Corporate Credit Default Swap Systematic Factors

Ka Kei Chan, Ming-Tsung Lin and Qinye Lu*

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

JEL: G12, G13, G23.

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Abstract

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1 Introduction

Corporate credit default swap (CDS) is a financial product, serving as an insurance to protect contract buyers against a loss due to a firm's default. Because of its simple product structure[1], implying that the price, or spread of CDS, should reflect an individual firm's default probability, CDS becomes the most popular tool for managing individual firm's default risk among institutional investors such as banks. The pricing of CDS is very important and has been the center of CDS studies. Early studies find that the modeling of firm's credit or default risk reflects the level of CDS spreads reasonably well, but fail to carefully explain the changes of the CDS spreads, which are crucial to investors (see, e.g., Duffie and Singleton, 1999; Jarrow et al., 1997; Merton, 1974, among the seminal papers).[2] After the Great Financial Crisis, researchers on CDS studies moved their focus to the determinants of the changes of CDS spreads, with a series of studies emerging and documenting that firm characteristics contain important information on CDS spreads. For example, Das and Hanouna (2009) and Pereira et al. (2018) find that the accounting- and market-based information explains the changes of CDS spreads, and some other studies complement that non-credit information, such as illiquidity (Tang and Yan, 2007) and transaction cost (Coró et al., 2013), are also influential in explaining the changes of CDS spreads. With the increasing number of CDS determinants being discovered and adopted in the analysis, although they are each statistically significant in their corresponding studies, the concern of a potential '*veritable zoo*' raises if the adopted determinants are strongly correlated, which may lead to biased estimations. It is also unclear that how systematic information influences CDS price dynamics differently from firm-specific information (or which information dominates), as very few studies explore this. Our study sheds light on the concerns mentioned by conducting a comprehensive review on how systematic and firm-specific factors perform in explaining the variations of CDS spreads, with the use of Variance Inflation Factor (VIF) to eliminate potential multicollinearity concern.

[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 period 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 CDS spread and conclude that the theoretical pricing models were in general working fine. But Lin et al. (2019) document that the CreditGrades model, a CDS pricing model based on Merton (1974), only captures 9% of the monthly variation of the CDS spreads.

We define the systematic factors as factors that influence all assets (satisfying certain conditions) and they are distinguished from firm-specific factors, which may only affect specific underlying firm or asset differently. Note that a systematic factor can be exogenous, e.g., bond market factor (Blanco et al., 2005), or endogenous, e.g., cross-sectional average of the changes of CDS spreads (Galil et al., 2014; Lin et al., 2019).

Among those existing studies with growing attention on CDS systematic factors, the impact of systematic factors is often studied at the index or portfolio level (e.g., Anderson, 2017), and is seldom emphasized at the individual CDS levels, on which we focus.[3] Additionally, when those studies attempt to control for systematic factors, they merely put all firm-specific variables with just one or two selective systematic factors together in one pooled regression. Such treatment on systematic factors overlooks the cross-sectional effect imposed by systematic factors. We split our factors into two groups, systematic and firm-specific factors, which are orthogonal to each other, and further examine how they affect the variations of changes of CDS spreads. Also, we distinguish the systematic factors into exogenous and endogenous for a better understanding on the influence of systematic factors. To the best of our knowledge, we are the first to systematically question the underestimation of the impact from systematic factors and conduct a comprehensive study on the topic with firm-specific factors orthogonal to the systematic factors.

In this study, we investigate comprehensively the importance of systematic and firm-specific factors to individual CDS spread changes. 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 have influenced individual CDS spreads. Prior studies usually focus on exogenous systematic factors (e.g., Norden and Weber, 2004, 2009; Doshi et al., 2013; Conrad et al., 2020), and more recently, a few begin to look at the endogenous factors (e.g., Galil et al., 2014; Lin et al., 2019). Here we investigate all systematic factors appeared in literature. Our exogenous systematic factors are constructed from stock, bond, and credit markets; the significance of

[3] In Online Appendix (see table A.1), we provide an overview how systematic factors had less attention than firm-specific factors and were often treated only as control variables.

the co-movement in these financial markets implies that the pricing of the individual CDSs is affected by some market conditions. Although these strong co-movements are also documented in prior studies (Forte and Pena, 2009; Norden and Weber, 2009), they are only examined at aggregated levels (e.g. CDS index or portfolios).

Although a few studies (e.g. Norden and Weber, 2009; Doshi et al., 2013; Hammoudeh et al., 2013) show certain systematic factors for CDS spreads that are endogenously embedded in the stock and bond markets of the underlying firms, they did not provide a comprehensive analysis 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.

We show that exogenous systematic factors and systematic risk of their peers also matter at entity level. Our findings suggest that peer information is more important than exogenous systematic factors explaining contemporaneous CDS spread changes. Furthermore, we show that peer information at three different levels (i.e. overall, rating, and sector levels) all contribute to CDS price variations, while prior studies only cover the peer information at selective levels, e.g. Galil et al. (2014) (sector, overall) and Lin et al. (2019) (overall). In our additional results, we also show that systematic factors exhibit power for out-of-sample prediction.

For the second research question, we regress the component unexplained by the systematic factors 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 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 variation 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.

Our main results are summarized as follows.

- By looking at a total of 259 U.S. non-financial firms over the sample period of January

2001 to June 2018, on average, about 35% of the monthly CDS spread variations are attributed to the nine systematic factors in the individual time-series regressions.

- Endogenous systematic factors are stronger in explaining contemporaneous CDS variations while exogenous systematic factors are stronger in explaining predictive CDS variations. Results are consistent in the sub-samples.

- The firm-specific variables are comparatively weak in explaining monthly CDS variations that are not explained by the systematic factors. In a panel regression setting, they can only account for 5% of the unexplained CDS (predictive) variations.

- Only 4 out of the total 28 firm-specific variables are statistically significant in explaining CDS predictive variations that are not explained by the systematic factors, indicating that many firm-specific CDS determinants are not as important as prior studies suggested.

- The insignificance of many firm-specific variables implies that these variables coincide with systematic information. The only four firm-specific variables that can provide independent information for the changes in CDS one month ahead are: the number of CDS contributors (CDSContr), firm's debt-to-asset ratio (DARatio), firm's market-to-book ratio (MBRatio) and underlying stock price (StoPrice). These four variables reflect unique aspects of firm-specific information, such as accounting and market information and CDS illiquidity.

- Six additional firm-specific variables – cash holding (CASHMTA), CashRatio, CDS high-minus-low (CDSHL), CDSSlope, firm's debt-to-equity ratio (DERatio, which replaces the DARatio) and net income (NIMTA) – explain the contemporaneous changes of the CDS spreads. Some of these variables highlight the illiquidity impact on individual CDS spread changes (Coró et al., 2013; Das and Hanouna, 2009; Lin et al., 2019). Having said that, merely one-third of the firm-specific variables included in this study show statistical significance and as we argue, casts doubt on the importance of firm-specific variables in explaining CDS variations.

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 sensitive to the overall financial market condition; we also find evidence from our sub-period analysis that this sensitivity 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, the systematic factors can provide important implications for the individual CDS pricing and for the modelling implied default probability, particularly for the firms with untraded or highly illiquid CDS contracts (therefore have limited trading information from market). Our approach would also be a simple but useful way of estimating the necessary risk capital so as to meet the requirement under the Basel framework regarding counterparty credit risk.

Overall, our study contributes to the understanding in CDSs in two ways. First of all, given that many CDS determinants, both systematic and firm-specific, are identified in prior studies, we provide an overview on all these factors and conduct a comprehensive study on how these factors affect CDS spread changes. There is growing evidence of the systematic dynamic of the CDS spread (Anderson, 2017); however, the importance of CDS systematic factors has seemingly been under-explored in the CDS literature. Prior studies have conducted comparison among different types of firm-specific information, e.g., market-based *vs.* accounting-based information (Das et al., 2009). However, we do not find CDS studies focusing on the comparison between systematic and firm-specific factors. Hence, our study fills the gap.

Second, we enhance the understanding of systematic factors on CDS spread changes. Particularly, we allow the systematic effect to be different at firm level, while firm-specific determinants' impact is orthogonal to the systematic factors (i.e., idiosyncratic changes of the CDS spreads). Using idiosyncratic values after controlling for systematic variables to examine the firm-specific effect is not new to financial studies, e.g., firm-characteristics in stock return (Green et al., 2017), but, to the best of our knowledge, we are the first to incorporate such separation in the strand of CDS literature. The separated investigations into systematic and firm-specific impact have several advantages. First, as said, since the systematic impact is allowed to be different across firms, the effect of systematic factors can be measured more precisely and it also fits in the modern asset pricing theories such as CAPM. Besides, when the idiosyncratic component is used to study the impact of firm-specific variables, it can clearly show how the individual firm's credit risk, which is orthogonal to the systematic factors, can be explained by firm-specific information as well as other aspects of firm-specific information that matter.

The rest of the paper is structured as follows: Section 2 outlines the relevant literature. Section 3 develops research design and testable regressions and describes the dataset. Section 4 presents empirical results, and Section 5 concludes.

2 Literature on CDS determinants

Our study is linked to several strands of CDS literature. After the seminal study of Merton (1974) regarding the corporate default risk and other early studies of CDS pricing model mostly emerged on 1990s, more recent studies examine if the CDS prices are indeed explained by the determinants described in the structure model. For example, 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, and the short-term deviation which is caused by CDS reacting before the credit event. 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 some determinants; Pires et al. (2015) further use quantile regression to document that the statistical significance of determinants are more pronounced in high-risk firms. In addition, Bai and Wu (2016) apply Merton (1974) distance to default together 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 find that CDS illiquidity is rather important, such as Coró et al. (2013) who show 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 are 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. Besides, 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, 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. They also find that, during salient events, CDS market is more likely to lead stock market. In contrast, 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 and destabilize the overall CDS market. Kiesel et al. (2016) show that stock market has a prominent influence on the CDS market, particularly during the two days before a credit event.

