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Re-examination of international bond market dependence: Evidence from a pair copula approach☆

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ABSTRACT

The finance literature provides substantial evidence on the dependence between international bond markets across developed and emerging countries. Early works in this area were based on linear models and multivariate GARCH models. However, based on the limitations of these models this paper re-examines the non-linearity, multivariate and tail dependence structure between government bond markets of the US, UK, Japan, Germany, Canada, France, Italy, Australia and the Eurozone, from January 1970 to February 2019 using ARMA-GARCH based pair- copula models. We find that the bond markets in our sample tend to have both upper tail dependence in terms of positive shocks and lower tail dependence in terms of negative shocks. The estimated C-vine shows Eurozone has the highest average dependency. The D-vine, with optimal chain dependency structure shows the best order of connectedness to be the UK, the USA, Italy, Japan, Eurozone, France, Canada, Germany and Australia. The R-vine copula results underline the complex dynamics of bond market relations existing between the selected economies. The estimated R-vine shows Eurozone, Germany and Australia are the most inter-connected nodes. The multivariate distribution structure (interdependency) of bond markets for all countries were modelled with the C-vine, D-vine and R-vine copulas. In this application, the R-vine copula allows for detailed modelling of all bond markets and hence provides a more accurate goodness of fit and mean square error for the interdependency between all markets. In light of the changing volatility in bond markets, we conduct additional tests using time-varying copulas and find that the dependence structure among the bond markets examined is time-varying with the dynamic dependence parameter plots revealing that the nature of the dependence structure is intense during crisis periods.

1. Introduction

The nature of dependence across bond yields and returns plays a crucial role in asset allocation management and investor's diversification strategies. The issue of international bond market co-movement dynamics is of great importance to investment practitioners and policy makers. Investment practitioners pay close attention to the co-movement between bond markets since a proper grasp of its nature and measurement affects international diversification because when markets are in turmoil, international portfolio diversification becomes less effective (Clare, Maras, & Thomas, 1995). On the other hand, policy makers are more interested in how strong linkages across bond markets affect the understanding of the global conduct of monetary policy. This is because government bonds serve as indicators of monetary policy actions; hence, if they are internationally integrated and influenced by movements in interest rates in another economy, then monetary policy

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dynamics in the domestic country will be limited to some extent (Kirchgässner & Wolters, 1987; Sutton, 2000). In other words, the integration of international bond markets could lead to the transmission of shocks across bond markets, which in effect makes the conduct of monetary policy sensitive to international and domestic developments. Additionally, DeGennaro, Kunkel, and Lee (1994) show that bond market linkages have implications on long-term interest rates. Following the removal of government imposed barriers on the international flow of capital in major industrialised countries in the early 1980s; the integration of international bond markets has increased intensely over the last two decades leading to comprehensive literature on the subject.

Most of the literature on the co-movement between international markets has concentrated on the equity market co-movement (Bessler & Yang, 2003; Brooks & Del Negro, 2004; Gil-Alana, Carcel, & Abakah, 2018; Graham, Kiviaho, & Nikkinen, 2012; Pukthuanthong & Roll, 2009) and stock-bond co-movement in a single country or multi-country context (Connolly, Stivers, & Sun, 2007; Kim, Moshirian, & Wu, 2006). Other studies have focused on bond and other financial assets class such as cryptocurrencies, Fintech and green bonds (Gil-Alana, Abakah, & Abakah, 2020; Le, Abakah, & Tiwari, 2021). Interestingly, literature on the dependence between international bond markets across developed and emerging countries has received less attention compared to equity markets comovement (Barassi, Caporale, & Hall, 2001; Barr & Priestley, 2004; Clare et al., 1995; Connolly et al., 2007; Engsted & Tanggaard, 2007; Kirchgässner & Wolters, 1987; Kumar & Okimoto, 2011; Nikkinen, Piljak, & Äijö, 2012; Pagano & Von Thadden, 2004; Piljak, 2013; Smith, 2002; Sutton, 2000; Yang, 2005a, 2005b).

Among the literature on international co-movement across government bond markets, various estimation techniques have been used leading to mixed findings. For example, earlier studies in this area were based on various linear models. Cointegration analysis has been used as the canonical measure of the linkages between bond markets even though these cointegration analyses do not examine the linkages in the underlying factors that affect bond yields (Clare et al., 1995; DeGennaro et al., 1994; Hafer, Kutan, & Zhou, 1997). Barr and Priestley (2004) using an international capital asset pricing model (CAPM), discovered that bond returns are predictable in different countries over time. Driessen, Melenberg, and Nijman (2003) using a linear factor and principal components analysis find a positive linkage in international bond markets. Campbell & Ammer (1993, Engsted & Tanggaard (2001) and Yang (2005b) make use of Vector Auto-Regressive (VAR) models to investigate international bond markets integration. Similarly, Engsted and Tanggaard (2007) employ VAR models to investigate bond co-movements between US and German bond markets. Owing to the drawbacks of linear correlation models, multivariate GARCH models have become the typical approach for modelling time-varying bond market dependence, and there is an exponential growth in research in this area (see, e.g., Barr & Priestley, 2004; Berben & Jansen, 2005; Garcia & Tsafack, 2011; Piljak, 2013; Tsukuda, Shimada, & Miyakoshi, 2017, among many others). Following Patton (2006) and Garcia and Tsafack (2011), we find that one major limitation of the multivariate GARCH approach is the assumption that bond return innovations are characterized by a symmetric multivariate normal or Student-*t* distribution. Consequently, this assumption is not in consonance with the empirics since the distribution of financial returns are characterized with heavier tails than those of the normal distribution, and the dependence between bond returns or yields are usually nonlinear and asymmetric (Embrechts, McNeil, & Straumann, 2002).

Following these limitations, researchers in recent times have resorted to the use of copulas as a new approach to investigate and model linkages between international markets. Copulas are functions that join multivariate distributions to their one-dimensional margins. For example, let us assume X_1 and X_2 are two random variables with $F_1(x_1)$ and $F_2(x_2)$ as marginal distributions respectively. Following Sklar (1959), we can express their joint distribution function as $F(x_1, x_2) = C[F_1(x_1), F_2(x_2)]$. From the joint distribution expression, it can be concluded that one needs to know how X_1 and X_2 are related, in addition to their marginal distributions that can be provided by the copula function. Thus, copulas by definition provide a realistic description of the dependence structure between random variables over their whole range of variation, including linear and non-linear dependence, symmetric and asymmetric dependence, and extreme or tail dependence. Moreover, copula functions are invariant to non-linear strictly increasing transformations of the data, unlike conventional measures of dependence, such as linear correlations (Embrechts et al., 2002). For instance, the correlation between X_1 and X_2 will be the same as the dependence between $\ln(X_1)$ and $\ln(X_2)$. Following the useful properties of copulas, researchers are currently paying special attention to the use of copula models in recent academic works. Comparing the use of copula models in the finance literature, an emerging stream of the literature has employed copula models to investigate dependence in international stock markets (Basher, Nechi, & Zhu, 2014; Bhatti & Nguyen, 2012; Mensah & Alagidede, 2017; Mensah & Premaratne, 2017; Nguyen, Bhatti, & Hayat, 2014; Tiwari, Abakah, Le, & Hiz, 2020; Yang, Cai, Li, & Hamori, 2015). Although studies abound on the application of copula models on international stock markets, there is no empirical evidence on the dependence structure of international bond markets using copula models. Following the importance of bond market linkages to investment practitioners and policy makers coupled with the limitations in earlier models employed to examine international bond market dependence, the current paper examines the tail dependence and multivariate distribution structure between government bond markets of nine industrialised countries (US, UK, Japan, Germany, Canada, Italy, France, Eurozone and Australia), during the time period from January 1970 to February 2019 and using various copula approaches (i.e., Canonical vine (C-vine), Drawable vine (D-vine) and Regular vine (R-vine)). We focus on these countries because of their importance in the international bond markets. For robustness purposes, we also use time-varying copulas including Normal, Clayton, Rotated Clayton, Gamble, SJC and Student-t to further test the nature of the dependence structure since the constant copula in light of changing volatility in bond markets would not yield convincing results as international markets dependence is clearly dynamic.

Our most important empirical results can be summarized as follows. From the bivariate static results, Student-t copula emerged as the best-fit model for the majority of bond pairs including Australia-Germany, Germany-France, USA-UK, Japan-Italy among others. This connotes that the dependence between these markets is characterized by symmetric upper and lower tail dependence, which suggests the co-movement in both positive and negative extreme events. For robustness purposes coupled with the fact that international bond markets are dynamic, we employ time-varying copulas further examining the nature of the dependence structure for the series examined. According to the log-likelihood, we find that the time-varying copula offers a better fit compared to the constant copulas in most cases, providing strong evidence that the relationship between the bond markets examined is time-varying. Overall, SJC copula emerged as the best copula fit for the majority of the bond pairs suggesting that these bond pairs are asymmetrically upper and lower tail dependent. In other words, this implies that there is a larger probability of joint crash than booming for the bond pairs best modelled by dynamic SJC. Finally, we further investigate the interdependency between all the countries bond yields using D-vine, C-vine and R-vine structures. Results shows that the best fit, by this measure, is given by the R-vine copula.

Our contribution to the literature is twofold. First, dependence modelling plays an important role in portfolio construction, risk management, and derivatives pricing, and any inappropriate method could lead to suboptimal portfolios, inaccurate assessment of risk exposures, and biased pricing, respectively. Studies in the last decade have supported the superiority of a copula-based approach over the traditional linear correlation method of measuring dependence as it offers more flexibility than the latter does. To the best of our knowledge, no paper to date has: (i) examined the dependence structure between international bond markets using the whole copula family; (ii) tested if the up and down spillovers are asymmetric or symmetric. Second, our findings can help international investors better understand the mechanism of risk transmission across countries and may provide additional insights into the asset allocation decision and risk hedging in the nine developed countries.

The rest of the paper is structured as follows. Section 2 presents a brief discussion of the methodology focusing on the marginal model, copula theory, pair copula models and goodness of fit tests used in the study. Section 3 describes the data, while the empirical results and analysis are undertaken in Section 4. This is followed by the conclusions in Section 5.

2. Empirical methodology

In this paper, we investigate the linkages between the bond markets conditions of nine industrialised countries by employing ARMA-GARCH based pair copula models. In the first step, we use ARMA-GARCH filters to model each country's bond yield to identify the features of the data from the country itself. In the second step, we estimate a bivariate copula to examine the standardized residuals' dependence of the pair countries' bond yield to categorize the tail dependence of each pair into a copula family. In the final step, we construct different vine copula structures by using several copula families, which are estimated in the second step to investigate the dependence feature of all the countries in our sample.

2.1. Marginal models

The initial step of the copula modelling is to specify the appropriate models for the conditional marginal distribution functions of the bond yields of all nine developed countries. To do this, we apply Autoregressive Moving Average {ARMA (p, q)} models to the conditional means (where p is the order of the autoregressive part and q is the order of the moving average part) and Generalised Autoregressive Conditional Heteroscedasticity {GARCH (p, q)} models to the conditional variances (where p and q the order of the GARCH and ARCH terms respectively) as outlined below. We employ the ARMA-GARCH models to our data because financial time series are characterized with fat tails, long memory behaviour and conditional heteroscedasticity. The specified model is then:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i Y_{t-1} + \sum_{i=1}^{p} \theta_i \varepsilon_{t-1} \tag{1}$$

$$\varepsilon_t = \sigma_t z_t, z_t \sim NIID(0,1) \tag{2}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-1}^2 \tag{3}$$

where Y_t is the log-difference of bond yield at time *t*; *c* is the constant term in the mean equation; ε_t is the real-valued discrete time stochastic process at time their joint distribution functheir joint distribution func; z_t is the unobservable random variable belonging to an i.i.d process; σ_t^2 is the conditional variance of ε_t; ω, a_i, β_i are the constant, ARCH parameter and GARCH parameters respectively. In the case of GARCH (1,1), we ensure that the following inequality restrictions are satisfied to ensure that the model if correctly specified: (i) $\omega \geq 0$, (ii) $a_1 \geq 0$, (iii) $\beta_1 \geq 0$ and (iv) $a_1 + \beta_1 < 1$. According to Bollerslev (1986), in the case where $a_1 + \beta_1 = 1$, it implies that the conditional variance will not converge on a constant unconditional variance in the long run. For the purposes of this study, we estimate the GARCH models by using maximum likelihood.

2.2. Copula theory

This section provides a brief overview of the theory of copulas and pair-copula construction for multivariate datasets. More details on the concept of copula can be found in Joe (1996) and Nelsen (2006). Further details about pair-copulas and vine copulas can also be found in Aas, Czado, Frigessi, and Bakken (2009); Addo and Chanda (2019); Kurowicka and Cooke (2006); Addo, Chanda, and Metcalfe (2018) and Bedford and Cooke (2002).

2.3. Definition of copulas

Copulas can be defined as multivariate uniform distribution (Addo & Chanda, 2019). From the definition of a cumulative distribution function (cdf), the cdf of any continuous random variables has a uniform distribution, which is referred to as the probability integral transform. Hence, any multivariate distribution has a copula form. This implies that copulas provide a much better approach to modelling multivariate datasets. Consider a random variable $Z = (z_1, \ldots, z_d)$ and define $u_i = F(z_i)$. Hence we can define a copula by its cdf $C(u_1, u_2, \ldots, u_d)$ and the probability density function (pdf) can be expressed as:

$$(u_1, u_2, \ldots, u_d) = \frac{\partial C(u_1, u_2, \ldots, u_d)}{\partial u_1 \partial u_2 \ldots \partial u_d} \tag{4}$$

The copula pdf links the, marginal pdfs to the multivariate pdf:

$$f(z_1, \ldots, z_d) = c(u_1, \ldots, u_d) f(z_1) \ldots f(z_d) \tag{5}$$

There are generally a wide variety of copulas that are normally used to model bivariate probability distributions, and they are given in "Appendix A". The elliptical copulas (i.e. Gaussian and Student-*t* copulas) are easily extended to more than two variables, but this is not the case for Archimedean copulas (i.e. Clayton, Frank, Gumbel, etc.). A much more flexible approach to modelling multivariate distributions is pair-copula: Drawable vines (D-vines), Canonical vines (C-vines) and Regular vines (R-vines), as described in Aas et al. (2009) and Bedford and Cooke (2002).

2.4. Pair copula

It follows from the multiplicative rule of probability that any multivariate distribution can be factorised in several ways using conditional distributions (Addo & Chanda, 2019). Generally, copulas can be factorised as a product of the marginal distributions and bivariate conditional copulas. This factorisation is called the pair-copula model. The pair-copula model assumes that all joint, marginal and conditional distributions are continuous with corresponding densities. Joe (1996) presented a construction for a pair-copula model for a multivariate copula based on the distribution functions. Following Joe's work, Bedford and Cooke (2002) came up with another construction based on densities. They sought to organise the construction in a graphical way involving a sequence of nested trees, which they called Regular vines. They further defined two popular sub-classes of pair-copula construction (PCC) models, which they named D-vines and C-vines. Kurowicka and Cooke (2006) advanced their work. The derivation of D-vines, C-vines and R-vines, which are presented in this study are outlined below.

