The joint credit risk of UK global-systemically important banks*

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Abstract

We study the joint credit risk in the UK banking sector using the weekly CDS spreads of global systemically important banks over 2007-2015. We show that the time-varying and asymmetric dependence structure of the CDS spread changes is closely related to the joint default probability that two or more banks simultaneously default. We are able to flexibly measure the joint credit risk at the high-frequency level by applying the combination of the reduced-form model and the GAS-based dynamic asymmetric copula model to the CDS spreads. We also verify that much of the dependence structure of the CDS spread changes are driven by the market factors. Overall, our study demonstrates that the market factors are key inputs for the effective management of the systemic credit risk in the banking sector.

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1 Introduction

The financial crisis of 2007–2008 and EU sovereign debt crisis have caused great concern about the credit risk of large financial institutions and sovereign entities. Both central banks and financial authorities have paid much more attention to the supervision of the credit risk in the large financial institutions since then (see the series of reports by Basel Committee on Banking Supervision, 2011, 2012; Bank of England, 2013, 2015) and several studies have recently focused on the credit risk of banks in the US, EU and Asia (see Dieckmann and Plank, 2012; Huang et al, 2012; Acharya et al., 2014, among others). Moreover, the UK voted for Brexit in 2016, which amplified uncertainty about the UK financial market as well as the global financial market. Since the UK has significant trade and financial linkages with the Euro-zone countries and London is one of World finance centres, banking activities in the UK and their default probabilities are not only important for the regional financial markets but also for the international financial markets. Therefore, studying the systemic credit risk in the UK banking sector at this point will provide important implications for policy makers and investors to decide how to cope with the coming financial shock from a hard Brexit.

Recent empirical studies show that estimating the joint default probability plays an important role in banking supervision (see Pianeti et al., 2012; Erlenmaier and Gersbach, 2014). This is because it can be viewed as an efficient measure of systemic risk, as the systemic default arises from the simultaneous defaults of multiple large banks. From the perspective of practitioners, modeling the joint default probability is also of great interest for credit risk management. For these reasons, it is essential to study how the credit risk of banks are contemporaneously correlated each other and how their correlation are varying over time. It will help the risk managers of banks to get a deeper understanding of the credit risk in the banking sector and properly model it by considering various market scenarios such as joint or conditional default.

In this paper, we employ a reduced-form model taking advantage of the CDS spread among several methods for estimating the default probability (see Hull and White, 2000; O'Kane and Turnbull, 2003). This is because the CDS spread is a good proxy for the credit risk of bank and contains market information which plays an important role in predicting future credit quality (see Bank of England, 2007; European Central Bank, 2007). Therefore, all our analyses are performed using the CDS spreads. What we intend in this paper are as follows: First, we introduce a method of modeling the joint credit risk of banks using the CDS spreads of the UK G-SIBs. The most important part here is the dependence structure between the CDS spreads of banks. Thus we conduct intensive research on this part. Second, we propose a time-varying asymmetric copula to model the dependence structure of the CDS spreads.[1] This copula combines the generalized hyperbolic skewed t copula (hereafter GHST) with the generalized autoregressive score (hereafter GAS) model. The GHST copula is popular in many empirical finance studies for modeling the asymmetric dependence (see Demarta and McNeil, 2005; Smith et al, 2012; Christoffersen et al., 2012), and the GAS model has recently been developed to model the time-varying dependence, which is increasingly popular in many empirical finance studies due to its attractive econometric properties (see Creal et al., 2013, 2014a; Janus et al, 2014; Lucas et al., 2014; Salvatierra and Patton, 2015). Third, we attempt an economic analysis of what drives the dynamics of the joint credit risk in the banking sector. We will focus on identifying the drivers of the CDS spreads comovement, motivated by the fact that the dynamics of the joint credit risk are closely related to the comovement of the CDS spreads. In particular, we use an economic factor model incorporating market factors to conduct further analysis on the drivers of the CDS spreads comovement.

We make two notable contributions to the literature on credit risk in the banking sector: First, we find the dependence structure of the CDS spread changes of UK G-SIBs is asymmetric and time-varying over time. This is closely related to measuring the systemic credit risk of banks such as the joint default probability. In particular, we demonstrate that the combination of the reduced-form model and the time-varying asymmetric copula can simply and flexibly measure the systemic credit risk using banks' CDS spreads. Unlike many other methods, our proposed method can not only incorporate market information properly but also more accurately model the dynamics of joint credit risk in the high-frequency level. Second, through a factor model based analysis of the comovement of the CDS spreads, we identify economic channels that generate the dependence structure of the CDS spread changes. So far, there have been many studies on the market factors as the determinants of individual CDS spreads (e.g. Longstaff and Schwartz, 1995; Collin-Dufresne et al., 2001; Ericsson et al., 2009; Liu and Zhang, 2008; Cooper and Priestley, 2011; Galil et al., 2014), but there are few studies on how the market factors are related to the joint credit risk of banks. Our analysis shows that the market factors can account for more than 60% of the correlation of the CDS spread changes; thereby, they are closely related to the joint credit risk. Another important finding is that the time-varying and asymmetric dependence of the CDS spread changes is mostly driven by the market factors.

The empirical results for the joint credit risk of the UK G-SIBs found in our study provide important

[1] See Oh and Patton (2016), they have recently studied the dependence structure of corporate CDS spreads using the factor copula model.

policy implications for the Bank of England (hereafter BoE) to supervise the systemic credit risk in the banking sector. First, our study suggests that the stability of the systemic credit risk should be secured by reducing the exposure of bank's credit risk to market. Second, the asymmetric dependence structure between banks' CDS spread changes suggests that the systemic credit risk becomes even more serious in the regime of market downturn. Therefore, the central bank should keep monitoring the comovement between the CDS spreads of banks and the market factors for the effective credit risk management.

The remainder of this paper is organized as follows. Section 2 details the way how we compute the joint default probability of the UK G-SIBs. Section 3 presents the empirical study on the joint credit risk of the UK G-SIBs using the dataset of weekly corporate CDS spreads. Section 4 further studies on the drivers of the joint credit risk based on a factor model analysis with various market factors. Section 5 concludes.

2 Modeling joint credit risk

In this section, we detail how we compute the joint default probability. First, we calibrate a marginal default probability for an individual bank. We then find a corresponding value of the CDS spread change to the calibrated default probability from its marginal probability distribution.[2] Hence, it is a threshold to determine the default of the individual bank. Second, we model the marginal probability distribution of the CDS spread change for each bank considering its distributional characteristics. Third, we model a dependence structure of banks' CDS spread changes which is a key input for constructing a joint probability distribution. Finally, we apply a Monte Carlo simulation to computing the joint default probability.

It is convenient to define the joint default probabilities mathematically before introducing each step in detail. Given the marginal default probability, $p_{i,t}$, of bank i at time t, we define the joint default probability that two or more banks simultaneously default out of n banks:

$$\begin{aligned} p_t = 1 - &\underbrace{\mathbb{P}\left[\bigcap_{i=1}^{n}\left\{z_{i,t} \le F_{i,t}^{-1}\left(1-p_{i,t}\right)\right\}\right]}_{(A)} \\ &- \underbrace{\sum_{k=1}^{n}\mathbb{P}\left[\left(\bigcap_{i=1, i\neq k}^{n}\left\{z_{i,t} \le F_{i,t}^{-1}\left(1-p_{i,t}\right)\right\}\right)\bigcap\left\{z_{k,t} > F_{k,t}^{-1}\left(1-p_{k,t}\right)\right\}\right]}_{(B)} \end{aligned} \tag{1}$$

[2] We measure the CDS spread change by the first-difference of the log CDS spread. It is not an asset return but the change of credit risk in the bank.

where $z_{i,t}$ denotes the filtered CDS spread change of bank i at time t and $F_{i,t}^{-1}(\cdot)$ denotes its inverse cumulative distribution function. The first term (A) refers to the probability that no bank will default, and (B) refers to the probability that only one bank will default.

2.1 Calibrating marginal default probability

It is essential to obtain a reliable default probability of a single reference entity. A number of statistical and econometric models have been proposed to obtain the term structure of default probabilities 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 by Merton (1974); (iii) Reduced-form models. In our study, we consider using the reduced-form model based on a bootstrapping method proposed by Hull and White (2000) and O'Kane and Turnbull (2003) to calculate a risk neutral default probability for each bank using CDS market quotes.[3]

Reasons for choosing this method are as follows: First, the rating information provided by the rating agencies cannot catch the speed of the market movement. Whereas, the market information used in the approach of Hull and White (2000) can reflect well the market agreed anticipation of evolution for the future credit quality. Second, although the credit rating agencies such as Moody's regularly publish short-term and long-term credit ratings for firms, these rating information normally lacks granularity. Unlike the information provided by the rating 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 can imply the full term structure of default probability. Finally, the bootstrapping procedure is a standard method for marking CDS positions to the market and has been widely used by the overwhelming majority of credit derivative trading desks in financial practice (see Li, 2000; 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; Lucas et al., 2014).

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

$$F_i(t) = \mathbb{P}(\tau \le t) = 1 - \mathbb{P}(\tau > t) = 1 - Q_i(t), \tag{2}$$

[3]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 volatility, see Campbell and Taksler (2003).

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 $\lambda(t)$

$$Q_i(t) = \exp\left[-\int_t^{t_n} \lambda(s)ds\right]. \tag{3}$$

See Appendix A for the detailed explanation on the hazard rate function.

In practice, we use the approximation of survival function (3) for the reference entity to time T conditional on surviving to time t, defined by

$$Q_i(t,T) = \begin{cases} \exp\left(-\lambda_{0,1}(\tau)\right) & \text{if } 0 < \tau < 1 \\ \exp\left(-\lambda_{0,1}, -\lambda_{1,3}(\tau-1)\right) & \text{if } 1 < \tau < 3 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - \lambda_{3,5}(\tau-3)\right) & \text{if } 3 < \tau < 5 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - 2\lambda_{3,5} - \lambda_{5,7}(\tau-5)\right) & \text{if } 5 < \tau < 7 \\ \exp\left(-\lambda_{0,1}, -2\lambda_{1,3} - 2\lambda_{3,5} - 2\lambda_{5,7} - \lambda_{7,10}(\tau-7)\right) & \text{if } \tau > 7 \end{cases} \tag{4}$$

where $\tau = T - t$ is the survival time and λ_{t_0,t_n} denotes the hazard rate from time t_0 to t_n. Given the market quotes of the CDS spread, $S_1, \ldots, S_N$, at dates $t_1, \ldots, t_N$, we can calibrate the hazard rate and calculate the default probability by inverting the CDS pricing formula in (A.9). See Appendx B and C for the details. We construct a term structure of survival probability for a set of maturity dates using the bootstrap algorithm[4] proposed by Hull and White (2000), O'Kane and Turnbull (2003) and O'Kane (2008). A detailed bootstrapping algorithm is provided in Appendix D.

2.2 Modeling CDS spread changes

Next, we need to model the CDS spread change. We model not only the univariate distribution for each bank but also the joint one.

