

Corporate credit default swap systematic factors

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Abstract

We examine a comprehensive set of systematic and firm-specific determinants of the credit default swap (CDS), using a two-step approach to explore the factor's effect on CDS spread changes. We show that systematic factors are important and account for the most changes in the CDS spreads (with average R^2 of 35%), while firm-specific factors are limited (with R^2 of 5% in panel regression) with only 4 out of 28 firm-specific factors being significant. It implies that the systematic factors are overlooked in the literature, and they can provide many implications for practitioners in CDS pricing and the firm's credit risk management.

KEYWORDS

CDS determinants, CDS firm-specific factors, CDS systematic factors, credit default swap, credit risk

JEL CLASSIFICATION

G12, G13, G23

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 its 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 is crucial to investors (see, e.g., Duffie & 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,

¹In 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 likelihood 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.

²Houweling and Vorst (2005) compared the model prices and the market prices of CDS spread and concluded 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.

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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 noncredit information, such as illiquidity (Tang & Yan, 2007) and transaction cost (Coró et al., 2013), is 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 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 concerns.

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, for example, bond market factor (Blanco et al., 2005), or endogenous, for example, 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 comprehensively investigate 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., Conrad et al., 2020; Doshi et al., 2013; Norden & Weber, 2004, 2009), 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 the comovement in these financial markets implies that the pricing of the individual CDSs is affected by certain market conditions. Although these strong comovements have also been documented in prior studies (Forte & Pena, 2009; Norden & Weber, 2009), they have only been examined at aggregated levels (e.g., CDS index or portfolios).

Although a few studies (e.g., Doshi et al., 2013; Hammoudeh et al., 2013; Norden & Weber, 2009) have identified 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 the entity level. In this study, we fill the gap in this strand of literature by providing a thorough investigation into the importance of systematic determinants of CDS spreads.

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

³In Supporting Information 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.

For the second research question, we regress the component unexplained by the systematic factors on a set of CDS firm-specific factors identified in the 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 into 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 is 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 examining a total of 259 US nonfinancial firms over the sample period of January 2001–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. These results are consistent in the subsamples.
- 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 1 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 & Hanouna, 2009; Lin et al., 2019). Having said that, merely one-third of the firm-specific variables included in this study show statistical significance, casting 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 subperiod 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 modeling implied default probability, particularly for the firms with untraded or highly illiquid CDS contracts (therefore they have limited trading information from the market). Our approach would also be a simple but useful way of estimating the necessary risk capital to meet the requirements under the Basel framework regarding counterparty credit risk.

Overall, our study contributes to the understanding in CDS in two ways. First, 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 underexplored in the CDS literature. Prior studies have conducted comparison among different types of firm-specific information, for example, market-based versus 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, for example, 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 data set. Section 4 presents empirical results, and Section 5 concludes.

2 | LITERATURE ON CDS DETERMINANTS

Our study is linked to several strands of CDS literature. Following the seminal study of Merton (1974) regarding the corporate default risk and other early studies of CDS pricing model mostly emerged in the 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 stemmed from the model imperfection and the measurement error, and the short-term deviation 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 intraday 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, for example, earning surprise (Callen et al., 2009), counterparty credit risk (Arora et al., 2012), CDS demand-supply imbalance (Tang & Yan, 2017), and bank-specific information (Chiaromonte & Casu, 2013; Coudert & 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 comovement 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 2 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 credit default swap (CDX) index subtracted by expected loss, and document that macroeconomic factors, for example, inflation, monetary policy, and global collateralized debt obligation issuance, affect the premium, indicating that investor's risk aversion is also priced. Anderson (2017) find that CDS comovement 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, for example, CDX (Amato, 2005) and iTraxx (Alexander & Kaeck, 2008), or CDS portfolio, for example, 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. First, 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 comovement 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 & 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 $i = 1, 2, \dots, N$):

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

where C_t^i is the CDS spread for firm i and \mathbf{X}_t^s is a set of systematic factors and Δ represents the monthly changes of \mathbf{X}_t^s . 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. US 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 & 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 included 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, for example, the 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 comove 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, 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 $\text{AvgSpr}^* = \text{AvgSpr} - \text{AvgSpr}_R - \text{AvgSpr}_S + \text{AvgSpr}_{RS}$, 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 comovement with their peer, and that the magnitude of comovement 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 subperiod regressions (before, during, and after the crisis) as described in Equation (1).

⁴GEPU 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.

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:

$$\Delta\text{Idio}_{it+1} = \gamma_0 + \gamma_1 \Delta\mathbf{X}_{it}^f + \zeta_{it}, \quad (2)$$

where ΔIdio_{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 heteroskedasticity-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, that is, 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 & Wu, 2016; Callen et al., 2009; Campbell et al., 2008; Cao et al., 2010; Tang & 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 in 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- 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.

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

3.3 | Data sources

Data used in this study are collected from multiple sources. CDS data are 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 are 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.

⁵As different studies may have a slightly different definition 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.

TABLE 1 Firm-specific variable definitions.

Variable	Definition	Relevant literature
<i>Panel A: Accounting and market mixed items and ratios</i>		
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), and 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) and 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) and 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), and 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), and Pires et al. (2015)
<i>Panel B: Balance sheet items and ratios</i>		
Asset	The natural logarithm of firm's total asset value.	Anderson (2017), Das et al. (2009), Mayordomo et al. (2014), and Tang and Yan (2017)
CARatio	Cash-to-Asset Ratio, defined as cash equivalent assets divided by total asset.	Anderson (2017), Das et al. (2009), and Tang and Yan (2017)
CashRatio	Cash Ratio, defined as cash equivalent assets divided by total liability.	Anderson (2017), Das et al. (2009), and Tang and Yan (2017)
DARatio	Debt-to-Asset Ratio, defined as total debt divided by total asset.	Anderson (2017), Bai and Wu (2016), and 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) and 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)
<i>Panel C: Financial market items and ratios</i>		
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), and 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), and Pires et al. (2015)

(Continues)

TABLE 1 (Continued)

Variable	Definition	Relevant literature
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), Blanco et al. (2005), 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), and 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), and Zhang et al. (2009)
<i>Panel D: Income statement items and ratios</i>		
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), and Das et al. (2009)
SaleGrowth	Sale Growth, calculated as the quarterly changes in sales divided by its current amount.	Das et al. (2009)
<i>Panel E: Liquidity measures</i>		
StoAmihud	The Amihud (2002) measure of the underlying stock over 1 year.	Das et al. (2009) and Lin et al. (2019)
CDSAmihud	The Amihud (2002) measure of the CDS spreads over 1 year.	Lin et al. (2019)
CDSHL	The high-minus-low of the 5-year CDS spread over 1 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)

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

Abbreviation: CDS, credit default swap.

