The Risk of Betting on Risk: Conditional Variance and Correlation of Bank Credit Default Swaps*

Xin Huang [a]
Federal Reserve Board

February 8, 2019

Abstract

Credit default swaps (CDS) have been used by market participants to speculate on the default risk of the reference entity. As a risk-betting tool, the risk of CDS can be measured by their second moments. This paper uses an extended GARCH model for the univariate conditional variance and a slightly modified DCC model for the multivariate conditional correlation of CDS returns. The empirical sample consists of the most actively traded single-name CDS contracts for six large U.S. banks from 2002 to 2018. The main empirical finding is that the risk of holding CDS contracts is time-varying, persistent, and exhibits both asymmetry and fat-tail properties. But in contrast to stock returns, a positive shock to CDS returns actually increases their conditional variance more than a negative shock does. Meanwhile, the conditional volatility and correlation extracted from the GARCH-DCC model show that even though the risk profiles of individual banks have improved since the crisis, their distress correlations have remained just as high as during the peak of the crisis. This contrasts with the decreased correlations of their stock returns in the past couple of years.

Keywords: credit default swap spread, GARCH, DCC.

JEL classification: C58, C22, C32.

---

*The analysis and conclusions set forth are those of the author and do not necessarily represent those of the Board of Governors or its staff.

[a]Principal Economist, Risk Analysis Section, Federal Reserve Board. Mail: Mail Stop K1-91, Federal Reserve Board, 20th & C St., NW, Washington, DC 20551, U.S.A., phone: 202-530-6211, e-mail: Xin.Huang@frb.gov.

1 Introduction

Credit default swaps (CDS) work like an insurance contract to protect their holders against the default loss of the reference entity. However, CDS holders are not required to hold the reference liability, which allows investors to speculate on the default risk of the reference entity through either buying or selling CDS contracts. As a risk-betting tool, the risk of a CDS contract can be measured by the variation of its value — that is, its second moments. This paper models both the univariate conditional variance and the multivariate conditional correlation of CDS contracts to measure this risk of betting on risk.

Literature measuring the risk of betting on values provides a rich set of tools to model the conditional second moments. For the univariate process, Engle (1982) proposes the Autoregressive Conditional Heteroscedasticity (ARCH) model for U.K. inflation. Bollerslev (1986) proposes the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model by adding past conditional variance as the explanatory variable in the variance equation as a parsimonious way to model the conditional variance of U.S. inflation. To allow for the potential fat-tailed property, Bollerslev (1987) extends the GARCH model with conditionally t-distributed errors for foreign exchange and stock index returns. To allow for asymmetry, Nelson (1991) proposes an exponential GARCH (E-GARCH) model for daily stock index returns, and finds that a negative return innovation increases future conditional variance more than a positive one does, while Glosten et al. (1993) propose an asymmetric GARCH (GJR) model for monthly stock index returns, and find that a positive return innovation reduces future conditional variance while a negative innovation increases it. For the multivariate process, several multivariate GARCH models have been proposed. Among them, the Dynamic Conditional Correlation (DCC) model, proposed by Engle (2002) for conditional correlations between stock indices, between stock and bond markets, and between exchange rates turns out to be the most popular, as it is parsimonious and avoids the dimensionality problem that other multivariate models may encounter.

Using the GARCH-DCC model, Li and Cheruvelil (2018) show the improved accuracy for the central counterparty clearing (CCP) margin of CDS contracts relative to that based on the GARCH-CCC model. Given such a practical application, I implement a more general conditional variance and correlation model so that the potential features have the opportunity to manifest themselves in the empirical results. More specifically, an extended GARCH model, i.e. the GJR model with conditionally t-distributed innovations, is chosen for the univariate conditional variance, and a slightly modified DCC model with multivariate t-distributed standardized residuals is chosen for the conditional correlation. The GJR model is chosen instead of the E-GARCH model mainly for possible future forecast exercises, as the transformation from expected log variance to expected variance is not straightforward, especially when we allow for fat-tailed distributions instead of the Gaussian distribution.

The empirical data in this paper consist of the daily single-name CDS contracts for six large U.S. banks from 2002 to 2018, the longest and most actively traded CDS contracts. There are two main findings. The first finding is that the extended GARCH-DCC model shows that the risk of holding CDS contracts is time-varying, persistent, and exhibits both asymmetry and fat-tail properties. The economic implication is that the risk of betting on risk changes over time, and high levels of risk tend to cluster together in several consecutive periods. The extreme outcomes of betting on risk are more likely to occur than the Gaussian distribution implies. A slight twist for CDS contracts is that, in contrast to stock returns, a positive shock to CDS returns actually increases the conditional variance more than a negative shock does. But the economic interpretation remains the same, because a positive shock to a CDS contract tends to occur when the situation of the reference entity gets worse

— i.e., it is still the case that bad news tends to increase conditional variance more than good news does. The second finding is that the conditional volatility time series extracted from the extended GARCH model peaked during the crisis period and has come down recently, while the conditional correlation time series extracted from the DCC model have stayed at the plateau since the crisis. This finding implies that the risk profile of individual banks has improved since the crisis, but their extreme-loss scenarios have remained as highly correlated as during the crisis.

2 Data

As a derivative directly tied to the risk of the reference entity, CDS differs from stocks in at least two aspects. First, for the same firm, there is only one stock, while there are multiple CDS contracts traded at the same time. As all of these contracts' values are driven by the risk of the same firm and differ in other dimensions, the sample CDS data in this paper always come from the contract that is most actively traded. For U.S. reference entities, this means the five-year maturity, senior unsecured (SNRFOR) tier, ex-restructuring (XR) document clause, and U.S. dollar denomination. Second, as the transaction prices for CDS contracts are still proprietary information, I use the publicly available daily CDS quote data provided by Markit.