2.4.1. Drawable vine distribution (D-vines)

More generally the pair-copula model can be described as a multivariate copula that seeks to approximate the target copula given that not all copulas can be expressed as a vine copula (Haff, Aas, & Frigessi, 2010). The composition however is not unique, for example a five-dimensional density can have over 240 different constructions. Generally, in the *D*-vines, the decomposition of the joint densities consists of the pair-copula densities evaluated at the conditional distributions functions and also for specified indices and marginal densities (Bedford & Cooke, 2002; Czado, 2010). Fig. 1 reproduced from Aas et al. (2009)

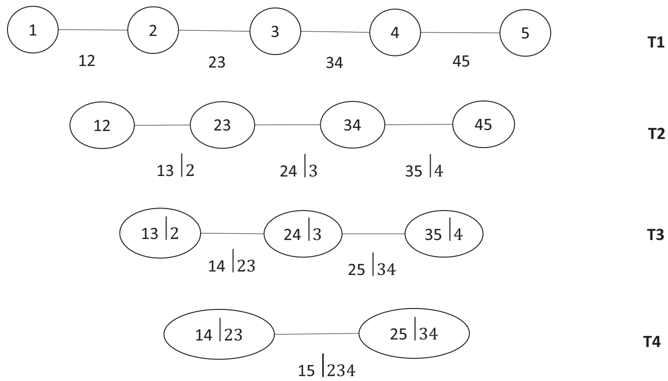

Fig. 1. D-vine for five variables.

$$f_{12345} = f_1(z_1) f_2(z_2) f_3(z_3) f_4(z_4) f_5(z_5) c_{12}(F_1(z_1), F_2(z_2)).c_{23}(F_2(z_2), F_3(z_3)).c_{34}(F_3(z_3), F_4(z_4)).c_{45}(F_4(z_4), F_5(z_5)).c_{13|2}(F_{1|2}(z_1|z_2), F_{3|2}(z_3|z_2)).\ c_{24|3}(F_{2|3}(z_2|z_3), F_{4|3}(z_4|z_3)) c_{35|4}(F_{3|4}(z_3|z_4), F_{5|4}(z_5|z_4)) c_{14|23}(F_{1|23}(z_1|z_2, z_3), F_{4|23}(z_4|z_2, z_3)) \cdot c_{25|34}(F_{2|34}(z|z_3, z_4), F_{5|34}(z_5|z_3, z_4)) c_{15|234}(F_{1|234}(z_1|z_2, z_3, z_4)) \tag{6}$$

shows the graphical model used to explain the D-vines for five variables. It consists of four trees: $Tj = 1, 2, 3, 4$. Tree T_j has $n + 1 - j$ nodes, where n is the number of variables. By using the decomposition shown in Fig. 1 and Eq. (6), the joint density of five random variables can be expressed using the D-vines as:

From Eq. (6), the D-vine distribution involves the computation of different conditional distributions functions and conditional bivariate copulas. Joe (1996) and Aas et al. (2009) define the conditional distribution functions $F(z|v)$ for an m-dimensional vector $v = (v_1, \ldots, v_m)$ using the recursive relationship below.

$$h(z|v) := F(z|v) = \frac{\partial C_{zv_j|v_{-j}}(F(z|v_{-j}), F(v_j|v_{-j}))}{\partial F(v_j|v_{-j})} \tag{7}$$

where $v_j (j = 1, \ldots, m)$ is an arbitrary component of v, and $v_{-j} = (v_1, \ldots, v_{j-1}, v_{j+1}, \ldots, v_m)$ denotes the vector v excluding element v_j. The bivariate copula function is also defined by $C_{zvj|vj}$. Generally, given $u_i (i = 1, \ldots, n)$ to denote $F_i(z_i)$ we can derive the conditional function $F(u_3|u_1, u_2)$ that is needed as an argument for $C_{14|23}$ in a five dimensional D-vine copula density using Eq. (7).

2.4.2. *Canonical vine distribution (C-vines)*

Canonical vines are generally used when a key variable that controls the relationships of the datasets can be highlighted. Fig. 2 is also reproduced after Aas et al. (2009), which shows the graphical model used to demonstrate the C-vines for five variables. The figure consists of four trees T_j, $j = 1, 2, 3, 4$ and Tree T_j has $6 - j$ nodes, $5 - j$ edges. Generally, the number of trees for m variables is $m - 1$. T_j has $m + 1 - j$ nodes. An edge shows the corresponding pair-copula and the label of the edge represents the subscript of the pair-copula (Aas et al., 2009). The nodes shown in Fig. 2 are normally used to decide the labels of the edges. From this figure, the decomposition of the joint density function for five variables using the C-vines can be expressed as follows in Eq. (8).

From Eq. (8), the conditional distribution functions and conditional bivariate copulas can be computed using Eq. (7).

2.4.3. *Regular vine distribution (R-vines)*

Regular vines distributions are much larger and considerably more flexible than the C-vine and D-vine distributions and there are few applications of these vines in the current literature. This is due to the enormous number of possible R-vines tree sequences to choose from. An R-vine on n elements is a nested set of $n - 1$ trees such that the edges of tree j becomes the nodes of tree $j + 1$. Moreover the proximity condition generally ensures that two nodes in tree $j + 1$ are connected by an edge if the nodes share a common node in tree j. In the first tree, the set of nodes contains all indices $1, \ldots, n$, while the set of edges is a set of $n - 1$ pairs of these indices. In the next tree (second), the set of nodes contains sets of pairs of indices and the set of edges is constructed on pars of pairs of indices, etc. Fig. 3 and Eq. (9) shows the R-vine distribution for five variables.

From Eq. (9), the conditional distribution functions and conditional bivariate copulas can be computed using Eq. (4).

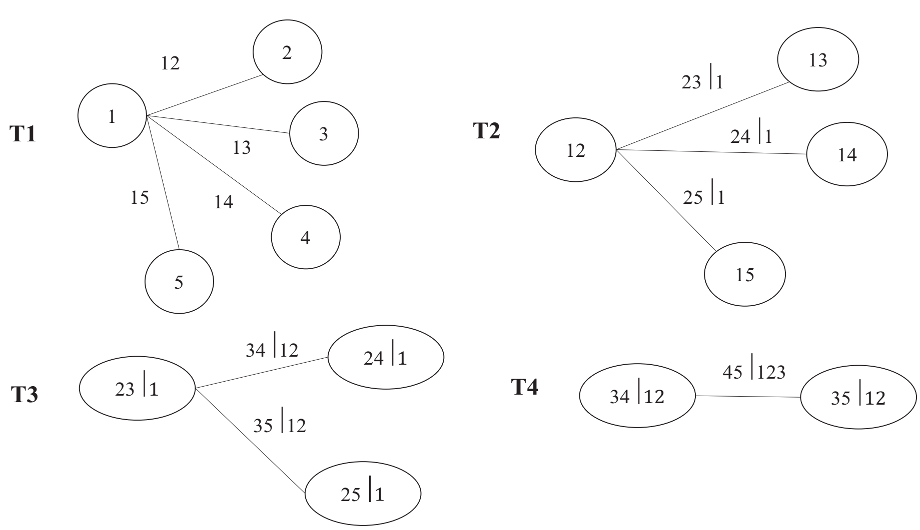

Fig. 2. C-vine for five variables.

$$f_{12345}(z_1, z_2, z_3, z_4, z_5) = f_1(z_1) \cdot f_2(z_2) \cdot f_3(z_3) \cdot f_4(z_4) \cdot f_5(z_5) \cdot c_{12}(F_1(z_1), F_2(z_2)) \cdot c_{13}(F_1(z_1), F_3(z_3)) \cdot c_{14}(F_1(z_1), F_4(z_4)) \cdot c_{15}(F_1(z_1), F_5(z_5)) \cdot c_{23|1}(F_{2|1}(z_2|z_1), F_{3|1}(z_3|z_1)) \cdot c_{24|1}(F_{2|1}(z_2|z_1), F_{4|1}(z_4|z_1)) \cdot c_{25|1}(F_{2|1}(z_2|z_1), F_{5|1}(z_5|z_1)) \cdot c_{34|12}(F_{3|12}(z_3|z_1, z_2), F_{4|12}(z_4|z_1, z_2)) \cdot c_{35|12}(F_{3|12}(z_3|z_1, z_2), F_{5|12}(z_5|z_1, z_2)) \cdot c_{45|123}(F_{4|123}(z_4|z_1, z_2, z_3), F_{5|123}(z_5|z_1, z_2, z_3)) \tag{8}$$

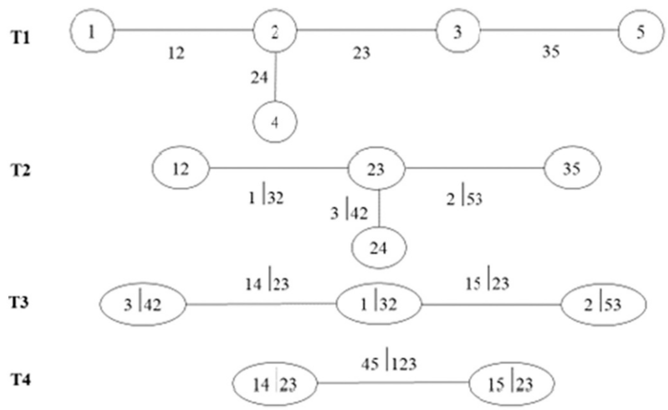

Fig. 3. R-vine for five variables.

$$\begin{aligned} f_{12345}(z_1,z_2,z_3,z_4,z_5) = {} & f_1(z_1)\cdot f_2(z_2)\cdot f_3(z_3)\cdot f_4(z_4)\cdot f_5(z_5)\cdot c_{12}(F_1(z_1), \\ & F_2(z_2))\cdot c_{23}(F_2(z_2),F_3(z_3))\cdot c_{24}(F_2(z_2),F_4(z_4))\cdot c_{35}(F_3(z_3), \\ & F_5(z_5))\cdot c_{32|1}(F_{2|1}(z_2|z_1),F_{3|1}(z_3|z_1))\cdot c_{24|3}(F_{2|3}(z_2|z_3), \\ & F_{4|3}(z_4|z_3))\cdot c_{53|2}(F_{3|2}(z_2|z_2),F_{5|2}(z_5|z_2))\cdot c_{23|14}(F_{2|14}(z_2|z_1,z_4), \\ & F_{3|14}(z_3|z_1,z_4))\cdot c_{15|23}(F_{1|12}(z_1|z_2,z_3), \\ & F_{5|12}(z_5|z_2,z_3))\cdot c_{45|123}(F_{4|123}(z_4|z_1,z_2,z_3)),F_{5|123}(z_5|z_1,z_2,z_3)) \end{aligned} \tag{9}$$

2.5. *Goodness of fit test*

The cumulative distribution function (cdf's) of the fitted pair copulas (i.e., D-vine, C-vine and R-vine) obtained with a Monte-Carlo procedure were plotted against the empirical copula $\widehat{C}_N$ in Eq. 10 (Addo et al., 2018) and Fig. 4.

$$\widehat{C}_N(r,s,\dots,z) = \frac{1}{N}\sum_{i=1}^{N} I\left(\frac{Aus_i}{N+1} \le r, \frac{Ger_i}{N+1} \le s, \dots, \frac{UK_i}{N+1} \le z\right) \tag{10}$$

where Aus_i, Ger_i, …. , UK_i are ranks of Australia, Germany, Canada, France, the Eurozone, Japan, Italy, the USA and the UK respectively. Points plotted correspond to $r = s = \dots z$ from 0.01 to 0.99 in steps of 0.01. The measure of fit in this plot is based on how close the points are to the diagonal line $y = x$. This is measured by calculating the mean squared vertical distances between the empirical copula and the fitted copula just before (when the empirical copula is below the fitted), or just after (when the empirical copula is above the fitted copula).

3. Data

Our dataset contains monthly time series of Government 10 years bond yields obtained from Thompson Reuters DataStream for the US, the UK, Japan, Germany, Canada, France, Italy, Australia and the Eurozone, during the time period from January 1970 to February 2019.We focused on these countries following their significance in the global economy and global international bond market. We also include Eurozone bond yields since European Monetary Union plays a key role in international monetary activities and can affect the monetary activities of the countries under study.

Table 1 shows the descriptive statistics; Fig. 4 shows the Pearson correlation (raw datasets) of all the bond markets countries. Comparing the means of bond yields, we find Italy (7.65) is the highest, followed by Canada (6.42) with Japan recording the lowest (3.23). In addition, with the exception of Germany all bond yield series are positively skewed and have excess kurtosis. Fig. 5 shows the histogram for all the bond markets countries. We test for the presence of autocorrelation using the Ljung-Box test with the results confirming the strong presence of autocorrelation. We also test for the presence of ARCH effects using ARCH-LM test of Engle (1982) and the results suggest the presence of ARCH effects in the series, which gives room for the series to be modelled using GARCH models. Lastly, we use the Jarque-Bera (JB) test to test for the normality assumption in the series. We reject the null hypothesis of normality for all series under examination. In Table 2, we report the linear Pearson correlation between the 9 countries. We find strong correlation between all country pairs. For instance, France-Canada (0.9369), Japan-France (0.8668), UK-US (0.8618) and Australia-UK (0.8130). Even though the linear correlation reported in Table 2 shows evidence of strong dependence, it is worth mentioning that the correlation coefficient reported in Table 2 only tells us about the average dependence over the entire distribution, thus, it will be misleading if we base our investment decisions on such results. Furthermore, correlation is a linear measure and is unable to capture the non-linear dependencies between the markets, hence the need to use the pair copula technique, which is more robust to measure dependences in government bond yields to aid diversification decisions.

4. Empirical results

4.1. *Estimate of ARMA-GARCH models*

To obtain the residuals for each country's bond yield for the copula estimation, we first use ARMA filters to examine the features of each country's bond yields to ensure the residuals are free from autocorrelation. Next, we test the fitted series for ARCH effects using ARCH-LM test with results showing evidence of heteroscedacity for each of the series. We determine the optimal lag length for each univariate GARCH and fit various specifications to the second moments. In Table 3, we report estimates of the ARMA-GARCH models for the bond yields where we select the best fitting models based on the Akaike Information Criterion (AIC) of all order combinations from (0,0) to (6,6). Using the AIC, we find the best fitting models are ARMA(3,4)-GJR-GARCH(1,1) for Australia, ARMA(4,1)-EGARCH(1,1) for Canada, ARMA(3,3)-EGARCH (1,1) for the Eurozone, ARMA(4,3)-EGARCH(1,1) for France, ARMA (4,3)-GJR-GARCH(1,1) for Germany, ARMA(4,3)-EGARCH(1,1) for Italy, ARMA(3,4)-GJR-GARCH(1,1) for Japan, ARMA(4,4)-EGARCH (1,1) for the UK and ARMA(4,4)-GJR-GARCH(1,1) for the US. We note that for Australia, Germany, Japan and US, the GJR-GARCH which captures the asymmetry in volatility is statistically significant. After obtaining the optimal models using the marginal specifications, we next employ the empirical distribution function (ecdf's) to transform the standardized i.i.d. residuals into uniform margins after which we carry out goodness of fit tests for the marginal models by employing the ARCH-LM test and Ljung-Box tests to the PIT residuals of the underlying error terms for each of the ARMA-GARCH (p,q) processes. We carry out the ARCH-LM test for the first four moments of the PIT of the standardized residuals from the marginal models. From Table 4, the results suggest the absence of serial correlation in the series, which justifies the appropriateness of the marginal models.

