credit markets, and the significance of the co-movement to these financial markets implies that the pricing of the individual CDSs is also affected by the market conditions. The strong co-movement between CDS and other financial markets is also documented in prior studies (Forte and Pena, 2009; Norden and Weber, 2009). But the co-movement was studied at aggregated levels (e.g. CDS index or portfolios). In this study, we further show that exogenous systematic factors also matter at entity level. Also importantly, the systematic risk of their peers is documented, in addition to the exogenous risks. CDS systematic risk was previously focused mainly on exogenous factors; our findings suggest that peer information is more important than exogenous systematic factors in terms of contemporaneous CDS spread changes. We also show that three levels of peer information (i.e. overall, rating, and sector levels) all contribute to the CDS price variations, while the prior studies only cover parts of the peer information, e.g. Galil et al. (2014) (sector, overall) and Lin et al. (2019) (overall). Although some studies (e.g. Doshi et al., 2013; Hammoudeh et al., 2013; Norden and Weber, 2009) showed certain systematic factors for CDS spreads that are endogenously embedded in the stock and bond markets of the underlying firms, we find that, at the time of writing, no previous study provides a comprehensive analyses on CDS systematic factors at entity level. In this study, we fill the gap in this strand of literature by providing a thorough investigation on the importance of systematic determinants of CDS spreads.

On the contrary, we find that firm-specific variables are rather weak in explaining monthly CDS variations that are not explained by the systematic factors. Twenty-eight (28) firm-specific variables altogether can merely account for 8% of the unexplained CDS (predictive) variations. Only 4 of the 28 firm-specific variables are statistically significant for CDS predictive variations. It indicates that firm-specific CDS determinants are not as important as prior studies argued. Also, the insignificance of most firm-specific variables implies that the variations of theses variables coincide with the variations of the systematic information. Specifically, the four variables that can provide independent information, contemporaneously and one month ahead, for the monthly changes in CDS are the number of CDS contributors (CDSContr), firm's debt-to-equity ratio (DERatio), net income (NITMA) and underlying stock price (StoPrice). These four variables are related to firm's accounting and market information as well as CDS illiquidity. It means that the idiosyncratic changes of the the CDS spread are affected by various aspects of the firm-specific information. However, our results suggest that many firm-specific variables covariate each other; hence using multivariate regression helps to identify which variable can outperforms the others in terms of statistical significance.

Additional 5 firm-specific variables – cash holding (CASHMTA), CashRatio, CDS high-minus-low (CDSHL), CDSSlope, and stock Amihud (StoAmihud) – are shown to explain the contemporaneous changes of the CDS srpeads, most of which are related to illiquidity. This highlights the illiquidity impact on individual CDS spread changes (Coró et al., 2013; Das and Hanouna, 2009; Lin et al., 2019). Albeit, overall merely one-third of the firm-specific variables included in this study show statistical significance in explaining CDS spread movement, which, as we argue, casts doubt on the importance of the firm-specific variables.

Our findings in systematic and firm-specific factors provide important implications. As individual CDS price variations are well explained by systematic factors, it implies that the variations are affected by information from different financial markets, and CDS market is therefore vulnerable to the overall financial market condition; we also find evidence from our sub-period analyses that this vulnerability is more pronounced when other financial markets are in turbulence. Our findings provide support for the importance of systematic factors in CDS market, which was largely overlooked by prior studies. In practice, our findings provide a foundation for a number of useful applications of CDS systematic factors. For example, a better estimation of CDS implied default probability for firms with untraded or highly illiquid CDS contracts, which can be used for, but not limited to, the calculation of risk capital attributed to counterparty credit risk according to Basel Accord.

Finally, we briefly discuss the development in several strands of CDS literature that are linked to our paper. After the seminal study of Merton (1974), several studies examine if the CDS prices are indeed explained by the determinants described in the structure model. Blanco et al. (2005) study the theoretical equilibrium between CDS spread and credit spread, and they find that the equilibrium largely holds. But they also document two types of the deviation between the actual CDS spread and the theoretical CDS spread derived from credit spread: the long-term deviation stems from the model imperfection and the measurement error, while the short-term deviation is caused when CDS reacts before credit spread in the face of credit events. Similarly, Ericsson et al. (2009) use linear regression to examine if the theoretical CDS determinants can explain the actual prices, and they find statistical significance in the determinant's coefficients; Pires et al. (2015) further use quantile regression to document that the statistical significance increases for high-risk firms. In addition, Bai and Wu (2016) propose to use Merton (1974) distance to default with a long list of firm-specific characteristics to estimate individual firm's CDS spreads; Campbell et al. (2008) propose several firm-specific accounting- and market-based factors to predict firm's default risk.

Some studies explore the CDS determinants in addition to the model-implied credit factors. Among these, one main strand is to understand the CDS illiquidity in relation to the CDS spread. Bongaerts et al. (2011) develop a theoretical asset pricing model incorporating derivative illiquidity, and they empirically document that CDS sellers earn the illiquidity premium, although the impact from illiquidity is economically small. On the other hand, some studies find the CDS illiquidity rather important. Coró et al. (2013) find that the bid-ask spreads of intra-day CDS trades dominate other credit risk factors in explaining the CDS spreads for 135 European entities. Tang and Yan (2007) examine trade-to-quote ratio and bid-ask spread of CDS trades, and report a positive effect of these illiquidity measures on CDS spreads; similar findings documented in financial CDSs (Annaert et al., 2013). Mayordomo et al. (2014)

examine the CDS illiquidity and they document that the individual CDS illiquidity is related to the market-wide illiquidity. In addition, Cao et al. (2010) and Das and Hanouna (2009) find that equity illiquidity and volatility are also priced in CDS spreads, implying the price connection between financial markets. In addition to CDS illiquidity as CDS spread determinants, some studies also document other factors, e.g. earning surprise (Callen et al., 2009), counterparty credit risk (Arora et al., 2012), CDS demand-supply imbalance (Tang and Yan, 2017), and bank-specific information (Chiaramonte and Casu, 2013; Coudert and Gex, 2013), to be influential on individual firm's CDS spreads. Das et al. (2009) study the accounting- and market-based firm-specific factors, and they argue that both types of CDS determinants are equally important in the pricing of CDS spreads.

Since a number of CDS determinants are constructed from equity or bond markets, and default risk structural model indicates that CDS market is linked to these financial markets, many studies focus on the co-movement among stock, bond, and CDS markets. Fung et al. (2008), Hilscher et al. (2015), and Lee et al. (2018) study the interaction between CDS and stock markets, but their findings are different. Fung et al. (2008) find a mutual effect between the two markets. Though, Hilscher et al. (2015) find that stock market more often leads CDS market, indicating that informed traders are more active in equity market. However, the authors find that, during salient events, CDS market is more likely to lead stock market. But Lee et al. (2018) find that CDS market predicts stock market. Similarly, Norden and Weber (2009) find that stock market more often leads bond and CDS markets, but CDS provides more information for price discovery; in addition, Alexander and Kaeck (2008) further show that the connection between these financial markets are time-varying. Hammoudeh et al. (2013) find that CDSs in financial sector affect CDSs in other sectors during the financial crisis, making the CDS market less stable.

Studies on CDS systematic factors are a small but growing strand in the literature. Alexander and Kaeck (2008) find that iTraxx index can be explained, time-varyingly, by the market-wide factors such as interest rate, stock return, and volatility. Amato (2005) studies the default risk premium, measured by the CDX index subtracted by expected loss, and document that macroeconomic factors, e.g. inflation, monetary policy, and global CDO (collateralized debt obligation) issuance, affect the premium, indicating that investor's risk aversion is priced in the default risk premium. Anderson (2017) find that CDS co-movement was increasing during the 2007–2009 financial crisis, possibly due that fundamental values became more correlated. Doshi et al. (2013) propose to use a reduced-form model incorporating macro covariates to estimate firm's CDS spread. Last but not at least, Galil et al. (2014) find that the sector median CDS spread can explain the individual CDS spread movements. Notably, most of the studies on CDS systematic factors use CDS index, e.g. CDX (Amato, 2005) and iTraxx (Alexander and Kaeck, 2008), or CDS portfolio, e.g. EDF (Expected Default Frequency)-sorted CDS portfolios in (Alexander and Kaeck, 2008).

2 Research Design

To answer our two main research questions, a two-step regression procedure is used in this study. Firstly, we run a regression of CDS spreads on systematic factors for each underlying firms to test how well the systematic factors can explain individual CDS spreads, and then we regress the residuals of the previous regressions on a comprehensive set of firm-specific variables.

2.1 Systematic Variables

Our first hypothesis is that there is a high explanatory power because of high co-movement of CDS market with other financial markets. Also, since CDS is also used to hedge other financial securities (e.g. its application to hedge stock for downside risk), hypothetically systematic risk is high in individual CDS contracts. Therefore, we formulate our first hypothesis as follows:

H1: The systematic factors have high explanatory power on the variations of the CDS spread.

To test hypothesis *H1*, we run a time-series regression for each underlying firm i:

$$\Delta \log(C_t^i) = \beta_0^i + \beta_1^i \, \Delta \mathbf{X^s}_t + \varepsilon_t^i \tag{1}$$

where C_t^i is CDS spread for firm i and $\mathbf{X^s}_t$ is a set of systematic factors and Δ represents the monthly changes of $\mathbf{X^s}_t$. As there are 259 individual regressions, we report the average of coefficient significance and that of goodness of fit measures across the regressions to understand the significance of our systematic factors. We use Newey-West t-statistics (12-month lags) to test the coefficient significance. As a robustness check, we also run the panel version of Equation (1).

Eight systematic factors are chosen from a number of CDS studies in which these systematic factors were found to link to CDS market. The systematic factors are then separated into two groups: there are five exogenous systematic factors which represent the influence to individual CDS from other financial markets, and three endogenous systematic factors which represents the influence from within the CDS market. The exogenous factors are as follows:

i Default Spread ($DftSpr$) is defined as the difference between Moody's AAA and BAA yields. Default spread represents the overall default risk in the view point of market participants. This factor appears in Doshi et al. (2013) and Galil et al. (2014).

ii Term Spread ($TermSpr$) is defined as the difference between the 10-year and 3-month

Treasury yields. Term spread represents investor's preference of liquidity. Since CDS is a hedging tool, funding liquidity is expected to affect the implementation of hedging. This factor is proposed in Conrad et al. (2011), Galil et al. (2014), and Longstaff et al. (2011).

iii VIX index gauges investor's fear of stock market uncertainty. Since stock market and CDS market are linked, stock market's uncertainty may spill over to CDS market. This factor is used as CDS determinants in Diaz et al. (2013), Doshi et al. (2013), and Galil et al. (2014).

vi We choose S&P500 index to test the link between equity and CDS markets, and U.S. Treasury yield in 5-year tenor to test the link between bond and CDS markets. Studies (e.g. Norden and Weber, 2004, 2009) show that there exists mutually causal linkage between equity, bond, and CDS markets.

The endogenous CDS systematic factors are captured by different averages of CDS spreads. The averaging approach can keep peer information but remove firm-specific information. Three cross-sectional averages are considered as endogenous systematic factors in this study:

i Total average of CDS spreads ($AvgSpr$) is used in Galil et al. (2014) and Lin et al. (2019).

ii Rating-averaged CDS spreads ($AvgSpr\_R$) is also included as Kolokolova et al. (2019) found that individual CDS spread has tendency to move to their rating-based estimates. Therefore, a firm's rating information provides systematic information.

iii Sector-averaged CDS spreads ($AvgSpr\_S$) is proposed in Galil et al. (2014).

Notably, when running multivariate regression, there is overlap between $AvgSpr$ and $AvgSpr\_R$ (or $AvgSpr\_S$). Therefore, we adjust the $AvgSpr$ variable by $AvgSpr^* = AvgSpr - AvgSpr\_R - AvgSpr\_S + AvgSpr\_RS$, where $AvgSpr\_RS$ is the averaged CDS spread by sector and rating. Endogenous (exogenous) factors represent the linkage to peer (other financial markets). Here, we conjecture that individual CDSs have higher co-movement with their peer, and that the magnitude of co-movement is more significant when financial market(s) is under higher uncertainty. Therefore, we expand our *H1* hypothesis to two relevant hypotheses as follows:

H2: The endogenous systematic factors are stronger than exogenous systematic factors, and

H3: Systematic factors are more pronounced when market is in turmoil.

We test hypothesis *H2* by running univariate regressions to compare the significance of the exogenous and endogenous factors, and test hypothesis *H3* by using running sub-period regressions as described in Equation (1).

2.2 Firm-specific Variables

The hypothesis on our second research question regarding firm-specific variables is formulated as follows:

H4: Only some of the firm-specific factors can explain and predict the variations of CDS spread that are not explained by systematic factors.