First, we need the filtered CDS spread changes for each bank to compute the default probabilities in (1). To this end we model the individual CDS spread changes, $\Delta CDS_{i,t}$, by ARMA-GJR-GARCH (Glosten et

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

al., 1993) and obtain the filtered ones,

$$z_{i,t} = \frac{\Delta CDS_{i,t} - \mu_{i,t}}{\sigma_{i,t}},\ i = 1,\ldots,n,\ t = 1,\ldots,T, \tag{5}$$

where the conditional mean ($\mu_{i,t}$) is modeled by ARMA(p,q)[5],

$$\Delta CDS_{i,t} = c_i + \epsilon_{i,t} + \sum_{j=1}^{p} \varphi_{ij} \Delta CDS_{i,t-j} + \sum_{j=1}^{q} \theta_{ij} \epsilon_{i,t-j},\ \epsilon_{i,t} = \sigma_{i,t} z_{i,t}, \tag{6}$$

and the conditional volatility ($\sigma_{i,t}$) by GJR-GARCH(p,p,q),

$$\sigma_{i,t}^2 = w_i + \sum_{j=1}^{p} \alpha_{ij} \epsilon_{i,t-j}^2 + \sum_{j=1}^{p} \delta_{ij} \epsilon_{i,t-j}^2 I_{i,t-1} + \sum_{j=1}^{q} \beta_{ij} \sigma_{i,t-j}^2, \tag{7}$$

where $I_{i,t-1} = 1$ if $\epsilon_{i,t-1} \geq 0$ and $I_{i,t-1} = 0$ if $\epsilon_{i,t-1} < 0$. We assume that $z_{i,t}$ follows the univariate skewed t distribution of Hansen (1994),

$$z_{i,t} \sim SkT(\upsilon, \eta), \tag{8}$$

where υ denotes a degrees of freedom and η skewness parameter.[6]

Second, given the modeling of the 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 the credit risk modeling and pricing. Various approaches have been proposed to model the correlated defaults and those 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 modeling of the marginal probability distribution. 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]

[5] 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).

[6] We use the skewed t distribution of Hansen (1994) for a parametric copula modeling and an empirical distribution for a semiparametric copula modeling. See Appendix of Cerrato et al. (2016) for the details of parametric and semiparametric copula modeling.

[7] Before the financial crisis of 2007-2008, 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 the Gaussian copula was one of the major reasons triggering to this crisis, see for

There are two notable features of the default correlation. Substantial evidences have been found to show that the default correlation is non-Gaussian, see for instance, Christoffersen et al. (2016). Another important feature is the time variation of the default correlation. It changes over time as firms' credit quality is varying over time. 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 CDS spread changes for the UK G-SIBs in our study. We test for the asymmetry of tail dependence (Patton, 2012). We also test for the time-varying nature of dependence structure of CDS spread changes using structural break tests in Patton (2012). There are the striking evidences of breaks around the 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. We therefore select a dynamic asymmetric copula for modeling the dependence structure of CDS spread changes.

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). For $\mathbf{z} = (z_{1,t}, \ldots, z_{n,t})'$, the GHST copula is given by

$$c_{skt}\left(\mathbf{z}; \upsilon, \eta, \Sigma_t\right) = \frac{2^{(\upsilon-2)(n-1)/2} K_{(\upsilon+n)/2}\left(\sqrt{\left(\upsilon + \mathbf{z}^{*\prime}\Sigma_t^{-1}\mathbf{z}^*\right)\eta'\Sigma_t^{-1}\eta}\right) e^{\mathbf{z}^{*\prime}\Sigma_t^{-1}\eta}}{\Gamma\left(\upsilon/2\right)|\Sigma|^{1/2}\left(\upsilon + \mathbf{z}^{*\prime}\Sigma_t^{-1}\mathbf{z}^*\right)^{(-\upsilon+n)/2}\left(1 + \upsilon^{-1}\mathbf{z}^{*\prime}\Sigma_t^{-1}\mathbf{z}^*\right)^{(-\upsilon+n)/2}}$$
$$\times \prod_{i=1}^{n} \frac{\left(\sqrt{\left(\upsilon + z_i^{*2}\right)\eta_i^2}\right)^{-(\upsilon+1)/2}\left(1 + \upsilon^{-1}(z_i^*)^2\right)^{(\upsilon+1)/2}}{K_{(\upsilon+1)/2}\left(\sqrt{\left(\upsilon + (z_i^*)^2\right)\eta_i^2}\right) e^{z_i^*\eta_i}} \tag{9}$$

where K, υ and η denote the modified Basel function of the third kind, the degree of freedom and the skewed parameter vector, respectively. $z_{i,t}^* \in \mathbf{z}^*$ is defined as $z_{i,t}^* = SkT^{-1}\left(u_{i,t}\right) = SkT^{-1}\left(SkT(z_{i,t}; \upsilon, \eta_i)\right)$, where SkT^{-1} is the inverse skewed Student's t distribution. Σ_t is the time-varying covariance matrix such that $\Sigma_t = D_t R_t D_t$, where D_t is an identity matrix in the copula modeling and R_t is the time-varying correlation matrix. 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 dependence structure is estimated by the generalized autoregressive score (GAS) model of Creal et al. (2013) and Lucas et al. (2014). The correlation parameter $\gamma_{i,j,t}$ of R_t should be

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).

in the range of $(-1,1)$, so we transform it, following Patton (2012), and the transformed one is denoted by $g_{i,j,t}$:

$$g_{i,j,t} = h\left(\gamma_{i,j,t}\right) \Leftrightarrow \gamma_{i,j,t} = h^{-1}\left(g_{i,j,t}\right), \tag{10}$$

where $\gamma_{i,j,t} = \left(1-e^{-g_{i,j,t}}\right) / \left(1+e^{-g_{i,j,t}}\right)$. Then the updating mechanism of the transformed correlation vector $\mathbf{g}_t$ is given by a function of a constant $\mathbf{w}$, the lagged $\mathbf{g}_t$, and the standardized score of the copula log-likelihood $Q_t^{-1/2}\mathbf{s}_t$:

$$\mathbf{g}_{t+1} = \mathbf{w} + \Pi Q_t^{-1/2}\mathbf{s}_t + \Lambda \mathbf{g}_t, \tag{11}$$

where $\mathbf{s}_t \equiv \partial \log c\left(u_{1,t},\ldots,u_{n,t};\gamma_t\right)/\partial\gamma_t$ and $Q_t \equiv \mathbb{E}_{t-1}\left[\mathbf{s}_t\mathbf{s}_t'\right]$. Cerrato et al. (2016) demonstrate the importance of modeling the dynamic and asymmetric dependence of equity portfolio using the GAS GHST copula in the market risk management.

2.3 Computing algorithm for joint default probability

As the final step of our proposed approach, we introduce a practical algorithm showing how we compute the joint default probability using a Monte Carlo simulation method. The procedure is as follows: First, we obtain the marginal default probabilities for each bank from the bootstrap based calibration procedure. We also estimate a copula correlation at time t by $\bar{\gamma}_{i,j,t} = \left(\gamma^P_{i,j,t} + \gamma^S_{i,j,t}\right)/2$, where $\gamma^P_{i,j,t}$ and $\gamma^S_{i,j,t}$ denote copula correlations implied by the GAS-based parametric and semiparametric copula model, respectively. Second, given the copula correlation and other parameters[8], we simulate B random vectors $\mathbf{z}^s_t = \left(z^s_{1,t},\ldots,z^s_{n,t}\right)$ 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 calculated by counting a case that two or more banks default from B simulations.

3 Empirical analysis of joint credit risk

In this section, we study the joint credit risk of the UK G-SIBs using their weekly corporate CDS spreads. First, we investigate the distributional stylized facts of the CDS spread change and search for the best univariate model for the individual CDS spread change. On the other hand, we calibrate a marginal default probability implied by the CDS pricing formula for the purpose of computing the joint probabilities. Next, we investigate the time-varying asymmetric dependence structure of the CDS spread changes using formal

[8]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.

statistical tests. This investigation provides useful information on the choice of multivariate model for computing the joint default probability. Finally, we estimate the joint default probabilities.

3.1 Data and descriptive analysis

We use a dataset of weekly corporate CDS spreads for five UK G-SIBs with a 5-year maturity. In this paper, we are interested in analysing the joint credit risk at the high-frequency level. However, daily CDS data usually suffers from the 'scanty' problem; e.g. Zhu (2006, see footnote 6) reports that valid daily quotes represent only 20% of the days in his sample. Consequently, we choose weekly CDS data as the most reliable high-frequency data. The reason for choosing the 5-year maturity among the various maturities is because it is the most liquid CDS contract in the market and the best representative of the entire CDS market owing to its largest market share.[9] The UK G-SIBs include Barclays, HSBC Holdings (hereafter HSBC), Lloyds Banking Group (hereafter Lloyds), Royal Bank of Scotland Group (hereafter RBS) and Standard Chartered (hereafter Standard).[10] 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 term-structure of the marginal default probability. Our data covers the period from September 7, 2007 to April 17, 2015.[11]

Table I reports the Augmented Dickey-Fuller (ADF) test for unit root for the log CDS spreads. All the log CDS spreads and their equal-weighted average are verified to be nonstationary. Thus we use the first-difference of the log CDS spreads rather than the level ones in our modeling. This table also reports descriptive statistics and time-series tests for the CDS spread changes.[12] The non-zero skewness and large value of kurtosis clearly indicate the non-Gaussian features of the CDS spread changes. Autocorrelation coefficient and ARCH LM test for residuals obtained from AR(1) regression indicate the necessity for modeling the conditional mean and volatility of the CDS spread change.

[INSERT TABLE I ABOUT HERE]

Table II reports the linear correlation coefficients of the CDS spread changes across banks. It indicates

[9] However, we use all the available maturities (1-year, 2-year, 3-year, 4-year, 5-year and 7-year) for calibrating the term-structure of the marginal default probability due to the nature of the reduced-form model.

[10] 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).

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

[12] Without loss of generality, the CDS spread changes denote the first-difference of the log CDS spreads in our paper.

that banks' CDS spread changes are highly correlated with each other. It is worth noting that the correlations of Standard Chartered with other banks are clearly lower than those between other four banks. This is possibly because Standard Chartered does not have a retail banking business in the UK, and about 90% of its profit comes from Asian, African and the Middle Eastern markets according to its annual report in 2013. Although HSBC and Barclays are also multinational banking and financial services companies, the UK market is still targeted as their home market.

[INSERT TABLE II ABOUT HERE]

Figure 1 plots the average CDS spreads, formed by the equal-weighted average of five CDS spreads, and the conditional volatility of the average CDS spread changes. Panel A illustrates the trend of the average CDS spreads 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 the skyrocketing of CDS spreads. For instance, after the S&P downgrades US sovereign debt, the average of CDS spreads goes up to 285 in November 2011. Panel B plots the conditional volatility of the average CDS spread changes estimated by GJR-GARCH. First, this shows that the CDS spread changes are extraordinarily volatile during the financial crisis in 2008-2009. Second, it also indicates that the turbulence of the CDS spread changes in the UK G-SIBs 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 one during the crisis even when the average CDS spreads increased sharply after the S&P downgraded US government debt in August 2011. This may indicate that the CDS spreads largely fluctuate during the global financial crisis due to the high market uncertainty. Therefore, we can infer from these two figures that market factors play important roles in determining the dynamics of the CDS spreads.

[INSERT FIGURE 1 ABOUT HERE]

Table III presents the parameter estimation and the goodness-of-fit tests of univariate model for each bank. The univariate model is specified by ARMA for the conditional mean, GJR-GARCH for the conditional volatility and the skewed *t* distribution for the standardized residuals. First, we model the 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 ARMA(1,1) is the best candidate for all the banks except Standard Chartered for which AR(1) is the best candidate. Second, the conditional volatility is implied by the GARCH family. We experiment with ARCH, GARCH and GJR-GARCH up to order (2,2) and choose the best model corresponding to a minimum BIC. It indicates that GJR-GARCH(1,1,1) provides the best fit. All the leverage parameters of the GJR-GARCH(1,1,1) model are negative indicating the asymmetric volatility clustering, i.e., the large positive changes of the CDS spread are more likely to be clustered than the negative changes. This is consistent with the fact that the CDS spread increases sharply and continuously during the recent financial crisis of 2007–2009. The bottom of Table III reports *p*-values of the Kolmogorov-Smirnov and Cramer-von Mises goodness-of-fit tests for the modeling of the standardised residuals by the skewed Student's *t* distribution. The *p*-values are obtained using the bootstrap in Patton (2012). All the *p*-values are clearly greater than 0.05, so we fail to reject the null hypothesis that the standardised residuals are well-specified by the skewed *t* distribution of Hansen (1994).