The sample reference entities consist of six large U.S. banks: Bank of America (BAC), Citigroup (C), Goldman Sachs (GS), J.P. Morgan Chase (JPM), Morgan Stanley (MS), and Wells Fargo (WFC). These banks are chosen for three reasons. First, they are the reference entities of the first traded corporate CDS contracts since the launch of CDS trading in the early 2000s. Second, their CDS contracts are almost always among the top 10 most traded CDS contracts based on annual average of daily quote counts. Third, these six banks are also among the earliest U.S. financial institutions designated as Globally Systemically Important Financial Institutions (G-SIFIs) by the Financial Stability Board. Thus, these banks form a natural sample for the study of the conditional variance-covariance of the CDS market, because they provide the best possible empirical sample for statistical analysis and convenient economic interpretations as homogeneous and important financial entities.

Figures 1 and 2 plot the daily log CDS spreads and their first differences of these sample banks from 2002 to 2018. The log CDS spreads in Figure 1 exhibit the unit-root property,

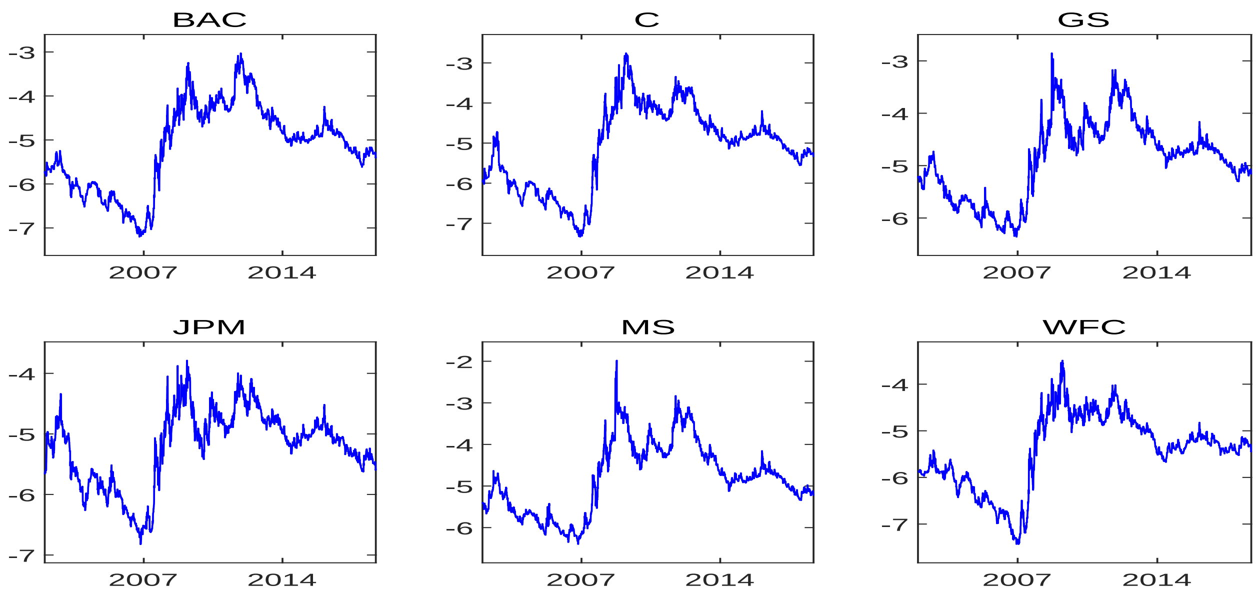

Figure 1: Daily log CDS spreads

as proved in Huang (2016). Their first difference in Figure 2 is calculated as

$$r_t = (p_t - p_{t-1}) \times 100\%,$$

where p_t is the log CDS spread. The first difference of log CDS spread can be treated approximately as the geometric return of the CDS contract if the CDS spread can be thought

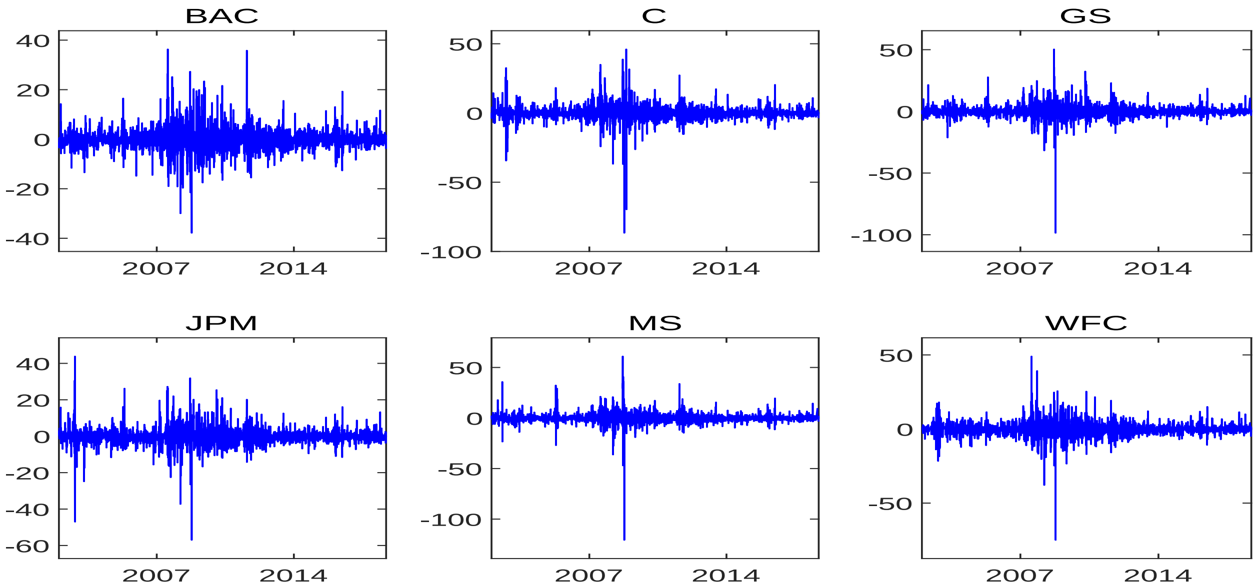

Figure 2: Daily CDS returns

of as the price of the CDS contract.[1] For convenience, I will call r_t the CDS return in the rest of this paper.

