Systematic and Firm-specific Risks of CDS Spreads: Credit and Liquidity under Scrutiny

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Abstract

Using a sample of 356 U.S. non-financial firms from 2002 to 2011, we derive endogenous systematic credit risk and Credit Default Swap (CDS) illiquidity factors, and show that they dominate firm-specific and exogenous market factors as determinants of individual firms' CDS spreads. Our model performs well for cross-sectional predictions and can be used for estimating CDS spreads for firms that do not have traded CDSs. Our findings question Basel III's adoption of CDS-implied probability for counterparty risk management, as CDS spread is not a pure individual firm default risk measure devoid of market credit and illiquidity premia.

Key words: CDS spread, credit risk, liquidity risk, systematic factors

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1 Introduction

Basel III stipulates that Credit Default Swap (CDS) implied default probability must be used in the calculation of risk capital attributed to counterparty credit risk.[1] CDS is a credit derivative that offers protection against bond default. However, not every counterparty has issued bonds that are publicly tradable. It is even a smaller subset of firms that have CDS contracts written on their bonds. Thus, financial institutions need to be able to estimate the CDS spreads for firms that do not have (actively traded) CDS contracts.

At the same time, previous research has suggested that CDS spreads may not be solely driven by individual firm default risk. For example, Tang and Yan (2007) and Corò, Dufour, and Varotto (2013) show that CDS spreads are affected by liquidity risk, and Doshi, Ericsson, Jacobs, and Turnbull (2013) show that bond market conditions affect CDS spreads, too. Thus, it is not implausible that a CDS spread is not a "pure" measure of credit risk.

In this paper, we explore another set of CDS drivers, namely, the endogenous systematic risk factors, derived from traded CDSs. We set out to answer a question to which extent one-year CDS spreads are driven by those systematic factors, and what is the role of other known types of factors in explaining the cross-sectional variations of CDS spreads.

We make several contributions to the literature. First, we develop a comprehensive empirical model of CDS changes. The model includes firm-specific and systematic factors addressing both credit and liquidity risks. Then, using a sample of 356 U.S. publicly listed non-financial firms, we show that individual credit risk measures can capture only up to 18% of the variation of changes in CDS spreads, which is comparable to the 16% captured by individual low frequency CDS liquidity measure. In contrast, the exogenous market factors (related to bond and equity markets) capture 30% of the variation.

We further derive three endogenous systematic CDS credit factors and two systematic CDS illiquidity factors. The systematic credit risk factors are constructed as rating-based (using the Nelson-Siegel (1984) model) and industry- and market-wide factors (using Leland-Toft (1996)

[1] ["When computing CVA (Credit Valuation Adjustment) risk capital charge,] s is the credit spread of the counterparty [...]. Whenever the CDS spread of the counterparty is available, this must be used. Whenever such a CDS spread is not available, the bank must use a proxy spread that is appropriate based on the rating, industry and region of the counterparty." *Basel III: A global regulatory framework for more resilient banks and banking systems*, p.32, http://www.bis.org/publ/bcbs189.pdf.

model). The liquidity factors are derived from the Leland-Toft (1996) model, too. We show that these endogenous systematic factors outperform all other sets of factors and capture 44% of variation in changes in CDS spreads. In the presence of these factors, the explanatory power of other factors is substantially weakened. Moreover, after the financial crisis of 2007, systematic CDS market illiquidity has a prominent effect on CDS spreads.

Finally, we show that our model has good cross-sectional predictive power. The out-of-sample R-square is 43%, compared to a historical average. Our model is well suited to approximate CDS spreads for firms with no (actively) traded CDSs. At the same time, our results suggest a relatively minor role of individual firm credit risk in determining CDS spreads, as compared to systematic factors.

2 Related Literature

Our study is grounded in two strands of literature: the first one suggests the importance of the systematic factors and peer CDS spreads for determining individual spreads; the second one highlights the role of the liquidity risk.

Doshi, Ericsson, Jacobs, and Turnbull (2013) find that market variables including 6-month Treasury yield and the difference between the 10-year and 6-month yields explain cross-sectional CDS variation. Conrad, Dittmar, and Hameed (2011) find changes in the CDS spreads of the systematically important financial institutions lead changes in the CDS spreads of other firms. Galil, Shapir, Amiram, and Ben-Zion (2014) find the median CDS spreads of mixed credit quality have a cross-sectional explanatory power for individual CDS spreads. For sovereign CDS, Longstaff, Pan, Pedersen, and Singleton (2011) find global factors are more important than individual country factors in explaining CDS spread changes.

Tang and Yan (2007) and Corò, Dufour, and Varotto (2013) explore the relation between CDS spreads and their liquidity. Tang and Yan (2007) investigate several liquidity measures based on CDS trades such as trade-to-quote ratio and bid-ask spread, and document a positive effect of illiqudiuty on CDS spreads. Corò, Dufour, and Varotto (2013) propose a liquidity measure based on the bid-ask spreads of the intra-day trades in CDSs. They find that, among the CDS spreads of the 135 European entities, the CDS liquidity risk dominates the credit risk.

The prevailing studies construct CDS liquidity measures relying on daily bid-ask spread or intra-day trading data. However, using such measures in not always possible, as many CDS data vendors report composite CDS prices.[2] Goyenko, Holden, and Trzcinka (2009) find, however, that low-frequency liquidity measures can capture the high-frequency liquidity effect in the stock market. Following this finding, we use the the low-frequency liquidity measure for the changes in CDS spreads in this paper.

Early studies such as Gennotte and Leland (1990) have modeled the effects of illiquidity in equilibrium asset pricing model. Cespa and Foucault (2014) extend the model of Gennotte and Leland (1990) and argue that illiquidity interacts between assets in the same or different markets, affecting the equilibrium asset prices, through cross-market learning of traders. Such "cross-learning" forms a feedback loop between assets according to the level of price informativeness and could lead to illiquidity spillover across markets. Supporting this idea, Das and Hanouna (2009) and Huang, Huang, and Oxman (2015) find the linkage between equity and CDS markets. Das and Hanouna (2009) find stock illiquidity can explain the changes in the individual CDS spreads; they argue that traders revert to equity markets to hedge their exposure to credit risk. Similarly, Huang, Huang, and Oxman (2015) find that stock illiquidity increases credit risk premium.

Motivated by the previous research, in this paper we construct a comprehensive list of factors, capturing both firm specific and systematic credit and illiduity risk, and control for possible cross-market spillovers.

3 Research Design

In order to investigate in detail the drives of CDS spreads, we estimate a panel regression of the quarterly changes of logarithmic CDS spreads ($\Delta \log CDS_{it}$) of firm i computed at month t on

[2] Our Markit database contains CDS spreads expressed as composite prices, where no bid and ask information is provided. Other CDS databases, such as Reuters EOD, and Credit Market Analysis (CMA), also provide composite prices for CDS, and CDS bid-ask spreads are not available in these databases either. See Mayordomo, Peña, and Schwartz (2014) for a comprehensive comparison of those databases.

a set of firm specific characteristics ($FirmSpecific_{it}$) and systematic factors ($Systematic_{it}$).

$$\Delta \log CDS_{it} = \beta_0 + \beta_1 \, \Delta FirmSpecific_{it} + \beta_2 \, \Delta Systematic_{it} + \varepsilon_{it} \tag{1}$$

In each set of factors, we distinguish between credit- and liquidity-risk related factors. The following subsections discuss each of the factors in detail.

3.1 Firm-specific Factors

3.1.1 Firm-specific credit-risk factors

We use several accounting- and market-based measures to capture the ability of a firm to pay its short- and long-term debt.

(1) Cash Ratio (*CR*) determines the firm's ability to pay its debt due immediately. We expect a negative relation between firm's cash ratio and its CDS spread. Individual firms' cash ratios are calculated as:

$$CR_{it} = \frac{\text{Cash}_{it} + \text{Short-term Investment}_{it}}{\text{Current Liabilities}_{it}}. \tag{2}$$

(2) Profitability (*Profit*) is related to the overall health of the firm and, thus, its ability to meet the long-term obligations. It is expected to be negatively related to the firm's CDS spread. We calculate firm's profitability as:

$$Profit_{it} = \frac{\text{Retain Earnings}_{it}}{\text{Total Assets}_{it}}. \tag{3}$$

(3) Size (*TA*) is another indicator for a probability of a firm's default. Larger firms are less likely to default, as they usually have more capital, better collateral, and larger loss buffers. We expect a negative relation between firm size and its CDS spread. The firm's total asset as filed to annual reports is used as a measure of size.

(4) Firm Leverage (*Lev*) is expected to be positively related to default risk and, thus, its

CDS spread. A higher leverage indicates that the firm relies more heavily on borrowing to fiance its activities. In this paper, we calculate firm's accounting leverage as:

$$Lev_{it} = \frac{\text{Total Liabilities}_{it}}{\text{Total Equity}_{it}}. \tag{4}$$

(5) Historical Volatility ($HVol$) is expected to be positively related to a firm's CDS spread. Doshi, Ericsson, Jacobs, and Turnbull (2013), e.g., show that historical volatility of the underlying stock predicts changes in CDS spreads. We estimate the historical volatility of daily stock returns over one month prior to the date of interest.

(6) Merton (1974) Distance to Default (DTD) reflects the required change in the firm's asset value, expressed as the number of its standard deviations, in order to trigger default.[3] It is expected to be negatively related to firm's CDS spread. We use the iterative method as in Vassalou and Xing (2004) to estimate a one year DTD using the past 12 months of daily stock prices as:

$$DTD = \frac{\log(V/D) + (\mu_V - \sigma_V^2/2)T]}{\sigma_V \sqrt{T}} \tag{5}$$

where V is the firm's asset value, T is time to maturity and D is the face value of the outstanding debt, μ_V is instantaneous mean and σ_V is instantaneous volatility of the return on the asset process.