The data of 259 US nonfinancial 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.

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

TABLE 2 Descriptive statistics.

Variables	#Observations	Mean	SD	Minimum	25%	50%	75%	Maximum
<i>Panel A: Systematic factors</i>								
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
<i>AvgSpr_R (bps)</i>								
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
<i>AvgSpr_S (bps)</i>								
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 Services	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
<i>Panel B: Firm-specific variables</i>								
Asset	37,676	23.37	1.22	19.54	22.53	23.41	24.21	26.82
CARatio	37,676	0.09	0.10	0.00	0.02	0.06	0.12	0.73
CASHMTA	37,535	0.01%	0.03%	0.00%	0.00%	0.01%	0.01%	0.82%
CashRatio	36,212	0.45	0.63	0.00	0.11	0.26	0.54	9.05
CBCnt	12,338	2.92	1.38	0.00	1.95	2.94	3.90	7.54
CBPrice	12,227	0.03	0.03	-0.88	0.02	0.03	0.04	0.87
CBVol	12,338	14.64	2.25	0.00	13.30	14.97	16.23	20.35
CDSAmihud	40,306	0.00	0.00	0.00	0.00	0.00	0.00	0.10
CDSHL	40,585	0.00	0.02	0.00	0.00	0.00	0.00	1.48
CDSSlope	38,993	0.00	0.01	-0.73	0.00	0.00	0.01	0.10
CDSContr	41,044	6.35	3.92	2.00	3.00	5.00	8.00	30.00
DARatio	37,299	0.31	0.16	0.00	0.20	0.29	0.39	1.90
DERatio	37,164	0.00	0.00	0.00	0.00	0.00	0.00	0.11

(Continues)

TABLE 2 (Continued)

Variables	#Observations	Mean	SD	Minimum	25%	50%	75%	Maximum
EBIT	37,043	0.01	0.01	-0.13	0.00	0.01	0.01	0.19
IntCover	36,938	22.30	401.36	-211.79	2.59	5.80	12.25	28,934.20
Inv2COGS	37,103	2.34	2.60	-0.33	0.79	1.81	2.86	49.21
Liab	37,670	0.66	0.19	0.14	0.54	0.65	0.76	2.32
LLB	36,071	0.00	0.00	0.00	0.00	0.00	0.00	0.09
MBRatio (10 ⁵)	37,535	0.02	1.37	-127.44	0.01	0.02	0.04	33.80
MktCap	38,634	30.06	1.49	24.42	28.99	30.12	31.03	34.45
NIGrowth	37,283	0.25	41.26	-821.00	-0.47	-0.04	0.31	4274.33
NIMTA	37,526	0.00	0.00	0.00	0.00	0.00	0.00	0.00
QuickRatio	36,101	1.59	0.86	0.20	1.03	1.38	1.91	10.66
RealVol	35,225	0.29	0.23	0.06	0.17	0.23	0.33	6.49
ReEarning	36,945	0.25	0.42	-3.07	0.09	0.27	0.45	2.07
ROA	37,661	0.00	0.01	-0.14	0.00	0.00	0.01	0.18
SaleGrowth	37,289	0.02	0.20	-0.82	-0.05	0.01	0.08	5.55
StoAmihud	38,404	0.00	0.01	0.00	0.00	0.00	0.00	0.24
StoMom	35,225	0.04	0.35	-2.98	-0.10	0.07	0.22	4.58
StoPrice	38,634	3.61	0.82	-2.98	3.20	3.73	4.14	6.87
StoVol	31,356	0.22	0.35	-2.01	0.06	0.25	0.43	1.71
TLMTA	37,535	0.00	0.00	0.00	0.00	0.00	0.00	0.14
WorkingCap	36,101	0.11	0.14	-0.62	0.00	0.09	0.20	0.77

Note: 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.

Abbreviations: CDS, credit default swap; CDSHL, CDS high-minus-low; EBIT, Earning Before Interest and Tax; GEP, Global Economic Policy Uncertainty; NIMTA, net income divided by market value of asset; ROA, Return of Asset; SP500, Standard and Poor's 500; TLMTA, total liabilities divided by market value of asset; VIX, volatility index.

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 & 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 & 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 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, that is, CARatio, LLB, MktCap, QuickRatio, and TLMTA, the average VIF is 2.51, with the maximum value of 6.99 (Return of Asset [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.

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 40,431 firm-month observations with 259 US nonfinancial 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%–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.

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 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 comovement among the CDS contracts.

In the multivariate result (left of Panel A), 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 comovement 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.

⁶The 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.

TABLE 3 Variable VIFs.

Panel A: Firm-specific variables		
Variable	Initial VIF	Final VIF
Δ Asset	1.78	1.52
Δ CARatio	8.81	Dropped
Δ CASHMTA	5.54	3.30
Δ CashRatio	7.57	3.43
Δ CBCnt	1.89	1.89
Δ CBPrice	1.01	1.01
Δ CBVol	1.89	1.89
Δ CDSAmihud	1.60	1.60
Δ CDSHL	1.61	1.61
Δ CDSslope	1.02	1.02
Δ CDSContr	1.01	1.01
Δ DARatio	2.99	1.97
Δ DERatio	11.87	3.79
Δ EBIT	5.89	5.88
Δ IntCover	4.31	4.31
Δ Inv2COGS	1.35	1.34
Δ Liab	3.34	2.70
Δ LLB	16.81	Dropped
Δ MBRatio	2.50	2.31
Δ MktCap	17.24	Dropped
Δ NIGrowth	1.24	1.24
Δ NIMTA	5.27	5.20
Δ QuickRatio	9.41	Dropped
Δ RealVol	1.95	1.94
Δ ReEarning	2.01	1.98
Δ ROA	7.06	6.99
Δ SaleGrowth	1.47	1.47
Δ StoAmihud	1.06	1.06
Δ StoMom	1.73	1.73
Δ StoPrice	13.46	4.57
Δ StoVol	1.93	1.93
Δ TLMTA	29.16	Dropped
Δ WorkingCap	7.86	1.66
Panel B: Systematic factors		
Variable		VIF
Δ DftSpr		1.06
Δ TrmSpr		1.19
Δ VIX		2.31

