Correlated Defaults of UK Banks: Dynamics and Asymmetries

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Abstract

We document asymmetric and time-varying features of dependence between the credit risks of global systemically important banks (G-SIBs) in the UK banking industry using a CDS dataset. We model the dependence of CDS spreads using a dynamic asymmetric copula. Comparing our model with traditional copula models, we find that they usually underestimate the probability of joint (or conditional) default in the UK G-SIBs. Furthermore, we show that dynamics and asymmetries between CDS spreads are closely associated with the probabilities of joint (or conditional) default through the extensive regression analysis. Especially, our regression analysis provides a policy implication that copula correlation or tail dependence coefficients are able to be leading indicators for the systemic credit event.

Key words: Calibrated marginal default probability, probability of joint default, probability of conditional default, GAS-based GHST copula.
JEL codes: C32, G32

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1 Introduction

The global financial crisis and EU sovereign debt crisis have caused great concern about the credit risk of large financial institutions and sovereign entities. The central banks and financial authorities have paid much more attention to the supervision of credit risk in large financial institutions since then. Understanding the joint credit risk of financial institutions is of particular important because their failures and losses can impose serious externalities on the rest of economy (Acharya et al., 2010). Acharya et al. (2014) also document that the bailouts of large banks in Eurozone triggered a significant increase of sovereign credit risk from 2007 to 2011.

Recent empirical literature shows that estimating the probability of joint default plays an important role in banking supervision (see Pianeti et al., 2012; Erlenmaier and Gersbach, 2014). This is because it can be viewed as the efficient measure of systemic risk, as the systemic default arises from the simultaneous defaults of multiple large banks. Some giant banks are "too big to fail" and the default of one bank can probably trigger a series of defaults in other banks and financial companies; for instance, the collapse of Lehman Brothers in September 2008 triggered turmoil in the financial markets and exacerbated the global financial crisis of 2007-2009.

From the perspective of practitioners, modeling the joint default probability of banks is also of great interest for credit risk management. For instance, a protection contract (e.g. Credit Default Swap (CDS)) written by one bank (CDS seller) to insure against the default of another bank (debtor) is exposed to the risk that both banks default. In other words, CDS buyer also takes the counterparty risk that CDS seller will fail to fulfill their obligations because of the OTC nature of the CDS market.

Therefore, it is important to study how the default risk of banks are contemporaneously correlated each other and the dynamic evolution of their correlation over time. This study is able to help the risk mangers of banks get the deeper understanding of default risk structure in the banking industry and properly model the credit risk considering various market scenarios such as joint default or conditional default. For this reason, we study the correlated default of global systemically important banks (G-SIBs) in the UK banking industry.

First, we model the dependence structure of CDS spreads in the UK G-SIBs and estimate the probability of joint default. In addition, the conditional default under "what if" circumstances is also an interesting scenario for credit risk management. Inspired by Lucas et al. (2014), we further investigate the default probability of one bank given a credit event occurring in another bank. From the perspective of financial institutions and authorities, it is obviously useful to quantify the interaction and contagions of corporate credit risks for a bad market scenario.

Second, we propose a dynamic asymmetric copula model combining the generalized hyperbolic skewed t (hereafter GHST) copula with the generalized autoregressive score (hereafter GAS) model. Our proposed model is able to capture all the empirical features of univariate and multivariate financial time series, such as heavy-tailedness, skewness, time-varying volatility and dynamic asymmetric dependence. This framework is closely related to two strands of literature on the copula modeling. One strand focuses on modeling the multivariate asymmetry using the GHST copula, see for example Demarta and McNeil (2005), Smith et al (2012), Christoffersen et al. (2012) and Christoffersen and Langlois (2013), among others. Another strand uses the GAS model, pioneered by Creal et al. (2013), to capture the dynamics of dependence. It has several attractive econometric properties and therefore has become increasingly popular in empirical finance studies in recent years, see for instance, Creal et al. (2014a), Janus et al (2014), Lucas et al. (2014) and Salvatierra and Patton (2015). There are two clear advantages of this dynamic asymmetric copula framework. First, it allows for non-negligible tail dependence and its asymmetry. Second, the time-varying nature of correlated credit risk can be captured well by the GAS process.

Third, the ongoing debate on the source of banking credit risk also motivates us to investigate if the dependence structure between the credit risks has explanatory and predictive power to the probability of joint or conditional default in the UK G-SIBs. Although the determinants of credit spreads have been extensively studied by both theoretical and empirical finance literature (see Merton, 1974; Collin-Dufresne et al., 2001; Campbell and Taksler, 2003; Ericsson et al., 2009; Christoffersen et al., 2013, among many others), research on the determinants of joint and conditional default risk is very limited. This is important because understanding the determinants of systematic credit risks of banks can not only help us explain the time-variation of default risk, but also improve the predictive accuracy of joint or conditional default probability in the future.

We make five empirical contributions to the literature: First, differently from existing literature on the joint credit risk of UK banks, such as Li and Zinna (2014), we document two important features of CDS: asymmetric and dynamic dependence between the CDS spreads. Using a threshold correlation and a model free test proposed by Hong et al. (2007), we find that there is no significant linear asymmetries. However, we find significant asymmetries by performing a test based on the tail dependence in Patton (2012). In addition, we also apply several widely used structure break tests and identify the presence of time-varying dependence. These documented features provide us with strong motivation to consider an econometric model which is able to accommodate them.

Second, we apply the GAS-based GHST copula to capture the time-varying asymmetric dependence of credit risks in the UK G-SIBs. Differently from the copula literature on the CDS market, such as Christoffersen et al. (2013) and Lucas et al. (2014), we consider not only a full parametric method, but also a semiparametric one that relies on fewer amounts of distributional assumptions, see Chen and Fan (2006a) and Chen and Fan (2006b). Surprisingly, we find that the semiparametric copula slightly underperforms compared with a full parametric copula. We attribute this result to the better fitness provided by the univariate skewed t distribution in the full parametric model. In general, we find the dynamic asymmetric copula outperforms the dynamic model based on the Gaussian or Student's t copula, as our framework is able to capture the multivariate asymmetry and dependence dynamics simultaneously. In addition, from the copula implied default correlation, we find that correlated credit risk between banks dramatically increases during times of stress and gradually decreases after 2013.

Third, we apply a copula-based simulation algorithm to estimating the joint default probability of UK G-SIBs. Our empirical results show that the probability of joint default estimated by the dynamic asymmetric copula is higher than that by the dynamic Gaussian or Student's t copula in most of the time during our sample period. This indicates that the Gaussian or Student's t copula-based models may underestimate a potential risk as neither of them can accommodate the multivariate asymmetries between the credit risks of banks. Using the marginal and joint probability, we also investigate the probability of conditional default under a hypothetical adverse market scenario.

Fourth, we find that the joint default probability of UK G-SIBs implied by the copula model has dramatic variation during 2007-2015. It remarkably increases during the global financial crisis, Eurozone debt crisis and after the downgrade of US sovereign debt. In addition, our result also implies that the monetary policy implemented by the Bank of England and European Central Bank also significantly affect the joint default probability.

Fifth, we perform an insightful regression analysis to investigate two questions: (1) Whether the copula correlation and tail dependence of CDS spreads implied by dynamic copulas are related to their probabilities of joint or conditional default; (2) Whether the copula correlation and tail dependence can provide useful information to predict the future probabilities of joint or conditional default. We find the copula correlation contains useful information which not only measures the current probabilities of joint and conditional default but also predicts the future probabilities in the banking industry. Our results also indicate that the modeling of asymmetric tail dependence between credit risks can provide useful information of measuring and forecasting the probabilities of joint and conditional default.

The remainder of this paper is organized as follows. Section 2 details the way how we compute the joint default probability of UK G-SIBs. Section 3 presents the empirical study on the correlated credit risk of UK G-SIBs using weekly corporate CDS spreads. Section 4 further studies how the dependence structure (i.e. copula correlation or upper/lower tail dependence) works for measuring and predicting the probability of joint or conditional default using insightful regression analysis. Section 5 concludes.

2 Modeling of Joint Default Probability

In this section, we detail the way how we compute the joint default probability of UK G-SIBs. It consists of four parts. First, we obtain a reliable default probability for individual bank. Given the probability of default, we find the corresponding value of CDS spread return from its marginal probability distribution.[1] Hence, it is a threshold to determine the default event of individual

[1]We measure the CDS spread return by the log-difference of CDS spreads. It is not an asset return but the change of credit risk in the bank. Without loss of generality, the CDS spread means the log-difference of CDS

bank. Second, we model the marginal probability distribution of univariate return series for each bank considering its distributional characteristics. Third, given the marginal probability distributions, we model their dependence structure which is the key input for constructing the joint probability distribution of multivariate return series across banks. Fourth, we apply Monte Carlo simulation to computing the probability of joint default.

It is convenient to define the probabilities of joint and conditional default mathematically before introducing each part in detail. Given the marginal default probability, $p_{i,t}$, of bank i at time t, the probability of joint default, $p_{i,j,t}$, for bank i and j at time t is given by

$$p_{i,j,t} = \mathbb{P}\left\{z_{i,t} > F_{i,t}^{-1}\left(1 - p_{i,t}\right), z_{j,t} > F_{j,t}^{-1}\left(1 - p_{j,t}\right)\right\} \tag{1}$$

where $z_{i,t}$ denotes the filtered CDS spreads of bank i at time t and $F_{i,t}^{-1}\left(\cdot\right)$ denotes its inverse cumulative distribution function. The probability of bank i's default conditional on the default of bank j is therefore defined by

$$p_{i|j,t} = \mathbb{P}\left\{z_{i,t} > F_{i,t}^{-1}\left(1 - p_{i,t}\right), z_{j,t} > F_{j,t}^{-1}\left(1 - p_{j,t}\right) \mid z_{j,t} > F_{j,t}^{-1}\left(1 - p_{j,t}\right)\right\} = \frac{p_{i,j,t}}{p_{j,t}} \tag{2}$$

2.1 Calibrating Marginal Default Probability

It is essential to obtain the reliable default probability and capture the default dynamics of a single reference entity. A number of statistical and econometric models have been proposed to obtain the term structure of default rates and they can be classified into three methods: (i) Historical default rate based on the internal rating systems from rating agencies (e.g. Moody's publishes historical default information regularly); (ii) Structural credit pricing models based on the option theoretical approach of Merton (1974); (iii) Reduced-form models. In our study, we consider using one reduced-form model based on the bootstrapping method proposed by Hull and White (2000a) and O'Kane and Turnbull (2003) to calculate the risk neutral probability of default for each bank using CDS market quotes.[2]

spread unless there is a specific notice on it in this paper.

[2] CDS is essentially a protection contract to insure against the default of a reference entity. The CDS spread can be viewed as a more direct measure of credit risk compared to bond or loan spreads. This is because the bond or loan spread is also driven by other factors, such as interest rate movements and firm-specific equity

The reasons we select this approach is as follows: Firstly, the rating information provided by agencies is not able to change as fast as the market movement. Whereas, the market information used in the approach of Hull and White (2000a) can reflect well the market agreed anticipation of evolution for the future credit quality; Secondly, although the credit rating agencies such as Moody's regularly publish short-term and long-term credit ratings for firms, this rating information normally lacks granularity. Different from the rating information provided by agencies, CDS market quotes normally have different maturities (6 month, 1-year, 2-year, 3-year, 4-year. 5-year, 7-year and 10-year) and thus could imply the full term structure of default probability; Thirdly, the bootstrapping procedure is a standard method for marking CDS positions to market and has been widely used by the overwhelming majority of credit derivative trading desks in financial practice, see Li (2000) and O'Kane and Turnbull (2003). Recently, this procedure has also been applied in empirical financial studies, see Huang et al (2009), Creal et al. (2014b) and Lucas et al. (2014), etc.

The reduced-form model defines the default probability function of bank i at time t by

$$F_i(t) = \mathbb{P}(\tau \leq t) = 1 - \mathbb{P}(\tau > t) = 1 - Q_i(t), \ t \geq 0 \tag{3}$$

where τ denotes the time to default (survival time) and $Q_i(t)$ is a survival function, defined in terms of a piecewise hazard rate by $\lambda(t)$[3],

$$Q_i(t) = \exp\left[-\int_t^{t_n} \lambda(s)ds\right]. \tag{4}$$

In practice, we use the approximation of survival function (4) for the reference entity to time

volatility, see Campbell and Taksler (2003).

[3]More discussion on the hazard rate function can be found in Appendix A.1.

T conditional on surviving to time t, defined by

$$Q_i(t,T) = \begin{cases} \exp\left(-\lambda_{0,1}\tau\right) & \text{if } 0 < \tau < 1 \\ \exp\left(-\lambda_{0,1}, -\lambda_{1,3}\left(\tau-1\right)\right) & \text{if } 1 < \tau < 3 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - \lambda_{3,5}\left(\tau-3\right)\right) & \text{if } 3 < \tau < 5 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - 2\lambda_{3,5} - \lambda_{5,7}\left(\tau-5\right)\right) & \text{if } 5 < \tau < 7 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - 2\lambda_{3,5} - 2\lambda_{5,7} - \lambda_{7,10}\left(\tau-7\right)\right) & \text{if } \tau > 7 \end{cases} \tag{5}$$

where $\tau = T - t$ is the time to default and λ_{t_0,t_n} denotes the hazard rate from time t_0 to t_n. Given the market quotes of CDS spreads, $S_1, ..., S_N$, at dates $t_1, ..., t_N$, we can calibrate the hazard rate and calculate the default probability by inverting the CDS pricing formula in Equation (A.10)[4]. We construct a survival probability curve for a set of maturity dates using the bootstrap algorithm[5] proposed by Hull and White (2000a), O'Kane and Turnbull (2003) and O'Kane (2008). A detailed bootstrapping algorithm is provided in Appendix A.4.

2.2 Modeling Returns of CDS Spread

Next, we need to model the returns of CDS spread. We model not only univariate distribution for each bank but also joint one of several banks. Based on both probability distributions, we compute the probabilities of joint and conditional default given the thresholds calibrated in section 2.1.

First, we define the return of CDS spread as the log-difference of weekly CDS spread and denote it by $r_{i,t}$. Hereafter we use "CDS spread" replacing the log-difference of CDS spread or return of CDS spread without loss of generality. We need the filtered CDS spreads for each bank to calculate default probabilities using Equation (1) and (2). To this end we model individual

[4]More details of premium leg, protection leg and breakeven quotes of CDS can be found in Appendix A.2 and A.3.

[5] Here, "bootstrap" is different from one used in statistics. It is an iterative process to construct a default probability curve using CDS market quotes. This method has been widely used in financial practice because of its computational simplicity and stability.

CDS spreads by ARMA(1,1)-GJR-GARCH(1,1,1) and obtain the filtered ones,

$$z_{i,t} = \frac{y_{i,t} - \mu_{i,t}}{\sigma_{i,t}}, \tag{6}$$

where a conditional mean ($\mu_{i,t}$) is modeled by ARMA(1,1)[6] and a conditional volatility ($\sigma_{i,t}$) by GJR-GARCH(1,1,1). The ARMA-GJR-GARCH family is one of the most popular models to capture the dynamics of conditional mean and the asymmetric volatility clustering in finance (see Glosten et al., 1993). For the parametric modeling, we assume that $z_{i,t}$ follows the univariate skewed t distribution, F_{skew-t}, of Hansen (1994) to accommodate its skewed and heavy-tailed features. For the semiparametric modeling, we use an empirical distribution function, $\hat{F}_i$. See Appendix of Cerrato et al. (2015) for the details of parametric and semiparametric modeling.