3.1.2 Firm-specific liquidity factors

Recent studies including Tang and Yan (2007), Das and Hanouna (2009), and Corò, Dufour, and Varotto (2013) find that CDS illiquidity risk is priced in CDS spreads. We consider several firm-specific illiquidity measures as suggested by Goyenko, Holden, and Trzcinka (2009) to address potentially different effects of various types of illiquidty measures.[4]

[3]Despite the proliferation of measures for credit quality, e.g., Moody's credit rating, Altman Z-score, physical PDs estimated from a reduced-form model such that in Duan, Sun, and Wang (2012) etc., DTD remains one of the most widely used measures, see, for example, Bharath and Shumway (2008).

[4]Another measure of illiquidity of individual CDS spread is its bid-ask spread (see Tang and Yan (2007) and Corò, Dufour, and Varotto (2013)). CDS bid-ask spread information, however, is not available in our sample, since the CDS spread is expressed as a composite price.

(1) Number of Contributors to CDS quotes (*Contr*) proxies for CDS trading volume (Bongaerts, Jong, and Driessen (2011)).[5] Trading volume is a useful indicator of the level of market liquidity. Higher trading volume implies more liquid markets. We, thus, expect, *Contr* to be negatively related to the CDS spread.

(2) High-minus-Low (*HL*) is the difference between highest and lowest quotes of CDS spread taken over one month. It is a proxy of a CDS bid-ask spread, and it is expected to be positively related to the spread itself.

(3) Roll (1984) measure (*Roll*) is the effective bid-ask spread for an asset, measured as two square roots of the negative of the serial covariance of the asset's price changes. Following Roll (1984), we calculate the individual CDS Roll measure over one month as:

$$Roll_{it} = \begin{cases} 2\sqrt{-cov(\Delta CDS_t, \Delta CDS_{t-1})} & \text{if } cov(\Delta CDS_t, \Delta CDS_{t-1}) < 0, \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where Δ is the operator of daily change and CDS is the corresponding CDS spread.

(4) Days of Zero Returns (*Zeros*) is another proxy for illiquidity proposed in Lesmond, Ogden, and Trzcinka (1999). The more zero returns a security exhibits, the less liquid it is. We expect $Zeros$ to be positively related to the CDS spread, and compute this measure over a one months as:

$$Zeros_{it} = \frac{\#\text{ days with zero return}_{it}}{T} \tag{7}$$

where T is the number of trading days in the month of interest.

(5) Amihud (2002) measure is one of the most widely used measures for illiquidity. We consider two versions of it: the one based on the daily CDS spreads ($Amihud_{CDS}$) and the one based on the stock ($Amihud_{Stock}$), as Das and Hanouna (2009) find that stock illiquidity also affects the CDS spread. We expect both these measures to be positively related to CDS spread.

[5] Since CDS spreads in the Markit database are composite prices, no information on the CDS trading volume is available.

We follow Bongaerts, Jong, and Driessen (2011) and compute $Amihud_{CDS}$ as:

$$Amihud_{CDS} = 1/N \sum \left(\frac{|r_t^C|}{Contr} \right) \tag{8}$$

where r^C is the daily return of the CDS spread, $Contr$ is the number of contributors to the CDS quotes, proxying for a trading volume, and N is the number of trading days in the past year.

$Amihud_{Stock}$ is computed as suggested by Das and Hanouna (2009):

$$Amihud_{Stock} = 1/T \sum \left(\frac{|r_t^S|}{P_t \times V_t} \times 10^6 \right) \tag{9}$$

where r^S is the daily stock return, P is the daily closing price, V is the daily trading volume, and T is the number of trading days in the previous five months.

3.2 Systematic Factors

Recent studies such as Diaz, Groba, and Serrano (2013) and Longstaff, Pan, Pedersen, and Singleton (2011) find that global or systematic factors do impact CDS spreads. We extend these studies and investigate a wide range of systematic factors, exogenous and endogenous to the CDS market, distinguishing, as in the case of firm specific factors, between credit and liquidity risk factors.

3.2.1 Exogenous Systematic Factors

(1) Bond market factors are expected to affect CDS spreads as bond and CDS markets co-move (Doshi, Ericsson, Jacobs, and Turnbull 2013). We use several systematic bond market factors: the U.S. 6-month Treasury yield ($US6mYield$) to proxi for the level of the yield curve, the difference between 10-year and 6-month yields ($Slope$) as proxy for its slope, and the difference between Moody's Baa and Aaa yields ($BaaMinusAaa$) as a proxy for the market credit risk premium. In addition, we include a cross-sectional average recovery rate ($Recovery$) as a systematic factor, since the recovery rate is highly related to market conditions (Tang and Yan

2013).

(2) Equity market factors can also affect CDS spreads either directly though cross-market hedging or indirectly by proving information on general investor sentiment. We use CBOE VIX index (VIX) as a proxy for the level of uncertainty in equity markets.

3.2.2 Endogenous Systematic Factors

In addition to the exogenous factors described above, we construct systematic factors, which are endogenous to the CDS market. We use two different models: a semi-parametric and a fully parametric structural model to derive endogenous CDS credit and liquidity factors.

(1) Semi-parametric model of Nelson and Siegel (1987) allows us to separate pure credit risk factor embedded in CDS spreads for each rating class of underlying bonds (Hu, Pan, and Wang 2013). For each rating, we construct the rating-based credit curves from the daily CDS spreads. The obtained fitted values of the CDS spread (y) are constant within the same rating category of the underlying, and can be used as a rating based systematic credit-risk factor. The absolute deviations of the individual CDS spreads from the fitted values (e) account for individual CDS liquidity as well as possible model errors. The details of the Nelson-Siegel decomposition are reported in Appendix A.

(2) Structural model of Leland and Toft (1996) allows us to decompose individual CDS spreads into their credit and liquidity components. Each logarithmic CDS spread is assumed to be a sum of its log credit component (λ) and the liquidity component (θ):

$$\log CDS = \log \lambda + \log \theta \tag{10}$$

The logarithmic representation makes sure that both credit and liquidity components take only positive values. We follow the methodology of Forte (2011) and calibrate λ_{it} and θ_{it} for each individual CDS spread at the end of each quarter. The technical details of the decomposition are described in Appendix B. We then construct the systematic credit and liquidity factors by averaging the respective individual λ-s and θ-s. We consider two types of systematic factors: the market- and industry-wide factors:

$$\log \lambda_{it}^{IND} \equiv \frac{1}{N_k - 1} \sum_{j \neq i, j \in k,} \log \lambda_{jt}, \text{ and } \log \theta_{it}^{IND} \equiv \frac{1}{N_k - 1} \sum_{j \neq i, j \in k,} \log \theta_{jt}$$

$$\log \lambda_{it}^{MKT} \equiv \frac{1}{N - N_k} \sum_{j \neq i, j \notin k} \log \lambda_{jt}, \text{ and } \log \theta_{it}^{MKT} \equiv \frac{1}{N - N_k} \sum_{j \neq i, j \notin k} \log \theta_{jt} \tag{11}$$

N_k and N are, respectively, the number of firms in industry k and the total number of firms at the and of a quarter t. We exclude the referenced firm i, or the referenced industry k, when computing the industry or market factors, in order to avoid spurious regression results.

We perform further tests in Appendix C of the endogenous systematic factors from above. We show that the systematic factors λ^{MKT} and θ^{MKT} indeed capture the credit and liquidity information in the CDS spreads respectively.

4 Data

We obtain daily CDS spreads from the Markit database. The Markit database provides daily information of CDS for maturities from 6 months to 30 years. As of 2011, our Markit database provides global, corporate, municipal, and sovereign single-name CDS data of approximately 2,650 individual entities and 3,000 entity-tiers. Our main sample covers 356 U.S. non-financial firms from January 2001 to May 2012. It contains the average of daily CDS spreads reported by different contributors, underlying debt seniority and the associated recovery rates. We drop the year 2001 in our sample, as our Markit database covers fewer than 100 companies in that year. The year 2012 was dropped as well because the data was incomplete for that year.

CDS spreads for the same firm may have different quoted prices due to the contract tier, which is related to the payback priority of the underlying bond. For example, secured debt has a higher priority in the payback order than subordinate debt. In our sample, there are, in total, 2.7 million individual CDS quotes. Most of these are for Senior Unsecured Debt (SNRFOR), which accounts for 75% of all data points. Subordinated Debt (SUBLT) accounts for another 20% while Junior Subordinated Debt (JRSUBUT2) and Preference Shares (PREFT1) account

Table 1: CDS Spreads Descriptive Statistics

The table reports the descriptive statistics of daily CDS spreads (in basis points) with maturities from 6 months to 10 years in our sample of 356 non-financial firms from January 2002 to December 2011. It contains means, medians, standard deviations (Std), and maximum and minimum values. "Missing Rate (%)" indicates the percentage of missing data points. The last row reports the total number of observations for a given maturity. "R. Rate" stands for reported recovery rate.

	CDS spread (bp)								R. Rate
	6m	1y	2y	3y	4y	5y	7y	10y	(in %)
Mean	151.27	171.68	184.29	205.00	220.70	236.19	234.96	237.62	40.05
Median	29.57	40.97	55.06	73.37	88.35	105.18	108.23	117.00	40.00
Std	728.38	672.18	603.90	573.07	547.42	510.59	507.98	489.60	6.20
Max	48,355.65	40,175.46	29,701.04	33,899.01	21,782.97	25,340.71	24,222.70	23,791.63	80.75
Min	0.58	0.81	0.79	1.28	1.45	1.00	3.27	4.34	1.25
Missing Rate (%)	42.96	21.63	23.19	16.71	43.25	9.64	18.36	20.20	1.35
# of Obs	510,428	701,372	687,346	745,410	507,910	808,637	730,570	714,181	882,804

for only 0.02% and less than 0.01%, respectively.[6] We use CDS quotes for senior unsecured debt. If this senior tier is not available for a given firm, the subordinated debt is chosen instead. The descriptive statistics of our initial sample are reported in Table 1.

