The Linkage between the Options and Credit Default Swap Markets during the Subprime Mortgage Crisis

Abstract

This study investigates the linkage between the options and credit default swap (CDS) markets around the subprime mortgage crisis period, using the unit recovery claim (URC) of Carr and Wu (2011). We demonstrate that the URCs from the two markets have tighter linkage, by estimating from the market implied option prices with strike price within firm-specific and time-varying default corridor as well as reflecting CDS term structure and firm-specific bond recovery rate. With our adjusted URCs for 259 firms, we find that after the crisis unfolded, the effect of macroeconomic variable on deviations between the two markets increased and options market's predictive power for future movement of the CDS markets was amplified.

JEL classification: G01, G12, G14, C32.

Keywords: credit default swap; American put option; unit recovery claim; VECM; subprime mortgage crisis.

1. Introduction

The recent subprime mortgage crisis led to a freeze in credit markets and the insolvency of some financial institutions. It also caused a substantial change in cross-market linkages and a major shift in the risk composition of financial markets. For managing financial assets and controlling relevant risks, it would be useful to examine changes in the linkage between the equity and debt markets after the big shock triggered extreme market movements.

Starting with Merton's (1974) model, the connection between the equity and debt markets has been explored by analyzing the equity put option and corporate bond credit spread. Under structural model perspective of corporate bond pricing, credit spread is mainly determined by a firm's financial leverage, risk-free interest rate, and asset value volatility, which is related to equity volatility. Hence, through empirical analysis, many studies have explored the linkage of corporate bond spreads to stock return realized volatility, stock option implied volatility, and stock option implied volatility skews and jump risks.[1]

On the other hand, recent studies usually investigate the connection between the equity put option and the credit default swap (CDS) spread rather than the corporate bond spread. Cao, Yu, and Zhong (2010) show that the implied volatility dominates historical volatility in explaining the time-series variation of CDS spreads and the volatility risk premium embedded in put option covaries with CDS spread. The authors also find that the implied volatility can forecast the change of the CDS spread in the future, but the reverse does not hold. Zhang, Zhou, and Zhu (2009) show that the realized volatility from the high-frequency transaction data and jump risks-jump mean, jump volatility, and jump skews- have substantial explanatory power on the CDS spread. Berndt and Ostrovnaya (2008) investigate the information flow before and after outstanding jumps of two observed measures, the implied volatility of at-the-money (ATM) put options and CDS spreads. The authors cannot provide any conclusive directions, however, because the options market moves ahead during the week around

[1] See Collin-Dufresne, Goldstein, and Martin (2001), Delianedis and Geske (2001), Campbell and Taksler (2003), Cremers, M., Driessen, J., and Maenhout, P.J. (2008).

the dramatically increasing implied volatility, but firms with lower credit rating or higher volatility show significant information flow from the CDS market to the options market.

Previous studies have used measures affected by stock price dynamics, default arrivals, and interest rate dynamics, and thus have difficulties directly comparing the magnitudes of the risk information content of the two markets. Therefore, Carr and Wu (2011) propose a simple and robust measure, referred to as a unit recovery claim (URC). A URC is a standardized credit insurance contract paying \$1 at default if the default event occurs before maturity. The vertical spread of American put options scaled by the difference in strikes with the corresponding maturity of the credit insurance contract can replicate the same payoff. Using this replication concept, we can project the risk information on the same measure from both the CDS and put options markets simultaneously.

The authors confirm strong co-movement between the two URCs through regression analysis and find that firm-specific variables such as stock return volatility and leverage measures can explain the deviation between the two estimates. They also perform error correction regression to predict future movements and find that strong two-way information flow between the two markets, which supports the strong linkage between the two URCs.

However, since Carr and Wu (2011) select option quotes with \$5 or less strike price and no larger than 15% absolute value of delta for the deep out-of-the-money (DOOM) options, it excludes most of investment-grade firms from their sample during ordinary economic circumstances. In addition, the maturity mismatches by the assumption of flat term structure of CDS spread and the usage of the fixed recovery rate for different companies can weaken the linkage between the two URCs.

One of our research motivations is that we need to redefine DOOM put option. Recent literatures usually define the moneyness of option not by absolute strike price but in terms of ratio. Xing, Zhang, and Zhao (2010, p.644) define that a put option is out-of-the-money (OTM) when the ratio of strike price to the stock price is ranging from 0.8 to 0.95. In addition, Cao at el. (2010, p.327) also define that the ratio between 0.8 and 1.2 is near-the-money option. Thus Carr and Wu (2011)'s requirement of no larger than 15% absolute value of delta is reasonable for defining DOOM but the requirement of \$5 or less strike price is somewhat restrictive.

In general, \$5 or less would be sufficient as default barrier for non-investment-grade firms and options with those strike prices are expected to have a strong linkage with the corresponding CDS contracts. However, the underlying reference entities in the CDS market include many investment-grade firms and it is not likely that their default barriers are always not larger than \$5 because of relatively higher bankruptcy costs and larger deadweight losses. In practice, as it is important for hedgers to estimate the proper corridor range, use of an absolutely-defined fixed barrier for all the CDSs would not be feasible.

Moreover, other research motivations are as follows. First, considering that the literature concerning corporate yield spreads has shown that the non-default component of observed credit spreads is larger for higher-rated firms,[2] or the credit spread puzzle[3] that observed credit spreads tend to be much wider than theoretically estimated for investment-grade firms in terms of fractions, we need to observe the behaviors of both investment-grade and non–investment-grade firms. Second, Acharya and Johnson (2007) demonstrate that information flows first into the CDS market and then into the more liquid stock market, when firms are facing negative credit news and firms expose or are more likely to expose credit worsening. Forte and Lovreta (2009) document the probability that CDS market leads stock market in credit risk discovery becomes high with the creasing frequency of severe credit downturns. Thus we need to focus on the changes in the linkages between the options market, which of underlying asset is equity, and CDS markets, conditional around the extreme market movement triggered by negative credit event.

Our study makes the following contributions to the existing literature. First, we suggest the implied unit recovery claims (IURCs) by using the market implied option prices with strike price within firm-specific and time-varying default corridor as well as reflecting CDS term structure and firm-specific bond recovery rate. With the larger dataset of IURCs, we can test whether or not there is the time-independent strong linkage between the two markets even for investment-grade firms. It also allows us not only to gauge the firm-specific strike level within default corridor that can replicate the

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[2] See Longstaff, Mithal, and Neis (2005)

[3] See Elton, Gruber, Agrawal, and Mann (2001), Amato and Remolona (2003), and Chen, Collin-Dufresne, and Goldstein (2009).

existing credit protection well but also to analyze the more accurate information flow between the two markets not with the limited rating-level dataset of companies but with the well-distributed rating-level dataset of companies.

Second, we shed light on the economic meaning behind the information flow between the American put options and CDS markets by exploring how negative shocks affected the two markets as the financial crisis unfolded, by investigating the factors that impact on short-term deviation between the two markets and examining the price and volatility spillover effects of the options and CDS markets, using the IURCs of 259 firms.

Our main empirical results are summarized as follows. First, we find that the IURCs show much tighter linkage than the URCs, when we follow and compare through the Carr and Wu (2011)'s testing methodology such as the cross-correlation statistics and regression frameworks for co-movement, and a vector error correction model (VECM) results showing the strong two-way information flow on average.

Second, the short-term deviations between the two markets are more affected by the change in macroeconomic variable during the crisis period than during the pre-crisis period since the VIX becomes a significant determinant for non-CDS-driven variation after the onset of the crisis and the changes in IURCs from the options market are more sensitively affected by the changes in the VIX across most sectors during the crisis period than the pre-crisis period.

Third, during the pre-crisis period, information mainly flows from CDS market to option markets across both most sectors and most ratings. However, after the crisis unfolded, the options market has developed strongly significant predictive power for the CDS market and bilateral volatility transmission between the two markets has increased enormously across the majority of sectors. These findings are consistent with Berndt and Ostrovnaya (2008)'s finding that prior to the credit events of a lower-than-expected earnings announcement or leveraged buyout, information flows from the CDS spread to implied volatility, while the incremental flow of information is reversed on the day of the announcement and the day after the news release, and that there is a strong spillover from the options market to the CDS market during the week around the substantial increase in implied volatility. Also, it is associated with the result that information flows first into the CDS market and then into the more liquid stock market, when firms are encountered by negative credit events according to Acharya and Johnson (2007).

Taken together, our results imply that since the recent crisis stem from the deterioration of credit market, during the pre-crisis period, the macroeconomic risk shock had been increasingly reflected in the CDS market first and that after the crisis happened, CDS market's information leading role disappears with the liquidity contraction and instead options market has more predictive power for the future CDS market movement.

The remainder of this paper is organized as follows. Section II explains the URC and proposes the IURC as the adjusted measure of the URC. Section III describes the data used in calculating the URC, the IURC and other risk variables. It also summarizes the statistics of the estimated URCs and IURCs, and briefly reviews the econometric methodologies. Section IV presents the empirical results. Section V summarizes the results and presents our conclusions.

2. The URC and the IURC

2.1. The Default Corridor and the URC

According to Carr and Wu (2011), "Recent literature[4] recognizes the strategic nature of the default event and finds that debt holders have incentives to induce or force bankruptcy well before equity value completely vanishes. Under these expectations, the stock price stays above a strictly positive barrier before default. On the other hand, firm and equity values often experience sudden drops upon default due to deadweight losses such as legal fees and liquidation costs related to the bankruptcy process." With these observations, the authors assumes that prior to default, stock prices are bounded below by a positive constant B and that after default, the stock prices drops and stays below another constant $A < B$. The authors refer to the range $[A, B]$ as the default corridor, within which the stock price can never exist. Given the availability of two American put options of the same maturity having

[4] See Leland and Toft (1996), Anderson and Sundaresan (1996), Hackbarth, Hennessy, and Leland (2007), and Carey and Gordy (2007).

strike prices within the default corridor ($A \leq K1 < K2 \leq B$), a spread between the two American put options scaled by the strike distance replicates a standardized credit insurance contract that pays $1 at default if the company defaults prior to the option expiry date, and zero otherwise. It becomes optimal to exercise both options at the default time, and the scaled American put spread nets a payoff of $1 at the default time.

This standardized credit insurance contract is referred as the URC. Since the two positions pay off the same amount at the same random time, replication of this contract is simple and robust to the dynamics of stock price, interest rates, and default arrival rates. Denoting the URC computed from the equity put options and the CDS spreads as *URC_O(t,T)* and *URC_C(t,T),* respectively, yields

$$URC\_O(t,T) = (P_t(K_2,T) - P_t(K_1,T))/(K_2 - K_1) \tag{1}$$

$$URC\_C(t,T) = \lambda(t,T)\frac{\{1-\exp(-(r(t,T)+\lambda(t,T))(T-t))\}}{r(t,T)+\lambda(t,T)} \tag{2}$$

where $\lambda(t,T) = \dfrac{CDS\ spread(t,T)}{(1-Recovery\ Rate)}$, $r(t,T)$ *: continuously compounding spot interest rate*

2.2. The IURC : the adjusted estimation of the URC

Carr and Wu (2011) estimate the URC_O with the assumption that the lower bound of the corridor is zero ($K_1 = 0$) since the stock price falls to zero at default, not in the case that the companies are too big to fail. They choose a list of companies with put options that satisfy the following standards: non-zero bid price, non-zero open interest, greater than the one-year of the time-to-maturity, $5 or less strike price, and no larger than 15% of the absolute value of the put's delta. For companies with several put options that satisfy the above standards, the put option with the highest open interest is selected. Then the URC_C of the corresponding company is inferred from fixed recovery rate and the five-year maturity CDS spread in order to obtain a larger universe of companies with reliable CDS quotes.

However, there are some disadvantages of such criteria: (1) the default corridor as $5 or less strike level seems not to be appropriate for investment-grade firms that can require relatively higher bankruptcy costs and tend to have larger deadweight loss while this criterion is somewhat sufficient as default barrier for non-investment-grade firms. However, if we consider that the underlying reference entities in the CDS market include many investment-grade firms and practitioners usually hedge their CDS positions with put options, it is important to estimate the proper or well-hedging strike price of put options, and this strike price within default corridor should reflect different bankruptcy cost for each firm's current scale or macroeconomic state. (2) The maturity mismatches by the assumption of flat term structure of CDS spread can weaken the linkage between the two URCs. (3) The usage of the same recovery rate for different companies can also bias the estimates.

We modify the estimating criteria both to get a larger dataset of companies and to modify above disadvantages as follows: We extract the URC_O values from the volatility surface across the delta levels from -70% to -20%.[5] In detail, at first we perform the regression of the implied volatility on the corresponding delta level (D), such as $\sigma(D,T) = \alpha + \beta \times D$, using data at time, t-1 for each firm. Second, we get the fitted implied volatility, $\hat{\sigma}(D',T) = \hat{\alpha} + \hat{\beta} \times D'$, for each candidate delta level within default corridor such as D' = -15%, -14.5%, -13%, …, -1% for each firm. Third, we calculate the implied option prices based on the Cox-Ross-Rubinstein (CRR) American option pricing tree model, reflecting each firm's dividends, the fitted implied volatilities, and the strike prices matched with the corresponding candidate delta levels within default corridor. Then we find the optimal delta level making the URC_O(t-1) value closest to the URC_C(t-1) value among the candidate delta levels. Finally, we construct the URC_O(t) from the current market implied put option price with the strike price corresponding to the optimal delta level estimated at the previous week, and generate the URC_C(t) by reflecting CDS spread term structure and firm-specific bond recovery rate for different firms. These adjusted URCs will be called the IURCs in this paper.

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[5] The OptionMetrics provides volatility surface data across delta levels -80% to -20% for put options. In this research, we use data with delta levels -70% to -20% for better extrapolation into the DOOM region excluding data which can be classified as deep in-the-money option. Further, when we change the starting point of delta levels for the robustness from -80% to 50%, the results are not much changed a lot.

To sum up, Carr and Wu's (2011) requirement of $5 or less tend to exclude most of investment-grade firms from their sample during the normal periods. Our modification allows us to include many investment-grade firms which might have been excluded otherwise. Our specific choice of estimation procedure is not to improve estimation precision per se but was dictated by our research objective. To accommodate the expanded sample space, an estimation method that can map out the DOOM put options from existing source of traded options is required.

Advantages of the modified URC (IURC) are; (1) we can test whether or not there is a time-independent linkage between the two markets even for the investment-grade firms; (2) it is also meaningful to gauge the firm-specific strike level within default corridor of put option that can replicate the existing credit protection well; (3) it allows us to analyze more accurate information flow between the two markets not with the limited rating-level dataset of companies but with the well-distributed rating-level dataset of companies.

3. Data and Methodologies

3.1. Data

3.1.1. CDS spread/recovery rate

The CDS spread and recovery rate data for senior unsecured U.S.-dollar-denominated debt are obtained from Markit. We use Markit data for two reasons: First, Carr and Wu (2011) use the CDS spreads dataset from Bloomberg and their CDS quotes are reliable at five years to maturity. By requiring companies to have reliable CDS quotes at one, two, and three-year terms, they ended up with a very small universe of companies. To obtain a larger universe of companies with reliable CDS quotes, they have decided to use five-year CDS spreads and assume flat term structure. However, Markit provides more reliable CDS quotes regarding fixed times to maturity of six months and one, two, three, four, five, seven, 10, 15, 20, and 30 years, and short term quotes are not easily obtainable from other data providers. According to Cao at el. (2010) and Jacoby, Jiang, and Theocharides (2009), it collects CDS spreads each day from more than 70 contributing market makers and performs the statistical procedure for eliminating outliers and stale prices and then generates the mean of contributions that passed the data quality tests.

Second, Markit offers daily credit curve including expected bond recovery rate for each company, thus we can calculate the URC with each individual firm's own recovery rate instead of using a fixed recovery rate (e.g., 40%), as in Carr and Wu (2011).

We exclude data with the unknown rating, or with the unknown recovery rate, and select firms that have CDS spread quotes regarding times to maturity of one, two, three, four, and five year in order to estimate URCs with reflecting the term structure of CDS spreads. 611 firms remain after matching with Compustat dataset and CRSP dataset.[6] Then we choose 288 firms with the complete 188 weekly observations over the sample period from January 4, 2006 to August 5, 2009.