[INSERT TABLE III ABOUT HERE]

3.2 Calibrating marginal default probability

We calibrate the reduced-from model using the market quotes of the CDS contracts with different maturities (1-year, 2-year, 3-year, 4-year, 5-year and 7-year) at each time t, and bootstrap the term structure of the marginal default probability following the procedure proposed by Hull and White (2000) and O'Kane and Turnbull (2003). This mark-to-market default probability of individual bank is derived from the observed CDS spread by inverting the CDS formula. Specifically, we use LIBOR rates with different maturities as discount factors and assume that the recovery rate is 40% suggested by O'Kane and Turnbull (2003). Following the recent literature, such as Huang et al (2009), Black et al. (2013), Creal et al. (2014b) and Lucas et al. (2014), we don't consider counter-party default risk. Given the assumption above, we are able to obtain the intensity of default using the bootstrap algorithm in the Appendix 5. Given the default intensity, we are also able to compute the default probabilities for different maturities as the default probability is just the function of default intensity. Note that in this case the default probability we obtain is the risk neutral one 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 explanation in Appendix B.

Figure 2 plots risk neutral default probabilities implied directly from the market quotes of the CDS contracts. The market-implied default probabilities significantly rise after the bankruptcy of Lehman Brothers and the downgrade of US sovereign debt. After May 2012, they decline dramatically and remained at a low level in the last two years. Since the default probabilities are directly implied from the CDS spreads, it is not surprising that they exhibit the dynamic patterns which are similar to the CDS spreads. Therefore, the market factors are likely to play important roles in determining the default probability.

[INSERT FIGURE 2 ABOUT HERE]

3.3 Asymmetric dependence between CDS spread changes

While asymmetric dependences 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. We fill this gap and investigate whether the dependence structure among the CDS spread changes is asymmetric or not. We test for the presence of the asymmetry by a tail dependence-based test described in Patton (2012).

Table IV reports the test results for the asymmetric dependence between the CDS spread changes. Given the five banks, there are ten different pairwise combinations of two banks. Panel A presents the estimates of lower and upper tail dependence coefficients for the filtered CDS spread changes based on the full parametric copula model. It also reports bootstrap based p-values for the test for the null hypothesis that the dependence structure is symmetric (i.e. the upper and lower tail dependence coefficients are equal). Half of pairs are rejected at the 5% significance level, verifying the statistical significance of the asymmetric tail dependence of the CDS spread changes. Interestingly, different from other asset returns which exhibit a greater correlation during the market downturn than the market upturn, the CDS spread changes have the higher upper tail dependence than the lower tail dependence. This may be explained by the nature of the 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 the CDS spreads may be due to the asymmetric reaction of the CDS spreads to negative and positive market news. The CDS spread normally incorporates negative news much faster than positive news, see for instance Lehnert and Neske (2006). Thus, when the credit market was deteriorated sharply during the crisis, firm's CDS spreads (insurance cost) tend to increase rapidly. Panel B presents the estimates of lower and upper tail dependence coefficients based on the semiparametric copula model and the results also confirm the presence of the asymmetric dependence between the CDS spread changes.

[INSERT TABLE IV ABOUT HERE]

3.4 Time-varying dependence between CDS spread changes

Several analyses have shown that the CDS spreads and the marginal default probabilities of individual banks are influenced by market news and that they comove over time. This makes us infer that the dependence structure of the CDS spread changes is time-varying over 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 points in the sample period, see (see Patton, 2012); (ii) A test for unknown break points in the rank correlation (see Andrews, 1993); (iii) A generalized break test without *a priori* point (see Andrews and Ploberger, 1994).

We implement these tests for the time-varying dependence using the filtered CDS spread changes. The test results are reported in Table V. Firstly, without *a priori* knowledge of breaking points, we consider using naïve tests for breaks at arbitrary three points in the sample period from September 7, 2007 to April 17, 2015, at $t*/T \in \{0.15, 0.50, 0.85\}$, which corresponds to the dates October 24, 2008, June 24, 2011 and February 21, 2014, respectively. Secondly, the "Any" column reports the results of test for the dependence break of unknown timing proposed by Andrews (1993). In order to detect whether the dependence structure 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 the rank correlation. The "US" and "EU" columns report the results for this test. Lastly, the *p*-values in column "QA" are based on a generalized break test without *a priori* point in (Andrews and Ploberger, 1994). 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 the rank correlation over the sample period) is significantly rejected by at least one test at the 5% significance level. These results are new in the literature and strongly support our reasoning.

[INSERT TABLE V ABOUT HERE]

3.5 Joint default probability in UK G-SIBs

Our empirical analysis verifies the asymmetric and time-varying dependence structure between the CDS spread changes of the UK G-SIBs. It suggests that we should select a time-varying asymmetric copula model for estimating the dependence structure of the CDS spread changes. Consequently, we select the GAS based GHST copula for modeling the joint credit risk.

Table VI reports the estimation results for both parametric and semiparametric GAS based GHST copula models. We find that their estimates are very close each other and the parametric copula model is 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)). Therefore, we use the parametric model for the estimation in our paper.

[INSERT TABLE VI ABOUT HERE]

For the comparison of goodness-of-fit with other copula models, we consider the GAS based Gaussian copula model and the GAS based Student's copula model. We compare the GAS based GHST model with those using a log-likelihood test, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). In Table VII, the GAS based GHST copula model shows better estimation results than the other two copula models for all pairs of banks and all banks; that is, it has higher likelihood ratios and lower information criteria than two other copula models. All the results strongly support the use of the GAS based GHST copula for modeling the dependence structure of the CDS spread changes.

[INSERT TABLE VII ABOUT HERE]

Figure 3 shows the time-series plot of the equal-weighted average of the copula correlations for ten pairs of banks. The copula correlations are implied by the GAS based GHST copula. 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 3 ABOUT HERE]

Given the calibrated marginal default probability for each bank and the estimated time-varying copula correlation matrix and parameters, we can simulate the joint probability that two or more banks simultaneously default during the sample period. Figure 4 shows the market-implied joint default probability among five UK G-SIBs over a five-year horizon. The arrows indicate the time points of several major events in the global financial market. First, the joint default probability 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 default probability is also affected by the monetary policy implemented by the BoE and European Central Bank, and gradually decreases after the cut of interest rate.

[INSERT FIGURE 4 ABOUT HERE]

In summary, we have found from the descriptive analysis that the CDS spreads of the UK G-SIBs commove over time and banks' CDS spread changes are highly correlated each other. In addition, we have found from the copula analysis that the tail dependence of the CDS spread changes is persistent over time and asymmetric. These results have helped us to measure the joint credit risk of the UK G-SIBs; e.g. joint default probability. In particular, the finding that the CDS spreads immediately respond to market news is likely to provide crucial information for understanding the joint credit risk through studies on channels generating the dependence structure of the CDS spread changes. For this reason, we will continue with further study of the dependence structure of the CDS spread changes in the next section.

4 Economic analysis of drivers of CDS spreads comovement

As the CDS spreads data has been shown since 2007, the joint default risk of the UK G-SIBS is closely related to the comovement of their CDS spreads. Therefore, identifying the driver of the CDS spreads comovement would be the key to understanding the dynamics of the joint credit risk. The comovement of the CDS spreads could be accessible through two channels. First, the investment portfolios of the commercial banks are typically exposed to market risk. In general, bank's credit risk is positively related to the market risk; that is, when the market is booming, the CDS spread of the bank will be small, and conversely, when the market is in a recession. We have already observed that the CDS spreads of the banks react immediately to the market news. Second, banks' financial structure or business are closely related to each other. In this case, their credit risks are closely related to each other even if the effects of the market risk are excluded. Therefore, if one of the banks with high correlation is bankrupt, the default probability of other banks also becomes high. Thus, if bank's CDS spreads increase, the CDS spreads of other banks will also increase. We have not directly observed this channel from our data, but it has already been identified during the finance crisis of 2007-2008. Therefore, we will continue our empirical analysis of the two channels in order to better understand the dynamics of the joint credit risk.

The common market factors have been examined in several studies on the determinants of the CDS spreads. Thus we can be easily verify the first channel. However, there are several limitations in directly examining the second channel. First, in our weekly frequency data, it is not easy to obtain data on bank's investment and financial structure. In addition, it is not easy to identify how banks are connected each other in business. For these reasons, we choose a way to indirectly investigate the second channel through a factor based regression analysis. We perform time-series regression analysis using common market factors explaining the first channel for each bank (see Collin-Dufresne et al., 2001; Ericsson et al., 2009; Annaert et al., 2013; Galil et al., 2014; Christoffersen et al., 2016),

$$\Delta CDS_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} F_{k,t} + e_{i,t}, \tag{12}$$

where $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$, $F_{k,t}$ the k-th common market factor and $e_{i,t}$ the unobserved idiosyncratic shock, respectively. We assume that variables describing the second channel are omitted from regressors and included in the error term. Therefore, the dependence structure of the CDS spread changes of two banks can be easily decomposed into the first- and second-channel separately in this regression model. Of course, there is a dependence structure created by the interaction between two channels, but the influence is normally expected to be small (or negligible).

4.1 Common market factors

For this economic analysis, we first choose market variables that can proxy market condition. Literatures generally include the market variables that represent credit, equity, bond, and capital market. Some of them also include variables such as foreign exchange rate, oil price, and inflation rate (see Liu and Zhang, 2008; Cooper and Priestley, 2011; Galil et al., 2014; Christoffersen et al., 2016). In our study, the oil price hardly explains the CDS spread and the inflation rate is difficult to obtain at the weekly frequency, so only the foreign exchange rate is included as a representative variable for the foreign exchange market. The following are the specific definitions and the expected effects of the variables.

Credit market We use an iTraxx crossover 5-year index which is the brand name for the family of CDS index. It is a benchmark for the credit protection seller of holding the on-the-run credit derivate transaction with the 5-year maturity against default and used to measure changes in credit quality. We expect the credit market condition to have a negative relationship with the CDS spreads. That is, if the credit market condition improves (positive change of iTraxx), the CDS spreads will be generally reduced (negative changes of CDS spreads).

Equity market We consider two variables representing equity market condition. First, we consider the equity market portfolio. Since bank's credit risk is usually lower when the equity market is good, we expect the equity market portfolio to have a negative relationship with the CDS spreads. Second, we consider the equity market volatility and use the FTSE100 volatility index as a proxy following Collin-Dufresne et al. (2001). The large market volatility implies a risky equity market, so it is expected to have a positive relationship with the CDS spreads.