Figure 2 shows that CDS returns for all the sample banks appear to be fast mean-reverting and exhibit volatility clustering. Moreover, CDS volatility response to shocks appears to be asymmetric, and extreme return movements seem to be more frequent than expected from the Gaussian distribution. Given the volatility clustering, asymmetry, and leptokurtic (fat-tail) properties, an extended GARCH model that allows for these features looks promising to capture the time-varying second moment of univariate CDS returns.

[1] Before the "Big Bang" implementation in 2009, CDS contracts were quoted by par spread. After the Big Bang, CDS contracts on investment-grade reference entities have been quoted most often by conventional spreads with a 100 basis point fixed coupon, and the high-yield ones by upfront points with a 500 basis point fixed coupon, according to Markit (2009). So the measurement of CDS contract value has varied over time, even for the same reference entity. In practice, dealers (big banks) continue to provide par spread data after the Big Bang, in addition to conventional spreads and upfront points. For time-series consistency and to ensure the longest possible sample, par spreads are used throughout this paper. Accordingly, r_t is interpreted as a proxy for CDS return.

3 Conditional Variance for Univariate CDS Returns

The time-series dynamics of the CDS returns observed in Figure 2 call for an extended GARCH model that allows for asymmetric and leptokurtic properties. Specifically, to allow for a potential asymmetric volatility response to positive and negative shocks, an additional term of the past squared raw innovation when the innovation is negative is added as proposed by Glosten et al. (1993). Notice that this setup follows the current common practice and differs slightly from the original setup in Glosten et al. (1993), where the additional term is defined when the innovation is positive. Meanwhile, to allow for the potential leptokurtic property of the standardized innovation, a t distribution, instead of a Gaussian distribution, as proposed by Bollerslev (1987), is used here. The resulting specification for the CDS returns of bank i takes the following form:

$$r_{i,t} = \mu_i + \gamma_i \cdot r_{i,t-1} + \epsilon_{i,t} \tag{1}$$

$$\epsilon_{i,t} = \sigma_{i,t} \cdot \sqrt{\frac{v-2}{v}} \cdot z_{i,t}, \quad z_{i,t} \sim t(v) \tag{2}$$

$$\sigma^2_{i,t} = \omega_i + \alpha_i \cdot \epsilon^2_{i,t-1} + \beta_i \cdot \sigma^2_{i,t-1} + \delta_i \cdot 1(\epsilon_{i,t-1} < 0) \cdot \epsilon^2_{i,t-1}, \tag{3}$$

where $1(\epsilon_{i,t-1} < 0)$ is 1 if $\epsilon_{i,t-1}$ is positive and 0 otherwise. Equation (1) for $r_{i,t}$ allows for a small serial correlation in the return process and a non-zero unconditional mean. Given information at $t-1$, Equations (2) and (3) imply that $\epsilon_{i,t}$ follows a non-standardized t distribution with a scale parameter $\sigma_{i,t}$: $t_v(0, \frac{v-2}{v}\sigma^2_{i,t})$. Its probability density function (PDF) is

$$f(\epsilon_{i,t}|I_{t-1}) = \frac{\Gamma(\frac{v+1}{2})}{\Gamma(\frac{v}{2})\sqrt{\pi(v-2)\sigma^2_{i,t}}}[1 + \frac{\epsilon^2_{i,t}}{(v-2)\sigma^2_{i,t}}]^{-\frac{v+1}{2}},$$

Table 1: GARCH model with potential asymmetry and t-distributed innovations

	μ	γ	ω	α	β	δ	ν
BAC	-0.108***	0.147***	0.122***	0.130***	0.892***	-0.045**	3.191***
	(0.028)	(0.015)	(0.002)	(0.025)	(0.019)	(0.025)	(0.251)
C	-0.115**	0.140***	0.309***	0.222***	0.807***	-0.058***	3.095***
	(0.064)	(0.022)	(0.010)	(0.024)	(0.029)	(0.024)	(0.206)
GS	-0.127***	0.120***	0.234***	0.179***	0.846***	-0.051**	3.067***
	(0.045)	(0.022)	(0.005)	(0.024)	(0.026)	(0.024)	(0.255)
JPM	-0.082	0.131***	0.401***	0.267***	0.799***	-0.133***	3.061***
	(0.083)	(0.037)	(0.010)	(0.026)	(0.036)	(0.026)	(0.314)
MS	-0.102**	0.127***	0.275***	0.228***	0.818***	-0.091***	3.178***
	(0.053)	(0.026)	(0.007)	(0.024)	(0.028)	(0.024)	(0.258)
WFC	-0.068**	0.075***	0.164***	0.173***	0.863***	-0.074***	3.075***
	(0.039)	(0.017)	(0.004)	(0.023)	(0.022)	(0.023)	(0.192)

Note: 1. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels.
2. Heteroscedasticity-robust standard errors are reported in parenthesis.

which allows us to estimate the model parameters by Maximum Likelihood Estimation (MLE).

Table 1 reports the estimation results. The conditional mean equation is not our focus. We just notice that the AR(1) coefficient, γ_i, is small but significant for all banks, showing the small serial correlation in the CDS return time series. The variance equation is our focus here. The parameters of the variance equation and the degree of freedom parameter for the t distribution are all very significant. There are three interesting observations for the variance equation estimation results.

First, just like the stock returns,[2] the conditional variance for the CDS returns exhibits high levels of persistency ($\alpha_i + \beta_i + \delta_i$ is very close to 1 for all banks), which means that the risk of left-tail risk is a highly persistency process. In other words, a period of rapidly

[2]Table 2 in the Appendix reports the counterpart results on the stock returns of the same sample banks.

changing left-tail risk is very likely to be followed by another period of volatile left-tail risk.