Studies examining the systematic factors are a small but growing strand in the CDS 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 also priced. Anderson (2017) find that CDS co-movement was high during the 2007–2009 financial crisis, possibly due to the fact 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 data, 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), but not firm-level data.

3 Research design and data

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 these systematic factors can explain individual CDS spreads, and then we regress the residuals from the previous regressions on a comprehensive set of firm-specific variables.

3.1 Systematic variables

Our first hypothesis is that there is a high explanatory power of systematic factors, due to the high co-movement of CDS market with other financial markets. Besides, the CDS is widely used to hedge other financial securities, such as its application to hedge stock for downside risk (Ratner and Chiu, 2013), which partly supports the view that systematic risk is present in individual CDS contracts. Therefore, we formulate our first hypothesis as follows:

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

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

$i = 1, 2, ..., N$):

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

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 $\mathbf{X^s}_t$. Therefore, we run a total of N individual regressions, and we report the average of coefficient significance and that of goodness of fit measures across the regressions to understand the significance of the chosen 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).

Nine systematic factors are chosen from a number of CDS studies in which these systematic factors were found closely linked to CDS market. The systematic factors are separated into two groups: six exogenous systematic factors which represent the influence to individual CDS from other financial markets and global condition, and three endogenous systematic factors which represent 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 by Longstaff et al. (2011), Galil et al. (2014), and Conrad et al. (2020).

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), Galil et al. (2014), and Andres et al. (2021).

iv. S&P500 index is chosen to test the link between equity and CDS markets.

v. U.S. Treasury yield in 5-year tenor is used to test the link between bond and CDS markets. As for variables iv and v, studies (e.g. Norden and Weber, 2004, 2009) show that there exists mutually causal linkage between equity, bond, and CDS markets.

vi. Global Economic Policy Uncertainty (GEPU) Index is also added to capture global monetary uncertainty.[4] Recently, Kaviani et al. (2020) find a significant positive relation between changes in policy uncertainty and firm's credit risk. Also, given that some firms covered in this study operate internationally, global economic uncertainty may also have great impacts on corporate credit risk.

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. There are two possible channels where peer information matters in CDS market. First of all, CDSs are traded over the counter; individual price information may be less efficient and therefore peer information obtained from, e.g., same rating class or sector, is important to price discovery for individual CDSs (Galil et al., 2014; Kolokolova et al., 2019). In addition, CDSs are also popularly used as a hedging tool for firm's default. It implies that the CDS spreads are also prone to demand-driven price pressure: when an asset that has close substitute available to arbitrageurs, they can hedge risks and trade against price shock; meanwhile, the same reason also leads the price impact to spill over across the close substitutes (Chaudhary et al., 2023). Similarly, CDSs with the same rating or sector are often viewed as close substitute, imply that the individual CDSs co-move with their peers. Three cross-sectional averages are considered as endogenous systematic factors in this study:

vii. Total average of CDS spreads ($AvgSpr$) is defined as the cross-sectional average of all CDS spreads (Galil et al., 2014; Lin et al., 2019).

viii. Rating-averaged CDS spreads ($AvgSpr\_R$) is the cross-sectional average of CDS spreads for each rating category (including AA, A, BBB, BB, B, and CCC); this factor is also used in Kolokolova et al. (2019) who found that individual CDS spread has tendency to move to their rating-based estimates. Therefore, a firm's rating information provides systematic information.

ix. Sector-averaged CDS spreads ($AvgSpr\_S$), proposed by Galil et al. (2014), is the cross-sectional average of individual CDS spreads in each industrial sector. Sectors include basic materials, consumer goods, consumer services, energy, healthcare, industrials, technology,

[4] GEPU index is based on Baker et al. (2016) and extended to global economies. The index is available in https://www.policyuncertainty.com/global_monthly.html.

telecommunications, and utilities.

Notably, when running multivariate regression, there is an 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 markets are under higher uncertainty. Therefore, we expand our *H1* hypothesis to the below two further hypotheses:

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 running sub-period regressions (before, during, and after the crisis) as described in Equation (1).

3.2 Firm-specific variables

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

H4: Only some 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 unique 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 of the CDS variation that cannot be captured by the chosen 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 gather an initial list of 33 firm-specific CDS determinants. Table 1 provides the detailed definition for these 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 in this study. We group the 33 variables into five categories: Accounting and Market Mixed, Balance Sheet, Financial Market, Income Statement, and Liquidity. In general, the accounting and market mixed variables, such as debt-to-equity ratio (e.g. Annaert et al., 2013; Bai and Wu, 2016; Callen et al., 2009; Campbell et al., 2008; Cao et al., 2010; Tang and Yan, 2017), provide an important risk profile of an entity. The asset, liability, equity, and other ratios reflected from the balance sheet provide insights into an entity's financial stability and solvency, and the income statement items and ratios, such as the net income growth (e.g. Das et al., 2009), indicate the entity's overall financial performance. Therefore, these variables are essential in the pricing of CDS spread and the evaluation of default risk. Besides, the financial market items and ratios have significant effects on the market sentiment and the risk perception, thereby affecting firm's perceived riskiness and the CDS pricing. The liquidity measures, such as the difference between the 5-year and 1-year CDS spread (e.g. Lin et al., 2019), imply the market expectations and investors' sentiment and play an important role in determining the level of CDS spread.

[Table 1 is around here.]

Notably, although the impacts of systematic and firm-specific factors are orthogonal by our construction of the two-step regressions, the effect of the systematic factors may still spill over

[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.

onto the second-step regression via various channels of, e.g., cash flow, and financial constraints, as well as other relevant risk channels. Therefore, our construction of the first-step regression (Eq. (1)) captures the direct systematic impact while the second step of regression (Eq. (2)) also captures a certain degree of indirect systematic impact.

3.3 Data sources

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 in total 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 2.

[Table 2 is around here.]

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

3.4 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).

3.5 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 3 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 3 is around here.]

We repeat the procedure to detect whether there is multicollinearity in the systematic factors. The VIF results are reported in Panel B and it shows that all the factors are free of multicollinearity with VIFs between 1.06 and 2.86, well below our threshold of 7. Therefore, we demonstrate that all the systematic factors capture different aspects of information. Note that ΔAvgSpr used in the VIF analysis is the adjusted version as explained in Section 3.1.

After we address the missing values and multicollinearity issues, the final sample contains 40431 firm-month observations with 259 US non-financial firms.

4 Empirical Results

4.1 Systematic factor results

Panel A of Table 4 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 of Panel A), except for term spread, all other systematic factors are statistically significant in explaining the change of the CDS spreads in most (57.14% 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 average of the adjusted R^2's of the univariate regressions, we find that in general the endogenous systematic factors (i.e. AvgSpr, AvgSpr_R, and AvgSpr_S) have higher explanatory power than the exogenous systematic factors.

[Table 4 is around here.]

The signs of the averaged coefficients are as expected in the univariate result.[6] The exogenous systematic factors, default spread and VIX, are positively related to the changes of the CDS

[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. Results are available upon request.

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 of Panel B), 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. The co-movement between the individual CDS spreads and the peer CDS spreads also supports our previous discussion on how peer information channels to the pricing of the individual CDS spreads. Also, the adjusted R^2 in the multivariate systematic factor model is 35%, which is much higher than the ones in the univariate regressions; this indicates that 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. Econometrically, the unexplained parts of a regression are the constant term and the residual. While residual represents zero-mean white noises, the constant term captures the average of CDS spread changes outside the effect of systematic factors. Since in general the constant terms are small and weak in significance, this implies that the systematic factors can sufficiently explain the CDS spread changes.

We then test the predictability of the systematic factors. Panel B of Table 4 reports the regression results with systematic factors lagged by one month. In general, we find lower percentages of significance and weaker adjusted R^2's, indicating the systematic factors mostly capture the contemporary information and are weak in predictability. However, we still find that default spread and VIX have relatively strong predicting power. The percentage of the significance is 34.75% (multi) and 49.81% (uni) for default risk and 36.29% (multi) and 45.95% (uni) for VIX. Panel C reports the quartile of the coefficients.

As a robustness check, we repeat in Table (5) a panel regression on all systematic factors, controlling for firm fixed effect. The signs and individual significance are consistent with our previous results, except that term spread, VIX, and Treasury yield are insignificant at 5% level in the panel regression.

[Table 5 is around here.]

The sub-sample analysis for different sectors and ratings is provided in Table 6. We find that, in general, the percentages of the significance and the adjusted R^2's do not vary much among industry sectors and ratings. In the sub-period analyses, we find the adjusted R^2's are highest during the financial crisis period (see Column *InCrisis* in Table 6). We also report the sub-sample panel regression results in Table 7. In general the two sets of sub-sample results are qualitatively comparable. This further confirms that systematic factors are most pronounced in explaining CDS spread changes when the financial market is in turmoil.

[Tables 6 and 7 are around here.]

4.2 Firm-specific variable results

Panel A of Table 8 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 6 of the 28 firm-specific variables show statistical significance at 5% level in univariate regression for predicting the monthly change of the CDS spreads one month later, we find that only 4 variables can still exhibit statistical predictability in the multivariate setting. The results indicate that most firm-specific variables 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 low prediction performance is observed in a versatile set of the firm-specific variables.

[Table 8 is around here.]

Since there can be potential omitted variable bias when interpreting the results in univariate regressions, we focus on 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 – number of contributors to 5-year CDS quotes (CDSContr), Debt-to-Asset Ratio (DARatio), Market-to-Book Ratio (MBRatio), and underlying stock price (StoPrice) – are related to firm's accounting and market information as well as CDS liquidity. DARatio is constructed mainly by accounting items, Market-to-Book Ratio and StoPrice reflect investor's perception about firm's value, 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 information.