Although we do not take any pre-conjecture in this regard, we hypothesize that not all of the factors are significant, because some of the firm-specific variables may reflect merely market information which is already captured in the controlled systematic variables. From this hypothesis, we can understand which firm-specific variables can truly provide firm-specific information in explaining and predicting CDS spread variations.

To test the hypothesis *H4*, we run a panel regression as follows:

$$\Delta Idio_{it+1} = \gamma_0 + \gamma_1 \, \Delta \mathbf{X^f}_{it} + \zeta_{it}, \tag{2}$$

where $\Delta Idio_{it}$ is the part that cannot captured by systematic factors and is calculated by $\beta_0^i + \varepsilon_t^i$ in Equation (1). $\mathbf{X^f}$ is the chosen set of firm-specific factors in this study. When we test the significance for the coefficients, we follow Hoechle (2007) to use heteroscasdaticity-robust and autocorrelation-robust (with 12-month lags) standard error.

There is a long list of literature on CDS determinants. We use Augustin et al. (2014) as a starting point of our search for firm-specific determinants of CDS spreads, and continue to search for other firm-specific variables used in more-recently published journal articles. After considering for data availability and other factors, we include 33 firm-specific CDS determinants in this study. Table 2 provides the detailed definition for all the firm-specific variables used in the study with the relevant literature[5]. We find that four studies, i.e. Anderson (2017), Bai and Wu (2016), Campbell et al. (2008), and Das and Hanouna (2009), include most of CDS determinants that we choose in this study. We group the 33 variables into five categories: Accounting and Market Mixed, Balance Sheet, Financial Market, Income Statement, and Liquidity.

[Table 2 is around here.]

[5]As different studies may have a slightly different definitions for the variables, our matching for the variables with literature is not perfect; for some variables we match the literature that has a very similar variable to the one being included in our list.

3 Data

Data used in this study is collected from multiple sources. CDS data is obtained from Markit. We use the most liquid 5-year CDS contracts. The CDS underlying equity data is obtained from Compustat/CRSP merged database. Option-related information is obtained from OptionMetrics. Underlying bond data is obtained from TRACE. All data is downloaded via WRDS. We use a commercial proprietary list, in which tickers and other identifiers of CDS underlying information are recorded, for the merging of data from different databases.

The data of 259 U.S. non-financial firms over the sample period from January 2001 to June 2018 is matched for the analysis in this study. The summary statistics of all the variables we include in the study is reported in Table 3.

[Table 3 is around here.]

Before performing the regression, we have addressed two issues which can affect the accuracy of the regression results: missing values and multicollinearity. In the following, we detail the procedures of addressing these two issues.

3.1 Resolving Missing Values

As we gather firm-specific variables from multiple sources, the data availability of some variables is more extensive than that of the others in the sample period; therefore, it is inevitable to have missing values when we combine multiple datasets. However, if we drop all observations with missing values, there are two major concerns affecting the robustness of the results: First, we do not have sufficient observations for the analysis, and second, omitting observations with missing values from the sample may potentially result in biased statistical inference, known as *missing not at random* (Casella and Berger, 2002). Hence, we avoid dropping observations with missing values from our sample.

To use all the observations available, we follow closely the steps of handling missing observations described in Green et al. (2017). The technique used by Green et al. is called zero-order regression proposed by Wilks (1932). Technically, we first winsorize the firm-specific variables at 1% and 99% levels; then standardize them by subtracting its sample mean and divide the difference by its sample standard deviation. The winsorization and standardization are performed for each firm. After that, we replace all the missing values by zero. With this approach, we are able to keep all the viable observations while avoiding biased statistical estimates (Afifi and Elashoff, 1966).

3.2 Multicollinearity Analysis

The other concern is the existence of multicollinearity from the large number of independent variables. Among the initial list of 33 firm-specific variables, some variables may capture similar information to some extent, resulting in highly correlated independent variables in the regressions.

Multicollinearity in a multivariate regression results in coefficients having wrong signs, huge magnitudes, and very high standard errors (therefore low significance levels) (Greene, 2011). Hence, we perform a Variance Inflation Factor (VIF) analysis to detect the existence of multicollinearity.

Methodologically, we calculate VIFs for all the variables and drop the one variable that has the highest VIF each time. We repeat the procedure until the VIFs for all firm-specific variables are less than 7. Although there is no specific threshold value for VIF, $VIF \leq 7$ is the most commonly used rule of thumb in empirical studies.

Table 4 reports the VIFs of the variables before and after dropping. Initially, the set of 33 firm-specific variables has an average VIF of 5.56, with the maximum value of 29.16 (TLMTA) and the minimum value of 1.01 (CBPrice and CDSContr). After dropping five firm-specific variables, i.e. CARatio, LLB, MktCap, QuickRatio, and TLMTA, the average VIF is 2.51, with the maximum value of 6.99 (ROA) and the minimum value of 1.01 (CBPrice and CDSContr). We update our set of variables and include the remaining *28* firm-specific variables in our analysis to tackle the problem of multicollinearity.

[Table 4 is around here.]

4 Results

4.1 Systematic Factor Results

Table 5 reports the individual time-series regressions of the firm's CDS spreads on the systematic factors. We report the average coefficients of the 259 regressions and the percentages of the significance of at least 5% level. The left-hand panel reports multivariate regression results and the right-hand panel reports univariate regression results according to Equation (1).

In the univariate result (right panel), except for term spread, all other systematic factors are statistically significant in explaining the change in the CDS spreads, in most (59.46% to 81.85%) of the 259 regressions. This indicates that the systematic factors effectively capture the information regarding the changes in individual CDS spreads. From the $\overline{Adj.R^2}$ of the univariate regressions, we find that in general endogenous systematic factors (i.e. AvgSpr, AvgSpr_R, and AvgSpr_S) have higher explanatory power than exogenous systematic factors.

[Table 5 is around here.]

The signs of the averaged coefficients is as expected in the univariate result.[6] The exogenous systematic factors, default spread and VIX, are positively related to the changes of the CDS spreads, while equity and Treasury bond market performance are negatively related to the changes of CDS spreads. For the three endogenous systematic factors, they are all positively related to the change of CDS spreads, indicating strong co-movement among the CDS contracts.

In the multivariate result (left panel), the signs of the averaged coefficients remain the same except for term spread and VIX. Interestingly, we observe higher percentages of significance for endogenous factors than those for exogenous factors, implying that peer information is more important than exogenous information in explaining contemporaneous changes in the CDS spreads. Also, the $\overline{Adj.\ R^2}$ in the multivariate systematic factor model is 35%, which is much higher than the ones in the univariate regressions; this indicates the systematic factors capture different aspects of market information and are not substitutes to each other.

Finally, we would like to highlight the low percentage of significance in constant term. Since the constant term partly represents the unexplained changes of the CDS spreads from the systematic factors, the weak significance implies that the systematic factors can sufficiently explain the CDS spread changes and therefore other factors, especially firm-specific factors,

[6] The averaged coefficients we report here include all 259 regressions. Some may argue to exclude insignificant coefficients in the average; we find such exclusion does not alter our conclusions.

may not be significant in explaining the spread changes. We will discuss further evidence in the next section.

We then test the predictability of the systematic factors. Table 6 reports the regression results with systematic factors lagged by one month. In general, we find lower percentages of significance and weaker $\overline{Adj.\ R^2}$, indicating the systematic factors mostly capture the contemporary information and are weak in predictability. However, we find that default spread has the strongest predictive power among the factors. The percentage of the significance is 33.20% and 49.81% in multivariate and univariate regressions respectively.

[Table 6 is around here.]

As robustness check, we perform a panel regression on all the systematic factors, controlling for firm fixed effect. The signs and individual significance are consistent with our previous results, except that term spread, VIX, and S&500 index, which are insignificant in the panel regression.

[Table 7 is around here.]

The sub-sample analysis for different sectors and ratings is provided in Table 8. We find that, in general, the percentages of the significance and the $\overline{Adj.\ R^2}$ do not vary much among industry sectors and ratings. In the sub-period analyses, we find the $\overline{Adj.\ R^2}$ is highest during the financial crisis period (Column InCrisis, Table 8). This indicates that systematic factors are most pronounced in explaining CDS spread changes when the financial market is in turmoil.

[Table 8 is around here.]

4.2 Firm-specific Variable Results

Table 9 reports the results for firm-specific factors. The right-hand panel provides the results for univariate regressions and the left-hand panel provides the results for multivariate regression. The dependent variable is the unexplained variation of the CDS spreads from our proposed systematic factors, $\Delta Idio_{it}$. Although half of the 28 firm-specific variables show statistical significance for predicting the monthly change of the CDS spreads one month later at 5% level in univariate regression, we find that only 4 variables can still exhibit statistical predictability in the multivariate setting. Such difference between univariate and multivariate results highlights the fact that most of the firm-specific variables are correlated with each other, and hence they share similar or overlapped information about the corporate credit risk. Therefore, most of them do not actually provide "independent" information in the prediction of CDS spread changes. It also implies that firm-specific factors may not be as important in predicting CDS spread changes as suggested in the prior studies, given that the low prediction performance is observed in a versatile set of the firm-specific variables.

[Table 9 is around here.]

Since there can be potential omitted variable bias when interpreting the results in univariate regressions, we move on to the multivariate regression results of the statistically significant variables, to explore which variables are truly the important determinants for the CDS spread variation that are not explained by systematic factors. At the first glance, the four variables – CDSContr, DERatio, NIMTA, and StoPrice – are related to firm's accounting and market information as well as CDS liquidity. DERatio and NIMTA are constructed mainly by accounting items, StoPrice is the market traded price and CDSContr reflects the trading activity in CDS market; it means that the idiosyncratic changes of the CDS spread is indeed affected by various aspects of firm-specific factors.

Three firm's fundamental variables are able to predict the monthly changes of the CDS spreads. DERatio represents firm's insolvency risk, with higher debt-to-equity ratio, the firm is more likely to default. Hence the change in the debt-to-equity ratio predicts the increases of the CDS spreads. As said, although there are other variables included in the multivariate regression e.g. interest coverage (IntCover) and accounting liabilities (Liab) to gauge firm's insolvency risk, theses variables also covariate DERatio and it turns out that DERatio only statistically explains the innovation of the CDS spread. We also document firm's profitability (NIMTA) can predict the monthly change of the CDS spread one month later. Higher profit indicates lower probability of default; hence the increase in profit predicts the decrease in CDS spread. Similarly, NIMTA stands out of other similar variables, such as ROA and net income growth, in predicting the monthly changes. Finally, we find that stock price strongly predicts the CDS spread movement. Higher stock price indicates better future performance; the negative coefficient meets our expectation of a negative relation between stock price and CDS spread. Importantly, many Merton-based structural models use underlying stock price to determine the corporate default risk, our result supports the importance of using stock price to capture the CDS price innovation.

In addition to firm's fundamental, CDS liquidity also predicts the future change in CDS spreads. we document that the number of CDS contributors is negatively related to the CDS spread, indicating that when there are more participants in the CDS market, the CDS prices are likely to decrease in the next month. On the other hand, we do not find other CDS liquidity measures i.e. CDS Amihud, CDS high-minus-low, and CDS slope, have predictability for the CDS spread movement. Prior studies find a positive contemporaneous impact of CDS illiquidity on the CDS spread[7]; it implies that a decrease in number of CDS contributors in the next period if we observe an increase in CDS trading activity, since CDS market is illiquid compared with other financial market. Hence it pushes down the CDS price due to lower number of quotes.

The relatively low R-squares in both the multivariate and univaraite regressions further support that firm-specific variables provide very limited predictability to CDS spread changes. To conclude, our results suggest that few firm-specific variables can predict CDS spread changes after we control for systematic factors, implying the firm-specific variables may be less important than previously suggested.

After exploring the predictability of firm-specific variables, we also look at the contemporary influence of firm-specific variables to CDS spread variations. We modify Equation (2) by putting contemporary firm-specific independent variables. The results are provided in Table 10. We find that these four firm-specific variables that provide independent predictability are also correlated to the contemporaneous changes of the CDS spreads, statistically significant at 5% level. In addition, the signs, except CDSContr, are the same as these in lagged analyses, which is expected.

[Table 10 is around here.]

We also document some more variables that are also correlated to the contemporaneous changes of the CDS spreads. CashRatio show that corporate insolvency is important determining corporate default risk. Interestingly, we observe positive coefficient on CASHMTA, indicating a positive correlation between cash holding and CDS spread. This phenomenon is explained by firm's precautious motive to reserve more cash when facing the coming credit risk. Similar empirical finding has been documented in Acharya et al. (2012), where the authors find positive correlation between credit spread (implied by corporate bonds with various ratings) and firm's cash holding. Here, we show that the motive of precautious saving is still important in the case of idiosyncratic changes of CDS spread.

[7] Our negative coefficient does not conflict with prior studies. Later in our contemporaneous analysis (shown in Table 10, we indeed document statistically significant and positive coefficients for the CDS liquidity variables. The results is consistent with prior studies. Instead, our lagged regression depict the overall impact of the CDS illiquidity on CDS spread.