Second, all the sample banks exhibit asymmetry in volatility response to CDS return shocks. In addition, their δ_i's are negative but smaller in magnitude than α_i. This means a negative CDS return shock increases the CDS volatility less than a positive shock does. This result differs from the finding of Glosten et al. (1993) in two aspects. Glosten et al. (1993) find that a negative stock index return shock increases volatility more than a positive shock does. In addition, they also find that a positive return shock actually decreases volatility. Indeed, the asymmetry of CDS return volatility is like the mirror image of what Nelson (1991) finds for daily stock index return volatility by his E-GARCH model. Thus, CDS volatility asymmetry is actually the opposite of the stock volatility asymmetry, which is confirmed for the sample banks by the stock return results reported in Table 2 of the Appendix. The intuition behind this observation is that as the value of a CDS contract comes from the riskiness of the reference entity, a positive CDS return shock actually means the reference entity becomes more risky; thus, it is bad news for the reference entity, so the CDS volatility surges more in response to a positive CDS return shock than to a negative CDS return shock.

Third, the CDS returns for all the sample large U.S. banks exhibit a conditional leptokurtic property (ν_i close to 3). Thus, if investors want to bet on the risk of bank liabilities, they should be prepared to face extreme outcomes more often than implied by the Gaussian distribution.

Figure 3 plots the extracted conditional volatility (standard deviation) of CDS returns. All the sample U.S. banks experienced volatility spikes during the peak of the recent financial crisis period, around the summer of 2007 to the spring of 2009.[3] Except for some periodic

[3]The conditional volatility of JPM and Citi also peaked in 2003 when SEC fined them for their roles in the Enron issue. See https://www.sec.gov/news/press/2003-87.htm.

small spikes, the conditional volatility time series for all banks have trended downward since the crisis, showing a lower risk of betting on individual banks' risk separately.

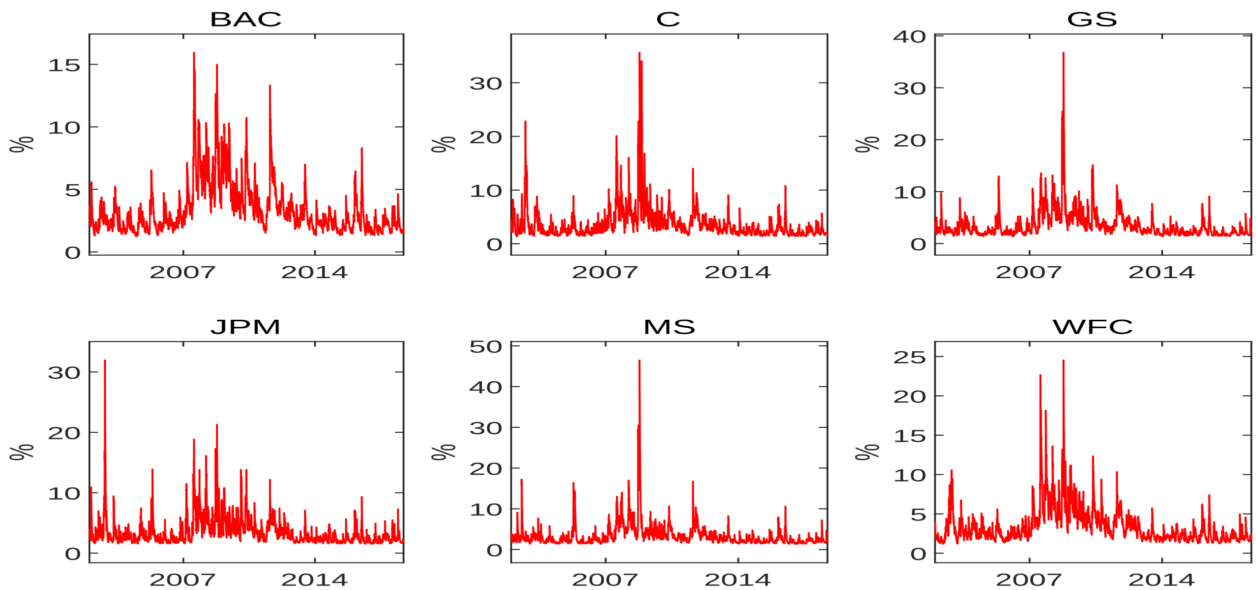

Figure 3: Extracted conditional volatility of CDS returns

4 Conditional Correlations for Multivariate CDS Returns

With the conditional variance of univariate CDS returns in place, we are ready to apply the DCC model proposed by Engle (2002), with a slight modification, to estimate the conditional correlations among CDS returns. A brief review of the DCC model with modification is as follows.

To transit from scalar to vector notations, let ϵ_t be the column vector of daily innovations of CDS returns for all banks on day t: $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t}, ..., \epsilon_{6,t})'$. The conditional covariance matrix of ϵ_t is

$$E(\epsilon_t \epsilon_t' | I_{t-1}) \equiv \Sigma_t.$$

The DCC model specifies Σ_t as follows:

$$\Sigma_t = D_t R_t D_t, \quad \text{where } D_t = diag\{\sqrt{\Sigma_{i,t}}\}.$$

D_t is a diagonal matrix with diagonal elements of $\sigma_{i,t}$ estimated in the previous section, and R_t is the conditional correlation matrix and our estimation target in this section.

To model the R_t process, let's assume that the conditional covariance matrix of the standardized innovations (i.e. unconditional mean 0 and variance 1) $e_t = (e_{1,t}, e_{2,t}, ...e_{6,t})'$ is Q_t. (In the context of Section 3, $e_{i,t} = \frac{\epsilon_{i,t}}{\sigma_{i,t}} = \sqrt{\frac{v-2}{v}} \cdot z_{i,t}$.) The i'th row, j'th column element $q_{i,j,t}$ of Q_t following the GARCH(1,1) model is

$$q_{i,j,t} = \bar{\rho}_{i,j} + \kappa(e_{i,t-1}e_{j,t-1} - \bar{\rho}_{i,j}) + \lambda(q_{i,j,t-1} - \bar{\rho}_{i,j}), \tag{4}$$

or

$$q_{i,j,t} = \bar{\rho}_{i,j}(1 - \kappa - \lambda) + \kappa e_{i,t-1}e_{j,t-1} + \lambda q_{i,j,t-1}, \tag{5}$$

where $\bar{\rho}_{i,j}$ is the unconditional correlation between $e_{i,t}$ and $e_{j,t}$, $\bar{q}_{i,j} = \bar{\rho}_{i,j}$. Equation (4) can be rewritten as

$$q_{i,j,t} = \bar{\rho}_{i,j}\frac{1 - \kappa - \lambda}{1 - \lambda} + \kappa \sum_{s=1}^{\infty} \lambda^{s-1}(e_{i,t-s}e_{j,t-s}). \tag{6}$$