Three firm's fundamental variables are able to predict the monthly changes of the CDS spreads. DARatio represents firm's insolvency risk, with higher debt-to-asset ratio, the firm is more likely to default. Hence the change in the debt-to-asset ratio predicts the increase 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 DARatio and it turns out that only DERatio statistically explains the changes of the CDS spreads. Higher market-to-book ratio or stock price implies 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 (e.g. Vassalou and Xing, 2004), our result supports the importance of using stock price to capture the CDS price variation.

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 due to lower liquidity premium. On the other hand, we do not find other CDS liquidity measures, i.e. CDS Amihud, CDS high-minus-low, and CDS slope, to have predicting power for the CDS spread movement.

To conclude, our results suggest that very few firm-specific variables can predict CDS spread changes after we control for systematic factors, and R^2's in both the multivariate (5%) and univariate regressions (all around 5%) are low, which further support the viewpoint that firm-specific variables provide very limited predictability to CDS spread changes and they are not as important as indicated in the previous studies.

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 using contemporary firm-specific independent variables instead. The results are provided in Panel B of Table 8. We find that three firm-specific variables discussed above provide independent predictability; DARatio is replaced by DERatio in terms of explaining the contemporaneous changes of the CDS spreads at 5% level. The signs, except for CDSContr and MBRatio, are the same as those in the lagged analyses. Besides, a few more firm-specific variables are documented as significant in explaining the contemporaneous changes of the CDS spreads, CashRatio for example, which shows that corporate insolvency is important to determine the corporate default risk. Interestingly, we observe a positive coefficient on CASHMTA, indicating a positive relation between cash holding and CDS spread. This phenomenon is explained by firm's precautionary 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 relation between credit spread (implied by corporate bonds with various ratings) and firm's cash holding.

Our findings strengthen the importance of liquidity-related variables that individual firm's CDS spread is affected by CDS liquidity measures. This is consistent with the prior literature, such as Tang and Yan (2007) and Coró et al. (2013). It is also worth mentioning that the liquidity measures are not appeared in our systematic variables, and thus it is essential and within expectation to see their explanatory power in the variations of monthly changes of individual CDS spreads. Besides, 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 that is used as a proxy of the exact number of CDS quotes. Since not all 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 for CDS protection, pushing up the price of CDS contracts. Hence, we observe positive association between CDS contributors and CDS spread. It is worth noting that many significant firm-specific variables in Panels A and B of Table 8 are related to liquidity. It implies that CDS price change is likely affected by mostly reflect the change in trading activities.

Finally, we perform sub-sample analyses. Table 9 reports the multivariate regression results by sectors, ratings, and sub-periods. In general, we observe inconsistency in statistically significant variables. The first row counts the number of statistically significant firm-specific variables at 5% significance threshold. The numbers range from 1 to 4. It implies that the firm-specific variables fail to provide equivocal predictability. In sector analysis, we find 4 firm-specific variables can predict CDS spreads one month later for firms in Consumer Goods sector, while merely 1 firm-specific variable can provide predictability in most of the sectors. We find liquidity to have comparably consistent significance in CDS spread prediction. CDSContr and StoAmihud are statistically significant at 5% level in two different sectors (Consumer Goods and Healthcare for CDSContr and Materials and Consumer Goods for StoAmihud). The statistical significance from liquidity-related variables indicates that the monthly changes in CDS spread are likely affected by CDS market trading activities. However, we do not find a single firm-specific variable to be consistently statistically significant in all the sectors.

[Table 9 is around here.]

When we study the firm-specific predictability across ratings, we find the predictability is slightly related to credit quality. The worst rating CDS spreads are barely predictable by any firm-specific information, while firm's fundamental information predicts better in firms with better credit rating. Similarly, we find CDS liquidity variables demonstrate relatively better predictability. Three CDS liquidity variables – CDSAmihud, CDSHL and CDSContr – can predict the CDS spread changes in the sample of AA rating firms. Finally, in sub-period analyses, firm-specific variables have better predictability during the crisis, but after the 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 Healthcare is the highest among all sectors.

4.3 Additional results

In this section, we provide additional analyses on the systematic and firm-specific determinants of CDS spreads.

4.3.1 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 period is longer. We run a panel regression with firm-fixed effect for the quarterly changes of the CDS spreads for both contemporaneous and lagged effects by one quarter of the systematic factors.

Reported in Table 10, we show that the 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 even more pronounced in the quarterly dataset.

[Table 10 is around here.]

4.3.2 Systematic effect conditional on firm-specific variables

In our main analysis, we have shown the importance of systematic factors. Some may question whether the systematic factors remain significant when the two-step procedure is reversed, i.e. first regress the CDS spreads on the firm-specific variables, and then regress the unexplained part from the first step on the systematic factors.

We conduct the reversed exercise and the results are reported in Table 11. Panel A reports the time-series regressions of the systematic factors for each firms. We find the results are in general similar to the main regression results where the CDS spreads are used as dependent variables. The average adjusted R^2 is 20%, showing that systematic factors still capture a large portion of CDS spread changes which are not explained by the firm-specific variables. In the panel regression shown in Panel B, we confirm that the systematic factors are still statistically important. 7 out of 9 systematic factors are statistically significant at 5% level; only DftSpr and TB5Y are insignificant. Hence, we show that the systematic factors are still statistically significant to capture the variations of CDS spreads that cannot be explained by the firm-specific variables.

[Table 11 is around here.]

4.3.3 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 spread 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, therefore our argument on the firm-specific variables might be overstated.

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.[7] 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 12 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 still do not find substantial changes in the regression results between non-zero observations (Table 12) and full observations (Table 8). 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 5% to 6%; but, only 2 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 MBRatio remain statistically significant predictors. All in all we find that our arguments are not altered by zero observations.

[Table 12 is around here.]

[7]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.

4.3.4 Out-of-sample prediction

To better demonstrate how our findings in this paper can be applied in practice, we carry out the following out-of-sample analysis. Out-of-sample (OS) prediction uses only the data available up to the time at which the prediction is made. If the factors can predict out of sample, it implies CDS market participants are able to make use of the factors to predict the future movement of the CDS spreads, thereby evaluating investment strategies such as hedging firm's default risk.

To test the predictability of factor (X) on CDS spreads (C), we first perform a predictive time-series regression on a training sub-sample for each firm by:

$$\Delta \log(C_t^i) = \beta_0^i + \beta_1^i \, \Delta X_{t-1} + \varepsilon_t^i. \tag{3}$$

Then, the one-month-ahead prediction for the changes in the individual CDS spread can be calculated by the coefficient estimates from the previous step: $\hat{y}_{t+1}^i = \hat{\beta}_0^i + \hat{\beta}_1^i \, \Delta X_t$; and the OS error for time $t+1$ is defined as $(y_{t+1}^i - \hat{y}_{t+1}^i)$, where $y_{i,t+1}$ is the actual change in $\log CDS$ spreads in month $t+1$. With rolling OS errors from the OLS model, the OS performance is evaluated by the adjusted out-of-sample R^2:

$$Adj.\ OSR_i^2 = 1 - \frac{\sum_t (y_{i,t+1} - \hat{y}_{i,t+1})^2 / df_A}{\sum_t (y_{i,t+1} - \bar{y}_{i,t+1})^2 / df_N}, \tag{4}$$

where $\bar{y}_{i,t+1}$ is our benchmark predicted value and *df* is the degree of freedom for the corresponding null (N) or alternative (A) hypothesis. The null hypothesis is that our proposed model ($\hat{y}$) does not perform better than the benchmark ($\bar{y}$). A positive adjusted OSR^2 indicates that the model prediction has less prediction error than the benchmark prediction.

We select three different training periods: 1 year, 2 years, and 5 years to test the predictability of our systematic and firm-specific factors, separately. Recall that we have 9 systematic factors and 28 firm-specific factors, the OLS model may suffer from insufficient observations when we perform OS analysis. To avoid this problem, we use the first principal component (PC) of the systematic or firm-specific factors, instead of the full set of the factors. We also restrict firms to have at least 150 months of observations (i.e., over 75% of the whole sample period).[8] We consider two benchmarks: (1) Historical Average: this is calculated by the average changes in logarithm of CDS spreads over the training period; (2) Firm-specific Factor Prediction: the one-month-ahead prediction for the changes in the individual CDS spread using the first PC of the firm-specific factors.

Table 13 reports the out-of-sample performance of the CDS factors. This table reports the CDS systematic and firm-specific factor out-of-sample performance. Panels A, B, and C report the results for different training periods. Column 1 reports the Adj. OSR^2 statistic under the alternative hypothesis that systematic factors have better prediction against the null hypothesis that firm-specific factors have better prediction. The mean of the Adj. OSR^2's are 0.11 (12-month case), 0.05 (24-month case), and 0.03 (60-month case), respectively, indicating that systematic factors indeed better predict the individual CDS changes than firm-specific factors do one month ahead, but the superiority decreases when the training period increases. Column 2 (or 3) report the Adj. OSR^2 statistic for the systematic (or firm-specific) factors against the historical average. We find that systematic factors have slightly better prediction power than the historical average, while the firm-specific factors on average do not show better prediction power than the historical average. The results depict a consistent picture of a positive adjusted OSR^2 for systematic factors; hence the proposed CDS-specific systematic factors indeed improve time-series predictions for changes in individual spreads.

[Table 13 is around here.]