The 10-year CDS spreads have the highest mean of 237.62 basis points (bp), while 6-month CDS spreads have the lowest mean of 151.27 bp. The average recovery rate is 40% across all maturities. Being particularly interested in the impact of liquidity risk, we choose to use 1-year CDS contracts in this paper instead of the more liquid 5-year CDS. 21% of the observations for the 1-year contracts are missing in the database. For the 1-year CDS contracts, the mean spread is 171.68 bp, and its standard deviation is 672.18 bp. The maximum spread is 40,175.46 bp while the minimum spread is 0.81 bp.[7]

We collect firm's market information from CRSP database, firm's accounting information from COMPUSTAT, and U.S. Treasury yields from the Federal Reserve, H15 report. Table 2 reports the descriptive statistics of our dependent and explanatory variables.

[6] On the 1st of August 2010, the Markit database changed the way how the composite CDS spreads are constructed. We control for this potential structural break when estimating the regressions.

[7] The maximum spread was reached just before Smurfit-Stone Container defaulted. The company was one of the largest forest, paper, and packaging companies in the world. Its CDS spread peaked on January 22, 2009, and the company filed for bankruptcy on January 27, 2009. The extraordinary large maximum spread is due to the procedure used to annualize CDS spreads.

Table 2: Summary Statistics of the Dependent and Independent Variables

The table reports the descriptive statistics of quarterly changes (Δ) in log CDS spread and other explanatory variables from 2002 to 2011. CR is firm's cash ratio; Profit is firm's accounting profitability; TA is firm's total book value of asset; DTD is Merton's distance to default; HVol is the historical volatility of the underlying stock; Lev is firm's leverage ratio; Contr is the number of contributors to CDS quotes; HL is the highest minus lowest CDS spread in a month; Roll is the Roll (1984) measure; Zeros is the share of days with zero returns in a month; $Amihud_{CDS}$ is the Amihud (2002) measure of the CDS spreads; $Amihud_{Stock}$ is the Amihud (2002) measure of the underlying stock; Recovery is the CDS recovery rate; US6mYield is the U.S. 6-month Treasury yield; Slope is the difference between 10-year and 6-month yields; BaaMinusAaa is the difference between Baa and Aaa yields; VIX is the CBOE VIX index; y and $|e|$ are the components from Nelson-Siegel model; and θ and λ are the components from Leland-Toft model. The total number of observations (# of Obs) for all variables is 12,545.

	Mean	Std	Max	Min
Δ log CDS	.015	.538	2.668	-2.122
Δ CR	.002	.256	5.470	-5.748
Δ Profit	-.001	.140	3.334	-6.391
Δ TA ($000)	230	2210	52653	-59661
Δ DTD	-.039	1.661	19.160	-9.565
Δ log HVol	.004	.153	1.042	-1.106
Δ log Lev	.001	.153	2.010	-1.596
Δ Contr	-.034	2.857	19.000	-21.000
Δ HL ($\times$100)	.022	.972	31.068	-45.603
Δ Roll ($\times$ 100)	.003	.243	9.615	-1.619
Δ Zeros	-.012	.158	1.000	-1.000
Δ log $Achimud_{CDS}$ ($\times$ 100)	.001	.249	3.705	-1.904
Δ log $Achimud_{Stock}$	-.017	.306	2.226	-3.090
Δ Recovery (%)	-.024	1.362	22.500	-21.286
Δ US6mYield	-.085	.501	.680	-1.830
Δ Slope	.014	.486	1.240	-.960
Δ BaaMinusAaa	.010	.412	1.910	-1.340
Δ VIX	.251	8.601	36.950	-19.560
Δ log y	.018	.421	1.584	-1.072
Δ log $\|e\|$	.018	1.129	8.731	-8.093
Δ log θ^{IND}	-.011	.245	.815	-1.644
Δ log λ^{IND}	.033	.358	1.366	-1.857
Δ log θ^{MKT}	-.011	.218	.558	-.575
Δ log λ^{MKT}	.032	.316	.689	-.690

5 Empirical Results

5.1 Univariate Analysis

Table 3 reports the correlation coefficients for all variables. The correlations between $\Delta \log CDS$ and all the factors generally exhibit the expected signs.

The three individual accounting-based credit risk factors are negatively correlated with the change in the CDS spread, but the correlation coefficients are rather low. The correlation with cash ratio (ΔCR) is -0.030, profitability ($\Delta Profit$) -0.012, and total assets (ΔTA) -0.003, suggesting that these variables may not be able to timely capture the changes in the CDS spread. The only accounting based variable that has a sizable correlation with the CDS spread is the leverage (ΔLev), with the positive correlation coefficient of of 0.332. The relations between $\Delta \log CDS$ and the market-based risk variables are stronger. Distance to default (ΔDTD) exhibits a negative correlation of -0.374, and historical volatility ($\Delta \log HVol$) of 0.346.

Changes in all CDS illiquidity measures are positively related to the changes in CDS spreads with the exception of $\Delta Zeros$, which has a negative but insignificant correlation coefficient. ΔHL has the highest correlation coefficient of 0.220. Interestingly, stock illiquidity is also strongly related to CDS spreads with the correlation coefficient between $\Delta \log Amihud_{Stock}$ and $\Delta \log CDS$ of 0.351.

$\Delta \log CDS$ exhibits high correlation with the exogenous systematic factors related to both bond and equity markets. The largest correlation coefficients in absolute values are with market volatility (ΔVIX) of 0.398, the short-term rate ($\Delta US6mYield$) of -0.410, and the credit spread ($\Delta BaaMinusAaa$) of 0.453. Similarly, we observe high correlation with endogenous systematic factors. The highest correlation of 0.608 is between $\Delta \log CDS$ and the rating-based market CDS factor $\Delta \log y$, followed by the market- and industry-wide systematic credit risk factors $\log \lambda^{MKT}$ and $\log \lambda^{IND}$ exhibiting correlations of 0.457 and 0.431 respectively. The systematic liquidity factors $\log \theta^{MKT}$ and $\log \theta^{IND}$ are also highly correlated with CDS spreads, with correlation coefficients exceeding 30%.

Table 3: Factors correlation matrix

The table reports the correlation coefficients for the changes in the log CDS spread and other explanatory variables from 2002 to 2011. Δ denotes quarterly changes. CR is firm's cash ratio; Profit is firm's accounting profitability; TA is firm's total book value of asset; DTD is Merton's distance to default; HVol is the historical volatility of the underlying stock; Lev is firm's leverage ratio; Contr is the number of contributors to CDS quotes; HL is the highest minus lowest CDS spread in a month; Roll is the Roll (1984) measure; Zeros is the days of zero returns; $Amihud_{CDS}$ is the Amihud (2002) measure of the CDS spreads; $Achimud_{Stock}$ is the Amihud (2002) measure of the underlying stock; Recovery is the CDS recovery rate; US6mYield is the U.S. 6-month Treasury yield; Slope is the difference between 10-year and 6-month yields; BaaMinusAaa is the difference between Baa and Aaa yields; VIX is the CBOE VIX index; y and $|e|$ are the components from Nelson-Siegel model; and θ and λ are the components from Leland-Toft model.

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1) Δ logCDS	-.030	-.012	-.003	-.374	.346	.332	.044	.220	.091	-.012	.017	.351	-.052	-.410	.092	.453	.398	.608	.135	.304	.431	.330	.457
(2) Δ CR		.090	.006	.053	-.014	-.021	-.003	-.003	-.002	.014	.026	-.039	.003	.026	.009	-.023	-.020	-.052	-.022	-.018	-.020	-.018	-.027
(3) Δ Profit			-.034	.019	-.004	.000	.003	-.018	-.009	-.031	.006	-.045	.008	.029	-.006	.001	.014	-.020	-.010	-.012	.008	-.016	.001
(4) Δ TA				-.038	-.030	.176	-.013	-.008	-.004	.011	.019	-.056	.010	.038	-.005	-.022	.001	-.017	-.026	-.045	.016	-.035	.012
(5) Δ DTD					-.675	-.567	-.007	-.107	-.046	-.008	.021	-.403	.002	.280	.005	-.381	-.359	-.484	-.191	-.387	-.166	-.411	-.188
(6) Δ HVol						.289	-.013	.146	.068	.028	-.023	.497	-.014	-.372	.101	.412	.268	.460	.193	.571	.010	.630	.014
(7) Δ Lev							.005	.129	.050	.000	.029	.355	-.021	-.243	.012	.338	.340	.375	.156	.260	.176	.253	.208
(8) Δ Contr								.000	-.011	-.064	-.017	-.003	.005	.007	-.017	-.001	-.007	.024	-.006	-.040	.058	-.038	.066
(9) Δ HL									.579	-.014	.064	.167	-.189	-.104	.032	.226	.202	.154	.095	.087	.089	.109	.100
(10) Δ Roll										-.017	.081	.076	-.089	-.048	.023	.103	.085	.068	.051	.044	.035	.058	.035
(11) Δ Zeros											-.016	.045	.012	-.027	.014	.048	.003	.011	.019	.047	-.005	.050	-.009
(12) Δ log $Amihud_{CDS}$												.007	-.005	-.076	.007	.011	.026	.003	.000	-.013	.026	-.026	.029
(13) Δ log $Achimud_{Stock}$													-.049	-.369	-.061	.477	.249	.475	.206	.378	.169	.405	.206
(14) Δ Recovery														.030	-.006	-.027	-.009	-.026	-.010	-.034	.009	-.036	.004
(15) Δ US6mYield															-.560	-.345	-.186	-.541	-.225	-.477	-.212	-.535	-.258
(16) Δ Slope																-.026	-.077	.085	.030	.322	-.113	.360	-.120
(17) Δ BaaMinusAaa																	.647	.648	.276	.327	.410	.357	.484
(18) Δ VIX																		.610	.266	.170	.443	.197	.509
(19) Δ log y																			.436	.440	.527	.493	.617
(20) Δ log $\|e\|$																				.186	.195	.212	.250
(21) Δ log θ^{IND}																					-.246	.821	-.160
(22) Δ log λ^{IND}																						-.178	.820
(23) Δ log θ^{MKT}																							-.203
(24) Δ log λ^{MKT}																							

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5.2 Multivariate Analysis

The estimation results for our panel regressions for changes in log CDS spreads are reported in Table 4. We, first, run individual regressions in which we include only one type of factors: individual credit risk factors (Model 1), individual liquidity risk factors (Models 2 and 3), systematic exogenous factors (Model 4), and systematic endogenous factors (Model 5). We, then, estimate the full specification including all the factors (Model 6). The results suggest that each set of factors contributes to explaining the variation of CDS spreads, and a comprehensive model should reflect all four sets of risks. Individual CDS liquidity, e.g., is as important as individual credit risk, as reflected in similar explanatory power of Models 1, 2 and 3. At the same time, the endogenous systematic factors have by far the highest explanatory power as compared to other factors. The adjusted R-square of the complete model (Model 6) of 46.8% is only 2.8 percentage points higher that that of the model based on endogenous systematic factors (Model 5) and 28.3 percentage points higher than that of the individual-credit-risk factor based model (Model 1). Below we discuss the estimation results of the individual models in detail.