The i'th row, j'th column element in the R_t matrix is

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}.$$

The matrix version of Equation (5) is

$$Q_t = S(1-\kappa-\lambda) + \kappa(e_{t-1}e'_{t-1}) + \lambda Q_{t-1},$$

where S is the unconditional covariance matrix of e_t's. So the conditional covariance matrix Q_t is positive definite, as it is a weighted average of a positive semidefinite and a positive definite matrix. Consequently, the correlation matrix R_t is positive definite, too.

To estimate the DCC model, I make the following statistical specification:

$$\begin{aligned}
&E(\epsilon_t\epsilon'_t|I_{t-1}) \equiv \Sigma_t,\\
&\Sigma_t = D_t R_t D_t,\\
&D_t^2 = diag\{\omega_i\} + diag\{\alpha_i\} \circ \epsilon_{t-1}\epsilon'_{t-1} + diag\{\beta_i\} \circ D_{t-1}^2 + diag\{\delta_i\} \circ diag\{1(\epsilon_{t-1} < 0)\} \circ \epsilon_{t-1}\epsilon'_{t-1},\\
&e_t = D_t^{-1}\epsilon_t,\\
&Q_t = S(1-\kappa-\lambda) + \kappa e_{t-1}e'_{t-1} + \lambda Q_{t-1},\\
&R_t = diag\{Q_t\}^{-\frac{1}{2}} Q_t diag\{Q_t\}^{-\frac{1}{2}},\\
&e_t|I_{t-1} \sim \mathbf{t}_v(\overrightarrow{0}, \frac{v-2}{v}R_t, n),
\end{aligned}$$

where $\circ$ is the Hadamard element-by-element product of two matrices of the same size. Notice that I modify the original DCC model by changing the conditional distribution for $e_t|I_{t-1}$ from a multivariate Gaussian distribution to a multivariate t distribution. As the univariate GARCH model estimation results in Section 3 show that all banks exhibit t distribution with the degree of freedom very close to 3, we can specify the multivariate t distribution for these banks jointly with a degree of freedom v, which is a free parameter to be estimated in this subsection. The location parameter vector $\overrightarrow{0}$ is a column vector of

0's because the conditional mean is 0 for all $e_{i,t}$ by construction. The scaling matrix is $\frac{v-2}{v}$ times the conditional correlation matrix R_t. n is the number of elements in e_t, so $n = 6$ in our setting. To estimate the DCC model by MLE, we need the PDF for $\mathbf{t_v}(\overrightarrow{0}, \frac{\mathbf{v-2}}{\mathbf{v}}\mathbb{R}_\mathbf{t}, \mathbf{n})$:

$$f(e_t|I_{t-1}) = \frac{\Gamma(\frac{v+n}{2})}{\Gamma(\frac{v}{2})[\pi(v-2)]^{\frac{n}{2}}|\mathbb{R}_t|^{\frac{1}{2}}}[1 + \frac{1}{v-2}e_t'\mathbb{R}_t^{-1}e_t]^{-\frac{v+n}{2}}, \quad v > 2.$$

DCC estimation involves two steps: the first step of conditional variance estimation and the second step of conditional correlation estimation. As Section 3 already reports the conditional variance estimation results, I only report the parameter estimates for the conditional correlation model of Equation (4): κ=0.00842(0.01025) and λ=0.99057(0.01235), as well as the degree of freedom parameter $v = 3.40151(0.34480)$. The parentheses contain the heteroscedasticity-robust standard errors for the parameter estimates. Just like the univariate conditional variance model, the conditional correlations are also very persistent: $\kappa + \lambda$ is very close to 1.

Figure 4 shows the pairwise conditional correlation time series extracted from the estimated DCC model. Compared with the univariate conditional volatility depicted in Figure 3, the time-series dynamics of the conditional correlation looks very different. Instead of peaking during the crisis and declining afterwards, the conditional correlations climbed during the crisis and stayed at the plateau all the way to the end of sample, September 2018.

To see the trend of the conditional correlation more clearly, Figure 5 reports the average conditional correlation. The persistently elevated conditional correlation of the CDS returns for the big U.S. banks since the 2007-08 financial crisis means the left-tail risks of these big banks have been tied together closely since the crisis and have shown no sign of divergence. This reflects the ever similar models against extreme losses by the big U.S. banks, possibly