4.2. *Bivariate copula family estimate analysis*

Following the purposes of the study, we rely on the transformed standardized residuals obtained from the marginal models to investigate the tail dependence of the nine countries bond yields since the tail dependence discloses movement linkages in extreme events. To begin the bivariate analysis, we first employ a bivariate copula selection to understand the relationship between each pair of countries. Table 5 reports the best of fit copula families by maximum likelihood using the function *fitCopula* in the package *Vine Copula* (Schepsmeier et al., 2016) and Kendall's τ for each pair of countries. All 36 country pairs fall into 5 different copula families out of 40. The best fits copula families are Student-*t* copula, Gumbel copula, BB1 copula, BB7 copula and rotated Gumbel copula (180 degrees; 'survival Gumbel').

Table 5 shows the Student-*t* copula dependence structure for country pairs such as Australia-Germany, Australia-UK, Germany-France, Germany-Japan, Canada-Italy, Canada-US, France-UK, Japan-UK, US-UK. The best copula fit for Eurozone-Italy, Eurozone-Japan, Eurozone-US and Eurozone- UK country pairs are estimated as Student-*t* copula. Student-*t* copula shows series' symmetric upper and lower tail dependence, which suggests the co-movement in both positive and negative extreme events. Thus, in a crisis period or during a negative extreme event, portfolio managers should desist from holdings these assets in the same portfolio since the negative events such as the recent COVID 19 outbreak can lead to underperformance in the international bond markets. The symmetric dependence in bond yield between Australia and Germany, France, Eurozone, Italy and UK imply that Australia's bond market is intertwined with the bond markets of Europe though from the Tau estimate, the magnitude of dependence is marginal. The low level of dynamic interaction among these markets might help international investors select target countries with the greatest diversification potential. Focusing on the linkages among the G7 countries in Europe, the marginal dependence evidence by the Tau estimate for Germany-France (0.2153), Germany-Italy (0.2377), Germany-UK (0.3087), France-Italy (0.2490), France-UK (0.2087), and Italy-UK (0.1575) is in consonance with the findings of Yang (2005a, 2005b) who documented weak relationship among European government bond for these countries. Our findings on the dependence between Germany and US (0.3156) bond markets agrees with the conclusion Engsted and Tanggaard (2007) who used a VAR approach to examine linkages between US and German Bond Markets.

Table 5 also displays Gumbel copula dependence structure with Italy-USA with Tau correlation coefficient of 0.1059. Gumbel copula models asymmetric dependence structure and is better known for upper tail dependence than in the lower tails. This connotes that Italy and USA bond markets will tend to decrease together but not increase together though the dependence is a weak following the Tau value. Thus, bond yield for Italy-USA will have a low level of dependence in negative events compared to positive events.

From Table 5, we also find BB1 copula dependence structure for Canada-UK (0.2373) and Canada-Eurozone (0.2176). The BB1 copula main advantage is that it can model and capture more than one type of dependence. It is normally suitable for data with tail dependence thus one parameter models upper tail and the other model the lower tail. These indicate that the countries exhibiting BB1 copula will experience bond yield co-movement both in periods of good and bad times. This implies that Canada bond returns is not a good hedge for UK and Eurozone bond returns since there is dependence at each point in time.

Results reported in Table 5 further show BB7 copula (Joe-Clayton) dependence structure with Australia-Canada as an example. These types of copulas are able to model the asymptotic tail dependence of all variables, and in addition the parameters of the copula are allowed to change over time, and their estimations are also very flexible. This reveals there is evidence of different upper and lower tail dependence. We also find same results for Germany-Canada. The BB7 copula dependence structure between Canada-Australia and Canada-Germany connotes a low dependence between these countries in both stress and crisis time as well as during positive events evidenced by Tau correlation coefficient of 0.2049 and 0.2153 respectively. The significant positive linkages between Australia-Canada and Canada-Germany indicates that the economy of Canada significantly affects the economic activities of these two developed countries.

Finally, Table 5 shows survival Gumbel copula, which only represents lower tail dependence rather than higher tail dependence for Canada-France. This suggests that the bond yield of Canada-France will tend to increase together but not decrease together. Thus, bond yield linkages have a higher level of dependence in negative events as opposed to positive events. This connotes that Canada bond returns are not a good hedge for France bond returns and do not protect investors during negative events, which can lead to under performance.

4.3. Pair-copula analysis using D-vine, C-vine and R-vine copulas

Following the bivariate copula family selections explained above, we further investigate the interdependence between all the countries bond yields using structured vine. Consequently, we adopt D-vine, C-vine and R-vine structures respectively to estimate the group of countries. The C-vine copula requires a node country that has the most dependence to every country, meaning it controls the relationship of all the countries. From Table 5, we find that the Eurozone has the highest average dependence with other countries using estimates from the Kendall's τ. Hence, we select the Eurozone as the node country for level 1C-vine structure as reported in Fig. 4 and Table 6. For level 2 of the C-vine structures reported in Table 5, USA emerged as the country with the second highest average dependence with other countries. The D-vine with optimal chain dependence structure is also used to model the interdependence between all the countries bond yields. D-vine distribution requires computation of several conditional distribution functions and bivariate copulas. From Table 7 and Fig. 6, the best order is the UK, USA, Italy, Japan, the Eurozone, France, Canada, Germany, and Australia. Focusing on a more flexible structure, we also estimate R-vine interdependency structure for all bond yields by introducing different "edges". The best-estimated R-vine copula first level is reported in Fig. 7 with Table 8 reporting all tree levels. From the fitting, the first level of R-vines shows that the Eurozone connects to three countries, these being Italy, France and Australia in terms of bond yield, which makes it the most connected country. Germany is also connected to USA and the Eurozone. The countries connected to the Eurozone represent the core of the Euro Area, in terms of potential channels of interconnection between the different economies. The R-vine structure also shows the tendency of clustering. We find that the bond yield of relatively stronger economies including Germany, USA, the UK, Canada and Japan are connected. From the Goodness of Fit test performed on all three pairs of copulas, we find that the R-vine best models the interdependence for all nine bonds yield countries as shown in Fig. 8. We further quantified the mean of the squared vertical distances between the empirical copula and the fitted copula. This gave values of 0.0002024724, 0.0007755429 and 0.0001791226 for C-vine, D-vine and R-vine copula respectively. The best fit, by this measure, is given by the R-vine copula, which confirms the earlier assertion.

4.4. Robustness checks: Time-varying bivariate dependence structure (copula)

For robustness checks, we replicate the bivariate static copula results reported in Table 5 using bivariate time-varying copulas including

Normal, Clayton, Rotated Clayton, Gumbel, SJC and Student-t to further examine the nature of the dependence structure since the constant copula in light of changing volatility in bond markets would not yield convincing results as international markets dependence is dynamic. The tail dependence structure between the nine bond markets using the time-varying copulas are discussed in this section. We present estimates for the returns and use the log likelihood (LL, hereafter) to obtain the best-fit copula model.

In Table 9,[1] we report the estimated results for the dependence between Australia bond market and bond markets of Germany, Canada, France, Eurozone, Japan, Italy, USA and UK. We note that from the time-varying estimates, the Symmetrized Joe-Clayton (SJC, hereafter) copula model provides a better fit for Australia bond market and bond markets of Canada, Germany, France, Eurozone, Japan, Italy, USA than the other models using the minimum log-likelihood. The emergence of SJC copula as the best fit for these bond markets indicates that the extreme co-movement between these bond markets is featured with asymmetric properties, which means that there is a larger probability of joint crash than booming. Thus, the news or shocks generating joint crash will be outdated more slowly than those generating joint bull markets. Consistent with the static models reported in Table 5, the time-varying Student-*t* copula model provides a better fit for Australia and UK pair. This implies that bond returns for Australia and UK jointly depreciate and appreciate together. In other words, whenever the Australia's bond value drops (rises), the UK's bond jointly rises (drop) in value.

For the bond pairs Germany-Canada, Germany-France, Germany-Eurozone, Germany-Japan, Germany-USA and Germany-UK, time varying dependence structure estimates reported in Table 10 once again shows SJC copula as the best copula fit with time-varying Student-t providing the best fit for Germany and Italy. From Table 11, we again find SJC copula as the best-fit model for Canada-France, Canada-Japan, Canada-Italy, Canada-USA and Canada-UK with time-varying Gumbel copula emerging as the best fit for Canada and Eurozone. With Gumbel copula providing the best fit for Canada and Eurozone that bond markets of these two countries tend to jointly depreciate more than appreciate. From the static copula modes reported in Table 5, the student-t copula appeared as the best-fit model for France-Eurozone, France-Japan, France-Italy, France-USA and France-UK. However, when time-varying copulas are used following the dynamic nature of bond markets, for the same country pairs, we find from Table 12 the best-fit model to be SJC copula. Table 13 reports the dependence structure between Eurozone and Japan, Eurozone-Italy, Eurozone-USA and Eurozone-UK and shows the best-fit model to be SJC copula. These findings imply that for these bond markets there is a larger probability of joint crash than booming.

From Table 14, the best time-varying copula model for Japan-Italy is Clayton copula while Japan-UK is best modelled by Gumbel copula. These Archimedean copulas (i.e. Clayton and Gumbel) suggest that greater upper tail dependence than the lower tail, signifying the presence of asymmetry in the bivariate relationships. Focusing on Japan-Italy, it implies that Japan bond market is a good hedge against Italy bond market, thus revealing the diversification benefits of Japan bond markets. Table 15 reports estimates from time-varying copulas for Italy-USA and Italy-UK with the best-fit model emerging to be Rotated Gumbel copula and SJC copula respectively. Table 16 display parameters estimates for USA-UK bond markets with results showing SJC copula as the best-fit model indicating UK and UK bond markets co-crashes each other than booming together. Thus, it is not prudent to have a portfolio including both UK and USA bonds.

The overall results from the time-varying copulas employed to examine the dependence structure of the nine bond markets indicates that the dependence structure is time-varying which connotes that using static models or linear correlation models to test the dependence across the bond markets of the nine developed economies can be misleading. According to the log-likelihood, we find that the dynamic copula offers a better fit compared to the constant copulas in most cases, providing strong evidence that the relationship between the bond markets examined is time-varying. Overall, SJC copula emerged as the best copula fit for majority of the bond pairs suggesting that these bond pairs in our sample are asymmetrically upper and lower tail dependent.

4.5. Robustness checks: Time-varying tail dependence structure parameter plots

To further cement the contribution of this paper we provide time varying dependence parameter plots across country pair bond markets in Appendix B to examine how bond markets dependence structure change as time changes. To compare the dependence structure in normal times and crisis periods, we use the Asian Financial Crisis spanning from July 1997 to 1999 and Global Financial Crisis from December 2007 to June 2009 as benchmark crisis period. From the parameter plots, we observe that the tail dependence structure is time-varying in both normal and crisis periods. However, the dependence structure is seen to be intense for some country pairs during the Global Financial Crisis period. We attribute these findings to the integration of global financial markets. This may be the case because integrated financial markets facilitate risk sharing (Marashdeh & Shrestha, 2010).

5. Conclusions

This paper re-examines the dependence structure between international bond markets 10 year government bond yields for nine countries, for the time-period from January 1970 to February 2019 using copulas. The empirical results presented shows that the magnitude of the dependence is heterogeneous across bond markets irrespective of the prevailing market conditions. We find that the Eurozone is the most connected node in our sample. We also provide evidence that the UK and the USA are less integrated with other markets. From the time-varying copula parameter estimates, results show that SJC is the best copula fit while for the time-invariant copula, Student-t copula emerged as the bit fit. Overall, comparing the log-likelihood, we find that the dependence among the bond markets examined is time-varying and not static.

Finally, the findings of this study carry out some important implications. First, the low level of dynamic interaction of markets examined in this study might help international investors select target countries with the greatest diversification potential. Second, our findings using time-varying copulas might also be useful in macroeconomic policy formulation, since understanding the dynamics of the international bond market co-movement is important for modelling and forecasting long-term interest rates in both good and bad times evidenced by the dependence parameter plots. There are several potential extensions for further research. In future, we recommend the application of fractional integration and cointegration techniques (Abakah et al., 2020Gil-Alana, Abakah, & Abakah, 2020; Gil-Alana, Abakah, & Rojo, 2020; Gil-Alana et al., 2018), which are also robust and rigorous econometric techniques to uncover the interdependence between international bond markets and thereby establish stylized facts relating to international bond markets dependence. In addition, we recommend in further research using regime-switching copulas under different time scales to further unravel the dependence across these bond markets under different time horizons.

[1] For the time-varying copula results reported across Tables 9–16, we do not present the standard errors for simplicity reasons. However, there are readily available upon request.

CRediT authorship contribution statement

Emmanuel Joel Aikins Abakah: Conceptualization, Data curation, Methodology, Validation, Visualization, Writing - review & editing, Software, Formal analysis, Resources, Investigation, Writing - original draft, Supervision. **Emmanuel Addo**: Investigation, Validation, Resources, Supervision. **Luis A. Gil-Alana**: Conceptualization, Methodology, Investigation, Supervision, Funding acquisition, Writing - review & editing; **Aviral Kumar Tiwari**: Software, Formal analysis, Supervision, Investigation, Validation, Writing - review & editing.

Appendix A. Table of results

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Skewness	Kurtosis	JB	Q(2)	$Q^2(2)$	ARCH
Australia	5.71	4.72	0.31	1.99	48.72***	258.94***	199.10***	189.47***
Canada	6.42	3.23	0.62	3.03	52.42***	219.36***	174.60***	83.24***
Eurozone	5.05	4.43	0.33	1.84	61.23***	289.89***	206.45***	204.90***
France	6.09	4.27	0.36	2.63	22.96***	226.26***	201.09***	195.30***
Germany	5.22	2.95	−0.51	2.19	58.87***	291.47***	205.69***	204.45***
Italy	7.65	4.53	0.92	3.16	118.47***	451.38***	378.71***	242.03***
Japan	3.23	3.21	0.50	1.69	94.39***	227.34***	204.81***	200.48***
UK	6.21	4.48	0.21	2.08	35.55***	285.52***	202.96***	186.99***
US	5.74	2.96	0.58	3.43	53.41***	271.94***	230.53***	171.67***

Notes: The table reports the summary statistics for monthly bond yield for the various countries from January 1970 to February 2019. Std.Dev denotes standard deviation. JB denotes the Jarque-Bera test for normality. Q(2) and $Q^2(2)$ are the Ljung-Box test for serial correlation of order 2 in bond yield and squared bond yield. ARCH(2) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 2.

*** Denotes significance at 1%.

Table 2
Linear correlations.

	Australia	Canada	Eurozone	France	Germany	Italy	Japan	UK	US
Australia	1								
Canada	0.8337	1							
Eurozone	0.9572	0.8659	1						
France	0.8127	0.9369	0.8618	1					
Germany	0.5562	0.8041	0.6393	0.8203	1				
Italy	0.7696	0.8982	0.8271	0.8256	0.6431	1			
Japan	0.7252	0.8312	0.8004	0.8668	0.7424	0.7371	1		
UK	0.8132	0.8596	0.8648	0.9123	0.7654	0.7443	0.8138	1	
US	0.8695	0.9586	0.8878	0.9328	0.7738	0.8308	0.8074	0.8618	1

Table 3
Estimate of marginal models.