4.3.5 Other robustness checks

In the Online Appendix, we provide additional results. First, we test if our proposed endogenous CDS factors is affected by different weighting method. Here we reconstruct the total-, rating-, and sector-averaged CDS spreads weighted by firm's value. Reported in Model 1 of Table A.2, we show that the endogenous systematic factors are still positively related to individual CDSs. In addition, we also consider different construction method of endogenous systematic factors. Reported in Model 2 of Table A.2, the first principal component of the monthly variation of all the CDS spreads shows positive relation to individual CDSs. It indicates that the endogenous

[8] Firm number in the OS analysis is then reduced to 182 because of this restriction.

systematic factors are stronger and unaffected by weighting or construction methods.

Additionally, we provide a test on firm-specific factor identification. In the main test, the CDS spread variation is obtained by the unexplained part (i.e., $\Delta idio_{i,t} = \beta_0^i + \varepsilon_t^i$ in Equation (1)) of the individual time-series regressions on the systematic factors. Here we use the unexplained part from the panel regression on the systematic factors (denoted as $\Delta \widetilde{idio}_{i,t}$), and repeat Equation (2) to identify effective firm-specific factors. The results are reported in Table A.3. We show that, similar to the main results, the explanatory power of the firm-specific factors is rather limited with the adjusted R^2 being 9% (lagged) and 18% (contemporaneous), respectively. The slightly increased goodness of fit reflects that the residuals from the panel regression is somehow underperformed than our original proposal. The number of statistically significant firm-specific factors is slightly increased (from 9 to 14) for contemporaneous case while there is no change for lagged regression. Interestingly, we observe some members of the effective firm-specific factors have changed, implying the potentially inconsistent effectiveness of firm-specific factors on CDS spread variation after controlling for systematic factors.

Finally, we repeat our analyses with the variables in level, instead of change of CDS spread. The relevant results are reported from Tables A.4 to A.8. We find the results qualitatively the same. Overall, we find the explanatory power of systematic factors remains strong and most systematic factors remain statistically significant. The firm-specific variables are 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 also worth mentioning that although the R^2's are higher when adopting variables in level than variables in difference, the coefficient estimations are very sensitive, and considering the persistence of CDS spread with small variations over time, it would be more suitable to use the changes of CDS spread which helps avoid the problem of non-stationary in the time series.

5 Conclusion

In this paper, we study the factors which explain the monthly changes of the 5-year CDS spreads 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 a 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 9 systematic factors (including 6 exogenous and 3 endogenous systematic factors) 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 change. In addition, the significance in both exogenous and endogenous systematic factors indicates that individual corporate CDSs are affected by both the information from other financial markets and from 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 change apart from systematic factors, we regress the unexplained part from the CDS systematic factors on a comprehensive set of firm-specific variables. We find that most of the firm-specific variables exhibit insignificance on CDS variation predictability, and the overall predictability power (R^2) is also weak; only 4 firm-specific variables provide independent and predictive information for the monthly changes of the CDS spread and 6 additional firm-specific factors 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 thus cast doubt on the importance of the firm-specific CDS determinants.

Combining our findings altogether, we conclude that CDS variation is not dominantly determined by firm-specific information as suggested in prior studies; instead, systematic factors play a major important role in explaining individual CDS dynamics. Our argument is not altered with the additional robustness checks. Our findings shed light on the literature in the understanding of the importance of systematic factors and firm-specific variables to CDS spread variation. 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 or at least include the identified firm-specific variables in this study, in order to conclude unbiased results.

For future research, our work can be extended to the international scale. Interestingly, the mainstream studies on CDSs focus on U.S. firms and studies on CDS in other countries are relatively rare. Besides, the investigation on the impact of global factors on the corporate CDS is still under-explored. Another potential research direction is to explore the corporate CDSs with different currencies. Recently, there is an increasing interest in quanto CDS spread (i.e. CDS spread difference of the same underlying but in different currency denominations) in sovereign CDS market. Since quanto CDS spread contains currency exchange information, one could investigate the quanto spreads in corporate CDSs and see how it links to a firm's currency risk management.

Data Availability

All data used is obtained from third-party data providers. Data will be made available on request with the permission of the data providers.

Conflict of Interest

All authors declare that they have no conflicts of interest.

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Table 1: Firm-specific Variable Definitions

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

Variable	Definition	Relevant Literature
Panel A: Accounting and Market Mixed Items and Ratios		
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), Zhang et al. (2009).

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 2: 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 nine 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
GEPU	197	116.98	43.34	54.42	79.93	112.72	146.03	274.53
AvgSpr (bps)	197	165.80	81.22	65.97	115.04	153.95	197.43	677.08
AvgSpr_R (bps)								
i. AA Rating	184	58.74	42.62	24.11	28.99	36.57	83.69	230.61
ii. A Rating	197	51.40	19.75	19.58	39.84	50.68	58.62	126.73
iii. BBB Rating	197	118.51	71.11	52.44	78.14	98.52	124.82	517.69
iv. BB Rating	197	234.69	124.01	111.10	159.98	202.22	269.20	864.66
v. B Rating	197	370.07	204.46	136.66	251.51	322.26	446.36	1569.28
vi. C Rating	197	859.00	642.53	174.88	386.15	745.27	1052.32	5386.28
AvgSpr_S (bps)								
i. Basic Materials	197	155.07	132.94	50.14	102.42	134.79	158.39	796.57
ii. Consumer Goods	197	156.74	84.99	51.38	109.21	145.69	175.71	631.80
iii. Consumer Serv	197	277.28	241.06	113.74	185.24	221.44	288.51	2385.64
iv. Energy	197	179.01	228.39	43.73	91.14	127.71	168.85	2019.56
v. Healthcare	197	118.04	45.42	53.34	86.26	106.87	142.02	313.25
vi. Industrials	197	140.47	79.01	46.98	81.62	127.85	157.78	454.05
vii. Technology	197	160.00	95.99	53.24	107.57	129.47	175.60	679.56
viii. Telecom Serv	197	260.19	183.20	110.67	166.10	209.82	281.34	1792.02
ix. Utilities	197	115.01	98.80	33.34	65.91	85.92	122.36	695.18
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 (10^5)	37535	0.02	1.37	-127.44	0.01	0.02	0.04	33.80
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 3: Variable VIFs

This table reports the Variance Inflation Factor (VIF) analysis. The sample period is from January 2001 to June 2018. Panel A reports the VIF for the firm-specific variables. 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. Panel B reports the VIFs for the systematic factors.

Panel A: Firm-specific Variables

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

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Panel B: Systematic Factors

Variable	VIF
ΔDftSpr	1.06
ΔTrmSpr	1.19
ΔVIX	2.31
ΔSP500	2.86
ΔTB5Y	1.23
ΔGEPU	1.09
ΔAvgSpr	1.26
ΔAvgSpr_R	1.33
ΔAvgSpr_S	1.71

Table 4: CDS Systematic Factors

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. We perform time-series regressions for each firm. The dependent variable is the monthly change of the CDS spreads. We 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. Panel A reports the contemporaneous regression results and Panel B reports the lagged regression results. Panel C reports the coefficient quartiles for the multivariate regressions. In panels A and B, the right part reports the univariate regressions and the left part reports the univariate regressions. Newey-West t-statistics with 12-month lags is used for testing coefficient significance.

Panel A: Contemporaneous Regression

	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Adj.\ R^2}$
ΔDftSpr (t)	4.651	(37.45%)	26.864	(68.34%)	0.05
ΔTrmSpr (t)	0.171	(14.67%)	-6.374	(22.78%)	0.01
ΔVIX (t)	0.000	(13.13%)	0.009	(70.27%)	0.07
ΔSP500 (t)	-0.234	(21.24%)	-1.386	(79.92%)	0.13
ΔTB5Y (t)	-2.439	(20.08%)	-14.346	(70.66%)	0.06
ΔGEPU (t)	0.029	(13.13%)	0.120	(57.14%)	0.02
ΔAvgSpr (t)	0.139	(39.38%)	0.368	(64.09%)	0.11
ΔAvgSpr_R (t)	0.290	(64.48%)	0.414	(81.85%)	0.20
ΔAvgSpr_S (t)	0.316	(55.60%)	0.421	(59.46%)	0.16
Const	0.001	(5.02%)			
$\overline{Adj.\ R^2}$	0.35				

(continued to the next page)

Panel B: Lagged Regression

	Multivariate Regression		Univariate Regression		
	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Coef}$	$\%(p \leq 0.05)$	$\overline{Adj.\ R^2}$
ΔDftSpr (t-1)	10.323	(34.75%)	14.845	(49.81%)	0.02
ΔTrmSpr (t-1)	6.455	(33.59%)	5.183	(19.31%)	0.01
ΔVIX (t-1)	0.005	(36.29%)	0.006	(45.95%)	0.03
ΔSP500 (t-1)	0.086	(13.51%)	-0.484	(32.05%)	0.02
ΔTB5Y (t-1)	-1.508	(10.42%)	-0.231	(11.20%)	0.00
ΔGEPU (t-1)	-0.025	(14.29%)	0.015	(7.72%)	0.00
ΔAvgSpr (t-1)	0.037	(13.90%)	0.125	(27.03%)	0.01
ΔAvgSpr_R (t-1)	0.024	(11.97%)	0.070	(15.06%)	0.01
ΔAvgSpr_S (t-1)	0.064	(13.51%)	0.095	(24.71%)	0.01
Const	0.001	(3.47%)			
$\overline{Adj.\ R^2}$	0.05				

Panel C: Coefficient Quartiles

	Q25	Q50	Q75
Contemporaneous Regression			
ΔDftSpr	-5.445	4.219	13.249
ΔTrmSpr	-3.561	0.054	3.634
ΔVIX	-0.002	0.000	0.003
ΔSP500	-0.687	-0.170	0.242
ΔTB5Y	-7.389	-2.193	2.056
ΔGEPU	-0.013	0.024	0.066
ΔAvgSpr	-0.014	0.126	0.265
ΔAvgSpr_R	0.122	0.267	0.435
ΔAvgSpr_S	0.109	0.266	0.477
Lagged Regression			
ΔDftSpr	1.130	9.792	18.371
ΔTrmSpr	2.369	6.480	10.175
ΔVIX	0.001	0.005	0.009
ΔSP500	-0.327	0.053	0.428
ΔTB5Y	-5.398	-1.226	3.091
ΔGEPU	-0.073	-0.021	0.023
ΔAvgSpr	-0.038	0.040	0.099
ΔAvgSpr_R	-0.054	0.018	0.103
ΔAvgSpr_S	-0.015	0.048	0.133