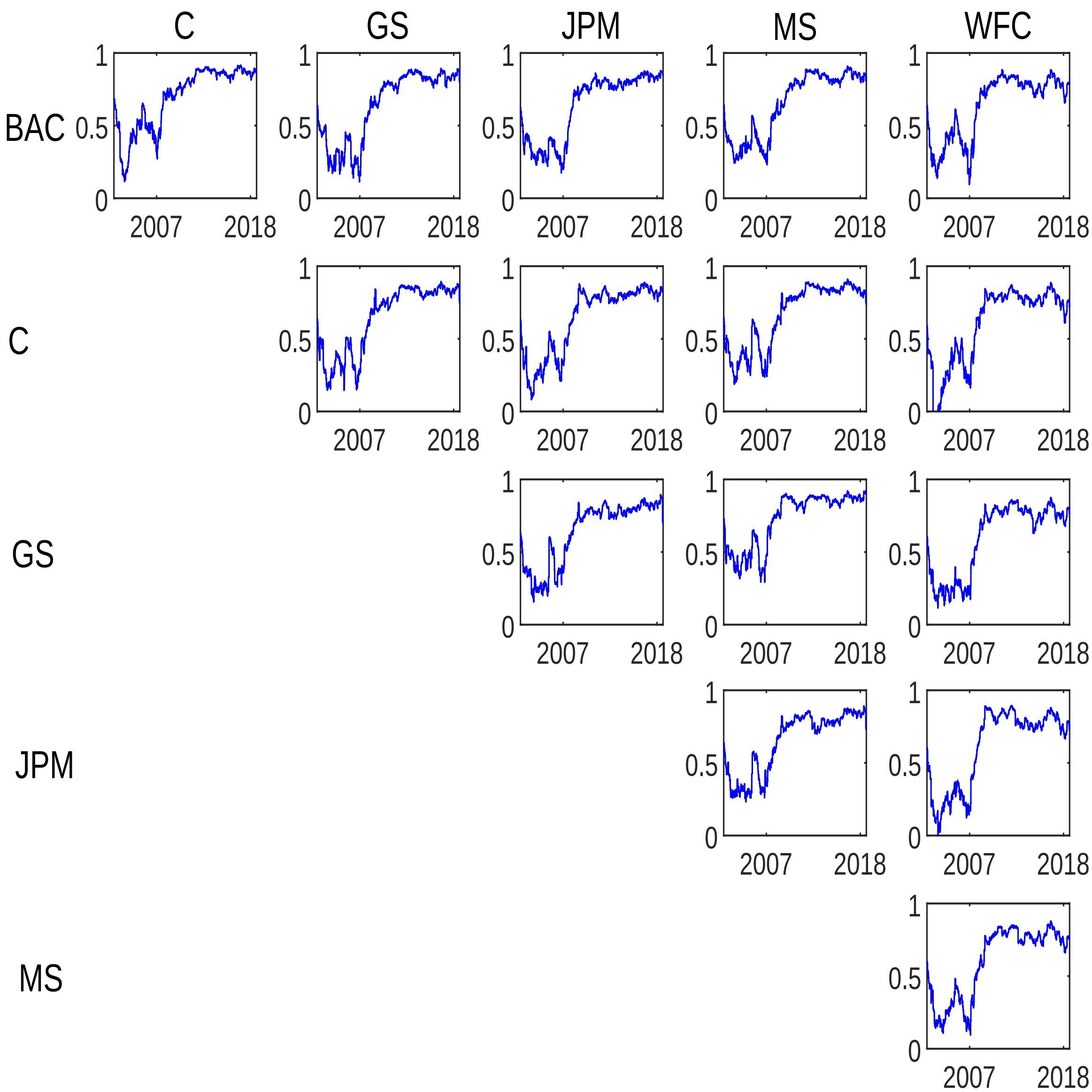

Figure 4: Extracted pairwise conditional correlation of CDS returns

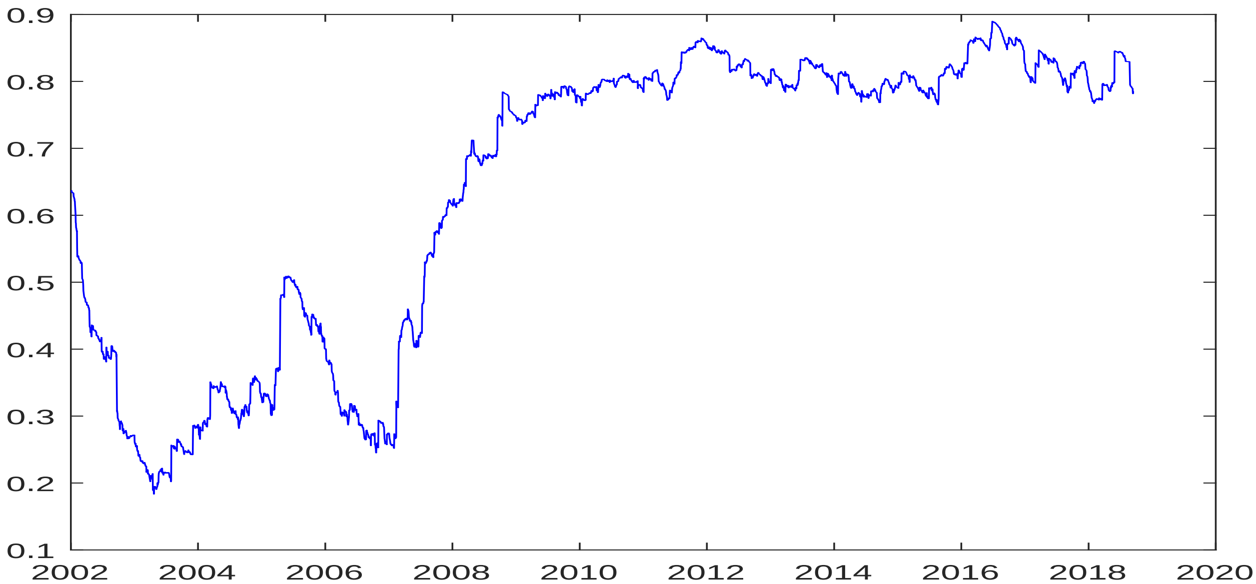

Figure 5: Average extracted conditional correlation of CDS returns

due to their incentive to avoid large idiosyncratic shocks during severe crises, at least as perceived by market participants. This result contrasts with the ups and downs in the bank stock return correlations, shown in Figures 6 and 7 in the Appendix, which reflects that banks' normal business gains and losses still diverge (low correlations) during good times and converge (high correlation) during bad times, as frequently observed in the empirical literature.

Combining the observations from Figures 3 and 5, we can see that even though the risk of betting on catastrophic losses of individual banks may have receded with the economic recovery after the crisis, the benefit of diversification in CDS contracts is greatly reduced as the risk of betting on one large U.S. bank is ever similar to the risk of betting on any other large U.S. bank.

5 Conclusion

A CDS contract protects its buyer from the potential default loss of the reference entity, but CDS holders are not required to hold the reference liability. Thus by longing or shorting a CDS contract, an investor is essentially betting on the risk of the reference entity. Consequently, the second moments of CDS returns measure the risk of such a behavior of betting on risk. For the univariate time series, a GARCH model with asymmetry and leptokurtosis is fitted to the conditional variance process. For the multivariate time series, a DCC model slightly modified with standardized residuals following a multivariate t distribution is fitted to the conditional correlation process.