Our findings in the importance of liquidity related variables supports prior literature in which many recent studies such as Tang and Yan (2007) and Coró et al. (2013) argue that individual firm's CDS spread is affected by CDS liquidity. Moreover, we show that several CDS liquidity measures are related to the monthly changes of the individual CDS spreads that are not explained by the systematic factors, suggesting the importance of CDS illiquidity. CDS high-minus-low, an alternative measure for CDS bid-ask spread, can explain CDS spread variations. We also document CDS term structure's impact on CDS idiosyncratic risk. CDS slope, defined as the difference between 5- and 1-year CDS spreads, captures the term structure of the CDS contracts in different times to maturity, and it shows that the preference to a longer maturity increases the CDS spreads. CDSContr is the number of CDS quote contributors; as we do not have exact number of the CDS quotes, we use the number of contributors to proxy this information. However, since not all the quotes eventually become actual trades, we treat this variable as a measure of search intensity (Tang and Yan, 2007). More intensive searching indicates the higher demand of CDS protection, pushing up the price of CDS contracts. Hence, we observe positive association between CDS contributors and CDS spread.

Furthermore, we document a positive association between stock illiquidity and CDS spread. Since CDS is often used as hedge tools for stock, it indicates that stock illiquidity, similar to CDS illiquidity, pose an impact on the CDS spread Das and Hanouna (2009).

It is worth noting that many significant firm-spefici variables in Table 9 and 10 are related to liquidity. It implies that the CDS price changes may mostly reflect the changes in trading activities.

Finally, we perform sub-sample analyses. Table 11 reports the multivariate regression results by sectors, ratings, and sub-periods. In general, we observe inconsistency of the variable significance. The first row counts the number of statistically significant firm-specific variables at 5% significance threshold. The numbers range from 0 to 6. It implies that the firm-specific variables fail to provide equivocal predictability. In sector analysis, we find 6 firm-specific variables can predict CDS spreads one month later for firms in technology sector, while none of the firm-specitific variables can provide predictability in materials and healthcare sectors. We find CDS liquidity to have comparably consistent significance in CDS spread prediction. CDSContr is statistically significant at 5% level in 3 sectors (consumer goods, industrials, and telecommunication). The statistical significance from CDS liquidity variables indicates that the monthly changes in CDS spread may mostly reflect the CDS market trading activities, instead of reflecting the information on credit risk. However, we do not find single firm-specific variables to be consistently statistically statistical in all the sectors.

[Table 11 is around here.]

When we study the firm-specific predictability across ratings, we find the predictability is slightly related to credit quality. The worse rating CDS spreads are barely predicted by firm-specific information, while firm's fundamental information performs better in firms with better credit rating. Similarly, we find CDS liquidity variables demonstrate relatively better predictability. Three CDS liquidity variables – CDSHL, CDSSlope, and CDSContr – can predict the CDS spread changes in the sample of A Rating firms. Finally, in sub-period analyses, firm-specific variables have better predictability in in-crisis period, but after Great Financial Crisis, the monthly CDS spread changes are mainly driven by systematic factors, only 2 firm-specific variables are able to predict the CDS spread. It implies that, most of the time, systematic factors dominate the changes of the CDS spreads.

For the R^2 in sub-sample regressions, we find that, during the crisis period, firm-specific variables have higher R^2, indicating stronger predictive power. Across the ratings, CDS contracts with higher rated underlying assets have lower R^2, indicating these CDS contracts have stronger co-movement with other CDS contracts. We also find that the R^2 for Energy is the highest.

In appendix, we repeat our analyses with the variables in level (instead of change), and the results are qualitatively the same.

4.3 Systematic Factor Multicollinearity Test

So far, we have presented the main results for the systematic and firm-specific CDS determinants; here we conduct additional tests for our systematic factors. The first test is to test the multicollinearity of the systematic factors. Similar to the VIF analysis for the firm-specific variables, we repeat the procedure to detect whether there is multicollinearity in the systematic factors. Although we do not expect multicollinearity appeared in exogenous factors, there is a potentiality of multicollinearity appeared in the endogenous factors. The VIF results for the systematic factors are reported in Table 12 and it shows that all the factors are free of multicollinearity with VIFs between 1.15 and 2.67, well below our threshold of 7. Therefore, we demonstrate that all the systematic factors capture different aspects of the information. Note that ΔAvgSpr used in the VIF analysis is the adjusted version, where we remove the overlap of the sector and rating averages.

[Table 12 is around here.]

4.4 Systematic Factor Quarterly Analysis

In our main analysis, we study the systematic factor's impact based on monthly frequency. Here we investigate whether the effect of the systematic factors is affected when the time horizon is larger. We run a panel regression with firm-fixed effect for the quarterly changes of the CDS spreads. We also study the contemporaneous effect and the lagged effect by one quarter of the systematic factors.

Reported in Table 13, we show that both endogenous and exogenous systematic factors still significantly explain the quarterly changes of individual CDS spreads. In addition, we find the goodness-of-fit are stronger in quarterly changes than in monthly changes, implying that the systematic information is still pronounced in longer term.

[Table 13 is around here.]

4.5 Systematic Effect Conditional on Firm-specific Variables

In our main analysis, we have shown the importance of systematic factors by directly regress the CDS spread on the systematic factors. One may argue that our two-step method potentially over-emphasizes the importance of the systematic factors while undermining the firm-specific variables. We address this concern by reversing our two-step procedure, i.e. we first regress the CDS spreads on the firm-specific variables, and then regress the unexplained part from the first step on the systematic factors.

The results are reported in Table 14. Although the goodness-of-fit is low at 7% because the unexplained part is much noisy, the systematic factors are still statistically important. 6 out of 8 systematic factors are statistically significant at 5% level; only DftSpr and VIX are insignificant. Hence, we show that the systematic factors are still statistically significant even after using the CDS spread residuals of the firm-specific variables.

[Table 14 is around here.]

4.6 Non-zero Observations

So far we find that firm-specific variables are not as important as prior studies argued, since only 4 firm-specific variables can predict the CDS spreads changes one month ahead. One may argue that such findings might result from our previous data treatment of filling zero values for the missing observations. Besides, since some firm-specific variables are updated on a quarterly basis, such as firm's accounting-related variables, the monthly variations of these variables are not observable. Therefore, the reasons related to zero-value observations might the main attribute to the low predicability of CDS spread variation that are not explained by systematic factors, then our augment on the firm-specific variables may be overestimated.

In order to answer the concern, we repeat the Equation (2) model specification only for non-zero observations. In addition, we remove three variables – CBPrice, CBCnt, and CBVol – because these variables are available only after 2012.[8] If the hypothesis that our results of idiosyncratic variations are purely driven by zero observations is true, we expect substantial improvement in statistical significance of firm-specific variables and model fitness.

Table 15 reports the results for including only non-zero firm-specific observations. We observe substantial drop in sample size by 37% (from 40339 to 25361). However, we do not find substantial changes in the regression results between non-zero observations (Table 15) and full observations (Table 9). In fact, we find the two tables are qualitatively similar in terms of variable significance and model fitness. We find the model fitness is slightly improved from 8% to 9%; still, only 4 firm-specific variables provide statistical prediction (at 5% level) and the composition of the significance variables are largely the same as those in the main results. CDSContr and DERatio remain statistically significant predictors. We see mild changes in statistical significance for firm's fundamental variables. E.g, CashRatio and StoMom (replacing NIMTA and StoPrice) become predictors in the case of non-zero observations. All in all we find that our arguments are not driven by zero observations.

[Table 15 is around here.]

[8] Since the complete set of firm-specific variables are changed, we re-do the VIF analysis on multicollinearity test, and it turns out ROA is also dropped.

5 Conclusion

In this paper, we study the factors to the monthly changes of the 5-year credit default swap (CDS) from January 2001 to June 2018. We divide the factors into systematic and firm-specific factors and study their effects separately using a novel two-step approach. We first run individual time-series regressions of CDS spreads on the list of systematic factors for each CDS underlying firms; in the second step, we regress the unexplained part taken from the first-step regressions on a set of CDS firm-specific factors identified in literature. The two-step regression procedure enables us to understand the *separate* importance of the systematic and firm-specific effects.

Two research questions are studied in this paper. The first research question is "Which and to what extent systematic factors can explain the individual CDS spread variations?". We propose 8 systematic factors (of which 5 systematic factors are exogenous and 3 systematic factors are endogenous) to capture the systematic risks of the monthly changes in the CDS spread. We find that the proposed systematic factors have strong explanatory power in the CDS spread changes. In addition, the systematic factors include both exogenous and endogenous risk factors, the significance of both types of factors indicates that the individual corporate CDS is affected by both information from other financial markets and their peer CDSs. Our findings in systematic factors further strengthen the importance of price co-movement in individual CDSs.

Our second research question is "Which and to what extent the firm-specific factors can predict CDS spread variations that are not explained by systematic factors?". To isolate the firm-specific effect on the CDS spread changes apart from systematic factors, we regress the unexplained part from the CDS systematic factors on a comprehensive set of the firm-specific variables. We find that most of the firm-specific variables exhibit insignificance on CDS variations predictability and the overall predictability power (R^2) is weak. However, we identify 4 firm-specific variables provide independent and predictive information for the monthly changes of the CDS spread, while additional 5 firm-specific can only explain the CDS spread variation contemporaneously. Overall only one-third of the firm-specific variables included in this study show statistical significance in explaining CDS spread movement; we cast doubt on the importance of the firm-specific CDS determinants.

Combining our findings altogether, we conclude that CDS variations are not dominantly determined by firm-specific information as suggested in prior studies; instead, systematic factors may play more an important role in explaining individual CDS dynamics. Our argument is not altered with additional robustness checks. Our findings shed light on the literature in the understanding of the importance of systematic factors and firm-specific variables in explaining CDS spread variations.

For research limitation, our identification of the systematic factors and firm-specific variables that provide independent information on the monthly changes of the CDS spread is subject to our current dataset. One may end up with different conclusion on important set of variables (especially firm-specific variables). However, to avoid the potentiality of data snooping and selection bias, we use, to our best, the most objective method to include the systematic and firm-specific variables from a long list of literature. Finally, our results are also beneficial for future empirical research on CDS determinants. When studying the price impact on CDS spread, one should use all the CDS systematic factors and at least include our identified firm-specific variables, in order to conclude unbiased results.

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Table 1: List of Literature on CDS Determinants

This table lists the publications on CDS determinants. We include only journal publications of empirical studies on CDS determinants. In addition, we exclude sovereign CDS studies and studies on CDS indexes or CDS portfolios. For the short-listed studies on individual CDS, we first read the article abstract and decide subjectively whether or not this article fits in our inclusion criteria. If the article of interest is related to CDS determinants, then we further read the article's empirical results and categorize the article into one of three groups–Systematic, Firm-specific and Both, depending on what factors the article used in the empirical results. $*$ indicates that the study uses systematic variables just as control variables.

Year	Literature	Sys Ft.	Firm Ft.	Both
2005	Blanco et al. (2005)			x
2009	Callen et al. (2009)		x	
2009	Das et al. (2009)			x*
2009	Das and Hanouna (2009)			x*
2009	Ericsson et al. (2009)			x
2009	Norden and Weber (2009)		x	
2010	Cao et al. (2010)			x*
2011	Bongaerts et al. (2011)			x
2013	Annaert et al. (2013)			x*
2013	Chiaramonte and Casu (2013)		x	
2013	Coró et al. (2013)			x*
2013	Coudert and Gex (2013)		x	
2014	Galil et al. (2014)			x
2014	Mayordomo et al. (2014)			x
2015	Hilscher et al. (2015)		x	
2015	Pires et al. (2015)		x	
2016	Bai and Wu (2016)		x	
2017	Tang and Yan (2017)			x*
2018	Pereira et al. (2018)		x	
2019	Lee et al. (2018)		x	
2019	Lin et al. (2019)			x

Table 2: Firm-specific Variable Definitions

This table reports all the firm-specific variable definitions used in the study, including the relevant reference.

Panel A: Accounting and Market Mixed Ratios

Variable	Definition	Relevant Literature
CASHMTA	Cash equivalent assets divided by market value of asset, where market value of asset is calculated by market cap and book value of liabilities.	Campbell et al. (2008).
DERatio	Debt-to-Equity Ratio, defined as total debt divided by market cap.	Annaert et al. (2013), Bai and Wu (2016) , Callen et al. (2009), Campbell et al. (2008), Cao et al. (2010), Tang and Yan (2017).
LLB	LLB is the sum of current liabilities and half of long-term liabilities divided by market cap.	Bai and Wu (2016).
MBRatio	Market-to-Book Ratio, defined as market cap divided by book value of equity.	Anderson (2017), Campbell et al. (2008).
NIMTA	Net income divided by market value of asset, where market value of asset is calculated by market cap and book value of liabilities.	Campbell et al. (2008), Pires et al. (2015).
RealVol	Realized Volatility is calculated by historical volatility of monthly stock return over past 12 months.	Alexander and Kaeck (2008), Annaert et al. (2013), Bai and Wu (2016), Campbell et al. (2008), Cao et al. (2010), Ericsson et al. (2009), Das et al. (2009), Mayordomo et al. (2014), Tang and Yan (2017).
TLMTA	Total liabilities divided by market value of asset, where market value of asset is calculated by market cap and book value of liabilities.	Campbell et al. (2008), Ericsson et al. (2009), Pires et al. (2015).