Bond market We consider two variables representing a bond market condition. First, we consider the spot rate. To be consistent with the five-year maturity of the CDS contracts, we measure the spot rate using the UK five-year Government Bond Yield.[13] Longstaff and Schwartz (1995) argue that the higher spot rate increases the future value of firm's investment. Collin-Dufresne et al. (2001) note that the higher spot rate reduces the probability of default. Both arguments support a negative relation between the spot rate and the credit spreads. Second, we consider the term-structure slope measured by a difference between the UK 10-year Government Bond Yield and the UK 2-year Government Bond Yield.[14] An expected relation between the term-structure slope and the credit spreads is inconclusive. Fama and French (1989) argue that the increase of the term-structure slope is associated with the improved economic growth. Thus a negative relationship is expected between the term-structure slope and the CDS spreads. On the other hand, slope steepening may reduce the number of projects that have positive net present values for companies. This effect increases the default probability, so the term-structure slope has a negative relationship with the CDS spreads.

Capital market We consider the capital market liquidity to capture the capital market condition. We use the capital markets liquidity index which is constructed based upon the total return of over 80 fixed income securities representing the investment grade market with a maturity less than 1 year, along with large CDS, commercial paper and banker acceptance securities. This index is collected from AMEX. The high liquidity index means low liquidity risk in the capital market; thereby, a bank is able to easily access to the capital market and its credit risk is lowered. Therefore, we expect the capital market liquidity to have a negative relationship with the CDS spreads.

[13] Galil et al. (2014) measure the spot rate using the five-year Treasury Constant Maturity Rate obtained from the St. Louis Federal Reserve. On the other hand, Christoffersen et al. (2016) use the 3-month US Constant Maturity Treasury index.

[14] Galil et al. (2014) use the differences between the 10-year Treasury Constant Maturity Rate and the 2-year Treasury Constant Maturity Rate obtained from FRED as the term-structure slope.

Foreign exchange market We consider a spot rate to capture the foreign exchange market condition. Note that its positive (negative) change means 'appreciation (depreciation)' of the British pound. In general, the higher the value of the British pound, the greater the confidence in UK banks, so we expect the CDS spreads to have a negative relationship with the foreign exchange rate.

As shown in Table VIII, all the variables are verified to be nonstationary by the Augmented Deckey-Fuller test for unit root. Thus we use the first-differenced variables rather than the level variables in the regression analysis (see Galil et al., 2014): change of iTraxx, $\Delta iTraxx_t = iTraxx_t - iTraxx_{t-1}$, equity market portfolio return, $Return_t^E = 100 * (\ln P_t - \ln P_{t-1})$, change of equity market volatility, $\Delta VIX_t = VIX_t - VIX_{t-1}$, change of bond spot rate, $\Delta Bond_t = Bond_t - Bond_{t-1}$, change of term structure slope, $\Delta Slope_t = Slope_t - Slope_{t-1}$, change of capital market liquidity, $\Delta Liquidity_t = Liquidity_t - Liqudity_{t-1}$ and return on foreign exchange rate, $Return_t^E = 100 * (\ln S_t - \ln S_{t-1})$. All the first-differenced variables have very small or insignificant autocorrelations, whereas residuals from the AR (1) regression have ARCH effects.

4.2 Relationship between CDS spread changes and common market factors

In this section we empirically test for the first channel we make. Table IX presents the correlation matrix of the average CDS spread changes and the common market factors. The average CDS spread change is defined as the first difference of the log average CDS spread, $\Delta\overline{CDS}_t := \ln\overline{CDS}_t - \ln\overline{CDS}_{t-1}$, where the average CDS spread ($\overline{CDS}_t$) is the equal-weighted average of five individual CDS spreads. As we can see in the first column, all the market factors show signs that are consistent with our expectations. However, unlike the most strong correlation coefficients, the change of term-structure slope and the change of capital market liquidity index have weak correlations with the CDS spread changes. Interestingly, the change of credit market performance is highly correlated with other market factors. In particular, it is strongly correlated with the equity market portfolio returns, the change of market volatility, the change of bond spot rate and the return on foreign exchange rate. But it would not be surprising to note that the credit market performance is also heavily influenced by the conditions of other markets.

[TABLE IX ABOUT HERE.]

Next, we try to analyse the relationship more formally through regression analysis. we first run the time-series regression of the CDS spread changes on the common market factors for each bank. We estimate the following regression model:

$$\Delta CDS_{i,t} = \alpha_i + \beta_{1i}\Delta iTraxx_t + \beta_{2i}Return_t^E + \beta_{3i}\Delta VIX_t + \beta_{4i}\Delta Bond_t \\ + \beta_{5i}\Delta Slope_t + \beta_{6i}\Delta Liquidity_t + \beta_{7i}Return_t^F + e_{i,t}, \quad (13)$$

where the CDS spread change is defined as the first difference of the log CDS spread, $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$. Table X shows the results of the regression analysis. The change of credit market performance is only significant and the remaining market factors are insignificant. These results seem to be related to the fact that the change of market performance is strongly correlated with other market factors. That is, other market factors seem to be insignificant due to the multicollinearity problem. Overall, the common market factors explain the CDS spread changes around 43% on average.

[TABLE X ABOUT HERE.]

We also run a time-series regression of average CDS spread changes on common market factors. We estimate the following regression model:

$$\Delta\overline{CDS}_t = \alpha + \beta_1\Delta iTraxx_t + \beta_2 Return_t^E + \beta_3\Delta VIX_t + \beta_4\Delta Bond_t \\ + \beta_5\Delta Slope_t + \beta_6\Delta Liquidity_t + \beta_7 Return_t^F + e_t. \quad (14)$$

The reason for using the average CDS spread change as a dependent variable is that it is advantageous to reduce the individual effects and to analyse the common effects of the entire banks. We also estimate the regression model with a single market factor to see its explanatory power independently. A comparison of regression models using a single factor and full factors may give some more insight into the multicollinearity problem that has been raised in the previous regression analysis. Table XI shows the result of the regression analysis. As expected, all factors except the change of term structure slope and the change of capital market liquidity are significant in the regression using a single factor. However, only the change of credit market performance is significant in the regression using full factors. When we use the change of credit market performance as a single factor, R^2 is 0.463 which is almost the same as that of the regression using full factors. Therefore, when all the results are taken into account, the credit market performance has already taken into account other market conditions. Consequently, when we use them together in the regression, the multicollinearity problem occurs due to information redundancy and some factors are no longer significant. These results support that the change of credit market performance alone can represent a market condition sufficiently.

[TABLE XI ABOUT HERE.]

Table XII strongly supports our argument above. We run the time-series regression of the change of credit market performance on the remaining market factors. We estimate the following regression model:

$$\Delta iTraxx_t = \alpha + \beta_1 Return_t^E + \beta_2 \Delta VIX_t + \beta_3 \Delta Bond_t + \beta_4 \Delta Slope_t + \beta_5 \Delta Liquidity_t + \beta_6 Return_t^F + e_t. \quad (15)$$

We also estimate the regression model with a single factor. As the estimation results show, equity, bond and foreign exchange market conditions are closely related to the credit market performance. For this reason, we use the change of credit market performance as the only market factor to decompose the dependence structure of the CDS spread changes in the next section.

[TABLE XII ABOUT HERE.]

In summary, bank's CDS spreads are largely accounted for by the market factors. In particular, the credit market performance has been found to be the most comprehensive and significant market factor. Therefore, it is empirically verified that the first channel is the very convincing hypothesis. In the next section, we will try to analyse the dependence structure of the CDS spread changes in more detail from different angles.

4.3 Decomposition of dependence structure of CDS spread changes

The regression analysis of the relationship between the CDS spread changes and the common market factors suggest to use only the credit market performance as the market factor. Thus we are able to present the CDS spread changes using the single factor:

$$\Delta CDS_{i,t} = \alpha_i + \beta_i \Delta iTraxx_t + e_{i,t}. \quad (16)$$

Therefore, we can decompose the correlation of two banks' CDS spread changes into three components based on the one-factor presentation in (16):

$$\frac{Cov\left(\Delta CDS_{i,t},\Delta CDS_{j,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right)Var\left(\Delta CDS_{j,t}\right)}}=\underbrace{\frac{\beta_i\beta_j Var\left(\Delta iTraxx_t\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right)Var\left(\Delta CDS_{j,t}\right)}}}_{(A)}+\underbrace{\frac{Cov\left(e_{i,t},e_{j,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right)Var\left(\Delta CDS_{j,t}\right)}}}_{(B)}$$
$$+\underbrace{\frac{\beta_i Cov\left(\Delta iTraxx_t,e_{j,t}\right)+\beta_j Cov\left(\Delta iTraxx_t,e_{i,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right)Var\left(\Delta CDS_{j,t}\right)}}}_{(C)}. \tag{17}$$

where (A) and (B) are correlations respectively generated by the first and second channels, and (C) is one generated by the interaction of two channels. Normally, (C) is relatively ineffective compared to the two channels. Table XIII presents the decomposition results for the 10 pairs of two banks. It shows that the contribution to the correlation by the first channel is the largest with 65% on average. As we have seen in the regression analysis, it also reaffirms that the market factor plays the most important role in generating the comovement of CDS spreads. The contribution by the second channel is 48% on average, which is smaller than the first channel by 17%. This is not a direct approach, but the results verify that the second channel also plays the important role in generating the comovement of the CDS spreads.

[TABLE XIII ABOUT HERE.]

4.4 Dependence structure of residuals

We examine how the dependence structure of the CDS spread changes is characterised by two channels using residuals obtained from the factor model in (16).

First, we test for the asymmetric dependence of the residuals using the test applied to the CDS spread changes. The results are reported in Table XIV. Compared with Table IV, the tail dependence is significantly reduced at both tails. We can deduce this reduction from that the market factor is the dominant contributor to the correlation of the CDS spread changes in (17). Here we should note that the upper tail dependence is reduced significantly more than the lower tail dependence. This would be because banks' CDS spreads very sensitively respond to bad market news, which increases the likelihood of outliers in the upper tail. As a result, the null of the symmetric dependence of the residuals is not rejected for most pairs; only two pairs are rejected at the 5% significance level. Therefore, these results verify that the asymmetric dependence of CDS spread changes is mainly generated by the market factor.

[TABLE XIV ABOUT HERE.]

Next, we test for the time-varying dependence of the residuals using various structural break tests applied to the CDS spread changes. The results are reported in Table XV. The structural breaks of the dependence structure of the CDS spread changes are detected for all pairs of banks in Table IV, but the structural breaks of the dependence structure of the residuals are identified for only four pairs of banks. It demonstrates that the time-varying nature of the dependence structure of the CDS spread changes is dominantly driven by the market factor. It is not surprising given the earlier finding that information generated by market news is transmitted into the CDS spread via the first channel.

[TABLE XV ABOUT HERE.]

Consequently, both tests, although not direct approaches, confirm that the time-varying and asymmetric dependence structures of the CDS spread changes are mostly characterized through the first channel. It implies that the market factors are the key inputs to understand the joint credit risk of large banks.

5 Conclusion

We have studied the joint credit risk of the UK G-SIBs from various angles using the CDS spreads and make a conclusion based on our findings: First, we are able to flexibly measure the systemic credit risk at the high-frequency level by applying the combination of the reduced-form model and the GAS-based dynamic asymmetric copula model to the CDS data. Second, we find that the credit risk of UK banks still largely relies on the market factors in spite of BoE's effort. Our factor analysis confirms that the comovement of the CDS spreads, a major source of the joint credit risk, is driven by the market factors. The decomposition of the correlation of the CDS spread changes shows that the market factor is a major contributor to the correlation. Moreover, it is verified that the time-varying and asymmetric dependence structure of the CDS spread changes is mostly generated by the market factors. Overall, our study re-assures "what" BoE has to manage for the stabilization of the systemic credit risk and provides the flexible way "how to" BoE measures the systemic credit risk in the banking sector. We hope that our research will help BoE or institutional investors prepare for the upcoming hard Brexit to cope with the systemic credit risk of the banking sector in the UK.