Country	Australia	Canada	Eurozone	France	Germany	Italy	Japan	UK	US
ARMA order	(3,4)	(4,1)	(3,3)	(4,3)	(4,3)	(4,3)	(3,4)	(4,4)	(4,4)
GARCH type	GJR-GARCH	EGARCH	EGARCH	EGARCH	GJR-GARCH	EGARCH	GJR-GARCH	EGARCH	GJR-GARCH
GARCH order	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)	(1,1)
Panel A: Conditional mean									
c	1.705	2.009***	1.673**	1.507	1.545***	−10.052	1.864***	1.634**	1.743***
φ_1	0.402***	0.150**	1.468***	−0.284**	0.409***	0.903***	1.122***	1.78***	−1.578***
φ_2	−0.344|***	0.905***	−0.470***	1.530***	−0.193***	0.785***	0.668*	0.017	0.183**
φ_3	0.940***	−0.114***	0.000	0.360***	0.980***	−0.665***	−0.790***	−1.739***	1.591***
φ_4		0.046		−0.608***	−0.218**	−0.024***		0.938***	0.771***
θ_1	0.800***	0.973***	−0.154***	1.384***	1.033***	0.512***	−0.107	−0.467***	2.956***
θ_2	1.129***		−0.056	−0.119	1.152***	−0.554***	−0.878***	−1.077***	3.325***
θ_3	0.240***		0.161**	−0.606***	0.195**	−0.181***	−0.057	0.683***	1.605***
θ_4	0.040*			−0.030			0.093*	0.335***	0.247***
Panel B: Conditional variance									
ω	9.48E-05****	−0.565***	0.027***	−0.547***	3.97E-05***	−0.639***	3.23E-03	−0.428***	1.27E-05***
α_1	0.058**	0.291***	−0.010	0.239***	0.100***	0.417***	1.193***	0.118***	0.103***
β_1	0.818***	0.948***	1.001***	0.939***	0.771***	0.950***	0.840***	0.950***	0.841***
Asym	0.164**	−0.026	−0.038***	−0.166***	0.3224***	0.034	0.147***	−0.086***	0.139***
Log Like	1099.683	1574.902	1222.915	1246.703	1387.901	1681.479	823.222	1333.127	1593.849
AIC	−3.668	−3.844	−4.129	−3.492	−3.709	−3.973	−2.592	−3.940	−4.017

Notes: The table shows the marginal model estimates for the bond yield for each country over the period January 1970 to February 2019. In Panel A, we report the estimates for the conditional mean, modelled using ARMA (p,q) model. In Panel B, we present the parameter estimates from GARCH (p,q) models of the conditional variance.

*** Denotes 1% significance.

** Denotes 5% significance.

Table 4
Goodness of fit tests.

	LAG 1	LAG 2	LAG 3	LAG 4
Panel A: ARCH LM TEST				
Australia	−0.227 [0.582]	−0.044 [0.287]	0.062 [0.128]	−0.017 [0.677]
Canada	0.045 [0.195]	−0.053 [0.135]	0.044 [0.213]	−0.047[0.184]
Eurozone	0.028 [0.498]	0.072 [0.860]	0.032 [0.449]	0.037 [0.370]
France	0.034 [0.361]	−0.012 [0.753]	−0.022 [0.559]	0.017[0.654]
Germany	0.087 [0.019]	−0.024 [0.525]	−0.003[0.943]	−0.007[0.841]
Italy	0.030 [0.377]	0.016 [0.654]	−0.053[0.124]	0.038[0.274]
Japan	0.042[0.302]	−0.028 [0.487]	−0.001[0.985]	−0.031[0.449]
UK	0.070 [0.073]	−0.016 [0.672]	0.071[0.070]	−0.005[0.907]
USA	0.029 [0.421]	−0.012 [0.744]	−0.008[0.818]	−0.001[0.970]
Panel C: Ljung-Box test on standardized squared residuals (Q^2)				
Australia	0.382[0.537]	1.541[0.463]	4.101[0.251]	4.302[0.367]
Canada	1.330[0.249]	3.098[0.212]	4.274[0.233]	5.636[0.228]
Eurozone	0.699[0.403]	4.138[0.126]	4.962[0.175]	6.155[0.188]
France	0.831 [0.362]	0.926 [0.629]	1.278[0.734]	1.450[0.835]
Germany	5.337 [0.021]	5.537 [0.063]	5.568[0.135]	5.614[0.230]
Italy	0.685 [0.408]	0.879 [0.644]	3.121[0.373]	4.160[0.385]
Japan	1.039[0.308]	1.455 [0.483]	1.467[0.690]	2.022[0.732]
UK	3.234 [0.072]	3.261 [0196]	6.454[0.091]	6.475[0.166]
USA	0.628 [0.428]	0.735 [0.692]	0.793[0.851]	0.794[0.939]

Notes: The table presents estimates and p-values for the test of serial correlation in the standardized residuals of the bond yield for each country, based on ARCH LM test and Ljung-Box test on squared residuals at 10 lags. The test was carried out for 4 lags. We report p-values in the parenthesis.

Table 5
Bivariate copula selection.

Country pair	Family	τ	Country pair	Family	τ
AUS-GER	2	0.2688**	FRA-EUR	2	0.3650***
AUS-CAN	9	0.2049, 0.6015***	FRA-JAP	2	0.1092
AUS-FRA	2	0.2565**	FRA-ITA	2	0.2490**
AUS-EUR	2	0.2967**	FRA-US	2	0.1822
AUS-JAP	2	0.1077	FRA-UK	2	0.2087**
AUS-ITA	2	0.1921			
AUS-US	2	0.2725**			
AUS-UK	2	0.2488**	EUR-JAP	2	0.0914
			EUR-ITA	2	0.4559***
			EUR-US	2	0.2758**
GER-CAN	9	0.2153, 0.6125***	EUR-UK	2	0.3059***
GER-FRA	2	0.2393**			
GER-EUR	2	0.4154***			
GER-JAP	2	0.1519	JAP-ITA	2	0.0425
GER-ITA	2	0.2377**	JAN-US	2	0.1189
GER-US	2	0.3156***	JAP-UK	2	0.1239
GER-UK	2	0.3087***			
			ITA-US	4	0.1059
CAN-FRA	14	0.1351	ITA-UK	2	0.1575
CAN-EUR	7	0.2176, 0.6234***			
CAN-JAP	2	0.1661	US-UK	2	0.2870**
CAN-ITA	2	0.1156			
CAN-US	2	0.3779***			
CAN-UK	7	0.2373, 0.6531***			

Notes: All the following family are tested, and the number shows the best fit. 0 = independence copula; 1 = Gaussian copula; 2 = Student-t copula (t-copula); 3 = Clayton copula; 4 = Gumbel copula; 5 = Frank copula; 6 = Joe copula; 7 = BB1 copula; 8 = BB6 copula; 9 = BB7 copula; 10 = BB8 copula; 13 = rotated Clayton copula (180 degrees; 'survival Clayton'); 14 = rotated Gumbel copula (180 degrees; 'survival Gumbel'); 16 = rotated Joe copula (180 degrees; 'survival Joe'); 17 = rotated BB1 copula (180 degrees; 'survival BB1'); 18 = rotated BB6 copula (180 degrees; 'survival BB6'); 19 = rotated BB7 copula (180 degrees; 'survival BB7'); 20 = rotated BB8 copula (180 degrees; 'survival BB8'); 23 = rotated Clayton copula (90 degrees); 24 = rotated Gumbel copula (90 degrees); 26 = rotated Joe copula (90 degrees); 27 = rotated BB1 copula (90 degrees); 28 = rotated BB6 copula (90 degrees); 29 = rotated BB7 copula (90 degrees); 30 = rotated BB8 copula (90 degrees); 33 = rotated Clayton copula (270 degrees); 34 = rotated Gumbel copula (270 degrees); 36 = rotated Joe copula (270 degrees); 37 = rotated BB1 copula (270 degrees); 38 = rotated BB6 copula (270 degrees); 39 = rotated BB7 copula (270 degrees); 40 = rotated BB8 copula (270 degrees).

*** *Denotes 1% significance respectively.*
** *Denotes 5% significance respectively.*

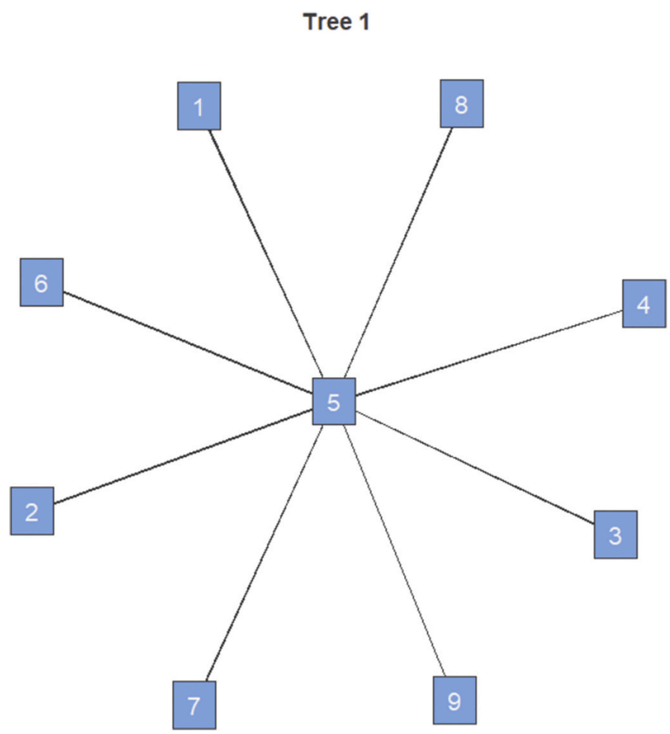

Fig. 5. C-vine Tree structure for the first Tree (T1). 1 <-> AUS, 2 <-> GEM, 3 <-> CAN, 4 <-> FRA, 5 <-> EUR, 6 <-> JAP, 7 <-> ITA, 8 <-> USA, 9 <-> UK>.

Table 6
C-vine tree level 1 to level.

Tree	Edge	Family	Cop	Par	Par2	Tau
1	5,2	2	t	0.61	3.28	0.42
	5,3	7	BB1	0.20	1.16	0.22
	5,4	2	t	0.54	2.81	0.37
	5,6	2	t	0.14	2.52	0.09
	5,7	2	t	0.66	4.69	0.46
	5,1	2	t	0.45	2.12	0.30
	5,8	2	t	0.42	9.96	0.28
	9,5	2	t	0.46	2.58	0.31
2	8,2;5	2	t	0.30	7.31	0.20
	8,3;5	2	t	0.48	8.23	0.32
	8,4;5	5	F	0.72	0.00	0.08
	8,6;5	20	SBB8	1.28	0.94	0.10
	8,7;5	1	N	−0.12	0.00	−0.08
	8,1;5	2	t	0.26	7.46	0.17
	9,8;5	5	F	1.99	0.00	0.21
3	1,2;8,5	7	BB1	0.10	1.04	0.08
	1,3;8,5	1	N	0.07	0.00	0.04
	1,4;8,5	20	SBB8	1.71	0.83	0.16
	1,6;8,5	2	t	0.09	4.45	0.06
	1,7;8,5	2	t	0.04	10.55	0.02
	9,1;8,5	2	t	0.17	5.33	0.11
4	9,2;1,8,5	2	t	0.17	12.03	0.11
	9,3;1,8,5	3	C	0.14	0.00	0.07
	9,4;1,8,5	2	t	0.09	9.70	0.06
	9,6;1,8,5	2	t	0.10	5.65	0.07
	9,7;1,8,5	224	Tawn2_90	−1.40	0.05	−0.03
5	6,2;9,1,8,5	1	N	0.12	0.00	0.08
	6,3;9,1,8,5	5	F	1.01	0.00	0.11
	6,4;9,1,8,5	2	t	0.06	14.43	0.04
	7,6;9,1,8,5	0	I	–	–	0.00
6	4,2;6,9,1,8,5	2	t	0.04	14.16	0.03
	4,3;6,9,1,8,5	0	I	–	–	0.00
	7,4;6,9,1,8,5	5	F	0.77	0.00	0.08
7	7,2;4,6,9,1,8,5	124	Tawn90	−8.23	0.00	−0.00
	7,3;4,6,9,1,8,5	6	J	1.04	0.00	0.02
8	3,2;7,4,6,9,1,8,5	0	I	–	–	0.00

Type: C-vine logLik: 1454.72 AIC: −2795.44 BIC: −2526.32
1 < −> AUS, 2 < −> GEM, 3 < −> CAN, 4 < −> FRA, 5 < −> EUR, 6 < −> JAP, 7 < −> ITA,8 < −> USA, 9 < −> UK.

Notes/: Tree Level 1 refers to the bivariate fit between individual countries. The edges in the first Tree are the nodes of the second Tree etc. Par and Par 2 refers to the fitted copula parameters. (i.e., Par and Par2 are Parameter 1 and Parameter 2 respectively).

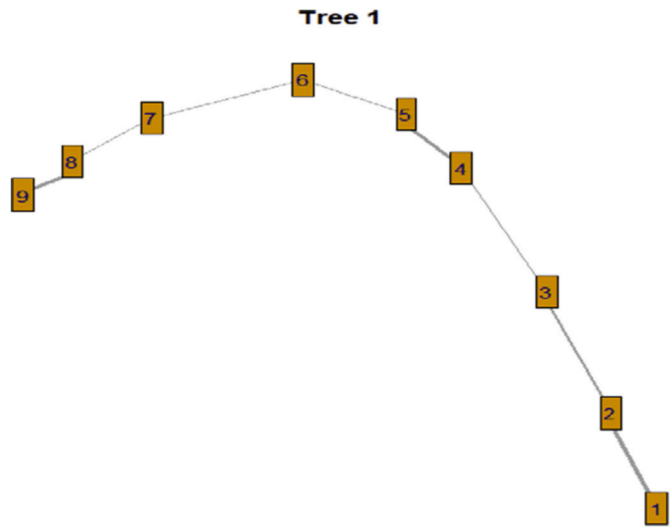

Fig. 6. D-vine tree structure for the first Tree (T1). 1 < −> AUS, 2 < −> GEM, 3 < −> CAN, 4 < −> FRA, 5 < −> EUR, 6 < −> JAP, 7 < −> ITA, 8 < −> USA, 9 < −> UK>.

Table 7
D-vine tree level 1 to level 8.