Panel B: Balance Sheet Items and Ratios

Asset	The natural logarithm of firm's total asset value.	Anderson (2017), Das et al. (2009), Mayordomo et al. (2014), Tang and Yan (2017).
CARatio	Cash-to-Asset Ratio, defined as cash equivalent assets divided by total asset.	Anderson (2017), Das et al. (2009), Tang and Yan (2017).
CashRatio	Cash Ratio, defined as cash equivelent assets divided by total liability.	Anderson (2017), Das et al. (2009), Tang and Yan (2017).
DARatio	Debt-to-Asset Ratio, defined as total debt divided by total asset.	Anderson (2017), Bai and Wu (2016), Mayordomo et al. (2014).
Liab	Total Liabilities, defined as total liability divided by total asset.	Das et al. (2009).
QuickRatio	Quick Ratio, defined as current asset divided by current liability.	Das et al. (2009).
ReEarning	Retained Earnings, defined as retained earning divided by total asset.	Bai and Wu (2016), Das et al. (2009).
WorkingCap	Working Capital, calculated as the difference between current asset and current liabilities divided by total asset.	Bai and Wu (2016)

Panel C: Financial Market Items and Ratios

CBCnt	CB Trade Count, defined as the natural logarithm of the CB trade count (month-end).	Tang and Yan (2017).
CBPrice	Month-end Corporate Bond Yield.	Annaert et al. (2013), Coudert and Gex (2013), Norden and Weber (2009).

CBVol	CB Trade Volume, defined as the natural logarithm of the CB trade volume (month-end).	Tang and Yan (2017).
MktCap	Market cap, defined as underlying stock price multiplied by its shares outstanding.	Anderson (2017), Bai and Wu (2016), Callen et al. (2009), Campbell et al. (2008), Pires et al. (2015).
StoMom	The stock return in the previous month is used as stock momentum proxy.	Bai and Wu (2016).
StoPrice	Underlying stock price, calculated as the natural logarithm of stock price.	Alexander and Kaeck (2008), Annaert et al. (2013), citetBlanco2005, Callen et al. (2009), Campbell et al. (2008), Cao et al. (2010), Fung et al. (2008), Das et al. (2009), Hilscher et al. (2015), Norden and Weber (2009), Tang and Yan (2017).
StoVol	Implied Volatility to Realized Volatility Ratio, defined as the natural logarithm of the option implied volatility (DELTA = 0.25) divided by realized volatility.	Alexander and Kaeck (2008), Bai and Wu (2016), Cao et al. (2010), Pires et al. (2015).

Panel D: Income Statement Items and Ratios

EBIT	Earning Before Interest and Tax (EBIT), calculated as EBIT divided by total asset.	Bai and Wu (2016).
IntCover	Interest Coverage, defined as EBIT divided by interest expense.	Das et al. (2009).
Inv2COGS	Inventory-to-COGS Ratio, defined as inventory divided by cost of good sold (COGS).	Das et al. (2009).
NIGrowth	Net Income Growth, defined as quarterly changes in net income divided by its current amount.	Das et al. (2009).
ROA	Return of Asset, defined as net income divided by total asset value.	Anderson (2017), Callen et al. (2009), Das et al. (2009).
SaleGrowth	Sale Growth, calculated as the quarterly changes in sales divided by its current amount.	Das et al. (2009).

Panel E: Liquidity Measures

StoAmihud	The Amihud (2002) measure of the underlying stock over one year.	Das et al. (2009), Lin et al. (2019).
CDSAmihud	The Amihud (2002) measure of the CDS spreads over one year.	Lin et al. (2019).
CDSHL	The high-minus-low of the 5-year CDS spread over one month.	Lin et al. (2019).
CDSSlope	The difference between 5-year CDS and 1-year CDS spreads	Lin et al. (2019).
CDSContr	The number of contributors to 5-year CDS quotes	Bongaerts et al. (2011).

Table 3: Descriptive Statistics

This table reports the descriptive statistics of all the variables used in this paper, including sample mean, standard deviation, minimum, maximum, and quintile statistics. The sample period is from January 2001 to June 2018. Panel A reports the statistics for the eight systematic factors and Panel B reports the firm-specific variables.

Variables	# Obs	Mean	STD	Min	25%	50%	75%	Max
Panel A: Systematic Factors								
DftSpr	197	0.01	0.00	0.01	0.01	0.01	0.01	0.03
TrmSpr	197	0.02	0.01	-0.01	0.01	0.02	0.03	0.04
VIX	197	19.24	8.28	9.51	13.45	16.74	22.72	59.89
SP500	197	7.26	0.32	6.60	7.03	7.19	7.54	7.95
TB5Y	197	0.03	0.01	0.01	0.02	0.02	0.03	0.05
AvgSpr	197	0.02	0.01	0.01	0.01	0.02	0.02	0.07
AvgSpr_R								
i. AA Rating	184	0.01	0.00	0.00	0.00	0.00	0.01	0.02
ii. A Rating	197	0.01	0.00	0.00	0.00	0.01	0.01	0.01
iii. BBB Rating	197	0.01	0.01	0.01	0.01	0.01	0.01	0.05
iv. BB Rating	197	0.02	0.01	0.01	0.02	0.02	0.03	0.09
v. B Rating	197	0.04	0.02	0.01	0.03	0.03	0.04	0.16
vi. C Rating	197	0.09	0.06	0.02	0.04	0.07	0.11	0.54
AvgSpr_S								
i. Basic Materials	197	0.02	0.01	0.01	0.01	0.01	0.02	0.08
ii. Consumer Goods	197	0.02	0.01	0.01	0.01	0.01	0.02	0.06
iii. Consumer Services	197	0.03	0.02	0.01	0.02	0.02	0.03	0.24
iv. Energy	197	0.02	0.02	0.00	0.01	0.01	0.02	0.20
v. Healthcare	197	0.01	0.00	0.01	0.01	0.01	0.01	0.03
vi. Industrials	197	0.01	0.01	0.00	0.01	0.01	0.02	0.05
vii. Technology	197	0.02	0.01	0.01	0.01	0.01	0.02	0.07
viii. Telecom Services	197	0.03	0.02	0.01	0.02	0.02	0.03	0.18
ix. Utilities	197	0.01	0.01	0.00	0.01	0.01	0.01	0.07
Panel B: Firm-specific Variables								
Asset	37676	23.37	1.22	19.54	22.53	23.41	24.21	26.82
CARatio	37676	0.09	0.10	0.00	0.02	0.06	0.12	0.73
CASHMTA (%)	37535	0.01%	0.03%	0.00%	0.00%	0.01%	0.01%	0.82%
CashRatio	36212	0.45	0.63	0.00	0.11	0.26	0.54	9.05
CBCnt	12338	2.92	1.38	0.00	1.95	2.94	3.90	7.54
CBPrice	12227	0.03	0.03	-0.88	0.02	0.03	0.04	0.87
CBVol	12338	14.64	2.25	0.00	13.30	14.97	16.23	20.35
CDSAmihud	40306	0.00	0.00	0.00	0.00	0.00	0.00	0.10
CDSHL	40585	0.00	0.02	0.00	0.00	0.00	0.00	1.48
CDSSlope	38993	0.00	0.01	-0.73	0.00	0.00	0.01	0.10
CDSContr	41044	6.35	3.92	2.00	3.00	5.00	8.00	30.00
DARatio	37299	0.31	0.16	0.00	0.20	0.29	0.39	1.90
DERatio	37164	0.00	0.00	0.00	0.00	0.00	0.00	0.11
EBIT	37043	0.01	0.01	-0.13	0.00	0.01	0.01	0.19
IntCover	36938	22.30	401.36	-211.79	2.59	5.80	12.25	28934.20
Inv2COGS	37103	2.34	2.60	-0.33	0.79	1.81	2.86	49.21
Liab	37670	0.66	0.19	0.14	0.54	0.65	0.76	2.32
LLB	36071	0.00	0.00	0.00	0.00	0.00	0.00	0.09
MBRatio (10^3)	37535	828.07	45517.86	-4247933.42	486.67	763.66	1238.75	1126718.30
MktCap	38634	30.06	1.49	24.42	28.99	30.12	31.03	34.45
NIGrowth	37283	0.25	41.26	-821.00	-0.47	-0.04	0.31	4274.33
NIMTA	37526	0.00	0.00	0.00	0.00	0.00	0.00	0.00
QuickRatio	36101	1.59	0.86	0.20	1.03	1.38	1.91	10.66
RealVol	35225	0.29	0.23	0.06	0.17	0.23	0.33	6.49
ReEarning	36945	0.25	0.42	-3.07	0.09	0.27	0.45	2.07
ROA	37661	0.00	0.01	-0.14	0.00	0.00	0.01	0.18
SaleGrowth	37289	0.02	0.20	-0.82	-0.05	0.01	0.08	5.55
StoAmihud	38404	0.00	0.01	0.00	0.00	0.00	0.00	0.24
StoMom	35225	0.04	0.35	-2.98	-0.10	0.07	0.22	4.58
StoPrice	38634	3.61	0.82	-2.98	3.20	3.73	4.14	6.87
StoVol	31356	0.22	0.35	-2.01	0.06	0.25	0.43	1.71
TLMTA	37535	0.00	0.00	0.00	0.00	0.00	0.00	0.14
WorkingCap	36101	0.11	0.14	-0.62	0.00	0.09	0.20	0.77

Table 4: Firm-specific Variable VIF

This table reports the Variance Inflation Factor (VIF) analysis for the 28 firm-specific variable. The sample period is from January 2001 to June 2018. We use the monthly changes of the variable in the VIF analysis. We drop one variable with the highest VIF value for each procedure until no VIF value is more than 7. The final VIFs are reported in the last column.

Variable	Initial VIF	Final VIF
ΔAsset	1.78	1.52
ΔCARatio	8.81	*dropped*
ΔCASHMTA	5.54	3.30
ΔCashRatio	7.57	3.43
ΔCBCnt	1.89	1.89
ΔCBPrice	1.01	1.01
ΔCBVol	1.89	1.89
ΔCDSAmihud	1.60	1.60
ΔCDSHL	1.61	1.61
ΔCDSSlope	1.02	1.02
ΔCDSContr	1.01	1.01
ΔDARatio	2.99	1.97
ΔDERatio	11.87	3.79
ΔEBIT	5.89	5.88
ΔIntCover	4.31	4.31
ΔInv2COGS	1.35	1.34
ΔLiab	3.34	2.70
ΔLLB	16.81	*dropped*
ΔMBRatio	2.50	2.31
ΔMktCap	17.24	*dropped*
ΔNIGrowth	1.24	1.24
ΔNIMTA	5.27	5.20
ΔQuickRatio	9.41	*dropped*
ΔRealVol	1.95	1.94
ΔReEarning	2.01	1.98
ΔROA	7.06	6.99
ΔSaleGrowth	1.47	1.47
ΔStoAmihud	1.06	1.06
ΔStoMom	1.73	1.73
ΔStoPrice	13.46	4.57
ΔStoVol	1.93	1.93
ΔTLMTA	29.16	*dropped*
ΔWorkingCap	7.86	1.66

Table 5: Contemporaneous CDS Systematic Factors

This table reports the regression results for contemporaneous systematic factors for the 259 U.S. firms over the sample period from January 2001 to June 2018. We perform time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5%, and the average adjusted R^2 for the 259 regressions. Δ is the operator of variable monthly change. The left panel reports the univariate regressions and the right panel reports the univariate regressions. Newey-West t-statistics with 12-month lags is used for testing coefficient significance.