Second, given the modelling of marginal probability distribution, we model the joint probability distribution. An empirically reliable model of correlated defaults between the reference entities plays a central role in credit risk modeling and pricing. Various approaches have been proposed to model correlated defaults and these models can be roughly classified into four categories: (i) CreditMetrics; (ii) Intensity-based models; (iii) Barrier-based firm's value models; (iv) Copula-based correlation models. We consider using the copula-based model in our study. A copula function has several attractive mathematical properties in the modeling of default. First, it allows more flexibility and heterogeneity in the marginal distribution modeling. It is straightforward and convenient to link random variables with different marginal distributions with one copula function. Second, there are various versions of copula function and that allows us to fit different default dependence between the reference entities.[7]

There are two notable features of default correlation. Substantial evidences have been found to show that the default correlation is non-Gaussian, see for instance, Christoffersen et al. (2013).

[6] We first consider all the possible models nested within the ARMA(2,2) and choose the optimal order according to the Bayesian Information Criterion (BIC). It turns out that for most banks, ARMA(1,1) gains the smallest BIC.

[7] Before the 2007-2008 global financial crisis, the Gaussian copula was the most popular copula model in derivatives pricing, especially the valuation of collateralized debt obligations (CDOs), because of its computational simplicity. However, many financial media commentators believed that the abuse of aussian copula was one of the major reasons contributing to this crisis, see for instance, " *Recipe for Disaster: The Formula That Killed Wall Street*" (Wired Magazine, 2009), "*Wall Street Wizards Forgot a Few Variables*" (New York Times, 2009), and "*The Formula That Felled Wall Street*" (The Financial Times, 2009).

Another important feature is the time variation of default correlation. It changes over time as the credit quality of firms is dynamic. It also varies with systematic risk factors, such as the state of economy in the business cycle and the financial market conditions (Crouhy et al., 2000).

The choice of copula is based on the empirical features of UK banks in our study. We test for the asymmetry of linear correlation (Hong et al., 2007) and that of tail dependence (Patton, 2012). We also test for the time-varying nature of dependence structure between banks using structural break tests in Patton (2012). There are the striking evidences of structure breaks around credit events (e.g. the CDS big bang, the downgrading for Greek's credit rating, etc.) and the upper tail dependence is usually stronger than the lower one.[8] We therefore select a dynamic asymmetric copula. Following the study of Christoffersen et al. (2012) , Christoffersen and Langlois (2013) and Lucas et al. (2014), we employ an asymmetric copula based on the generalized hyperbolic skewed t (GHST) distribution discussed in Demarta and McNeil (2005).[9] Since the joint default is defined in the upper tails of which dependence is stronger than the lower one, the GHST copula is able to more accurately measure the probability of joint default than a symmetric copula. Furthermore, the time varying nature of dependence structure is implied by the generalized autoregressive score (GAS) model of Creal et al. (2013) and Lucas et al. (2014). Cerrato et al. (2015) demonstrate the importance of modeling the dynamic and asymmetric dependence of equity portfolio using the GAS-GHST copula in the risk management application.

2.3 Computing Algorithm for Joint Default Probability

As the final step of our proposed approach, we introduce a practical algorithm how we compute the probability of joint default by utilizing a Monte Carlo simulation method. The procedure is as follows: Firstly, we obtain the marginal probabilities of default for bank i, $p_{i,t}$, and bank j, $p_{j,t}$, from the bootstrap based calibration procedure. We also estimate a copula correlation at time t by

$$\bar{\delta}_{i,j,t} = \frac{\left(\delta^{P}_{i,j,t} + \delta^{S}_{i,j,t}\right)}{2}, \tag{7}$$

[8] We discuss about empirical results more specifically in section 3.3 and 3.4.

[9] Cerrato et al. (2015) provide the mathematical details of the GHST copula.

where $\delta^P_{i,j,t}$ and $\delta^S_{i,j,t}$ denote copula correlations implied by the GAS-based parametric and semi-parametric copula model, respectively. Secondly, given the copula correlation and other parameters[10], we simulate n random vectors $\mathbf{z}^s_t = \left(z^s_{i,t}, z^s_{j,t}\right)$ from the GAS-based GHST copula at each time t. Finally, the probability of joint default for banks i and j at time t is given by

$$p_{i,j,t} = \frac{\sum_{i=1}^{n} \mathbf{1}\left\{z^s_{i,t} > F^{-1}_{i,t}\left(1 - p_{i,t}\right), z^s_{j,t} > F^{-1}_{j,t}\left(1 - p_{j,t}\right)\right\}}{n} \tag{8}$$

where $F^{-1}_t(\cdot)$ denotes the inverse of marginal distribution function modeled by ARMA(1,1)-GJR-GARCH(1,1,1) with skewed t distribution or empirical distribution.

3 Empirical Analysis of Credit Risk

In this section, we study the correlated credit risk of UK G-SIBs using weekly corporate CDS spreads. Firstly, we investigate the distributional stylized facts of CDS spreads. Based on the descriptive analysis, we search for the best univariate model for an individual CDS spread. On the other hand, we calibrate a marginal default probability implied by the CDS pricing formula for the purpose of computing the probabilities of joint and conditional default. Next, we investigate the asymmetric and dynamic dependence of credit risk using formal statistical tests. This investigation is able to provide useful information on the choice of multivariate model for computing the probability of joint default. Finally, we estimate the probabilities of joint and conditional default of G-SIBs by GAS based GHST copula, T copula and Gasussian copula. We demonstrate the importance of modeling dynamic and asymmetric dependence of credit risk through the comparison of three copula models.

3.1 Data and Descriptive Analysis

We use a dataset of weekly corporate CDS spreads for five UK G-SIBs with different maturities (6-month, 1-year, 2-year, 3-year, 4-year and 5-year). The UK G-SIBs include the Barclays, HSBC Holdings (hereafter HSBC), Lloyds Banking Group (hereafter Lloyds), Royal Bank of

[10] We only allow the copula correlation to vary over time whilst fix the other parameters to be constant over time. For the GHST copula, the degree of freedom and skewness parameter are constant.

Scotland Group (hereafter RBS) and Standard Chartered (hereafter Standard).[11] All the CDS contracts are denominated in Euro. The London Interbank Offered Rate (henceforth Libor) data with different maturities are also collected to calibrate the marginal default probability curve. Our data cover the period from September 7, 2007 to April 17, 2015[12]. We use weekly data to avoid non-synchronicity and other problems with daily data. All the CDS market quotations and financial variables data are collected from Bloomberg. For the dependence analysis, we mainly focus on 5-year CDS contracts on all banks as these are the most liquid and take up the largest percentage of the entire CDS market.

Table 1 reports descriptive statistics and time series test results for the log-differences of weekly 5-year CDS spreads across five UK G-SIBs from September 7, 2007 to April 17, 2015. The basic statistics in Panel A describe the main features of CDS spread, such as univariate asymmetry, heavy-tailness and leptokurtosis. The non-zero skewness and large value of kurtosis clearly indicate the non-Gaussian features of CDS spreads. In particular, we find that the Standard Chartered obtains the largest skewness (0.793) as well as the largest kurtosis (10.041). Panel B reports that the results of Jarque-Bera test for normality, Ljung-Box Q-test for autocorrelation and Engle's Lagrange Multiplier test for the ARCH effect. Basic statistics and p-values of JB test show the solid evidence against the assumption of normality. Also the results for Ljung-Box Q-test and Engle's Lagrange Multiplier test indicate the necessity for modeling of conditional mean and volatility before specifying the dependence structure between the CDS spreads of UK G-SIBs.

[INSERT TABLE 1 ABOUT HERE]

Table 2 reports the Pearson's linear correlation coefficients and Spearman's rank ones between UK G-SIBs. The statistics indicate that the credit risk of banks are highly correlated with each other. It is worth noting that the correlations of Standard Chartered with other banks are clearly lower than the correlations between other four banks. This is possibly because the Standard Chartered does not have retail banking business in the UK, and about 90% of its profit comes

[11] The first version of G-SIBs published by the Financial Stability Board in 2011 only includes Barclays, HSBC, RBS and Lloyds. Standard Chartered has been added in this list since 2013. All these banks are also listed as "Domestic Systemically Important Banks (D-SIBs)", see Bank of England (2013).

[12] The CDS data of Standard Chartered is only available since June 27, 2008.

from Asian, African and the Middle Eastern markets according to its annual report in 2013. Althrough HSBC and Barclays are also multinational banking and financial services companies, the UK market is still targeted as their "home market".

[INSERT TABLE 2 ABOUT HERE]

Figure 2 plots the level of average CDS spread and the conditional volatility of average CDS spread for five UK G-SIBs. It indicates some important patterns regarding the CDS spread in our sample period. Panel A illustrates the trend of average CDS spread across five UK G-SIBs. The arrows in each figure indicate several major events in the CDS market from 2007 to 2015. We can see that the occurrence of major credit events is always accompanied with CDS spread's skyrocketing. For instance, after the S&P downgrades US sovereign debt, the average CDS spread goes up to 285 in November 2011. Panel B plots the time series of conditional volatility estimated by the GJR-GARCH (1,1,1). First, this shows that the CDS spread is extraordinarily volatile during the financial crisis in 2008-2009. Second, it also indicates that the turbulence of CDS spreads of UK banks is closely related to the credit events in the global financial market. Another worth noting fact is that the conditional volatility stabilized since the end of global and EU financial crisis. It is significantly smaller than the volatility during the crisis even when the average CDS spread increased sharply after the S&P downgraded US government debt in August 2011. This may indicate that the CDS spread largely fluctuates during the global financial crisis due to high market uncertainty.

[INSERT FIGURE 2 ABOUT HERE]

Table 3 presents the parameter estimation and the results of goodness-of-fit test for univariate models: ARMA for conditional mean, GJR-GARCH for conditional volatility and skewed t distribution for standardized residuals. First, we model the dynamics of conditional mean using the ARMA model up to order (2,2) and use Bayesian Information Criterion (BIC) to select the optimal order. It turns out that the ARMA(1,1) is the best candidate for all the cases except Standard Chartered. Second, the conditional volatility is implied by the GARCH family. We experiment with ARCH, GARCH and GJR-GARCH models up to order (2,2) and choose the best candidate according to BIC. It indicates that GJR-GARCH(1,1,1) provides the best performance. All the leverage parameters of the GJR-GARCH(1,1,1) model are significantly negative indicating asymmetric volatility clustering, i.e., large positive changes of CDS spreads are more likely to be clustered than negative changes. This is consistent with the fact that the CDS spreads increase sharply and continuously during the recent financial crisis of 2007-2009. The bottom of Table 3 reports p-values from the Kolmogorov-Smirnov and Cramer-von Mises goodness-of-fit tests for the modelling of conditional marginal distributions. The p-values are obtained using the bootstrap approach in Patton (2012). All the p-values are clearly greater than 0.05, so we fail to reject the null hypothesis that the filtered CDS spreads are well-specified by the skewed t distribution of Hansen (1994).

[INSERT TABLE 3 ABOUT HERE]

3.2 Calibrating Marginal Default Probability

In this section, we calibrate the reduced-from model using the market quotes of CDS with different maturities (6-month, 1-year, 2-year, 3-year, 4-year and 5-year) at each time t, and bootstrap the term structure of default probability following the procedure proposed in Hull and White (2000a) and O'Kane and Turnbull (2003). This mark-to-market default probability of individual bank is derived from the observed spread of CDS contract by inverting the CDS formula. Specifically, we use the Libor rate with different maturities as discount factors and assume that the recovery rate is 40% suggested by (see O'Kane and Turnbull, 2003). Following the recent finance literature, such as Huang et al (2009), Black et al. (2013), Creal et al. (2014b) and Lucas et al. (2014), we consider no counter-party default risk. Given the assumption above, we are able to obtain the intensity of default using the bootstrap algorithm in the Appendix A.4. Given the default intensity, we are also able to compute the probability of default for different maturities as this is just the function of default intensity. Note that in this case the probability we obtain is a risk neutral as the bootstrap method assumes that the present value premium leg should be exactly equal to the present value of the protection leg, see a detailed discussion in Appendix A.3.

Figure 3 illustrates the risk neutral default probabilities for individual banks inferred directly from the market quotes of CDS spread. Panel A plots the bank-specific marginal probabilities of default over a one year horizon and Panel B plots the bank-specific marginal probabilities of default over a five year horizon. The market-implied default probabilities vary over time. It significantly rises after the bankruptcy of Lehman Brothers and the downgrade of US sovereign debt. After May 2012, the probabilities of default for all the banks decline dramatically and remained at a low level in the last two years. Thus, empirical models of CDS spread should account for this important feature. Our proposed methodology accomplishes this task.

[INSERT FIGURE 3 ABOUT HERE]

3.3 Asymmetric Dependence between CDS Spreads

While asymmetric dependence in equity, currency and energy markets have been extensively studied in empirical finance literature, very little has been done for the credit market and the banking sector. Hence, we investigate whether the dependence structure between the CDS spreads is asymmetric. We consider two methods to test for the presence of asymmetric dependence: a model-free test proposed by Hong et al. (2007) and a tail dependence-based test described in Patton (2012).

Table 4 reports the test results on the bivariate asymmetry. Given the five banks, $n = 5$, there are $n(n-1)/2 = 10$ different pairwise combinations of two banks. Panel A reports the test statistics and corresponding p-values of model-free test on the threshold correlation (Hong et al., 2007). We find that there is no statistically significant asymmetry on the threshold correlations.[13]

Panel B presents the estimates of lower and upper tail dependence coefficients for the filtered CDS spreads based on the full parametric copula model. It also reports bootstrap based p-values for the test on a null hypothesis that the dependence structure is symmetric (i.e. the upper and lower tail dependence coefficients are equal). Differently from the test based on the linear correlation, half of the pairs are rejected at 5% significance level showing evidence of significant difference between upper and lower tail dependence coefficients. Interestingly,

[13] We compute the threshold correlations using the filtered CDS spreads.

different from the asymmetries of other assets which exhibit greater correlation during market downturns than market upturns, the CDS spread has higher upper tail dependence than lower tail dependence. This may be explained by the nature of CDS spread as a credit derivative contract to insure the protection buyer against any uncertainty on the reference name. The higher upper tail dependence of CDS spreads may be due to the asymmetric reaction of CDS spreads to negative and positive news. The CDS spreads normally incorporate negative news much faster than positive news, see for instance Lehnert and Neske (2006). Thus, when the credit market deteriorated sharply during the crisis, the CDS spreads (insurance costs) of firms tend to increase rapidly.

Panel C presents the estimates of lower and upper tail dependence coefficients based on the semiparametric copula model and the results also confirm the presence of asymmetric dependence between CDS spreads for UK banks.

[INSERT TABLE 4 ABOUT HERE]

3.4 Time-varying Dependence between CDS Spreads

Figure 2 shows that the CDS spread and its volatility are time-varying. Could it be that the dependence structure between the CDS spreads also vary through time? We address this important issue in this section. We consider three tests widely used in literature: (i) A simple test that examines a structure break in the rank correlation at some specified point in the sample period, see Patton (2012); (ii) A test for unknown break points in the rank correlation, see Andrews (1993); (iii) A generalized break test without an *a priori* point, see Andrews and Ploberger (1994).

We implement these tests for time-varying dependence using the filtered CDS spreads of 5-year maturity. Summary results are reported in Table 5. First, without *a priori* knowledge of breaking points, we consider using naïve tests for breaks at three chosen points in sample period, at $t^*/T \in \{0.15, 0.50, 0.85\}$, which corresponds to the dates 24-Oct-2008, 24-Jun-2011, 21-Feb-2014. Second, the "Any" column reports the results of test for dependence break of unknown timing proposed by Andrews (1993). The p-values in column "QA" are based on a generalized break test without an *a priori* point in (Andrews and Ploberger, 1994). In order to detect whether the dependence structures between the CDS spreads of different banks significantly changed after the US and EU crisis broke out, we use 15-Sep-2008 (the collapse of Lehman Brothers) and 01-Jan-2010 (EU sovereign debt crisis) as two break points in rank correlation and "US" and "EU" panels report the results for this test. Overall, the test results indicate that for all the bank pairs, except for Lloyds and Standard Chartered, the null hypothesis (that there is no break point in rank correlation over the sample period) is significantly rejected by at least one test at 5%. These results strongly support the choice of our model.