Based on more than one and a half decades of daily CDS returns for six large U.S. banks, I find that both the conditional variances and correlations are highly persistent. Volatility asymmetry and leptokurtosis are significant for all the sample banks. But in contrast to the conventional findings on stock return volatility asymmetry, a positive shock to CDS returns increases volatility more than a negative shock does. Nevertheless, the economic fundamental stays the same: bad news increases volatility more than good news does, whether for stock or CDS returns.

Moreover, the conditional variance processes for the univariate CDS return time series track the overall economic situations well: surging during the financial crisis and declining afterwards. In contrast, the conditional correlation processes for the multivariate CDS return time series climbed during the crisis but have not subsequently returned. The CDS correlation dynamics also form a sharp contrast with the stock correlation dynamics for the same sample banks. As similar modelling strategies are applied to both the univariate and multivariate CDS return time series, as well as the stock return time series, the differences between the dynamics of the CDS conditional correlations with those of the CDS conditional volatility, as well as with those of the stock conditional correlations, reveal their intrinsically different economic fundamentals. The risk of betting on the risk of an individual bank may have decreased after the crisis, but the lack of diversification in investing in a basket of large U.S. banks' CDS contracts has remained as severe as during the peak of the crisis, even though the diversification in investing in their stocks might improve from time to time. The economic reason behind this observation may be that even though each large U.S. bank has taken actions to improve its risk profile, and their regular gains and losses may converge or diverge over time, their models against extreme losses have remained similar to each other at such a historical level that the tendency for them to collapse together is now just as high as during the peak of the crisis.

6 Appendix: Conditional Variance and Correlation of Stock Returns

This appendix provides the counterpart results of Sections 3 and 4 on the stock returns of the same sample banks.

First, Table 2 reports the estimation results of the conditional variance model in Equations (1) to (3) on stock returns. The main qualitative difference between the results of stock returns and those of CDS returns is that the leverage parameter δ is positive for stock returns while it is negative for CDS returns, and both are statistically significant. This means that bad news for stocks increases stock volatility more than good news does, while good news for CDS increases CDS volatility more. However, notice that good news for CDS (i.e., higher CDS spreads) actually is bad news for the reference entity. So the economic fundamental stays the same: bad news for the reference entity increases volatility, no matter whether for

Table 2: GARCH model with potential asymmetry and t-distributed innovations

	μ	γ	ω	α	β	δ	ν
BAC	0.045***	-0.033***	0.023***	0.056***	0.908***	0.071***	5.224***
	(0.005)	(0.008)	(0.001)	(0.019)	(0.015)	(0.019)	(0.574)
C	0.011**	0.006	0.027***	0.050***	0.906***	0.087***	5.419***
	(0.006)	(0.008)	(0.001)	(0.019)	(0.016)	(0.019)	(0.560)
GS	0.056***	-0.032***	0.039***	0.026	0.930***	0.063***	6.690***
	(0.007)	(0.006)	(0.000)	(0.022)	(0.011)	(0.022)	(0.876)
JPM	0.052***	-0.044***	0.027***	0.031*	0.917***	0.096***	5.635***
	(0.005)	(0.007)	(0.001)	(0.019)	(0.015)	(0.019)	(0.597)
MS	0.042***	-0.019***	0.045***	0.026	0.926***	0.078***	6.700***
	(0.008)	(0.007)	(0.000)	(0.025)	(0.013)	(0.025)	(0.800)
WFC	0.034***	-0.073***	0.017***	0.029**	0.921***	0.096***	6.030***
	(0.004)	(0.007)	(0.001)	(0.017)	(0.015)	(0.017)	(0.700)

Note: 1. *, **, and *** refer to statistical significance at 10%, 5%, and 1% levels.
2. Heteroscedasticity-robust standard errors are reported in parenthesis.

stock or CDS returns.

Second, for stock returns, the two DCC model parameters in Equation (4) and the degree of freedom for the t distribution are estimated as κ=0.01329(0.00398), λ=0.98030(0.01134), and $v = 5.45627(0.66209)$. The qualitative difference between stock and CDS DCC model results are in the extracted conditional correlation time series, as shown in Figures 6 and 7. Unlike CDS correlations, stock correlations have ups and downs, peaking during the financial crisis, European sovereign debt crisis and around the 2016 election period. This shows that banks' normal business gains and losses, as opposed to extreme loss scenarios, still diverge during good times and converge during bad times. There are no persistent elevated correlations for stock returns after the financial crisis.