	Dependent Variable: ΔSpr (i,t)				
	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Adj.\ R^2}$
ΔDftSpr (t)	4.791	(36.29%)	26.864	(68.34%)	0.05
ΔTrmSpr (t)	0.701	(16.60%)	-6.374	(22.78%)	0.01
ΔVIX (t)	-0.0001	(12.74%)	0.009	(70.27%)	0.07
ΔSP500 (t)	-0.270	(22.39%)	-1.386	(79.92%)	0.13
ΔTB5Y (t)	-2.927	(19.31%)	-14.346	(70.66%)	0.06
ΔAvgSpr (t)	0.138	(38.22%)	0.368	(64.09%)	0.11
ΔAvgSpr_R (t)	0.290	(65.64%)	0.414	(81.85%)	0.20
ΔAvgSpr_S (t)	0.318	(55.60%)	0.421	(59.46%)	0.16
Const	0.002	(6.18%)			
$\overline{Adj.\ R^2}$	0.35				
#Obs	40431				
#Firm	259				

Table 6: Lagged CDS Systematic Factors

This table reports the regression results for systematic factors lagged by one month for the 259 U.S. firms over the sample period from January 2001 to June 2018. Δ is the operator of variable monthly change. We perform time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5% (in parentheses), and the average adjusted R^2 for the 259 regressions. The left panel reports the multivariate regressions and the right panel reports the univariate regressions. Newey-West t-statistics with 12-month lags is used for testing coefficient significance.

	Dependent Variable: ΔSpr (i,t)				
	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	%($p \leq 0.05$)	$\overline{Coef}$	%($p \leq 0.05$)	$\overline{Adj.\ R^2}$
ΔDftSpr (t-1)	10.379	(33.20%)	14.845	(49.81%)	0.02
ΔTrmSpr (t-1)	5.974	(27.80%)	5.183	(19.31%)	0.01
ΔVIX (t-1)	0.005	(37.45%)	0.006	(45.95%)	0.03
ΔSP500 (t-1)	0.118	(15.44%)	-0.484	(32.05%)	0.02
ΔTB5Y (t-1)	-0.994	(9.27%)	-0.231	(11.20%)	0.00
ΔAvgSpr (t-1)	0.038	(15.44%)	0.125	(27.03%)	0.01
ΔAvgSpr_R (t-1)	0.023	(13.51%)	0.070	(15.06%)	0.01
ΔAvgSpr_S (t-1)	0.061	(14.29%)	0.095	(24.71%)	0.01
Const	0.000	(3.86%)			
$\overline{Adj.\ R^2}$	0.05				
#Obs	40129				
#Firm	259				

Table 7: Systematic Factor Panel Regression

This table reports the panel regression on contemporaneous CDS systematic factors over the sample period from January 2001 to June 2018. Δ is the operator of variable monthly change. Firm fixed effect is controlled in the panel regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: ΔSpr (i,t)	
ΔDftSpr (t)	***6.995***
	[2.68]
ΔTrmSpr (t)	0.579
	[0.43]
ΔVIX (t)	0.000
	[0.20]
ΔSP500 (t)	-0.463
	[-1.79]
ΔTB5Y (t)	***-4.808***
	[-2.96]
ΔAvgSpr (t)	***0.138***
	[3.01]
ΔAvgSpr_R (t)	***0.318***
	[5.86]
ΔAvgSpr_S (t)	***0.242***
	[3.47]
Adj. R^2	0.28
#Obs	40558
Firm FE	Yes

Table 8: Sub-sample CDS Systematic Factors

This table reports the regression results for contemporaneous systematic factors for the 259 U.S. firms by sectors, ratings, and periods. Δ is the operator of variable monthly change. We perform multivariate time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5% (in parentheses), and the average adjusted R^2 for the 259 regressions. Newey-West t-statistics with 12-month lags is used to test coefficient significance.

Dependent Variable: ΔSpr (i,t)																		
	Sector									Rating						Period		
	Materials	ConGoods	ConServices	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	PreCrisis	InCrisis	PostCrisis
ΔDftSpr (t)	8.383	9.261	1.998	20.913	1.258	2.542	-0.411	0.947	-0.792	1.869	1.144	9.447	7.602	-0.191	0.165	6.616	-2.341	-0.872
?%($p \leq 0.05$)	(36.36%)	(37.78%)	(26.47%)	(57.14%)	(19.05%)	(37.25%)	(21.74%)	(36.36%)	(51.61%)	(26.47%)	(40.30%)	(29.31%)	(45.21%)	(31.58%)	(25.00%)	(13.86%)	(46.08%)	(20.58%)
ΔTrmSpr (t)	-0.354	1.030	-1.785	-5.281	3.945	2.753	2.121	0.667	1.134	0.635	1.965	-1.797	0.571	4.454	0.769	-1.324	-1.934	4.189
	(4.55%)	(15.56%)	(26.47%)	(33.33%)	(19.05%)	(13.73%)	(4.35%)	(54.55%)	(3.23%)	(5.88%)	(16.42%)	(18.97%)	(21.92%)	(10.53%)	(12.50%)	(23.76%)	(46.08%)	(18.52%)
ΔVIX (t)	-0.002	0.000	0.001	0.000	0.001	-0.001	0.000	0.001	0.000	-0.001	0.001	0.001	-0.001	-0.001	-0.001	0.003	0.003	-0.002
	(9.09%)	(11.11%)	(14.71%)	(19.05%)	(4.76%)	(9.80%)	(26.09%)	(18.18%)	(9.68%)	(5.88%)	(13.43%)	(10.34%)	(16.44%)	(10.53%)	(25.00%)	(19.31%)	(52.53%)	(11.11%)
ΔSP500 (t)	-0.586	-0.350	-0.533	-0.580	0.179	-0.380	-0.034	0.410	0.031	-0.343	0.021	-0.197	-0.587	-0.312	0.074	0.364	0.789	-0.660
	(36.36%)	(26.67%)	(35.29%)	(23.81%)	(4.76%)	(17.65%)	(34.78%)	(9.09%)	(6.45%)	(17.65%)	(14.93%)	(17.24%)	(32.88%)	(36.84%)	(12.50%)	(17.82%)	(58.06%)	(30.04%)
ΔTB5Y (t)	-2.363	-4.057	-1.185	2.518	-5.143	-4.638	-3.525	-2.693	-2.606	-3.336	-3.762	-2.258	-2.224	-3.566	-3.931	-1.008	-2.915	-4.074
	(13.64%)	(13.33%)	(23.53%)	(9.52%)	(23.81%)	(21.57%)	(26.09%)	(27.27%)	(19.35%)	(17.65%)	(23.88%)	(15.52%)	(19.18%)	(15.79%)	(25.00%)	(18.32%)	(56.22%)	(16.87%)
ΔAvgSpr (t)	0.047	-0.052	-0.026	0.291	0.269	0.256	0.266	0.050	0.208	0.167	0.135	0.131	0.144	0.149	0.010	0.227	0.209	0.106
	(18.18%)	(6.67%)	(14.71%)	(71.43%)	(61.90%)	(58.82%)	(69.57%)	(0.00%)	(41.94%)	(38.24%)	(35.82%)	(37.93%)	(38.36%)	(42.11%)	(50.00%)	(42.08%)	(60.83%)	(29.63%)
ΔAvgSpr_R (t)	0.273	0.186	0.306	0.350	0.261	0.411	0.279	0.292	0.223	0.324	0.432	0.232	0.227	0.225	0.103	0.431	0.596	0.246
	(63.64%)	(33.33%)	(55.88%)	(90.48%)	(85.71%)	(82.35%)	(82.61%)	(45.45%)	(61.29%)	(73.53%)	(77.61%)	(51.72%)	(63.01%)	(68.42%)	(50.00%)	(52.48%)	(67.74%)	(62.96%)
ΔAvgSpr_S (t)	0.151	0.287	0.187	0.316	0.513	0.200	0.484	0.712	0.425	0.244	0.303	0.273	0.351	0.436	0.495	0.333	0.500	0.364
	(22.73%)	(55.56%)	(32.35%)	(76.19%)	(71.43%)	(49.02%)	(69.57%)	(63.64%)	(77.42%)	(58.82%)	(58.21%)	(51.72%)	(54.79%)	(63.16%)	(37.50%)	(46.53%)	(57.60%)	(46.91%)
Const	0.003	0.004	0.003	0.003	0.002	0.003	-0.002	-0.006	0.000	0.002	0.000	0.002	0.003	0.006	0.003	-0.006	0.016	0.005
	(4.55%)	(2.22%)	(11.76%)	(4.76%)	(9.52%)	(5.88%)	(4.35%)	(18.18%)	(3.23%)	(5.88%)	(1.49%)	(5.17%)	(10.96%)	(10.53%)	(0.00%)	(7.92%)	(43.78%)	(11.93%)
$\overline{Adj.\ R^2}$	0.26	0.30	0.36	0.52	0.36	0.34	0.37	0.42	0.31	0.33	0.37	0.28	0.37	0.40	0.42	0.31	0.58	0.35
#Obs	3582	7677	5228	3091	3356	7796	3442	1587	4672	5125	11679	8814	10920	2845	1048	11999	4055	22542
#Firm	22	45	34	21	21	51	23	11	31	34	67	58	73	19	8	202	217	243

Table 9: Firm-specific Variable Prediction

This table reports the panel regression results for firm-specific variables over the sample period from January 2001 to June 2018. Δ is the operator of variable monthly change. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the firm-specific characteristics lagged by one period. Left panel reports the multivariate panel regression and right panel reports the univariate regression. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: ΔIdio (i,t)					
	Multivariate Regression		Univariate Regression		
	Coef	*t*-stats	Coef	*t*-stats	Adj. R^2
ΔAsset(i,t-1)	0.000	[-0.07]	0.001	[0.16]	0.07
ΔCASHMTA(i,t-1)	0.001	[0.07]	***0.017***	***[3.22]***	0.07
ΔCashRatio(i,t-1)	-0.008	[-0.92]	-0.006	[-1.35]	0.07
ΔCBCnt(i,t-1)	0.015	[1.34]	***0.017***	***[2.08]***	0.07
ΔCBPrice(i,t-1)	0.004	[0.41]	0.009	[0.81]	0.07
ΔCBVol(i,t-1)	0.002	[0.29]	0.012	[1.74]	0.07
ΔCDSAmihud(i,t-1)	0.010	[0.82]	0.000	[0.02]	0.07
ΔCDSHL(i,t-1)	-0.022	[-1.73]	-0.012	[-1.31]	0.07
ΔCDSSlope(i,t-1)	0.005	[0.84]	0.006	[1.06]	0.07
ΔCDSContr(i,t-1)	***-0.020***	***[-2.71]***	***-0.021***	***[-2.70]***	0.07
ΔDARatio(i,t-1)	-0.009	[-1.20]	0.007	[1.50]	0.07
ΔDERatio(i,t-1)	***0.023***	***[2.09]***	***0.049***	***[5.93]***	0.07
ΔEBIT(i,t-1)	-0.001	[-0.08]	***-0.016***	***[-3.08]***	0.07
ΔIntCover(i,t-1)	-0.007	[-0.86]	***-0.016***	***[-3.68]***	0.07
ΔInv2COGS(i,t-1)	-0.007	[-1.28]	0.000	[-0.04]	0.07
ΔLiab(i,t-1)	0.004	[0.35]	***0.013***	***[1.98]***	0.07
ΔMBRatio(i,t-1)	-0.001	[-0.23]	***-0.032***	***[-4.05]***	0.07
ΔNIGrowth(i,t-1)	-0.003	[-0.51]	***-0.010***	***[-2.23]***	0.07
ΔNIMTA(i,t-1)	***-0.024***	***[-2.18]***	***-0.015***	***[-2.54]***	0.07
ΔRealVol(i,t-1)	0.005	[0.71]	0.006	[1.00]	0.07
ΔReEarning(i,t-1)	-0.010	[-1.15]	***-0.015***	***[-2.68]***	0.07
ΔROA(i,t-1)	0.016	[1.10]	***-0.017***	***[-2.74]***	0.07
ΔSaleGrowth(i,t-1)	-0.008	[-1.18]	-0.008	[-1.58]	0.07
ΔStoAmihud(i,t-1)	0.006	[0.99]	0.010	[1.39]	0.07
ΔStoMom(i,t-1)	0.017	[1.71]	***-0.030***	***[-4.00]***	0.07
ΔStoPrice(i,t-1)	***-0.058***	***[-3.43]***	***-0.061***	***[-6.01]***	0.07
ΔStoVol(i,t-1)	0.002	[0.31]	0.004	[0.64]	0.07
ΔWorkingCap(i,t-1)	0.005	[1.00]	-0.004	[-0.94]	0.07
Adj. R^2	0.08				
#Obs	40339				
Firm FE	Yes				
Time FE	Yes				

Table 10: Firm-specific Variable Contemporaneous Panel Regression

This table reports the panel regression results for firm-specific variables over the sample period from January 2001 to June 2018. Δ is the operator of variable monthly change. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the contemporaneous firm-specific characteristics. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. *t*-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: ΔIdio (i,t)		
	Coef	*t*-stats
ΔAsset(i,t)	-0.009	[-1.62]
ΔCASHMTA(i,t)	***0.035***	***[3.44]***
ΔCashRatio(i,t)	***-0.041***	***[-4.38]***
ΔCBCnt(i,t)	0.009	[0.59]
ΔCBPrice(i,t)	0.019	[1.88]
ΔCBVol(i,t)	0.005	[0.41]
ΔCDSAmihud(i,t)	-0.005	[-0.27]
ΔCDSHL(i,t)	***0.132***	***[3.68]***
ΔCDSSlope(i,t)	***0.207***	***[3.54]***
ΔCDSContr(i,t)	***0.045***	***[7.19]***
ΔDARatio(i,t)	-0.008	[-0.98]
ΔDERatio(i,t)	***0.044***	***[3.78]***
ΔEBIT(i,t)	0.006	[0.56]
ΔIntCover(i,t)	0.006	[0.52]
ΔInv2COGS(i,t)	0.003	[0.74]
ΔLiab(i,t)	-0.009	[-1.22]
ΔMBRatio(i,t)	0.013	[1.85]
ΔNIGrowth(i,t)	0.005	[0.95]
ΔNIMTA(i,t)	***-0.052***	***[-3.18]***
ΔRealVol(i,t)	0.014	[1.26]
ΔReEarning(i,t)	0.010	[0.99]
ΔROA(i,t)	0.035	[1.84]
ΔSaleGrowth(i,t)	0.002	[0.34]
ΔStoAmihud(i,t)	***0.015***	***[2.39]***
ΔStoMom(i,t)	0.017	[1.40]
ΔStoPrice(i,t)	***-0.116***	***[-7.79]***
ΔStoVol(i,t)	0.012	[1.17]
ΔWorkingCap(i,t)	0.006	[1.32]
Adj. R^2	0.15	
#Obs	40431	
Firm FE	Yes	
Time FE	Yes	

Table 11: Sub-sample Firm-specific Variable Prediction

This table reports the panel regression results for firm-specific variables by sectors, ratings, and periods. Δ is the operator of variable monthly change. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the contemporaneous firm-specific characteristics. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold. The first row reports the counts of variables with 5% statistical significance.