[INSERT TABLE 5 ABOUT HERE]

3.5 Probability of Joint Default in UK G-SIBs

Our previous empirical results show the strong evidence of multivariate asymmetry and time-varying dependence between the CDS spreads of UK G-SIBs. We thus select the GAS-based GHST copula employed by Cerrato et al. (2015) for estimating the dependence structure between banks. We further use the estimated dependence to simulate the joint default probability of UK G-SIBs.

We estimate the time-varying correlation coefficients for the 10 pairs of banks using the GAS-based GHST copula. For the sake of comparison, we also use the GAS-based Gaussian copula and t copula. Table 6 and Table 7 report the estimates for parametric and semiparametric dynamic copula models, respectively. We find that their estimates are very close and the parametric copula models are able to provide relatively higher log-likelihood in general. This is probably due to the better fit of univariate models (see the skewed t distribution in Hansen (1994)).

[INSERT TABLE 6 AND 7 ABOUT HERE]

Figure 4 shows the dynamic evolution of average correlation. We average the 10 pairs of correlations implied by the GAS-Gaussian copula, GAS-Student's t copula and GAS-GHST copula at each time and plot the average correlation. For each model specification, we use the same filtered CDS spreads. The figure shows that the average correlation significantly increases during the crisis. It goes up to over 0.9 during the global financial crisis in 2008 and has a sharp decrease after 2013. Notice that the sharp decrease on June 27, 2008 is due to the inclusion of Standard Chartered, which has a much lower average correlation with other banks.

[INSERT FIGURE 4 ABOUT HERE]

Figure 5 shows the difference of estimated average correlations by the three copulas. To simplify the comparison, we take average of differences for each year. The solid line plots the difference between the GHST copula and the Student's t copula and the dash line plots the difference between the GHST copula and the Gaussian copula. We find that both the Gaussian copula and Student's t copula relatively underestimate the correlation compared to the GHST copula whilst they overestimate it in 2015. This result is in line with the properties that both copulas cannot capture the asymmetric tail dependence. We can see that both differences are close to each other. The slight difference is only explained by the fact that Student's t copula is able to take into account the tail dependence. However, both the copula fail to capture the asymmetric tail dependence (this produces the significant difference with respect to the GHST copula). Thus, the GHST copula is a more general framework which is able to capture not only tail dependence but also its asymmetry.

[INSERT FIGURE 5 ABOUT HERE]

Given the calibrated marginal probability of default for each bank, the estimated time-varying correlation matrix and the copula parameters, we can simulate the probability that two or more credit events occur in five UK G-SIBs during the sample period. Figure 6 shows the market-implied joint probability of default (i.e. two or more credit events occurring) among five UK G-SIBs over a five year horizon. The probabilities are estimated based on three different multivariate models: GAS-Gaussian copula, GAS-Student's t copula and GAS-GHST copula. The arrows indicate time points of several major events in the global financial market. First, the probability of joint default sharply rises during the crisis or after the major credit events took place. The highest default probability happens after the S&P downgraded the US sovereign debt. The joint probability is also affected by the monetary policy implemented by the Bank of England and European Central Bank, and gradually decreases after the cut of interest rate.

[INSERT FIGURE 6 ABOUT HERE]

Figure 7 shows the difference of joint default probabilities estimated by the three copulas. To simplify the comparison, we take averages of differences for each year. The solid line plots for the difference between the GHST copula and the Student's t copula and the dash line plots for the difference between the GHST copula and the Gaussian copula. We find that both the Gaussian copula and the Student's t copula relatively underestimate the joint probability compared to the GHST. In particular, we can see that there is significant underestimation of the joint probability by the Gaussian copula compared to the Studnet's t copula. This result is in line with the fact that Gaussian fails to take into account tail dependence. Finally, this figure also shows that the GHST copula is a more general framework which is able to capture the tail dependence as well as the asymmetric dependence.

[INSERT FIGURE 7 ABOUT HERE]

3.6 Probability of Conditional Default in UK G-SIBs

Given the marginal default probability and the probability of joint default, we further investigate the probability of conditional default under a hypothetical adverse market scenario. Recently, the Bank of England published a new document to list all the key elements of stress testing for UK banks. A counterparty default is considered as the key risk of many traded risk scenarios in this document, because a large amount of risk exposures to individual counterparties is contained in the banks' trading books (Bank of England, 2015). We consider a hypothetical scenario that a credit event happens in RBS and estimate the default probabilities of other banks conditional on this adverse market scenario. The reason why we choose RBS instead of other banks is because it has the highest average market-implied default probability (0.1287) among five G-SIBs.

Figure 8 shows the probability of conditional default for four UK G-SIBs assuming a credit event of RBS. The conditional probabilities are estimated by the Gaussian copula, Student's t copula and GHST copula. The estimates of conditional default probability sharply increase during the financial crisis. In addition, those also remarkably increases after S&P downgrades the US sovereign debt. These findings are consistent with the empirical results reported with the probability of joint default.

[INSERT FIGURE 8 ABOUT HERE]

Figure 9 shows the difference of conditional default probabilities estimated by the three copulas. To simplify the comparison, we take averages of differences for each year. We find that the Gaussian copula model usually underestimates the conditional default probabilities compared to other two copulas. Furthermore, we find that the Student's t copula frequently underestimates the conditional default probabilities compared to the GHST copula. This is because the Student's t copula cannot take into account the asymmetric tail dependence that the upper tail dependence is stronger than the lower tail dependence. It clearly shows that the modelling of asymmetric tail dependence is closely related to the accurate estimation of conditional default probability.

[INSERT FIGURE 9 ABOUT HERE]

4 Relation between Correlated Default and Dependence Structure of CDS spreads

In the previous section, we find that the dependence structure between the CDS spreads of UK G-SIBs is time-varying and asymmetric. Furthermore, these features are closely associated with the probability of joint (or conditional) default. For this reason, it is important for risk managers to understand a systematic relation between the probability of joint (or conditional) default and the dependent structure of CDS spreads. Thus we further study how the dependence structure (i.e. copula correlation or upper/lower tail dependence) works for measuring and predicting the probability of joint (or conditional) default using insightful regression analysis.

4.1 Dependence

It is our apparent reasoning that the dependence structure of CDS spreads is closely related with the probability of joint (or conditional) default from the empirical analysis in section 3. To test this, we use a copula correlation as a dependence measure. Its advantage is that it can be easily incorporated with time-varying nature and asymmetry of dependence structure via copula modeling. We investigate not only a contemporaneous relationship but also the predictability of copula correlation for the default probability. Hence, this analysis is able to provide the risk managers of bank with insight on the use of dependence structure for the credit risk management.

4.1.1 Probability of Joint Default

Let the joint default probability of bank i and j be $p_{i,j,t}$ and their copula correlation be $\delta_{i,j,t}$ at time t. We estimate the probability of joint default by parametric and semiparametric GAS-based GHST copula models. We compute an average probability as Equation (7), $\bar{p}_{i,j,t} = \left(p^P_{i,j,t} + p^S_{i,j,t}\right)/2$. Analogously, an average correlation, $\bar{\delta}_{i,j,t}$, is computed by taking the average of time-varying pairwise correlations in Equation (7). We regress $\bar{p}_{i,j,t}$ on $\bar{\delta}_{i,j,t}$ and test for a contemporaneous relationship between the probability of joint default and the correlation. We specify the following linear regression equation

$$\bar{p}_{i,j,t} = \alpha + \beta\bar{\delta}_{i,j,t} + \epsilon_{i,j,t} \tag{9}$$

for $i > j$ and $t = 1, \ldots, T$. If β is significant and positive, the probability of joint default would increase as the correlation becomes stronger.

Panel A of Table 9 presents the regression results. We consider three possible estimators: (i) pooled OLS (POLS); (ii) fixed effects (FE); (iii) random effects (RE). First, we test the existence of fixed effects by comparing POLS and FE. We perform the F-test under the null of no fixed effects and it is rejected. Hence, we should consider the fixed effects in the regression to get consistent and efficient results. Second, we test if regressors are correlated with the fixed effects using the Hausman test. Since the test statistic is not rejected, RE is consistent and more efficient than FE. Hence, we interpret the estimation results based on RE.

We find that $\hat{\beta}$ is significantly positive, implying that a higher contemporaneous correlation is positively associated with the higher probability of joint default. We find that the correlation is able to explain the variation of the joint default probability by 14.5%. Overall, the regression results show that the correlation plays an important role in measuring the probability of joint default.

Next, we test the predictability of correlation. To this end we included a lagged correlation as a regressor in the regression equation:

$$\bar{p}_{i,j,t} = \alpha + \beta \bar{\delta}_{i,j,t-k} + \epsilon_{t,j,t}. \tag{10}$$

We estimate Equation (10) by RE for $k = 1, \ldots, 5$.

Panel B presents the regression results. We find that $\hat{\beta}$ is significant and positive for all lags and the size of estimated coefficient decreases as the lag increases. R^2 also slowly decreases from 0.143 (first lag) to 0.131 (fifth lag). This implies that the correlation is able to explain the variation of joint default probability in five weeks by 13.1%. Thus both the current and lagged correlations contain an evident signal for predicting the probability of joint default. This may tell us that if we continuously observe a high copula correlation, it would signal the high risk of joint default in the UK G-SIBs.

[INSERT TABLE 9 ABOUT HERE]

4.1.2 Probability of Conditional Default

Next, we investigate a relation between the probability of conditional default and the correlation. Given the probability of joint default, we are able to obtain the conditional probability (see Equation (2)). Let the conditional default probability of bank i given the default of bank j be $p_{i|j,t}$ at time t. Analogous to the joint default, we also compute the average of conditional default probability, $\bar{p}_{i|j,t}$. We then regress $\bar{p}_{i|j,t}$ on $\bar{\delta}_{i,j,t}$ and test a contemporaneous relationship between the probability of conditional default and the correlation. The linear regression equation is thus specified by

$$\bar{p}_{i|j,t} = \alpha + \beta \bar{\delta}_{i,j,t} + \epsilon_{i,j,t}. \tag{11}$$

Panel A of Table 10 presents the regression results. We perform the F-test under the null of no fixed effects and it is rejected. On the other hand, the Hausman test statistic is not rejected.

Hence, RE is consistent and more efficient than FE. For this reason, we interpret the estimation results based on RE.

We find that $\hat{\beta}$ is significantly positive, indicating that a higher dependence between the CDS spreads of banks is positively associated with a higher conditional default risk. We find that the correlation is able to explain the variation of conditional default probability by 23.6% .

Next, we test if the correlation has any predictive power for the probability of conditional default. To this end we included a lagged correlation in the regression equation:

$$\bar{p}_{i|j,t} = \alpha + \beta\bar{\bar{\delta}}_{i,j,t-k} + \epsilon_{t,j,t}. \tag{12}$$

We estimate (12) by RE for $k = 1, \ldots, 5$ and report results in Panel B.

We find that $\hat{\beta}$ is significant and positive for all lags and its magnitude slowly decreases as the lag increases. This suggests that the higher dependence usually leads to the higher risk of conditional default. R^2 also slowly decreases as the lag increases from 0.228 (first lag) to 0.194 (fifth lag). Hence, both the current and lagged correlations contain a significant and strong signal for the future conditional default risk.

[INSERT TABLE 10 ABOUT HERE]

In sum, the (copula) correlation contains useful information which not only explains the current joint default probability but also predicts the future risk of joint default in the banking industry. Thus the modeling of dynamic dependence between the CDS spreads can improve the accuracy of measuring and forecasting the joint default risk of banks. Furthermore, it could be a key input for practical credit risk management. Hence, the risk managers of bank are able to utilize it as an leading indicator for the systemic credit event in the UK G-SIBs.

4.2 Asymmetry

The empirical results in section 3.3 show that the asymmetric tail dependence is statistically significant and we should incorporated this feature in the multivariate modeling. In this section we investigate if the asymmetry is also economically important and therefore if it contains information which is useful for the credit risk management. Thus this analysis is able to provide risk managers with insight on how the asymmetric tail dependence works for credit risk management.

4.2.1 Probability of Joint Default

Following McNeil et al. (2005), we define the lower tail dependence (LTD) by

$$\lambda_{i,j,t}^{LL} = \lim_{q \to 0+} \frac{C_t(q,q)}{q}, \tag{13}$$

and the upper tail dependence (UTD) by

$$\lambda_{i,j,t}^{UU} = \lim_{q \to 1-} \frac{1 - 2q + C_t(q,q)}{1-q}. \tag{14}$$

We estimate the parametric and semiparametric GAS-based GHST copula models for all pairs of banks. For each pair, we compute average tail dependences, $\bar{\lambda}_{i,j,t}^{LL}$ and $\bar{\lambda}_{i,j,t}^{UU}$. Then, we regress $\bar{p}_{i,j,t}$ on $\bar{\lambda}_{i,j,t}^{LL}$ and $\bar{\lambda}_{i,j,t}^{UU}$, and test the impact of LTD and UTD on the probability of joint default using the following linear regression equation

$$\bar{p}_{i,j,t} = \alpha + \beta_{i,j}^{LL} \bar{\lambda}_{i,j,t}^{LL} + \beta_{i,j}^{UU} \bar{\lambda}_{i,j,t}^{UU} + \epsilon_{i,j,t}. \tag{15}$$

Panel A of Table 11 presents the regression results. We perform the F-test under the null of no fixed effects and it is rejected. The Hausman test statistic is also rejected. Thus FE is consistent while RE is inconsistent. We interpret the estimation results based on FE.

We find that $\hat{\beta}^{LL}$ is insignificant while $\hat{\beta}^{UU}$ is significantly positive and $\hat{\beta}^{UU} > \hat{\beta}^{LL}$. Thus the higher UTD from credit deterioration is closely associated with the higher risk of joint default. This may be explained by the nature of CDS spread as a credit derivative contract to insure the protection buyer against any uncertainty on the reference name. Hence, the upper tail of CDS spread indicates the credit deterioration of bank. We also find that both tail dependences are able to explain the variation of joint default probability by 12.1%. Overall, the regression results show that UTD is more informative than LTD for measuring the probability of joint default.

Next, we test the predictability of tail dependence. To this end, we include the lagged tail dependences as regressors in the regression equation:

$$\bar{p}_{i,j,t} = \alpha + \beta^{LL}\bar{\lambda}^{LL}_{i,j,t-k} + \beta^{UU}\bar{\lambda}^{UU}_{i,j,t-k} + \epsilon_{t,j,t}. \tag{16}$$

We estimate (16) by FE for $k = 1, \ldots, 5$.

Panel B reports the regression results. Only $\hat{\beta}^{UU}$ is significant and positive for all lags and its magnitude slowly decreases as the lag increases. On the other hand, $\hat{\beta}^{LL}$ is insignificant for all lags. R^2 also slowly decreases as the lag increases from 0.119 (first lag) to 0.116 (fifth lag). Hence, both the current and lagged UTD contain a significant and strong signal for the future risk of joint default.