TABLE 3 (Continued)

Panel B: Systematic factors	
Variable	VIF
Δ SP500	2.86
Δ TB5Y	1.23
Δ GEPU	1.09
Δ AvgSpr	1.26
Δ AvgSpr_R	1.33
Δ AvgSpr_S	1.71

Note: 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.

Abbreviations: CDS, credit default swap; CDSHL, CDS high-minus-low; EBIT, Earning Before Interest and Tax; GEPU, Global Economic Policy Uncertainty; NIMTA, net income divided by market value of asset; ROA, Return of Asset; SP500, Standard and Poor's 500; TLMTA, total liabilities divided by market value of asset; VIX, volatility index.

We then test the predictability of the systematic factors. Panel B of Table 4 reports the regression results with systematic factors lagged by 1 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.

The subsample 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 subperiod 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 subsample panel regression results in Table 7. In general the two sets of subsample 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.

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, Δ Idio_{it}. Although 6 of the 28 firm-specific variables show statistical significance at a 5% level in univariate regression for predicting the monthly change of the CDS spreads 1 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.

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

TABLE 4 CDS systematic factors.

Panel A: Contemporaneous regression					
	Multivariate regression		Univariate regression		
	<i>Coef</i>	% ($p \leq 0.05$)	<i>Coef</i>	% ($p \leq 0.05$)	<i>Adjusted R²</i>
$\Delta DftSpr(t)$	4.651	(37.45%)	26.864	(68.34%)	0.05
$\Delta TrmSpr(t)$	0.171	(14.67%)	-6.374	(22.78%)	0.01
$\Delta VIX(t)$	0.000	(13.13%)	0.009	(70.27%)	0.07
$\Delta SP500(t)$	-0.234	(21.24%)	-1.386	(79.92%)	0.13
$\Delta TB5Y(t)$	-2.439	(20.08%)	-14.346	(70.66%)	0.06
$\Delta GEPU(t)$	0.029	(13.13%)	0.120	(57.14%)	0.02
$\Delta AvgSpr(t)$	0.139	(39.38%)	0.368	(64.09%)	0.11
$\Delta AvgSpr_R(t)$	0.290	(64.48%)	0.414	(81.85%)	0.20
$\Delta AvgSpr_S(t)$	0.316	(55.60%)	0.421	(59.46%)	0.16
Const	0.001	(5.02%)			
<i>Adjusted R²</i>	0.35				
Panel B: Lagged regression					
	Multivariate regression		Univariate regression		
	<i>Coef</i>	% ($p \leq 0.05$)	<i>Coef</i>	% ($p \leq 0.05$)	<i>Adjusted R²</i>
$\Delta DftSpr(t-1)$	10.323	(34.75%)	14.845	(49.81%)	0.02
$\Delta TrmSpr(t-1)$	6.455	(33.59%)	5.183	(19.31%)	0.01
$\Delta VIX(t-1)$	0.005	(36.29%)	0.006	(45.95%)	0.03
$\Delta SP500(t-1)$	0.086	(13.51%)	-0.484	(32.05%)	0.02
$\Delta TB5Y(t-1)$	-1.508	(10.42%)	-0.231	(11.20%)	0.00
$\Delta GEPU(t-1)$	-0.025	(14.29%)	0.015	(7.72%)	0.00
$\Delta AvgSpr(t-1)$	0.037	(13.90%)	0.125	(27.03%)	0.01
$\Delta AvgSpr_R(t-1)$	0.024	(11.97%)	0.070	(15.06%)	0.01
$\Delta AvgSpr_S(t-1)$	0.064	(13.51%)	0.095	(24.71%)	0.01
Const	0.001	(3.47%)			
<i>Adjusted R²</i>	0.05				
Panel C: Coefficient quartiles					
	Q25		Q50		Q75
<i>Contemporaneous regression</i>					
$\Delta DftSpr$	-5.445		4.219		13.249
$\Delta TrmSpr$	-3.561		0.054		3.634
ΔVIX	-0.002		0.000		0.003
$\Delta SP500$	-0.687		-0.170		0.242
$\Delta TB5Y$	-7.389		-2.193		2.056
$\Delta GEPU$	-0.013		0.024		0.066
$\Delta AvgSpr$	-0.014		0.126		0.265
$\Delta AvgSpr_R$	0.122		0.267		0.435
$\Delta AvgSpr_S$	0.109		0.266		0.477

TABLE 4 (Continued)

Panel C: Coefficient quartiles			
	Q25	Q50	Q75
<i>Lagged regression</i>			
$\Delta DftSpr$	1.130	9.792	18.371
$\Delta TrmSpr$	2.369	6.480	10.175
ΔVIX	0.001	0.005	0.009
$\Delta SP500$	-0.327	0.053	0.428
$\Delta TB5Y$	-5.398	-1.226	3.091
$\Delta GEPU$	-0.073	-0.021	0.023
$\Delta AvgSpr$	-0.038	0.040	0.099
$\Delta AvgSpr_R$	-0.054	0.018	0.103
$\Delta AvgSpr_S$	-0.015	0.048	0.133

Note: This table reports the regression results for systematic factors for the 259 US 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 multivariate regressions. Newey–West t statistics with 12-month lags is used for testing coefficient significance. Abbreviations: CDS, credit default swap; GEPU, Global Economic Policy Uncertainty; SP500, Standard and Poor's 500; VIX, volatility index.

TABLE 5 Systematic factor panel regression.