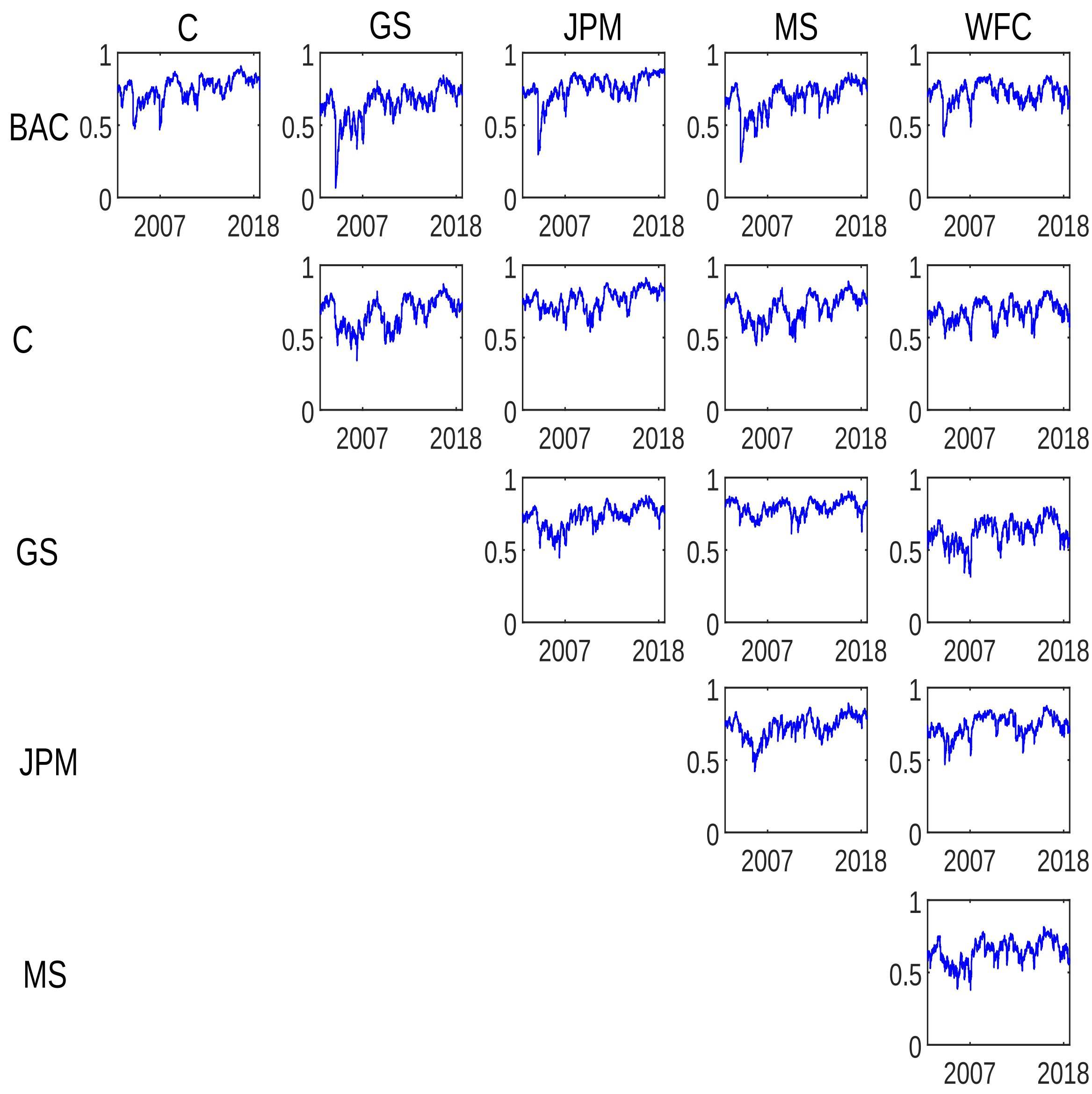

Figure 6: Extracted pairwise conditional correlation of stock returns

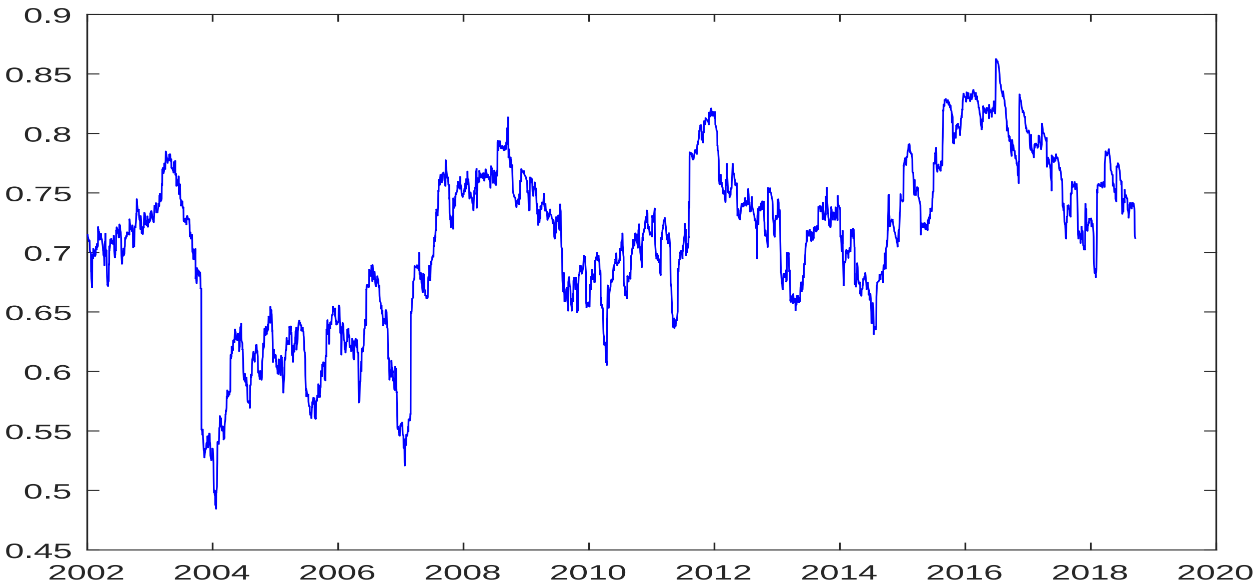

Figure 7: Average extracted conditional correlation of stock returns

7 References

Bollerslev, Tim (1986), "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics* 31, 307–327.

Bollerslev, Tim (1987), "A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates ofReturn," *Review of Economics and Statistics* 69, 542–547.

Engle, Robert F. (1982), "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica* 50, 987–1007.

Engle, Robert F. (2002), "Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models," *Journal of Business and Economic Statistics* 20, 339–350.

Glosten, Lawrence R., Ravi Jagannathan, and David E. Runkle (1993), "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *The Journal of Finance* 48, 1779–1801.

Huang, Xin (2016), "Persistency of Bank Credit Default Swap Spreads," .

Li, David and Roy Cheruvelil (2018), "Correlation Impact to CCP Margin Uisng GARCH-DCC Framework," Presented at 2018 Redux of Quantitative Workshop on CCP Risk Management, Federal Reserve Board.

Markit (2009), "The CDS Big Bang: Understanding the Changes to the Global CDS Contract and North American Conventions," Markit Group Limited.

Nelson, Daniel B. (1991), "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica* 59, 347–370.