[INSERT TABLE 11 ABOUT HERE]

4.2.2 Probability of Conditional Default

We regress $\bar{p}_{i|j,t}$ on $\bar{\lambda}^{LL}_{i,j,t}$ and $\bar{\lambda}^{UU}_{i,j,t}$ and test the impact of LTD and UTD between bank i and j on the probability of conditional default using the following regression

$$\bar{p}_{i|j,t} = \alpha + \beta^{LL}_{i,j}\bar{\lambda}^{LL}_{i,j,t} + \beta^{UU}_{i,j}\bar{\lambda}^{UU}_{i,j,t} + \epsilon_{i,j,t}. \tag{17}$$

Panel A of Table 12 presents the regression results. We perform the F-test under the null of no fixed effects and it is rejected. The Hausman test statistic is also rejected. Thus FE is consistent while RE is inconsistent. We interpret the estimation results based on FE.

Both $\hat{\beta}^{LL}$ and $\hat{\beta}^{UU}$ are significant and positive. Thus the higher dependence under extreme circumstances is closely associated with the higher risk of conditional default. We apply the equality test to $H_0 : \beta^{LL} = \beta^{UU}$ to investigate the asymmetric effect. Although quantitatively $\hat{\beta}^{LL} < \hat{\beta}^{UU}$, the null of equality is statistically not rejected. We find that both tail dependences are able to explain the variation of conditional default probability by 17.4%. The estimation results therefore show that UTD is quantitatively more informative than LTD while it is not statistically validated. Hence, we conclude that the tail dependence plays an important role for measuring the probability of conditional default.

Next, we test the predictability of tail dependence. To this end, we included lagged tail dependence coefficients as regressors in the regression equation:

$$\bar{p}_{i|j,t} = \alpha + \beta^{LL}\bar{\lambda}^{LL}_{i,j,t-k} + \beta^{UU}\bar{\lambda}^{UU}_{i,j,t-k} + \epsilon_{t,j,t}. \tag{18}$$

We estimate (18) by FE for $k = 1, \ldots, 5$.

Panel B reports the regression results. Both $\hat{\beta}^{LL}$ and $\hat{\beta}^{UU}$ are significant and positive for all lags and its magnitude slowly decreases as the lag increases. Thus the higher dependence under extreme circumstances leads to the higher risk of conditional default. Quantitatively, $\hat{\beta}^{LL} < \hat{\beta}^{UU}$ for all lags but the inequality is not statistically validated. R^2 also slowly decreases as the lag increases from 0.170 (first lag) to 0.156 (fifth lag). These results indicate that both tail dependence coefficients contain a significant and strong signal for the future conditional default risk.

[INSERT TABLE 12 ABOUT HERE]

In sum, UTD contains useful information which not only explains the current joint default probability but also predicts the future one. Furthermore, both tail dependences contain useful information for measuring and predicting the probability of conditional default. Thus the modeling of asymmetric tail dependence between the CDS spreads is able to improve the accuracy of measuring and predicting the probability of conditional default. These results contain important economic implications. First, the ignorance of asymmetric features could lead to underestimate the probability of joint default in the banking industry. Second, risk managers are able to utilize tail dependence measures as good leading indicators for the systemic credit event. Especially, if they continuously observe that UTD is significantly higher than LTD, it could be a strong warning about coming credit crash in the banking industry.

5 Conclusion

We document the time-varying and asymmetric dependence between the CDS spreads using a dataset in the UK G-SIBs. We find substantial evidence that the upper tail dependence of CDS spreads is significantly higher than the lower tail dependence. Also, the results from structure break tests are strongly against the constant dependence structure over the sample period. Our findings highlight the importance of modelling the dynamics and asymmetries of dependent structure simultaneously. We calibrate a marginal model using the market quotes of CDS to obtain the market-implied risk neutral default probability for each bank using the bootstrap algorithm and apply the GAS-based GHST copula to model the dependence between the credit risks of banks. We find that the dependence dramatically increases during times of stress and gradually decreases after 2013. Using marginal default probability and estimated copula model, we perform the simulation algorithm to obtain the probabilities of joint and conditional default in the UK G-SIBs. Our empirical results show that the probability of joint default estimated by the dynamic asymmetric copula is higher than one estimated by the dynamic Gaussian or Student's t copula in most of the time during our sample period indicating that the Gaussian or Student's copula-based models may underestimate the potential risk as neither of them can accommodate the multivariate asymmetries between credit risks of banks. Furthermore, we perform the insightful cross-sectional regression analysis and find the clear evidence that the dependence and tail dependence implied by copula models are closely related to the probabilities of joint and conditional default in the banking industry. Also, we empirically show that both dependence and tail dependence are very informative to predict future risks of joint and conditional default. Overall, our empirical findings have important implications for credit risk management in financial practice and a possible extension for further studies is to apply our framework to the firms in other sectors or markets or find the economic sources of asymmetric dependence of credit risks.

A Appendix

A.1 Hazard Rate Function

The hazard rate function $\lambda(t)$ is the conditional instantaneous default probability of reference entity, given that it survived until time t.

$$\mathbb{P}(t < \tau \leq t + \triangle t \mid \tau > t) = \frac{F(t + \triangle t) - F(t)}{1 - F(t)} \approx \frac{f(t)\triangle t}{1 - F(t)} \tag{A.1}$$

The association of hazard rate function $\lambda(t)$ at time t with the default probability $F(t)$ and survival probability $S(t)$ is as follows

$$\lambda(t) = \frac{f(t)}{1 - F(t)} = -\frac{Q'(t)}{Q(t)} \tag{A.2}$$

The survival function $Q(t)$ can be defined in terms of hazard rate function $\lambda(t)$

$$Q(t) = \exp\left(-\int_t^{t_n} \lambda(s)\, ds\right)$$

Proof:

$$S'(t) = \frac{d(Q(t))}{dt} = \frac{d(1 - F(t))}{dt} = -f(t)$$

$$\lambda(t) = -\frac{d(Q(t))}{dt}\frac{1}{Q(t)} = \frac{f(t)}{Q(t)} = -\frac{d\log(Q(t))}{d(Q(t))} \cdot \frac{d(Q(t))}{dt} = -\frac{d\log(Q(t))}{dt}$$

Taking integral on both sides

$$-\log(Q(t)) = \int_t^{t_n} \lambda(s)\, ds$$

and taking exponentials of both sides, we get

$$Q(t) = \exp\left(-\int_t^{t_n} \lambda(s)\, ds\right)$$

A.2 Valuing the Premium Leg and Protection Leg

The premium leg is a stream of the scheduled fee payments of CDS made to maturity if the reference entity survivies or to the time of first credit event occurs. The present value of the premium leg of an existing CDS contract is given by

$$\mathrm{PV}_{\text{premium}}\left(t, t_N\right) = S_0 \cdot \mathrm{RPV01}\left(t, t_N\right) \tag{A.3}$$

$$\begin{aligned} \mathrm{RPV01}\left(t, t_N\right) &= \sum_{n=1}^{N} \Delta\left(t_{n-1}, t_n, B\right) Z\left(t, t_n\right) Q\left(t, t_n\right) \\ &+ \sum_{n=1}^{N} \int_{t_{n-1}}^{t_n} \Delta\left(t_{n-1}, s\right) Z\left(t, s\right)\left(-dQ\left(t, s\right)\right), \ n = 1, ..., N, \end{aligned} \tag{A.4}$$

where t, t_n, t_N denotes the effective date, the contractual payment dates, and the maturity date of the CDS contract, respectively. $S\left(t_0, t_N\right)$ represents the fixed contractual spread of CDS with maturity date t_N at time t_0, $\Delta\left(t_{n-1}, t_n, B\right)$ represents the day count fraction between premium date t_{n-1} and t_n in the selected day count convention B, $Z\left(t, t_n\right)$ is the Libor discount factor from the valuation date t to premium payment date t_n and $Q\left(t, t_n\right)$ is the arbitrage-free survival probability of the reference entity from t to t_n. O'Kane (2008) show that in practice, the integral part can be approximated by

$$\int_{t_{n-1}}^{t_n} \Delta\left(t_{n-1}, s\right) Z\left(t, s\right)\left(-dQ\left(t, s\right)\right) \backsimeq \frac{1}{2}\Delta\left(t_{n-1}, t_n\right) Z\left(t, t_n\right)\left(Q\left(t, t_{n-1}\right) - Q\left(t, t_n\right)\right) \tag{A.5}$$

Thus, it can be simplified as

$$\mathrm{RPV01}\left(t, t_N\right) = \frac{1}{2}\sum_{n=1}^{N} \Delta\left(t_{n-1}, t_n, B\right) Z\left(t, t_n\right)\left(Q\left(t, t_{n-1}\right) + Q\left(t, t_n\right)\right) \tag{A.6}$$

The protection leg is the compensation that the protection seller pays to the buyer for the loss associated to a given reference entity at the time of default. It is a contingent payment of $(100\% - R)$ on the par value of the protection when the credit event occurs. R is the expected recovery rate of the cheapest-to-deliver (CTD) obligation into the protection at the time of credit event. So the expected present value of protection payment is given by

$$\text{PV}_{\text{protection}}\left(t, t_N\right) = (1 - R) \int_t^{t_N} Z\left(t, s\right)\left(-dQ\left(t, s\right)\right) \tag{A.7}$$

The computation of the integral part is normally tedious. Nevertheless, following O'Kane and Turnbull (2003) and O'Kane (2008), we could assume that the credit event only happens on a finite number M of several specific discrete points per year without much loss of accuracy. We can discrete the time between t and t_N into K equal intervals, where $K = \text{int}\left(M \times (T - t) + 0.5\right)$. Defining $\epsilon = (T - t)/K$, we can calculate the approximation of expected present value of the protection payment as

$$\text{PV}_{\text{protection}} = (1 - R) \sum_{k=1}^{K} Z\left(t, k\epsilon\right)\left(Q\left(t, (k-1)\epsilon\right) - Q\left(t, k\epsilon\right)\right) \tag{A.8}$$

Clearly, more accurate results can be obtained by increasing discrete points M.

A.3 Relationship between Market Quotes and Survival Probability

In order to compute the survival probabilities from the market quote of CDS spread, it is important to understand their relationship. For a fair market trade, the present value premium leg should be exactly equal to the present value of protection leg

$$\text{PV}_{\text{premium}} = \text{PV}_{\text{protection}}$$

New quotes for CDS contracts at time t_0 can be obtained by substituting and rearranging Equation A.3 and A.8

$$S\left(t_0, t_N\right) = \frac{(1 - R)}{2} \frac{\sum_{k=1}^{K}\left(Z\left(t_0, t_{k-1}\right) + Z\left(t_0, t_k\right)\right)\left(Q\left(t_0, t_{k-1}\right) + Q\left(t_0, t_k\right)\right)}{\text{RPV01}\left(t_0, t_N\right)} \tag{A.10}$$

where the RPV01 is given by

$$\text{RPV01}\left(t_0, t_N\right) = \frac{1}{2} \sum_{n=1}^{N} \Delta\left(t_{n-1}, t_n, B\right) Z\left(t_0, t_n\right)\left(Q\left(t_0, t_{n-1}\right) + Q\left(t_0, t_n\right)\right)$$

A.4 Bootstrapping a Survival Probability Curve

The bootstrap is a fast and stable curve construction approach, which has been widely used in financial practice as a standard method for constructing CDS survival curves. The bootstrap algorithm works by starting with shortest maturity contract and works out to the CDS contract with the longest maturity. At each step it uses the spread of next CDS contract to solve for the survival probability of next maturity and to extend the survival curve (see Hull and White, 2000a; O'Kane and Turnbull, 2003; Schönbucher, 2003; O'Kane, 2008, etc.). The default probability can be easily obtained by calculating the complement of survival probability.

First, we define the market quotes of CDS as a set of maturity dates $T_1, T_2, ..., T_M$ and corresponding CDS spread $S_1, S_2, ..., S_M$. All the CDS quotes are sorted in order of increasing maturity. Second, we need to extrapolate the survival curve below the shortest maturity CDS by assuming that the forward default rate is flat at a level of 0, and we also extrapolate the survival curve beyond the longest maturity T_M by assuming that the forward default rate is flat at its latest interpolated value.

The bootstrap algorithm to calculate the survival probability from CDS market quotes is as follows: (i) We initialize the first point of survival curve by defining $Q(T_0 = 0) = 1$ and $m = 1$. (ii) The survival probability $Q(T_m)$ can be calculated by solving Equation (A.10). Note that the no-arbitrage bound on $Q(T_m)$ is $0 < Q(T_m) \leq Q(T_{m-1})$. (iii) Given the value of $Q(T_m)$ which reprices the CDS with maturity T_m, we can extend the survival curve to time T_m. (iv) Set $m = m + 1$ and go back and repeat step (ii) - (iv) iteratively until $m \leq M$. (v) Given $M + 1$ points values of survival probability $1, Q(T_1), Q(T_2), ..., Q(T_M)$ at time $0, T_1, T_2, ..., T_M$.