Appendix

A. 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

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

B. 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 survives or to the time of first credit event occurs. The present value of the premium leg of an existing CDS contract is given by

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

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

where t, t_n, t_N denotes the effective date, the contractual payment dates, and the maturity date of the CDS contract, respectively. $S(t_0,t_N)$ represents the fixed contractual spread of CDS with maturity date t_N at time t_0, $\Delta(t_{n-1},t_n,B)$ represents the day count fraction between premium date t_{n-1} and t_n in the selected day count convention B, $Z(t,t_n)$ is the Libor discount factor from the valuation date t to premium payment date t_n and $Q(t,t_n)$ 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

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

Thus, it can be simplified as

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

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

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

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 $K = \mathrm{int}(M \times (T-t) + 0.5)$. Defining $\epsilon = (T-t)/K$, we can calculate the approximation of expected present value of the protection payment as

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

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

C. 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 A.3 and A.8

$$S(t_0,t_N) = \frac{(1-R)}{2}\frac{\sum_{k=1}^{K}\left(Z(t_0,t_{k-1}) + Z(t_0,t_k)\right)\left(Q(t_0,t_{k-1}) + Q(t_0,t_k)\right)}{\text{RPV01}(t_0,t_N)} \tag{A.9}$$

where the RPV01 is given by

$$\text{RPV01}(t_0,t_N) = \frac{1}{2}\sum_{n=1}^{N}\Delta(t_{n-1},t_n,B)\,Z(t_0,t_n)\left(Q(t_0,t_{n-1}) + Q(t_0,t_n)\right) \tag{A.10}$$

D. 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, 2000; 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 $T_1, T_2, \ldots, T_M$ and corresponding CDS spread $S_1, S_2, \ldots, S_M$. 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 (A.9). 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 $0, T_1, T_2, ..., T_M$.

References

Acharya, V., Drechsler, I., & Schnabl, P. (2014). A pyrrhic victory? Bank bailouts and sovereign credit risk. *Journal of Finance*, 69(6), 2689-2739.

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica* 61(4), 821-856.

Annaert, J., De Ceuster, M., Van Roy, P., & Vespro, C. (2013). What determines Euro area bank CDS spreads? *Journal of International Money and Finance* 32, 444-461.

Andrews, D. W., & Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica* 62(6), 1383-1414.

Bank of England (2007). Financial stability report. Bank of England, London.

Bank of England (2013). A framework for stress testing the UK banking system. Bank of England, London.

Bank of England (2015). Stress testing the UK banking system: guidance on the traded risk methodology for participating banks and building societies. Bank of England, London.

Basel Committee on Banking Supervision (2011). Globally systemically important banks: assessment methodology and the additional loss absorbency requirement. Bank for International Settlements, Basel.

Basel Committee on Banking Supervision (2012). A framework for dealing with domestic systemically important banks. Bank for International Settlements, Basel.

Black, L., Correa, R., Huang, X., & Zhou, H. (2013). The systemic risk of European banks during the financial and sovereign debt crisis. *FRB International Finance Discussion Paper*, (1083).

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *Journal of Finance* 58(6), 2321-2350.

Cerrato, M., Kim, M., & Zhao, Y. (2016). Relation between higher order comoments and dependence structure of equity portfolio. *Journal of Empirical Finance*, forthcoming.

Christoffersen, P., Errunza, V., Jacobs, K., & Langlois, H. (2012). Is the potential for international diversification disappearing? A dynamic copula approach. *Review of Financial Studies* 25(12), 3711-3751.

Christoffersen, P., & Langlois, H. (2013). The joint dynamics of equity market factors. *Journal of Financial and Quantitative Analysis* 48(5), 1371-1404.

Christoffersen, P., Jacobs, K., Jin, X., & Langlois, H. (2016). Dynamic dependence and diversification in corporate credit. *Working paper*, University of Toronto.

Collin-Dufresne, P., Goldstein, R. S., & Martin, J. S. (2001). The determinants of credit spread changes. *Journal of Finance* 56(6), 2177-2207.

Cooper, I., & Priestley, R. (2011). Real investment and risk dynamics. *Journal of Financial Economics* 101, 182-205.

Creal, D., Koopman, S. J., & Lucas, A. (2013). Generalized autoregressive score models with applications. *Journal of Applied Econometrics* 28(5), 777-795.

Creal, D., Schwaab, B., Koopman, S. J., & Lucas, A. (2014). Observation-Driven Mixed-Measurement dynamic factor models with an application to credit risk. *Review of Economics and Statistics* 96(5), 898-915.

Creal, D. D., Gramacy, R. B., & Tsay, R. S. (2014). Market-based credit ratings. *Journal of Business & Economic Statistics*, 32(3), 430-444.

Crouhy, M., Galai, D., & Mark, R. (2000). A comparative analysis of current credit risk models. *Journal of Banking & Finance* 24(1), 59-117.

Das, S. R., Duffie, D., Kapadia, N., & Saita, L. (2007). Common failings: How corporate defaults are correlated. *Journal of Finance* 62(1), 93-117.

Demarta, S., & McNeil, A. J. (2005). The t copula and related copulas. *International Statistical Review*, 73(1), 111-129.

Dieckmann, S., & Plank, T. (2012). Default risk of advanced economies: An empirical analysis of credit default swaps during the financial crisis. *Review of Finance*, 16(4), 903-934.

Erlenmaier, U., & Gersbach, H. (2014). Default Correlations in the Merton Model. *Review of Finance* 18(5), 1775-1809.

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis* 44(1), 109-132.

European Central Bank. (2007). Financial stability review. European Central Bank, Frankfurt

Fama, E. F., & French, K. R. (1989). Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25, 23-49.

Galil, K., Shapir, O. M., Amiram, D., & Ben-Zion, U. (2014). The determinants of CDS spreads. *Journal of Banking & Finance* 41, 271-282.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance* 48(5), 1779-1801.

Hansen, B. E. (1994). Autoregressive conditional density estimation. *International Economic Review* 35(3), 705-730.

Huang, X., Zhou, H., & Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance* 33(11), 2036-2049.

Huang, X., Zhou, H., & Zhu, H. (2012). Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis. *Journal of Financial Stability*, 8(3), 193-205.

Hull, J. C., & White, A. D. (2000), Valuing Credit Default Swaps I: No Counterparty Default Risk, *Journal of Derivatives* 8, 29-40.

Janus, P., Koopman, S. J., & Lucas, A. (2014). Long memory dynamics for multivariate dependence under heavy tails. *Journal of Empirical Finance* 29, 187-206.

Jones, S. (2009). The formula that felled Wall Street. *The Financial Times*, 22(04).

Lehnert, T., & Neske, F. (2006). On the relationship between credit rating announcements and credit default swap spreads for European reference entities. *Journal of Credit Risk* 2(2), 83-90.

Li, D. X. (2000). On default correlation: A copula function approach. *Journal of Fixed Income* 9(4), 43-54.

Liu, L. X., & Zhang, L. (2008). Momentum profits, factor pricing, and macroeconomic risk. *Review of Financial Studies* 21, 457-475.

Longstaff, F. A., & Schwartz, E. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *Journal of Finance* 50(3), 789-819.

Lucas, A., Schwaab, B., & Zhang, X. (2014). Conditional euro area sovereign default risk. *Journal of Business & Economic Statistics* 32(2), 271-284.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance* 29(2), 449-470.

Lohr, S. (2009). Wall Street's math wizards forgot a few variables. *New York Times* 13, 3Pritchard.

Oh, D. H. and A. Patton (2016). Time-varying systemic risk: Evidence from a dynamic copula model of CDS spreads. *Journal of Business & Economic Statistics*, forthcoming.

O'Kane, D., & Turnbull, S. (2003). Valuation of credit default swaps. *Lehman Brothers Quantitative Credit Research Quarterly*, 2003, Q1-Q2.

O'Kane, D. (2008). *Modelling single-name and multi-name credit derivatives* (Vol. 573). John Wiley & Sons.

Patton, A. (2012). Copula methods for forecasting multivariate time series. *Handbook of Economic Forecasting* 2, 899-960.

Pianeti, R., Giacometti, R., & Acerbis, V. (2012). Estimating the joint probability of default Using credit default swap and bond data. *Journal of Fixed Income* 21(3), 44-58.

Salmon, F. (2009). Recipe for disaster: The formula that killed Wall Street. *Wired Magazine* 17(3), 17-03.

Salvatierra, I. D. L., & Patton, A. J. (2015). Dynamic copula models and high frequency data. *Journal of Empirical Finance* 30, 120-135.

Schönbucher, P. J. (2003). *Credit derivatives pricing models: models, pricing and implementation*. John Wiley & Sons.

Smith, M. S., Gan, Q., & Kohn, R. J. (2012). Modelling dependence using skew t copulas: Bayesian inference and applications. *Journal of Applied Econometrics* 27(3), 500-522.

Zhu, H. (2006). An empirical comparison of credit spreads between the bond market and the credit default swap market. *Journal of Financial Services Research* 29, 211-235.

Table I: Descriptive statistics of CDS spread changes

This table presents the Augmented Dickey-Fuller (ADF) test for unit root for the log CDS spreads of the UK G-SIBs 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 available from June 27, 2008. “Average” denotes the equal-weighted average of five CDS spreads. The ADF test includes five lagged differenced terms and reports *p*-values with a test static in [·]. This table also presents descriptive statistics for the first difference of log CDS spreads. The statistics include mean, median, standard deviation, skewness, kurtosis and time-series characteristics include autocorrelation (AC(1)) and ARCH LM test. Note that mean, median and standard deviation are reported in %. The ARCH LM test is applied to residuals obtained from the AR(1) regression and includes five lagged terms. The *p*-values are reported in [·] with the test statistic. *, ** and *** indicate the significance levels of AC(1) at 10%, 5% and 1%, respectively.

	Barclay	HSBC	Lloyds	RBS	Standard	Average
ADF test	-3.040	-3.748	-2.743	-3.294	-2.744	-3.380
	[0.031]	[0.004]	[0.067]	[0.015]	[0.067]	[0.012]
Mean	0.079	0.201	0.256	0.211	0.060	0.186
Median	-0.243	-0.012	0.141	0.432	0.000	0.081
Std. Dev.	11.857	10.466	10.872	11.968	9.208	10.561
Skewness	-0.176	0.122	0.287	-0.055	0.748	0.110
Kurtosis	6.443	5.305	6.112	8.783	8.979	6.517
AC(1)	-0.094	-0.038	-0.021	-0.090	-0.094	-0.060
ARCH LM	53.162	48.817	43.422	49.633	24.966	55.366
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table II: Correlation of CDS spread changes

This table presents the correlation matrix for the CDS spread changes of the UK G-SIBs 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 available from June 27, 2008.

	Barclay	HSBC	Lloyds	RBS	Standard
Barclay	1.000				
HSBC	0.841	1.000			
Lloyds	0.876	0.830	1.000		
RBS	0.875	0.823	0.869	1.000	
Standard	0.762	0.804	0.711	0.781	1.000

Table III: ARMA-GJR-GARCH estimation of CDS spread changes

This table presents the estimated parameters from the ARMA(1,1) model for the conditional mean,

$$\Delta CDS_{i,t} = c_i + \epsilon_{i,t} + \varphi_i \Delta CDS_{i,t-1} + \theta_i \epsilon_{i,t-1},\ \epsilon_{i,t} = \sigma_{i,t} z_{i,t},$$

and GJR-GARCH(1,1,1) model for the conditional variance of CDS spread changes,

$$\sigma^2_{i,t} = w_i + \alpha_i \epsilon^2_{i,t-1} + \delta_i \epsilon^2_{i,t-1} I_{i,t-1} + \beta_i \sigma^2_{i,t-1}.$$

We assume that $z_{i,t}$ follows the skewed Student's t distribution, $SkT(\upsilon, \eta)$, where υ denotes a degrees of freedom and η skewness parameter, respectively. 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 for Standard Chartered available from June 27, 2008. The values in parenthesis represent the standard errors of the parameters estimates. We also report the p-values of two goodness-of-fit tests for the skewed Student's t distribution: Kolmogorov-Smirnov test and Cramer-von Mises test. *, ** and *** indicate the significance levels at 10%, 5% and 1%, respectively.