Tree	Edge	Family	Cop	Par	Par2	Tau
1	1,2	2	t	0.41	4.30	0.29
	2,3	9	BB7	1.14	0.40	0.22
	3,4	14	rG_180	1.16	0.00	0.14
	4,5	2	t	0.54	2.81	0.37
	5,6	2	t	0.14	2.52	0.09
	6,7	2	t	0.07	7.01	0.04
	7,8	4	G	1.12	0.00	0.11
	8,9	2	t	0.44	7.52	0.29
2	1,3;2	33	rC_270	−0.13	0.00	−0.06
	2,4;3	5	F	−0.71	0.00	−0.08
	3,5;4	23	rC_90	−0.09	0.00	−0.04
	4,6;5	40	rBB8_270	−1.21	−0.87	−0.06
	5,7;6	1	N	−0.10	0.00	−0.07
	6,8;7	23	rC_90	−0.03	0.00	−0.01
	8,9;8	23	rC_90	−0.06	0.00	−0.03
3	1,4;2,3	6	J	1.03	0.00	0.02
	2,5;3,4	5	F	0.13	0.00	0.01
	3,6;4,5	13	rC_90	0.03	0.00	0.02
	4,7;5,6	5	F	0.32	0.00	0.04
	5,8;6,7	16	rJ_180	1.03	0.00	0.02
	6,9;7,8	5	F	0.17	0.00	0.02
4	1,5;2,3,4	1	N	−0.02	0.00	−0.01
	2,6;3,4,5	1	N	0.01	0.00	0.00
	3,7;4,5,6	1	N	−0.02	0.00	−0.01
	4,8;5,6,7	1	N	−0.01	0.00	−0.01
	5,9;6,7,8	24	rG_90	−1.01	0.00	−0.01
5	1,6;2,3,4,5	5	F	−0.02	0.00	0.00
	2,7;3,4,5,6	5	F	0.03	0.00	0.00
	3,8;4,5,6,7	16	rJ_180	1.00	0.00	0.00
	4,9;5,6,7,8	5	F	0.07	0.00	0.01
6	1,7;2,3,4,5,6	1	N	−0.01	0.00	0.00
	2,8;3,4,5,6,7	1	N	−0.01	0.00	−0.00
	3,9;4,5,6,7,8	23	rC_90	−0.02	0.00	−0.01
7	1,8;2,3,4,5,6,7	5	F	0.05	0.00	0.01
	2,9;3,4,5,6,7,8	5	F	0.06	0.00	0.01
8	1,9;2,3,4,5,6,7,8	4	G	113.62	0.00	0.99

1 < −> AUS, 2 < −> GEM, 3 < −> CAN, 4 < −> FRA, 5 < −> EUR, 6 < −> JAP, 7 < −> ITA, 8 < −> USA, 9 < −> UK>
Notes: Tree Level 1 refers to the bivariate fit between individual countries. The edges in the first Tree are the nodes of the second Tree etc. Par and Par 2 refers to the fitted copula parameters. (i.e., Par and Par2 are Parameter 1 and Parameter 2 respectively)

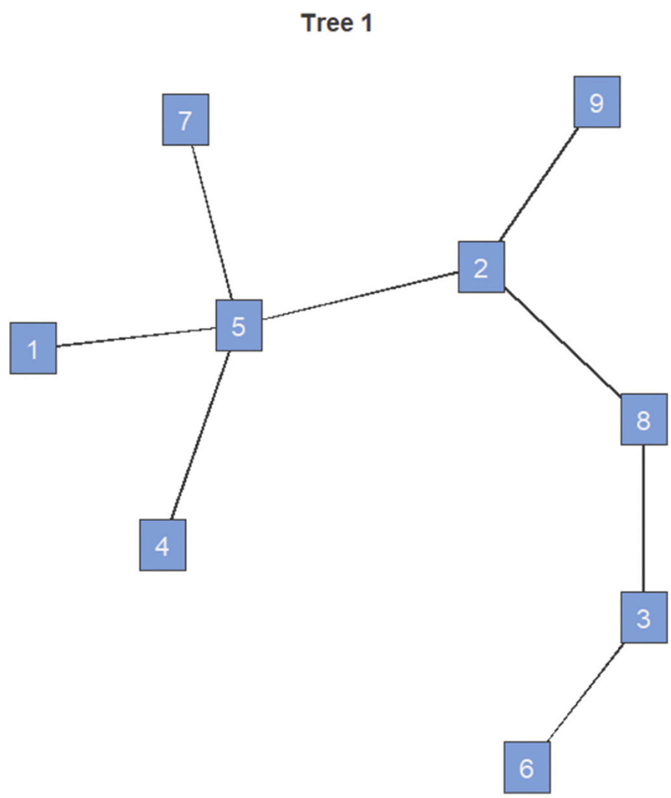

Fig. 7. R-vine tree structure for the first tree (T1). 1 < −> AUS, 2 < −> GEM, 3 < −> CAN, 4 < −> FRA, 5 < −> EUR, 6 < −> JAP, 7 < −> ITA, 8 < −> USA, 9 < −> UK>.

Table 8
R-vine tree level 1 to level 8.

Tree	Edge	Family	Cop	Par	Par2	Tau
1	5,7	2	t	0.66	4.69	0.46
	5,4	2	t	0.54	2.81	0.37
	5,1	2	t	0.45	2.12	0.30
	2,5	2	t	0.61	3.28	0.42
	3,6	2	t	0.26	7.30	0.17
	8,3	2	t	0.56	8.43	0.38
	2,8	2	t	0.48	4.99	0.32
	9,2	2	t	0.47	5.05	0.31
2	4,7;5	2	t	0.10	10.48	0.07
	1,4;5	20	SBB8	1.64	0.87	0.16
	2,1;5	7	BB1	0.18	1.05	0.13
	9,5;2	2	t	0.27	2.99	0.17
	8,6;3	3	C	0.10	0.00	0.05
	2,3;8	2	t	0.10	10.52	0.06
	9,8;2	5	F	1.78	0.00	0.19
3	1,7;4,5	2	t	−0.01	10.33	0.00
	2,4;1,5	2	t	0.06	12.29	0.04
	9,1;2,5	2	t	0.19	5.02	0.12
	8,5;9,2	5	F	0.81	0.00	0.09
	2,6;8,3	19	SBB7	1.08	0.12	0.10
	9,3;2,8	2	t	0.15	16.47	0.09
4	2,7;1,4,5	2	t	−0.05	13.31	−0.03
	9,4;2,1,5	2	t	0.08	11.71	0.05
	8,1;9,2,5	5	F	1.37	0.00	0.15
	3,5;8,9,2	4	G	1.04	0.00	0.04
	9,6;2,8,3	2	t	0.04	5.24	0.03

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Table 8 (*continued*)

Tree	Edge	Family	Cop	Par	Par2	Tau
5	9,7;2,1,4,5	2	t	−0.06	15.82	−0.04
	8,4;9,2,1,5	0	I	–	–	0.00
	3,1;8,9,2,5	0	I	–	–	0.00
	6,5;3,8,9,2	2	t	−0.03	5.85	−0.02
6	8,7;9,2,1,4,5	5	F	−0.59	0.00	−0.06
	3,4;8,9,2,1,5	0	I	–	–	0.00
	6,1;3,8,9,2,5	2	t	0.05	8.64	0.03
7	3,7;8,9,2,1,4,5	2	t	0.01	13.86	0.01
	6,4;3,8,9,2,1,5	10	BB8	1.17	0.90	0.05
8	6,7;3,8,9,2,1,4,5	0	I	–	–	0.00

type: R-vine logLik: 1426.36 AIC: −2736.72 BIC: −2462.87

1 < −> AUS, 2 < −> GEM, 3 < −> CAN, 4 < −> FRA, 5 < −> EUR, 6 < −> JAP, 7 < −> ITA, 8 < −> USA, 9 < −> UK>

Notes: Tree Level 1 refers to the bivariate fit between individual countries. The edges in the first Tree are the nodes of the second Tree etc. Par and Par 2 refers to the fitted copula parameters. (i.e., Par and Par2 are Parameter 1 and Parameter 2 respectively)

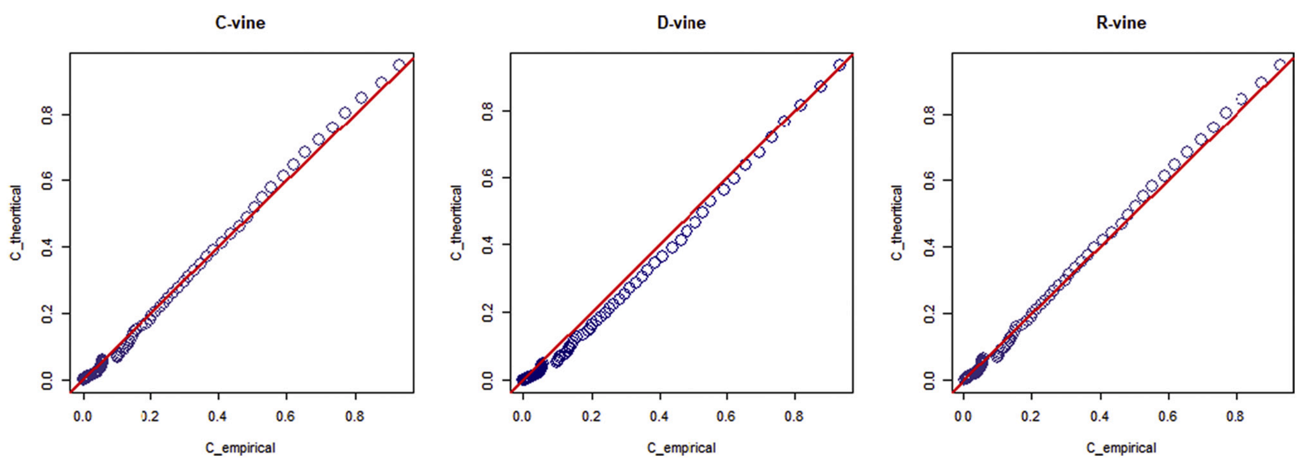

Fig. 8. Fitted C-vine against empirical copulas (left), fitted D-vine against empirical copulas (centre) and fitted R-vine against empirical copulas (right).

Table 9

Parameter estimates of time-varying dependence copulas between Australia and other bond markets.

	Australia-Germany	Australia-Canada	Australia-France	Australia-Eurozone	Australia-Japan	Australia-Italy	Australia-USA	Australia-UK
TVP Normal copula								
ψ_o	1.0329	0.3128	−0.0137	0.0422	0.5721	0.5545	−0.0018	0.0124
ψ_1	0.9379	0.4932	0.1180	0.2403	0.3089	−0.1941	0.1433	0.4314
ψ_2	−1.5445	0.9986	2.0970	1.8773	−0.2515	−0.6662	2.0254	1.9173
Log-like	−50.4796	−72.6770	−67.5654	−80.2516	−25.9672	−10.8314	−68.2203	−114.2267
TVP Clayton copula								
ψ_o	1.3516	0.8681	0.7318	0.8058	0.8681	0.4539	1.3044	1.2076
ψ_1	−0.3824	0.3508	0.3921	0.3735	0.3570	0.6429	−0.2698	0.1138
ψ_2	−1.6149	−1.4088	−0.7776	−1.1949	−1.4712	−0.4542	−1.6374	−1.9625
Log-like	−45.7178	−64.4144	−64.5815	−69.8877	−44.0523	−9.8912	−50.8458	−85.0307
TVP Rotated Clayton copula								
ψ_o	1.0666	0.9050	0.7168	2.2268	0.7559	0.2546	1.4176	2.3106
ψ_1	0.1738	0.3350	0.4089	−0.4679	0.4001	−1.1333	0.0272	−0.0603
ψ_2	−1.9231	−1.4354	−0.8859	−4.5122	−1.1348	1.4243	−3.0460	−6.4920
Log-like	−32.6305	−75.7423	−55.8592	−64.5317	−42.7304	−10.0031	−47.8141	−95.5818
TVP Gumbel copula								
Ω	0.7880	0.3304	0.1341	0.2679	0.1494	0.4528	0.9802	1.8540
β	0.0965	0.4138	0.4837	0.4380	0.4824	−0.1687	0.0939	−0.0673
α	−1.4794	−1.2726	−0.8646	−1.1326	−0.9884	0.2718	−2.2745	−5.0000

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Table 9 (*continued*)

	Australia-Germany	Australia-Canada	Australia-France	Australia-Eurozone	Australia-Japan	Australia-Italy	Australia-USA	Australia-UK
Log-like	−42.8986	−84.0256	−69.6363	−90.0062	−49.4020	−8.8962	−58.7672	−110.0690
TVP Rotated Gumbel copula								
ω_U	1.3985	0.3005	0.2296	0.1443	0.2235	−0.7886	−0.0775	1.2834
α_U	−0.3657	0.4238	0.4528	0.4828	0.4536	1.0680	0.5716	0.0004
β_U	−1.4090	−1.2204	−1.1451	−0.9082	−1.0987	−0.2207	−0.4685	−2.7410
Log-like	−49.3747	−76.1178	−71.5044	−82.1150	−51.3270	−11.1074	−60.0052	−100.6243
TVP SJC copula								
ω_U	**1.2903**	**1.4349**	**−1.7747**	**−1.6033**	**3.0533**	**−6.3242**	**3.6629**	4.0223
α_U	**−13.8955**	**−11.1524**	**−1.9115**	**−2.0829**	**−22.2828**	**7.8832**	**−24.9974**	−20.9968
β_U	**0.9894**	**0.5929**	**4.0821**	**3.8892**	**−0.4795**	**7.1580**	**−0.5500**	−1.6354
ω_L	**0.7015**	**−1.3960**	**−1.2162**	**2.7191**	**−1.3751**	**−0.7808**	**0.2781**	−1.7844
α_L	**−3.5526**	**−4.0515**	**−4.1117**	**−16.7895**	**−3.1282**	**−8.5937**	**−0.0881**	−1.0485
β_L	**−3.1805**	**3.9947**	**3.6759**	**−1.9350**	**3.8405**	**5.1065**	**−5.3097**	3.8586
Log-like	**−53.3899**	**−88.4180**	**−77.5139**	**−94.9004**	**−57.5573**	**−15.4130**	**−65.9995**	−110.7038
TVP Student t copula								
ψ_o	0.0355	0.1332	−0.0115	0.0352	0.6128	0.7020	−0.0149	**0.0189**
ψ_1	0.0825	0.1775	0.0785	0.1418	0.1841	−0.1373	0.0558	**0.2241**
ψ_2	1.8790	1.5839	2.0720	1.9057	−0.0322	−1.7371	2.0960	**1.9726**
υ	4.9999	4.9999	4.9999	4.9999	4.9996	5.0000	4.9551	**5.0000**
Log-like	−49.3724	−67.0197	−64.2592	−83.3050	−36.9349	−8.4710	−62.0764	**−114.8058**

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 10
Parameter estimates of time-varying dependence copulas between Germany and other bond markets.