3.1.2. Equity options

To compare the URCs with the IURCs, we collected both the market prices of American put options and the volatility surface dataset which includes the implied volatilities estimated from standardized put option prices across the corresponding delta levels, from OptionMetrics for the same sample period as the CDS data. It is known that a standardized option is only included if there exists enough option price data on that date to accurately interpolate the required values. When we choose the put option prices according to Carr & Wu (2011) criteria as mentioned in Section 2.2., 4,847 option prices of 123 companies among above 288 firms are selected for the URCs. On the other hand, our criteria that require the volatility surface dataset for the IURCs allow us to choose 46,477 options of 259 companies.

3.1.3. Inferring URCs and IURCs from American put options

We perform our analysis based on the formula as $URC\_O_t = (P_t(K),T))/K$. For each selected company, we estimate the URC value from American puts at the shortest option expiry, because options with long-term maturity tend to have less liquidity. We construct the IURC value based on the

[6] We remove the firms that do not have the exactly same name on merging with Compustat data.

same formula, but we regress the implied volatilites on the corresponding delta levels of -70%, -65%, -60%, -55%, -50%, -45%, -40%, -35%, -30%, -25%, -20%,[7] at time, t-1 and get the fitted implied volatility for each candidate delta level across -15% to -1%. Then, we compute the implied option price reflecting each firm's dividends, the fitted implied volatility, and the strike price matched with each candidate delta level within default corridor. Then we determine the delta level of which URC_O_{t-1} is the closest with URC_C_{t-1} among above candidate delta levels. Finally, we construct URC_O_t from the implied option price with the one-year maturity[8] and the strike price corresponding to the optimal delta level.

3.1.4. Extracting URC and IURC values from CDS spreads

We interpolate the CDS spreads across fixed times to maturity to obtain the CDS spread at the corresponding expiry date of the chosen options. We then compute the corresponding URC value based on the linearly-interpolated CDS spread and the prevailing interest rates. Thus we can avoid maturity mismatch problem through not assuming flat term structure but using this interpolated CDS spread.

In addition, we calculate the IURC value using the one-year CDS spread and the one-year spot rate in order to match with the one-year option prices. The following formula is used for both the URC value and the IURC value from CDS market:

$$\lambda(t,T)\frac{\{1-\exp(-(r(t,T)+\lambda(t,T))(T-t))\}}{r(t,T)+\lambda(t,T)},\ \lambda(t,T)=\frac{\mathit{CDS\ spread(t,T)}}{(1-\mathit{Recovery\ Rate})} \qquad (3)$$

[7] The volatility surface file of Optionmetrics contains the interpolated volatility surface for each security on each day, using a methodology based on a kernel smoothing algorithm. However, in this research, we use the regression of option price on delta level or strike price, since Dumas, Fleming, and Whaley (1998) document that models whose diffusion term is a deterministic function of the strike price and maturity are no better than the ad hoc model based on a simple OLS regression of implied volatility on a polynomial in strike price and maturity.

[8] We fix the one-year maturity since each firm's dividends data from OptionMetrics are available until the year 2010 and thus we can reflect the exact future dividends at each reference date for the only one-year intervals when we implement CRR tree model.

where T is the maturities, $r(t,T)$ denotes the continuously compounded spot interest rate of the relevant maturities T, and $\lambda(t,T)$ is calculated by the CDS spread and each firm's recovery rate. We compute the continuously compounded zero coupon interest rate curve using bootstrapping methodology and linear interpolation of LIBOR-swap rates obtained from Bloomberg.

3.1.5. Other firm-, industry-, and market-level variables

Longstaff and Rajan (2008) propose a three-jump model to extract the information about credit risk for pricing the CDO. Their model considers that credit spread might be a composite of three types of credit risk: economy-wide or systemic risk, sector-wide risk at the level of correlated firms within an industry group, and idiosyncratic or firm-specific risk. Based on this risk decomposition, we determine the risk factors that may explain the discrepancy of the two URCs as follows. Items (1), (2), and (3) are related to the macroeconomic risk, (4) is relevant to industry-level risk, and (5) and (6) can consist of the individual-level risk:

(1) Business cycle (BUSI_C),

(2) Volatility index (VIX),

(3) Risk free rate (R^f),

(4) Credit spread index (SP),

(5) Option's moneyness (M), and

(6) Stock return volatility (VOL).

As the non-CDS-driven variations in put options can contain other credit risk information, we select macroeconomy-wide, sector-wide, and firm-specific variables related to credit risk. We select the VIX as a macroeconomic variable related to credit risk since the VIX is referred to as the investor's fear gauge or global risk aversion following Eichengreen, Mody, Nedeljkovic, and Sarno (2009). The risk free rate is also an important determinant for credit risks because it can increase the risk neutral drift of firm value process, and decrease the probability of default according to Collin-

Dufresne at el. (2001). The VIX time series are obtained from Bloomberg, and the two-year maturity Treasury bond yield time series for R^f are collected from FRED dataset.

In addition, considering that the credit risk can change depending on overall state of the economy as Collin-Dufresne at el. (2001) point out, we include the proxy for business cycle. By the way, Petkova and Zhang(2005) suggest that since the ex-post realized market return is a noisy measure for marginal utility or business cycle, the expected market risk premium can be more precise measures for aggregate economic conditions. Thus we construct the business cycle index from estimating the expected market risk premium. Figure 1 presents the relevant regression equation and results.

[Figure 1 goes here]

For the industry-level credit risk variable, we select the credit spread indexes classified by nine industry groups (industrial, retail, bank, gas transmission, finance, insurer, media, utility, and phone), with two to four rating levels for each industry, which is provided by Bloomberg. Accordingly, we collect the credit spread index matched by the industry group[9] and rating status of each firm. We determine the rating status closest to the majority of the ratings from Moody's, Fitch, and Standard & Poor's.

For the individual-level credit risk variable, we select the two variables, moneyness level (M) and stock return volatility (VOL) among variables used by Carr and Wu (2011). We generate the option's moneyness level measured by the log strike price (K) deviation from the spot level (S) of the stock, ln(K/S) in order to examine that the chosen option's specific characteristic remains on the deviation. Stock return volatility time series for each firm were computed using an exponentially weighted moving average model on daily returns during past three-months downloaded from CRSP. The reason of not considering the leverage measures as firm specific variables is that moneyness measure is

[9] We have already defined 10 sectors, so some missing sectors, such as capital goods, are classified as the industrial sector. Further, consumer goods, consumer services, and health care are classified under the retail sector.

related to the variation of stock price level and thus leverage measures which contain market price of equity can cause a multicollinearity problem in the multivariate regressions.

3.1.6. Summary statistics of the URCs and the IURCs

Tables 1 and 2 report the summary statistics across sectors and across ratings of the URC value series and the IURC value series, respectively. Since the two series are values on the same credit protection but estimated from different markets, we expect them to have similar summary statistics and show strong co-movements.

[Table 1 goes here]

Table 1 satisfies our expectation to some degree, showing that the average mean values of URC_O and URC_C are 0.132 and 0.101, respectively, and the average standard deviations of URC_O and URC_C are 0.09 and 0.083, respectively. The average correlation of the URCs ranges from 42.97% for health care sector to 80.31% for consumer services, and lower-rated firms such as B and CCC ratings show the higher correlation than higher-rated firms if we put aside the one firm of AAA rating.

[Figure 2 goes here]

Even though the URCs are estimated by the improved data of CDS spread and recovery rate, the total average correlation of the URCs is about 62%, which is less than 70.34% of Carr and Wu (2011). However, this difference can stem from that they use different sample period as Feb. 2005 to Aug. 2008. Thus we generate and compare the time-series of our cross-sectional average URCs with the cross-sectional average URCs estimated by the five-year maturity CDS spread following Carr and Wu (2011), to observe the effect of maturity-matching over our sample period in Figure 2. They are much similar after the economic downturn, but the time series of URC_C estimated from the five-year CDS spread in the left-hand graph tend to be much higher level than the URC_O during the pre-crisis period, whereas the time series of URC_C inferred from the selected option maturity-matched CDS spread in the right-hand graph are slightly lower than URC_O and show the much smaller gap.

[Table 2 goes here]

In Table 2, the mean values of the IURCs are of more comparable magnitude than those of the URCs: The average mean values of IURC_O and IURC_C are 0.017 and 0.019, respectively, and the average standard deviations of IURC_O and IURC_C are 0.021 and 0.025, respectively. The average correlation of the IURCs is 89.51%, ranging from 79.39% for health care sector to 98.42% for telecommunication sector, which shows much tighter linkage than the URCs. Contrary to the statistics of the URCs, investment-grade firms show much strong correlation than non-investment-grade firms. Since we compute the IURCs based on almost ten times options contracts used for the URCs, which include many of investment-grade firms, these statistics gives the evidence that American put options with the one-year maturity and time-varying strike price within less than 15% absolute value of delta can replicate well credit protection for investment-grade firms.

This result also can be confirmed in the time series of the cross-sectional average IURCs in the left-hand graph of Figure 2: in general, the deviations of the IURCs are much smaller than those of the URCs in Figure 1. In addition, the trend of time series of average IURCs is different from the URCs, but similar to that of time series of expected market risk premium in Figure 1, which allow us to presume that the IURCs can be related with macroeconomic risks. In addition, when we compare the number of companies selected at each reference dates of the URCs and the IURCs in the right-hand graph of Figure 3, the IURCs are generated by data of the stationary and much larger number of companies over the sample period, but the URCs are constructed by data of the small but intensively increased number of companies during crisis period. Therefore, the IURCs are more appropriate measures to observe the information flow of the overall CDS and options markets.

[Figure 3 goes here]

Finally, in Figure 4, the left-hand graph presents the scatter plots of the 4,847 URC pairs for 123 different companies at 188 reference dates, and the right-hand graph depicts those of the 46,477 IURC pairs for 259 different companies. Both scatters of the URCs and IURCs distributed around the 45-degree line are supporting well the null hypothesis that the two sources of estimates are the same. Since some large scattering deviations from the 45-degree line are detected around the URC_O axis, and the IURCs show more intensive scatters around the 45- degree line than the URCs, it can be interpreted as that the IURCs are more convergent.

[Figure 4 goes here]

3.2. Methodologies

3.2.1. Regressions

3.2.1.1. Regressions for explaining equity American puts with CDS market variations

To compare co-movements of the two URCs and two IURCs, we regress the scaled American put value on the URC value estimated from the corresponding CDS spreads as follows.

$$URC\_O_t^i = \alpha_0{}^i + \beta_0{}^i \times URC\_C\_5Y_t^i + \varepsilon 0_t^i \qquad (4)$$

$$URC\_O_t^i = \alpha_1{}^i + \beta_1{}^i \times URC\_C_t^i + \varepsilon 1_t^i \qquad (5)$$

$$IURC\_O_t^i = \alpha_2{}^i + \beta_2{}^i \times IURC\_C_t^i + \varepsilon 2_t^i \qquad (6)$$

Through the equation (4) and the equation (5), we can compare the impact of maturity matching on the co-movement of the two URCs, and the equation (6) can demonstrate how much degree of co-movement can be improved by the IURCs, compared with the URCs. Here, $URC\_C\_5Y_t^i$ stand for the URC estimated from the five-year maturity CDS spread for company *i* at period *t*.

3.2.1.2. Regressions for analyzing the discrepancy between two markets

The regression residuals ($\varepsilon 1_t^i, \varepsilon 2_t^i$) capture variations in the American put options that are not explained by the CDS variation. Carr and Wu (2011) pointed out that these non–CDS-driven variations result from either measurement errors related to strike prices or to demand shock or jump risk from the options market. In other words, American puts can contain market risk components such as non-zero delta and vega risk exposures, or the stock price and stock return volatility themselves can contain the credit risk information not revealed in the CDS market, thus authors performed the univariate regressions of deviations on delta measures, stock return volatility measures, and the financial leverage measures, respectively. In this research, we assume that the non–CDS-driven variations can be affected by macroeconomy-wide risk, sector-wide risk, as well as firm-specific risk. To test this hypothesis, we perform multivariate regressions of weekly non–CDS-driven variations of American puts against the option's moneyness level (M), the stock return volatility (VOL), the corresponding industry credit spread (SP), the risk free rate (R^f), the business cycle index (BUSI_C), and the VIX:

$$\Delta\varepsilon 1_t^i = c1^i + x1^i \Delta M_t^i + x2^i \Delta VOL_t^i + x3^i \Delta SP_t^i + x4^i \Delta R_t^f + x5^i \Delta BUSI\_C_t + x6^i \Delta VIX_t + \zeta 1_t^i \quad (7)$$

$$\Delta\varepsilon 2_t^i = c2^i + y1^i \Delta M_t^i + y2^i \Delta VOL_t^i + y3^i \Delta SP_t^i + y4^i \Delta R_t^f + y5^i \Delta BUSI\_C_t + y6^i \Delta VIX_t + \zeta 2_t^i \quad (8)$$

The equation (7) is the regression for the residual of the URCs and the equation (8) is the regression for that of the IURCs.

3.2.2. VECM

To address the issue of whether credit risk is priced equally between the two markets, the VECM (Engle and Granger, 1987) with exogenous variables is also employed. Cointegration test confirms that the theoretical parity relation between the two markets holds as a long-run equilibrium condition at first:

$$\begin{bmatrix} \Delta URC\_C_t^i \\ \Delta URC\_O_t^i \end{bmatrix} = \begin{bmatrix} c_1^i \\ c_2^i \end{bmatrix} + \begin{bmatrix} a_1^i \Delta M_t^i \\ a_2^i \Delta M_t^i \end{bmatrix} + \begin{bmatrix} b_1^i \Delta VOL_t^i \\ b_2^i \Delta VOL_t^i \end{bmatrix} + \begin{bmatrix} d_1^i \Delta SP_t^i \\ d_2^i \Delta SP_t^i \end{bmatrix} + \begin{bmatrix} e_1^i \Delta R_t^f \\ e_2^i \Delta R_t^f \end{bmatrix} + \begin{bmatrix} f_1^i \Delta BUSI\_C_t \\ f_2^i \Delta BUSI\_C_t \end{bmatrix} + \begin{bmatrix} g_1^i \Delta VIX_t \\ g_2^i \Delta VIX_t \end{bmatrix}$$
$$+ \begin{bmatrix} \gamma_1^i \\ \gamma_2^i \end{bmatrix} (URC\_O_{t-1}^i - \alpha_{urc}^i - \beta_{urc}^i URC\_C_{t-1}^i) + \begin{bmatrix} h_1^i & h_2^i \\ h_3^i & h_4^i \end{bmatrix} \begin{bmatrix} \Delta URC\_C_{t-1}^i \\ \Delta URC\_O_{t-1}^i \end{bmatrix} + \begin{bmatrix} \upsilon 1_t^i \\ \upsilon 2_t^i \end{bmatrix} \quad (9)$$

$$\begin{bmatrix} \Delta IURC\_C_t^i \\ \Delta IURC\_O_t^i \end{bmatrix} = \begin{bmatrix} c_1^i \\ c_2^i \end{bmatrix} + \begin{bmatrix} k_1^i \Delta M_t^i \\ k_2^i \Delta M_t^i \end{bmatrix} + \begin{bmatrix} l_1^i \Delta VOL_t^i \\ l_2^i \Delta VOL_t^i \end{bmatrix} + \begin{bmatrix} m_1^i \Delta SP_t^i \\ m_2^i \Delta SP_t^i \end{bmatrix} + \begin{bmatrix} n_1^i \Delta R_t^f \\ n_2^i \Delta R_t^f \end{bmatrix} + \begin{bmatrix} o_1^i \Delta BUSI\_C_t \\ o_2^i \Delta BUSI\_C_t \end{bmatrix} + \begin{bmatrix} p_1^i \Delta VIX_t \\ p_2^i \Delta VIX_t \end{bmatrix}$$
$$+ \begin{bmatrix} \lambda_1^i \\ \lambda_2^i \end{bmatrix} (IURC\_O_{t-1}^i - \alpha_{iurc}^i - \beta_{iurc}^i IURC\_C_{t-1}^i) + \begin{bmatrix} q_1^i & q_2^i \\ q_3^i & q_4^i \end{bmatrix} \begin{bmatrix} \Delta URC\_C_{t-1}^i \\ \Delta URC\_O_{t-1}^i \end{bmatrix} + \begin{bmatrix} \omega 1_t^i \\ \omega 2_t^i \end{bmatrix} \quad (10)$$

In both equation (9) for the URCs and equation (10) for the IURCs, the two equations constitute a first-order difference VAR model with an error correction term that provides an added explanatory variable for changes in credit risk. The exogenous variables used in this model are the changes in factors that are assumed to impact on the deviations between the CDS and options markets in the regression analysis.