Taking alone individual accounting- and market-based credit factors explain up to 18.5% of the variation in CDS spread changes (Model 1). The strongest effect is associated with the $\Delta \log Lev$, $\Delta \log HVol$, and ΔDTD. The corresponding loadings of 0.755, 0.727, and -0.037 are highly significant. The magnitude of these coefficients decreases substantially to 0.274, 0.120, and -0.010, respectively, when the full specification (Model 6) is considered. The corresponding t-statistics ranging from 8.8 to 21.3 in absolute values in Model 1 drop to a range of 2.8 to 9.0 in Model 6, again reflecting the dominant role of the systematic factors.

Individual CDS liquidity factors (Models 2 and 3) capture up to 15.4% and 16.1% of the variation of the changes in CDS spreads.[8] These adjusted R-squares are comparable with the one in Model 1, indicating that individual CDS liquidity factors capture approximately as much variation in CDS spreads as credit risk factors. Almost all of the liquidity variables are significant at 1% level, except for $\Delta Amihud_{CDS}$, which gains significance only after 2010. The signs of the loadings on liquidity factors largely corroborate the intuition that CDS spreads are more likely to increase when CDSs turn less liquid, which is also supported by findings in

[8] Compared to Model 2, in Model 3 we also control for the effect of the change in the reporting style of the Markit database on the August 1, 2010.

Table 4: Panel regression results for quarterly changes in log CDS spread

The table reports the panel regressions results for the quarterly changes in log CDS spreads from 2002 to 2011. The explanatory variables are described in Sections 3. D is a dummy variable taking a value of 1 after August 2010 to control for the reporting changes of the Markit database. ***, **, and * stand for the significance at 1%, 5%, and 10% levels.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.011**	0.022***	0.023***	-0.022***	-0.004	-0.009**
	[2.574]	[4.875]	[5.253]	[-5.317]	[-1.112]	[-2.547]
Δ CR	-0.032*					-0.003
	[-1.876]					[-0.204]
Δ Profit	-0.034					-0.011
	[-1.088]					[-0.430]
Δ TA	-0.000***					-0.000
	[-4.677]					[-1.125]
Δ DTD	-0.037***					-0.010***
	[-8.797]					[-2.828]
Δ log HVol	0.727***					0.120***
	[18.639]					[3.068]
Δ log Lev	0.755***					0.274***
	[21.346]					[8.977]
Δ Contr		0.008***	0.005***			0.003**
		[5.235]	[3.322]			[2.359]
Δ HL		10.559***	10.030***			7.011***
		[18.718]	[17.510]			[15.075]
Δ Roll		-9.776***	-9.838***			-6.588***
		[-4.377]	[-4.289]			[-3.603]
Δ Zeros		-0.076***	-0.086***			-0.070***
		[-2.723]	[-3.050]			[-3.103]
$\Delta \log Amihud_{CDS}$		1.307	-2.461			-0.082
		[0.734]	[-1.225]			[-0.050]
$\Delta \log Amihud_{Stock}$		0.569***	0.563***			0.019
		[38.833]	[38.547]			[1.224]
Δ Contr × D			0.052***			0.018***
			[7.117]			[2.954]
Δ HL × D			15.014***			9.884***
			[5.169]			[4.238]
Δ Roll × D			-2.780			-0.776
			[-0.297]			[-0.104]
Δ Zeros × D			0.167			-0.119
			[1.027]			[-0.914]
$\Delta \log Amihud_{CDS} \times$ D			11.202***			-0.897
			[2.581]			[-0.257]
Δ Recovery				-3.402***		-4.124***
				[-3.268]		[-4.412]
Δ US6mYield				-0.373***		-0.040***
				[-34.889]		[-3.444]
Δ Slope				-0.091***		0.011
				[-8.803]		[1.086]
Δ BaaMinusAaa				0.264***		-0.014
				[19.307]		[-1.070]
Δ VIX				0.012***		-0.001**
				[19.890]		[-2.019]
$\Delta \log y$					0.348***	0.300***
					[18.161]	[15.081]
$\Delta \log \lvert e \rvert$					-0.069***	-0.070***
					[-19.517]	[-20.104]
$\Delta \log \theta^{IND}$					0.295***	0.237***
					[10.736]	[8.661]
$\Delta \log \lambda^{IND}$					0.305***	0.286***
					[16.262]	[15.575]
$\Delta \log \theta^{MKT}$					0.484***	0.356***
					[13.600]	[9.263]
$\Delta \log \lambda^{MKT}$					0.375***	0.348***
					[14.392]	[13.025]
Adj R-sqr	0.185	0.154	0.161	0.306	0.440	0.468

Corò, Dufour, and Varotto (2013). For example, higher HL implies larger bid-ask spread, thus, lower liquidity. Consistently, the loading on ΔHL is 10.559, significant at the 1% level. High and significant loading on the CDS Amihud after August 2010 also supports a positive relation between CDS illiquidity and its spread. Surprisingly, we find negative coefficient on $\Delta Roll$. This result can be driven by relatively high correlation between ΔHL and $\Delta Roll$ (57.90%), as both these variables proxy for CDS bid-ask spread. $Contr$ and $Zeros$ reflect the depth the CDS market. The coefficients on $\Delta Contr$ and $\Delta Zeros$ are 0.008 and -0.076, respectively. An increase of $Contr$ or a decrease of $Zeros$ indicates higher trading activity in the CDS market. The estimated signs imply that the activity increase is driven by higher demand for protection by CDS buyers, thus, leading to higher CDS spreads. Consistent with Das and Hanouna (2009), we find a positive loadings on $\Delta \log Amihud_{Stock}$ (0.569) significantly at the 1% level. CDS spreads tend to increase when the related stock becomes less liquid, which can be attributed to cross-market hedging by CDS sellers. When individual liquidity factors are considered within the full specification (Model 6), the magnitude of the estimated coefficients decreases similar to the individual credit-risk factors. Importantly, individual equity liquidity $\Delta \log Amihud_{Stock}$ turns from highly significant to insignificant (the t-statistics drops from 38.2 to 1.2), indicating that its effect on CDS spreads is completely surpassed by systematic factors. The same holds for $\Delta \log Amihud_{CDS}$.

The adjusted R-square increases substantially to 30.6% if only the exogenous systematic factors are used instead of individual factors (Model 4). Negative and highly significant coefficients on $\Delta US6mYield$ and $\Delta Slope$ imply that higher level and larger slope of the Treasury yield curve, associated with better economic conditions, predict lower CDS spreads. Whereas higher credit risk premium ($\Delta BaaMinusAaa$) and higher uncertainty (ΔVIX) lead to increase in CDS spreads. The corresponding loadings of 0.264 and 0.012, respectively, are highly significant. These factors, however, lose their statistical support when considered within the full specification (Model 6). The factor that remains significant at the 1% level is $\Delta US6mYield$, although the corresponding loading changes from -0.373 (Model 4) to -0.040 (Model 6). ΔVIX even flips the sign due to multicellularity, but the corresponding loading is very small in absolute value (-0.001) despite still being significant at the 5% level.

The adjusted R-square increases further to 44% if the endogenous, model-calibrated CDS systematic factors are used (Model 5). Our model-calibrated systematic factors are obtained from the peer CDS spreads. The high explanatory power is in line with the prediction of the theoretical model in Cespa and Foucault (2014) that shows that the price of an individual security is affected by the peer information, in additional to its fundamental value. Our three endogenous systematic credit risk factors (rating-based y, industry-based λ^{IND}, and market-based λ^{MKT}) seem to capture different aspects of the CDS spread changes. They do not jeopardise each other's significance and have similar effect on the changes of CDS spreads. The corresponding coefficients of 0.348, 0.305, and 0.375 are all significant at the 1% level. The loadings on two systematic liquidity factors (industry-based θ^{IND} and market-based θ^{MKT}) of 0.295 and 0.484, respectively, are also significant at 1% level. This results highlight the comparable effect of systematic liquidity and systematic credit risk factors on the dynamics of CDS spreads.[9] Moreover, in the full specification (Model 6) the adjusted R-square increases just slightly to 46.8% compared to Model 5. Importantly, none of the endogenous systematic factors looses significance. The estimated coefficients as well as the corresponding t-statistics remain comparable in the full model.

Overall, the results unambiguously show the dominant role of the endogenous CDS-market specific credit and liquidity factors in determining CDS spreads. Any analysis that relies on individual factors only will suffer from the omitted variable bias and may provide inaccurate results.

5.3 Sub-period Analysis

To assess the stability of our results, we repeat the analysis for two sub-samples of equal length: before the financial crisis of 2007 (from 2002 to 2006) and during and after the crisis (from 2007 to 2011). Table 5 reports the correlation coefficients between $\Delta \log CDS$ and the explanatory variables in two sub-periods.

[9] Note, the coefficient of $\Delta \log |e|$ is negative of -0.069. $|e|$ is the distance from individual CDS spread to the rating-based CDS spread, and capture the idiosyncratic noise with respect to the model. The smaller noise is associated with less uncertainty about the actual level of the CDS spread, which corresponds to worse quality borrowers, and higher CDS spread changes.