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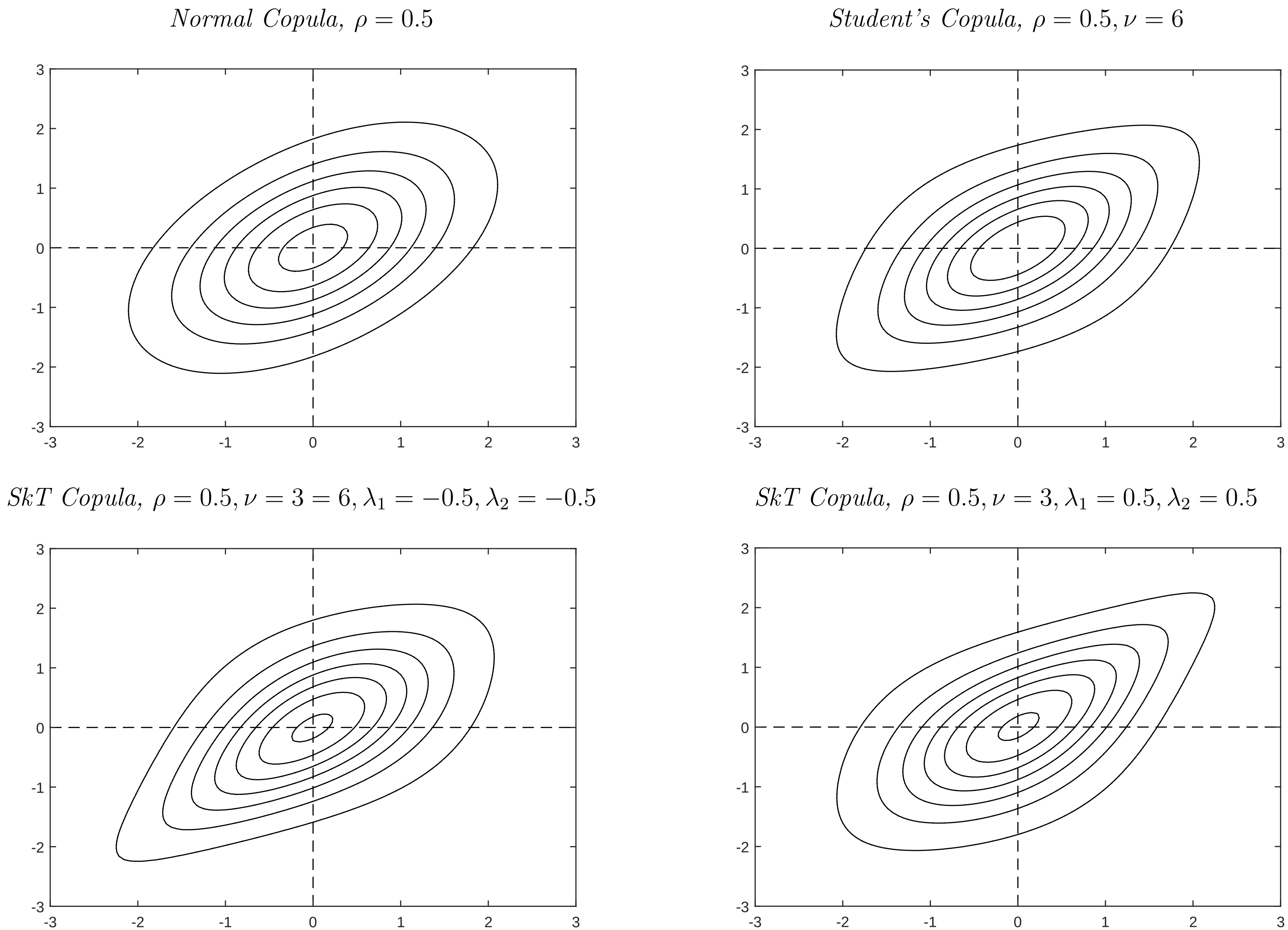
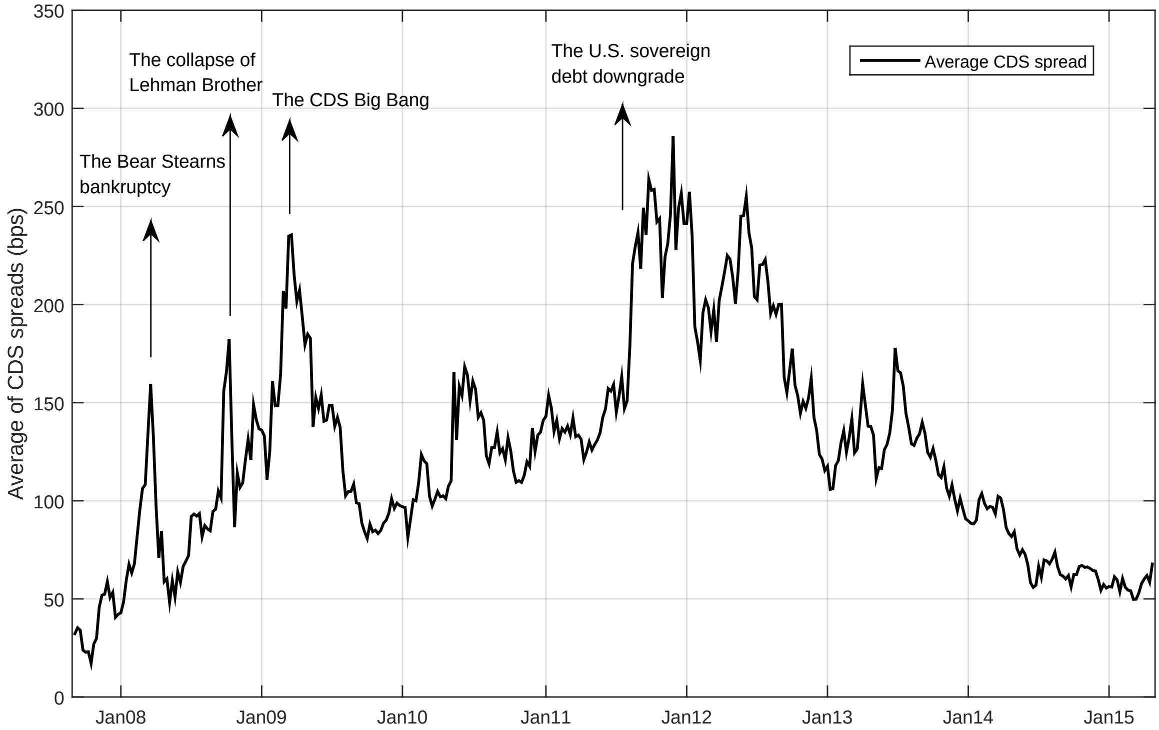
Figure 1: Contour Probability Plots for Copulas



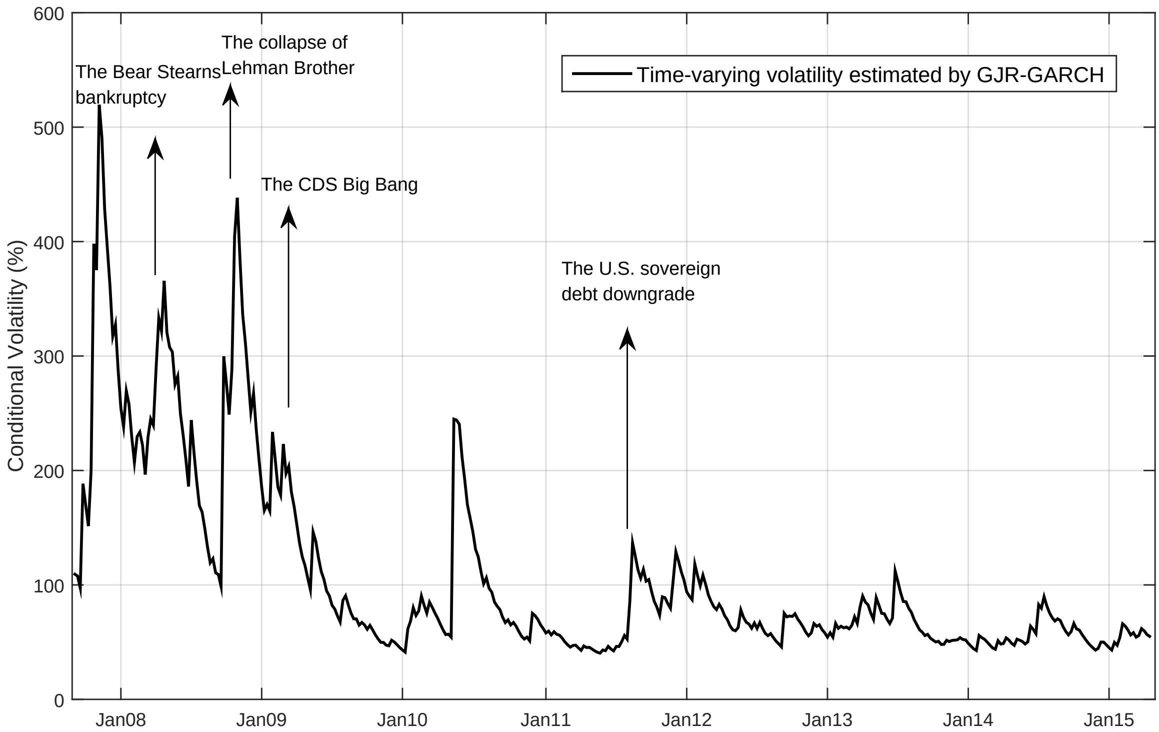
Note: This figure shows contour probability plots for the normal, Student's t, and GHST copulas. The probability levels for each contour are held fixed across four panels. The marginal distributions are assumed to be normally distributed. ρ denotes the correlation coefficient, ν denotes the degree of freedom, and λ denotes the asymmetric parameters of copulas.

Figure 2: Dynamics of CDS Spread from 2007 to 2015

A. Average CDS Spread



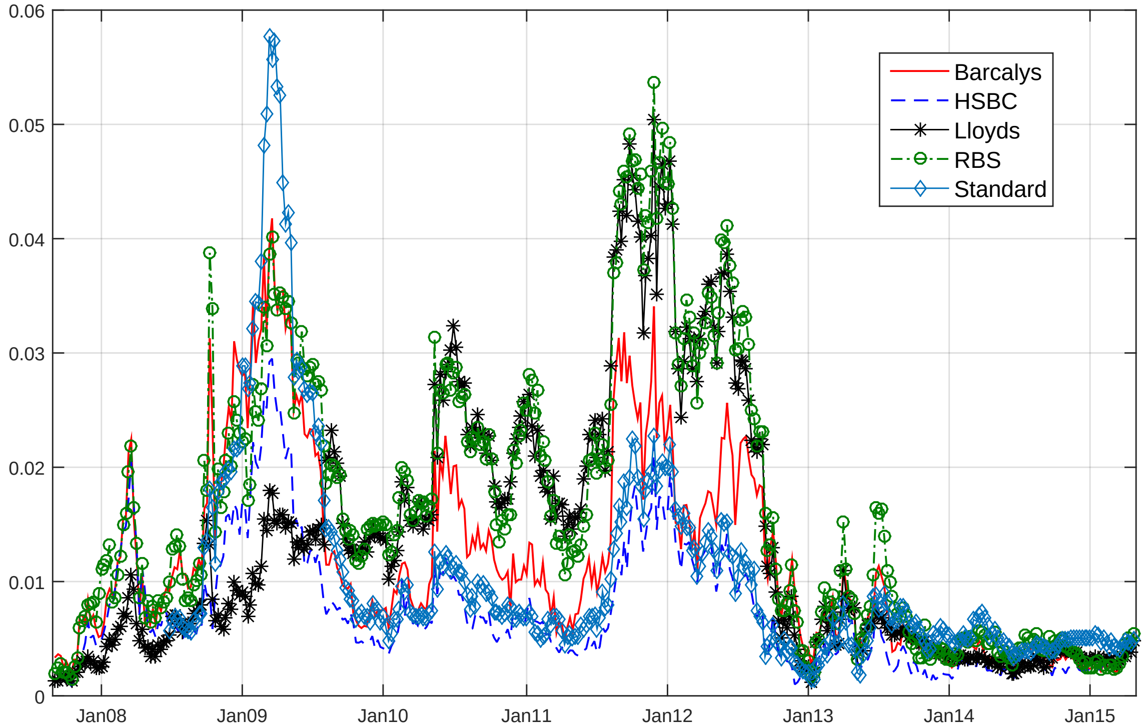
B. Conditional Volatility of Average CDS spread



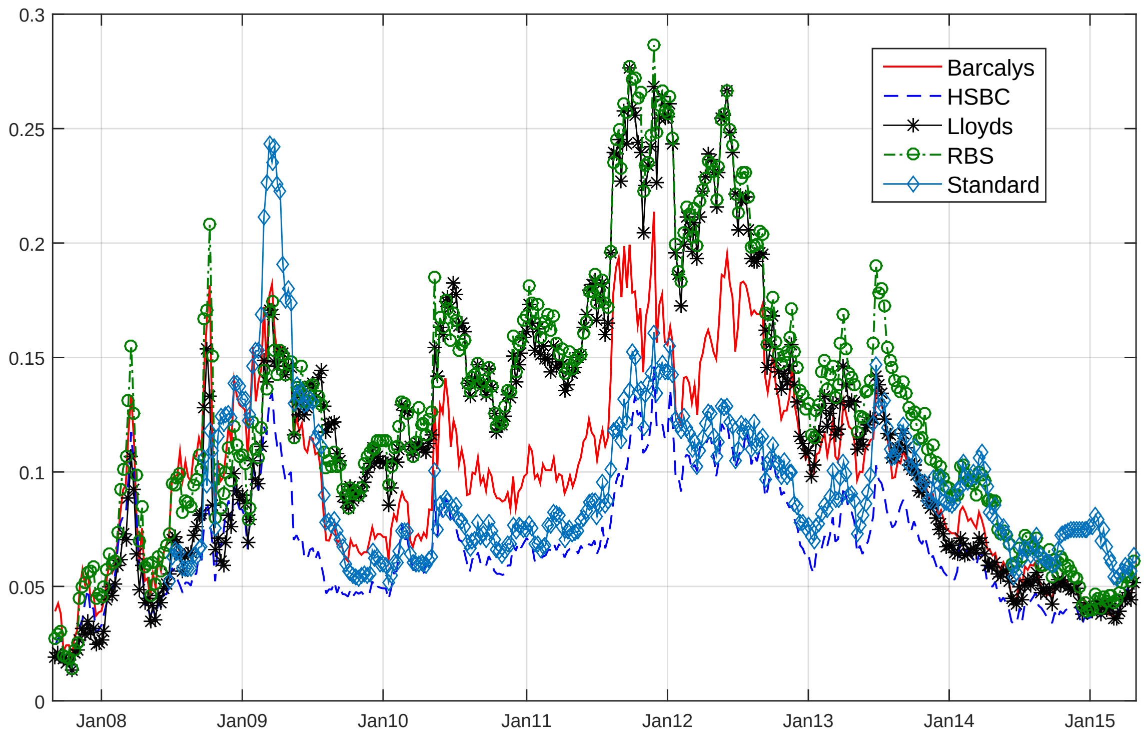
Notes: This figure shows the levels and conditional volatility of average 5-year CDS spread of five UK top tier banks from September 7, 2007 to April 17, 2015. The conditional volatility of average CDS spread changes is estimated by the GJR-GARCH(1,1,1) of Glosten et al. (1993). The arrows in each figure indicate several major events in CDS market during the sample period.