Dependent variable: $\Delta Spr(i, t)$	
$\Delta DftSpr(t)$	6.483 <i>[3.04]</i>
$\Delta TrmSpr(t)$	-0.079 [-0.07]
$\Delta VIX(t)$	0.000 [0.55]
$\Delta SP500(t)$	-0.331 <i>[-2.15]</i>
$\Delta TB5Y(t)$	-2.641 [-1.78]
$\Delta GEPU(t)$	0.051 <i>[3.29]</i>
$\Delta AvgSpr(t)$	0.073 <i>[3.39]</i>
$\Delta AvgSpr_R(t)$	0.313 <i>[5.77]</i>
$\Delta AvgSpr_S(t)$	0.139 <i>[3.57]</i>
Adjusted R^2	0.24

Note: 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. Abbreviations: CDS, credit default swap; GEPU, Global Economic Policy Uncertainty; SP500, Standard and Poor's 500; VIX, volatility index.

TABLE 7 Subsample CDS systematic factors (panel).

Dependent variable: $\Delta\text{Spr}(i, t)$	Sector											Rating					Period		
	Materials	Con-Goods	Con-Services	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA			A		CCC	Pre-Crisis	In-Crisis	Post-Crisis	
										AAA	AA	A	BBB	BB					B
$\Delta\text{DFSpr}(t)$	7.680 [3.65]	4.775 [2.39]	6.202 [1.88]	15.472 [3.40]	4.857 [1.82]	6.388 [2.41]	2.108 [0.99]	5.923 [2.79]	4.013 [1.63]	4.700 [2.31]	3.552 [1.12]	6.268 [2.72]	8.694 [4.74]	6.723 [3.60]	5.852 [1.69]	10.661 [1.65]	-0001 [-0.79]	0.871 [0.35]	
$\Delta\text{TrmSpr}(t)$	-0.087 [-0.11]	-1.183 [-0.76]	-0.327 [-0.17]	-3.492 [-1.56]	3.076 [2.91]	0.579 [0.42]	0.857 [0.49]	-0.016 [-0.01]	1.118 [1.13]	-1.191 [-1.11]	1.763 [1.18]	-1.677 [-1.15]	-0.376 [-0.31]	-0.024 [-0.02]	3.340 [3.32]	-0.905 [-1.06]	-3.401 [-2.32]	3.478 [1.77]	
$\Delta\text{VIX}(t)$	-0.002 [-2.06]	0.001 [0.71]	0.002 [1.47]	0.002 [1.30]	0.001 [1.32]	-0.000 [-0.59]	-0.001 [-0.64]	0.001 [1.73]	0.001 [1.08]	-0.000 [-0.34]	0.001 [1.16]	0.001 [1.29]	-0.001 [-0.85]	0.001 [1.35]	-0.000 [-0.36]	0.005 [2.36]	0.004 [4.51]	-0.001 [-1.04]	
$\Delta\text{SP500}(t)$	-0.491 [-3.00]	-0.246 [-1.60]	-0.518 [-3.15]	-0.244 [-0.81]	0.006 [0.04]	-0.453 [-3.12]	-0.223 [-1.24]	-0.072 [-0.63]	-0.006 [-0.04]	-0.287 [-2.27]	-0.218 [-1.04]	-0.252 [-1.68]	-0.468 [-3.29]	-0.270 [-1.84]	-0.489 [-2.93]	0.192 [1.14]	0.806 [8.14]	-0.728 [-3.11]	
$\Delta\text{TB5Y}(t)$	-1.854 [-1.49]	-1.787 [-1.01]	-2.679 [-1.15]	0.764 [0.30]	-6.134 [-3.41]	-3.604 [-2.15]	-2.365 [-1.44]	-1.701 [-0.81]	-2.508 [-2.40]	-1.868 [-1.37]	-4.429 [-2.77]	-1.412 [-0.82]	-1.965 [-1.24]	-0.730 [-0.62]	-4.425 [-2.61]	0.124 [0.11]	-5.087 [-2.11]	-4.151 [-1.33]	
$\Delta\text{GEPU}(t)$	0.022 [1.17]	0.038 [2.44]	0.059 [2.45]	0.118 [4.74]	0.047 [2.66]	0.026 [1.47]	0.047 [2.13]	0.036 [1.74]	0.060 [3.36]	0.057 [4.19]	0.030 [1.66]	0.055 [3.07]	0.060 [3.78]	0.057 [3.07]	0.018 [0.66]	0.057 [1.80]	0.025 [1.70]	0.048 [4.47]	
$\Delta\text{AVgSpr}(t)$	0.006 [0.38]	-0.088 [-2.75]	-0.003 [-0.06]	0.149 [1.80]	0.069 [2.35]	0.085 [2.60]	0.177 [2.90]	-0.174 [-3.13]	0.108 [2.10]	0.077 [2.23]	0.108 [2.82]	0.056 [1.86]	0.044 [3.03]	0.123 [4.05]	0.055 [1.38]	0.060 [3.44]	0.203 [5.21]	0.069 [1.77]	
$\Delta\text{AVgSpr}_R(t)$	0.292 [7.73]	0.163 [4.65]	0.270 [3.29]	0.312 [4.51]	0.223 [3.85]	0.324 [5.03]	0.330 [6.32]	0.058 [1.25]	0.271 [4.08]	0.394 [5.92]	0.467 [4.69]	0.258 [6.55]	0.251 [6.20]	0.290 [6.20]	0.223 [3.85]	0.436 [6.04]	0.679 [8.70]	0.239 [4.93]	
$\Delta\text{AVgSpr}_S(t)$	0.055 [1.32]	0.232 [3.75]	0.077 [1.83]	0.172 [2.42]	0.327 [3.99]	0.087 [2.77]	0.209 [4.04]	0.131 [2.47]	0.233 [2.67]	0.108 [2.95]	0.174 [3.63]	0.146 [3.30]	0.110 [3.47]	0.184 [3.88]	0.143 [2.32]	0.109 [3.73]	0.329 [6.68]	0.149 [2.61]	
AdjustedR 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	

Note: This table reports the regression results for contemporaneous systematic factors for the 259 US 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.