Table 5: Factors correlation: sub-sample analysis

The table reports the correlation coefficients between the $\Delta \log CDS$ spread and other explanatory variables across two sub-samples: from 2002 to 2006, and 2007 to 2011. Δ denotes quarterly changes. CR is firm's cash ratio; Profit is firm's accounting profitability; TA is firm's total book value of asset; DTD is Merton's distance to default; HVol is the historical volatility of the underlying stock; Lev is firm's leverage ratio; Contr is the number of contributors to CDS quotes; HL is the highest minus lowest CDS spreads in a month; Roll is the Roll (1984) measure; Zeros is the days of zero returns; $Amihud_{CDS}$ is the Amihud (2002) illiqudity measure of the CDS spreads; $Amihud_{Stock}$ is the Amihud (2002) illiqudity measure of the underlying stock; Recovery is the CDS recovery rate; US6mYield is the U.S. 6-month Treasury yield; Slope is the difference between 10-year and 6-month yields; BaaMinusAaa is the difference between Baa and Aaa yields; VIX is the CBOE VIX index; y and $|e|$ are the components from Nelson-Siegel model; and θ and λ are the components from Leland-Toft model.

	2002–2006	2007–2011
Δ CR	-.027	-.034
Δ Profit	-.029	-.006
Δ TA	.006	.000
Δ DTD	-.234	-.408
Δ HVol	.153	.379
Δ Lev	.198	.366
Δ Contr	.087	.029
Δ HL	.183	.235
Δ Roll	.085	.095
Δ Zeros	-.047	.008
$\Delta \log Amihud_{CDS}$	-.039	.027
$\Delta \log Amihod_{Stock}$	.144	.388
Δ Recovery	-.068	-.047
Δ US6mYield	-.049	-.451
Δ Slope	.003	.030
Δ BaaMinusAaa	.280	.506
Δ VIX	.180	.437
Δ log y	.420	.638
Δ log $\|e\|$	.022	.152
Δ log θ^{IND}	.059	.321
Δ log λ^{IND}	.371	.453
Δ log θ^{MKT}	.042	.342
Δ log λ^{MKT}	.412	.470

Majority of the correlation coefficients increases substantially in 2007–2011. Among the set of the individual credit-risk factors, the correlation coefficient of $\Delta \log CDS$ with ΔDTD increases in absolute value from -23.4% to -40.8%; with $\Delta HVol$ it increases from 15.3% to 37.9%, and with ΔLev it increases from 19.8% to 36.6%. From the set of individual liquidity measures, the correlation with equity illiquidity exhibits the highest change increasing from 14.4% to 38.8%. Systematic factors become more correlated with the CDS spread during 2007–2011 period, too. The correlation of $\Delta US6mYield$ and $\Delta \log CDS$ change from -4.9% to -45.1%, the one with $\Delta BaaMinusAaa$ increases from 28% to 50.6%, and the one with ΔVix increases from 18% to 43.7%. Similar increase in correlation is observed for the endogenous systemic risk factors with $\Delta \log y$ reaching the correlation coefficient of 63.8% with $\Delta \log CDS$, indicating very strong comovements in the CDS market after the crisis. One of the largest increases, however, are associated with the correlation with the endogenous liquidity factors (θ^{IND} and θ^{MKT}). They increase from around 5% in 2002–2006 to over 30% in 2007–2011, implying a more important role of systematic liquidity risk in determining CDS spreads in the later part of our sample.

Table 6 reports the panel regression results for the two sub-periods. Consistent with the increase in the correlation coefficients, the adjusted R-squares in 2007–2011 are all higher than in 2002–2006. For the complete specification (Model 6), the R-square increases from 31.4% to 50.4%.

There are also several important changes in the significance of the explanatory variables. Among the individual credit-risk related variables, $\Delta \log \text{Lev}$ has consistent strong effect on CDS spread in both periods, when the full model is used, whereas ΔDTD is significant only during the first period. As for individual liquidity measures, only ΔHL has consistent positive impact in both periods, with ΔZeros and $\Delta \log Amihud_{Stock}$ being significant only before the crisis. Systematic exogenous factors are also significant only during earlier sub-sample. The strong negative relation of ΔUS6mYield and positive relation of ΔBaaMinusAaa with the changes in the CDS spread before the crisis turns insignificant in 2007–2011. The only set of factors with strong and consistent effect on the changes in CDS spreads is the set of endogenous systematic factors. All these factors retain their significance in both periods. The loadings on endogenous systematic credit-risk factors ($\Delta \log y$, $\Delta\lambda^{IND}$, and $\Delta\lambda^{MKT}$) increase in during the second period, consistent with the higher interdependence between CDS spreads after the crisis.

Importantly, the systematic CDS market liquidity factors turn substantially more important during and after the crisis. The loadings on $\Delta \log \theta^{IND}$ go up from 0.183 to 0.250, both being significant at the 1% level. The loading on $\Delta \log \theta^{MKT}$ increase from insignificant 0.120 to highly significant 0.454.

Thus, the subperiod analysis confirms the decisive role of the systematic factors in determining changes of CDS spreads. The systematic liquidity risk used to play a relatively smaller role during calm market conditions as compared to systematic credit risk, but its importance has increased substantially after the financial crisis of 2007.

5.4 Out of Sample Prediction

One potential application of our model is estimation of (changes in) CDS spreads for firms that do not have (actively) traded CDS. One can choose, for example, the last CDS quote available or an industry/rating average CDS as the initial value as suggested by Basel III, and then apply our model to refine the spread estimate for a particular firm.

In order to assess the quality of cross-sectional predictability of our model, we randomly choose 100 firms as a test sample with the remaining firms being a training sample. The model is estimated based on the training sample and the CDS changes are predicted for the test sample. We then compute the adjusted out-of-sample R-square $\overline{R}^2_{OOS}$ using a simple average of the past CDS changes as a benchmark ($\bar{s}_i$), following Welch and Goyal (2008). The procedure is repeated 1,000 times.

$$\overline{R}^2_{OOS} = 1 - \frac{\sum_i \sum_t (s_{it} - \hat{s}_{it})^2 \; / \; DF_A}{\sum_i \sum_t (s_{it} - \bar{s}_i)^2 \; / \; DF_N} \tag{12}$$

$$\bar{s}_i = \frac{1}{T} \sum_t s_{it} \tag{13}$$

where s_{it} is the change in $\log CDS$ spread of firm i over quarter t, and T is the number of past quarters used, $\hat{s}_{it}$ is the predicted change of $\log CDS$ spread based on our model with parameters estimated using a training sub-sample, and DF is the number of degrees of freedom for the

Table 6: Panel regression results: sub-sample analysis

The table reports the panel regressions results for the quarterly changes in log CDS spreads for two sub-periods 2002–2006, and 2007–2011. The explanatory variables are described in Sections 3. D is a dummy variable taking a value of 1 after August 2010 to control for the reporting changes of the Markit database. ***, **, and * stand for the significance at 1%, 5%, and 10% levels.

	2002–2006					2007–2011				
	Model 1	Model 2	Model 3	Model 5	Model 6	Model 1	Model 3	Model 4	Model 5	Model 6
Constant	-0.102***	-0.105***	-0.039***	-0.028***	-0.021	0.062***	0.080***	-0.022***	0.005	0.004
	[-14.596]	[-14.825]	[-3.511]	[-2.775]	[-1.482]	[11.098]	[14.198]	[-3.866]	[1.055]	[0.750]
Δ CR	-0.030				-0.012	-0.026				0.009
	[-1.298]				[-0.613]	[-1.088]				[0.493]
Δ Profit	-0.107				-0.066	-0.014				-0.002
	[-1.512]				[-1.076]	[-0.398]				[-0.087]
Δ TA	-0.000***				-0.000	-0.000***				-0.000
	[-2.870]				[-0.842]	[-2.681]				[-0.978]
Δ DTD	-0.041***				-0.026***	-0.040***				0.002
	[-6.170]				[-4.343]	[-7.612]				[0.414]
Δ log HVol	0.295***				0.148**	0.711***				0.176***
	[3.603]				[2.035]	[15.583]				[3.694]
Δ log Lev	0.444***				0.259***	0.796***				0.294***
	[7.433]				[4.933]	[18.307]				[7.862]
Δ Contr		0.009***			0.002		0.001			0.004*
		[4.856]			[1.377]		[0.346]			[1.917]
Δ HL		21.007***			16.768***		9.252***			6.624***
		[9.740]			[9.040]		[15.227]			[13.606]
Δ Roll		10.483			8.137		-10.484***			-7.069***
		[1.303]			[1.183]		[-4.297]			[-3.687]
Δ Zeros		-0.077**			-0.101***		-0.072*			-0.026
		[-2.163]			[-3.257]		[-1.754]			[-0.811]
$\Delta \log Amihud_{CDS}$		-6.307**			-2.306		-5.210*			1.436
		[-2.340]			[-0.965]		[-1.877]			[0.654]
$\Delta \log Amihud_{Stock}$		0.253***			0.089***		0.587***			-0.010
		[8.261]			[3.155]		[34.997]			[-0.538]
Δ Contr $\times$ D							0.059***			0.015**
							[7.593]			[2.334]
Δ HL $\times$ D							14.698***			9.975***
							[4.920]			[4.208]
Δ Roll $\times$ D							1.302			-0.204
							[0.135]			[-0.027]
Δ Zeros $\times$ D							0.257			-0.165
							[1.519]			[-1.231]
$\Delta Amihud_{CDS} \times$ D							15.518***			-1.865
							[3.208]			[-0.486]
Δ Recovery			-15.480***		-7.928***			14.423***		0.425
			[-11.320]		[-6.049]			[8.460]		[0.250]
Δ US6mYield			-0.169***		-0.099***			-0.438***		-0.004
			[-6.254]		[-3.787]			[-33.002]		[-0.245]
Δ Slope			0.044**		0.002			-0.154***		0.010
			[2.069]		[0.106]			[-12.941]		[0.776]
Δ BaaMinusAaa			1.383***		0.356***			0.255***		0.003
			[20.986]		[4.735]			[16.995]		[0.221]
Δ VIX			0.026***		0.007***			0.010***		-0.002***
			[12.106]		[3.314]			[15.572]		[-3.069]
Δ log y				0.391***	0.238***				0.296***	0.277***
				[13.137]	[7.749]				[11.449]	[10.373]
Δ log $\lvert e \rvert$				-0.046***	-0.044***				-0.078***	-0.080***
				[-7.177]	[-7.241]				[-18.331]	[-19.027]
Δ log θ^{IND}				0.248***	0.183***				0.307***	0.250***
				[6.212]	[4.619]				[7.122]	[5.854]
Δ log λ^{IND}				0.246***	0.226***				0.345***	0.324***
				[8.960]	[8.605]				[13.458]	[12.844]
Δ log θ^{MKT}				0.365***	0.120				0.538***	0.454***
				[4.903]	[1.565]				[10.081]	[7.930]
Δ log λ^{MKT}				0.339***	0.275***				0.408***	0.394***
				[8.866]	[7.071]				[11.361]	[9.925]
Adj R-sqr	0.067	0.056	0.168	0.248	0.314	0.215	0.194	0.367	0.479	0.504

null hypothesis that the proposed model ($\hat{s}$) does not perform better than that benchmark ($\bar{s}$).