The estimated adjustment coefficients λ_1 (γ_1) and λ_2 (γ_2) measure the degree to which prices in a particular market adjust to correct pricing discrepancies from their long-term trend. For example, if λ_1 (γ_1) is significantly positive, the CDS market adjusts to correct the pricing error. Alternatively, if λ_2 (γ_2) is significantly negative, the options market moves after the CDS market (the CDS market moves ahead of the options market in reflecting changes in credit conditions). If both coefficients are significant with correct signs, the relative magnitude of the two coefficients reveals which of the two markets leads in terms of price discovery.

3.2.3. Multivariate GARCH Model: The BEKK Model

Multivariate generalized autoregressive conditional heteroskedasticity (GARCH) model is commonly used to explain whether the volatility of one market is leading the volatility of others. Cheung and Ng (1996) note that "the arrival of information and the extent to which the market evaluates and assimilates new information can be reflected by changes in variance." To investigate the volatility spillover between the CDS and options markets, we use the BEKK (Baba–Engle–Kraft–Krone (1988), hereafter) model, which incorporates quadratic forms to ensure the positive semi-definiteness of the variance–covariance matrix. The advantage of the BEKK specification is that it needs to estimate relatively small number of parameters.

The errors of the VECM model are assumed to follow a conditional multivariate normal distribution, $\varepsilon_t^i \mid I_{t-1} \sim N(0, H_t)$, under the BEKK GARCH framework. The BEKK(p,q) representation of the conditional variance–covariance matrix of the error term H_t is

$$H_t = C'C + \sum_{i=1}^{q} A_i' \varepsilon_{t-1} \varepsilon_{t-1}' A_i + \sum_{i=1}^{p} B_i' H_{t-1} B_i \tag{11}$$

where *C* is a *k* × *k* upper triangular matrix and *A* and *B* are *k* × *k* parameter metrics. We select a BEKK(1,1) model introduced by Engle and Kroner (1995), which can be written as

$$H_t = C'C + \begin{bmatrix} \alpha_{11} & \alpha_{21} \\ \alpha_{12} & \alpha_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{bmatrix} H_{t-1} \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix} \tag{12}$$

The elements α_{ij} of the symmetric matrix *A* capture the impact of market shocks or unexpected events in market i on market j —autoregressive conditional heteroskedastic (ARCH) elements, and the elements β_{ij} of the symmetric matrix *B* indicate the degree of transmission or persistence in conditional volatility between markets *i* and *j* (GARCH elements).

4. Empirical Results

4.1. Determining Volatility Break Points

Our sample period includes the recent subprime mortgage crisis, which may have caused a structural break. In that case we need to divide the full sample period into a pre-crisis period and a crisis period and examine the behavior of URCs and IURCs before and after the crisis. Considering that the market crash caused an extreme shift in volatility, it may be more appropriate to identify the volatility break point rather than the mean break point. Therefore, we perform the iterated cumulative sums of squares (ICSS) volatility break test of Inclan and Tiao (1994) to investigate structural changes in volatility, and then apply this break point in the subsequent analysis. The detailed procedures are described in Appendix A.

We estimate break points among weekly average URC and IURC time series from CDS spreads and American put options shown in Figure 2 and Figure 3, based on the ICSS algorithm. We calculate the annualized standard deviation of URC and IURC log returns over each interval and choose break point as the end point of the interval with the highest volatility. Finally, the selected break point was September 19, 2007, which is reasonable in that it is near the outbreak of Subprime Mortgage crisis.

4.2. Regression Analysis

4.2.1. Explaining the equity American puts with the CDS market variations

Table 3 reports the coefficient estimates and *t*-statistics when we regress the scaled American put value $URC\_O_t = (P_t(K),T))/K$ on the unit recovery claim value estimated from the corresponding CDS spreads over the full sample, the pre-crisis period, and crisis period.[10] Under the null hypothesis that the two time series URC_C and URC_O , or IURC_C and IURC_O, represent values for the same contract, we have $\alpha = 0$ and $\beta = 1$. In this regard, Carr & Wu (2011) perform total least square regression as well as ordinary least square regression, because the two variables have measurement

[10] We perform the regressions for the companies with more than 10 time series observations of the URCs and the IURCs, respectively.

errors. However, in this research, we perform the only ordinary least square regression because we focus on the differences among three regression results.

[Table 3 goes here]

As the results of regressions relating URC_O on URC_5Y in Panel A, the average slope estimates during the pre-crisis period and the crisis period are 0.611 and 1.643, respectively. On the other hand, in the results of regressions relating URC_O on URC_C in Panel B, the average slope estimates during the pre-crisis period and the crisis period are 0.833 and 1.56, respectively, which shows relatively more convergent to the null value of one, even though it is not a big improvement.

Moreover, we find the more improved results of regression relating IURC_O on IURC_C in Panel C; the average slope estimates during the pre-crisis period and the crisis period are slightly around one at 0.65 and 1.01, respectively. Hence the adjusted URCs from the market implied option prices with time-varying strike prices within less than 15% absolute delta value can have much tighter linkages than the URCs from option prices with strike prices of $5 or less.

It is noticeable that estimates of slope are less than one for the pre-crisis period whereas they are about equal to one for the crisis period. It is a consistent result to that "practitioners have considered short overvalued credit insurance through the CDS market and long undervalued deep out-of-the-money puts as a profitable trading strategy. However, this general strategy has been not functional after the financial crisis in 2007" as Carr and Wu (2011) point out.

The adjusted R-squared values of the three regression equations over the full sample are 57.8%, 57.1%, and 87%, respectively, which suggest that the variation in the American puts shown in the IURC_O can be mostly well explained by the CDS market variation in the IURC_C. On the other hand, the adjusted R-squared values of the three regression equations during the pre-crisis period are 44.8%, 47.8%, and 58.4%, respectively. This result is also confirming that reflecting term structure of CDS spread can enhance the convergence.

4.2.2. Regression on non–CDS-driven variations in American puts

Panel A of Table 4 reports the summary statistics of the average coefficient estimates and the *t*-statistics of regressions on non-CDS-driven variations in URC_O. Most of variables except the industry level credit spread are not strongly significant during the pre-crisis period, and the coefficient of industry level credit spread variable is not the expected sign to impact on the credit risk. On the other hand, the coefficients of changes in the option's moneyness level, stock return volatility, and the VIX are significant during the crisis period, and the coefficient of these variables are all positive, consistent to the expected signs of the effect on credit risks, which can be interpreted as that non-CDS-driven variation have other credit risk information during the crisis-period.

[Table 4 goes here]

On the other hand, Panel B of Table 4 shows the summary statistics of regressions on non-CDS-driven variations in IURC_O. Differently to the results of Panel A, during the pre-crisis period, most variables are not significant and the coefficient of change in stock return volatility is marginally significant. However, during the crisis period, changes in the VIX are strongly significant, and its absolute value of the coefficient is bigger than that during the pre-crisis period. These results can give the evidence that the deviations between the two markets are largely driven by the changes in macroeconomic variable during the crisis period.

The average R-squared values are around 26.5% and 16.2% for the deviation of the URCs and that of the IURCs, respectively, during the pre-crisis period, and around 39.5% and 12%, respectively, during the crisis period. Even though the deviation of IURCs are not largely explained by credit risk variables, we find that some portion of the non–CDS-driven variation of American puts is mainly driven by macroeconomic risk variable after the crisis unfolded, and this result is more convincing since the IURCs are computed by the less limited dataset of companies both during the pre-crisis and the crisis period. After all, these results suggest that American puts contain other credit risk information not present in the CDS market and affect put option prices.

4.3. Results of Vector Error Correction Methodology: Long- and Short-Run Dynamics between Options and CDS Markets

Based on the theoretical framework, since the URCs and the IURCs from the two markets should be equivalent in the long run, the short-term discrepancy will disappear quickly. That is, if credit risk information currently absent from the CDS market is contained in the non–CDS-driven variation of American puts, we expect such information to be reflected in the CDS market in the long run. On the other hand, if credit risk information currently included in the CDS market is not reflected in the non–CDS-driven variation of American puts, we expect such information to be eventually revealed in the options market. To test the two cases, we use the vector error correction methodology[11].

4.3.1. Long-term consistency between options and CDS markets

We tested the cointegration relationship between the two IURCs for 207 companies that have the complete IURC observations over 187 weekly reference date as the representative sample. We first perform the ADF unit root test on the two IURC series to confirm their non-stationarity, and then we examine the existence of a cointegration relationship between two series based on residual series, $\varepsilon 2_t^i$ in the equation (6). As a result, the group statistics show that IURC from the CDS market and that from the options market are cointegrated in a way the theory predicts. This result suggests that, in general, the two markets share a common stochastic trend, pricing the credit risk equally in the long run. After all, they can be two measures of the same risk, and the arbitrage opportunity between the two markets would eventually dissipate through market movements.

4.3.2. Dynamic interactions between the options and CDS markets across ratings

We examine the short-term dynamic linkages between the two URCs and between the two IURCs, particularly which market is more efficient in reflecting changes in the credit risk information of

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[11] We perform VECM for the companies with more than 20 time series observations of the URCs and the IURCs, respectively.

underlying entities. Furthermore, we analyze these linkages over the entire observed time period, the pre-crisis period, and the crisis period, respectively. We use the VECM model with the exogenous variables presented in Section 3.2.2, equation (9) and equation (10). The significance and magnitude of the two coefficients, $\gamma_1(\lambda_1)$ and $\gamma_2(\lambda_2)$ of the error correction term, tell us which of the two markets moves to adjust for their discrepancies, and the speed of the adjustment. In addition, the relative magnitude of the two coefficients, $\gamma_1(\lambda_1)$ and $\gamma_2(\lambda_2)$ can indicate the role of each market in price discovery.

[Table 5 goes here]

Panel A of Tables 5 summarizes the average error correction terms, their ratios, and *t*-statistics across the ratings for the URCs. For the entire observed time period and the crisis period, firms of BBB and BB ratings show significantly positive γ_1 and significantly negative γ_2, which means lower-rated firms generally show the strong two-way information flow. However, samples that consist of only non-investment-grade firms show that only γ_2 is significantly negative for the pre-crisis period, and firms of AA and A ratings show that only γ_2 is significantly negative during the crisis period, which implies the CDS market's leading behavior. Even in the last row of Panel A showing the total average coefficient and *t*-statistics of the URCs, during the full sample period and the crisis period, the URCs show the strong two-way information flow, whereas the CDS market tends to lead the options market in price discovery during the pre-crisis period.

Panel B of Tables 5 summarizes the average error correction terms, their ratios, and *t*-statistics across the ratings for the IURCs. Similarly to the results of the URCs, for the crisis period, the most investment-grade firms show significantly positive λ_1 and significantly negative λ_2, showing strong two way information flows. Moreover, for the pre-crisis period, firms of A and BBB ratings, which have the relatively larger samples, show two-way interactions, whereas firms of AAA, BB and B ratings show that only λ_2 is significantly negative; that is, the options market adjusts its price in response to price discrepancies. However, in the last row of Panel B reporting the total average coefficient and *t*-statistics of the IURCs, during the full sample, the pre-crisis, and the crisis period, the IURCs show the strong two-way information flow, which can be the evidence that the linkage between the two markets shown in the IURCs are much tighter than the URCs.

4.3.3. Dynamic interactions between the options and CDS markets across sectors

We also analyze the short-term dynamic interactions between the two URCs and between the two IURCs across sectors.

[Table 6 goes here]

Panel A of Tables 6 summarizes the average error correction terms, their ratios, and *t*-statistics across the sectors for the URCs. During the pre-crisis period, firms of all sectors except health care show that only γ_2 is significantly negative, which implies the CDS market's leading behavior. On the contrary, during the crisis period, firms of only financials sector show significantly positive γ_1 and significantly negative γ_2, and the other five sectors show that only γ_2 is significantly negative. Therefore, most of sectors show the CDS market's leading role.

On the other hand, Panel B of Tables 5 summarizes the average error correction terms, their ratios, and *t*-statistics across the sectors for the IURCs. Contrary to the results of the URCs, during the pre-crisis period, firms of basic materials sector show the two-way flows, firms of other six sectors show that only λ_2 is significantly negative, and firms of another two sectors show that only λ_1 is significantly positive. Thus we can conclude the information flows from CDS market to options market on average during the pre-crisis period. After crisis unfolded, firms of six sectors show that only λ_1 is significantly positive and firms of the other three sectors show the strong two-way interactions, which means the options market's strong forecasting power of future movement in CDS market.

Next, we consider the magnitude of the two coefficients, $\gamma_1(\lambda_1)$ and $\gamma_2(\lambda_2)$. Following Gonzalo and Granger (1995), we compute a measure that reflects each market's contribution to price discovery. The measure is defined as the ratio of the speed of adjustment in the two markets, $\gamma_1/(\gamma_1-\gamma_2)$ or $\lambda_1/(\lambda_1-\lambda_2)$.When the measure is close to zero, the CDS market plays a leading role in price discovery and the options market moves afterward to correct for pricing discrepancies. When the measure is close to one, the dynamics are in the reverse direction, and the options market leads the CDS market. When the measure is close to 1/2, both markets contribute to price discovery and there is no clear evidence of which market is more important.

Shown in the last columns of Panel A for the URCs of Tables 5 and Table 6, except that firms of BB rating show 0.712 ratio and firms of consumer goods and technology sectors show slightly more than 0.6 ratios during crisis period, most of ratios are less than 1/2 across the ratings and across the sectors over the full sample, pre-crisis, and crisis periods. It means that CDS market movement can forecast the future options market movement in general. However, if we consider that many insignificant coefficients are used to calculate these ratios, this result is not strongly convincing.

On the contrary, shown in the last columns of Panel B for the IURCs of Tables 5 and Table 6, this measure gives us the different results from those of the URCs. During the pre-crisis period, the BBB rating, which has the largest sample firms, shows the ratio of 0.395, and ratios are ranging from -0.177 to 0.48 across all ratings. In addition, seven sectors show ratios under 0.5, and therefore we conclude that during the pre-crisis period, information mainly flows from CDS market to option markets.

However, after the crisis unfolded, these ratios shifted to more than 0.5 both across most ratings and across most sectors and they are computed by most of significant coefficients. Especially, firms of financials, health care, industrial, oil & gas, technology, and utility sectors show ratios over 0.7 and firms of AA and A ratings also shows more than 0.7 ratios on average. This finding supports the hypothesis that the options market moves ahead of the CDS market during the crisis period.

[Table 7 goes here]

Table 7 shows the cross-sectional summary of VECM results for the IURCs across ratings. We find that the changes in IURCs from the CDS market are generally influenced by the significantly positive moneyness level, and negative risk-free rate variable during the pre-crisis period, but they are mainly affected by the changes in the moneyness level, stock return volatility and business cycle during the crisis period. In addition, we find that the changes in IURCs from the options market are mainly affected by the VIX as well as the moneyness level during the crisis period across ratings. It is also interesting to note that the coefficients of the VIX are amplified, compared with those of the pre-crisis period.