	Dependent Variable: ΔIdio (i,t)																	
	Sector									Rating						Period		
	Materials	ConGoods	ConServices	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	PreCrisis	InCrisis	PostCrisis
?#($p \leq 0.05$)	**0**	**4**	**3**	**2**	**0**	**1**	**6**	**2**	**3**	**1**	**6**	**3**	**3**	**0**	**2**	**3**	**6**	**2**
ΔAsset (i,t-1)	-0.016	-0.009	0.016	0.008	-0.013	0.010	-0.006	-0.055	***0.080***	0.018	0.005	-0.008	-0.011	-0.001	-0.026	0.002	***-0.034***	0.000
t-stats	[-0.61]	[-0.58]	[0.77]	[0.33]	[-0.55]	[0.61]	[-0.29]	[-1.49]	***[2.12]***	[0.92]	[0.38]	[-0.59]	[-0.92]	[-0.03]	[-0.51]	[0.20]	***[-2.69]***	[-0.03]
ΔCASHMTA(i,t-1)	-0.013	0.030	***-0.061***	0.032	0.028	0.000	***0.061***	-0.131	0.001	-0.038	-0.009	0.003	0.012	0.000	0.061	-0.016	0.022	0.006
	[-0.37]	[1.61]	***[-3.02]***	[0.87]	[0.66]	[0.02]	***[2.08]***	[-1.90]	[0.03]	[-1.40]	[-0.41]	[0.13]	[0.59]	[-0.00]	[1.09]	[-0.96]	[1.15]	[0.50]
ΔCashRatio(i,t-1)	0.012	-0.019	***0.062***	-0.045	-0.057	-0.021	-0.018	0.194	-0.038	0.019	0.003	-0.027	-0.006	-0.022	***-0.109***	-0.008	-0.031	-0.005
	[0.39]	[-0.98]	***[2.34]***	[-1.79]	[-1.41]	[-0.86]	[-0.60]	[1.90]	[-1.09]	[0.83]	[0.14]	[-1.25]	[-0.26]	[-0.68]	***[-2.12]***	[-0.43]	[-1.17]	[-0.43]
ΔCBCnt(i,t-1)	0.015	-0.005	0.013	0.070	0.028	0.016	0.016	0.103	-0.007	0.003	0.001	0.046	0.004	-0.028	0.044			0.010
	[0.33]	[-0.40]	[0.48]	[1.48]	[0.57]	[0.57]	[0.93]	[1.04]	[-0.22]	[0.11]	[0.05]	[1.58]	[0.16]	[-0.72]	[0.26]			[0.85]
ΔCBPrice(i,t-1)	-0.036	-0.004	-0.035	-0.045	0.026	0.023	0.004	-0.003	***0.090***	0.007	0.013	-0.004	0.007	-0.006	-0.145			0.001
	[-1.59]	[-0.27]	[-1.32]	[-1.72]	[1.22]	[1.25]	[0.12]	[-0.11]	***[4.96]***	[0.17]	[0.73]	[-0.19]	[0.41]	[-0.18]	[-1.57]			[0.10]
ΔCBVol(i,t-1)	-0.006	0.023	-0.013	-0.062	0.013	-0.015	0.028	-0.060	0.014	0.011	0.011	-0.022	0.009	0.012	-0.179			0.003
	[-0.22]	[1.12]	[-0.31]	[-1.38]	[0.30]	[-0.55]	[1.12]	[-0.79]	[0.48]	[0.32]	[0.81]	[-1.08]	[0.55]	[0.26]	[-1.25]			[0.33]
ΔCDSAmihud(i,t-1)	0.031	0.029	0.013	0.016	-0.022	0.008	***0.070***	-0.015	-0.025	0.038	-0.014	0.027	0.025	0.015	0.057	-0.008	0.070	0.003
	[0.95]	[1.29]	[0.56]	[0.63]	[-0.53]	[0.29]	***[3.05]***	[-0.43]	[-1.01]	[1.59]	[-0.91]	[1.28]	[1.25]	[0.47]	[0.86]	[-0.66]	[1.32]	[0.26]
ΔCDSHL(i,t-1)	-0.033	-0.024	-0.029	-0.040	0.011	-0.029	***-0.060***	0.014	0.008	-0.045	***-0.039***	-0.012	-0.014	-0.018	-0.081	-0.010	***-0.067***	-0.004
	[-1.05]	[-1.17]	[-1.06]	[-1.66]	[0.38]	[-1.20]	***[-2.20]***	[0.34]	[0.42]	[-1.65]	***[-2.29]***	[-0.94]	[-0.87]	[-0.49]	[-1.18]	[-0.51]	***[-2.76]***	[-0.40]
ΔCDSSlope(i,t-1)	-0.034	-0.002	0.000	0.021	0.042	-0.002	0.032	0.000	0.009	0.007	***0.039***	-0.005	-0.021	0.021	-0.056	0.015	0.008	0.000
	[-1.59]	[-0.12]	[-0.02]	[1.31]	[1.95]	[-0.13]	[1.43]	[-0.01]	[0.50]	[0.46]	***[4.82]***	[-0.35]	[-1.75]	[0.81]	[-0.93]	[1.87]	[1.06]	[0.03]
ΔCDSContr(i,t-1)	-0.013	***-0.019***	-0.009	-0.015	-0.027	***-0.031***	-0.003	***-0.059***	-0.018	***-0.049***	***-0.037***	-0.025	0.004	0.038	-0.015	***-0.027***	-0.025	-0.005
	[-0.59]	***[-2.03]***	[-0.55]	[-0.66]	[-1.51]	***[-2.53]***	[-0.16]	***[-2.05]***	[-0.77]	***[-3.19]***	***[-2.98]***	[-1.87]	[0.36]	[1.74]	[-0.44]	***[-2.70]***	[-1.67]	[-0.61]
ΔDARatio(i,t-1)	-0.016	-0.025	0.004	0.020	-0.017	0.003	-0.012	-0.046	0.001	0.000	-0.001	-0.015	-0.013	-0.050	0.103	-0.014	***-0.034***	-0.007
	[-0.62]	[-1.50]	[0.22]	[0.66]	[-0.48]	[0.18]	[-0.41]	[-0.60]	[0.03]	[-0.02]	[-0.06]	[-0.97]	[-1.08]	[-1.43]	[1.72]	[-1.01]	***[-2.40]***	[-0.96]
ΔDERatio(i,t-1)	-0.016	***0.056***	0.034	0.041	-0.019	0.027	-0.040	0.018	-0.023	0.024	0.019	***0.056***	0.011	0.048	-0.106	***0.048***	0.004	0.020
	[-0.40]	***[2.11]***	[1.17]	[1.23]	[-0.44]	[1.03]	[-1.42]	[0.19]	[-0.30]	[0.96]	[0.94]	***[2.44]***	[0.59]	[0.92]	[-1.89]	***[2.40]***	[0.17]	[1.69]
ΔEBIT(i,t-1)	-0.001	0.007	-0.017	0.041	-0.003	-0.030	***0.057***	-0.303	-0.051	0.025	0.022	***-0.056***	0.000	0.026	-0.074	0.006	-0.046	0.010
	[-0.02]	[0.31]	[-0.43]	[1.04]	[-0.09]	[-1.00]	***[2.03]***	[-1.78]	[-0.85]	[0.73]	[1.50]	***[-1.99]***	[0.01]	[0.37]	[-0.50]	[0.27]	[-1.35]	[0.58]
ΔIntCover(i,t-1)	0.021	-0.017	0.003	-0.028	0.001	0.018	***-0.087***	0.120	0.059	-0.037	-0.007	0.046	-0.025	-0.019	0.062	-0.014	***0.052***	-0.014
	[0.50]	[-0.84]	[0.11]	[-1.17]	[0.01]	[0.71]	***[-3.13]***	[0.89]	[0.96]	[-1.78]	[-0.63]	[1.81]	[-1.11]	[-0.37]	[0.43]	[-1.35]	***[2.10]***	[-1.10]
ΔInv2COGS(i,t-1)	0.019	0.010	-0.009	-0.006	0.011	-0.019	0.013	-0.059	***-0.035***	-0.004	0.003	0.009	-0.016	-0.021	-0.006	-0.010	0.016	-0.011
	[0.84]	[0.70]	[-0.37]	[-0.28]	[0.36]	[-1.51]	[0.55]	[-1.71]	***[-2.23]***	[-0.31]	[0.24]	[1.00]	[-1.21]	[-0.89]	[-0.13]	[-0.79]	[1.39]	[-1.68]
ΔLiab(i,t-1)	0.010	-0.011	0.018	-0.029	-0.013	-0.004	0.037	-0.033	0.002	-0.018	-0.026	0.022	***0.042***	-0.006	0.043	0.009	-0.006	-0.006
	[0.24]	[-0.52]	[0.76]	[-1.07]	[-0.42]	[-0.17]	[1.05]	[-0.63]	[0.08]	[-0.99]	[-1.62]	[1.15]	***[2.39]***	[-0.14]	[0.37]	[0.39]	[-0.34]	[-0.73]
ΔMBRatio(i,t-1)	0.007	-0.002	-0.003	0.021	0.000	-0.020	0.024	-0.008	0.051	-0.017	0.005	0.018	-0.012	0.018	-0.063	-0.004	0.017	-0.002
	[0.24]	[-0.16]	[-0.15]	[0.82]	[0.01]	[-1.11]	[0.95]	[-0.17]	[1.56]	[-0.76]	[0.52]	[1.09]	[-1.03]	[0.87]	[-1.57]	[-0.41]	[1.15]	[-0.25]
ΔNIGrowth(i,t-1)	0.000	-0.006	0.028	0.012	0.002	-0.010	-0.024	-0.040	0.013	-0.022	-0.007	-0.004	0.007	-0.011	-0.090	0.002	-0.011	-0.001
	[-0.03]	[-0.44]	[1.65]	[0.68]	[0.12]	[-0.82]	[-1.10]	[-1.20]	[0.82]	[-1.08]	[-0.68]	[-0.29]	[0.80]	[-0.44]	[-1.80]	[0.13]	[-1.34]	[-0.18]
ΔNIMTA(i,t-1)	-0.012	***-0.059***	-0.004	-0.001	-0.011	-0.028	-0.054	-0.019	0.008	0.009	0.007	***-0.067***	-0.006	-0.029	0.075	***-0.052***	***-0.042***	0.005
	[-0.21]	***[-2.86]***	[-0.15]	[-0.03]	[-0.24]	[-0.70]	[-1.07]	[-0.24]	[0.17]	[0.19]	[0.29]	***[-2.04]***	[-0.30]	[-0.59]	[1.83]	***[-2.33]***	***[-3.09]***	[0.31]
ΔRealVol(i,t-1)	-0.052	***0.040***	-0.026	0.023	-0.025	-0.013	0.008	-0.044	0.019	-0.021	0.027	-0.012	-0.002	-0.015	0.044	0.000	0.002	0.011
	[-1.95]	***[2.15]***	[-1.34]	[1.02]	[-1.02]	[-0.49]	[0.26]	[-0.81]	[0.80]	[-0.76]	[1.70]	[-0.67]	[-0.11]	[-0.41]	[1.03]	[-0.01]	[0.10]	[1.17]
ΔReEarning(i,t-1)	-0.018	-0.008	0.015	***-0.050***	-0.026	-0.005	0.021	-0.070	0.006	0.003	***-0.024***	0.003	0.013	-0.013	0.088	-0.022	***-0.048***	-0.003
	[-0.59]	[-0.39]	[0.87]	***[-2.12]***	[-1.14]	[-0.28]	[0.77]	[-1.18]	[0.20]	[0.15]	***[-2.23]***	[0.13]	[0.88]	[-0.32]	[0.69]	[-1.54]	***[-3.41]***	[-0.50]
ΔROA(i,t-1)	-0.009	0.043	-0.007	-0.017	-0.021	0.001	0.046	***0.228***	-0.009	-0.027	-0.020	0.065	0.011	-0.004	-0.029	0.035	0.056	-0.022
	[-0.18]	[1.90]	[-0.22]	[-0.34]	[-0.37]	[0.02]	[0.96]	***[2.20]***	[-0.19]	[-0.52]	[-0.58]	[1.91]	[0.44]	[-0.07]	[-0.30]	[1.61]	[1.68]	[-0.94]
ΔSaleGrowth(i,t-1)	-0.002	0.019	-0.025	-0.027	-0.012	-0.007	-0.023	-0.024	-0.017	0.009	0.000	0.013	***-0.023***	-0.039	-0.079	-0.009	-0.018	-0.006
	[-0.07]	[1.08]	[-1.10]	[-1.20]	[-0.41]	[-0.45]	[-0.81]	[-0.64]	[-0.70]	[0.48]	[0.01]	[0.91]	***[-1.99]***	[-1.44]	[-1.47]	[-0.51]	[-1.15]	[-0.99]
ΔStoAmihud(i,t-1)	0.020	0.018	-0.007	-0.022	-0.011	0.000	0.036	0.028	-0.010	0.019	-0.011	0.003	0.009	0.006	0.065	[0.01]	[0.00]	0.002
	[0.93]	[1.46]	[-0.37]	[-0.95]	[-0.55]	[-0.04]	[1.69]	[0.50]	[-0.66]	[0.98]	[-1.27]	[0.22]	[0.61]	[0.23]	[1.32]	[1.21]	[0.01]	[0.13]
ΔStoMom(i,t-1)	-0.013	0.023	0.036	0.059	0.035	0.021	0.057	-0.066	-0.008	0.020	***0.038***	0.002	0.013	0.023	0.018	0.003	-0.005	***0.025***
	[-0.39]	[1.42]	[1.21]	[1.67]	[1.13]	[0.94]	[1.78]	[-0.93]	[-0.24]	[0.86]	***[2.50]***	[0.09]	[1.02]	[0.51]	[0.33]	[0.13]	[-0.47]	***[3.32]***
ΔStoPrice(i,t-1)	-0.050	-0.033	***-0.107***	-0.091	-0.075	-0.027	***-0.073***	-0.008	-0.113	-0.039	***-0.070***	-0.041	***-0.063***	-0.041	***-0.195***	-0.061	-0.043	***-0.048***
	[-1.04]	[-1.10]	***[-2.49]***	[-1.52]	[-1.61]	[-1.07]	***[-2.03]***	[-0.10]	[-1.18]	[-1.60]	***[-2.26]***	[-1.30]	***[-3.24]***	[-0.86]	***[-4.43]***	[-1.51]	[-1.94]	***[-3.31]***
ΔStoVol(i,t-1)	-0.024	0.039	-0.038	0.018	-0.015	-0.031	0.003	-0.019	0.043	-0.041	0.006	-0.011	0.018	0.026	0.054	0.013	-0.014	0.003
	[-0.91]	[1.89]	[-1.76]	[0.71]	[-0.67]	[-1.05]	[0.11]	[-0.48]	[1.95]	[-1.14]	[0.31]	[-0.56]	[1.31]	[0.71]	[0.97]	[0.80]	[-0.74]	[0.41]
ΔWorkingCap(i,t-1)	[0.01]	[-0.01]	[-0.00]	***[-0.04]***	[0.03]	[0.02]	[-0.02]	[-0.01]	[0.02]	[-0.00]	[0.01]	[0.01]	[0.00]	[-0.01]	[-0.01]	[0.02]	[0.01]	[-0.00]
	[0.28]	[-0.75]	[-0.10]	***[-2.00]***	[0.69]	[0.89]	[-0.83]	[-0.25]	[1.16]	[-0.09]	[0.81]	[0.97]	[0.09]	[-0.37]	[-0.17]	[1.87]	[0.48]	[-0.21]
Adj. R^2	0.13	0.11	0.16	0.24	0.18	0.13	0.13	0.16	0.17	0.12	0.14	0.09	0.09	0.11	0.23	0.06	0.14	0.07
#Obs	3574	7654	5211	3086	3351	7777	3436	1585	4665	5114	11641	8796	10901	2840	1047	12180	4111	22736
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Systematic Factor VIF