Table 5: 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)	***6.483***
	[3.04]
ΔTrmSpr (t)	-0.079
	[-0.07]
ΔVIX (t)	0.000
	[0.55]
ΔSP500 (t)	***-0.331***
	[-2.15]
ΔTB5Y (t)	-2.641
	[-1.78]
ΔGEPU (t)	***0.051***
	[3.29]
ΔAvgSpr (t)	***0.073***
	[3.39]
ΔAvgSpr_R (t)	***0.313***
	[5.77]
ΔAvgSpr_S (t)	***0.139***
	[3.57]
Adj. R^2	0.24

Table 6: Sub-sample CDS Systematic Factors (Individual)

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)	8.311	8.839	1.611	21.656	1.308	2.268	-0.965	0.802	-0.493	1.640	1.040	9.279	7.477	-0.336	0.193	8.253	-2.374	-1.138
%($p \leq 0.05$)	(36.36%)	(40.00%)	(26.47%)	(61.90%)	(28.57%)	(37.25%)	(21.74%)	(27.27%)	(51.61%)	(26.47%)	(44.78%)	(29.31%)	(45.21%)	(31.58%)	(25.00%)	(16.83%)	(52.07%)	(20.58%)
ΔTrmSpr (t)	-0.468	0.481	-2.710	-6.328	3.290	2.568	1.324	0.680	0.643	-0.062	1.664	-2.404	-0.098	3.834	1.064	-2.000	-1.979	3.808
	(4.55%)	(13.33%)	(14.71%)	(33.33%)	(9.52%)	(17.65%)	(8.70%)	(54.55%)	(0.00%)	(5.88%)	(10.45%)	(18.97%)	(19.18%)	(15.79%)	(12.50%)	(22.28%)	(43.78%)	(18.52%)
ΔVIX (t)	-0.002	0.001	0.002	0.000	0.001	-0.001	0.000	0.002	0.000	-0.001	0.001	0.001	-0.001	-0.001	-0.001	0.004	0.003	-0.001
	(9.09%)	(11.11%)	(11.76%)	(23.81%)	(4.76%)	(9.80%)	(26.09%)	(18.18%)	(12.90%)	(5.88%)	(14.93%)	(10.34%)	(16.44%)	(10.53%)	(25.00%)	(18.81%)	(51.61%)	(8.64%)
ΔSP500 (t)	-0.571	-0.331	-0.452	-0.526	0.218	-0.364	0.027	0.412	0.064	-0.294	0.045	-0.162	-0.544	-0.271	0.067	0.414	0.777	-0.607
	(31.82%)	(22.22%)	(29.41%)	(28.57%)	(9.52%)	(17.65%)	(34.78%)	(9.09%)	(6.45%)	(17.65%)	(14.93%)	(17.24%)	(30.14%)	(31.58%)	(12.50%)	(19.31%)	(58.53%)	(30.04%)
ΔTB5Y (t)	-2.224	-3.536	-0.304	3.369	-4.460	-4.433	-2.922	-2.657	-2.188	-2.667	-3.500	-1.654	-1.668	-2.967	-4.046	-0.412	-2.725	-3.714
	(13.64%)	(15.56%)	(29.41%)	(9.52%)	(23.81%)	(23.53%)	(17.39%)	(27.27%)	(19.35%)	(11.76%)	(20.90%)	(17.24%)	(23.29%)	(21.05%)	(37.50%)	(15.84%)	(50.23%)	(16.05%)
ΔGEPU (t)	0.007	0.029	0.043	0.066	0.041	0.009	0.037	-0.002	0.031	0.038	0.018	0.037	0.029	0.040	-0.015	0.035	0.012	0.022
	(4.55%)	(13.33%)	(8.82%)	(33.33%)	(19.05%)	(11.76%)	(13.04%)	(0.00%)	(12.90%)	(20.59%)	(8.96%)	(15.52%)	(15.07%)	(5.26%)	(0.00%)	(15.84%)	(46.54%)	(17.28%)
ΔAvgSpr (t)	0.050	-0.048	-0.025	0.283	0.269	0.254	0.268	0.049	0.211	0.168	0.135	0.131	0.145	0.151	0.010	0.228	0.195	0.105
	(18.18%)	(8.89%)	(11.76%)	(71.43%)	(66.67%)	(58.82%)	(69.57%)	(9.09%)	(45.16%)	(38.24%)	(38.81%)	(37.93%)	(41.10%)	(42.11%)	(37.50%)	(42.57%)	(64.06%)	(30.45%)
ΔAvgSpr_R (t)	0.277	0.189	0.304	0.352	0.257	0.409	0.280	0.292	0.224	0.322	0.433	0.233	0.229	0.221	0.104	0.430	0.600	0.247
	(63.64%)	(33.33%)	(52.94%)	(90.48%)	(85.71%)	(80.39%)	(82.61%)	(45.45%)	(58.06%)	(70.59%)	(77.61%)	(51.72%)	(63.01%)	(57.89%)	(50.00%)	(52.48%)	(67.74%)	(62.96%)
ΔAvgSpr_S (t)	0.152	0.288	0.193	0.313	0.501	0.202	0.473	0.707	0.418	0.244	0.303	0.272	0.347	0.426	0.507	0.332	0.485	0.358
	(22.73%)	(55.56%)	(35.29%)	(76.19%)	(71.43%)	(47.06%)	(69.57%)	(63.64%)	(77.42%)	(58.82%)	(58.21%)	(51.72%)	(54.79%)	(63.16%)	(37.50%)	(46.53%)	(60.83%)	(46.50%)
Const	0.003	0.003	0.002	0.002	0.001	0.003	-0.003	-0.006	0.000	0.002	0.000	0.002	0.002	0.005	0.003	-0.006	0.016	0.004
	(4.55%)	(0.00%)	(2.94%)	(4.76%)	(9.52%)	(7.84%)	(8.70%)	(9.09%)	(3.23%)	(11.76%)	(1.49%)	(5.17%)	(4.11%)	(10.53%)	(0.00%)	(8.42%)	(45.16%)	(10.70%)
$\overline{Adj.\ R^2}$	0.26	0.31	0.36	0.53	0.37	0.35	0.38	0.41	0.31	0.34	0.37	0.29	0.37	0.40	0.42	0.31	0.59	0.36

Table 7: Sub-sample CDS Systematic Factors (Panel)

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. 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)																		
	Sector									Rating						Period		
	Materials	ConGoods	ConServices	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	PreCrisis	InCrisis	PostCrisis
ΔDftSpr (t)	***7.680***	***4.775***	6.202	***15.472***	4.857	***6.388***	2.108	***5.923***	4.013	***4.700***	3.532	***6.268***	***8.694***	***6.723***	5.852	10.661	-0001	0.871
	[3.65]	***[2.39]***	[1.88]	***[3.40]***	[1.82]	***[2.41]***	[0.99]	***[2.79]***	[1.63]	***[2.31]***	[1.12]	***[2.72]***	***[4.74]***	***[3.60]***	[1.69]	[1.65]	[-0.79]	[0.35]
ΔTrmSpr (t)	-0.087	-1.183	-0.327	-3.492	***3.076***	0.579	0.857	-0.016	1.118	-1.191	1.763	-1.677	-0.376	-0.024	***3.340***	-0.905	***-3.401***	3.478
	[-0.11]	[-0.76]	[-0.17]	[-1.56]	***[2.91]***	[0.42]	[0.49]	[-0.01]	[1.13]	[-1.11]	[1.18]	[-1.15]	[-0.31]	[-0.02]	***[3.32]***	[-1.06]	***[-2.32]***	[1.77]
ΔVIX (t)	***-0.002***	0.001	0.002	0.002	0.001	-0.000	-0.001	0.001	0.001	-0.000	0.001	0.001	-0.001	0.001	-0.000	***0.005***	***0.004***	-0.001
	[-2.06]	[0.71]	[1.47]	[1.30]	[1.32]	[-0.59]	[-0.64]	[1.73]	[1.08]	[-0.34]	[1.16]	[1.29]	[-0.85]	[1.35]	[-0.36]	***[2.36]***	***[4.51]***	[-1.04]
ΔSP500 (t)	***-0.491***	-0.246	***-0.518***	-0.244	0.006	***-0.453***	-0.223	-0.072	-0.006	***-0.287***	-0.218	-0.252	***-0.468***	-0.270	***-0.489***	0.192	***0.806***	***-0.728***
	[-3.00]	[-1.60]	***[-3.15]***	[-0.81]	[0.04]	***[-3.12]***	[-1.24]	[-0.63]	[-0.04]	***[-2.27]***	[-1.04]	[-1.68]	***[-3.29]***	[-1.84]	***[-2.93]***	[1.14]	***[8.14]***	***[-3.11]***
ΔTB5Y (t)	-1.854	-1.787	-2.679	0.764	***-6.134***	***-3.604***	-2.365	-1.701	***-2.508***	-1.868	***-4.429***	-1.412	-1.965	-0.730	***-4.425***	0.124	***-5.087***	-4.151
	[-1.49]	[-1.01]	[-1.15]	[0.30]	***[-3.41]***	***[-2.15]***	[-1.44]	[-0.81]	***[-2.40]***	[-1.37]	***[-2.77]***	[-0.82]	[-1.24]	[-0.62]	***[-2.61]***	[0.11]	***[-2.11]***	[-1.33]
ΔGEPU (t)	0.022	***0.038***	***0.059***	***0.118***	***0.047***	0.026	***0.047***	0.036	***0.060***	***0.057***	0.030	***0.055***	***0.060***	***0.057***	0.018	0.057	0.025	***0.048***
	[1.17]	***[2.44]***	***[2.45]***	***[4.74]***	***[2.66]***	[1.47]	***[2.13]***	[1.74]	***[3.36]***	***[4.19]***	[1.66]	***[3.07]***	***[3.78]***	***[3.07]***	[0.66]	[1.80]	[1.70]	***[4.47]***
ΔAvgSpr (t)	0.006	***-0.088***	-0.003	0.149	***0.069***	***0.085***	***0.177***	***-0.174***	***0.108***	***0.077***	***0.108***	0.056	***0.044***	***0.123***	0.055	***0.060***	***0.203***	0.069
	[0.38]	***[-2.75]***	[-0.06]	[1.80]	***[2.35]***	***[2.60]***	***[2.90]***	***[-3.13]***	***[2.10]***	***[2.23]***	***[2.82]***	[1.86]	***[3.03]***	***[4.05]***	[1.38]	***[3.44]***	***[5.21]***	[1.77]
ΔAvgSpr_R (t)	***0.292***	***0.163***	***0.270***	***0.312***	***0.223***	***0.324***	***0.330***	0.058	***0.271***	***0.394***	***0.467***	***0.258***	***0.251***	***0.290***	***0.223***	***0.436***	***0.679***	***0.239***
	[7.73]	***[4.65]***	***[3.29]***	***[4.51]***	***[3.85]***	***[5.03]***	***[6.32]***	[1.25]	***[4.08]***	***[5.92]***	***[4.69]***	***[6.55]***	***[6.20]***	***[6.20]***	***[3.85]***	***[6.04]***	***[8.70]***	***[4.93]***
ΔAvgSpr_S (t)	0.055	***0.232***	0.077	***0.172***	***0.327***	***0.087***	***0.209***	***0.131***	***0.233***	***0.108***	***0.174***	***0.146***	***0.110***	***0.184***	***0.143***	***0.109***	***0.329***	***0.149***
	[1.32]	***[3.75]***	[1.83]	***[2.42]***	***[3.99]***	***[2.77]***	***[4.04]***	***[2.47]***	***[2.67]***	***[2.95]***	***[3.63]***	***[3.30]***	***[3.47]***	***[3.88]***	***[2.32]***	***[3.73]***	***[6.68]***	***[2.61]***
Adj. R^2	0.20	0.25	0.25	0.40	0.25	0.25	0.26	0.20	0.23	0.27	0.31	0.20	0.22	0.26	0.19	0.18	0.45	0.25