We consider two cases for the out-of-sample prediction. The first one mimics a situation in which a firm of interest does have CDSs, but they are not frequently traded. Using the past quotes, the individual CDS liquidity measures can still be computed, and the unobserved current level of CDS spread can be forecasted based on our full model specification. The second case presents a situation in which a firm does not have CDSs. Individual CDS liquidity information is, thus, not available either. For this scenario, we exclude the firm-specific liquidity factors from the model when estimating its parameters and forming forecasts. The descriptive statistics of $\overline{R}^2_{OOS}$ for both scenarios are reported in Table 7. Panel A reports the results for the case with the individual liquidity measures, Panel B reports the results excluding them. The model that excludes individual CDS liquidity characteristics has only marginally smaller out-of-sample R-squares, again, highlighting the determinant role of the systematic information. The mean square error of the cross-sectional out-of-sample predictions improves on average by 43% compared to a simple average. The out-of-sample R-square reaches 46% after 2007, and even in the earlier sub-sample it is solid 25% when individual liquidity factors are used and almost 24% when they are excluded. Thus, our model consistently improves the quality of forecasts of CDS spreads and can be a helpful tool to approximate CDS spreads when needed.[10]

6 Conclusion

In this paper, we investigate determinants of individual firms' CDS spreads. Using quarterly changes of 1-year CDS spreads of 356 U.S. non-financial firms over the sample period from 2002 to 2011, we show that four types of factors affect CDS spreads: firm specific credit risk factors, firm specific liquidity factors, exogenous systematic factors, and endogenous credit and liquidity systematic factors. Taken together, these factors explain up to 46.7% of the variation of changes of individual CDS spreads. Our model performs well out-of-sample, substantially improving cross-sectional predictability, with the reduction in the mean square error by 43%

[10] In addition, we perform the time-series rolling-window out-of-sample analysis. We use the initial sample period from January 2002 to January 2005, and then roll the sample forward by one month. In this setting, we perform a general time-series out-of-sample prediction, but found a negative $\overline{R}^2_{OOS}$. Hence, the model should not be used for predicting future changes in CDS spreads, unless the reliable estimates of future values of the systematic factors are available.

Table 7: Out-of-sample Results

This table reports the descriptive statistics of the adjusted out-of-sample R-square ($\overline{R}^2_{OOS}$) for quarterly changes in log CDS spreads for non-financial firms. In the cross-sectional prediction, we randomly choose 100 firms as a test sample and use the remaining firms as a training sample. The procedure is repeated 1,000 times. The results are reported for the complete sample period from 2002 to 2011, and two sub-sample periods before- and after- the financial crisis of 2007. Panel A uses the full model including individual liquidity measures. Panel B uses a reduced form excluding individual liquidity measures.

	2002–2011	2002–2006	2007–2011
Panel A: Including individual liquidity			
Mean	0.434	0.251	0.464
Std	0.028	0.033	0.033
Max	0.500	0.352	0.545
Min	0.309	0.068	0.302
Panel B: Excluding individual liquidity			
Mean	0.431	0.237	0.460
Std	0.022	0.033	0.026
Max	0.498	0.326	0.525
Min	0.358	0.092	0.370

compared with the sample average.

Among individual credit risk factors, a firm leverage has the strongest effect on CDS spread which is also stable across different market conditions. Individual CDS liquidity factors are as important as credit risk factors, with the difference between the highest and the lowers quote for the CDS spread (a low frequency proxy for a bid-ask spread) being the strongest and robust predictor.

Most importantly, we find that endogenous systematic factors dominate in terms of the explanatory power individual CDS factors and suppress exogenous systematic factors, especially after the financial crisis of 2007. We derive three endogenous systematic CDS credit factors based on peer information: a rating-based (using a Nelson and Siegel (1987) decomposition) and industry- and market-wide (using the structural model of Leland and Toft (1996)). These factors capture different angles of systematic risk and are all significant predictors of CDS changes. Moreover, to the best knowledge, our paper is the first to construct systematic CDS illiquidity factors: industry- and market-wide CDS illiquiduty. We show that systematic CDS illiquidty is as important as systematic credit risk in explaining changes in the spreads, and its effect increases substantially after the financial crisis.

Financial regulations, such as BASEL III, stipulate that CDS spreads must be used to produce market estimates of the default probability of a counterparty. Our findings challenge this approach as changes of individual firms' CDS spreads are driven mainly by systematic factors, including systematic liquidity risk, and not firm's default risk. Our new systematic CDS market illiquidity factors can be potentially used in the context of other asset pricing models, improving the predictive power of, e.g., models for bonds and derivatives.

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Appendices

A Calibration of the Nelson-Siegel (1987) Model

Following Nelson-Siegel (1987) model, we assume the firm's default intensity (h) at time τ can be expressed as

$$h(\tau) = y(\tau) + e(\tau) \tag{14}$$

where y is the fitted value specific to the credit rating class, and e is the residual. $y(\tau)$ has the following form, which allows for a hump-shaped term structure:

$$y(\tau|\beta_0, \beta_1, \beta_2, m) = \beta_0 + \beta_1 \left(\frac{1 - \exp(-\tau/m)}{\tau/m} \right) + \beta_2 \left(\frac{1 - \exp(-\tau/m)}{\tau/m} - \exp(-\tau/m) \right) \tag{15}$$

where β_0 and β_1 are the long-term and short-term hazard rates, β_2 captures a hump at the medium term, and m determines the shape and the position of the hump. We set $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\beta_0 + \beta_1 + \beta_2 > 0$ and $m > 0$ to avoid negative values of h. $y(\tau)$ is fitted to a group of CDSs with the same credit rating, and it is constant for all CDSs with the same maturity and belonging to the same rating class.

We calculate CDS-implied default intensity using the Carr and Wu (2011) framework. The authors define a unit recovery claim (URC) as a security that pays one unit if a firm defaults before time T. Under this assumption, the default intensity h can be calculated as $h = C/(1-R)$, where C is the CDS spread and R is the recovery rate. We use the URC-implied default intensity to perform Nelson-Siegel calibration. Then, using the calibrated parameters, we compute y and e for one-year CDS contract in each rating class for each date of interest.

B Calibration of the Leland-Toft (1996) Model

Following Forte (2011), we assume the following form for a CDS spread, which prevents negative spreads:

$$\begin{aligned} CDS =& \lambda \times \theta \\ \log CDS =& \log \lambda + \log \theta \end{aligned} \tag{16}$$

where CDS is the observed CDS spread, λ is the credit spread calibrated using the Leland and Toft (1996) model, and θ is the illiquidity (or noise) of CDS spread.

Forte (2011) provides detailed discussion of the calibration procedure of CDS spreads to the Leland and Toft (1996) model. We modify this procedure by also using the reported recovery rates, which allows us to obtain both λ and θ components. Our modified procedure is detailed below.

B.1 Calibrating Individual Firm's Credit Spread

For a firm's value V_t, following a geometric Brownian motion, Leland and Toft (1996) show that the value of debt with maturity τ can be expressed as

$$\mathbf{d}(V_t, \tau) = \frac{c(\tau)}{r} + \left\{ e^{-r\tau}[k(\tau) - \frac{c(\tau)}{r}][1 - F_t(\tau)] \right\} + \left\{ [R(\tau)V_B - \frac{c(\tau)}{r}]G_t(\tau) \right\} \tag{17}$$

where $c(\tau)$ is the bond coupon payment, $k(\tau)$ is the bond principle, r is the risk-free rate, V_B is the default barrier, $R(\tau)$ is the recovery rate at default, $1 - F(\tau)$ is the firm's survival probability and $G(\tau)$ is the probability of default.[11]

The debt value in Equation (17) consists of three terms: $c(\tau)/r$ is the present value of coupons, the first and the second sets of curly brackets are the present values of bonds in the case of no default and in the case of a default respectively.

[11] See Leland and Toft (1996) for detailed discussion.