This table reports the Variance Inflation Factor (VIF) analysis for the eight systematic factors. The sample period is from January 2001 to June 2018. We use the monthly changes of the variables in the VIF analysis.

Variable	VIF
ΔDftSpr	1.15
ΔTrmSpr	1.72
ΔVIX	2.29
ΔSP500	2.67
ΔTB5Y	1.96
ΔAvgSpr	1.40
ΔAvgSpr_R	1.37
ΔAvgSpr_S	1.40

Table 13: Systematic Factor Quarterly Regression

This table reports the regression results for systematic factors for the 259 U.S. firms over the sample period from January 2001 to June 2018. Δ is the operator of the variable quarterly change. Firm fixed effect is controlled in the panel regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

	Dependent Variable.: ΔSpr	
	Contemporaneous	Lagged
ΔDftSpr	***5.118***	3.782
	[2.23]	[1.66]
ΔTrmSpr	***4.212***	***6.399***
	[2.81]	***[3.38]***
ΔVIX	0.001	***0.009***
	[1.22]	***[5.35]***
ΔSP500	-0.216	0.169
	[-0.91]	[0.67]
ΔTB5Y	***-5.129***	-2.329
	[-3.72]	[-0.96]
ΔAvgSpr	***0.152***	***0.117***
	[3.62]	***[4.55]***
ΔAvgSpr_R	***0.439***	***0.295***
	[10.01]	***[9.55]***
ΔAvgSpr_S	***0.248***	***0.193***
	[3.26]	***[3.65]***
Adj. R^2	0.40	0.26
#Obs	39934	39586
Firm FE	Yes	Yes

Table 14: Systematic Factors Reverse Regression

This table reports the regression results for systematic factors for the 259 U.S. firms over the sample period from January 2001 to June 2018. Δ is the operator of the variable monthly change. We reverse our two-step methods by first regressing the CDS spreads on firm-specific variables, to get the idiosyncratic part of the CDS spreads:

$$\Delta \log (CDS_{i,t}) = \gamma_1 \Delta X^f_{i,t} + u_t + v_i + \Delta Idio_{i,t},$$

where X^f is a set of the firm-specific variables listed in Table 2, u and v are time and firm fixed effects respectively, and the $\Delta Idio_{i,t}$ is the residual, unexplained of the firm-specific variables. Then we regress the $\Delta Idio_{i,t}$ on the systematic factors:

$$\Delta Idio_{i,t} = \beta_1 \Delta X^s_t + v_i + \varepsilon_{i,t},$$

where X^s is a set of systematic factors and v are firm fixed effects. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

	Dependent Variable: ΔIdio (i,t)
ΔDftSpr (t)	-3.232
	[-1.31]
ΔTrmSpr (t)	***-12.202***
	[-5.34]
ΔVIX (t)	0.000
	[-0.17]
ΔSP500 (t)	***0.774***
	[6.12]
ΔTB5Y (t)	***4.974***
	[2.84]
ΔAvgSpr (t)	***0.484***
	[7.79]
ΔAvgSpr_R (t)	***0.279***
	[11.99]
ΔAvgSpr_S (t)	***0.339***
	[6.97]
Adj. R^2	0.07
#Obs	38993
Firm FE	Yes

Table 15: Non-zero Observations

This table reports the panel regression results using the non-zero observations. Δ is the operator of variable monthly change. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the contemporaneous firm-specific characteristics. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. *t*-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: ΔIdio (i,t)		
	Coef	*t*-stats
ΔAsset(i,t-1)	-0.008	[-0.93]
ΔCASHMTA(i,t-1)	0.015	[1.58]
ΔCashRatio(i,t-1)	***-0.026***	***[-2.21]***
ΔCDSAmihud(i,t-1)	-0.005	[-0.34]
ΔCDSHL(i,t-1)	-0.022	[-1.46]
ΔCDSSlope(i,t-1)	-0.001	[-0.09]
ΔCDSContr(i,t-1)	***-0.027***	***[-2.47]***
ΔDARatio(i,t-1)	-0.008	[-0.85]
ΔDERatio(i,t-1)	***0.033***	***[2.22]***
ΔEBIT(i,t-1)	-0.011	[-0.72]
ΔIntCover(i,t-1)	0.000	[-0.04]
ΔInv2COGS(i,t-1)	-0.011	[-1.83]
ΔLiab(i,t-1)	0.004	[0.41]
ΔMBRatio(i,t-1)	-0.007	[-1.07]
ΔNIGrowth(i,t-1)	0.005	[0.65]
ΔNIMTA(i,t-1)	-0.001	[-0.07]
ΔRealVol(i,t-1)	0.021	[1.84]
ΔReEarning(i,t-1)	-0.008	[-0.82]
ΔSaleGrowth(i,t-1)	-0.016	[-1.95]
ΔStoAmihud(i,t-1)	0.007	[0.72]
ΔStoMom(i,t-1)	***0.022***	***[2.09]***
ΔStoPrice(i,t-1)	-0.036	[-1.95]
ΔStoVol(i,t-1)	0.012	[1.06]
ΔWorkingCap(i,t-1)	0.011	[1.68]
Adj. R^2	0.09	
#Obs	25361	
Firm FE	Yes	
Time FE	Yes	

Appendix

We use level variables and repeat the regression analyses shown in the main sections. Table A.1 reports the results for contemporaneous time-series regressions of CDS spreads on systematic factors, Table A.2 reports the lagged time-series regressions of the CDS spreads on systematic factors, and Table A.3 reports the regression results of systematic factors for sub-samples. Likewise, Table A.4 and A.5 report the results for firm-specific variables, analogue to Table 9 and 10, respectively. Note that the composition of the firm-specific variables for the level of CDS spread is slightly different from that for the changes of CDS spread, because we redo our VIF for the firm-specific variables.

Overall, we find the explanatory power of systematic factors remains strong and most systematic factors remains statistically significant. The firm-specific variables also remain weak in predicting and explaining the CDS spread changes. Hence, the conclusion from the level variables is qualitatively the same as the change variables in the main section. It is worth mentioning that although the R^2's are stronger in level variables than in change variables, we find the coefficients are unstable, indicating that, de facto, CDS spread variations are comparatively stable over time, implying that it might be suitable to analyze CDS spreads in using change variables to avoid the problem of non-stationary in the time series.

Table A.1: Contemporaneous CDS Systematic Factors (Level)

This table reports the regression results for contemporaneous systematic factors for the 259 U.S. firms over the sample period from January 2001 to June 2018. We perform time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5%, and the average adjusted R^2 for the 259 regressions. The left panel reports the univariate regressions and the right panel reports the univariate regressions. Newey-West t-statistics with 12-month lags is used for testing coefficient significance.

	Dependent Variable: Spr (i,t)				
	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	%($p \leq 0.05$)	$\overline{Coef}$	%($p \leq 0.05$)	$\overline{Adj.\ R^2}$
DftSpr (t)	-3.966	(45.56%)	51.218	(74.13%)	0.22
TrmSpr (t)	2.329	(40.54%)	18.949	(63.71%)	0.21
VIX (t)	-0.002	(28.96%)	0.029	(72.20%)	0.23
SP500 (t)	0.011	(51.35%)	-0.351	(45.17%)	0.19
TB5Y (t)	-3.773	(59.07%)	-21.324	(67.95%)	0.31
AvgSpr (t)	0.153	(48.26%)	0.785	(76.83%)	0.37
AvgSpr_R (t)	0.458	(69.88%)	0.801	(89.96%)	0.50
AvgSpr_S (t)	0.440	(55.98%)	0.751	(80.31%)	0.41
Const	-0.438	(49.42%)			
$\overline{Adj.\ R^2}$	0.82				
#Obs	41044				
#Firm	259				

Table A.2: Lagged CDS Systematic Factors (Level)

This table reports the regression results for systematic factors lagged by one month for the 259 U.S. firms over the sample period from January 2001 to June 2018. We perform time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5% (in parentheses), and the average adjusted R^2 for the 259 regressions. The left panel reports the univariate regressions and the right panel reports the univariate regressions. Newey-West t-statistics with 12-month lags is used for testing coefficient significance.