[Table 8 goes here]

Table 8 shows the cross-sectional summary of VECM results for the IURCs across sectors. We find that the changes in IURCs from the CDS market are influenced by the significantly positive sector-wide credit spread across the majority of sectors during the pre-crisis period, but they are mostly affected by the changes in the moneyness level, stock return volatility, business cycle, and the VIX during the crisis period. In addition, we find that the changes in IURCs from the options market are also influenced by the significantly positive sector-wide credit spread across the majority of sectors during the pre-crisis period, but are mainly affected by the VIX as well as stock return volatility during the crisis period across most sectors. Furthermore, we find that the sensitivity of changes in IURCs from the options market to the changes in the VIX is bigger during the crisis period than the pre-crisis period across most sectors. This result also implies that during the crisis, the economic-wide risk shock had been increasingly reflected in the options market.

4.4. Results of the Multivariate GARCH (BEKK) Model: Volatility Spillover

This section focuses on how and to what extent the volatility caused by the financial crisis was transmitted between the CDS and options markets. We analyze the volatility spillover effect for the full sample period, the pre-crisis period, and the crisis period, using IURC sector indexes which are constructed from the average IURCs across sectors.

Using the bivariate BEKK representation of volatility[12], equation (12), we study the direction and speed of volatility transmission. The parameter β_{12} indicates the spillover from the CDS to the options market, while β_{21} measures the volatility spillover from the options to the CDS market. Thus these parameters suggest the direction of volatility spillover. Moreover, since the IURCs from both markets should have the same magnitude, the size of these parameters can show how much the volatility of one market moves ahead of the volatility of the other. Panel A, Panel B, and Panel C of Table 9 shows the volatility spillover effect during the full sample period, the pre-crisis period, and the crisis period, respectively.

[Table 9 goes here]

The major finding of the multivariate GARCH model in this paper is that the strong two-way volatility spillovers between the options and the CDS market are shown during the crisis period. There are three sectors for which the only β_{21} is significant, one sector for which the only β_{12} is significant, and three sectors that show significant bidirectional spillover for the full sample period. There are the one sector for which the only β_{21} is significant, and one sector that show significant bidirectional spillover for the pre-crisis period, while there are six sectors showing significant bilateral spillover and just one sector showing significant β_{21} during the crisis period. This strong two-way volatility transmission during the crisis period can be another evidence of the strong linkage between the estimated two IURCs, in addition to the strong two-way price information flow on average shown in VECM results.

5. Conclusions

[12] We compute the multivariate GARCH model using University of California-San Diego (UCSD) GARCH toolbox in Matlab developed by Kevin Sheppard.

The 2007 subprime crisis caused the substantial increase in cross-market linkages. Hence, it is meaningful to review the changes in the linkage between stock markets and debt markets after the big shock triggered extreme market movements. Recent studies investigating the connection between the stock and debt markets have usually explored by analyzing the equity put options and CDS markets. However, previous studies have made comparisons using measures affected by stock price dynamics, default arrivals, and interest rate dynamics, and thus have had difficulties directly comparing the magnitudes or impacts of the risk information content of the two markets. Therefore Carr and Wu (2011) propose a simple and robust measure referred to as the URC, a standardized credit insurance contract paying \$1 at default if the default event occurs before maturity. Since the URC is estimated from both the CDS spread and American put option prices, we can compare the credit risk information between the two markets at the same random time.

In this paper, we demonstrate that the deviations between the two URCs become more convergent, by considering time-varying and firm-specific default corridor extrapolated from the implied volatility curve as well as reflecting CDS term structure and firm-specific bond recovery rate. It is supported by the results through the cross-correlation statistics, regression results for co-movement, a vector error correction model (VECM) results showing the strong two-way information flow on average.

Based on the adjusted URCs, we focus on the information flow between the CDS and stock options markets around the subprime mortgage crisis period. We find that the impact of macroeconomic variable on the deviations between the two markets increased during the crisis-period. Through VECM analysis, we also find that the CDS market's leading role is apparent during the pre-crisis period, but the options market has developed strongly significant predictive power for the CDS market and bilateral volatility spillover between the two markets has increased enormously across the majority of sectors after the crisis unfolded. These results imply that since the recent crisis stem from the deterioration of credit market, during the pre-crisis period, the macroeconomic risk shock had been increasingly reflected in the CDS market first and that after the crisis happened, CDS market's information leading role disappears with the liquidity contraction and instead options market has more predictive power for the future CDS market movement.

Appendix A. Volatility Break Test.

Betbekh, Osborn, Sensier, and Dijk (2007) point out that causality in the variance test suffers from severe size distortions in the presence of structural breaks in volatility if such breaks are not taken into account.

We use the iterated cumulative sums of squares (ICSS) algorithm by Inclan and Tiao (1994) to detect points of sudden change in variance. The ICSS methodology assumes that the time series of interest has a stationary variance over an initial period until a sudden change in variance happens. The variance is then stationary again until the next sudden change. This process is repeated until the test detects no further changes in the variance. The test produces the estimated point and magnitude of each sudden change in the variance.

Let $C_k = \sum_{t=1}^{k} \varepsilon_t^2, \mathrm{k} = 1,2,...,\mathrm{T}$ be the cumulative sum of the squared observations from the start of the series to the *k*th point in time. Then define the statistic D_k as $D_k = (C_k / C_T) - k/T, \mathrm{k} = 1,2,...,\mathrm{T}$ with $D_o = D_t = 0$. If there are one or more sudden variance changes in the series, the D_k values drift either up or down from zero. When the maximum of the absolute value of D_k is greater than the critical value, the null hypothesis of no changes, homogeneous variance, is rejected. Let k^* be the value of k at which $\max_k \left|D^*\right|$ is attained. If $\max_k \sqrt{T/2}\left|D^*\right|$ exceeds the predetermined boundary, then k^* is taken as an estimate of the change point. This allows us to identify the change points. The upper and lower boundaries of $\pm$1.36 are the critical value at the 95th percentile of the asymptotic distribution of $\max_k \sqrt{T/2}\left|D^*\right|$. Exceeding these boundaries is treated as a significant change in variance in the series analyzed. (Aggarwal, Inclan, and Leal, 1999)

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Figure 1. Business cycle.

Following the idea of Petkova and Zhang(2005), we construct the business cycle index by regressing the realized market return from t to t+1 on macroeconomic variables known at t as the following first equation, and getting the expected market risk premium estimates with the fitted value of regression as the below second equation.

$$R^M_{t+1} = \alpha_0 + \alpha_1 DIV_t + \alpha_2 DEF_t + \alpha_3 TERM_t + \alpha_4 RF_t + \varepsilon^M_{t+1}$$

$$E_t[R^M_{t+1}] = \hat{\alpha}_0 + \hat{\alpha}_1 DIV_t + \hat{\alpha}_2 DEF_t + \hat{\alpha}_3 TERM_t + \hat{\alpha}_4 RF_t$$

where *DIV* is the aggregate dividend yield, *DEF* denotes the default spread, *TERM* is the term spread, and *RF* is the risk-free rate. In more detail, the default spread is the difference between the yields of a long-term corporate Baa bond and a long-term government bond, the risk-free rate is the three-month T-bill yield, the term spread is the difference between the yields of a 10-year and a one-year government bond, and the aggregate dividend yield is the dividend yield of the CRSP value-weighted portfolio, computed as the sum of dividends over the last 12 months, divided by the level of the index. The data on bond yields are from the FRED database of the Federal Reserve Bank of St. Louis. The in-sample period of data used for estimating parameters is from Jan. 1986 to Dec. 2005. The below graph illustrates the estimated daily expected market risk premium over the period between Jan. 2006 and Aug. 2009. The shaded area represents the December 2007 National Bureau of Economic Research (NBER) period of peak (the expansion ended in December 2007).

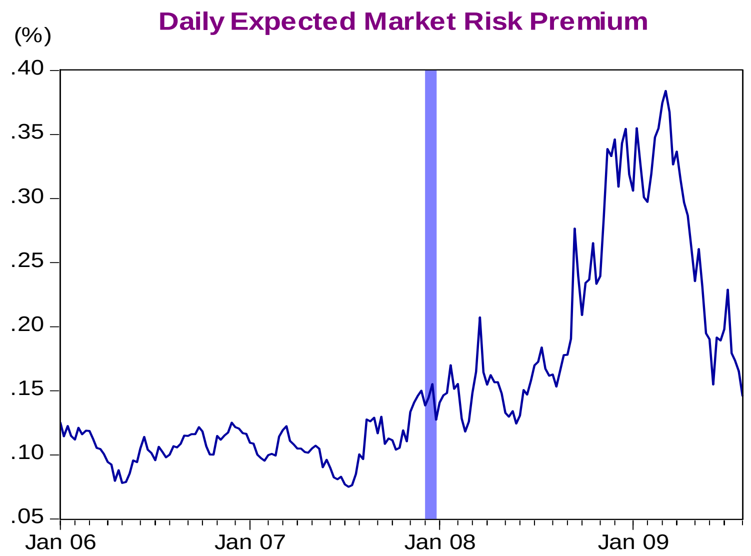


Figure 2. Time series of the average URCs from the CDS market and from American puts.
The symbolic purple lines are the time series of the cross-sectional average URCs created from the deep out-of-money American puts. The blue solid lines are the time series of the cross-sectional average URCs constructed from the CDS spread and recovery rate. In both graphs, URC_Os are estimated from the same option quotes on the firm's stock. However, the left-hand graph shows URC_Cs estimated from the five-year CDS spread, following Carr and Wu(2011), and the right-hand graph shows URC_Cs inferred from the selected option maturity-matched CDS spreads on the firm's bond.

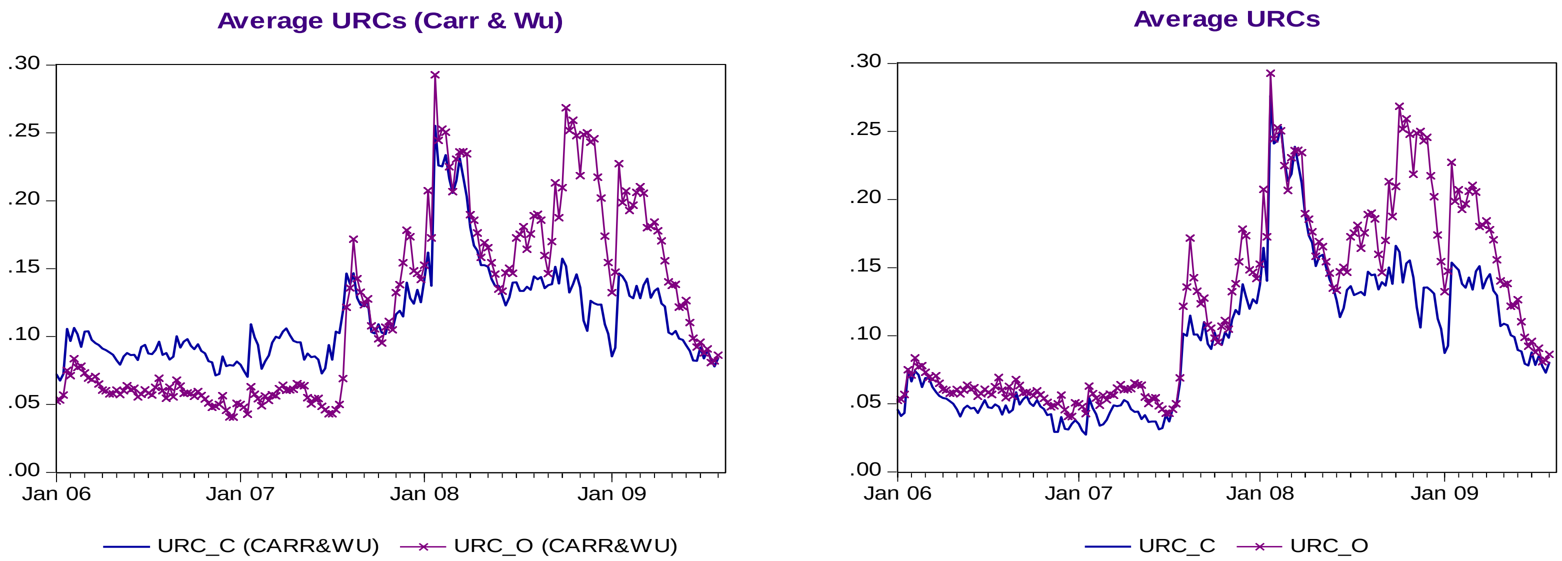
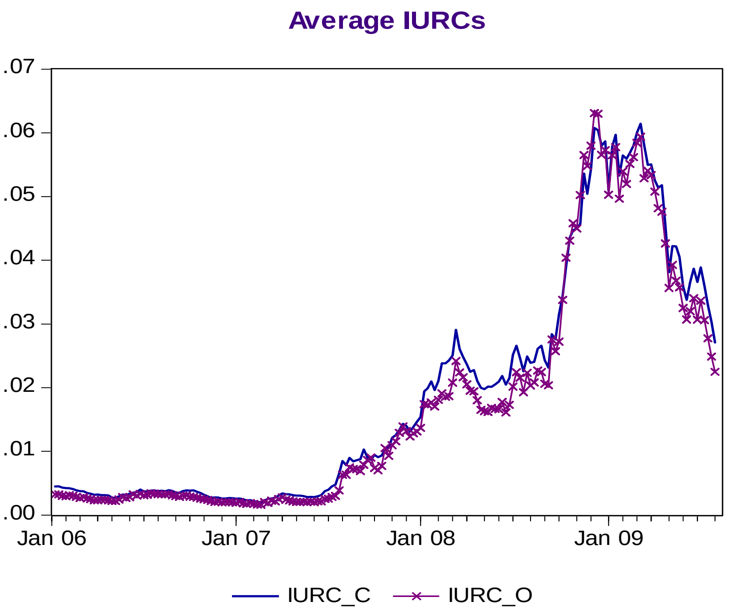


Figure 3. Characteristics of the IURCs.
The left-hand graph presents the time series of the cross-sectional average IURCs. The symbolic purple lines are the time-series of the cross-sectional average IURC_Os estimated from the 1-year maturity option prices with default corridor strike level, implied on market quotes, and the blue solid lines are IURC_Cs inferred from the 1-year maturity CDS spread. The right-hand graph present the number of companies selected at each reference date over our sample period between Jan.2006 and Aug.2009, comparing the IURCs with the URCs.



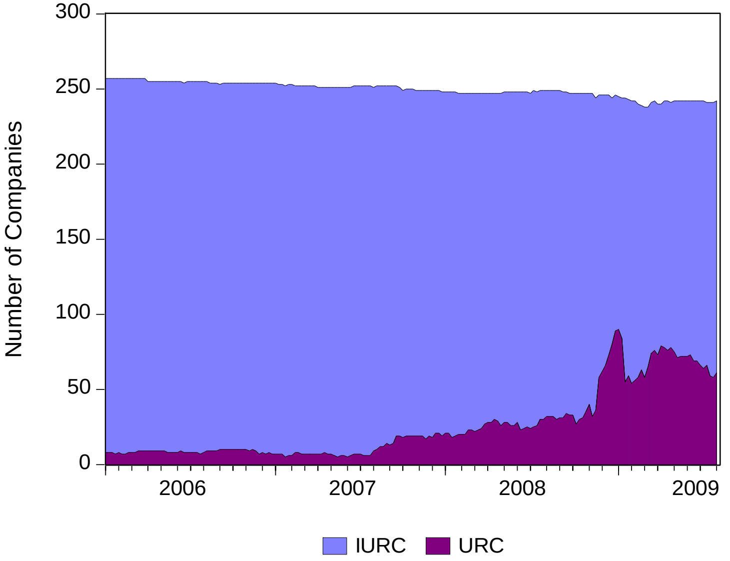


Figure 4. Scatter plots of the two pairs of URCs and the two pairs of IURCs.
Circles depict the two pairs of unit recovery claim estimates. The left graph shows the scatter plots of 4,847 URC pairs for 123 different companies, and the right graph shows the scatter plots of 46,477 IURC pairs for 259 different companies.