Figure 3: CDS-implied Marginal Risk Neutral Default Probabilities

A. Probability of Default over One Year Horizon

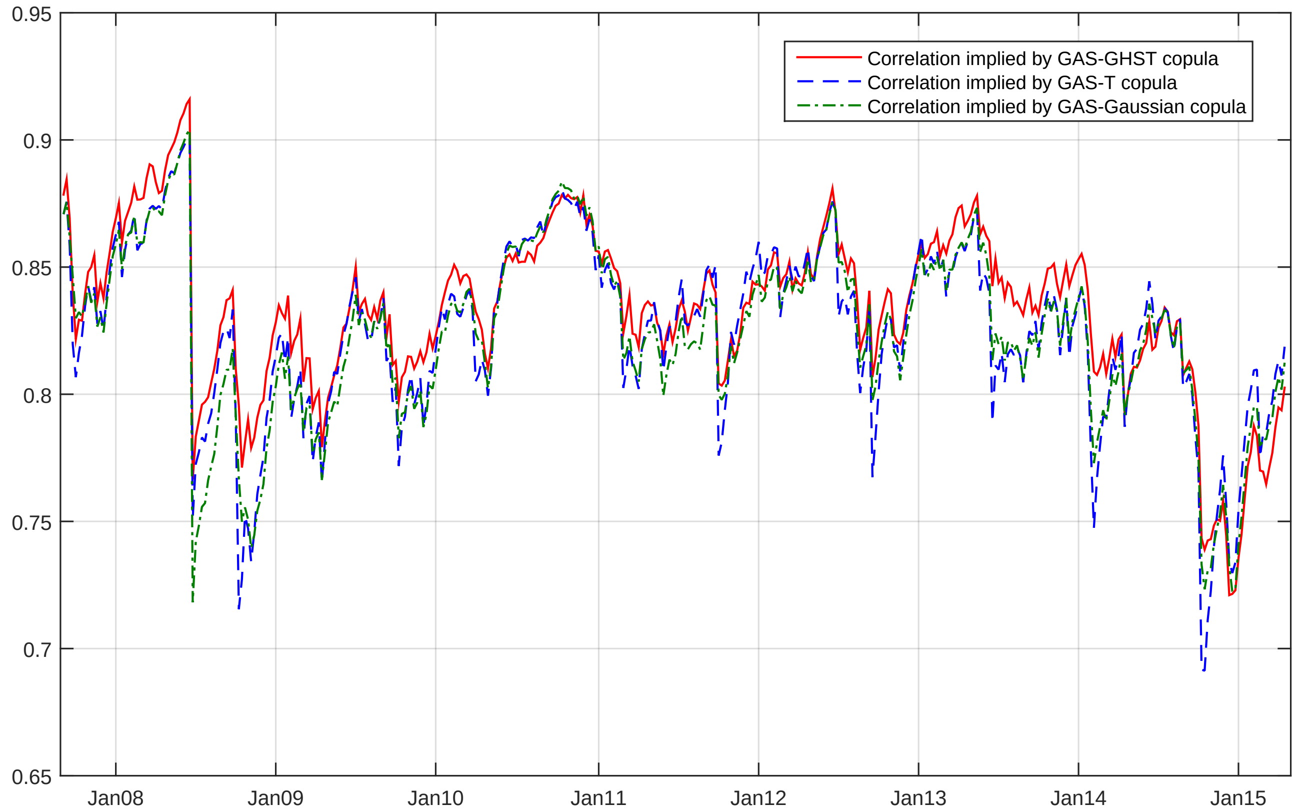


B. Probability of Default over Five Year Horizon



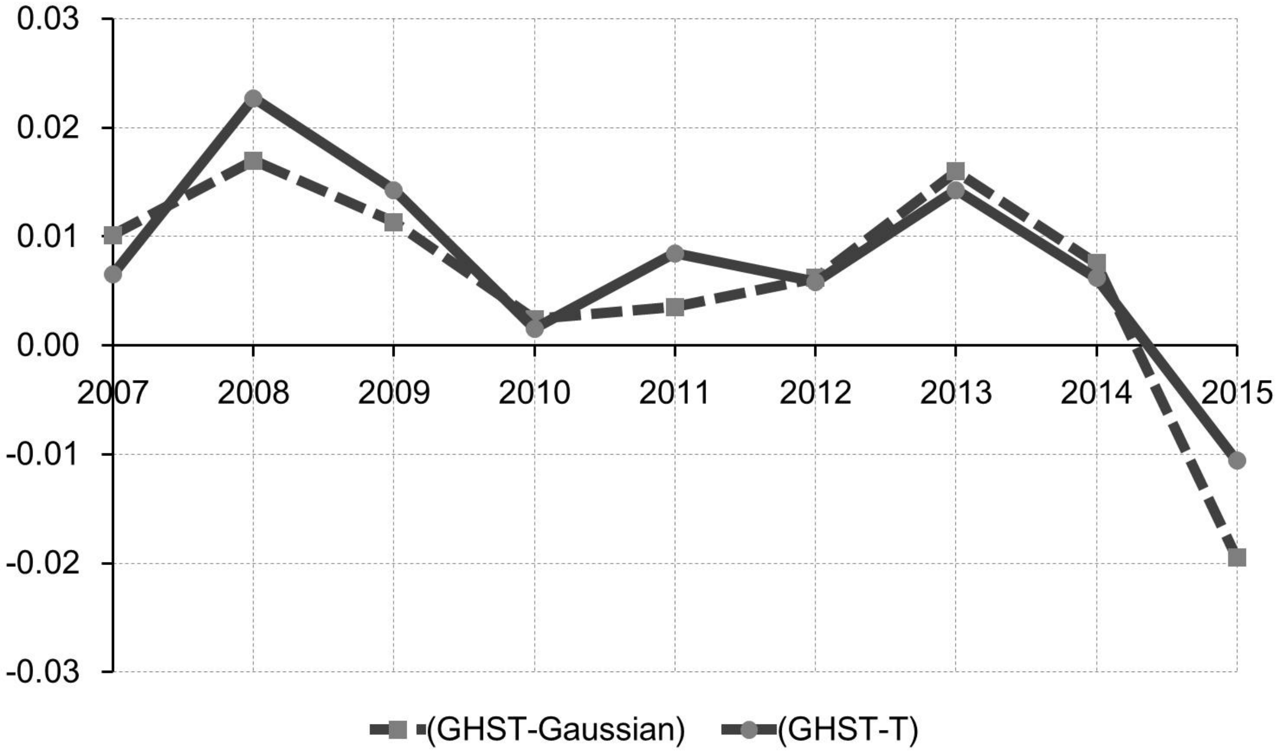
Notes: This figure plots risk neutral marginal probabilities of default for five top tier banks in UK. These probabilities are directly inferred from weekly CDS prices with different maturities using bootstrap algorithm described in Appendix A.4. The sample period is from September 7, 2007 to April 17, 2015.

Figure 4: Average Correlation Impiled by GAS Over Time



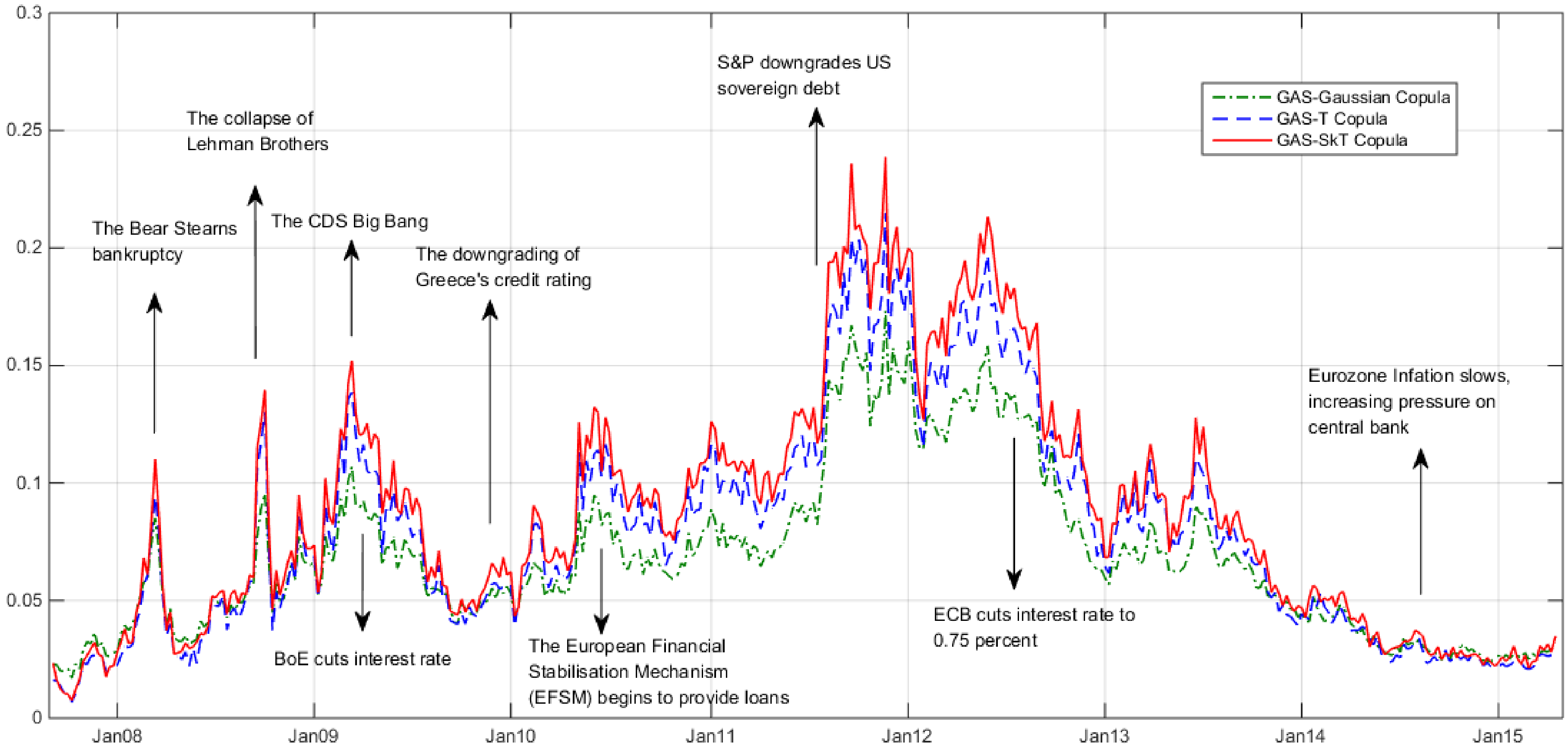
Notes: This figures shows the estimated average correlation implied by three GAS-based copula models from September 7, 2007 to April 17, 2015. The copula correlations are obtained by taking average of estimated correlation series between 10 pairs of banks. The correlation coefficients are estimated by both parametric copula and semiparametric copula. The solid line represents the time-varying correlation estimated by the GAS-GHST copula. The dashed line and dash-dot line represent the time-varying correlation estimated by the GAS-Student's t copula and GAS-Gaussian copula. The sudden decreases of correlations on June 27, 2008 are caused by the fact that we include the data of the Standard Chartered, which has much lower average correlation with other banks.

Figure 5: Difference of Average Correlations of UK Top-tier Banks from 2008 to 2015



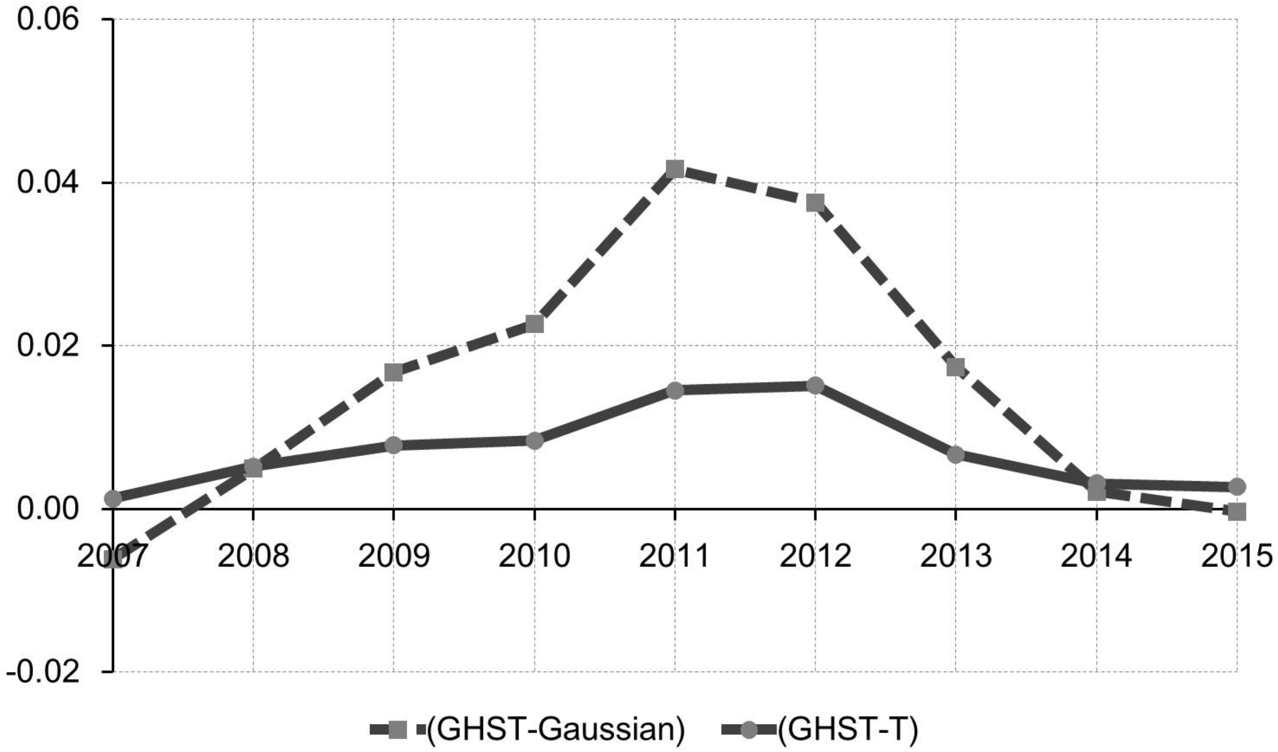
Note: This figure shows the difference of the estimated average correlations implied by three GAS-based copula models from September 7, 2007 to April 17, 2015. For simplifying comparison, it plots the average difference for each year. The solid line plots for the difference between the GAS-GHST copula and GAS-Student's t copula, $GHST - T$, and the dash line plots for the difference between the GAS-GHST copula and the GAS-Gaussian copula, $GHST - Gaussian$. The figure clearly shows that both the Gaussian copula and Student's t copula relatively underestimate the correlation compared to the GHST copula while they overestimate it in 2015.

Figure 6: The Joint Credit Risk of UK Top-tier Banks from 2007 to 2015



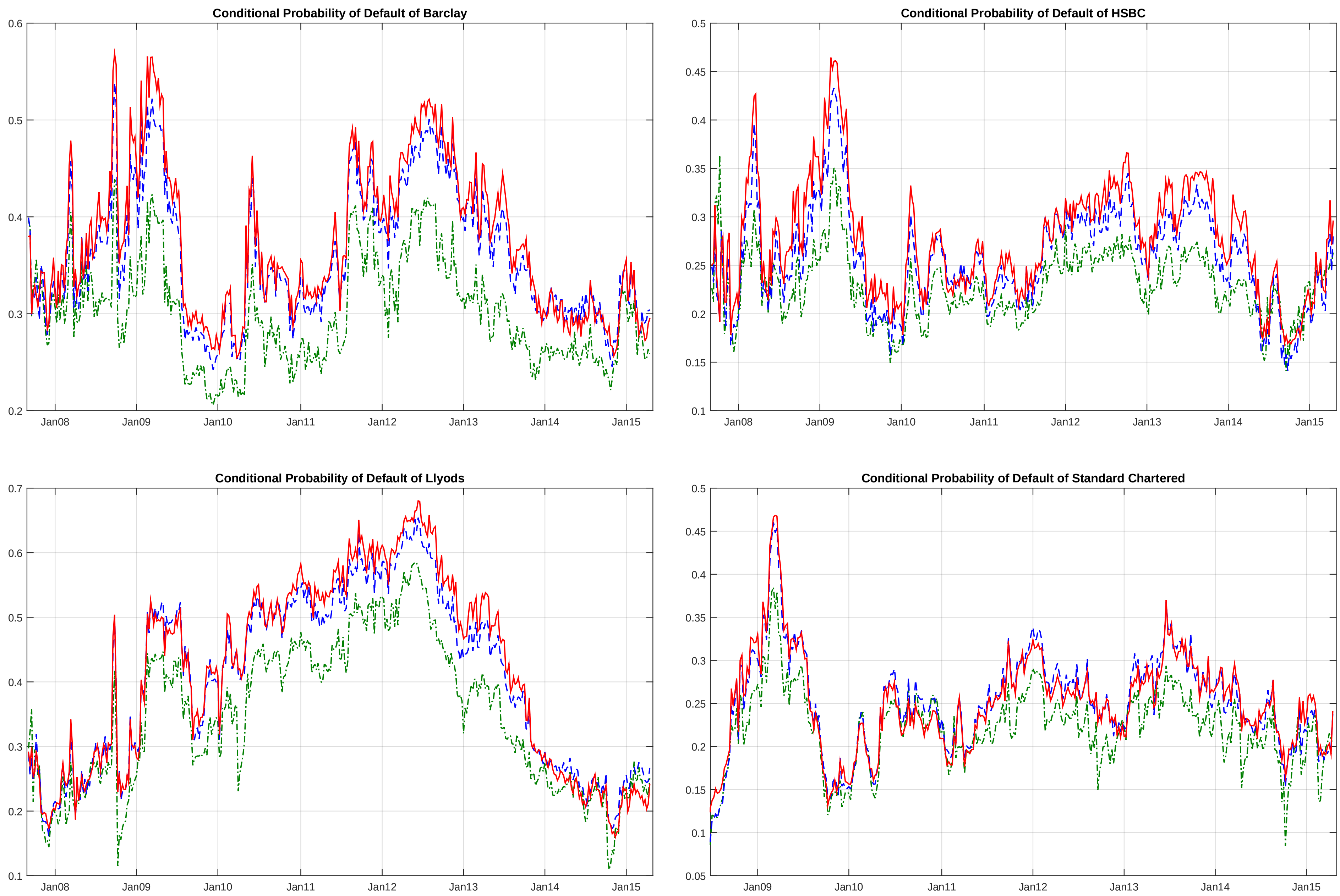
Notes: This figure plots the estimated time-varying probabilities of two or more credit events over the five year horizon from September 7, 2007 to April 17, 2015. The probabilities are estimated based on three different multivariate models: GAS-Gaussian copula, GAS-Student's t copula and GAS-GHST copula. The solid line represents the joint probability of default estimated by the GHST copula. The dashed line and dash-dot line represent the joint probability of default estimated by the Student's t copula and Gaussian copula. The arrows indicate time points of several major events in global financial market.