Abbreviations: CDS, credit default swap; GEPU, Global Economic Policy Uncertainty; SP500, Standard and Poor's 500; VIX, volatility index.

TABLE 8 Firm-specific variable results.

Panel A: Lagged regression					
	Multivariate regression		Univariate regression		
	Coef	<i>t</i> Statistics	Coef	<i>t</i> Statistics	Adjusted <i>R</i> ²
Δ Asset(<i>i</i> , <i>t</i> - 1)	-0.002	[-0.23]	-0.000	[-0.03]	0.05
Δ CASHMTA(<i>i</i> , <i>t</i> - 1)	-0.009	[-0.73]	0.008	[1.55]	0.05
Δ CashRatio(<i>i</i> , <i>t</i> - 1)	0.003	[0.25]	-0.000	[-0.09]	0.05
Δ CBCnt(<i>i</i> , <i>t</i> - 1)	-0.000	[-0.04]	0.004	[0.41]	0.05
Δ CBPrice(<i>i</i> , <i>t</i> - 1)	-0.002	[-0.33]	-0.001	[-0.11]	0.05
Δ CBVol(<i>i</i> , <i>t</i> - 1)	0.007	[0.79]	0.007	[0.69]	0.05
Δ CDSAmihud(<i>i</i> , <i>t</i> - 1)	0.005	[0.39]	-0.003	[-0.35]	0.05
Δ CDSHL(<i>i</i> , <i>t</i> - 1)	-0.016	[-1.00]	-0.012	[-1.06]	0.05
Δ CDSSlope(<i>i</i> , <i>t</i> - 1)	-0.006	[-0.79]	-0.006	[-0.81]	0.05
Δ CDSContr(<i>i</i> , <i>t</i> - 1)	-0.018	[-2.73]	-0.018	[-2.69]	0.05
Δ DARatio(<i>i</i> , <i>t</i> - 1)	-0.014	[-2.20]	-0.005	[-1.07]	0.05
Δ DERatio(<i>i</i> , <i>t</i> - 1)	0.012	[0.97]	0.023	[2.78]	0.05
Δ EBIT(<i>i</i> , <i>t</i> - 1)	-0.016	[-1.13]	-0.012	[-2.08]	0.05
Δ IntCover(<i>i</i> , <i>t</i> - 1)	0.005	[0.48]	-0.009	[-1.68]	0.05
Δ Inv2COGS(<i>i</i> , <i>t</i> - 1)	-0.004	[-0.83]	-0.001	[-0.26]	0.05
Δ Liab(<i>i</i> , <i>t</i> - 1)	0.006	[0.58]	0.002	[0.35]	0.05
Δ MBRatio(<i>i</i> , <i>t</i> - 1)	-0.013	[-1.98]	-0.025	[-4.22]	0.05
Δ NIGrowth(<i>i</i> , <i>t</i> - 1)	-0.001	[-0.13]	-0.005	[-0.99]	0.05
Δ NIMTA(<i>i</i> , <i>t</i> - 1)	-0.014	[-1.05]	-0.008	[-1.16]	0.05
Δ RealVol(<i>i</i> , <i>t</i> - 1)	-0.003	[-0.37]	0.001	[0.18]	0.05
Δ ReEarning(<i>i</i> , <i>t</i> - 1)	-0.007	[-0.82]	-0.007	[-0.95]	0.05
Δ ROA(<i>i</i> , <i>t</i> - 1)	0.013	[0.70]	-0.009	[-1.28]	0.05
Δ SaleGrowth(<i>i</i> , <i>t</i> - 1)	-0.004	[-0.53]	-0.004	[-0.74]	0.05
Δ StoAmihud(<i>i</i> , <i>t</i> - 1)	0.009	[1.47]	0.010	[1.63]	0.05
Δ StoMom(<i>i</i> , <i>t</i> - 1)	0.009	[0.91]	-0.017	[-2.14]	0.05
Δ StoPrice(<i>i</i> , <i>t</i> - 1)	-0.029	[-2.25]	-0.034	[-3.79]	0.05
Δ StoVol(<i>i</i> , <i>t</i> - 1)	-0.005	[-0.62]	0.000	[0.09]	0.05
Δ WorkingCap(<i>i</i> , <i>t</i> - 1)	0.007	[1.14]	0.003	[0.63]	0.05
Adjusted <i>R</i> ²	0.05				

Panel B: Contemporaneous regression		
	Coef	<i>t</i> Statistics
Δ Asset(<i>i</i> , <i>t</i>)	-0.009	[-1.39]
Δ CASHMTA(<i>i</i> , <i>t</i>)	0.026	[2.45]
Δ CashRatio(<i>i</i> , <i>t</i>)	-0.029	[-2.91]
Δ CBCnt(<i>i</i> , <i>t</i>)	-0.007	[-0.75]
Δ CBPrice(<i>i</i> , <i>t</i>)	0.004	[0.41]
Δ CBVol(<i>i</i> , <i>t</i>)	0.010	[1.30]

TABLE 8 (Continued)

Panel B: Contemporaneous regression		
	Coef	<i>t</i> Statistics
Δ CDSAmihud(<i>i, t</i>)	0.011	[0.70]
Δ CDSHL(<i>i, t</i>)	0.083	[2.54]
Δ CDSslope(<i>i, t</i>)	0.151	[3.77]
Δ CDSContr(<i>i, t</i>)	0.036	[5.39]
Δ DARatio(<i>i, t</i>)	-0.002	[-0.29]
Δ DERatio(<i>i, t</i>)	0.022	[2.44]
Δ EBIT(<i>i, t</i>)	-0.001	[-0.11]
Δ IntCover(<i>i, t</i>)	0.011	[0.85]
Δ Inv2COGS(<i>i, t</i>)	-0.005	[-0.94]
Δ Liab(<i>i, t</i>)	-0.011	[-1.49]
Δ MBRatio(<i>i, t</i>)	0.012	[1.99]
Δ NIIGrowth(<i>i, t</i>)	0.006	[1.26]
Δ NIMTA(<i>i, t</i>)	-0.037	[-2.42]
Δ RealVol(<i>i, t</i>)	0.009	[0.93]
Δ ReEarning(<i>i, t</i>)	0.006	[0.62]
Δ ROA(<i>i, t</i>)	0.022	[1.17]
Δ SaleGrowth(<i>i, t</i>)	0.001	[0.08]
Δ StoAmihud(<i>i, t</i>)	0.008	[1.24]
Δ StoMom(<i>i, t</i>)	0.010	[1.05]
Δ StoPrice(<i>i, t</i>)	-0.091	[-6.26]
Δ StoVol(<i>i, t</i>)	0.008	[0.93]
Δ WorkingCap(<i>i, t</i>)	0.005	[1.08]
Adjusted R^2	0.09	

Note: 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 (Δ Idio(*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.