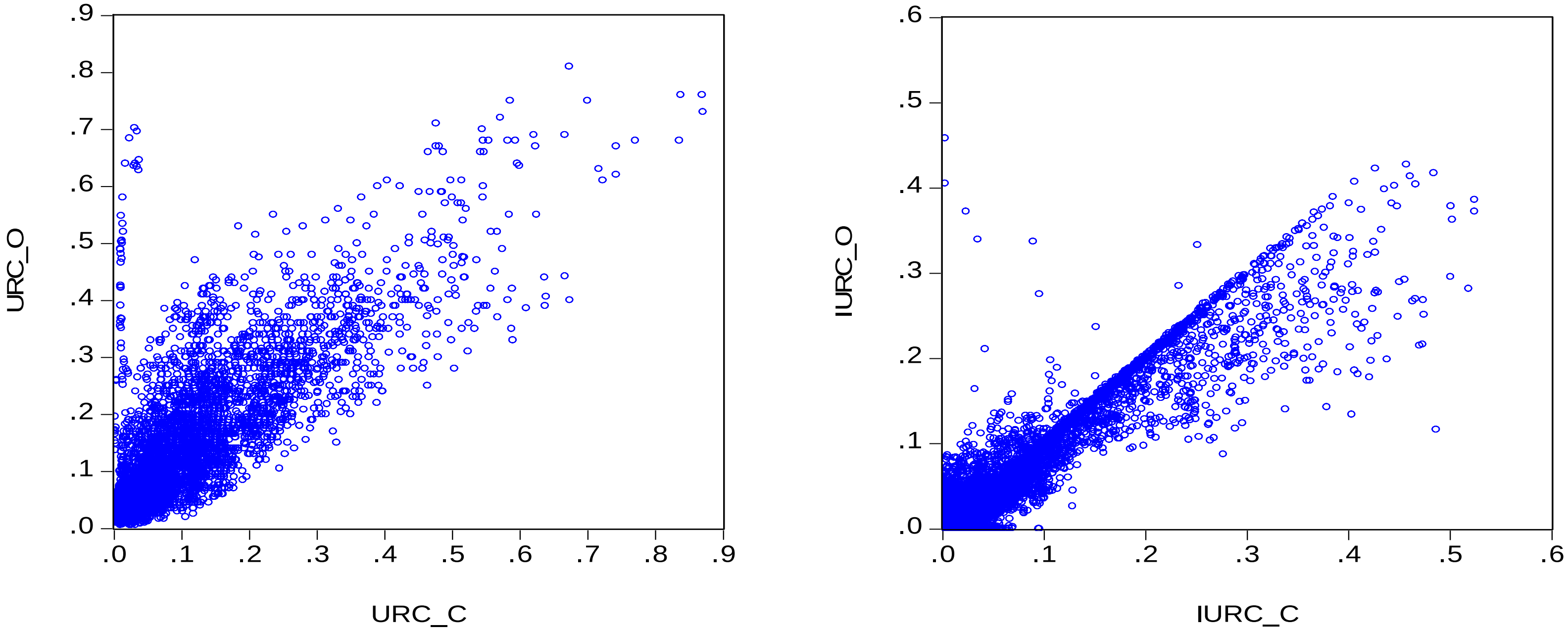


Table 1. Summary statistics of URCs.

This table shows the cross-sectional averages of the mean (Mean), the cross-sectional standard deviation (Std), maximum (Max), and minimum (Min) of URC values extracted from the CDS spread and American put options across 9 sectors and 7 ratings. URC_Os are estimated from option quotes on the firm's stock, and URC_Cs are from the selected option maturity-matched CDS spread on the firm's bond. The last columns report the averages of cross-correlation (Corr.) of the two corresponding time series, the number of pairs (N. of Pairs), and the number of firms (Num. of Firms) for each sector and each rating. The last row reports the average of the statistics on 4,847 URC pairs for 123 different companies over 188 reference dates.

	URC_O				URC_C						
Industry	**Mean**	**Std**	**Max**	**Min**	**Mean**	**Std**	**Max**	**Min**	**Corr.(%)**	**N. of Pairs**	**N. of Firms**
Basic Materials	0.110	0.061	0.380	0.015	0.096	0.056	0.343	0.011	67.16	227	9
Consumer Goods	0.165	0.116	0.810	0.000	0.120	0.099	0.673	0.000	50.88	1289	26
Consumer Services	0.129	0.081	0.760	0.007	0.099	0.082	0.871	0.005	80.31	1032	26
Financials	0.168	0.114	0.750	0.000	0.134	0.108	0.717	0.000	49.67	817	21
Health Care	0.070	0.035	0.260	0.011	0.041	0.034	0.187	0.005	42.97	243	8
Industrials	0.117	0.070	0.430	0.006	0.094	0.060	0.413	0.004	63.80	321	13
Oil & Gas	0.092	0.042	0.435	0.009	0.082	0.049	0.289	0.008	70.92	351	10
Technology	0.116	0.027	0.702	0.010	0.056	0.038	0.600	0.002	77.89	514	7
Telecom.											
Utilities	0.089	0.028	0.195	0.035	0.099	0.049	0.214	0.021	79.05	53	3
Rating											
AAA	0.067	0.000	0.284	0.006	0.074	0.000	0.316	0.009	89.32	49	1
AA	0.095	0.049	0.365	0.007	0.061	0.045	0.221	0.005	36.02	261	9
A	0.130	0.101	0.710	0.008	0.093	0.086	0.567	0.006	64.12	792	33
BBB	0.117	0.088	0.750	0.000	0.093	0.085	0.717	0.000	63.15	1296	54
BB	0.193	0.098	0.810	0.010	0.139	0.092	0.838	0.002	60.60	1284	32
B	0.187	0.118	0.760	0.000	0.160	0.119	0.871	0.000	75.47	1096	22
CCC	0.319	0.060	0.442	0.124	0.317	0.053	0.667	0.151	67.70	69	4
Total	0.132	0.090	0.810	0.000	0.101	0.083	0.871	0.000	62.79	4847	123

Table 2. Summary statistics of IURCs.

This table shows the cross-sectional averages of the mean (Mean), the cross-sectional standard deviation (Std), maximum (Max), and minimum (Min) of IURC values extracted from the CDS spread and American put options across 10 sectors and 7 ratings. The IURC_Os are estimated from the 1-year maturity option prices with default corridor strike level, implied on market quotes, and the IURC_Cs are from the 1-year maturity CDS spread. The last columns report the averages of cross-correlation (Corr.) of the two corresponding time series, the number of pairs (N. of Pairs), and the number of firms (Num. of Firms) for each sector and each rating. The last row reports the average of the statistics on 46,477 IURC pairs for 259 different companies over 187 reference dates.

	IURC_O				IURC_C						
Industry	**Mean**	**Std**	**Max**	**Min**	**Mean**	**Std**	**Max**	**Min**	**Corr.(%)**	**N. of Pairs**	**N. of Firms**
Basic Materials	0.013	0.009	0.372	0.000	0.014	0.011	0.424	0.000	94.41	3686	20
Consumer Goods	0.024	0.029	0.386	0.000	0.027	0.034	0.525	0.000	94.66	9221	51
Consumer Services	0.018	0.019	0.375	0.000	0.021	0.024	0.474	0.000	83.07	7081	41
Financials	0.031	0.029	0.427	0.000	0.033	0.035	0.524	0.000	88.09	4773	27
Health Care	0.009	0.012	0.149	0.000	0.009	0.011	0.152	0.000	79.39	4146	24
Industrials	0.013	0.013	0.458	0.000	0.014	0.016	0.369	0.000	90.74	7805	44
Oil & Gas	0.013	0.009	0.339	0.000	0.013	0.010	0.171	0.000	93.42	3957	22
Technology	0.014	0.024	0.320	0.000	0.015	0.028	0.455	0.000	95.61	2243	12
Telecom.	0.006	0.002	0.045	0.000	0.006	0.002	0.044	0.001	98.42	374	2
Utilities	0.006	0.006	0.169	0.000	0.010	0.008	0.163	0.000	85.42	3191	18
Rating											
AAA	0.004	0.006	0.176	0.000	0.006	0.008	0.175	0.000	97.16	395	4
AA	0.009	0.012	0.147	0.000	0.010	0.017	0.146	0.000	94.80	2648	17
A	0.014	0.035	0.427	0.000	0.015	0.038	0.524	0.000	89.53	13806	83
BBB	0.021	0.040	0.423	0.000	0.023	0.045	0.501	0.000	93.40	19612	124
BB	0.049	0.062	0.458	0.000	0.053	0.074	0.501	0.001	80.75	6320	56
B	0.066	0.064	0.375	0.000	0.078	0.073	0.486	0.001	67.88	3575	34
CCC	0.202	0.050	0.386	0.075	0.268	0.045	0.525	0.072	74.34	121	4
Total	0.017	0.021	0.458	0.000	0.019	0.025	0.525	0.000	89.51	46477	259

Table 3. Explaining equity American puts with CDS market variations

The entries show the cross-sectional average coefficient estimates and *t*-statistics, when we regress the scaled American put value $URC\_O_t = (P_t(K),T))/K$ on the unit recovery claim value estimated from the corresponding CDS spreads over the full sample, the pre-crisis period, and crisis period. The right-hand entries show the R-squared (R^2) and adjusted R-squared (adj. R^2) of the regression, and the last columns show the number of firms (N. of Firms) for the sample over each period. The panel A shows the result of the equation, $URC\_O_t^i = \alpha_0{}^i + \beta_0{}^i \times URC\_C\_5Y_t^i + \varepsilon_t^i$, where *URC_C_5Y* is estimated from the 5-year CDS spread, following Carr and Wu(2011). The panel B shows the result of the equation, $URC\_O_t^i = \alpha_1{}^i + \beta_1{}^i \times URC\_C_t^i + \varepsilon_t^i$, and the panel C shows the result of the equation, $IURC\_O_t^i = \alpha_2{}^i + \beta_2{}^i \times IURC\_C_t^i + \varepsilon_t^i$.

Panel A : regressions relating URC_O on URC_C_5Y

		α	$URC\_C\_5Y_t^i$	R^2	adj. R^2	N. of Firms
Coefficients	Full sample	-0.001	1.660	59.1%	57.8%	99
	Pre-Crisis	0.004	0.611	45.9%	44.8%	12
	Crisis	0.004	1.643	58.2%	56.8%	97
t-stats	Full sample	-0.090	9.715			
	Pre-Crisis	0.620	8.505			
	Crisis	0.520	9.495			

Panel B : regressions relating URC_O on URC_C

		α	$URC\_C_t^i$	R^2	adj. R^2	N. of Firms
Coefficients	Full sample	0.018	1.589	58.5%	57.1%	99
	Pre-Crisis	0.026	0.833	48.9%	47.8%	12
	Crisis	0.022	1.560	57.6%	56.2%	97
t-stats	Full sample	2.883	9.040			
	Pre-Crisis	3.331	8.148			
	Crisis	3.150	8.961			

Panel C : regressions relating IURC_O on IURC_C

		α	$IURC\_C_t^i$	R^2	adj. R^2	N. of Firms
Coefficients	Full sample	0.000	0.990	87.1%	87.0%	259
	Pre-Crisis	0.001	0.652	58.9%	58.4%	258
	Crisis	0.001	1.013	83.8%	83.6%	251
t-stats	Full sample	0.486	31.929			
	Pre-Crisis	3.693	23.153			
	Crisis	2.473	22.838			

Table 4. Cross-sectional analysis for explaining non–CDS-driven variation in American puts.

The upper panel shows the results to explain non–CDS-driven variation in URC_O, and the lower panel shows the results to explain non–CDS-driven variation in IURC_O. In each panel, the top rows report the regression results over the full sample, and the middle and bottom rows report the results during the pre-crisis period and crisis period, respectively. The independent variables are the option's moneyness level (M), the stock return volatility (VOL), the corresponding industry credit spread (SP), risk free rate (R^f), the business cycle index (BUSI_C), and the VIX. The right-hand entries show the R-squared (R^2) and adjusted R-squared (adj. R^2) of the regression.

Panel A : explaining non-CDS driven variation in URC_O

		C	**ΔM_t^i**	**ΔVOL_t^i**	**ΔSP_t**	**ΔR_t^f**	**$\Delta BUSI\_C_t$**	**ΔVIX_t**	**R^2**	**adj. R^2**
	Full sample	0.001	0.105	0.014	-0.013	-0.556	-0.009	0.096	49.3%	39.5%
Coefficients	Pre-Crisis	0.000	0.039	0.022	-0.007	0.119	0.106	0.055	34.9%	26.5%
	Crisis	0.001	0.107	0.014	-0.013	-0.626	-0.010	0.095	49.9%	39.5%
	Full sample	1.772	16.444	3.173	-0.846	-1.903	-0.298	6.638		
t-stats	Pre-Crisis	1.081	1.941	2.255	-2.528	0.206	1.157	1.432		
	Crisis	1.566	16.009	2.902	-0.844	-2.088	-0.338	6.450		

Panel B : explaining non-CDS driven variation in IURC_O

		C	**ΔM_t^i**	**ΔVOL_t^i**	**ΔSP_t**	**ΔR_t^f**	**$\Delta BUSI\_C_t$**	**ΔVIX_t**	**R^2**	**adj. R^2**
	Full sample	0.000	0.003	0.002	0.000	-0.055	0.002	0.015	16.0%	12.9%
Coefficients	Pre-Crisis	0.000	-0.003	0.001	0.000	-0.022	0.001	0.001	22.1%	16.2%
	Crisis	0.000	0.004	0.002	0.000	-0.063	0.004	0.021	17.7%	12.0%
	Full sample	-3.145	1.933	2.812	-0.595	-1.273	0.412	4.429		
t-stats	Pre-Crisis	-2.343	-1.841	2.339	1.434	-1.440	0.157	0.732		
	Crisis	-2.012	2.176	1.608	-0.354	-1.077	0.857	6.224		

Table 5. Lead–lag relation between the CDS and option markets across ratings.
The left-hand columns of panel A report the error correction coefficient γ_1 and t-statistics (in parentheses) for the dependent variable, ΔURC_C over full sample, the pre-crisis, and crisis period across ratings. The middle columns report the other error correction coefficient, γ_2, for the dependent variable, ΔURC_O. The last columns show the ratio defined as $\gamma_1/(\gamma_1 - \gamma_2)$. The panel B reports the error correction coefficient λ_1 and t-statistics (in parentheses) for the dependent variable ΔIURC_C and the other error correction coefficient, λ_2, for the dependent variables ΔIURC_O for the entire data set, the data set before the crisis, and the data set after the crisis. The last columns show the ratio defined as $\lambda_1/(\lambda_1 - \lambda_2)$. The last row of both panel shows the average error correction coefficients, t-statistics (in parentheses) and the average ratio across 123 firms and across 259 firms, respectively.