Figure 7: Difference of Joint Credit Risk of UK Top-tier Banks from 2007 to 2015



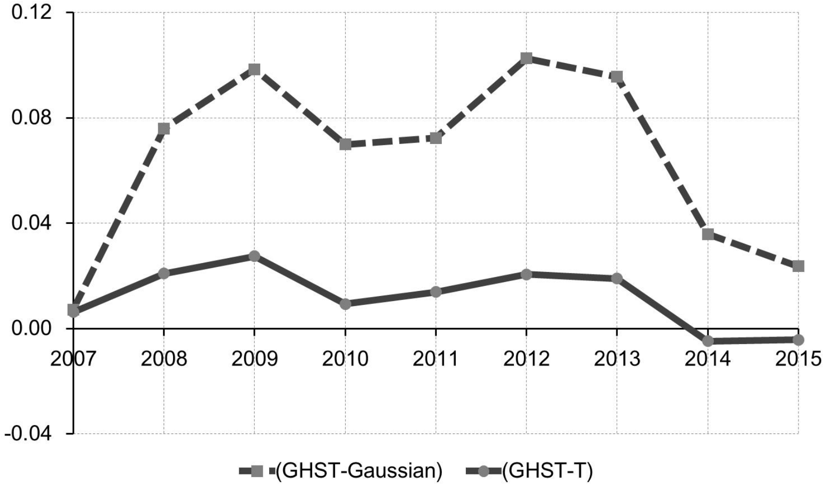
Note: This figure shows the difference of the estimated time-varying probabilities of two or more credit events over the five year horizon from September 7, 2007 to April 17, 2015. For simplifying comparison, it plots the average difference for each year. The probabilities are estimated based on three different multivariate models: GAS-Gaussian copula, GAS-Student's t copula and GAS-GHST copula. The solid line plots for the difference between the GAS-GHST copula and GAS-Student's t copula, $GHST-T$, and the dash line plots for the difference between the GAS-GHST copula and the GAS-Gaussian copula, $GHST-Gaussian$. The figure clearly shows that both the Gaussian copula and Student's t copula relatively underestimate the joint probability compared to the GHST copula.

Figure 8: Conditional Probabilities of Default Given the Default of RBS

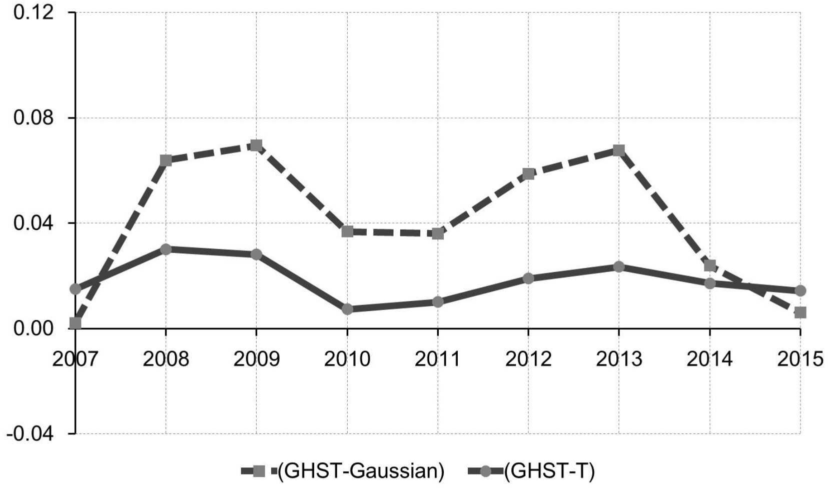


Note: This figure plots the conditional probability of a credit event for four top tier UK banks given a credit event of RBS. The solid line represents the conditional probability of default estimated by the GHST copula. The dashed line and dash-dot line represent the conditional probability of default estimated by the Student's t copula and Gaussian copula.

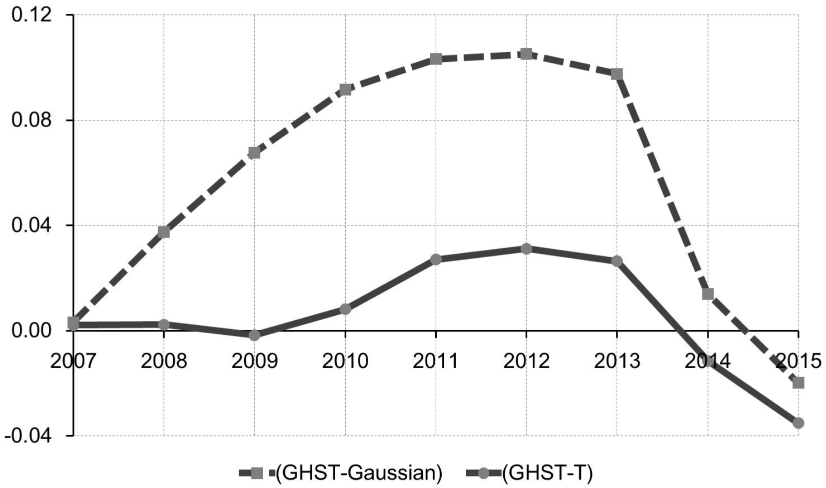
Figure 9: Difference of Conditional Probabilities of Default Given the Default of RBS



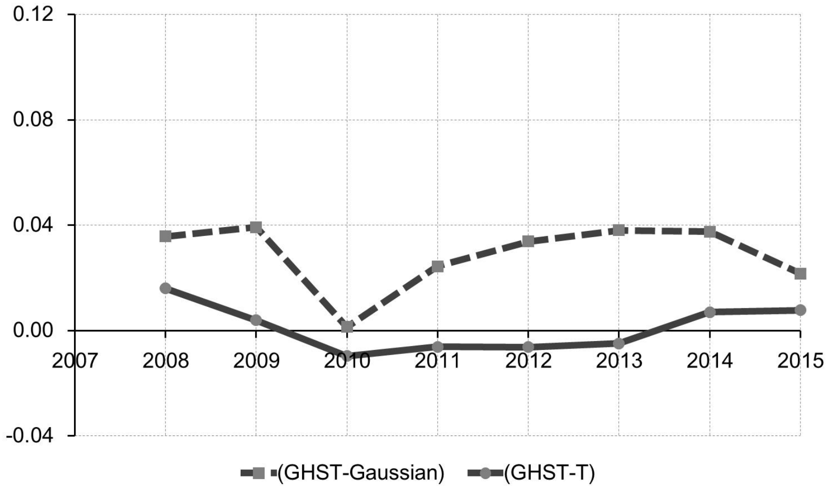
A. Barclay



B. HSBC



C. Lloyd



D. Standard Chartered

Note: This figure plots the difference of the estimated conditional probability of a credit event for four top tier UK banks given a credit event of RBS over the five year horizon from September 7, 2007 to April 17, 2015. For simplifying comparison, it plots the average difference for each year. The probabilities are estimated based on three different multivariate models: GAS-Gaussian copula, GAS-Student's t copula and GAS-GHST copula. The solid line plots for the difference between the GAS-GHST copula and GAS-Student's t copula, $GHST - T$, and the dash line plots for the difference between the GAS-GHST copula and the GAS-Gaussian copula, $GHST - Gaussian$. The figure clearly shows that both the Gaussian copula and Student's t copula relatively underestimate the joint probability compared to the GHST copula. Overall, the figure shows that both the Gaussian copula and Student's t copula relatively underestimate the conditional probability compared to the GHST copula.

Table 1: Descriptive Statistics and Time Series Tests on 5-year CDS Spreads

	Barclays	HSBC	Lloyds	RBS	Standard
			A. Descriptive Statistics		
Mean	0.079	0.200	0.256	0.211	0.054
Median	-0.243	-0.012	0.141	0.432	0.000
Std.	11.857	10.466	10.872	11.968	8.707
Skewness	-0.176	0.122	0.287	-0.055	0.793
Kurtosis	6.443	5.305	6.112	8.783	10.041
Max	49.320	48.432	51.173	57.738	48.906
Min	-55.131	-36.795	-44.802	-68.245	-38.349
			B. Time Series Tests		
JB test	0.000	0.000	0.000	0.000	0.000
LB Q(12)	0.101	0.047	0.083	0.011	0.077
LB Q(12)^2	0.000	0.000	0.000	0.000	0.000
LM ARCH	0.000	0.000	0.001	0.001	0.000

Notes: This table reports descriptive statistics and time series test results for log-differences of 5-year weekly CDS spreads across five top tier UK banks in FTSE 100 index from September 7, 2007 to April 17, 2015, which correspond to a sample of 398 observations for Barclays, HSBC, Lloyds and RBS and a sample of 356 Standard Chartered (Note: The CDS data of Standard Chartered is available from June 27, 2008.). Note that the means, standard deviations, minima, and maxima are reported in %. JB test denotes the Jarque–Bera test for normal distribution. LB test lag 5 and 10 denote the *p*-values of the Ljung-Box Q-test for autocorrelation at lags 5 and 10, respectively. In addition, we report the p-values of Engle's Lagrange Multiplier test for the ARCH effect on the residual series.

Table 2: Correlation Matrix of Weekly Log-differences of CDS spreads

A. Linear Correlation

	Barclays	HSBC	Lloyds	RBS	Standard
Barclays	1.000				
HSBC	0.854	1.000			
Lloyds	0.873	0.847	1.000		
RBS	0.897	0.855	0.862	1.000	
Standard	0.762	0.803	0.711	0.781	1.000

B. Rank Correlation

	Barclays	HSBC	Lloyds	RBS	Standard
Barclays	1.000				
HSBC	0.835	1.000			
Lloyds	0.879	0.837	1.000		
RBS	0.885	0.840	0.879	1.000	
Standard	0.746	0.785	0.710	0.727	1.000

Notes: This table reports the correlation matrix for log-differences of 5-year weekly CDS spreads across five top tier UK banks in FTSE 100 index from September 7, 2007 to April 17, 2015, which correspond to a sample of 398 observations for Barclays, HSBC, Lloyds and RBS and a sample of 356 Standard Chartered (The CDS data of Standard Chartered is available from June 27, 2008.). Panel A reports the Pearson's linear correlation coefficients and Panel B reports the Spearman's rank correlation coefficients.

Table 3: Summary of ARMA-GJR-GARCH Estimation on Weekly Log-Differences

	Barclays	HSBC	Lloyds	RBS	Standard
ARMA					
$\phi 1$	-0.671***	-0.848***	-0.794***	-0.697***	-0.094*
	(0.238)	(0.114)	(0.173)	(0.203)	(0.053)
$\phi 2$	0.580**	0.791***	0.757***	0.593***	_
	(0.261)	(0.132)	(0.187)	(0.228)	_
GARCH					
ω	3.168***	3.28***	2.663***	3.361***	7.089***
	(0.099)	(1.761)	(1.683)	(1.599)	(0.149)
α	0.096***	0.101**	0.078*	0.067*	0.106***
	(0.026)	(0.047)	(0.040)	(0.036)	(0.000)
δ	-0.096***	-0.080	-0.027	-0.044	-0.107***
	(0.031)	(0.054)	(0.059)	(0.049)	(0.007)
β	0.916***	0.894***	0.905***	0.915***	0.850***
	(0.022)	(0.041)	(0.036)	(0.033)	(0.003)
SkT					
υ	5.511***	7.385***	7.179***	5.269***	3.159***
η	0.017*	0.079***	0.001	-0.012*	0.016*
KS p-value	0.83	0.94	0.22	0.23	0.16
CvM p-value	0.58	0.91	0.15	0.41	0.25

Note: This table presents the estimated parameters with p-values from the ARMA model for the conditional mean and GJR-GARCH(1,1) models for the conditional variance of log-differences of 5-year weekly CDS spread. We estimate all parameters using the sample from September 7, 2007 to April 17, 2015, which correspond to a sample of 398 observations for Barclays, HSBC, Lloyds and RBS and a sample of 356 Standard Chartered (The CDS data of Standard Chartered is available from June 27, 2008.). The values in parenthesis represent the standard errors of the parameters. We also report the p-values of two goodness-of-fit tests for the skewed Student's t distribution. KS and CvM denote Kolmogorov-Smirnov test and Cramer-von Mises test, respectively.

Table 4: Tests of Bivariate Asymmetry

	A. Threshold Correlation		B. Full parametric tail dependence				C. Semiparametric tail dependence			
	HTZ	p-value	Lower	Upper	Diff	p-value	Lower	Upper	Diff	p-value
B-H	16.445	0.997	0.379	0.509	-0.130	0.315	0.279	0.390	-0.111	0.468
B-L	19.702	0.983	0.287	0.543	-0.255	0.015	0.428	0.661	-0.233	0.045
B-R	12.524	0.998	0.328	0.647	-0.319	0.002	0.274	0.598	-0.324	0.004
B-S	31.214	0.652	0.299	0.220	0.079	0.462	0.305	0.282	0.023	0.867
H-L	14.342	0.999	0.217	0.239	-0.022	0.869	0.339	0.341	-0.002	0.992
H-R	15.487	0.998	0.217	0.537	-0.320	0.002	0.257	0.606	-0.349	0.013
H-S	18.250	0.991	0.511	0.153	0.358	0.003	0.559	0.171	0.389	0.015
L-R	9.652	1.000	0.312	0.538	-0.226	0.037	0.242	0.698	-0.457	0.001
L-S	41.811	0.199	0.233	0.300	-0.066	0.673	0.200	0.453	-0.253	0.109
R-S	25.528	0.879	0.291	0.167	0.125	0.244	0.220	0.186	0.035	0.747
Average	20.495		0.308	0.385	-0.078		0.310	0.438	-0.128	

Notes: This table presents the statistics and p-values from two asymmetric tests. Given the number of banks $n = 5$, there are $n(n-1)/2 = 10$ different pairwise combinations of banks. "B", "H", "L", "R" and "S" denote Barclays, HSBC, Lloyds, RBS and Standard Charted, respectively. "HTZ" denotes the statistic from a model-free symmetry test proposed in (Hong et al., 2007) to examine whether the exceedance correlations between the 5-year weekly CDS spreads of different banks are asymmetric at all. "LUTD", "ULTD" and "Diff" denote the coefficients of lower-upper tail dependence and upper-lower tail dependence estimated by Student's t copula, and the difference between them for all the portfolios pairs. The estimations are calculated by both parametric and semiparametric approach in Patton (2012). The p-values from the tests that the low tail and upper tail dependence coefficients are computed with 500 bootstrap replications.

Table 5: Structural Break Test for Time-varying Dependence Structures

	0.15	0.5	0.85	Any	US	EU	QA
B-H	0.053	0.310	0.369	0.110	0.035	0.360	0.020
B-L	0.040	0.106	0.296	0.080	0.019	0.282	0.152
B-R	0.021	0.087	0.190	0.040	0.014	0.250	0.030
B-S	0.837	0.767	0.357	0.500	0.951	0.247	0.048
H-L	0.026	0.154	0.485	0.020	0.015	0.226	0.595
H-R	0.024	0.227	0.407	0.070	0.012	0.225	0.005
H-S	0.542	0.403	0.571	0.720	0.806	0.161	0.048
L-R	0.043	0.062	0.320	0.090	0.013	0.241	0.010
L-S	0.721	0.965	0.540	0.460	0.945	0.319	0.521
R-S	0.993	0.840	0.280	0.240	0.883	0.490	0.014

Notes: This table reports the p-values from tests for time-varying dependence between 5-year weekly CDS spreads changes of different banks. "B", "H", "L", "R" and "S" denote Barclays, HSBC, Lloyds, RBS and Standard Charted, respectively. Without *a priori* knowledge of breaking points, we consider using naïve tests for breaks at three chosen points in sample period, at $t^*/T \in \{0.15, 0.50, 0.85\}$, which corresponds to the dates 24-Oct-2008, 24-Jun-2011, 21-Feb-2014. The "Any" column reports the results of test for dependence break of unknown timing proposed by Andrews (1993). The p-values in column "QA" is based on a generalized break test without priori point in (Andrews and Ploberger, 1994). In order to detect whether the dependence structures between CDS spreads changes of different banks significantly changed after the US and EU crisis broke out, we use 15-Sep-2008 (the collapse of Lehman Brothers) and 01-Jan-2010 (EU sovereign debt crisis) as two break points in rank correlation and the "US" and "EU" panels report the results for this test. We use * and ** to indicate significance at the 5% and 1%, respectively.