Dependent Variable: Spr (i,t)					
	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Adj.\ R^2}$
DftSpr (t-1)	-3.028	(40.93%)	50.190	(72.59%)	0.21
TrmSpr (t-1)	4.788	(43.63%)	18.934	(62.55%)	0.21
VIX (t-1)	0.004	(33.20%)	0.030	(73.75%)	0.24
SP500 (t-1)	0.163	(53.28%)	-0.329	(45.56%)	0.18
TB5Y (t-1)	-3.321	(50.97%)	-20.335	(66.41%)	0.29
AvgSpr (t-1)	0.111	(41.31%)	0.772	(77.61%)	0.36
AvgSpr_R (t-1)	0.399	(64.09%)	0.768	(88.42%)	0.46
AvgSpr_S (t-1)	0.397	(54.44%)	0.731	(79.54%)	0.39
Const	-2.228	(51.74%)			
$\overline{Adj.\ R^2}$	0.78				
#Obs	40689				
#Firm	259				

Table A.3: Sub-sample CDS Systematic Factors (Level)

This table reports the regression results for contemporaneous systematic factors for the 259 U.S. firms by sectors, ratings, and periods. We perform multivariate time-series regressions for each firm, and report the average coefficients, the percentage of statistical significance at 5% (in parentheses), and the average adjusted R^2 for the 259 regressions. Newey-West t-statistics with 12-month lags is used to test coefficient significance.

Dependent Variable: Spr (i,t)																		
	Sector									Rating						Period		
	Materials	ConGoods	ConServices	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	PreCrisis	InCrisis	PostCrisis
DftSpr (t)	9.058	-0.408	-5.624	8.453	-16.917	-4.687	-11.984	4.986	-12.239	-7.949	-4.668	-1.093	-0.290	-11.617	-17.372	11.514	0.515	-8.400
?%($p \leq 0.05$)	(40.91%)	(53.33%)	(41.18%)	(57.14%)	(38.10%)	(49.02%)	(26.09%)	(27.27%)	(54.84%)	(44.12%)	(35.82%)	(44.83%)	(54.79%)	(52.63%)	(37.50%)	(39.41%)	(49.32%)	(42.21%)
TrmSpr (t)	3.877	1.562	1.229	-0.675	4.222	2.289	3.824	2.106	3.340	-0.419	4.657	0.911	3.156	-1.684	6.771	1.432	2.233	-0.340
	(36.36%)	(40.00%)	(38.24%)	(33.33%)	(38.10%)	(33.33%)	(39.13%)	(72.73%)	(54.84%)	(29.41%)	(44.78%)	(43.10%)	(41.10%)	(31.58%)	(50.00%)	(45.32%)	(50.68%)	(39.75%)
VIX (t)	-0.003	-0.005	0.004	-0.001	-0.003	-0.002	-0.005	0.000	-0.001	-0.003	0.001	-0.001	-0.003	-0.004	-0.007	-0.002	-0.001	-0.001
	(18.18%)	(37.78%)	(23.53%)	(33.33%)	(19.05%)	(27.45%)	(21.74%)	(36.36%)	(38.71%)	(47.06%)	(23.88%)	(25.86%)	(27.40%)	(21.05%)	(50.00%)	(43.84%)	(58.90%)	(31.97%)
SP500 (t)	0.216	0.152	0.005	0.135	-0.016	-0.174	0.071	0.035	-0.148	-0.140	0.149	0.145	-0.195	-0.058	0.559	0.147	0.355	-0.135
	(50.00%)	(51.11%)	(52.94%)	(57.14%)	(28.57%)	(54.90%)	(65.22%)	(45.45%)	(48.39%)	(58.82%)	(49.25%)	(50.00%)	(45.21%)	(52.63%)	(100.00%)	(53.20%)	(62.56%)	(57.38%)
TB5Y (t)	-10.573	-7.387	-2.487	-4.169	-2.575	-0.759	-6.108	-0.030	-0.208	0.246	-2.658	-8.352	-3.423	1.129	-11.830	-0.124	1.455	-3.333
	(68.18%)	(57.78%)	(55.88%)	(61.90%)	(47.62%)	(52.94%)	(65.22%)	(54.55%)	(70.97%)	(58.82%)	(65.67%)	(55.17%)	(56.16%)	(68.42%)	(37.50%)	(33.50%)	(51.60%)	(60.25%)
AvgSpr (t)	0.057	-0.224	-0.009	0.304	0.395	0.337	0.431	-0.317	0.337	0.178	0.124	0.157	0.137	0.329	-0.010	0.297	0.113	0.121
	(18.18%)	(51.11%)	(26.47%)	(52.38%)	(66.67%)	(60.78%)	(60.87%)	(9.09%)	(58.06%)	(47.06%)	(55.22%)	(46.55%)	(43.84%)	(47.37%)	(50.00%)	(52.71%)	(56.16%)	(35.66%)
AvgSpr_R (t)	0.472	0.210	0.545	0.661	0.526	0.525	0.563	0.282	0.399	0.479	0.503	0.457	0.424	0.546	0.080	0.534	0.510	0.422
	(54.55%)	(40.00%)	(67.65%)	(100.00%)	(85.71%)	(84.31%)	(86.96%)	(36.36%)	(70.97%)	(79.41%)	(70.15%)	(72.41%)	(64.38%)	(73.68%)	(50.00%)	(53.69%)	(68.04%)	(69.26%)
AvgSpr_S (t)	0.305	0.568	0.311	0.358	0.609	0.368	0.466	0.420	0.537	0.391	0.395	0.370	0.452	0.516	1.240	0.383	0.593	0.371
	(27.27%)	(66.67%)	(38.24%)	(52.38%)	(71.43%)	(54.90%)	(65.22%)	(63.64%)	(64.52%)	(67.65%)	(56.72%)	(50.00%)	(52.05%)	(57.89%)	(75.00%)	(55.17%)	(63.01%)	(46.72%)
Const	-2.878	-1.279	-0.567	-0.972	0.456	0.638	-0.453	-0.057	0.518	0.156	-1.844	-1.732	1.367	0.606	-0.758	-1.880	-2.380	0.220
	(45.45%)	(40.00%)	(50.00%)	(57.14%)	(23.81%)	(66.67%)	(60.87%)	(27.27%)	(48.39%)	(61.76%)	(47.76%)	(53.45%)	(39.73%)	(47.37%)	(75.00%)	(54.68%)	(66.67%)	(66.80%)
Adj. R^2	0.76	0.81	0.78	0.89	0.82	0.83	0.81	0.81	0.85	0.80	0.83	0.79	0.83	0.82	0.87	0.81	0.88	0.79
#Obs	3665	7776	5296	3117	3391	7932	3510	1603	4754	5215	11802	8984	11086	2883	1074	12403	4104	22695
#Firm	22	45	34	21	21	51	23	11	31	34	67	58	73	19	8	203	219	244

Table A.4: Firm-specific Variable Prediction (Level)

This table reports the panel regression results for firm-specific variables over the sample period from January 2001 to June 2018. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the firm-specific characteristics lagged by one period. Left panel reports the multivariate panel regression and right panel reports the univariate regression. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: Idio (i,t)					
	Multivariate Regression		Univariate Regression		
Variable	Coef	t-stats	Coef	t-stats	Adj. R^2
Asset(i,t-1)	***0.056***	***[2.94]***	0.038	[1.62]	0.05
CASHMTA(i,t-1)	***0.059***	***[3.09]***	***0.092***	***[3.95]***	0.05
CashRatio(i,t-1)	***-0.055***	***[-3.24]***	-0.011	[-1.12]	0.05
CBCnt(i,t-1)	0.021	[1.17]	***0.068***	***[4.71]***	0.05
CBPrice(i,t-1)	0.013	[1.22]	***0.075***	***[3.16]***	0.05
CBVol(i,t-1)	0.006	[0.97]	***0.039***	***[3.41]***	0.05
CDSAmihud(i,t-1)	***-0.156***	***[-7.24]***	-0.025	[-1.07]	0.05
CDSHL(i,t-1)	***0.274***	***[6.65]***	***0.232***	***[6.00]***	0.08
CDSSlope(i,t-1)	***0.135***	***[4.28]***	***0.166***	***[3.93]***	0.06
CDSContr(i,t-1)	-0.002	[-0.14]	***0.054***	***[2.28]***	0.05
DARatio(i,t-1)	0.005	[0.31]	***0.077***	***[4.63]***	0.05
EBIT(i,t-1)	0.011	[0.60]	***-0.079***	***[-4.82]***	0.05
IntCover(i,t-1)	-0.009	[-0.51]	***-0.081***	***[-4.90]***	0.05
Inv2COGS(i,t-1)	***0.022***	***[2.46]***	***0.039***	***[3.89]***	0.05
Liab(i,t-1)	0.021	[1.13]	***0.075***	***[3.85]***	0.05
LLB(i,t-1)	0.015	[0.44]	***0.176***	***[5.60]***	0.07
MBRatio(i,t-1)	0.010	[0.73]	***-0.082***	***[-6.03]***	0.05
MktCap(i,t-1)	***-0.096***	***[-2.19]***	***-0.173***	***[-8.29]***	0.06
NIGrowth(i,t-1)	0.001	[0.17]	-0.012	[-1.25]	0.05
NIMTA(i,t-1)	-0.029	[-1.48]	***-0.042***	***[-3.65]***	0.05
RealVol(i,t-1)	0.045	[1.38]	***0.067***	***[3.10]***	0.05
ReEarning(i,t-1)	***0.038***	***[3.47]***	***-0.033***	***[-2.80]***	0.05
ROA(i,t-1)	0.007	[0.35]	***-0.076***	***[-4.71]***	0.05
SaleGrowth(i,t-1)	***0.012***	***[2.04]***	-0.008	[-1.34]	0.05
StoAmihud(i,t-1)	-0.018	[-0.67]	***0.088***	***[3.63]***	0.05
StoMom(i,t-1)	-0.003	[-0.14]	***-0.091***	***[-5.34]***	0.05
StoPrice(i,t-1)	-0.021	[-1.06]	***-0.145***	***[-6.96]***	0.06
StoVol(i,t-1)	0.030	[1.34]	-0.014	[-0.81]	0.05
WorkingCap(i,t-1)	0.011	[0.98]	***-0.020***	***[-2.57]***	0.05
Adj. R^2	0.13				
#Obs	40949				
Firm FE	Yes				
Time FE	Yes				

Table A.5: Firm-specific Variable Contemporaneous Panel Regression (Level)

This table reports the panel regression results for firm-specific variables over the sample period from January 2001 to June 2018. The dependent variable is the unexplained CDS spread changes by the systematic factors and the independent variables are the contemporaneous firm-specific characteristics. Firm fixed effect and time fixed effect are controlled in the regression. We use heteroskedasticity and autocorrelation (with 12-month lags) robust standard errors to test coefficient significance. t-statistics is reported in square parentheses. Statistical significance of 5% is expressed in italic and bold.

Dependent Variable: Idio (i,t)		
	Coef	t-stats
Asset(i,t)	***0.052***	***[2.87]***
CASHMTA(i,t)	***0.075***	***[4.07]***
CashRatio(i,t)	***-0.066***	***[-3.81]***
CBCnt(i,t)	0.007	[0.57]
CBPrice(i,t)	0.021	[1.61]
CBVol(i,t)	0.008	[0.97]
CDSAmihud(i,t)	***-0.178***	***[-8.51]***
CDSHL(i,t)	***0.328***	***[7.61]***
CDSSlope(i,t)	***0.169***	***[5.14]***
CDSContr(i,t)	0.017	[0.84]
DARatio(i,t)	0.008	[0.60]
EBIT(i,t)	0.022	[1.11]
IntCover(i,t)	-0.011	[-0.66]
Inv2COGS(i,t)	***0.020***	***[2.24]***
Liab(i,t)	0.016	[0.85]
LLB(i,t)	0.001	[0.02]
MBRatio(i,t)	0.015	[1.03]
MktCap(i,t)	***-0.083***	***[-1.98]***
NIGrowth(i,t)	-0.001	[-0.19]
NIMTA(i,t)	-0.015	[-0.54]
RealVol(i,t)	0.046	[1.44]
ReEarning(i,t)	***0.037***	***[3.57]***
ROA(i,t)	-0.006	[-0.23]
SaleGrowth(i,t)	***0.018***	***[2.50]***
StoAmihud(i,t)	-0.006	[-0.25]
StoMom(i,t)	-0.002	[-0.09]
StoPrice(i,t)	-0.025	[-1.31]
StoVol(i,t)	0.034	[1.49]
WorkingCap(i,t)	0.011	[1.08]
Adj. R^2	0.15	
#Obs	41044	
Firm FE	Yes	
Time FE	Yes	