Panel A : predicting future market movement in URCs

Rating	γ_1			γ_2			Ratio		
	Full	**Pre-crisis**	**Crisis**	**Full**	**Pre-crisis**	**Crisis**	**Full**	**Pre-crisis**	**Crisis**
AAA									
AA	0.099		0.099	-0.1069		-0.107	0.481		0.481
	(1.19)		(1.19)	(-3.272)		(-3.272)			
A	0.028		0.028	-0.1029		-0.103	0.213		0.213
	(1.615)		(1.615)	(-3.186)		(-3.186)			
BBB	0.062		0.062	-0.0732		-0.073	0.460		0.460
	(2.999)		(2.999)	(-3.119)		(-3.119)			
BB	0.054	-0.081	0.064	-0.0573	-0.221	-0.026	0.484	-0.583	0.712
	(2.713)	(-1.267)	(2.867)	(-2.217)	(-2.415)	(-1.433)			
B	0.080	0.049	0.100	-0.0913	-0.135	-0.122	0.466	0.268	0.452
	(2.463)	(1.002)	(2.602)	(-2.862)	(-4.206)	(-2.973)			
CCC									
Total	0.107	-0.004	0.112	-0.141	-0.231	-0.151			
	(5.925)	(-0.07)	(5.995)	(-6.802)	(-5.468)	(-6.898)			

Panel B : predicting future market movement in IURCs

Rating	λ_1			λ_2			Ratio		
	Full	**Pre-crisis**	**Crisis**	**Full**	**Pre-crisis**	**Crisis**	**Full**	**Pre-crisis**	**Crisis**
AAA	-0.0602	0.058	-0.016	-0.333	-0.134	-0.326	-0.221	0.303	-0.050
	(-0.458)	(0.756)	(-0.102)	(-1.351)	(-7.357)	(-1.3)			
AA	0.146	0.093	0.338	-0.192	-0.298	0.027	0.432	0.237	1.087
	(1.071)	(0.547)	(3.066)	(-1.256)	(-2.14)	(0.319)			
A	0.243	0.176	0.277	-0.082	-0.191	-0.068	0.749	0.480	0.804
	(5.181)	(3.379)	(5.482)	(-1.977)	(-5.474)	(-1.493)			
BBB	0.226	0.126	0.241	-0.119	-0.192	-0.158	0.656	0.395	0.605
	(8.112)	(4.322)	(6.264)	(-4.308)	(-6.813)	(-4.016)			
BB	0.073	0.016	0.117	-0.233	-0.217	-0.295	0.239	0.067	0.283
	(2.199)	(0.202)	(3.601)	(-5.409)	(-3.015)	(-6.3)			
B	0.059	-0.047	0.145	-0.367	-0.314	-0.402	0.138	-0.177	0.265
	(1.755)	(-1.093)	(2.929)	(-5.51)	(-6.972)	(-4.507)			
CCC	0.286		0.286	-0.207		-0.207	0.581		0.581
	(8.463)		(8.463)	(-1.257)		(-1.257)			
Total	0.213	0.109	0.258	-0.116	-0.233	-0.128			
	(12.08)	(4.388)	(12.666)	(-6.686)	(-11.103)	(-6.033)			

Table 6. Lead–lag relation between the CDS and option markets across industries.
The left-hand columns of panel A report the error correction coefficient γ_1 and t-statistics (in parentheses) for the dependent variable, ΔURC_C over full sample, the pre-crisis, and crisis period across industries. The middle columns report the other error correction coefficient, γ_2, for the dependent variable, ΔURC_O. The last columns show the ratio defined as $\gamma_1/(\gamma_1 - \gamma_2)$. The panel B reports the error correction coefficient λ_1 and t-statistics (in parentheses) for the dependent variable ΔIURC_C and the other error correction coefficient, λ_2, for the dependent variables ΔIURC_O for the entire data set, the data set before the crisis, and the data set after the crisis. The last columns show the ratio defined as $\lambda_1/(\lambda_1 - \lambda_2)$.

Panel A : predicting future market movement in URCs

Industry	γ_1			γ_2			Ratio		
	Full	Pre-crisis	Crisis	Full	Pre-crisis	Crisis	Full	Pre-crisis	Crisis
Basic Materials									
Consumer Goods	0.195	0.087	0.195	-0.124	-0.261	-0.124	0.611	0.250	0.611
	(2.283)	(0.735)	(2.283)	(-2.264)	(-3.986)	(-2.264)			
Consumer Services	0.036	0.018	0.035	-0.115	-0.188	-0.159	0.237	0.085	0.178
	(2.502)	(0.736)	(1.758)	(-3.804)	(-4.952)	(-3.566)			
Financials	0.186		0.192	-0.201		-0.210	0.482		0.478
	(4.301)		(4.293)	(-3.688)		(-3.664)			
Health Care	0.055	-0.047	0.055	-0.117	-0.079	-0.117	0.321	-1.444	0.319
	(1.692)	(-1.095)	(1.684)	(-3.809)	(-1.382)	(-3.808)			
Industrials	0.025		0.055	-0.152		-0.182	0.144		0.234
	(1.264)		(1.156)	(-3.445)		(-3.545)			
Oil & Gas	0.063	-0.392	0.063	-0.281	-0.526	-0.281	0.184	-2.938	0.184
	(1.179)	(-1.549)	(1.179)	(-2.435)	(-3.006)	(-2.435)			
Technology	0.095	-0.003	0.125	-0.094	-0.162	-0.077	0.503	-0.018	0.619
	(2.036)	(-0.282)	(2.502)	(-1.553)	(-2.751)	(-1.271)			
Telecom.									
Utilities	0.176		0.188	0.009		-0.002	1.053		0.987
	(1.863)		(1.775)	(0.18)		(-0.046)			

Panel B : predicting future market movement in IURCs

Industry	λ_1			λ_2			Ratio		
	Full	Pre-crisis	Crisis	Full	Pre-crisis	Crisis	Full	Pre-crisis	Crisis
Basic Materials	0.210	0.102	0.243	-0.063	-0.246	-0.210	0.770	0.293	0.536
	(2.642)	(2.513)	(2.522)	(-1.326)	(-5.176)	(-2.052)			
Consumer Goods	0.139	0.014	0.170	-0.082	-0.233	-0.193	0.631	0.058	0.469
	(5.481)	(0.357)	(5.29)	(-7.792)	(-4.668)	(-4.791)			
Consumer Services	0.164	0.067	0.228	-0.076	-0.252	-0.198	0.683	0.210	0.536
	(3.826)	(0.996)	(5.323)	(-4.053)	(-4.235)	(-3.473)			
Financials	0.201	0.410	0.208	-0.045	-0.132	-0.056	0.817	0.756	0.788
	(3.889)	(2.742)	(3.784)	(-3.627)	(-1.389)	(-1.241)			
Health Care	0.149	0.157	0.236	-0.069	-0.221	-0.093	0.684	0.414	0.718
	(2.944)	(1.835)	(5.523)	(-2.843)	(-3.847)	(-3.508)			
Industrials	0.339	0.075	0.425	-0.018	-0.214	0.019	0.951	0.260	1.046
	(5.848)	(1.772)	(5.787)	(-1.562)	(-4.69)	(0.305)			
Oil & Gas	0.229	0.065	0.231	-0.034	-0.263	-0.052	0.871	0.198	0.815
	(4.531)	(0.787)	(4.008)	(-1.366)	(-4.281)	(-0.851)			
Technology	0.349	0.107	0.450	-0.004	-0.280	0.028	0.988	0.276	1.066
	(4.458)	(1.662)	(4.48)	(-0.268)	(-3.839)	(0.327)			
Telecom.	0.159	0.074	0.095	-0.105	-0.038	-0.561	0.604	0.660	0.145
	(1.104)	(2.114)	(0.792)	(-13.582)	(-2.177)	(-2.288)			
Utilities	0.230	0.117	0.266	-0.129	-0.014	-0.063	0.640	0.895	0.809
	(3.974)	(6.255)	(4.402)	(-3.086)	(-0.762)	(-1.873)			

Table 7. Cross-sectional summary of VECM results across ratings.

The panel A to C report results of VECM regarding IURC_O across ratings for the full sample, the pre-crisis, and the crisis periods, respectively. The panel D to F report values of VECM regarding IURC_C for the full sample, the pre-crisis, and the crisis periods, respectively. In each panel, the independent variables are the error correction term (ERR), the lagged URC variables, ($IURC\_O_{t-1}$, $IURC\_C_{t-1}$), the option's moneyness level (M), the stock return volatility (VOL), the corresponding industry credit spread (SP), risk free rate (R^f), the business cycle index (BUSI_C), and the VIX. The right-hand entries show the R-squared (R^2) and adjusted R-squared (adj. R^2).

Panel A : results for dependent variable, $\Delta IURC\_O_t$ over full sample period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	-0.333	0.173	-0.046	0.008	-0.002	-0.001	-0.027	0.043	0.011	30.8%	22.4%
	(1.318)	(-1.351)	(1.029)	(-0.236)	(1.514)	(-0.588)	(-0.698)	(-1.903)	(1.117)	(1.353)		
AA	0.000	-0.192	0.061	0.033	0.002	0.013	0.001	-0.093	0.029	0.029	41.0%	36.3%
	(1.732)	(-1.256)	(0.568)	(0.264)	(0.712)	(2.541)	(1.536)	(-0.631)	(1.286)	(3.461)		
A	0.000	-0.082	-0.084	0.132	0.010	0.005	0.002	-0.204	0.035	0.029	39.2%	34.6%
	(1.715)	(-1.977)	(-2.258)	(2.943)	(4.339)	(5.231)	(2.34)	(-2.554)	(4.494)	(5.19)		
BBB	0.000	-0.119	-0.063	0.091	0.017	0.008	0.002	-0.014	0.049	0.017	37.6%	33.0%
	(0.579)	(-4.308)	(-2.038)	(2.621)	(5.012)	(5.729)	(2.158)	(-0.148)	(4.124)	(2.934)		
BB	0.000	-0.233	-0.009	0.035	0.026	0.008	0.018	-0.387	0.054	0.022	43.3%	36.6%
	(0.484)	(-5.409)	(-0.276)	(1.235)	(3.239)	(2.777)	(1.153)	(-2.582)	(1.803)	(1.756)		
B	-0.001	-0.367	-0.084	-0.058	0.051	0.014	0.010	-0.798	0.045	0.061	49.3%	43.4%
	(-1.363)	(-5.51)	(-2.674)	(-0.685)	(5.305)	(3.016)	(4.047)	(-3.107)	(1.728)	(4.469)		
CCC	-0.003	-0.207	0.036	-0.140	0.102	0.059	0.004	-1.526	-0.093	0.108	53.7%	40.7%
	(-1.217)	(-1.257)	(0.292)	(-0.703)	(0.999)	(1.987)	(0.339)	(-19.74)	(-1.63)	(2.677)		

Panel B : results for dependent variable, $\Delta IURC\_O_t$ during the pre-crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	-0.134	0.066	0.029	0.000	0.000	0.000	-0.003	0.001	0.001	37.2%	29.8%
	(1.41)	(-7.357)	(1.01)	(0.2)	(0.957)	(86.789)	(1.161)	(-0.864)	(5.766)	(2.681)		
AA	0.000	-0.298	-0.098	-0.045	0.003	0.004	0.000	-0.083	0.011	0.011	52.3%	46.7%
	(1.71)	(-2.14)	(-1.143)	(-0.731)	(2.484)	(1.506)	(0.582)	(-2.005)	(1.714)	(2.706)		
A	0.000	-0.191	-0.083	-0.005	0.001	0.002	0.001	-0.045	0.004	0.003	42.1%	35.1%
	(1.518)	(-5.474)	(-2.377)	(-0.117)	(0.743)	(1.591)	(3.186)	(-3.551)	(3.19)	(3.259)		
BBB	0.000	-0.192	-0.054	0.011	0.002	0.001	0.001	-0.058	0.007	0.003	41.7%	34.6%
	(2.653)	(-6.813)	(-2.179)	(0.42)	(2.661)	(2.369)	(6.235)	(-4.522)	(4.688)	(7.311)		
BB	0.000	-0.217	-0.004	0.028	-0.003	0.005	0.008	-0.079	0.011	-0.002	44.5%	37.7%
	(1.462)	(-3.015)	(-0.084)	(0.752)	(-0.247)	(1.338)	(1.096)	(-0.862)	(0.349)	(-0.154)		
B	0.000	-0.314	0.035	0.009	0.007	0.002	0.003	-0.302	0.051	0.018	44.7%	37.7%
	(0.635)	(-6.972)	(0.911)	(0.194)	(1.29)	(1.134)	(2.676)	(-3.183)	(2.336)	(2.713)		
CCC												

Panel C : results for dependent variable, $\Delta IURC\_O_t$ during the crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	-0.326	0.165	-0.046	0.010	-0.003	-0.001	-0.064	0.047	0.014	31.6%	20.0%
	(1.209)	(-1.3)	(0.979)	(-0.236)	(1.465)	(-0.683)	(-0.723)	(-3.502)	(1.107)	(1.281)		
AA	0.000	0.027	-0.048	0.164	0.001	0.011	0.001	0.039	0.050	0.024	40.1%	31.8%
	(1.318)	(0.319)	(-0.487)	(1.568)	(0.255)	(2.386)	(0.913)	(0.342)	(2.92)	(2.87)		
A	0.000	-0.068	-0.103	0.149	0.010	0.006	0.002	-0.196	0.038	0.031	42.2%	34.9%
	(2.159)	(-1.493)	(-2.685)	(3.078)	(4.124)	(6.74)	(2.45)	(-2.369)	(4.657)	(5.155)		
BBB	0.000	-0.158	-0.050	0.072	0.019	0.011	0.002	-0.007	0.052	0.021	41.5%	34.0%
	(1.491)	(-4.016)	(-1.426)	(1.884)	(4.853)	(6.316)	(2.314)	(-0.066)	(4.211)	(3.437)		
BB	0.000	-0.295	-0.003	0.030	0.030	0.011	0.021	-0.330	0.086	0.034	47.6%	38.4%
	(-0.223)	(-6.3)	(-0.073)	(1.021)	(4.193)	(3.163)	(1.169)	(-2.065)	(2.253)	(3.006)		
B	-0.001	-0.402	-0.116	-0.061	0.079	0.017	0.014	-1.053	0.047	0.086	56.9%	48.9%
	(-1.118)	(-4.507)	(-1.933)	(-0.566)	(5.607)	(2.272)	(3.94)	(-2.672)	(1.441)	(3.856)		
CCC	-0.003	-0.207	0.036	-0.140	0.102	0.059	0.004	-1.526	-0.093	0.108	53.7%	40.7%
	(-1.217)	(-1.257)	(0.292)	(-0.703)	(0.999)	(1.987)	(0.339)	(-19.74)	(-1.63)	(2.677)		

Panel D : results for dependent variable, $\Delta IURC\_C_t$ over full sample period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	-0.060	0.200	-0.060	0.012	0.004	0.002	-0.305	0.016	0.022	32.3%	24.8%
	(1.244)	(-0.458)	(1.132)	(-0.426)	(1.397)	(1.02)	(1.44)	(-1.281)	(1.996)	(1.127)		
AA	0.000	0.146	0.072	-0.060	0.014	0.010	0.002	-0.311	0.007	0.032	38.7%	33.0%
	(2.303)	(1.071)	(0.798)	(-0.771)	(3.645)	(2.012)	(1.164)	(-1.875)	(0.462)	(2.427)		
A	0.000	0.243	-0.024	0.030	0.015	0.003	0.001	-0.167	0.030	0.026	37.7%	32.5%
	(1.617)	(5.181)	(-0.654)	(0.834)	(6.601)	(3.517)	(1.783)	(-2.17)	(3.57)	(4.467)		
BBB	0.000	0.226	0.051	0.001	0.023	0.006	0.001	-0.086	0.043	0.014	37.8%	33.1%
	(2.483)	(8.112)	(1.488)	(0.016)	(7.502)	(4.662)	(2.81)	(-1.275)	(6.431)	(4.256)		
BB	0.000	0.073	0.071	-0.018	0.032	0.009	0.029	-0.227	0.053	0.033	38.3%	29.7%
	(1.514)	(2.199)	(1.853)	(-0.495)	(6.062)	(2.765)	(1.062)	(-2.005)	(3.14)	(5.652)		
B	-0.001	0.059	0.020	0.027	0.057	0.015	0.003	-0.967	0.060	0.046	37.1%	28.9%
	(-1.142)	(1.755)	(0.667)	(0.873)	(5.516)	(3.148)	(1.816)	(-3.065)	(1.824)	(3.159)		
CCC	0.004	0.286	0.056	-0.028	0.061	0.078	-0.035	3.980	0.334	0.113	48.7%	33.0%
	(5.112)	(8.463)	(0.726)	(-0.093)	(9.37)	(5.913)	(-6.819)	(1.239)	(4.863)	(0.792)		

Panel E : results for dependent variable, $\Delta IURC\_C_t$ during the pre-crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	0.058	0.107	-0.007	0.000	0.000	0.000	-0.012	0.002	0.000	35.6%	28.1%
	(-0.975)	(0.756)	(2.272)	(-0.535)	(0.069)	(5.554)	(2.112)	(-19.081)	(11.303)	(1.084)		
AA	0.000	0.093	0.005	-0.103	0.004	0.004	0.000	-0.076	0.008	0.011	45.0%	38.5%
	(1.717)	(0.547)	(0.044)	(-1.537)	(2.392)	(1.421)	(2.675)	(-3.079)	(1.152)	(2.327)		
A	0.000	0.176	-0.037	-0.049	0.003	0.002	0.000	-0.013	0.008	0.004	31.2%	22.9%
	(1.308)	(3.379)	(-0.791)	(-1.201)	(3.254)	(1.604)	(0.641)	(-0.574)	(1.742)	(2.403)		
BBB	0.000	0.126	0.042	-0.091	0.005	0.000	0.001	-0.064	0.006	0.002	32.3%	24.2%
	(1.857)	(4.322)	(1.578)	(-3.23)	(6.074)	(1.707)	(5.865)	(-5.399)	(3.692)	(6.129)		
BB	0.000	0.016	0.137	-0.137	0.016	0.006	0.010	-0.128	0.034	0.015	34.1%	26.0%
	(1.362)	(0.202)	(1.822)	(-2.672)	(3.459)	(1.665)	(1.294)	(-1.549)	(1.822)	(3.083)		
B	0.000	-0.047	0.068	-0.115	0.026	0.002	0.003	-0.393	0.059	0.019	28.5%	19.6%
	(0.313)	(-1.093)	(0.836)	(-2.088)	(4.73)	(0.832)	(4.139)	(-3.937)	(3.748)	(3.275)		
CCC												