Table 8: Firm-specific Variable Results

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 (ΔIdio (i,t)) and the independent variables are the firm-specific characteristics. Panel A reports the contemporaneous regression results and Panel B reports the lagged regression results. 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.

Panel A: Lagged Regression

	Multivariate Regression		Univariate Regression		
	Coef	*t*-stats	Coef	*t*-stats	Adj. R^2
ΔAsset(i,t-1)	-0.002	[-0.23]	-0.000	[-0.03]	0.05
ΔCASHMTA(i,t-1)	-0.009	[-0.73]	0.008	[1.55]	0.05
ΔCashRatio(i,t-1)	0.003	[0.25]	-0.000	[-0.09]	0.05
ΔCBCnt(i,t-1)	-0.000	[-0.04]	0.004	[0.41]	0.05
ΔCBPrice(i,t-1)	-0.002	[-0.33]	-0.001	[-0.11]	0.05
ΔCBVol(i,t-1)	0.007	[0.79]	0.007	[0.69]	0.05
ΔCDSAmihud(i,t-1)	0.005	[0.39]	-0.003	[-0.35]	0.05
ΔCDSHL(i,t-1)	-0.016	[-1.00]	-0.012	[-1.06]	0.05
ΔCDSSlope(i,t-1)	-0.006	[-0.79]	-0.006	[-0.81]	0.05
ΔCDSContr(i,t-1)	***-0.018***	***[-2.73]***	***-0.018***	***[-2.69]***	0.05
ΔDARatio(i,t-1)	***-0.014***	***[-2.20]***	-0.005	[-1.07]	0.05
ΔDERatio(i,t-1)	0.012	[0.97]	***0.023***	***[2.78]***	0.05
ΔEBIT(i,t-1)	-0.016	[-1.13]	***-0.012***	***[-2.08]***	0.05
ΔIntCover(i,t-1)	0.005	[0.48]	-0.009	[-1.68]	0.05
ΔInv2COGS(i,t-1)	-0.004	[-0.83]	-0.001	[-0.26]	0.05
ΔLiab(i,t-1)	0.006	[0.58]	0.002	[0.35]	0.05
ΔMBRatio(i,t-1)	***-0.013***	***[-1.98]***	***-0.025***	***[-4.22]***	0.05
ΔNIGrowth(i,t-1)	-0.001	[-0.13]	-0.005	[-0.99]	0.05
ΔNIMTA(i,t-1)	-0.014	[-1.05]	-0.008	[-1.16]	0.05
ΔRealVol(i,t-1)	-0.003	[-0.37]	0.001	[0.18]	0.05
ΔReEarning(i,t-1)	-0.007	[-0.82]	-0.007	[-0.95]	0.05
ΔROA(i,t-1)	0.013	[0.70]	-0.009	[-1.28]	0.05
ΔSaleGrowth(i,t-1)	-0.004	[-0.53]	-0.004	[-0.74]	0.05
ΔStoAmihud(i,t-1)	0.009	[1.47]	0.010	[1.63]	0.05
ΔStoMom(i,t-1)	0.009	[0.91]	***-0.017***	***[-2.14]***	0.05
ΔStoPrice(i,t-1)	***-0.029***	***[-2.25]***	***-0.034***	***[-3.79]***	0.05
ΔStoVol(i,t-1)	-0.005	[-0.62]	0.000	[0.09]	0.05
ΔWorkingCap(i,t-1)	0.007	[1.14]	0.003	[0.63]	0.05
Adj. R^2	0.05				

(continued to the next page)

Panel B: Contemporaneous Regression

	Coef	t-stats
ΔAsset(i,t)	-0.009	[-1.39]
ΔCASHMTA(i,t)	***0.026***	***[2.45]***
ΔCashRatio(i,t)	***-0.029***	***[-2.91]***
ΔCBCnt(i,t)	-0.007	[-0.75]
ΔCBPrice(i,t)	0.004	[0.41]
ΔCBVol(i,t)	0.010	[1.30]
ΔCDSAmihud(i,t)	0.011	[0.70]
ΔCDSHL(i,t)	***0.083***	***[2.54]***
ΔCDSSlope(i,t)	***0.151***	***[3.77]***
ΔCDSContr(i,t)	***0.036***	***[5.39]***
ΔDARatio(i,t)	-0.002	[-0.29]
ΔDERatio(i,t)	***0.022***	***[2.44]***
ΔEBIT(i,t)	-0.001	[-0.11]
ΔIntCover(i,t)	0.011	[0.85]
ΔInv2COGS(i,t)	-0.005	[-0.94]
ΔLiab(i,t)	-0.011	[-1.49]
ΔMBRatio(i,t)	***0.012***	***[1.99]***
ΔNIGrowth(i,t)	0.006	[1.26]
ΔNIMTA(i,t)	***-0.037***	***[-2.42]***
ΔRealVol(i,t)	0.009	[0.93]
ΔReEarning(i,t)	0.006	[0.62]
ΔROA(i,t)	0.022	[1.17]
ΔSaleGrowth(i,t)	0.001	[0.08]
ΔStoAmihud(i,t)	0.008	[1.24]
ΔStoMom(i,t)	0.010	[1.05]
ΔStoPrice(i,t)	***-0.091***	***[-6.26]***
ΔStoVol(i,t)	0.008	[0.93]
ΔWorkingCap(i,t)	0.005	[1.08]
Adj. R^2	0.09	