The total debt value of the firm is the sum of all N outstanding debts:

$$D(V_t) = \sum_{i=1}^{N} \mathbf{d}(V_t, \tau_i). \tag{18}$$

In Equation (17), $R(\tau)V_B$ is the residual value of a firm, or default barrier, in the case of a default:

$$R(\tau)V_B = (1-\alpha)\beta k(\tau) \tag{19}$$

where α is the bankruptcy cost and β is the default point expressed as a percentage of the face value of debt, $k(\tau)$. Forte (2011) equates $(1-\alpha)\beta$ to the recovery rate. Since our Markit database provides an estimate of a recovery rate (R), we set $\beta = \frac{R}{1-\alpha}$ with $\alpha = 0.3$ following Leland (2004). Hence, $\mathbf{d}(V_t, \tau)$ can be re-expressed as

$$\mathbf{d}(V_t, \tau) = \frac{c(\tau)}{r} + e^{-r\tau}[k(\tau) - \frac{c(\tau)}{r}][1 - F_t(\tau)] + [(1-\alpha)\beta k(\tau) - \frac{c(\tau)}{r}]G_t(\tau). \tag{20}$$

Therefore, the bond yield for τ-year debt is

$$yield(V_t, \tau) = \frac{c(\tau)}{\mathbf{d}(V_t, \tau)} \tag{21}$$

and the implied credit spread, λ_t, is[12]

$$\lambda_t(\tau) = yield(V_t, \tau) - r_t. \tag{22}$$

B.2 Estimating a Firm's Value From its Equity Value

Asset value V_t is needed to calculate $F_t(\tau)$ and $G_t(\tau)$ in Equation (20). As V_t is unobservable, it has to be calibrated using observable equity prices. We use the firm's capital structure to

[12] Forte (2011) uses individual firm CDS to calibrate the β value in Equation (19) for each firm, and shows that the calibrated λ_t is indeed very close to the market observed CDS spread, and has the same trend. We fixed the value of β by using the Markit recovery rate, and provide a CDS independent credit spread calibration. The fixing of β value turns out not to be decisive for our results, as the choice of α and β only affect the level, but not the time series variations, of calibrated credit spreads. In all our empirical tests, only changes in these factors are used.

obtain the implied asset value. We denote the equity value by $S(V_t)$, and the firm's capital structure satisfies

$$V_t = S(V_t) + D(V_t) + BC(V_t)$$
$$S(V_t) = V_t - D(V_t) - BC(V_t) \tag{23}$$

where, according to Forte (2011), $BC(V_t) = D(V_t|\alpha = 0) - D(V_t)$ is the bankruptcy cost. Therefore, by setting $\alpha = 0$, Equation (23) becomes

$$S(V_t) = V_t - D(V_t|\alpha = 0) \tag{24}$$

We first calibrate V_t to the observed stock price S_t using Equation (24) and an iterative process, and then use the calibrated V_t to calculate $F_t(\tau)$, $G_t(\tau)$ and $yield(V_t, \tau)$.

We calibrate the individual firm's credit spread on a daily basis, and then compute individual daily residuals from Equation (16): $\log CDS_{it} - \log \lambda_{it}$. To instill stability into the noisy daily estimate of the illiquidity component, we then calculated θ_{it} as the average of the daily residuals over the last 12 months.

C Analysis of Endogenous Systematic Factors

In this appendix, we analyse in detail the information content of the our endogenous systematic credit and liquidity factors.

Figure 1 plots the log systematic market-wide credit risk component ($\log \lambda_t^{MKT}$) in which all industries are used and the log market CDS spread, which is the average of the individual CDS spreads ($\log CDS_t^{MKT}$). Subplot (a) shows that although $\log \lambda_t^{MKT}$ is almost always above $\log CDS_t^{MKT}$, they exhibit common trends. The times of peaks and troughs are similar for both series, despite them being derived from prices of instruments traded in different markets (CDS market for CDS spreads and stock market for systematic credit risk component). The scatter plot in subplot (b) clearly demonstrates a linear dependence between the two variables, indicating that the systematic credit risk factor captures well the average dynamics of CDS spreads.

Figure 2 plots the time series of the CDS market insipidity factor θ_t^{MKT}. Until 2008, θ_t^{MKT} is very small and continues to decline over time. It peaks in the immediate post-crisis era, and declines from mid 2009 to just about the pre-crisis level as of the end of 2011.

To make sure that our CDS market illiquidity factor, θ_t^{MKT}, does indeed contain liquidity-related information, and not pure noise, we run a regression of $\log\theta_t^{MKT}$ on various well known liquidity determinants. Following Bedendo, Cathcart, and El-Jahel (2011), we include the CBOE VIX index (VIX), the average of individual firms' 30-day historical stock volatility ($30DHistVol$), the average of individual stocks' log Amihud illiquidity measures ($\log Amihud_{Stock}$), and the difference between the Moody's Baa and Aaa yields ($BaaMinusAaa$) to capture 'overall' market illiquidity (Hu, Pan, and Wang 2013). We also include the average pairwise correlation of stock returns for all firms in our sample ($StockPairCorr$) to proxy for equity correlation risk, which usually increases on illiquid markets.

Figure 3 shows that our CDS market illiquidity factor ($\Delta\log\theta_t^{MKT}$) and the five illiquidity determinants have similar time-series dynamics: all of them responded strongly to the subprime crisis 2007–2009. Figure 4 further shows the scatter plots of individual liquidity determinants against our CDS market illiquidity factor. The clearest linear association is between $\Delta\log\theta_t^{MKT}$ and the cross-sectional average Amihud stock illiquidity measure. Interestingly, there is a non-linear relation between $\Delta\log\theta_t^{MKT}$ and the other four liquidity determinants. The positive association holds only for positive values of $\Delta\log\theta_t^{MKT}$, when CDS market turns more illiquid.

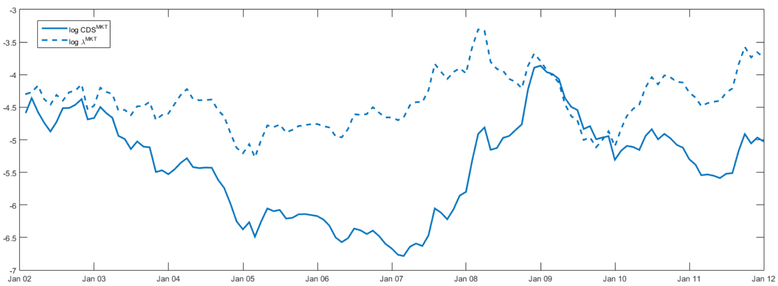
The results of the formal analysis of our systematic CDS illiqudity factor are reported in Table 8. Consistent with the previous analysis, Panel A reports positive correlation coeffcients between $\Delta\log\theta_t^{MKT}$ and the five illiquidity determinants. The highest correlation coefficient is that with $\Delta\log Amihud_{Stock}$ (0.52), followed by $\Delta 30DHistVol$ (0.36) and $\Delta BaaMinusAaa$ (0.34). The correlation with VIX (0.23) and $\Delta StockPairCorr$ (0.18) are much smaller.

Panel B of Table 8 reports the estimation results for the following regression of quarterly

Figure 1: Systematic Market-Wide Credit Component (λ) vs. Average CDS Spread (CDS)

Sub-figure (i) plots the time series of the average log CDS spreads and log of our market-wide credit component (λ). Sub-figure (ii) contains a scatter plot of the quarterly changes in these variables.

(i) Time-series plot of $\log CDS_t^{MKT}$ and $\log \lambda_t^{MKT}$



(ii) Changes in $\log \lambda_t^{MKT}$ vs. $\log CDS_t^{MKT}$

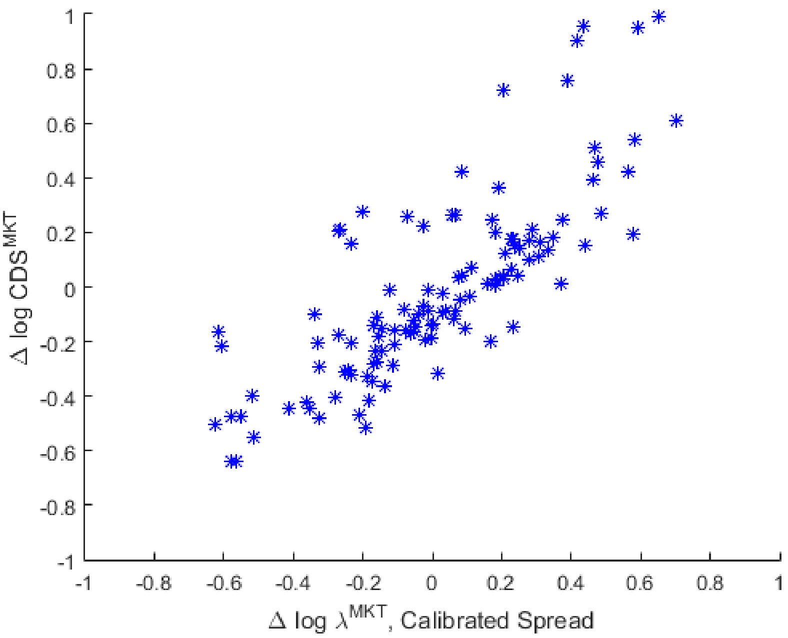
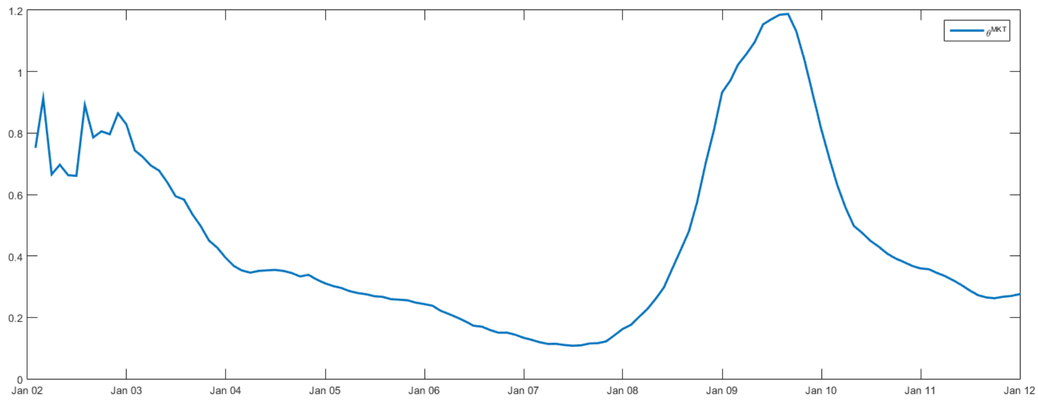


Figure 2: CDS Market Illiquidity Factor (θ_t^{MKT})

The figure plots the time series of our systematic CDS market illiqudiuty measure θ^{MKT} from January 2002 to May 2011.



changes in the systematic CDS illiquidity:

$$\begin{aligned}\Delta \log \theta_t^{MKT} = \quad & \beta_0 + \beta_1 \Delta \log Amihud_{Stockt} + \beta_2 \Delta VIX_t + \beta_3 \Delta BaaMinusAaa \\ & + \beta_4 \Delta 30DHistVol_t + \beta_5 \Delta StockPairCorr_t + \varepsilon_t \end{aligned} \tag{25}$$

where $\log Amihud_{Stockt}$ is the average of individual stock log Amihud measures, VIX_t is the CBOE VIX spot index, $BaaMinusAaa_t$ is the difference between the Moody's Baa and Aaa yields, $30DHistVol_t$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr_t$ is the average of pairwise correlation of stock returns for all firms in our sample.