	Barclays	HSBC	Lloyds	RBS	Standard
ARMA specification					
φ	-0.671**	-0.848**	-0.794**	-0.697**	-0.094*
	(0.238)	(0.114)	(0.173)	(0.203)	(0.053)
θ	0.580**	0.791**	0.757**	0.593**	
	(0.261)	(0.132)	(0.187)	(0.228)	
GJR-GARCH specification					
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 specification					
υ	5.511**	7.385**	7.179**	5.269**	3.159*
η	0.017*	0.079**	0.001	-0.012	0.016
Kolmogorov-Smirnov test	[0.83]	[0.94]	[0.22]	[0.23]	[0.16]
Cramer-von Mises test	[0.58]	[0.91]	[0.15]	[0.41]	[0.25]

Table IV: Tests of asymmetric dependence

This table presents the coefficient of lower tail dependence ("Lower"), the coefficient of upper tail dependence ("Upper") and their difference for each pair of banks. We estimate the tail dependence from Student's *t* copula 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 for Standard Chartered available from June 27, 2008. We use both parametric and semiparametric estimation methods developed in Patton (2012). The *p*-values of testing a zero difference are computed by a bootstrapping with 500 replications and reported in [·].

	A. Parametric estimation			B. Semiparametric estimation		
	Lower	Upper	Diff [p-value]	Lower	Upper	Diff [p-value]
B-H	0.379	0.509	-0.130 [0.315]	0.279	0.390	-0.111 [0.468]
B-L	0.287	0.543	-0.255 [0.015]	0.428	0.661	-0.233 [0.045]
B-R	0.328	0.647	-0.319 [0.002]	0.274	0.598	-0.324 [0.004]
B-S	0.299	0.220	0.079 [0.462]	0.305	0.282	0.023 [0.867]
B-L	0.217	0.239	-0.022 [0.869]	0.339	0.341	-0.002 [0.992]
H-R	0.217	0.537	-0.320 [0.002]	0.257	0.606	-0.349 [0.013]
H-S	0.511	0.153	0.358 [0.003]	0.559	0.171	0.389 [0.015]
L-R	0.312	0.538	-0.226 [0.037]	0.242	0.698	-0.457 [0.001]
L-S	0.233	0.300	-0.066 [0.673]	0.200	0.453	-0.253 [0.109]
R-S	0.291	0.167	0.125 [0.244]	0.220	0.186	0.035 [0.747]

Table V: Structural break test for time-varying dependence structures

This table presents the p-values of structural break tests for time-varying dependence between CDS spread changes of a pair of 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 a naïve test for breaks at three points in the sample period from September 7, 2007 to April 17, 2015; thereby, $t*/T \in \{0.15, 0.50, 0.85\}$ correspond to the dates October 24, 2008, June 24, 2011 and February 21, 2014, respectively. "Any" denotes a test for the dependence break at unknown timing proposed by Andrews (1993). In order to detect whether the dependence structure significantly changed after the US/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 a rank correlation. "QA" denotes a generalized break test without *a priori* knowledge of breaking points proposed by Andrews and Ploberger (1994).

	Naïve break test						
	(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

Table VI: Estimation of the GAS based GHST copula model

This table presents estimation results of parametric and semiparametric GAS based bivariate GHST copula model. "B", "H", "L", "R" and "S" denote Barclays, HSBC, Lloyds, RBS and Standard Charted, respectively. The sample period is from September 7, 2007 to April 17, 2015. $\mathbf{w}$, Π and Λ denote the parameters of GAS model, η^{-1} and λ denote the inverse of degree of freedom and the skewness parameter of GHST copula, and *log L* denotes the log-likelihood of estimated copula model. The "Joint" reports the estimates of parameters for high-dimensional copula models with five banks. Notice that we estimate this high-dimensional copula following the method described in Lucas et al. (2014).

	B-H	B-L	B-R	B-S	H-L	H-R	H-S	L-R	L-S	R-S	Joint
A. Parametric estimation											
$\mathbf{w}$	0.390	0.402	0.406	0.269	0.364	0.382	0.285	0.380	0.269	0.330	0.348
Π	0.047	0.072	0.038	0.026	0.060	0.142	0.199	0.192	0.155	0.168	0.109
Λ	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
B. Semiparametric estimation											
$\mathbf{w}$	0.390	0.396	0.410	0.281	0.364	0.373	0.284	0.380	0.274	0.320	0.348
Π	0.090	0.073	0.039	0.199	0.069	0.194	0.199	0.192	0.155	0.166	0.137
Λ	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

Table VII: Log-likelihood, AIC and BIC for model comparisons

This table presents the comparisons for three dynamic bivariate copula models: GAS based Gaussian copula model (GAS-G), GAS Student's *t* copula model (GAS-T) and GAS based GHST copula (GAS-GHST). "B", "H", "L", "R" and "S" denote Barclays, HSBC, Lloyds, RBS and Standard Charted, respectively. The sample period is from September 7, 2007 to April 17, 2015. Panel A reports the log-likelihood and the *p*-values of likelihood ratio test for GAS-T and GAS-GHST. Panel B and C report the values of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). All the copula models are parametrically estimated. The "Joint" reports the estimates of parameters for high-dimensional copula models with five banks. Notice that we estimate this high-dimensional copula following the method described in Lucas et al. (2014).

	B-H	B-L	B-R	B-S	H-L	H-R	H-S	L-R	L-S	R-S	Joint
A. Log-likelihood											
GAS-G	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	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
B. Akaike Information Criterion (AIC)											
GAS-G	-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)											
GAS-G	-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

Table VIII: Descriptive statistics of common market factors

This table presents the Augmented Dickey-Fuller (ADF) test for unit root for level variables and the descriptive statistics for first-differenced variables of common market factors: iTraxx, equity market portfolio ($\ln P$), equity market volatility (VIX), bond spot rate ($Bond$), term structure slope ($Slope$), capital market liquidity ($Liquidity$) and foreign exchange rate ($\ln S$). The ADF test includes five lagged differenced terms and reports p-values with test statistic in $[\cdot]$. It also presents descriptive statistics including mean, median, standard deviation, skewness, kurtosis and time-series characteristics including autocorrelation (AC(1)) and ARCH LM test for first-difference variables: change of iTraxx ($\Delta iTraxx$), equity market portfolio return $\left(Return^E\right)$, change of market volatility (ΔVIX), change of bond spot rate ($\Delta Bond$), change of term structure slope ($\Delta Slope$), change of capital market liquidity ($\Delta Liquidity$) and return on foreign exchange rate $\left(Return^F\right)$. The ARCH LM test is applied to residuals from the AR(1) regression and includes five lagged terms. The p-value is reported in $[\cdot]$ with the test statistic. *, ** and *** denote the significance of AC(1) at 10%, 5% and 1% significance level.

	$iTraxx$	$\ln P$	VIX	$Bond$	$Slope$	$Liquidity$	$\ln S$
ADF test	-2.346	1.069	-1.483	-3.191	-3.158	-2.343	-2.593
	[0.158]	[0.995]	[0.542]	[0.021]	[0.023]	[0.159]	[0.094]

	$\Delta iTraxx$	$Return^E$	ΔVIX	$\Delta Bond$	$\Delta Slope$	$\Delta Liquidity$	$Return^F$
Mean	0.210	0.026	-0.015	-0.007	0.004	1.012	-0.075
Median	0.232	0.193	-0.074	-0.015	0.002	0.515	-0.066
Std. Dev.	1.565	2.856	3.814	0.131	0.112	17.936	1.405
Skewness	-0.517	-1.426	1.358	0.410	0.027	1.635	-0.783
Kurtosis	4.772	16.494	27.244	4.597	8.484	22.160	7.923
AC(1)	-0.102	-0.123*	-0.133*	-0.048	-0.013	-0.011	-0.028
ARCH LM	9.518	20.844	44.297	8.473	24.873	91.222	95.537
	[0.090]	[0.001]	[0.000]	[0.132]	[0.000]	[0.000]	[0.000]

Table IX: Correlation of average CDS spread changes and common market factors

This table presents a correlation matrix of average CDS changes $\left(\Delta\overline{CDS}\right)$ and common market factors: change of iTraxx ($\Delta iTraxx$), equity market portfolio return $\left(Return^E\right)$, change of market volatility (ΔVIX), change of bond spot rate ($\Delta Bond$), change of term structure slope ($\Delta Slope$), change of capital market liquidity ($\Delta Liquidity$) and return on foreign exchange rate $\left(Return^F\right)$. See Section 4 for the details of variable definition. Note that $\Delta\overline{CDS}_t := \ln\overline{CDS}_t - \ln\overline{CDS}_{t-1}$, where $\overline{CDS}$ is the equal-weight average of individual CDS spreads.

	$\Delta\overline{CDS}$	$\Delta iTraxx$	$\Delta Return^E$	ΔVIX	$\Delta Bond$	$\Delta Slope$	$\Delta Liquidity$	$Return^F$
$\Delta\overline{CDS}$	1.000							
$\Delta iTraxx$	-0.682	1.000						
$Return^E$	-0.403	0.642	1.000					
ΔVIX	0.332	-0.588	-0.810	1.000				
$\Delta Bond$	-0.337	0.405	0.326	-0.278	1.000			
$\Delta Slope$	-0.095	0.089	0.011	0.000	0.190	1.000		
$\Delta Liquidity$	0.012	-0.052	-0.078	0.060	-0.243	-0.065	1.000	
$Return^F$	-0.220	0.283	0.267	-0.206	0.069	-0.166	-0.009	1.000

Table X: Regression analysis of a relationship between CDS spread changes and common market factors

This presents a time-series regression of CDS spread changes on common market factors: change of iTraxx ($\Delta iTraxx$), equity market portfolio return $\left(Return^E\right)$, change of market volatility (ΔVIX), change of bond spot rate ($\Delta Bond$), change of term structure slope ($\Delta Slope$), change of capital market liquidity ($\Delta Liquidity$) and return on foreign exchange rate $\left(Return^F\right)$. We estimate the following regression model for each bank:

$$\begin{aligned}\Delta CDS_{i,t} = \alpha_i + \beta_{1i}\Delta iTraxx_t + \beta_{2i}Return_t^E + \beta_{3i}\Delta VIX_t + \beta_{4i}\Delta Bond_t \\ + \beta_{5i}\Delta Slope_t + \beta_{6i}\Delta Liquidity_t + \beta_{7i}Return_t^F + e_{i,t},\end{aligned} \quad (18)$$

where $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$. All the standard errors reported in $(\cdot)$ are obtained by the Newey-West method with 5 lags. *, ** and *** denote the significance of estimate at 10%, 5% and 1% significance level. See Section 4 for the details of variable definition.