	Germany-Canada	Germany-France	Germany-Eurozone	Germany-Japan	Germany-Italy	Germany-USA	Germany-UK
TVP Normal copula							
ψ_o	0.24673	−0.0233	1.5214	0.4773	−0.0017	0.7036	**1.3601**
ψ_1	0.06887	0.0119	0.1553	0.0847	0.0581	−0.0803	**−0.2183**
ψ_2	1.40226	2.1364	−1.7265	−0.1816	2.0307	0.5589	**0.1615**
Log-like	−46.39440	−22.5161	−52.7328	−14.7239	−26.2896	−56.3008	**−120.5070**
TVP Clayton copula							
ψ_o	1.01069	0.6541	1.5689	1.8181	1.1753	−0.6740	0.5966
ψ_1	0.00119	0.1113	−0.5682	−0.2720	−0.3903	−0.1132	0.3073
ψ_2	−1.23947	−0.4396	−1.8327	−4.3264	−1.6029	−0.1624	0.3448
Log-like	−35.89800	−18.9977	−53.3072	−17.8209	−22.9264	−54.2868	−96.5906
TVP Rotated Clayton copula							
ψ_o	0.84247	0.1899	1.3106	0.7097	0.8689	1.5146	1.5022
ψ_1	−0.52077	0.5307	−0.5283	0.0201	0.1390	−0.3880	−0.5625
ψ_2	0.49296	0.6410	−1.4455	−0.7171	−1.3019	−2.5317	−0.6601
Log-like	−37.55360	−14.4798	−33.9267	−12.3259	−17.9931	−37.8477	−88.1627
TVP Gumbel copula							
Ω	0.42269	−0.5455	1.9660	0.5483	0.5880	1.6249	1.8355
β	0.13118	0.7318	−0.7763	0.0398	0.0988	−0.4650	−0.5763
α	−0.16776	0.3497	−1.4605	−0.6741	−0.9528	−1.7447	−0.8721
Log-like	−44.40700	−17.9041	−45.9808	−15.7854	−22.7842	−50.3689	−106.7700
TVP Rotated Gumbel copula							
ω_U	0.71247	0.3231	1.9535	1.7810	1.1772	1.9182	0.2016
α_U	0.02163	0.1024	−0.7432	−0.4299	−0.3355	−0.8225	0.3360
β_U	−0.75634	−0.0599	−1.4444	−3.0782	−1.1386	−0.8300	0.1273
Log-like	−42.45640	−21.7221	−56.8256	−20.1025	−25.0167	−59.2650	−110.3745
TVP SJC copula							
ω_U	**−1.28099**	**−5.0752**	**0.4855**	**−1.2766**	1.5465	**4.2352**	4.2711
α_U	**3.39647**	**7.5434**	**−12.5111**	**−6.3764**	−15.4817	**−23.9205**	−19.2903
β_U	**−4.11775**	**3.2709**	**1.9095**	**0.8050**	−1.2599	**−4.8687**	−4.2125
ω_L	**0.30544**	**−1.8746**	**1.8196**	**1.6847**	1.1083	**−1.4803**	−1.9849
α_L	**−7.21085**	**−2.9128**	**−5.4455**	**−11.7637**	−7.7746	**2.1708**	3.7106
β_L	**0.15418**	**5.5193**	**−4.2318**	**−1.2296**	−6.5967	**0.4933**	1.8220
Log-like	**−47.92190**	**−24.3665**	**−59.7510**	**−20.1641**	−25.6337	**−62.2651**	−119.8462
TVP Student t copula							
ψ_o	1.63508	0.3190	0.4118	0.0003	**−0.0252**	0.7258	0.4528
ψ_1	−0.15731	0.0862	−0.0673	0.0177	**0.0231**	−0.0669	−0.0730
ψ_2	−2.04705	0.5031	1.1755	2.0148	**2.1446**	0.4775	1.5574
υ	4.99997	5.0000	4.9999	4.9998	**4.9427**	5.0000	4.9999
Log-like	−44.66150	−18.1528	−54.8562	−18.3623	**−30.2513**	−56.8949	−115.5785

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 11
Parameter estimates of time-varying dependence copulas between Canada and other bond markets.

	Canada-France	Canada-Eurozone	Canada-Japan	Canada-Italy	Canada-USA	Canada-UK
TVP Normal copula						
ψ_o	0.1106	0.3021	2.8764	0.4492	−0.2020	0.0263
ψ_1	0.2291	0.5192	−0.3971	0.1790	0.0239	0.3190
ψ_2	1.8123	1.4692	−1.3558	−1.1642	2.5953	1.8793
Log-like	−100.7529	−167.0702	−182.3384	−6.6768	−78.3669	−85.3457
TVP Clayton copula						
ψ_o	0.9210	1.1920	1.7558	0.8067	1.2465	0.8713
ψ_1	0.3123	−1.6377	−0.9056	0.5723	0.1195	0.3355
ψ_2	−1.4834	0.0098	−0.0099	−1.8632	−2.3153	−1.3421
Log-like	−97.3238	−89.9658	−111.6082	−7.5429	−63.4899	−65.5661
TVP Rotated Clayton copula						
ψ_o	0.9986	1.7987	1.4223	0.4919	0.9625	1.0283
ψ_o	0.2880	−0.9626	−1.0172	0.7232	0.2844	0.2963
ψ_o	−1.6401	−0.0318	−0.0802	−0.7133	−1.4245	−1.8499
Log-like	−113.9501	−107.5555	−74.1855	−8.8620	−76.7889	−85.1944
TVP Gumbel copula						
Ω	0.4814	**0.5863**	0.6398	−0.5691	0.4208	0.4178
β	0.3498	**0.3094**	0.2930	0.9578	0.3542	0.3807
α	−1.4571	**−1.3976**	−1.5382	−0.6248	−1.1898	−1.4174
Log-like	−132.6340	**−211.8669**	−193.4146	−8.2151	−87.1171	−93.7515
TVP Rotated Gumbel copula						
ω_U	0.3891	0.6051	0.7198	−0.2952	0.5432	0.3566
α_U	0.3761	0.3072	0.2752	0.8092	0.2953	0.3955
β_U	−1.2366	−1.5960	−1.7844	−1.0179	−1.4139	−1.2506
Log-like	−124.5700	−190.8330	−200.7658	−9.6804	−76.9730	−81.4498
TVP SJC copula						
ω_U	**−0.0762**	0.9820	**−1.7178**	**3.2530**	**−1.744**	**−0.5736**
α_U	**−6.3711**	−5.6151	**−1.4039**	**−24.4454**	**−1.212**	**−5.6062**
β_U	**2.1953**	0.3576	**3.9018**	**−4.9747**	**3.912**	**3.0109**
ω_L	**1.9256**	3.2529	**−1.7661**	**−0.2458**	**2.130**	**3.0467**
α_L	**−12.0809**	−20.5410	**−2.3898**	**−11.7002**	**−15.065**	**−15.7520**
β_L	**−1.2857**	−0.9797	**4.2620**	**5.3297**	**−0.717**	**−5.1586**
Log-like	**−128.8114**	−205.0350	**−211.8707**	**−10.9409**	**−93.439**	**−96.0654**
TVP Student t copula						
ψ_o	2.3465	0.1509	3.0422	0.4458	−0.180	0.0243
ψ_1	0.4821	0.1210	−0.2783	0.0831	0.019	0.1636
ψ_2	−2.6340	2.0386	−1.4481	−1.1445	2.545	1.9135
υ	4.9998	4.9999	5.0000	5.0000	4.917	4.9999
Log-like	−115.9286	−178.5333	−191.4659	−6.0931	−80.371	−79.5618

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 12
Parameter estimates of time-varying dependence copulas between France and other bond markets.

	France -Eurozone	France–Japan	France–Italy	France–USA	France–UK
TVP Normal copula					
ψ_o	0.0540	1.2339	0.1130	0.0039	0.0105
ψ_1	0.2282	−0.1255	0.1614	0.0763	0.1831
ψ_2	1.8486	−0.5572	1.1251	2.0245	1.9195
Log-like	−70.7572	−58.3182	−8.3058	−47.7560	−47.6067
TVP Clayton copula					
ψ_o	0.9321	0.8713	1.4279	1.3071	0.8649
ψ_1	0.3127	0.3381	−1.3902	0.1541	0.3489
ψ_2	−1.6023	−1.4733	−3.1771	−2.8243	−1.4800
Log-like	−74.3188	−61.8915	−5.5921	−53.1886	−40.3098
TVP Rotated Clayton copula					
ψ_o	0.8216	0.7820	0.4021	1.1106	1.1014
ψ_1	0.3521	0.3661	0.6258	0.2626	0.2986
ψ_2	−1.1918	−1.0885	−0.3096	−2.4611	−2.5321

(continued on next page)

Table 12 (*continued*)

	France -Eurozone	France–Japan	France–Italy	France–USA	France–UK
Log-like	−75.4711	−67.5706	−6.9394	−41.8770	−37.6978
TVP Gumbel copula					
Ω	0.4944	0.2375	−0.8062	0.5070	0.4220
β	0.3552	0.4323	1.0898	0.3498	0.4017
α	−1.7156	−1.0134	−0.2787	−1.8249	−1.7925
Log-like	−90.6214	−80.0382	−7.1906	−52.6339	−45.4557
TVP Rotated Gumbel copula					
ω_U	0.4254	0.3026	−0.6040	1.7101	0.3425
α_U	0.3732	0.4121	0.9704	−0.0921	0.4155
β_U	−1.5057	−1.2066	−0.5644	−4.5478	−1.4919
Log-like	−88.4239	−76.7877	−7.1553	−60.7356	−45.3584
TVP SJC copula					
ω_U	**−1.5976**	**−1.8064**	**−3.4349**	**0.3830**	**1.4097**
α_U	**−3.2282**	**−1.9368**	**−0.8903**	**−11.4572**	**−16.1517**
β_U	**4.0001**	**4.1473**	**12.8878**	**2.0861**	**1.6813**
ω_L	**0.8104**	**2.6493**	**0.4482**	**1.3123**	**−0.8356**
α_L	**−10.2307**	**−17.9736**	**−19.4228**	**−10.6922**	**−4.9666**
β_L	**0.9927**	**−0.6701**	**7.3664**	**0.3408**	**2.8437**
Log-like	**−96.8993**	**−87.5419**	**−9.2546**	**−62.9832**	**−49.1978**
TVP Student t copula					
ψ_o	0.0420	0.4324	0.0926	−0.0023	0.0039
ψ_1	0.1613	0.0410	0.0879	0.0485	0.0312
ψ_2	1.9007	1.1168	1.3157	2.0468	2.0648
υ	4.9998	4.4941	4.9999	4.9999	4.9586
Log-like	−84.1943	−70.2305	−4.1023	−52.7909	−43.8664

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 13
Parameter estimates of time-varying copulas between Eurozone and other bond markets.

	Eurozone-Japan	Eurozone-Italy	Eurozone-USA	Eurozone-UK
TVP Normal copula				
ψ_o	0.2569	0.0948	−0.0797	−0.1241
ψ_1	0.5829	0.1184	0.0946	0.1318
ψ_2	0.9535	1.6073	2.3039	2.3952
Log-like	−50.456	−26.3176	−87.3879	−113.5918
TVP Clayton copula				
ψ_o	0.8756	0.4897	1.1265	2.1503
ψ_1	0.3281	0.5977	0.1607	−0.4563
ψ_2	−1.4484	−0.4462	−1.6988	−3.4821
Log-like	−69.2588	−18.8369	−87.3982	−106.7581
TVP Rotated Clayton copula				
ψ_o	1.2990	0.4932	1.2393	1.0453
ψ_1	0.2067	0.6144	0.2407	0.2776
ψ_2	−2.9697	−0.4560	−2.7697	−1.8616
Log-like	−73.3044	−23.8204	−82.2797	−88.4530
TVP Gumbel copula				
Ω	0.4851	−0.3908	0.8341	0.4612
β	0.3521	0.7824	0.2496	0.3577
α	−1.6523	−0.3908	−2.4772	−1.3611
Log-like	−87.5436	−26.2836	−98.908	−114.7258
TVP Rotated Gumbel copula				
ω_U	0.3508	−0.4024	0.6241	0.3916
α_U	0.3915	0.7792	0.2747	0.3750
β_U	−1.3308	−0.3313	−1.5739	−1.0975
Log-like	−82.6446	−23.0606	−100.8523	−128.9202
TVP SJC copula				
ω_U	**−0.5141**	**−1.8246**	**−1.4148**	**0.8179**
α_U	**−6.2928**	**−2.5470**	**−4.4152**	**−11.6201**
β_U	**2.8400**	**4.8424**	**4.0500**	**1.4472**
ω_L	**−1.3651**	**−1.9154**	**0.5058**	**1.4368**

(*continued on next page*)

Table 13 (*continued*)

	Eurozone-Japan	Eurozone-Italy	Eurozone-USA	Eurozone-UK
α_L	**−4.7697**	**−3.9595**	**−5.5765**	**−8.8052**
β_L	**3.8383**	**6.1054**	**0.2426**	**0.1451**
Log-like	**−89.8041**	**−28.1248**	**−108.7154**	**−131.2807**
TVP Student t copula				
ψ_o	0.0230	0.0420	−0.0835	−0.1981
ψ_1	0.0835	0.0632	0.0706	0.0583
ψ_2	2.0025	1.7952	2.3142	2.5710
υ	4.9998	5.0000	4.9492	4.9944
Log-like	−53.9848	−25.8557	−93.6075	−123.1063

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 14
Parameter Estimates of time-varying copulas between Japan and other bond markets.

	Japan-Italy	Japan-USA	Japan-UK
TVP Normal copula			
ψ_o	0.0206	−0.0076	0.0072
ψ_1	−0.1077	0.0219	0.0877
ψ_2	1.7523	2.0668	1.9326
Log-like	−2.7777	−22.2962	−21.9036
TVP Clayton copula			
ψ_o	**1.4414**	1.5848	1.2282
ψ_1	**−1.0781**	0.0826	0.2488
ψ_2	**−3.1550**	−3.8847	−3.1694
Log-like	**−3.5853**	−33.7991	−24.7785
TVP Rotated Clayton copula			
ψ_o	−0.2157	0.7786	1.4014
ψ_1	0.7897	0.3380	0.2312
ψ_2	1.0725	−1.0806	−4.0198
Log-like	−2.0673	−25.2514	−32.7908
TVP Gumbel copula			
Ω	−1.2814	0.1704	**0.7358**
β	0.9852	0.4371	**0.3255**
α	1.0854	−0.8308	**−3.0494**
Log-like	−1.946	−33.6716	**−35.8726**
TVP Rotated Gumbel copula			
ω_U	0.1039	0.3059	0.6491
α_U	0.6303	0.3793	0.3337
β_U	−2.1552	−1.0052	−2.5801
Log-like	−2.7979	−37.8160	−32.3136
TVP SJC copula			
ω_U	−13.2796	**−0.0727**	4.2200
α_U	−1.5700	**−7.4800**	−24.9997
β_U	−0.0157	**0.7180**	−1.6670
ω_L	−14.4031	**0.8935**	2.9753
α_L	−0.0039	**−9.9323**	−21.6306
β_L	0.0000	**1.2529**	−0.9734
Log-like	−0.0082	**−43.5895**	−34.9183
TVP Student t copula			
ψ_o	−0.0011	0.1604	0.0068
ψ_1	−0.0219	0.0145	0.0622
ψ_2	2.0501	1.4624	1.9349
υ	4.9946	3.5205	4.9999
Log-like	3.3052	−38.5223	−20.3294

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 15
Parameter estimates of time-varying copulas between Italy and other bond markets.

	Italy -USA	Italy -UK
TVP Normal copula		
ψ_o	0.2262	0.1253
ψ_1	0.1903	0.2775
ψ_2	0.5470	1.1755
Log-like	−9.7960	−14.3194
TVP Clayton copula		
ψ_o	0.9015	1.5343
ψ_1	−0.1479	−0.5543
ψ_2	−1.3042	−2.9180
Log-like	−11.2076	−17.1937
TVP Rotated Clayton copula		
ψ_o	0.6725	0.4201
ψ_1	0.3807	0.6427
ψ_2	−1.2370	−0.3498
Log-like	−7.8352	−7.5293
TVP Gumbel copula		
Ω	1.1151	−0.3233
β	−0.3647	0.7097
α	−1.3809	−0.4031
Log-like	−8.8067	−11.9941
TVP Rotated Gumbel copula		
ω_U	**1.0707**	1.8160
α_U	**−0.3136**	−0.7702
β_U	**−1.1625**	−1.8394
Log-like	**−13.8302**	−16.9909
TVP SJC copula		
ω_U	2.3789	**−12.8548**
α_U	−24.9999	**24.9996**
β_U	−4.0849	**2.7974**
ω_L	−0.4548	**3.6982**
α_L	−5.6688	**−18.6812**
β_L	−1.9490	**−3.3885**
Log-like	−12.6650	**−18.9498**
TVP Student t copula		
ψ_o	0.4084	0.0665
ψ_1	0.1079	0.0546
ψ_2	−0.1831	1.6524
υ	5.0000	5.0000
Log-like	−12.3360	−17.9124

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Table 16
Parameter Estimates of time-varying copulas between USA and UK bond market.