Abbreviations: CDS, credit default swap; CDSHL, CDS high-minus-low; EBIT, Earning Before Interest and Tax; NIMTA, net income divided by market value of asset; ROA, Return of Asset.

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 are 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, for example, interest coverage (IntCover) and accounting liabilities (Liab), to gauge firm's insolvency risk, these 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 & 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, that is, 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 a 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 & 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 subsample analyses. Table 9 reports the multivariate regression results by sectors, ratings, and subperiods. In general, we observe inconsistency in statistically significant variables. The first row counts the number of statistically significant firm-specific variables at a 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 1 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.

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 subperiod analyses, firm-specific variables have better predictability during the crisis, but after the Great Financial Crisis, the monthly CDS spread changes are mainly driven

TABLE 9 (Continued)

Sector	Rating										Period							
	Materials	Consumer Goods	Services	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	Pre-Crisis	Post-Crisis	
$\Delta EBIT(i, t-1)$	-0.012 [-0.20]	0.010 [0.42]	-0.033 [-0.76]	0.004 [0.10]	-0.019 [-0.49]	-0.035 [-0.88]	-0.000 [-0.01]	-0.145 [-1.00]	-0.049 [-0.64]	0.046 [1.24]	-0.001 [-0.05]	-0.070 [-2.72]	-0.031 [-0.74]	0.019 [0.28]	-0.260 [-2.12]	-0.008 [-0.41]	-0.100 [-2.28]	0.008 [0.58]
$\Delta IntCover(i, t-1)$	0.023 [0.45]	-0.015 [-0.66]	0.012 [0.41]	0.009 [0.32]	0.017 [0.39]	0.020 [0.68]	-0.040 [-1.31]	0.022 [0.24]	0.080 [1.28]	-0.037 [-2.06]	-0.000 [-0.00]	0.039 [1.66]	0.021 [0.64]	0.011 [0.25]	0.205 [1.53]	0.001 [0.12]	0.109 [6.25]	-0.011 [-0.85]
$\Delta Inv2COGS(i, t-1)$	0.027 [1.04]	0.006 [0.42]	0.015 [0.67]	0.006 [0.24]	0.028 [1.18]	-0.018 [-1.12]	-0.006 [-0.34]	-0.064 [-1.53]	-0.034 [-1.78]	0.005 [0.30]	-0.002 [-0.16]	-0.005 [-0.54]	-0.003 [-0.29]	0.016 [0.44]	0.016 [-0.13]	-0.001 [-0.11]	-0.025 [-4.55]	-0.006 [-0.99]
$\Delta Liab(i, t-1)$	-0.015 [-0.39]	-0.008 [-0.31]	0.025 [1.11]	-0.039 [-1.32]	-0.009 [-0.28]	0.025 [0.86]	0.056 [1.35]	-0.089 [-1.78]	-0.001 [-0.02]	-0.015 [-0.79]	-0.027 [-1.52]	0.009 [0.39]	0.048 [2.29]	0.025 [0.62]	0.089 [0.93]	0.002 [0.08]	0.016 [0.54]	-0.002 [-0.20]
$\Delta MBRatio(i, t-1)$	0.028 [0.87]	-0.018 [-0.96]	0.011 [0.53]	0.038 [0.94]	0.006 [0.13]	-0.052 [-2.10]	-0.001 [-0.03]	0.028 [0.65]	0.030 [0.83]	-0.032 [-1.33]	-0.021 [-1.30]	0.012 [0.87]	-0.017 [-1.22]	0.028 [1.21]	-0.079 [-1.59]	-0.004 [-0.36]	-0.017 [-0.83]	-0.010 [-1.49]
$\Delta NIGrowth(i, t-1)$	-0.003 [-0.28]	0.000 [0.02]	0.021 [1.46]	0.012 [0.93]	-0.002 [-0.11]	0.005 [0.43]	-0.016 [-0.76]	-0.036 [-1.23]	0.004 [0.24]	-0.011 [-0.56]	-0.007 [-0.52]	0.003 [0.19]	0.002 [0.21]	-0.005 [-0.23]	0.015 [-0.41]	0.002 [0.17]	-0.023 [-1.99]	0.003 [0.37]
$\Delta NIMTA(i, t-1)$	-0.007 [-0.16]	-0.059 [-2.36]	0.035 [1.60]	-0.000 [-0.01]	-0.014 [-0.35]	0.004 [0.10]	-0.087 [-1.92]	0.005 [0.08]	0.047 [1.15]	0.043 [0.68]	0.033 [0.74]	-0.047 [-1.94]	-0.006 [-0.29]	0.109 [1.46]	0.109 [-0.61]	-0.009 [-2.17]	-0.053 [-0.78]	0.012 [0.78]
$\Delta RealVol(i, t-1)$	-0.028 [-1.03]	0.017 [0.82]	-0.041 [-1.82]	-0.015 [-0.45]	-0.018 [-0.73]	0.004 [0.16]	0.035 [0.90]	-0.001 [-0.02]	-0.016 [-0.56]	-0.044 [-1.52]	0.008 [0.52]	-0.021 [-0.89]	0.000 [0.00]	0.039 [0.63]	-0.008 [-1.11]	0.029 [3.09]	-0.010 [-0.89]	0.004 [0.04]
$\Delta ReEarning(i, t-1)$	-0.024 [-0.91]	-0.016 [-0.84]	0.020 [1.08]	-0.056 [-2.24]	-0.026 [-1.04]	0.011 [0.44]	0.043 [1.34]	-0.085 [-1.31]	0.007 [0.28]	0.017 [0.78]	-0.027 [-2.27]	-0.007 [-0.39]	0.011 [0.69]	0.108 [1.10]	-0.022 [-1.99]	-0.040 [-1.65]	0.004 [0.57]	0.004 [0.57]
$\Delta ROA(i, t-1)$	-0.011 [-0.26]	0.036 [1.58]	-0.034 [-0.91]	-0.006 [-0.10]	-0.020 [-0.40]	-0.011 [-0.23]	0.088 [1.73]	0.114 [0.80]	-0.055 [-1.00]	-0.078 [-1.14]	-0.032 [-0.60]	0.070 [2.24]	0.010 [0.41]	0.054 [0.76]	-0.069 [-0.70]	0.005 [0.28]	0.076 [1.29]	-0.031 [-1.34]
$\Delta SaleGrowth(i, t-1)$	0.027 [1.08]	0.012 [0.79]	-0.006 [-0.33]	-0.037 [-1.69]	0.007 [0.32]	-0.009 [-0.47]	-0.026 [-1.21]	-0.049 [-1.31]	-0.015 [-0.59]	0.017 [0.77]	-0.002 [-0.13]	0.014 [1.01]	-0.025 [-1.98]	-0.019 [-1.01]	-0.045 [-1.01]	0.006 [0.41]	-0.049 [-4.95]	-0.003 [-0.35]
$\Delta StoAmihud(i, t-1)$	0.041 [2.21]	0.026 [2.19]	-0.013 [-0.80]	-0.003 [-0.12]	-0.011 [-0.46]	-0.002 [-0.17]	0.013 [0.63]	0.003 [0.07]	-0.009 [-0.61]	0.020 [1.19]	-0.006 [-0.71]	0.007 [0.52]	0.006 [0.48]	0.011 [0.45]	0.024 [2.49]	0.001 [0.01]	0.03 [1.20]	-0.007 [-0.50]