Table 6: Full Parametric Dynamic Copula Parameter Estimation

	B-H	B-L	B-R	B-S	H-L	H-R	H-S	L-R	L-S	R-S	Joint
						A. GAS-Gaussian					
ω	0.377	0.410	0.401	0.290	0.376	0.389	0.262	0.367	0.268	0.301	0.347
α	0.058	0.070	0.058	0.136	0.068	0.043	0.149	0.190	0.175	0.225	0.117
β	0.852	0.857	0.860	0.838	0.849	0.843	0.877	0.878	0.851	0.826	0.854
log L	259	309	317	149	249	250	181	338	143	140	1238
						B. GAS-T					
ω	0.382	0.403	0.417	0.274	0.371	0.398	0.279	0.376	0.268	0.317	0.348
α	0.075	0.083	0.098	0.174	0.091	0.108	0.190	0.196	0.200	0.242	0.145
β	0.850	0.860	0.856	0.854	0.852	0.837	0.866	0.881	0.854	0.833	0.856
η^{-1}	0.215	0.200	0.186	0.168	0.201	0.200	0.166	0.178	0.211	0.166	0.189
log L	268	318	324	155	256	257	190	350	155	154	1296
						C. GAS-GHST					
ω	0.390	0.402	0.406	0.269	0.364	0.382	0.285	0.380	0.269	0.330	0.348
α	0.047	0.072	0.038	0.026	0.060	0.142	0.199	0.192	0.155	0.168	0.109
β	0.866	0.858	0.840	0.854	0.852	0.890	0.908	0.871	0.825	0.890	0.867
η^{-1}	0.210	0.200	0.185	0.164	0.192	0.190	0.168	0.177	0.192	0.165	0.184
λ	0.122	0.216	0.120	-0.043	0.105	0.117	-0.179	0.104	0.138	-0.119	0.127
log L	298	343	341	174	279	281	210	361	180	163	1412

Notes: This table reports parameter estimates for three different parametric dynamic copula models: Gaussian copula, Student's t copula and GHST copula. The sample period is from September 7, 2007 to April 17, 2015. ω, α and β denote the parameters of GAS model, η^{-1}denotes the inverse of degree of freedom of t and GHST copula, λ denotes the skewness parameter of GHST copula and log L denotes the log-likelihood of estimated copula model. The "Joint" column reports the estimates of parameters for five-dimensional copula models. Notice that we estimate this high-dimensional copula following the method described in Lucas et al. (2014).

Table 7: Semiparametric Dynamic Copula Parameter Estimation

	B-H	B-L	B-R	B-S	H-L	H-R	H-S	L-R	L-S	R-S	JOINT
					A. GAS-Gaussian						
ω	0.369	0.410	0.400	0.290	0.379	0.389	0.261	0.360	0.269	0.301	0.344
α	0.064	0.069	0.050	0.132	0.061	0.045	0.150	0.200	0.168	0.220	0.115
β	0.858	0.859	0.862	0.850	0.850	0.844	0.880	0.881	0.851	0.843	0.858
log L	255	310	312	150	248	247	183	329	140	144	1209
					B. GAS-T						
ω	0.376	0.404	0.428	0.282	0.375	0.401	0.279	0.376	0.268	0.310	0.350
α	0.072	0.087	0.098	0.180	0.088	0.105	0.190	0.194	0.196	0.250	0.146
β	0.855	0.862	0.859	0.849	0.852	0.841	0.870	0.875	0.854	0.837	0.855
η^{-1}	0.218	0.209	0.186	0.161	0.201	0.200	0.166	0.178	0.215	0.161	0.190
log L	266	321	326	155	252	254	186	342	150	148	1251
					C. GAS-GHST						
ω	0.390	0.396	0.410	0.281	0.364	0.373	0.284	0.380	0.274	0.320	0.348
α	0.090	0.073	0.039	0.199	0.069	0.194	0.199	0.192	0.155	0.166	0.137
β	0.860	0.857	0.858	0.841	0.851	0.836	0.851	0.875	0.852	0.886	0.857
η^{-1}	0.210	0.209	0.185	0.165	0.199	0.190	0.163	0.177	0.206	0.165	0.187
λ	0.119	0.177	0.141	-0.050	0.115	0.132	-0.198	0.100	0.141	-0.136	0.125
log L	296	351	340	171	282	287	208	358	183	168	1390

Notes: This table reports parameter estimates for three different semiparametric dynamic copula models: Gaussian copula, Student's t copula and GHST copula. The sample period is from September 7, 2007 to April 17, 2015. ω, α and β denote the parameters of GAS model, η^{-1}denotes the inverse of degree of freedom of t and GHST copula, λ denotes the skewness parameter of GHST copula and log L denotes the log-likelihood of estimated copula model. The "Joint" column reports the estimates of parameters for five-dimensional copula models. Notice that we estimate this high-dimensional copula following the method described in Lucas et al. (2014).

Table 8: Log-Likelihood, AIC and BIC for Model Comparisons

Portfolios	B-H	B-L	B-R	B-S	H-L	H-R	H-S	L-R	L-S	R-S	JOINT
					A. Log-Likelihood						
Gaussian	259	309	317	149	249	250	181	338	143	140	1238
GAS-T	268	318	324	155	256	257	190	350	155	154	1296
GAS-GHST	298	343	341	174	279	281	210	361	180	163	1412
LR test	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
					B. Akaike Information Criterion (AIC)						
Gaussian	-509	-610	-626	-290	-490	-493	-354	-668	-277	-272	-2449
GAS-T	-527	-627	-638	-300	-503	-505	-369	-690	-299	-298	-2565
GAS-GHST	-584	-674	-670	-335	-545	-550	-408	-710	-348	-315	-2793
					C. Bayesian Information Criterion (BIC)						
Gaussian	-493	-594	-610	-274	-475	-477	-338	-652	-261	-256	-2398
GAS-T	-507	-607	-618	-280	-483	-485	-349	-670	-279	-279	-2509
GAS-GHST	-560	-650	-646	-311	-521	-526	-384	-686	-324	-291	-2733

Notes: This table presents the results of model comparison via statistical criteria. Panel A reports the log-likelihood from three GAS based copula models: Gaussian, Student's t and GHST. The bottom row of Panel A shows the p-values of likelihood ratio test for Student's t and GHST copula models. Panel B and C report the values of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for different model specifications, respectively.

Table 9: Joint Default Probability and Dependence

A. Contemporaneous Relationship

	POLS	FE	RE
Corr	0.110***	0.125**	0.124***
	(0.005)	(0.046)	(0.045)
Cons	-0.052***	-0.064	-0.063*
	(0.004)	(0.038)	(0.036)
R^2	0.145	0.145	0.145
T-test	[0.000]	[0.004]	[0.003]
F-test	[0.000]		
Hausman		[0.409]	

B. Predictability

	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)
Corr(-1)	0.121***	0.118***	0.115***	0.110**	0.106**
	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)
Cons	-0.061*	-0.058*	-0.056	-0.052	-0.048
	(0.036)	(0.035)	(0.035)	(0.035)	(0.034)
R^2	0.143	0.141	0.139	0.135	0.131
T-test	[0.004]	[0.004]	[0.005]	[0.007]	[0.008]

Notes: This table reports the regression analysis of the impact of dependence (copula correlation) on the joint default probability. We estimate the average dependence and average joint default probability by taking average of correlations and joint default probabilities estimated from six time-varying copula models (parametric and semiparametric Gaussian, Student's t and GHST copulas). In Panel A, we regress the joint default probability on the correlation in Equation (9). We consider three panel data estimators; pooled OLS (POLS), fixed effects (FE), and random effects (RE), and choose a consistent and efficient estimator. We test the existence of fixed effects by F-test and apply Hausman approach to test if regressors are correlated with the fixed effects. T-test tests the null of $\beta = 0$ against $\beta > 0$. In Panel B, we regress the joint default probability on the lagged correlation in Equation (10). We estimate regression equations by one selected from Panel A. In both panels, $[\cdot]$ reports the p-value of the test and $(\cdot)$ reports the standard error of the estimate, respectively. We use *, ** and *** to indicate the significance levels at 10%, 5% and 1%.

Table 10: Conditional Default Probability and Dependence

A. Contemporaneous Relationship

	POLS		FE		RE
Corr	0.669***		0.848***		0.846***
	(0.011)		(0.159)		(0.158)
Cons	-0.194***		-0.340**		-0.337***
	(0.009)		(0.131)		(0.127)
R^2	0.236		0.236		0.236
T-test	[0.000]		[0.000]		[0.000]
F-test		[0.000]			
Hausman				[0.160]	

B. Predictability

	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)
Corr	0.816***	0.786***	0.754***	0.720***	0.685***
	(0.158)	(0.157)	(0.157)	(0.156)	(0.155)
Cons	-0.312**	-0.288**	-0.261**	-0.233*	-0.205*
	(0.126)	(0.126)	(0.126)	(0.125)	(0.124)
R^2	0.228	0.220	0.211	0.203	0.194
T-test	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: This table reports the regression analysis of the impact of dependence (copula correlation) on the conditional default probability of bank i given the default of bank j. We estimate the average dependence and average conditional default probability by taking average of correlations and conditional default probabilities estimated from six time-varying copula models (parametric and semiparametric Gaussian, Student's t and GHST copulas). In Panel A, we regress the conditional default probability on the correlation in Equation (11). We consider three panel data estimators; pooled OLS (POLS), fixed effects (FE), and random effects (RE), and choose a consistent and efficient estimator. We test the existence of fixed effects by F-test and apply Hausman approach to test if regressors are correlated with the fixed effects. T-test tests the null of $\beta = 0$ against $\beta > 0$. In Panel B, we regress the conditional default probability on the lagged correlation in Equation (12). We estimate regression equations by one selected from Panel A. In both panels, $[\cdot]$ reports the p-value of the test and $(\cdot)$ reports the standard error of the estimate, respectively. We use *, ** and *** to indicate the significance levels at 10%, 5% and 1%.

Table 11: Joint Default Probability and Asymmetry

A. Contemporaneous Relationship

	POLS	FE	RE
LTD	0.022***	0.020	0.054***
	(0.003)	(0.054)	(0.011)
UTD	0.049***	0.174*	0.118***
	(0.002)	(0.087)	(0.010)
Cons	0.013	-0.035	-0.023
	(0.001)	(0.028)	(0.004)
R^2	0.125	0.121	0.125
T-test (LTD)	[0.000]	[0.361]	[0.000]
T-test (UTD)	[0.000]	[0.038]	[0.000]
F-test	[0.000]		
Hausman		[0.000]	

B. Predictability

	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)
LTD	0.013	0.010	0.008	0.009	0.008
	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)
UTD	0.177**	0.176*	0.174*	0.165*	0.160*
	(0.088)	(0.090)	(0.090)	(0.092)	(0.092)
Cons	-0.034	0.090	-0.031	-0.028	-0.026
	(0.028)	(-0.033)	(0.028)	(0.029)	(0.029)
R^2	0.119	0.118	0.118	0.117	0.116
T-test (LTD)	[0.403]	[0.427]	[0.442]	[0.433]	[0.437]
T-test (UTD)	[0.022]	[0.025]	[0.026]	[0.036]	[0.041]

Notes: This table reports the regression analysis of the impact of tail dependence on the joint default probability. We estimate the bivariate dynamic GHST copula models across all possible pairs of banks. For each pair, we compute average tail dependence by taking average of parametric and semiparametric tail dependence coefficients. The average joint default probability is computed by taking average of joint default probabilities estimated from six time-varying copula models (parametric and semiparametric Gaussian, Student's t and GHST copulas). In Panel A, we regress the joint default probability on the lower tail dependence (LTD) and the upper tail dependences (UTD) in Equation (13). We consider three panel data estimators; pooled OLS (POLS), fixed effects (FE), and random effects (RE), and choose a consistent and efficient estimator. We test the existence of fixed effects by F-test and apply Hausman approach to test if regressors are correlated with the fixed effects. T-test (LTD) (T-test (UTD)) tests the null of $\beta^{LL} = 0$ against $\beta^{LL} > 0$ ($\beta^{UU} = 0$ against $\beta^{UU} > 0$). In Panel B, we regress the joint default probability on the lagged tail dependences in Equation (16). We estimate regression equations by one selected from Panel A. In both panels, $[\cdot]$ reports the p-value of the test and $(\cdot)$ reports the standard error of the estimate, respectively. We use *, ** and *** to indicate the significance levels at 10%, 5% and 1%.

Table 12: Conditional Default Probability and Asymmetry

A. Contemporaneous Relationship

	POLS	FE	RE
LTD	0.269***	0.506***	0.532***
	(0.011)	(0.152)	(0.143)
UTD	0.216***	0.639***	0.592***
	(0.008)	(0.159)	(0.138)
Cons	0.190***	-0.045	-0.032
	(0.004)	(0.062)	(0.061)
R^2	0.179	0.174	0.177
t-test (LTD)	[0.000]	[0.002]	[0.000]
t-test (UTD)	[0.000]	[0.001]	[0.000]
F-test	[0.000]		
Hausman		[0.000]	

B. Predictability

	Lag(1)	Lag(2)	Lag(3)	Lag(4)	Lag(5)
LTD	0.477***	0.460***	0.446***	0.438***	0.422***
	(0.153)	(0.154)	(0.150)	(0.149)	(0.143)
UTD	0.630***	0.610***	0.588***	0.557***	0.534***
	(0.162)	(0.168)	(0.171)	(0.179)	(0.177)
Cons	-0.032	-0.019	-0.006	0.009	0.022
	(0.062)	(0.063)	(0.064)	(0.065)	(0.065)
R^2	0.170	0.166	0.162	0.159	0.156
t-test (LTD)	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
t-test (UTD)	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]

Notes: This table reports the regression analysis of the impact of tail dependence on the conditional default probability. We estimate the bivariate dynamic GHST copula models across all possible pairs of banks. For each pair, we compute average tail dependence by taking average of parametric and semiparametric tail dependence coefficients. The average conditional default probability is computed by taking average of conditional default probabilities estimated from six time-varying copula models (parametric and semiparametric Gaussian, Student's t and GHST copulas). In Panel A, we regress the conditional default probability on the lower tail dependence (LTD) and the upper tail dependences (UTD) in Equation (17). We consider three panel data estimators; pooled OLS (POLS), fixed effects (FE), and random effects (RE), and choose a consistent and efficient estimator. We test the existence of fixed effects by F-test and apply Hausman approach to test if regressors are correlated with the fixed effects. T-test (LTD) (T-test (UTD)) tests the null of $\beta^{LL} = 0$ against $\beta^{LL} > 0$ ($\beta^{UU} = 0$ against $\beta^{UU} > 0$). In Panel B, we regress the conditional default probability on the lagged tail dependences in Equation (18). We estimate regression equations by one selected from Panel A. In both panels, $[\cdot]$ reports the p-value of the test and $(\cdot)$ reports the standard error of the estimate, respectively. We use *, ** and *** to indicate the significance levels at 10%, 5% and 1%.