Panel F : results for dependent variable, $\Delta IURC\_C_t$ during the crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
AAA	0.000	-0.016	0.173	-0.044	0.012	0.004	0.003	-0.334	0.015	0.027	34.1%	23.4%
	(1.123)	(-0.102)	(0.935)	(-0.302)	(1.39)	(1.02)	(1.435)	(-1.276)	(2.185)	(1.111)		
AA	0.000	0.338	-0.037	0.048	0.014	0.006	0.002	-0.375	0.026	0.016	39.6%	30.3%
	(1.757)	(3.066)	(-0.538)	(0.902)	(3.164)	(1.783)	(1.643)	(-1.846)	(2.418)	(1.675)		
A	0.000	0.277	-0.052	0.056	0.017	0.004	0.002	-0.177	0.032	0.026	40.3%	32.4%
	(2.07)	(5.482)	(-1.382)	(1.431)	(6.911)	(3.993)	(2.079)	(-2.01)	(3.627)	(4.53)		
BBB	0.000	0.241	0.043	0.002	0.026	0.009	0.002	-0.097	0.047	0.016	41.3%	33.6%
	(3.196)	(6.264)	(1.164)	(0.047)	(7.702)	(5.166)	(2.932)	(-1.317)	(6.557)	(4.588)		
BB	0.000	0.117	0.056	0.000	0.036	0.010	0.035	-0.197	0.048	0.032	43.5%	32.2%
	(1.537)	(3.601)	(1.362)	(-0.001)	(5.694)	(2.803)	(1.034)	(-1.445)	(3.361)	(3.569)		
B	0.000	0.145	-0.029	0.056	0.078	0.019	0.004	-1.091	0.068	0.061	42.4%	30.8%
	(-0.475)	(2.929)	(-0.618)	(1.264)	(4.69)	(1.997)	(1.587)	(-2.829)	(1.549)	(2.468)		
CCC	0.004	0.286	0.056	-0.028	0.061	0.078	-0.035	3.980	0.334	0.113	48.7%	33.0%
	(5.112)	(8.463)	(0.726)	(-0.093)	(9.37)	(5.913)	(-6.819)	(1.239)	(4.863)	(0.792)		

Table 8. Cross-sectional summary of VECM results across industries.

The panel A to C report results of VECM regarding IURC_O across industries for the full sample, the pre-crisis, and the crisis periods, respectively. The panel D to F report values of VECM regarding IURC_C for the full sample, the pre-crisis, and the crisis periods, respectively. In each panel, the independent variables are the error correction term (ERR), the lagged URC variables, ($IURC\_O_{t-1}$, $IURC\_C_{t-1}$), the option's moneyness level (M), the stock return volatility (VOL), the corresponding industry credit spread (SP), risk free rate (R^f), the business cycle index (BUSI_C), and the VIX. The right-hand entries show the R-squared (R^2) and adjusted R-squared (adj. R^2).

Panel A : results for dependent variable, $\Delta IURC\_O_t$ over full sample period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	-0.202	-0.107	0.055	0.011	0.006	0.003	-0.268	0.022	0.024	36.9%	33.6%
	(-0.07)	(-2.145)	(-1.771)	(0.554)	(1.559)	(2.241)	(1.397)	(-0.987)	(1.484)	(4.273)		
Consumer Goods	0.000	-0.172	-0.022	0.093	0.030	0.006	0.002	-0.348	0.041	0.031	38.0%	34.8%
	(2.99)	(-5.15)	(-0.731)	(1.845)	(5.186)	(2.687)	(3.437)	(-3.793)	(5.45)	(5.235)		
Consumer Services	0.000	-0.179	-0.005	0.048	0.026	0.006	0.003	-0.160	0.039	0.041	37.7%	33.9%
	(0.566)	(-3.746)	(-0.109)	(0.817)	(5.1)	(4.341)	(2.918)	(-1.945)	(2.729)	(3.917)		
Financials	0.000	-0.052	-0.247	0.174	0.023	0.015	0.031	-0.211	0.130	0.055	34.3%	30.5%
	(2.956)	(-1.246)	(-4.291)	(2.181)	(3.284)	(4.786)	(1.112)	(-1.289)	(6.213)	(4.282)		
Health Care	0.000	-0.097	-0.008	0.057	0.000	0.004	0.001	-0.114	0.007	0.009	27.2%	22.7%
	(2.579)	(-3.872)	(-0.182)	(1.265)	(0.136)	(2.529)	(2.561)	(-2.461)	(1.574)	(2.4)		
Industrials	0.000	0.013	-0.084	0.132	0.021	0.004	0.002	-0.199	0.012	0.008	38.9%	35.5%
	(1.957)	(0.313)	(-1.716)	(2.83)	(2.815)	(3.998)	(2.784)	(-2.196)	(0.59)	(0.714)		
Oil & Gas	0.000	-0.038	-0.095	0.148	0.013	0.010	0.002	-0.108	0.015	0.034	33.4%	28.9%
	(4.092)	(-0.682)	(-1.611)	(2.461)	(1.959)	(2.209)	(3.041)	(-2.138)	(2.333)	(3.69)		
Technology	0.000	0.004	-0.215	0.221	0.016	0.007	0.002	-0.160	0.012	0.035	41.6%	37.5%
	(2.687)	(0.051)	(-1.508)	(1.599)	(2.076)	(1.99)	(2.087)	(-1.891)	(1.201)	(2.282)		
Telecom.	0.0000	-0.2953	-0.2555	0.1803	0.0132	0.0075	0.0001	-0.154	0.0163	0.003	37.8%	34.6%
	(5.349)	(-0.945)	(-0.807)	(1.763)	(8.169)	(4.188)	(0.326)	(-30.51)	(3.053)	(6.423)		
Utilities	0.000	-0.075	-0.061	-0.036	-0.005	0.012	0.002	-0.115	0.012	0.010	39.3%	36.2%
	(1.675)	(-2.231)	(-1.202)	(-0.796)	(-0.431)	(5.654)	(3.865)	(-2.923)	(2.847)	(4.62)		

Panel B : results for dependent variable, $\Delta IURC\_O_t$ during the pre-crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	-0.246	-0.073	0.019	0.000	0.001	0.001	-0.060	0.002	0.003	36.5%	29.0%
	(-1.072)	(-5.176)	(-1.79)	(0.428)	(0.199)	(1.674)	(5.547)	(-2.176)	(0.675)	(2.433)		
Consumer Goods	0.000	-0.233	-0.012	0.068	0.008	0.006	0.000	-0.080	0.034	0.010	40.8%	33.9%
	(2.644)	(-4.668)	(-0.34)	(1.621)	(3.26)	(2.432)	(1.544)	(-1.837)	(2.691)	(3.014)		
Consumer Services	0.000	-0.252	0.015	-0.067	0.002	0.000	0.001	-0.091	0.007	0.005	45.8%	39.4%
	(-1.683)	(-4.235)	(0.385)	(-1.396)	(0.825)	(0.33)	(1.991)	(-2.524)	(1.243)	(2.728)		
Financials	0.000	-0.132	-0.185	-0.047	0.004	0.008	0.010	-0.130	0.015	0.012	52.8%	47.2%
	(2.293)	(-1.389)	(-2.142)	(-0.568)	(1.778)	(1.909)	(1.106)	(-3.109)	(2.999)	(3.447)		
Health Care	0.000	-0.221	-0.048	0.003	-0.006	0.000	0.000	0.033	0.012	0.005	37.4%	29.7%
	(1.159)	(-3.847)	(-0.612)	(0.049)	(-0.791)	(-0.873)	(2.83)	(0.559)	(1.503)	(1.285)		
Industrials	0.000	-0.214	-0.012	-0.002	-0.005	-0.001	0.000	-0.096	-0.011	-0.009	41.3%	34.2%
	(1.08)	(-4.69)	(-0.365)	(-0.067)	(-0.517)	(-1.791)	(1.024)	(-1.759)	(-0.565)	(-0.818)		
Oil & Gas	0.000	-0.263	-0.152	0.049	0.003	0.000	0.002	-0.141	0.012	0.003	43.8%	36.3%
	(-2.307)	(-4.281)	(-4.527)	(1.021)	(1.258)	(0.741)	(3.623)	(-2.781)	(2.3)	(1.892)		
Technology	0.000	-0.280	-0.059	-0.004	0.005	0.000	0.001	-0.018	0.014	0.008	47.3%	40.1%
	(0.776)	(-3.839)	(-1.137)	(-0.052)	(1.328)	(1.034)	(1.854)	(-0.546)	(1.572)	(2.331)		
Telecom.	0.0000	-0.0381	-0.0535	0.1278	-0.0027	-0.0015	0.0008	-0.026	0.0054	0.002	30.9%	22.9%
	(1.023)	(-2.177)	(-0.401)	(7.817)	(-1.72)	(-32.703)	(8.934)	(-0.774)	(0.978)	(0.646)		
Utilities	0.000	-0.014	-0.046	0.011	0.001	0.001	0.001	-0.059	0.002	0.005	45.5%	39.1%
	(0.726)	(-0.762)	(-0.906)	(0.961)	(0.222)	(4.06)	(2.864)	(-1.791)	(1.096)	(2.522)		

Panel C : results for dependent variable, $\Delta IURC\_O_t$ during the crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	-0.210	-0.105	0.050	0.014	0.005	0.004	-0.419	0.024	0.029	41.3%	35.1%
	(-0.323)	(-2.052)	(-1.624)	(0.495)	(1.637)	(0.871)	(1.307)	(-1.018)	(1.458)	(4.138)		
Consumer Goods	0.000	-0.193	-0.008	0.083	0.033	0.006	0.002	-0.428	0.035	0.035	42.4%	36.2%
	(-0.299)	(-4.791)	(-0.256)	(1.616)	(4.932)	(2.553)	(3.367)	(-3.588)	(4.445)	(4.976)		
Consumer Services	0.000	-0.198	0.003	0.046	0.033	0.011	0.004	-0.167	0.040	0.059	42.8%	36.2%
	(0.947)	(-3.473)	(0.065)	(0.691)	(5.383)	(5.577)	(2.549)	(-1.662)	(2.412)	(3.846)		
Financials	0.001	-0.056	-0.244	0.172	0.024	0.017	0.033	-0.228	0.139	0.068	37.0%	29.4%
	(2.023)	(-1.241)	(-4.187)	(2.078)	(3.034)	(5.1)	(1.13)	(-1.24)	(6.027)	(4.29)		
Health Care	0.000	-0.093	-0.004	0.046	0.001	0.007	0.002	-0.155	0.005	0.010	29.2%	21.9%
	(0.716)	(-3.508)	(-0.07)	(0.839)	(0.175)	(3.985)	(2.556)	(-2.525)	(0.796)	(2.107)		
Industrials	0.000	0.019	-0.105	0.142	0.025	0.006	0.002	-0.166	0.034	0.024	42.9%	37.0%
	(3.172)	(0.305)	(-1.654)	(2.47)	(5.724)	(4.372)	(3.969)	(-1.778)	(5.764)	(6.73)		
Oil & Gas	0.000	-0.052	-0.102	0.136	0.019	0.015	0.002	-0.028	0.017	0.043	38.2%	31.9%
	(4.204)	(-0.851)	(-1.717)	(2.281)	(2.158)	(3.261)	(2.334)	(-0.557)	(2.255)	(3.287)		
Technology	0.000	0.028	-0.232	0.219	0.019	0.008	0.003	-0.209	0.012	0.044	41.8%	35.9%
	(2.801)	(0.327)	(-1.396)	(1.392)	(1.978)	(1.866)	(2.081)	(-2.16)	(0.996)	(2.177)		
Telecom.	0.0000	-0.5610	-0.1493	0.0778	0.0136	0.0083	0.0002	-0.188	0.0156	0.003	41.8%	35.9%
	(0.202)	(-2.288)	(-0.496)	(0.954)	(9.504)	(3.841)	(6.258)	(-9.226)	(2.988)	(2.311)		
Utilities	0.000	-0.063	-0.068	-0.042	-0.011	0.014	0.002	-0.104	0.012	0.011	43.2%	37.4%
	(2.83)	(-1.873)	(-1.316)	(-0.897)	(-0.786)	(5.441)	(3.589)	(-2.652)	(2.841)	(3.648)		

Panel D : results for dependent variable, $\Delta IURC\_C_t$ over full sample period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	0.210	-0.034	0.110	0.019	0.003	0.001	-0.044	0.022	0.020	29.9%	26.2%
	(2.441)	(2.642)	(-0.561)	(1.479)	(4.327)	(1.492)	(0.935)	(-0.59)	(1.723)	(3.615)		
Consumer Goods	0.000	0.139	0.083	-0.047	0.032	0.008	0.002	-0.320	0.055	0.029	34.7%	31.3%
	(1.421)	(5.481)	(2.666)	(-1.459)	(6.129)	(3.498)	(4.317)	(-3.396)	(4.608)	(4.922)		
Consumer Services	0.000	0.164	0.136	-0.014	0.030	0.006	0.001	0.004	0.055	0.033	37.8%	33.9%
	(3.599)	(3.826)	(3.028)	(-0.294)	(5.633)	(2.989)	(0.718)	(0.047)	(3.492)	(5.298)		
Financials	0.000	0.201	-0.126	0.116	0.033	0.013	0.053	-0.342	0.091	0.056	34.1%	30.3%
	(2.81)	(3.889)	(-2.127)	(1.788)	(4.06)	(2.782)	(1.042)	(-1.955)	(3.968)	(3.244)		
Health Care	0.000	0.149	0.034	-0.023	0.008	0.003	0.001	-0.195	0.008	0.004	27.8%	23.2%
	(3.766)	(2.944)	(0.868)	(-0.659)	(3.665)	(3.456)	(2.757)	(-3.069)	(2.728)	(1.558)		
Industrials	0.000	0.339	-0.010	0.034	0.024	0.004	0.003	-0.226	0.024	0.018	38.2%	34.7%
	(2.874)	(5.848)	(-0.186)	(0.778)	(5.763)	(3.505)	(4.44)	(-3.275)	(5.556)	(5.876)		
Oil & Gas	0.000	0.229	0.001	0.101	0.013	0.007	0.000	-0.043	0.022	0.014	32.5%	28.2%
	(4.583)	(4.531)	(0.01)	(1.994)	(4.705)	(2.949)	(-0.158)	(-0.595)	(4.652)	(4.824)		
Technology	0.000	0.349	-0.087	0.093	0.020	0.008	0.001	-0.109	0.018	0.022	44.3%	39.5%
	(1.418)	(4.458)	(-0.65)	(0.72)	(2.917)	(2.001)	(2.114)	(-2.125)	(1.892)	(2.704)		
Telecom.	0.0000	0.1595	-0.2975	0.2202	0.0156	0.0054	0.0002	-0.166	0.0139	0.005	38.6%	35.4%
	(0.368)	(1.104)	(-1.113)	(2.479)	(122.09)	(111.8)	(1.27)	(-9.991)	(4.542)	(18.016)		
Utilities	0.000	0.230	-0.004	-0.164	0.006	0.010	0.001	-0.073	0.016	0.007	33.6%	30.2%
	(4.011)	(3.974)	(-0.053)	(-2.46)	(1.037)	(4.383)	(1.198)	(-1.206)	(1.883)	(2.529)		