Variable	Barclay	HSBC	Lloyd	RBS	Standard
$\Delta iTraxx$	-0.052***	-0.045***	-0.045***	-0.047***	-0.038***
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
$Return^E$	0.001	-0.003	-0.002	0.000	-0.001
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
ΔVIX	-0.003	-0.004	-0.004	-0.002	-0.003
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta Bond$	-0.099*	-0.057	-0.046	-0.075	0.002
	(0.052)	(0.044)	(0.047)	(0.061)	(0.045)
$\Delta Slope$	-0.082	0.023	-0.058	-0.009	-0.035
	(0.075)	(0.057)	(0.078)	(0.083)	(0.035)
$\Delta Liquidity$	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Return^F$	-0.003	-0.004	-0.002	-0.005	-0.005
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
α	0.011***	0.011***	0.012***	0.011**	0.009**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
$adj.R^2$	0.465	0.460	0.410	0.391	0.406
N	398	398	398	398	398

Table XI: Regression analysis of a relationship between average CDS spread changes and common market factors

This presents a time-series regression of average CDS spread changes $\left(\Delta\overline{CDS}\right)$ on common market factors: change of iTraxx ($\Delta iTraxx$), equity market portfolio return $\left(Return^E\right)$, change of market volatility (ΔVIX), change of bond spot rate ($\Delta Bond$), change of term structure slope ($\Delta Slope$), change of capital market liquidity ($\Delta Liquidity$) and return on foreign exchange rate $\left(Return^F\right)$. We estimate the following regression model:

$$\Delta\overline{CDS}_t = \alpha + \beta_1 \Delta iTraxx_t + \beta_2 Return_t^E + \beta_3 \Delta VIX_t + \beta_4 \Delta Bond_t + \beta_5 \Delta Slope_t + \beta_6 \Delta Liquidity_t + \beta_7 Return_t^F + e_t, \quad (19)$$

where $\Delta\overline{CDS}_t := \ln\overline{CDS}_t - \ln\overline{CDS}_{t-1}$, where $\overline{CDS}$ is the equal-weight average of individual CDS spreads. We also estimate the regression model with a single variable to see its explanatory power independently. All the standard errors reported in $(\cdot)$ are obtained by the Newey-West method with 5 lags. *, ** and *** denote the significance of estimate at 10%, 5% and 1% significance level. See Section 4 for the details of variable definition.

Variable	M1	M2	M3	M4	M5	M6	M7	ALL
$\Delta iTraxx_t$	-0.046***							-0.047***
	(0.004)							(0.004)
$Return^E$		-0.015***						-0.001
		(0.005)						(0.002)
ΔVIX			0.009**					-0.003
			(0.004)					(0.003)
$\Delta Bond$				-0.272***				-0.069
				(0.056)				(0.049)
$\Delta Slope$					-0.089			-0.025
					(0.073)			(0.062)
$\Delta Liquidity$						0.000		0.000
						(0.000)		(0.000)
$Return^F$							-0.017***	-0.003
							(0.004)	(0.004)
α	0.012***	0.002	0.002	0.000	0.002	0.002	0.001	0.011***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
$adj.R^2$	0.463	0.160	0.108	0.112	0.007	-0.002	0.103	0.471
N	398	398	398	398	398	398	398	398

Table XII: Regression analysis of a relationship between iTraxx and other common market factors

This presents a time-series regression of iTraxx change ($\Delta iTraxx$) on common market factors: equity market portfolio return $\left(Return^E\right)$, change of market volatility (ΔVIX), change of bond spot rate ($\Delta Bond$), change of term structure slope ($\Delta Slope$), change of capital market liquidity ($\Delta Liquidity$) and return on foreign exchange rate $\left(Return^F\right)$. We estimate the following regression model:

$$\Delta iTraxx_t = \alpha + \beta_1 Return_t^E + \beta_2 \Delta VIX_t + \beta_3 \Delta Bond_t + \beta_4 \Delta Slope_t + \beta_5 \Delta Liquidity_t + \beta_6 Return_t^F + e_t, \tag{20}$$

We also estimate the regression model with a single variable to see its explanatory power independently. All the standard errors reported in $(\cdot)$ are obtained by the Newey-West method with 5 lags. *, ** and *** denote the significance of estimate at 10%, 5% and 1% significance level. See Section 4 for the details of variable definition.

Variable	M1	M2	M3	M4	M5	M6	ALL
$Return^E$	0.352***						0.208***
	(0.049)						(0.044)
ΔVIX		-0.241***					-0.080*
		(0.044)					(0.041)
$\Delta Bond$			4.846***				2.585***
			(0.729)				(0.580)
$\Delta Slope$				1.243			0.978
				(1.249)			(0.822)
$\Delta Liquidity$					-0.005		0.004
					(0.007)		(0.003)
$Return^F$						0.315***	0.154***
						(0.058)	(0.045)
α	0.201***	0.207***	0.246***	0.206***	0.215***	0.234***	0.227***
	(0.054)	(0.064)	(0.068)	(0.076)	(0.074)	(0.070)	(0.049)
$adj.R^2$	0.411	0.344	0.162	0.005	0.000	0.078	0.481
N	398	398	398	398	398	398	398

Table XIII: Decomposition of correlation of CDS spread changes

This table presents a decomposition of correlation of CDS spread changes relying on a factor model:

$$\Delta CDS_{i,t} = \alpha_i + \beta_i \Delta iTraxx_t + e_{i,t},$$

where $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$. We only include a single market factor: change of iTraxx ($\Delta iTraxx$), since it has been verified that the most relevant market factor in Table X - XII. From the single factor model, it is straightforward to decompose the correlation of two banks' CDS spread changes into three components:

$$\frac{Cov\left(\Delta CDS_{i,t}, \Delta CDS_{j,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right) Var\left(\Delta CDS_{j,t}\right)}} = \underbrace{\frac{\beta_i \beta_j Var\left(\Delta iTraxx_t\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right) Var\left(\Delta CDS_{j,t}\right)}}}_{(A)} + \underbrace{\frac{Cov\left(e_{i,t}, e_{j,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right) Var\left(\Delta CDS_{j,t}\right)}}}_{(B)}$$

$$+ \underbrace{\frac{\beta_i Cov\left(\Delta iTraxx_t, e_{j,t}\right) + \beta_j Cov\left(\Delta iTraxx_t, e_{i,t}\right)}{\sqrt{Var\left(\Delta CDS_{i,t}\right) Var\left(\Delta CDS_{j,t}\right)}}}_{(C)}.$$

(A) and (B) are correlations respectively generated by our first and second hypothetical channels, and (C) is a correlation generated by the interaction of two channels. Normally, (C) is relatively ineffective compared to the two channels. $(\cdot)$ represents the relative influence by each component in percentage.

Correlation coefficient		(A)	(B)	(C)
$Corr(Barclay, HSBC)$	0.841	0.613	0.381	-0.153
		(73%)	(45%)	(-18%)
$Corr(Barclay, Lloyds)$	0.876	0.563	0.446	-0.133
		(64%)	(51%)	(-15%)
$Corr(Barclay, RBS)$	0.875	0.561	0.465	-0.151
		(64%)	(53%)	(-17%)
$Corr(Barclay, Standard)$	0.762	0.489	0.332	-0.059
		(64%)	(44%)	(-8%)
$Corr(HSBC, Lloyds)$	0.830	0.569	0.389	-0.127
		(69%)	(47%)	(-15%)
$Corr(HSBC, RBS)$	0.823	0.567	0.402	-0.146
		(69%)	(49%)	(-18%)
$Corr(HSBC, Standard)$	0.804	0.494	0.363	-0.053
		(61%)	(45%)	(-7%)
$Corr(Lloyds, RBS)$	0.869	0.520	0.475	-0.127
		(60%)	(55%)	(-15%)
$Corr(Lloyds, Standard)$	0.711	0.454	0.300	-0.043
		(64%)	(42%)	(-6%)
$Corr(RBS, Standard)$	0.781	0.452	0.387	-0.058
		(58%)	(50%)	(-7%)

Table XIV: Tests of asymmetric dependence of residuals

This table presents the coefficient of lower tail dependence ("Lower"), the coefficient of upper tail dependence ("Upper") and their difference for each pair of banks using the residuals from a factor model:

$$\Delta CDS_{i,t} = \alpha_i + \beta_i \Delta iTraxx_t + e_{i,t},$$

where $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$. We estimate the tail dependence from Student's t copula 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 for Standard Chartered available from June 27, 2008. We use both parametric and semiparametric estimation methods developed in Patton (2012). The p-values of testing a zero difference are computed by a bootstrapping with 500 replications and reported in $[\cdot]$.

	A. Parametric estimation			B. Semiparametric estimation		
	Lower	Upper	Diff [p-value]	Lower	Upper	Diff [p-value]
B-H	0.255	0.270	-0.015 [0.810]	0.226	0.292	-0.067 [0.358]
B-L	0.332	0.389	-0.057 [0.356]	0.319	0.403	-0.084 [0.268]
B-R	0.232	0.290	-0.058 [0.470]	0.310	0.439	-0.129 [0.325]
B-S	0.178	0.137	0.042 [0.642]	0.300	0.181	0.119 [0.313]
H-L	0.201	0.210	-0.009 [0.910]	0.265	0.339	-0.074 [0.350]
H-R	0.193	0.359	-0.167 [0.007]	0.208	0.456	-0.248 [0.013]
H-S	0.161	0.175	-0.013 [0.863]	0.150	0.165	-0.016 [0.843]
L-R	0.204	0.257	-0.052 [0.491]	0.159	0.279	-0.120 [0.239]
L-S	0.265	0.306	-0.041 [0.698]	0.145	0.387	-0.243 [0.040]
R-S	0.228	0.102	0.127 [0.059]	0.206	0.195	0.011 [0.920]

Table XV: Structural break test for time-varying dependence structures of residuals

This table presents the p-values of structural break tests for time-varying dependence between residuals of a pair of banks. The residuals are from a factor model:

$$\Delta CDS_{i,t} = \alpha_i + \beta_i \Delta iTraxx_t + e_{i,t},$$

where $\Delta CDS_{i,t} := \ln CDS_{i,t} - \ln CDS_{i,t-1}$. "B", "H", "L", "R" and "S" denote Barclays, HSBC, Lloyds, RBS and Standard Charted, respectively. Without *a priori* knowledge of breaking points, we consider a naïve test for breaks at three points in the sample period from September 7, 2007 to April 17, 2015; thereby, $t*/T \in \{0.15, 0.50, 0.85\}$ correspond to the dates October 24, 2008, June 24, 2011 and February 21, 2014, respectively. "Any" denotes a test for the dependence break at unknown timing proposed by Andrews (1993). In order to detect whether the dependence structure significantly changed after the US/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 a rank correlation. "QA" denotes a generalized break test without a priori knowledge of breaking points proposed by Andrews and Ploberger (1994).