TABLE 9 (Continued)

Sector		Rating											Period						
		Materials	Con-Goods	ConServices	Energy	Healthcare	Industrials	Tech	Telecom	Utilities	AA	A	BBB	BB	B	CCC	Pre-Crisis	Post-Crisis	
Dependent variable: $\Delta \text{Idio}(i, t)$																			
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]
$\Delta \text{StoPrice}$	$(i, t-1)$	-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]
$\Delta \text{WorkingCap}$	$(i, t-1)$	-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]
Adjusted 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

Note: 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.

Abbreviations: CDS, credit default swap; CDSHL, CDS high-minus-low; EBIT, Earning Before Interest and Tax; NIMTA, net income divided by market value of asset; ROA, Return of Asset.

by systematic factors, only two 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 subsample 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 comovement 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 is stronger in

TABLE 10 Systematic factor quarterly regression.

Dependent variable: Δ Spr		
	Contemporaneous	Lagged
Δ DftSpr	5.996 [3.28]	4.175 [2.73]
Δ TrmSpr	2.789 [2.56]	4.670 [3.13]
Δ VIX	0.000 [0.04]	0.006 [7.06]
Δ SP500	-0.100 [-0.74]	0.187 [1.11]
Δ TB5Y	-3.056 [-2.90]	-1.346 [-0.68]
Δ GEPU	0.092 [4.58]	0.056 [1.18]
Δ AvgSpr	0.099 [4.13]	0.081 [4.66]
Δ AvgSpr_R	0.455 [8.74]	0.317 [8.18]
Δ AvgSpr_S	0.146 [3.64]	0.114 [3.81]
Adjusted R^2	0.36	0.26

Note: This table reports the regression results for systematic factors for the 259 US 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.

Abbreviations: GEPU, Global Economic Policy Uncertainty; SP500, Standard and Poor's 500; VIX, volatility index.

quarterly changes than in monthly changes, implying that the systematic information is even more pronounced in the quarterly data set.

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, that is, 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

TABLE 11 Systematic factors reverse regression.

Dependent variable: $\Delta\text{Idio}^*(i, t)$			
Panel A: TS regression		Panel B: Panel regression	
	Coef /% ($p \leq 0.05$)		Coef/[t Statistics]
$\Delta\text{DftSpr}(t)$	1.841	$\Delta\text{DftSpr}(t)$	0.060
% ($p \leq 0.05$)	(15.12%)	[t statistics]	[0.05]
$\Delta\text{TrmSpr}(t)$	-2.363	$\Delta\text{TrmSpr}(t)$	-9.012
	(30.23%)		[-5.86]
$\Delta\text{VIX}(t)$	-0.001	$\Delta\text{VIX}(t)$	-0.001
	(12.79%)		[-3.02]
$\Delta\text{SP500}(t)$	0.186	$\Delta\text{SP500}(t)$	0.412
	(16.28%)		[5.56]
$\Delta\text{TB5Y}(t)$	-1.623	$\Delta\text{TB5Y}(t)$	0.244
	(12.79%)		[0.38]
$\Delta\text{GEP}(t)$	-0.000	$\Delta\text{GEP}(t)$	-0.000
	(8.14%)		[-2.33]
$\Delta\text{AvgSpr}(t)$	0.237	$\Delta\text{AvgSpr}(t)$	0.598
	(59.88%)		[19.95]
$\Delta\text{AvgSpr}_R(t)$	0.184	$\Delta\text{AvgSpr}_R(t)$	0.382
	(62.79%)		[27.83]
$\Delta\text{AvgSpr}_S(t)$	0.276	$\Delta\text{AvgSpr}_S(t)$	0.554
	(69.19%)		[21.45]
Constant	-0.001		
	(5.81%)		
Adjusted R^2	0.20	Adjusted R^2	0.15

Note: This table reports the regression results for systematic factors for the 259 US 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 (TS) 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.

Abbreviations: CDS, credit default swap; GEP, Global Economic Policy Uncertainty; SP500, Standard and Poor's 500; VIX, volatility index.

important. Seven out of nine systematic factors are statistically significant at a 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.

4.3.3 | Nonzero 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 1 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 be the main attribute to the low predictability of CDS spread variation that is not explained by systematic factors, therefore our argument on the firm-specific variables might be overstated.