Panel E : results for dependent variable, $\Delta IURC\_C_t$ during the pre-crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	0.102	0.024	-0.189	0.008	0.000	0.001	-0.080	0.005	0.005	28.8%	20.4%
	(-1.089)	(2.513)	(0.316)	(-5.066)	(1.938)	(-0.526)	(2.304)	(-1.888)	(1.246)	(1.923)		
Consumer Goods	0.000	0.014	0.025	-0.013	0.014	0.006	0.001	-0.095	0.038	0.008	29.7%	21.4%
	(1.722)	(0.357)	(0.553)	(-0.275)	(4.541)	(2.093)	(3.564)	(-1.975)	(2.724)	(2.825)		
Consumer Services	0.000	0.067	0.131	-0.149	0.008	0.000	0.000	-0.061	0.009	0.006	34.8%	27.1%
	(0.621)	(0.996)	(3.509)	(-4.11)	(3.923)	(0.792)	(1.856)	(-2.195)	(2.271)	(2.548)		
Financials	0.000	0.410	-0.158	-0.013	0.007	0.007	0.010	-0.024	0.027	0.013	47.1%	40.9%
	(1.968)	(2.742)	(-1.196)	(-0.126)	(2.983)	(2.327)	(1.011)	(-0.362)	(2.147)	(2.786)		
Health Care	0.000	0.157	0.023	0.010	0.005	0.000	0.001	-0.102	0.003	0.004	32.6%	24.3%
	(1.92)	(1.835)	(0.255)	(0.14)	(2.739)	(0.191)	(2.826)	(-1.805)	(0.545)	(2.093)		
Industrials	0.000	0.075	0.078	-0.133	0.003	0.000	0.001	-0.099	0.005	0.006	31.5%	23.1%
	(-0.556)	(1.772)	(2.123)	(-4.452)	(1.196)	(-1.214)	(2.57)	(-2.243)	(1.667)	(2.175)		
Oil & Gas	0.000	0.065	-0.059	-0.075	0.007	0.001	0.002	-0.193	0.010	0.002	30.5%	21.7%
	(-2.408)	(0.787)	(-0.794)	(-1.26)	(4.76)	(0.866)	(2.981)	(-2.797)	(2.228)	(0.98)		
Technology	0.000	0.107	0.077	-0.071	0.008	0.000	0.001	-0.040	0.007	0.010	36.1%	26.8%
	(0.226)	(1.662)	(0.99)	(-0.808)	(2.073)	(-0.37)	(1.5)	(-1.073)	(1.103)	(1.894)		
Telecom.	0.0000	0.0738	-0.1417	-0.0205	0.0005	-0.0009	0.0011	-0.069	0.0023	0.002	19.4%	9.9%
	(-0.541)	(2.114)	(-1.609)	(-0.273)	(0.558)	(-2.343)	(1.025)	(-0.733)	(0.326)	(1.744)		
Utilities	0.000	0.117	0.122	-0.197	0.003	0.000	0.001	-0.046	0.006	0.002	24.9%	16.1%
	(-1.425)	(6.255)	(1.861)	(-5.236)	(1.195)	(0.888)	(5.037)	(-2.719)	(0.892)	(1.269)		

Panel F : results for dependent variable, $\Delta IURC\_C_t$ during the crisis period

	C	ERRt	$\Delta IURC\_O_{t-1}$	$\Delta IURC\_C_{t-1}$	ΔM_t^i	ΔVOL_t^i	ΔSP_t	ΔR_t^f	$\Delta BUSI\_C_t$	ΔVIX_t	R^2	adj. R^2
Basic Materials	0.000	0.243	-0.054	0.133	0.023	0.004	0.000	-0.023	0.023	0.024	33.6%	26.3%
	(2.038)	(2.522)	(-0.779)	(1.575)	(3.984)	(1.336)	(0.585)	(-0.338)	(1.419)	(3.511)		
Consumer Goods	0.000	0.170	0.073	-0.039	0.037	0.009	0.003	-0.361	0.052	0.034	39.1%	32.5%
	(0.223)	(5.29)	(2.29)	(-1.239)	(5.362)	(3.326)	(3.993)	(-3.212)	(4.451)	(4.703)		
Consumer Services	0.000	0.228	0.118	-0.011	0.037	0.009	0.001	0.041	0.061	0.047	42.6%	35.9%
	(3.155)	(5.323)	(2.367)	(-0.205)	(5.785)	(2.821)	(0.516)	(0.413)	(3.203)	(5.017)		
Financials	0.001	0.208	-0.131	0.118	0.035	0.014	0.058	-0.441	0.095	0.063	36.4%	28.6%
	(2.229)	(3.784)	(-2.215)	(1.824)	(3.939)	(2.76)	(1.051)	(-2.152)	(3.512)	(3.094)		
Health Care	0.000	0.236	0.006	-0.042	0.008	0.005	0.001	-0.159	0.009	0.003	30.7%	23.5%
	(1.419)	(5.523)	(0.16)	(-1.183)	(3.169)	(3.658)	(2.45)	(-3.513)	(3.069)	(1.088)		
Industrials	0.000	0.425	-0.043	0.082	0.029	0.005	0.002	-0.203	0.027	0.021	43.2%	37.3%
	(3.18)	(5.787)	(-0.711)	(1.619)	(6.279)	(4.037)	(4.756)	(-2.618)	(6.206)	(6.414)		
Oil & Gas	0.000	0.231	-0.020	0.117	0.017	0.012	-0.001	0.025	0.025	0.017	35.8%	29.2%
	(4.515)	(4.008)	(-0.339)	(2.046)	(4.909)	(3.967)	(-1.26)	(0.326)	(4.806)	(5.047)		
Technology	0.000	0.450	-0.137	0.123	0.024	0.014	0.001	-0.117	0.026	0.024	46.3%	40.8%
	(1.895)	(4.48)	(-0.871)	(0.795)	(2.986)	(1.844)	(1.993)	(-2.376)	(1.763)	(2.858)		
Telecom.	0.0000	0.0950	-0.2795	0.1955	0.0161	0.0058	0.0002	-0.205	0.0134	0.005	39.9%	33.7%
	(-2.13)	(0.792)	(-1.048)	(2.6)	(114.98)	(23.134)	(3.459)	(-7.002)	(3.916)	(6.046)		
Utilities	0.000	0.266	-0.014	-0.160	0.007	0.012	0.001	-0.076	0.016	0.008	36.6%	30.1%
	(4.829)	(4.402)	(-0.182)	(-2.339)	(1.005)	(4.167)	(1.185)	(-1.207)	(1.879)	(2.515)		

Table 9. Multivariate-GARCH (BEKK) results of IURCs sector indexes.

The panel A to C report the estimated parameters and t-statistics (in parentheses) of the BEKK model using IURC sector indexes for data sets over full sample period, during the pre-crisis and crisis periods, respectively.

Panel A : predicting future volatility movement in IURCs over full sample period

	c_{11}	c_{12}	c_{22}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Basic Materials	0.001	0.001	0.000	1.312	-0.508	-0.371	1.222	0.335	0.334	0.228	0.368
	(0.079)	(0.071)	(-0.3)	(0.15)	(-0.052)	(-0.058)	(0.165)	(0.207)	(0.147)	(0.183)	(0.208)
Consumer Goods	0.001	0.001	0.000	1.105	0.301	-0.089	0.732	-0.211	-0.037	0.110	-0.108
	(3.481)	(2.45)	(-1.02)	(21.244)	(4.441)	(-2.554)	(15.829)	(-4.632)	(-0.436)	(2.768)	(-1.417)
Consumer Services	0.001	0.001	0.000	1.052	-0.096	-0.064	1.037	0.124	0.253	0.228	0.209
	(1.433)	(1.417)	(-7.309)	(4.63)	(-0.2)	(-0.454)	(3.59)	(0.1)	(0.128)	(0.325)	(0.178)
Financials	0.001	0.002	0.000	0.773	0.151	0.202	0.841	-0.002	-0.033	0.035	-0.018
	(0.155)	(0.096)	(1.756)	(0.765)	(0.254)	(0.286)	(2.174)	(-0.02)	(-3.162)	(0.067)	(-0.112)
Health Care	0.000	0.000	0.000	0.968	-0.010	0.038	1.010	0.087	0.062	-0.216	-0.228
	(1.318)	(0.4)	(33.101)	(370.72)	(-8.668)	(11.275)	(538.81)	(5.682)	(9.738)	(-34.459)	(-21.68)
Industrials	0.000	0.001	0.000	0.969	-0.130	-0.037	1.053	-0.237	-0.013	0.582	0.396
	(4.991)	(4.997)	(1.248)	(69.728)	(-11.647)	(-2.054)	(77.377)	(-7.13)	(-4.069)	(17.407)	(22.583)
Oil & Gas	0.001	0.001	0.000	1.030	-0.321	-0.035	1.267	0.128	0.039	-0.481	-0.470
	(3.189)	(2.438)	(0.105)	(57.489)	(-29.19)	(-2.092)	(104.62)	(4.79)	(1.584)	(-15.942)	(-13.934)
Technology	0.000	0.000	0.000	0.849	0.021	0.166	1.016	0.045	0.074	-0.139	-0.108
	(5.535)	(5.068)	(-0.026)	(0.67)	(0.013)	(0.157)	(0.744)	(0.045)	(0.054)	(-0.153)	(-0.086)
Telecom.	0.000	0.000	0.000	1.024	0.363	-0.058	0.580	0.304	-0.344	0.053	0.752
	(196.34)	(40.205)	(0)	(346.52)	(31.181)	(-61.772)	(98.796)	(159.95)	(-38.512)	(64.086)	(149.94)
Utilities	0.000	0.000	0.000	0.828	0.143	0.040	0.864	0.629	0.062	-0.033	0.429
	(9.99)	(7.798)	(-11.848)	(68.53)	(2.183)	(11.967)	(38.32)	(19.66)	(0.503)	(-6.18)	(11.827)

Panel B : predicting future volatility movement in IURCs during the pre-crisis period

	c_{11}	c_{12}	c_{22}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Basic Materials	0.001	0.001	0.000	0.734	-0.239	0.153	1.112	-0.118	0.152	-0.054	-0.386
	(4.399)	(3.65)	(-0.132)	(20.873)	(-3.33)	(8.231)	(27.934)	(-0.245)	(0.498)	(-0.372)	(-4.809)
Consumer Goods	0.000	0.000	0.000	0.933	0.151	0.070	0.904	1.422	2.946	-0.923	-2.013
	(9.804)	(7.467)	(1.155)	(10.579)	(0.786)	(2.243)	(12.16)	(0.495)	(0.568)	(-0.474)	(-0.57)
Consumer Services	0.001	0.002	0.000	0.958	0.198	-0.010	0.788	-0.577	0.111	0.234	-0.349
	(9.209)	(8.483)	(23.628)	(30.909)	(2.281)	(-0.689)	(15.619)	(-4.789)	(0.469)	(3.66)	(-2.6)
Financials	0.000	0.000	0.000	3.084	3.112	-1.296	-1.072	1.056	1.911	-0.956	-1.770
	(-0.923)	(-0.863)	(-127.4)	(0.153)	(0.073)	(-0.198)	(-0.082)	(0.02)	(0.02)	(-0.061)	(-0.059)
Health Care	0.000	0.000	0.000	0.809	-0.127	0.102	1.054	0.685	0.257	-0.156	0.164
	(65.299)	(57.862)	(-0.002)	(16.623)	(-3.021)	(2.64)	(27.884)	(10.667)	(2.391)	(-1.6)	(0.719)
Industrials	0.001	0.001	0.000	0.791	-0.005	0.015	0.805	0.445	-0.167	-0.104	0.455
	(11.298)	(8.629)	(0.602)	(31.967)	(-1.334)	(0.706)	(77.246)	(2.536)	(-0.536)	(-1.126)	(2.558)
Oil & Gas	0.001	0.001	0.000	0.912	-0.039	0.064	1.021	-0.431	0.042	0.093	-0.372
	(14.198)	(9.332)	(-129.46)	(2.992)	(-0.092)	(0.186)	(2.127)	(-0.212)	(0.015)	(0.056)	(-0.162)
Technology	0.001	0.001	0.000	0.111	-0.585	0.653	1.369	0.116	-0.280	0.322	0.688
	(19.728)	(19.326)	(-0.013)	(2.687)	(-10.167)	(13.538)	(17.414)	(1.065)	(-0.792)	(1.801)	(1.458)
Telecom.	0.000	-0.001	0.000	1.062	0.367	-0.042	0.701	0.097	-0.645	0.045	0.651
	(-67.186)	(-12.376)	(-0.007)	(120.72)	(14.73)	(-45.271)	(104.18)	(4.869)	(-20.851)	(73.641)	(58.995)
Utilities	0.001	0.002	0.000	0.643	0.288	0.078	0.680	-0.644	0.247	0.214	-0.168
	(1.582)	(0.526)	(-196.32)	(23.287)	(3.031)	(6.735)	(4.672)	(-0.624)	(0.037)	(0.954)	(-0.102)

Panel C : predicting future volatility movement in IURCs during the crisis period

	c_{11}	c_{12}	c_{22}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Basic Materials	0.003	0.003	0.002	2.110	1.173	-0.943	-0.013	0.175	0.047	-0.233	-0.136
	(0.08)	(0.861)	(2.673)	(0.778)	(2.578)	(-0.997)	(-0.936)	(0.857)	(0.455)	(-3.833)	(-0.4)
Consumer Goods	0.001	0.002	0.000	0.888	0.261	0.064	0.709	-0.348	0.024	0.077	-0.331
	(0.382)	(0.564)	(19.942)	(19.377)	(4.187)	(1.753)	(14.167)	(-40.926)	(48.366)	(9.358)	(-54.69)
Consumer Services	0.001	0.001	0.000	0.909	-0.011	0.083	1.020	-0.056	-0.237	0.142	0.258
	(3.062)	(1.947)	(-6.543)	(94.188)	(-0.932)	(13.091)	(121.58)	(-3.823)	(-6.155)	(6.773)	(3.67)
Financials	0.001	0.001	0.000	0.694	-0.230	0.292	1.239	0.523	0.718	-0.717	-0.853
	(0.009)	(0.007)	(-13.391)	(5.339)	(-1.842)	(2.433)	(10.714)	(4.868)	(6.278)	(-6.925)	(-7.426)
Health Care	0.002	0.002	0.000	0.695	-0.226	0.261	1.181	-0.926	-1.287	1.006	1.366
	(0.985)	(0.925)	(63.586)	(7.255)	(-1.684)	(2.721)	(8.575)	(-2.737)	(-3.177)	(3.672)	(3.724)
Industrials	0.000	0.001	0.000	0.846	-0.045	0.123	1.015	0.099	0.293	-0.066	-0.218
	(0.021)	(0.044)	(0.036)	(6.115)	(-0.289)	(0.967)	(6.108)	(0.089)	(0.365)	(-0.086)	(-0.285)
Oil & Gas	0.001	0.001	0.000	0.940	-0.178	-0.007	1.077	-0.311	0.067	-0.229	-0.656
	(1.727)	(1.029)	(5.717)	(8.729)	(-0.906)	(-0.098)	(8.004)	(-0.808)	(0.179)	(-0.7)	(-1.959)
Technology	0.001	0.001	0.000	0.935	0.055	0.070	0.974	0.097	0.010	0.090	0.115
	(0.682)	(0.648)	(1.459)	(10.159)	(0.46)	(0.981)	(9.938)	(3.157)	(12.695)	(20.417)	(6.727)
Telecom.	0.000	0.000	0.000	0.759	0.310	0.266	0.718	0.120	0.008	-0.028	0.168
	(0.014)	(0.02)	(-0.655)	(1.151)	(0.544)	(0.437)	(1.385)	(2.077)	(0.243)	(-0.659)	(4.101)
Utilities	0.001	0.001	0.000	1.033	0.224	-0.063	0.829	-1.489	-2.308	1.160	1.693
	(2.615)	(1.325)	(1.446)	(11.045)	(1.613)	(-1.324)	(11.487)	(-3.543)	(-2.846)	(6.689)	(4.994)