	Naïve break test (0.15	0.5	0.85)	Any	US	EU	QA
B-H	0.362	0.856	0.898	0.630	0.163	0.458	0.000
B-L	0.160	0.213	0.733	0.530	0.083	0.123	0.412
B-R	0.135	0.196	0.743	0.570	0.085	0.145	0.067
B-S	0.880	0.644	0.641	1.000	0.615	0.892	0.023
H-L	0.072	0.163	0.823	0.220	0.017	0.030	0.746
H-R	0.190	0.656	0.905	0.500	0.071	0.239	0.787
H-S	0.800	0.582	0.678	0.840	0.904	0.697	0.431
L-R	0.163	0.110	0.760	0.350	0.053	0.082	0.516
L-S	0.638	0.772	0.652	0.920	0.518	0.374	0.508
R-S	0.506	0.933	0.329	0.940	0.353	0.545	0.000

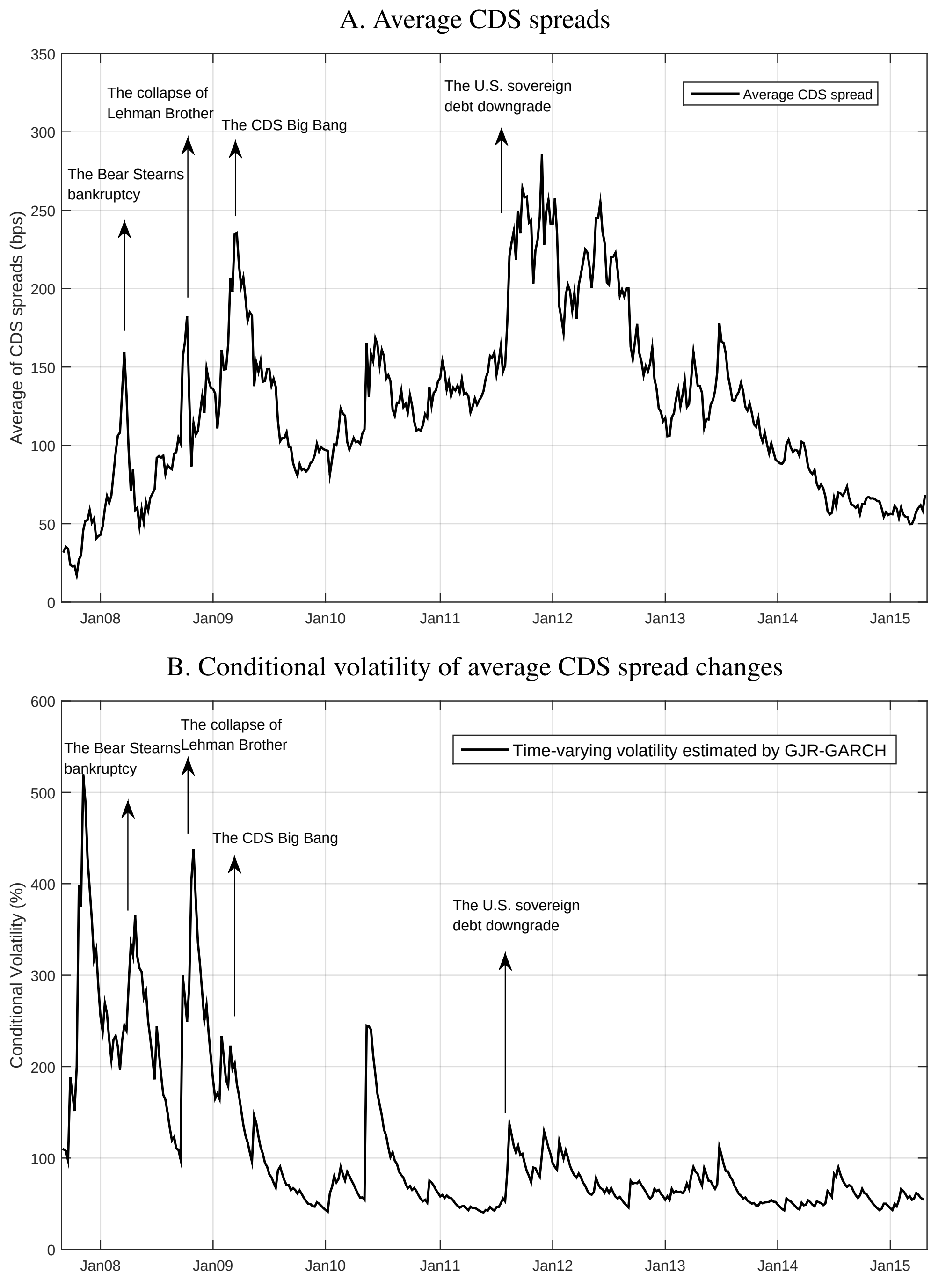

Figure 1: Dynamics of CDS spread

This figure shows the equal-weighted average of CDS spreads of five UK G-SIBs and the conditional volatility of average CDS spread changes 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.

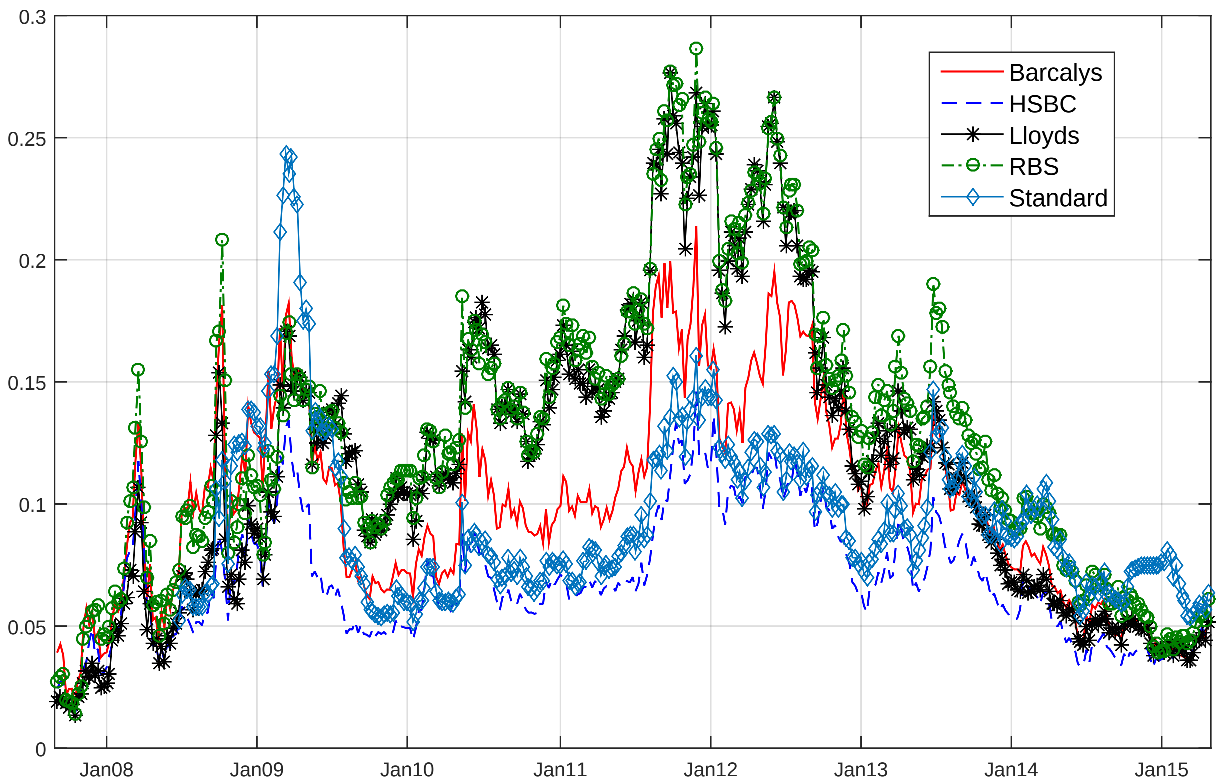

Figure 2: CDS-implied marginal risk neutral default probabilities

This figure plots risk neutral marginal probabilities of default for five UK G-SIBs. These probabilities are directly inferred from CDS spreads with different maturities using bootstrap algorithm described in Appendix 5. The sample period is from September 7, 2007 to April 17, 2015.

Figure 3: Average copula correlation implied by GAS over time

This figure shows the average copula correlation implied by the GAS GHST copula from September 7, 2007 to April 17, 2015. The average copula correlation is obtained by the equal-weighted average of estimated copula correlations of 10 pairs of banks.

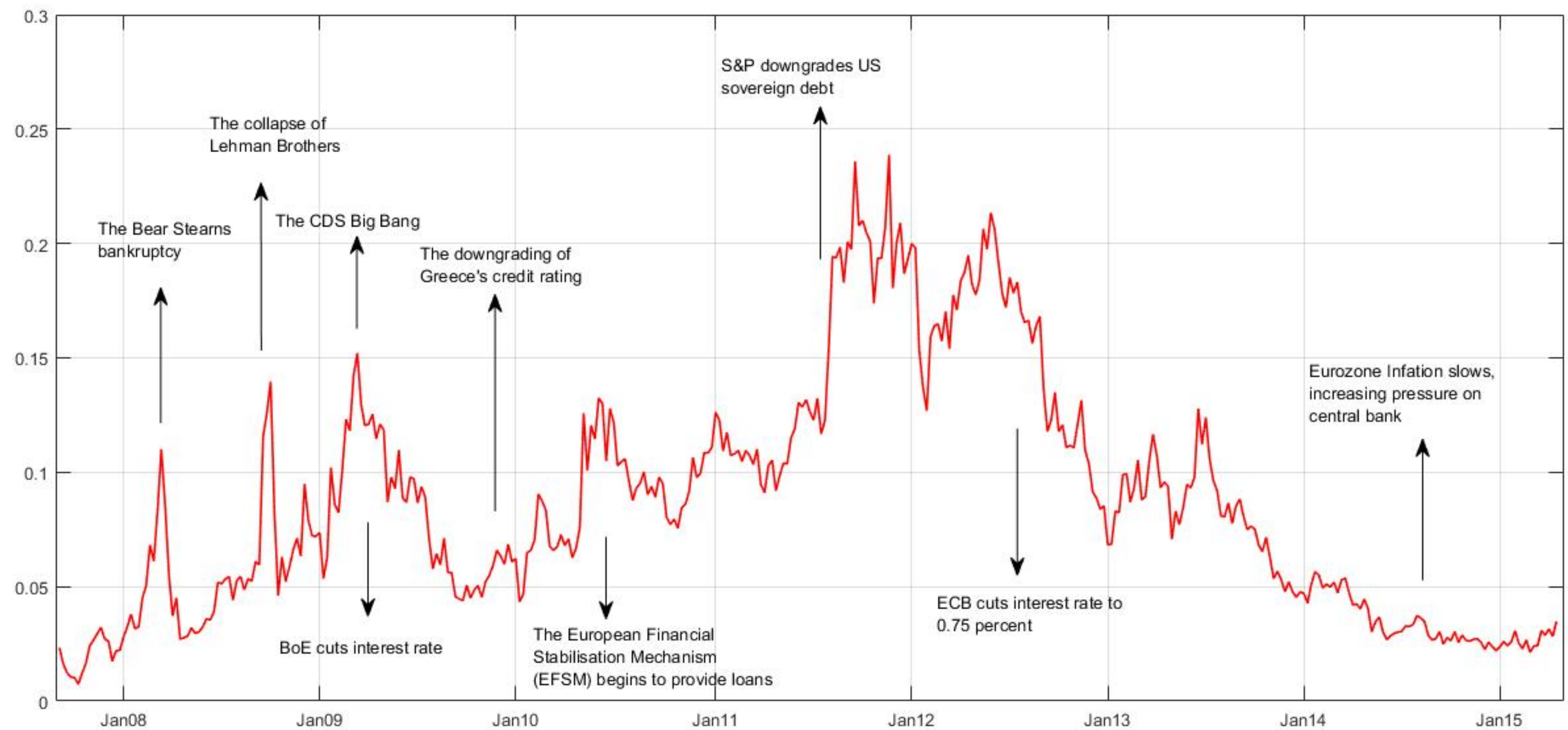

Figure 4: The joint default probabilities of UK G-SIBs

This figure plots the estimated joint default probabilities over the five-year horizon from September 7, 2007 to April 17, 2015. The probabilities are estimated based on the GAS GHST copula model. The arrows indicate the time points of several major events in global financial market.