To answer the concern, we repeat the Equation (2) model specification only for nonzero 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 nonzero firm-specific observations. We observe a substantial drop in sample size by 37% (from 40,339 to 25,361). However, we still do not find substantial changes in the regression results between nonzero 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 two firm-specific variables provide statistical prediction (at 5% level), and the composition of the significance variables is 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.

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 OS analysis. 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 subsample for each firm by

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

Then, the 1-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_{t+1}^i 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 :

$$\text{Adjusted OSR}_i^2 = 1 - \frac{\sum_t (y_{i,t+1} - \hat{y}_{i,t+1})^2 / df_A}{\sum_t (y_{i,t+1} - \bar{y}_{i,t+1})^2 / df_N}, \quad (4)$$

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

⁷Since 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.

TABLE 12 Nonzero observations.

Dependent variable: $\Delta\text{Idio}(i, t)$		
	Coef	<i>t</i> Statistics
$\Delta\text{Asset}(i, t - 1)$	-0.010	[-1.07]
$\Delta\text{CASHMTA}(i, t - 1)$	0.009	[0.66]
$\Delta\text{CashRatio}(i, t - 1)$	-0.011	[-0.69]
$\Delta\text{CDSAmihud}(i, t - 1)$	-0.001	[-0.08]
$\Delta\text{CDSHL}(i, t - 1)$	-0.018	[-1.06]
$\Delta\text{CDSSlope}(i, t - 1)$	-0.016	[-1.77]
$\Delta\text{CDSContr}(i, t - 1)$	-0.024	[-2.73]
$\Delta\text{DARatio}(i, t - 1)$	-0.009	[-0.99]
$\Delta\text{DERatio}(i, t - 1)$	0.007	[0.41]
$\Delta\text{EBIT}(i, t - 1)$	-0.028	[-1.57]
$\Delta\text{IntCover}(i, t - 1)$	0.016	[0.99]
$\Delta\text{Inv2COGS}(i, t - 1)$	-0.005	[-0.94]
$\Delta\text{Liab}(i, t - 1)$	0.006	[0.50]
$\Delta\text{MBRatio}(i, t - 1)$	-0.024	[-2.30]
$\Delta\text{NIGrowth}(i, t - 1)$	0.004	[0.58]
$\Delta\text{NIMTA}(i, t - 1)$	0.003	[0.36]
$\Delta\text{RealVol}(i, t - 1)$	0.011	[0.97]
$\Delta\text{ReEarning}(i, t - 1)$	-0.003	[-0.28]
$\Delta\text{SaleGrowth}(i, t - 1)$	-0.007	[-0.65]
$\Delta\text{StoAmihud}(i, t - 1)$	-0.001	[-0.07]
$\Delta\text{StoMom}(i, t - 1)$	0.011	[1.17]
$\Delta\text{StoPrice}(i, t - 1)$	-0.013	[-0.92]
$\Delta\text{StoVol}(i, t - 1)$	0.004	[0.40]
$\Delta\text{WorkingCap}(i, t - 1)$	0.006	[0.77]
Adjusted R^2	0.06	

Note: This table reports the panel regression results using the nonzero 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.

Abbreviations: CDS, credit default swap; CDSHL, CDS high-minus-low; EBIT, Earning Before Interest and Tax; NIMTA, net income divided by market value of asset.

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, 2, and 5 years to test the predictability of our systematic and firm-specific factors, separately. Recall that we have nine 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 the logarithm of CDS spreads over the training period;

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

(2) Firm-specific Factor Prediction: the 1-month-ahead prediction for the changes in the individual CDS spread using the first PC of the firm-specific factors.

Table 13 reports the OS performance of the CDS factors. This table reports the CDS systematic and firm-specific factor OS performance. Panels A–C report the results for different training periods. Column (1) reports the Adjusted OSR² 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 Adjusted OSR²'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 1 month ahead, but the superiority decreases when the training period increases. Column (2) (or 3) reports the Adjusted OSR² 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 OSR² for systematic factors; hence the proposed CDS-specific systematic factors indeed improve time-series predictions for changes in individual spreads.

4.3.5 | Other robustness checks

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

TABLE 13 Factor OS prediction.

Adjusted OSR ²			
Tested strategy:	Systematic factor	Systematic factor	Firm-specific factor
Benchmark strategy:	Firm-specific factor	Historical average	Historical average
<i>Panel A: 12-month training period</i>			
Mean	0.11	0.01	−0.18
SD	0.15	0.06	0.53
Maximum	0.82	0.27	0.16
Minimum	−0.13	−0.16	−4.89
<i>Panel B: 24-month training period</i>			
Mean	0.05	0.02	−0.08
SD	0.11	0.06	0.62
Maximum	0.89	0.16	0.12
Minimum	−0.16	−0.20	−7.95
<i>Panel C: 60-month training period</i>			
Mean	0.03	0.01	−0.07
SD	0.14	0.10	0.72
Maximum	0.91	0.20	0.15
Minimum	−0.92	−0.90	−9.48

Note: This table reports the CDS systematic and firm-specific factor out-of-sample performance. Panels A–C report the results for 12, 24, and 60 months of training periods, respectively. Column (1) reports the Adjusted OSR² statistic that systematic factors have better prediction against firm-specific factors. Columns (2) (or 3) report the Adjusted OSR² statistic that shows that systematic (or firm-specific) factors have better prediction against historical average of CDS spread changes.

Abbreviations: CDS, credit default swap; OS, out-of-sample.

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., $\Delta\text{idio}_{i,t} = \beta_0^i + \varepsilon_t^i$ 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 $\widetilde{\Delta\text{idio}}_{i,t}$), and repeat Equation (2) to identify effective firm-specific factors. The results are reported in Supporting Information 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 are somehow underperformed than our original proposal. The number of statistically significant firm-specific factors is slightly increased (from 9 to 14) for contemporaneous cases 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 Supporting Information 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 nonstationary 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 the 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 nine 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 comovement 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 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, to conclude unbiased results.

For future research, our work can be extended to the international scale. Interestingly, the mainstream studies on CDSs focus on US 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 underexplored. 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 the 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.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

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

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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