	USA-UK
TVP Normal copula	
ψ_o	1.6183
ψ_1	1.1387
ψ_2	−2.2573
Log-like	−85.7685
TVP Clayton copula	
ψ_o	1.4255
ψ_1	−0.1066
ψ_2	−2.3306
Log-like	−72.4103
TVP Rotated Clayton copula	
ψ_o	1.7534
ψ_1	0.0032
ψ_2	−4.1240
Log-like	−80.4294
TVP Gumbel copula	
Ω	1.3129
β	0.0354
α	−3.1384
Log-like	−94.9144
TVP Rotated Gumbel copula	
ω_U	1.4391
α_U	−0.1370
β_U	−2.5461
Log-like	−88.3129
TVP SJC copula	
ω_U	**5.1914**
α_U	**−24.9983**
β_U	**−3.1628**
ω_L	**0.0185**
α_L	**−4.4134**
β_L	**0.1437**
Log-like	**−95.9199**
TVP Student t copula	
ψ_o	−0.0040
ψ_1	0.0823
ψ_2	2.1121
υ	4.9999
Log-like	−88.2831

Notes: This table reports the ML estimates for the different dynamic bivariate copula models for the bond returns. All coefficients are significantly different from zero at 1% level. The minimum log likelihood value (value on bold) indicates the best copula fit.

Appendix B. Time varying dependence parameter plots

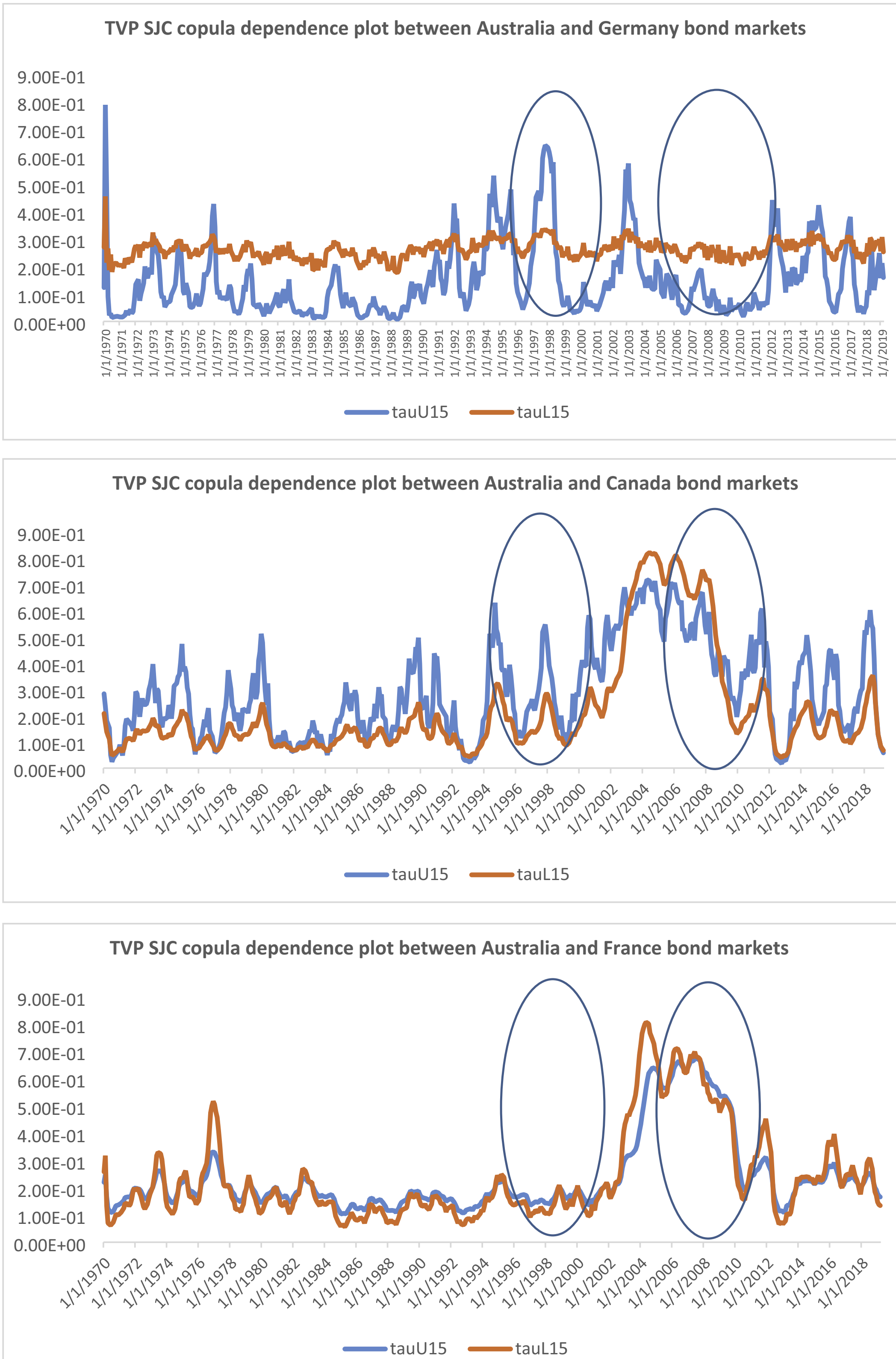


Fig. 9. Time varying dependence parameter plots between Australia and other bond markets.

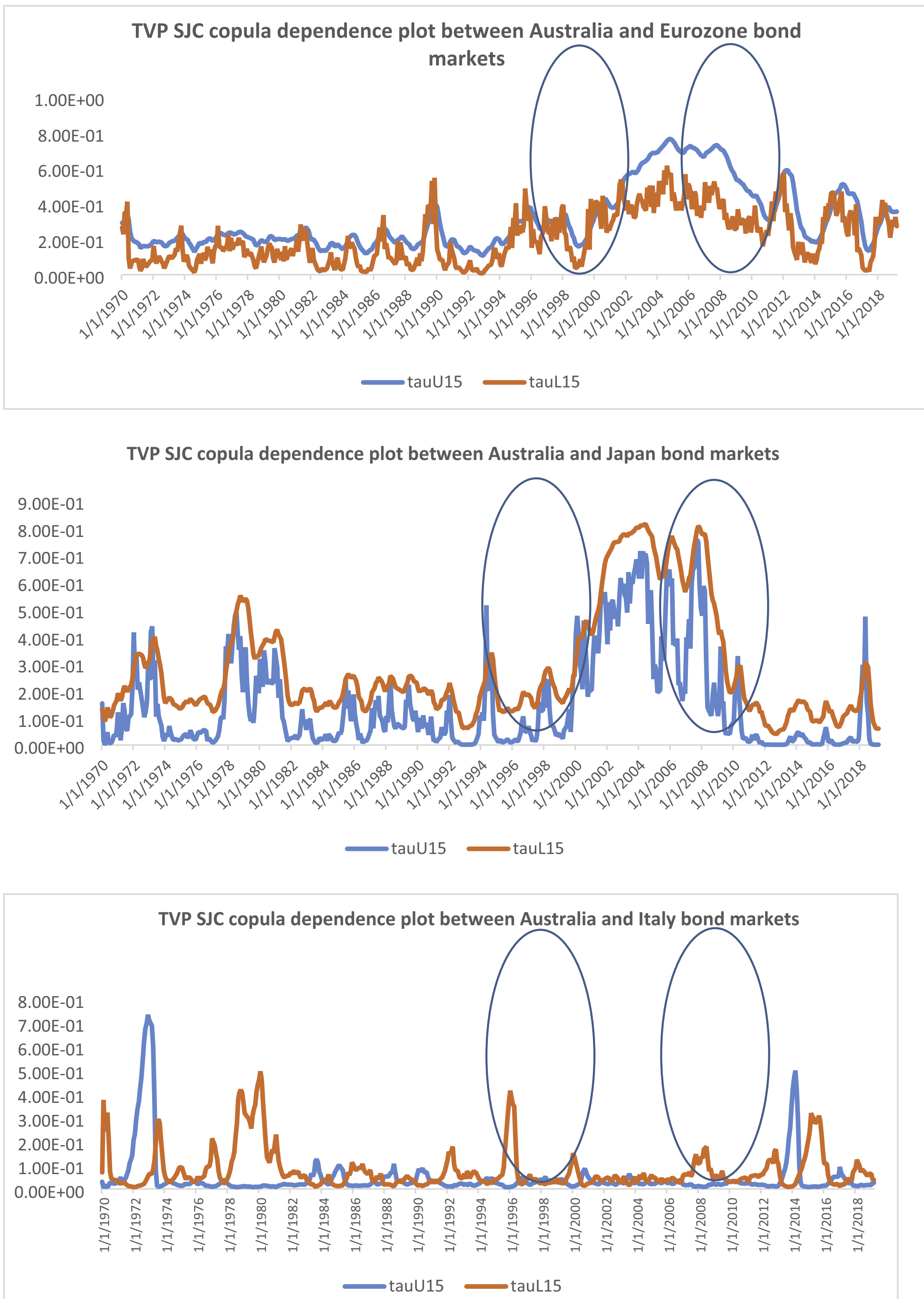


Fig. 9. (*continued*).

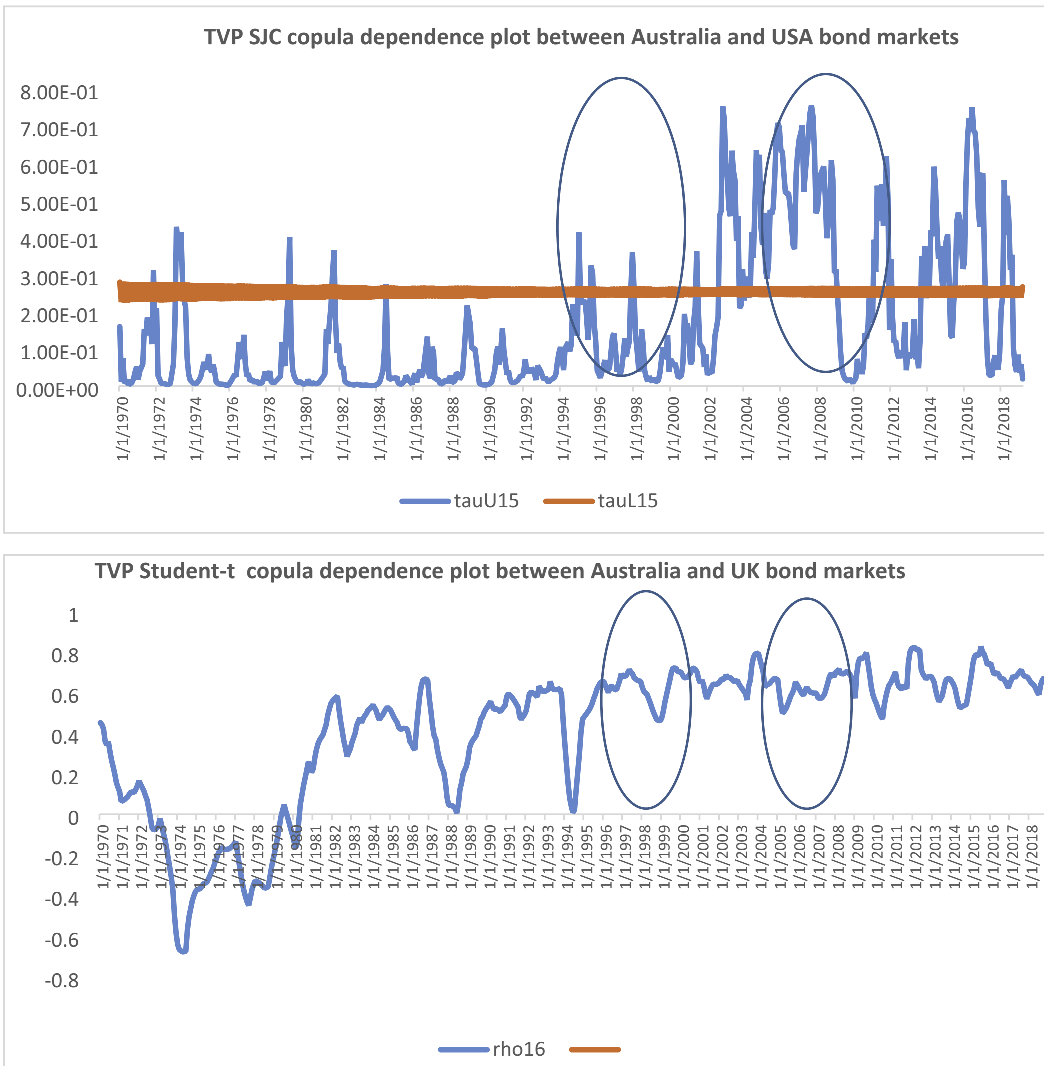


Fig. 9. (*continued*).