Table 9: 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
#($p \leq 0.05$)	**1**	**4**	**3**	**2**	**1**	**1**	**1**	**1**	**1**	**4**	**2**	**3**	**4**	**0**	**2**	**4**	**12**	**2**
ΔAsset (i,t-1)	-0.012	0.009	0.011	0.007	-0.030	-0.000	0.003	-0.020	0.048	0.013	-0.014	-0.011	0.002	0.022	-0.020	0.010	***-0.051***	-0.003
t-stats	[-0.42]	[0.52]	[0.57]	[0.25]	[-1.27]	[-0.01]	[0.14]	[-0.44]	[1.55]	[0.64]	[-0.97]	[-0.70]	[0.16]	[0.97]	[-0.39]	[1.01]	***[-3.09]***	[-0.28]
ΔCASHMTA(i,t-1)	-0.001	-0.003	***-0.056***	0.019	0.023	-0.011	0.038	-0.102	-0.020	-0.034	-0.008	-0.007	-0.009	-0.034	0.080	-0.039	0.036	-0.003
	[-0.03]	[-0.11]	***[-2.39]***	[0.61]	[0.71]	[-0.36]	[1.64]	[-1.89]	[-0.45]	[-1.18]	[-0.28]	[-0.32]	[-0.42]	[-0.98]	[1.33]	[-1.75]	[1.70]	[-0.22]
ΔCashRatio(i,t-1)	0.014	0.015	0.058	***-0.070***	-0.029	-0.003	-0.016	***0.203***	-0.011	0.010	0.017	-0.022	0.020	-0.016	-0.051	0.018	***-0.070***	0.006
	[0.40]	[0.61]	[1.78]	***[-2.85]***	[-0.84]	[-0.09]	[-0.54]	***[2.29]***	[-0.33]	[0.36]	[0.67]	[-1.11]	[0.78]	[-0.57]	[-0.98]	[1.06]	***[-2.73]***	[0.36]
ΔCBCnt(i,t-1)	0.039	0.005	0.015	0.023	-0.017	0.019	-0.031	0.100	-0.022	0.003	-0.019	0.027	-0.007	-0.025	-0.029	-	-	-0.003
	[0.86]	[0.40]	[0.36]	[0.44]	[-0.32]	[0.78]	[-1.61]	[1.07]	[-0.47]	[0.10]	[-1.05]	[0.80]	[-0.33]	[-0.73]	[-0.23]	-	-	[-0.29]
ΔCBPrice(i,t-1)	-0.052	0.006	-0.048	-0.081	0.047	0.021	-0.009	-0.037	0.065	0.018	0.024	-0.018	-0.034	-0.001	-0.078	-	-	-0.004
	[-1.89]	[0.45]	[-1.46]	[-1.71]	[1.59]	[1.26]	[-0.36]	[-1.03]	[1.92]	[0.62]	[1.15]	[-0.44]	[-1.75]	[-0.03]	[-1.10]	-	-	[-0.53]
ΔCBVol(i,t-1)	0.033	0.004	-0.009	-0.004	0.028	-0.002	0.018	-0.036	-0.017	0.051	0.030	-0.031	-0.009	0.019	***-0.219***	-	-	0.006
	[1.08]	[0.16]	[-0.23]	[-0.08]	[0.49]	[-0.12]	[0.61]	[-0.52]	[-0.42]	[1.06]	[1.80]	[-1.28]	[-0.45]	[0.53]	***[-2.17]***	-	-	[0.67]
ΔCDSAmihud(i,t-1)	0.017	0.021	0.009	0.028	0.000	-0.012	0.025	0.022	-0.040	***0.049***	-0.006	0.024	-0.001	-0.019	0.009	-0.020	0.076	0.001
	[0.43]	[0.98]	[0.41]	[1.26]	[0.01]	[-0.48]	[1.42]	[0.63]	[-1.84]	***[2.43]***	[-0.35]	[1.49]	[-0.05]	[-0.59]	[0.14]	[-1.65]	[1.56]	[0.09]
ΔCDSHL(i,t-1)	-0.039	-0.027	-0.036	-0.046	0.027	-0.015	-0.037	-0.043	***0.043***	***-0.054***	-0.028	-0.007	-0.003	0.006	-0.051	0.012	***-0.087***	0.006
	[-0.96]	[-0.95]	[-0.92]	[-1.91]	[1.06]	[-0.76]	[-1.45]	[-1.04]	***[2.12]***	***[-2.03]***	[-1.34]	[-0.43]	[-0.14]	[0.15]	[-0.88]	[0.74]	***[-3.96]***	[0.63]
ΔCDSSlope(i,t-1)	-0.042	0.007	-0.003	-0.038	0.016	-0.010	0.022	-0.038	-0.002	-0.005	0.019	-0.018	-0.017	-0.014	-0.022	0.005	0.018	***-0.018***
	[-1.79]	[0.47]	[-0.15]	[-1.84]	[0.85]	[-0.52]	[0.87]	[-0.91]	[-0.13]	[-0.30]	[1.66]	[-1.32]	[-1.00]	[-0.54]	[-0.59]	[0.55]	[1.78]	***[-2.14]***
ΔCDSContr(i,t-1)	-0.022	***-0.020***	0.000	-0.023	***-0.034***	-0.018	-0.005	-0.032	-0.025	***-0.038***	***-0.030***	***-0.021***	0.002	0.039	-0.040	***-0.023***	-0.023	-0.007
	[-1.26]	***[-2.02]***	[0.00]	[-0.96]	***[-2.21]***	[-1.21]	[-0.30]	[-0.87]	[-1.19]	***[-2.56]***	***[-2.99]***	***[-2.15]***	[0.16]	[1.94]	[-1.04]	***[-2.64]***	[-1.66]	[-0.94]
ΔDARatio(i,t-1)	-0.006	-0.028	-0.024	0.011	-0.015	-0.027	0.002	-0.031	0.005	-0.002	-0.010	-0.007	***-0.025***	-0.047	0.026	-0.021	-0.019	-0.014
	[-0.24]	[-1.34]	[-1.38]	[0.44]	[-0.56]	[-1.68]	[0.05]	[-0.38]	[0.16]	[-0.07]	[-0.71]	[-0.47]	***[-2.30]***	[-1.55]	[0.48]	[-1.86]	[-1.46]	[-1.93]
ΔDERatio(i,t-1)	-0.005	0.028	0.045	0.038	-0.031	0.036	***-0.062***	-0.034	-0.035	0.010	0.019	0.044	-0.019	0.039	-0.042	***0.042***	-0.039	***0.025***
	[-0.16]	[0.72]	[1.65]	[1.03]	[-0.76]	[1.01]	***[-2.60]***	[-0.31]	[-0.52]	[0.34]	[1.05]	[1.36]	[-1.08]	[0.78]	[-0.58]	***[3.10]***	[-1.88]	***[2.44]***
ΔEBIT(i,t-1)	-0.012	0.010	-0.033	0.004	-0.019	-0.035	-0.000	-0.145	-0.049	0.046	-0.001	***-0.070***	-0.031	0.019	***-0.260***	-0.008	***-0.100***	0.008
	[-0.20]	[0.42]	[-0.76]	[0.10]	[-0.49]	[-0.88]	[-0.01]	[-1.00]	[-0.64]	[1.24]	[-0.05]	***[-2.72]***	[-0.74]	[0.28]	***[-2.12]***	[-0.41]	***[-2.28]***	[0.58]
ΔIntCover(i,t-1)	0.023	-0.015	0.012	0.009	0.017	0.020	-0.040	0.022	0.080	***-0.037***	-0.000	0.039	0.021	0.011	0.205	0.001	***0.109***	-0.011
	[0.45]	[-0.66]	[0.41]	[0.32]	[0.39]	[0.68]	[-1.31]	[0.24]	[1.28]	***[-2.06]***	[-0.00]	[1.66]	[0.64]	[0.25]	[1.53]	[0.12]	***[6.25]***	[-0.85]
ΔInv2COGS(i,t-1)	0.027	0.006	0.015	0.006	0.028	-0.018	-0.006	-0.064	-0.034	0.005	-0.002	-0.005	-0.003	-0.007	0.016	-0.001	***-0.025***	-0.006
	[1.04]	[0.42]	[0.67]	[0.24]	[1.18]	[-1.12]	[-0.34]	[-1.53]	[-1.78]	[0.30]	[-0.16]	[-0.54]	[-0.29]	[-0.21]	[0.44]	[-0.13]	***[-4.55]***	[-0.99]
ΔLiab(i,t-1)	-0.015	-0.008	0.025	-0.039	-0.009	0.025	0.056	-0.089	-0.001	-0.015	-0.027	0.009	***0.048***	0.025	0.089	0.002	0.016	-0.002
	[-0.39]	[-0.31]	[1.11]	[-1.32]	[-0.28]	[0.86]	[1.35]	[-1.78]	[-0.02]	[-0.79]	[-1.52]	[0.39]	***[2.29]***	[0.62]	[0.93]	[0.08]	[0.54]	[-0.20]
ΔMBRatio(i,t-1)	0.028	-0.018	0.011	0.038	0.006	***-0.052***	-0.001	0.028	0.030	-0.032	-0.021	0.012	-0.017	0.028	-0.079	-0.004	-0.017	-0.010
	[0.87]	[-0.96]	[0.53]	[0.94]	[0.13]	***[-2.10]***	[-0.03]	[0.65]	[0.83]	[-1.33]	[-1.30]	[0.87]	[-1.22]	[1.21]	[-1.59]	[-0.36]	[-0.83]	[-1.49]
ΔNIGrowth(i,t-1)	-0.003	0.000	0.021	0.012	-0.002	0.005	-0.016	-0.036	0.004	-0.011	-0.007	0.003	0.002	-0.005	-0.015	0.002	***-0.023***	0.003
	[-0.28]	[0.02]	[1.46]	[0.93]	[-0.11]	[0.43]	[-0.76]	[-1.23]	[0.24]	[-0.56]	[-0.52]	[0.19]	[0.21]	[-0.23]	[-0.41]	[0.17]	***[-1.99]***	[0.37]
ΔNIMTA(i,t-1)	-0.007	***-0.059***	0.035	-0.000	-0.014	0.004	-0.087	0.005	0.047	0.043	0.033	-0.047	-0.006	-0.116	0.109	-0.009	***-0.053***	0.012
	[-0.16]	***[-2.36]***	[1.60]	[-0.01]	[-0.35]	[0.10]	[-1.92]	[0.08]	[1.15]	[0.68]	[0.74]	[-1.94]	[-0.29]	[-1.78]	[1.46]	[-0.61]	***[-2.17]***	[0.78]
ΔRealVol(i,t-1)	-0.028	0.017	-0.041	-0.015	-0.018	0.004	0.035	-0.001	-0.016	-0.044	0.008	-0.021	0.000	-0.021	0.039	-0.008	***0.029***	-0.010
	[-1.03]	[0.82]	[-1.82]	[-0.45]	[-0.73]	[0.16]	[0.90]	[-0.02]	[-0.56]	[-1.52]	[0.52]	[-0.89]	[0.00]	[-0.64]	[0.63]	[-1.11]	***[3.09]***	[-0.89]
ΔReEarning(i,t-1)	-0.024	-0.016	0.020	***-0.056***	-0.026	0.011	0.043	-0.085	0.007	0.017	***-0.027***	-0.007	0.011	0.011	0.108	***-0.022***	-0.040	0.004
	[-0.91]	[-0.84]	[1.08]	***[-2.24]***	[-1.04]	[0.44]	[1.34]	[-1.31]	[0.28]	[0.78]	***[-2.27]***	[-0.39]	[0.69]	[0.31]	[1.10]	***[-1.99]***	[-1.65]	[0.57]
ΔROA(i,t-1)	-0.011	0.036	-0.034	-0.006	-0.020	-0.011	0.088	0.114	-0.055	-0.078	-0.032	***0.070***	0.010	0.054	-0.069	0.005	0.076	-0.031
	[-0.26]	[1.58]	[-0.91]	[-0.10]	[-0.40]	[-0.23]	[1.73]	[0.80]	[-1.00]	[-1.14]	[-0.60]	***[2.24]***	[0.41]	[0.76]	[-0.70]	[0.28]	[1.29]	[-1.34]
ΔSaleGrowth(i,t-1)	0.027	0.012	-0.006	-0.037	0.007	-0.009	-0.026	-0.049	-0.015	0.017	-0.002	0.014	***-0.025***	-0.019	-0.045	0.006	***-0.049***	-0.003
	[1.08]	[0.79]	[-0.33]	[-1.69]	[0.32]	[-0.47]	[-1.21]	[-1.31]	[-0.59]	[0.77]	[-0.13]	[1.01]	***[-1.98]***	[-0.86]	[-1.01]	[0.41]	***[-4.95]***	[-0.35]
ΔStoAmihud(i,t-1)	***0.041***	***0.026***	-0.013	-0.003	-0.011	-0.002	0.013	0.003	-0.009	0.020	-0.006	0.007	0.006	0.011	0.024	***[0.01]***	[0.03]	-0.007
	[2.21]	***[2.19]***	[-0.80]	[-0.12]	[-0.46]	[-0.17]	[0.63]	[0.07]	[-0.61]	[1.19]	[-0.71]	[0.52]	[0.48]	[0.45]	[0.53]	***[2.49]***	[1.20]	[-0.50]
ΔStoMom(i,t-1)	-0.009	***0.039***	0.011	0.028	0.047	-0.001	0.000	-0.026	-0.017	0.022	0.013	-0.010	0.015	0.026	-0.030	0.007	-0.011	0.014
	[-0.26]	***[2.49]***	[0.41]	[0.81]	[1.59]	[-0.05]	[0.00]	[-0.42]	[-0.58]	[0.85]	[0.80]	[-0.51]	[0.97]	[0.87]	[-0.51]	[0.37]	[-0.70]	[1.45]
ΔStoPrice(i,t-1)	-0.058	-0.035	***-0.081***	-0.068	-0.084	0.040	-0.016	-0.055	-0.085	-0.018	-0.009	-0.015	***-0.064***	-0.020	-0.052	-0.044	***-0.049***	-0.003
	[-1.49]	[-1.45]	***[-2.59]***	[-0.96]	[-1.74]	[1.66]	[-0.49]	[-0.64]	[-1.00]	[-0.60]	[-0.41]	[-0.39]	***[-2.97]***	[-0.40]	[-0.65]	[-1.53]	***[-2.35]***	[-0.25]
ΔStoVol(i,t-1)	-0.011	0.013	***-0.065***	-0.039	-0.045	-0.014	0.022	-0.005	0.015	-0.064	-0.015	-0.005	0.020	-0.009	0.037	0.002	***0.033***	-0.016
	[-0.41]	[0.58]	***[-2.53]***	[-0.97]	[-1.69]	[-0.48]	[0.64]	[-0.13]	[0.62]	[-1.86]	[-0.91]	[-0.25]	[1.50]	[-0.23]	[0.62]	[0.19]	***[2.07]***	[-1.81]
ΔWorkingCap(i,t-1)	-0.000	-0.024	0.014	-0.005	0.007	0.014	0.019	-0.036	0.031	-0.004	0.004	0.010	0.006	0.013	0.024	0.015	0.017	-0.000
	[-0.02]	[-1.77]	[0.55]	***[-0.24]***	[0.20]	[0.57]	[0.95]	[-0.76]	[1.54]	[-0.24]	[0.44]	[0.78]	[0.43]	[0.59]	[0.48]	[1.39]	[0.99]	[-0.06]
Adj. R^2	0.12	0.13	0.11	0.15	0.19	0.10	0.12	0.16	0.17	0.09	0.09	0.07	0.06	0.12	0.29	0.06	0.09	0.04