In Panel B Column (1), only the loading on the stock Amihud measure is significant at the 1% level with the adjusted R-square being 25%. The result does not alter when an additional dummy variable for the post-crisis period is included (Column 2). The loading on the dummy variable is positive and significant, supporting potential structural break after the financial crisis, but the Amihud measure remains significant at the 1% level. Thus, on average, our systematic CDS illiquidity measure is significantly positively related to stock market illiquidity, but it still contains substantial information, orthogonal to the stock illiquidity only.

The scatter plots in Figure 4 suggest a non-linear association between our systematic CDS illiquidity measure and other factors. We repeat the regression in Equation (25) separately for positive and negative changes in $\log \theta^{MKT}$. Panel C reports the regression results. When only the positive changes in $\log \theta^{MKT}$ are included, all the liquidity determinants, except for

Table 8: CDS Market Illiquidity Factor

Panel A of the table reports the correlation coefficients between of our CDS market illiquidity factor $\Delta \log \theta^{MKT}$ and other illiquidity determinant, and Panels B and C report the corresponding regression results for the the quarterly changes from 2002 to 2011. In Panel C the regressions are estimated separately for positive and negative changes in systematic CDS illiquidity measure. $\log Amihud_{Stock}$ is the average log Amihud illiquidity measure of all stocks in our sample; VIX is VIX index; $BaaMinusAaa$ is the difference between the Moody's Baa and Moody's Aaa bond yields; $30DHistVol$ is 30-day historical stock volatility; $StockPairCorr$ is the pairwise stock correlation over the 12-month horizon; $D_{2007-2011}$ is dummy variable taking a value of 1 between 2007 and 2011. In Panlel C, the sign of negative $\Delta \log \theta^{MKT}$ is flipped to ease the interpretation of the results.

Panel A: Correlation	(1)	(2)	(3)	(4)	(5)	
(1) $\Delta \log \theta^{MKT}$						
(2) $\Delta \log Amihud_{Stock}$	0.52					
(3) ΔVIX	0.23	0.40				
(4) $\Delta BaaMinusAaa$	0.34	0.64	0.61			
(5) $\Delta 30DHistVol$	0.36	0.62	0.67	0.87		
(6) $\Delta StockPairCorr$	0.18	0.16	0.14	0.34	0.29	
		(1)			(2)	
Panel B: Regression Result	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const	-0.02	-1.21	0.23	-0.07	-3.30	0.00
$\Delta \log Amihud$	0.50	4.68	0.00	0.49	4.76	0.00
ΔVIX	0.00	0.03	0.98	0.00	-0.16	0.87
$\Delta BaaMinusAaa$	-0.06	-0.64	0.52	-0.06	-0.68	0.50
$\Delta 30DHistVol$	0.15	0.64	0.52	0.17	0.74	0.46
$\Delta StockPairCorr$	0.18	1.25	0.22	0.16	1.18	0.24
$D_{2007-2011}$				0.11	3.37	0.00
R-square	0.28			0.35		
R-adjust	0.25			0.31		
	$\Delta \log \theta^{MKT} \geq 0$			$\Delta \log \theta^{MTK} < 0$		
Panel C: Asymmetric Effect	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	0.27	10.72	0.00	0.12	11.34	0.00
$\Delta \log Amihud$	-0.42	-3.09	0.00	-0.13	-1.59	0.12
ΔVIX	0.00	1.88	0.07	-0.00	-0.31	0.76
$\Delta BaaMinusAaa$	0.18	2.26	0.03	0.09	0.92	0.36
$\Delta 30DHistVol$	-0.11	-0.64	0.53	-0.15	-0.66	0.51
$\Delta StockPairCorr$	0.68	3.16	0.00	0.11	1.22	0.23
R-square	0.61			0.09		
R-adjust	0.54			0.03		

Table 9: Regression based on the first principal component of five illiquidity determinants

This table reports the results for the regression of our CDS market liquidity factor, $\Delta \log \theta^{MKT}$, against the first principal component of the five liquidity determinants (viz. $\log Amihud$, VIX, $BaaMinusAaa$, $30DHistVol$, and $StockPairCorr$) over the period from 2002 to 2011. "Explain" reports the share of variation in the liquidity determinants explained by the first principal component. In the analysis of asymmetric impact, we flip the sign of negative $\Delta \log \theta^{MKT}$ to ease the interpretation of the results.

	All Sample			$\Delta \log \theta^{MKT} \geq 0$			$\Delta \log \theta^{MKT} < 0$		
	Coef.	t-stat	p-value	Coef.	t-stat	p-value	Coef.	t-stat	p-value
Const.	-0.03	-1.55	0.12	0.23	9.67	0.00	0.13	14.17	0.00
1st PC	0.05	5.06	0.00	0.05	4.24	0.00	0.01	1.90	0.06
R-square	0.18			0.36			0.04		
R-adjust	0.18			0.34			0.03		
Explain	0.61			0.73			0.54		

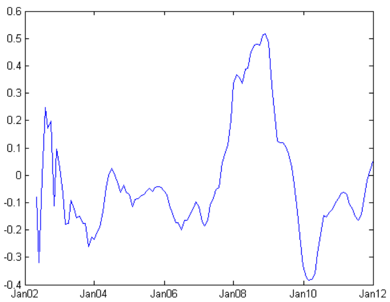
$30DHistVol$, become significant at least at the 10% level, and the adjusted R-square improves substantially to 54%. This indicates that CDS market illiquidity is more closely related to the liquidity determinants when the CDS market becomes more illiquid. On the contrary, we do not find any statistically significant relations for negative changes in $\log \theta_t^{MKT}$. This finding provides evidence of the asymmetric association between CDS market illiquidity and other liquidity determinants. As the liquidity determinants are derived from both bond and equity markets, our finding here suggests a possible liquidity contagion among bond, equity and CDS markets in times of liquidity dry out.

The loading on the stock Amihud measure in Panel C of Table 8 flips the sign, which is likely to be driven by multicollinearity with other regressors. We use the PCA decomposition of all the liquidity determinants and re-run the regression by using only the first principal component (PC). This first PC captures between 54% and 73% of the variation of the individual factors. The regression results reported in Table 9 confirm an asymmetric effect of the first liquidity factors' PC on the CDS market illiquidity. Consistent with our previous results, the adjusted R-square is 34% when the CDS market becomes more illiquid, whereas it is only 3% when the CDS market becomes more liquid. Overall, there is a positive association between our CDS market illiquidity factor and the first PC of the set of liquidity determinants, confirming that our systematic CDS market illiquidity measure indeed captures illiquidity risk.

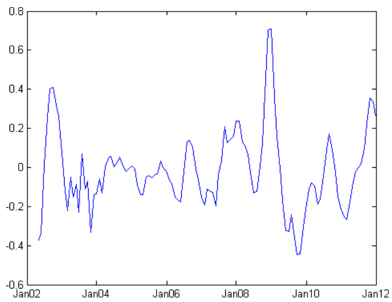
Figure 3: Time Series Plots of Liquidity Determinants

The figure shows the time series plots of our systematic CDS market illiquidity factor ($\log \theta^{MKT}$), and five other illiquidity determinants, over the period from 2002 to 2011. Δ represents quarterly changes. $\log Amihud_{Stock}$ is the average of individual stock log Amihud measures, VIX is the CBOE VIX spot index, $BaaMinusAaa$ is the difference between the Moody's Baa and Aaa yields, $30DHistVol$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr$ is the average of pairwise correlation of stock returns for all firms in our sample.

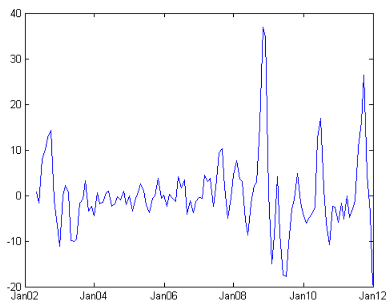
(i) $\Delta \log \theta^{MKT}$



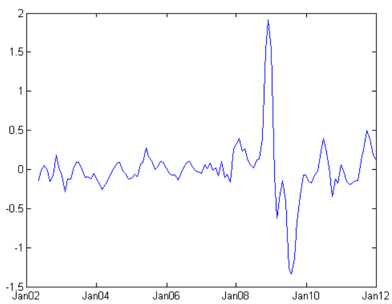
(ii) $\Delta \log Amihud_{Stock}$



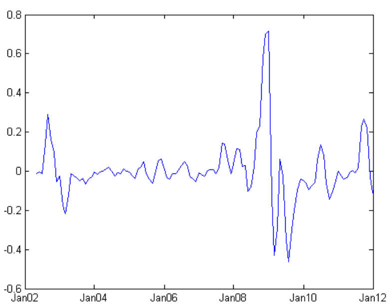
(iii) ΔVIX



(iv) $\Delta BaaNinusAaa$



(v) $\Delta 30DHistVol$



(vi) $\Delta StockPairCorr$

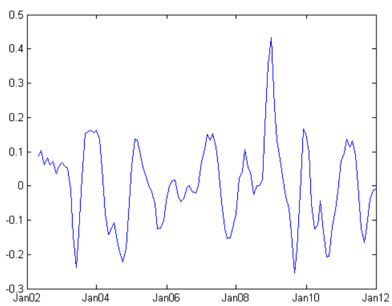


Figure 4: Scatter Plots of Liquidity Determinants

The figure shows the scatter plots of five illiquidity determinants against $\Delta \log \theta^{MKT}$, the quarterly changes of our CDS market illiquidity factor. The sample period is from 2002 to 2011. $\log Amihud_{Stock}$ is the average of individual stock log Amihud measures, VIX is the CBOE VIX spot index, $BaaMinusAaa$ is the difference between the Moody's Baa and Aaa yields, $30DHistVol$ is the average of individual firms' 30-day historical stock volatility, and $StockPairCorr$ is the average of pairwise correlation on stock returns for all firms in our sample.