Table 10: 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	***5.996***	***4.175***
	[3.28]	***[2.73]***
ΔTrmSpr	***2.789***	***4.670***
	[2.56]	***[3.13]***
ΔVIX	0.000	***0.006***
	[0.04]	***[7.06]***
ΔSP500	-0.100	0.187
	[-0.74]	[1.11]
ΔTB5Y	***-3.056***	-1.346
	[-2.90]	[-0.68]
ΔGEPU	***0.092***	0.056
	[4.58]	[1.18]
ΔAvgSpr	***0.099***	***0.081***
	[4.13]	***[4.66]***
ΔAvgSpr_R	***0.455***	***0.317***
	[8.74]	***[8.18]***
ΔAvgSpr_S	***0.146***	***0.114***
	[3.64]	***[3.81]***
Adj. R^2	0.36	0.26

Table 11: 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 spread changes on firm-specific variables, and obtain the regression residuals (denoted as ΔIdio*). Then we regress the residuals (from the previous step) on the systematic factors. Panel A reports the results for time-series regression; Panel B reports the results for panel regression, controlled for firm fixed effect. 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)			
Panel A: TS Reg		Panel B: Panel Reg	
	Coef. / %($p \leq 0.05$)		*Coef.* / [t-stat]
ΔDftSpr (t)	1.841	ΔDftSpr (t)	0.060
%($p \leq 0.05$)	(15.12%)	[t-stat]	[0.05]
ΔTrmSpr (t)	-2.363	ΔTrmSpr (t)	***-9.012***
	(30.23%)		***[-5.86]***
ΔVIX (t)	-0.001	ΔVIX (t)	***-0.001***
	(12.79%)		***[-3.02]***
ΔSP500 (t)	0.186	ΔSP500 (t)	***0.412***
	(16.28%)		***[5.56]***
ΔTB5Y (t)	-1.623	ΔTB5Y (t)	0.244
	(12.79%)		[0.38]
ΔGEPU (t)	-0.000	ΔGEPU (t)	***-0.000***
	(8.14%)		***[-2.33]***
ΔAvgSpr (t)	0.237	ΔAvgSpr (t)	***0.598***
	(59.88%)		***[19.95]***
ΔAvgSpr_R (t)	0.184	ΔAvgSpr_R (t)	***0.382***
	(62.79%)		***[27.83]***
ΔAvgSpr_S (t)	0.276	ΔAvgSpr_S (t)	***0.554***
	(69.19%)		***[21.45]***
Constant	-0.001		
	(5.81%)		
Adj. R^2	0.20	Adj. R^2	0.15

Table 12: 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)	-0.010	[-1.07]
ΔCASHMTA(i,t-1)	0.009	[0.66]
ΔCashRatio(i,t-1)	-0.011	[-0.69]
ΔCDSAmihud(i,t-1)	-0.001	[-0.08]
ΔCDSHL(i,t-1)	-0.018	[-1.06]
ΔCDSSlope(i,t-1)	-0.016	[-1.77]
ΔCDSContr(i,t-1)	***-0.024***	***[-2.73]***
ΔDARatio(i,t-1)	-0.009	[-0.99]
ΔDERatio(i,t-1)	0.007	[0.41]
ΔEBIT(i,t-1)	-0.028	[-1.57]
ΔIntCover(i,t-1)	0.016	[0.99]
ΔInv2COGS(i,t-1)	-0.005	[-0.94]
ΔLiab(i,t-1)	0.006	[0.50]
ΔMBRatio(i,t-1)	***-0.024***	***[-2.30]***
ΔNIGrowth(i,t-1)	0.004	[0.58]
ΔNIMTA(i,t-1)	0.003	[0.36]
ΔRealVol(i,t-1)	0.011	[0.97]
ΔReEarning(i,t-1)	-0.003	[-0.28]
ΔSaleGrowth(i,t-1)	-0.007	[-0.65]
ΔStoAmihud(i,t-1)	-0.001	[-0.07]
ΔStoMom(i,t-1)	0.011	[1.17]
ΔStoPrice(i,t-1)	-0.013	[-0.92]
ΔStoVol(i,t-1)	0.004	[0.40]
ΔWorkingCap(i,t-1)	0.006	[0.77]
Adj. R^2	0.06	

Table 13: Factor OS Prediction

This table reports the CDS systematic and firm-specific factor out-of-sample performance. Panels A, B, and C report the results for 12, 24, and 60 months of training periods, respectively. Column 1 reports the Adj. OSR^2 statistic that systematic factors have better prediction against firm-specific factors. Columns 2 (or 3) report the Adj. OSR^2 statistic which shows that systematic (or firm-specific) factors have better prediction against historical average of CDS spread changes.

	Adj. OSR^2		
Tested Strategy:	Sys. Ft.	Sys. Ft.	Firm Ft.
Benchmark Strategy:	Firm Ft.	Hist. Avg.	Hist. Avg.
Panel A: 12-month Training Period			
Mean	0.11	0.01	-0.18
STD	0.15	0.06	0.53
Max	0.82	0.27	0.16
Min	-0.13	-0.16	-4.89
Panel B: 24-month Training Period			
Mean	0.05	0.02	-0.08
STD	0.11	0.06	0.62
Max	0.89	0.16	0.12
Min	-0.16	-0.20	-7.95
Panel C: 60-month Training Period			
Mean	0.03	0.01	-0.07
STD	0.14	0.10	0.72
Max	0.91	0.20	0.15
Min	-0.92	-0.90	-9.48