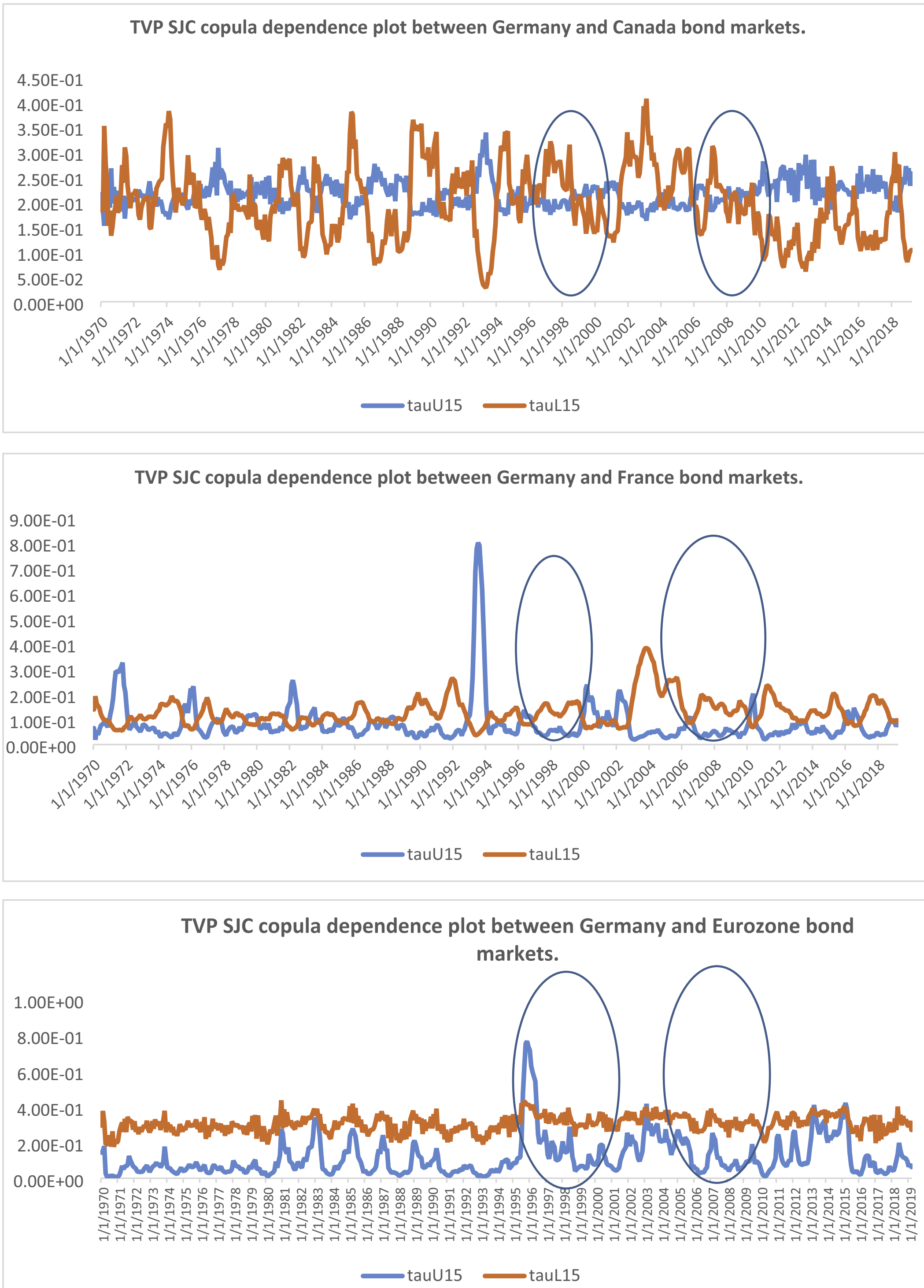


Fig. 10. Time varying dependence parameter plots between Germany and other bond markets.

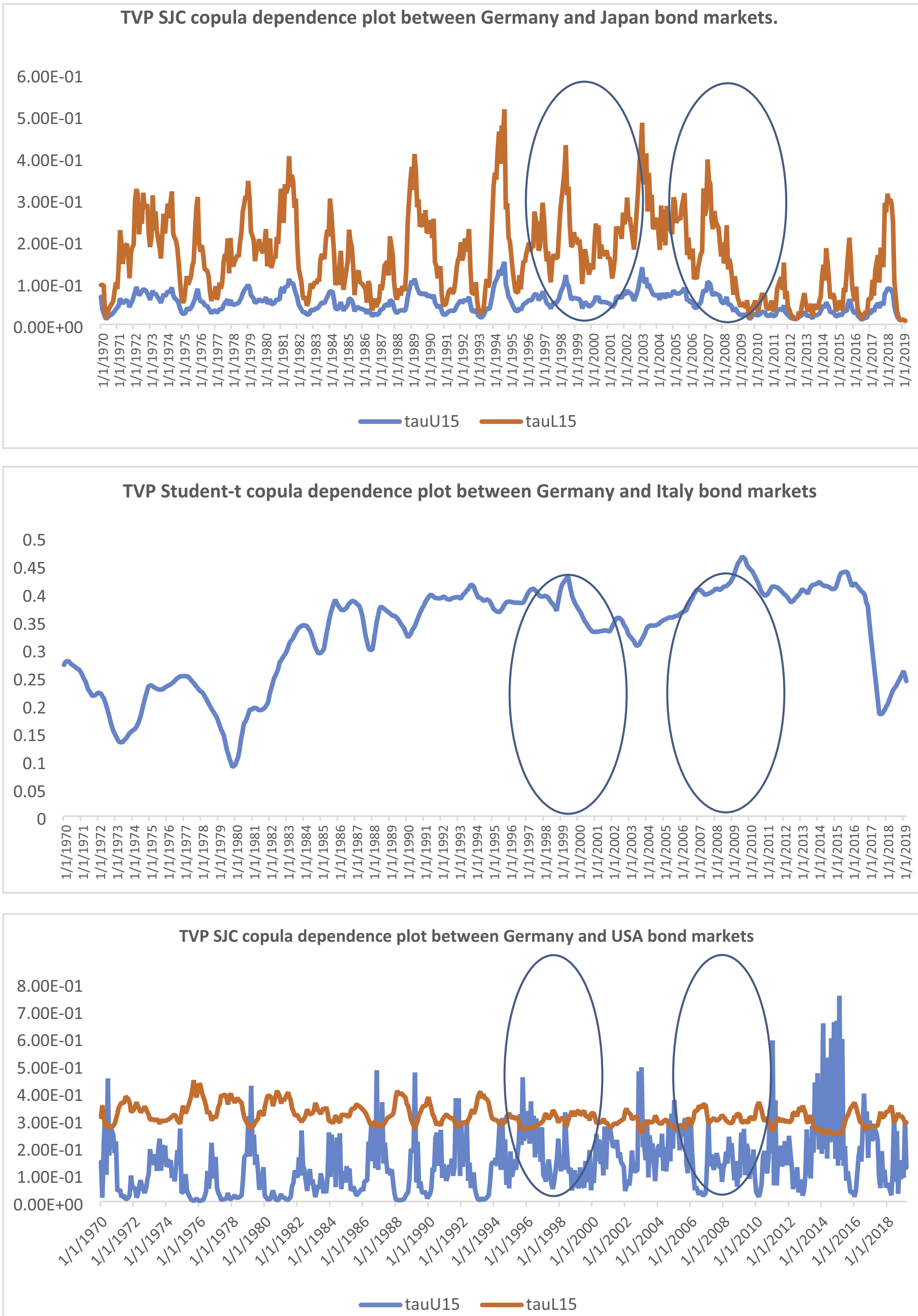


Fig. 10. (*continued*).

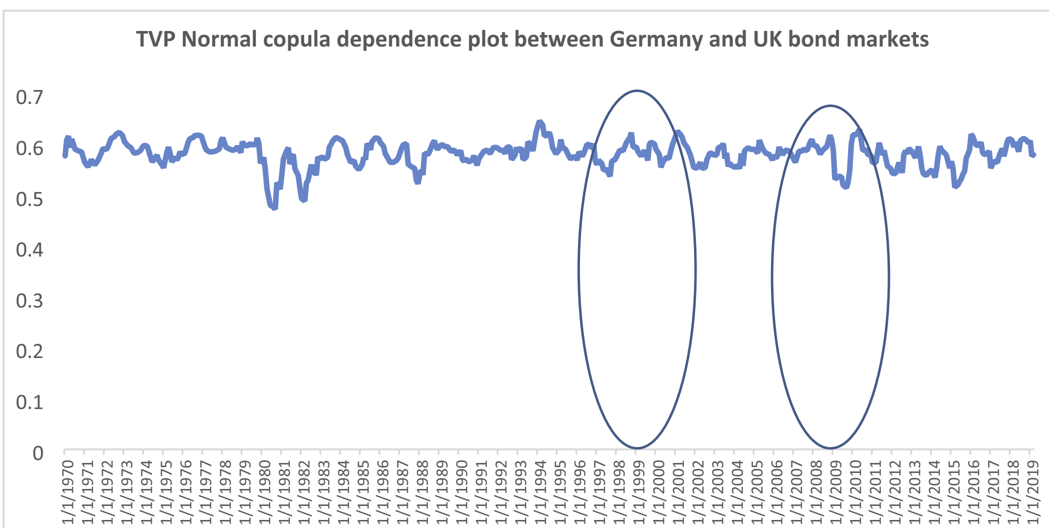


Fig. 10. (*continued*).

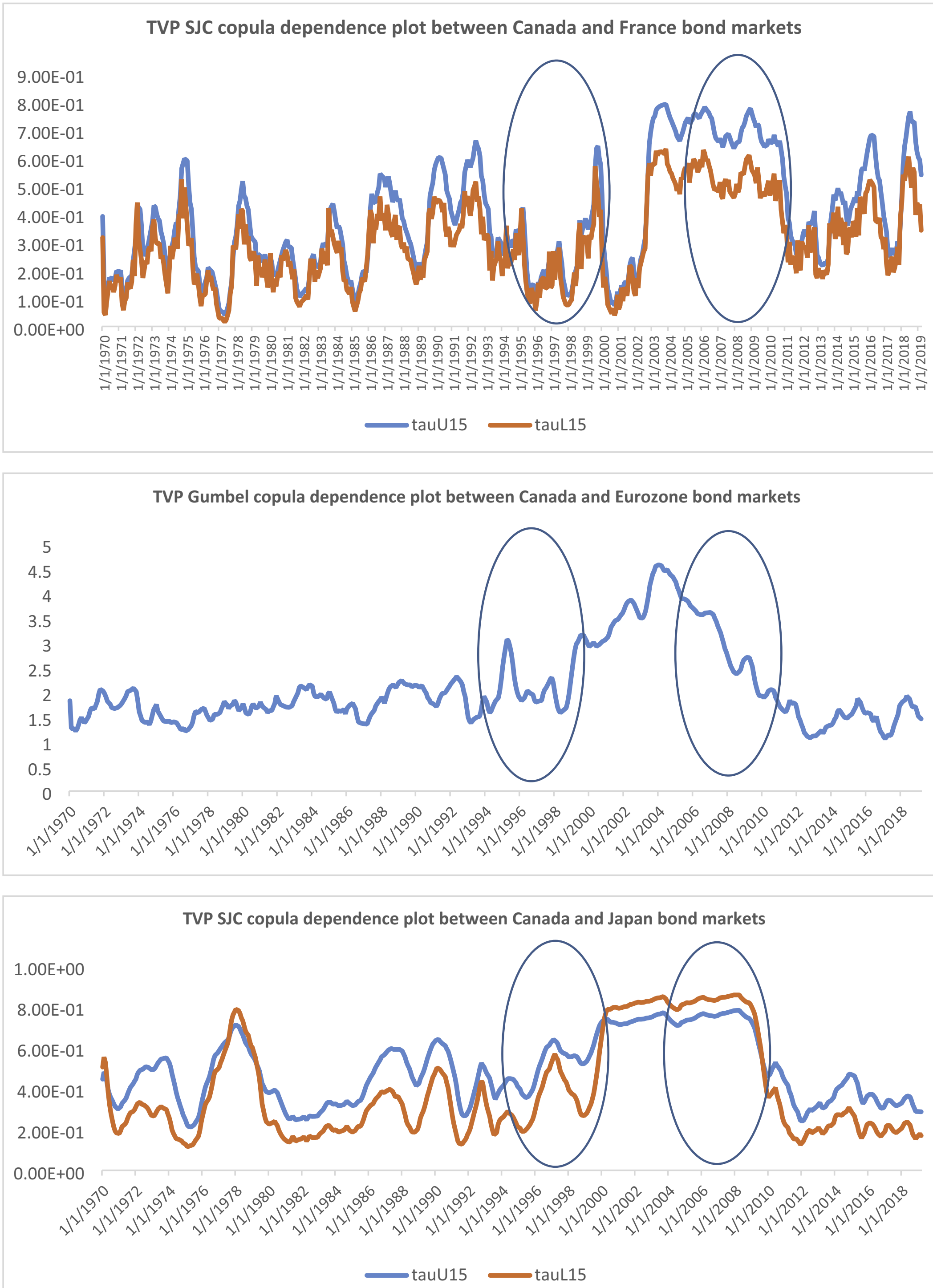


Fig. 11. Time varying dependence parameter plots between Canada and other bond markets.

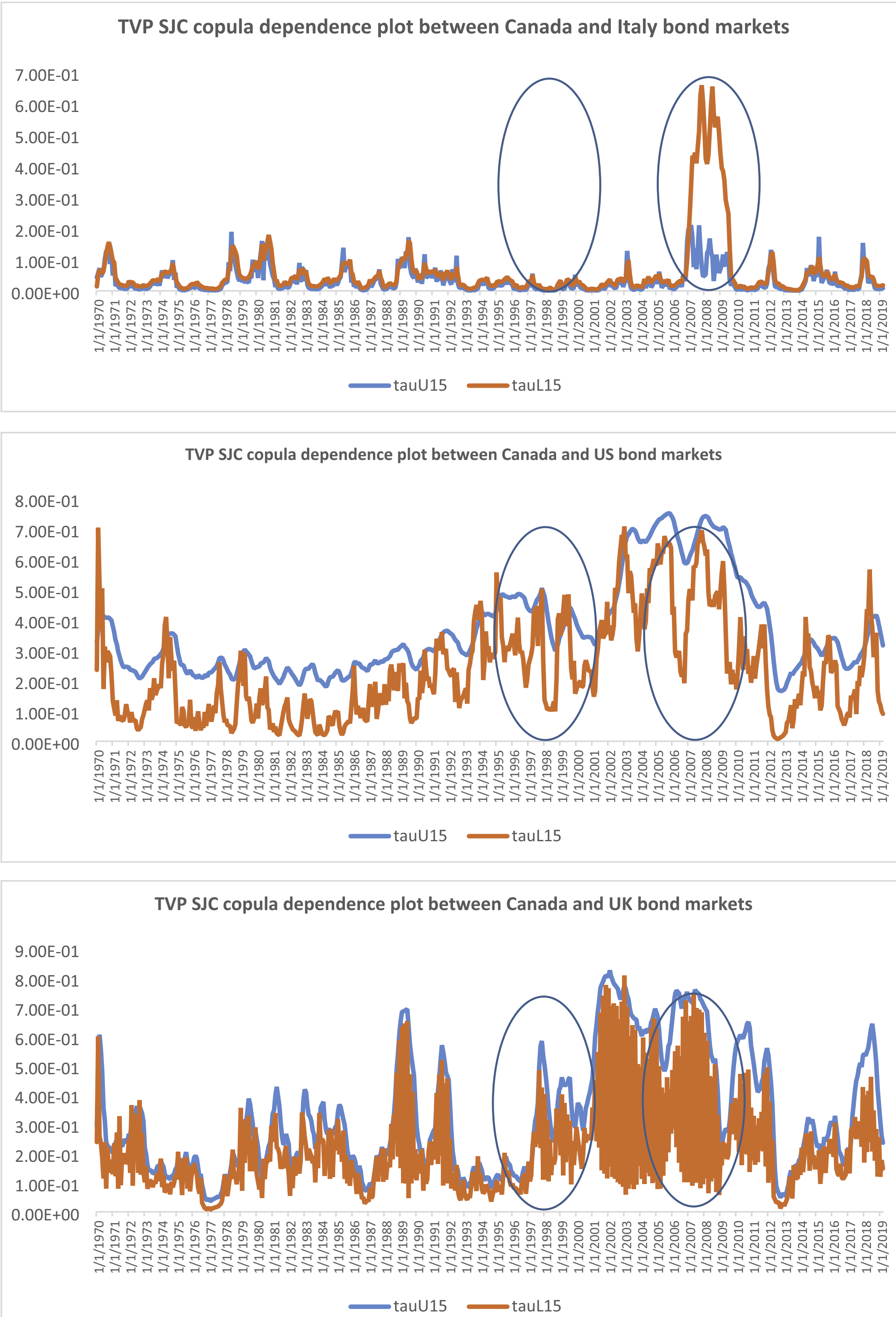


Fig. 11. (*continued*).

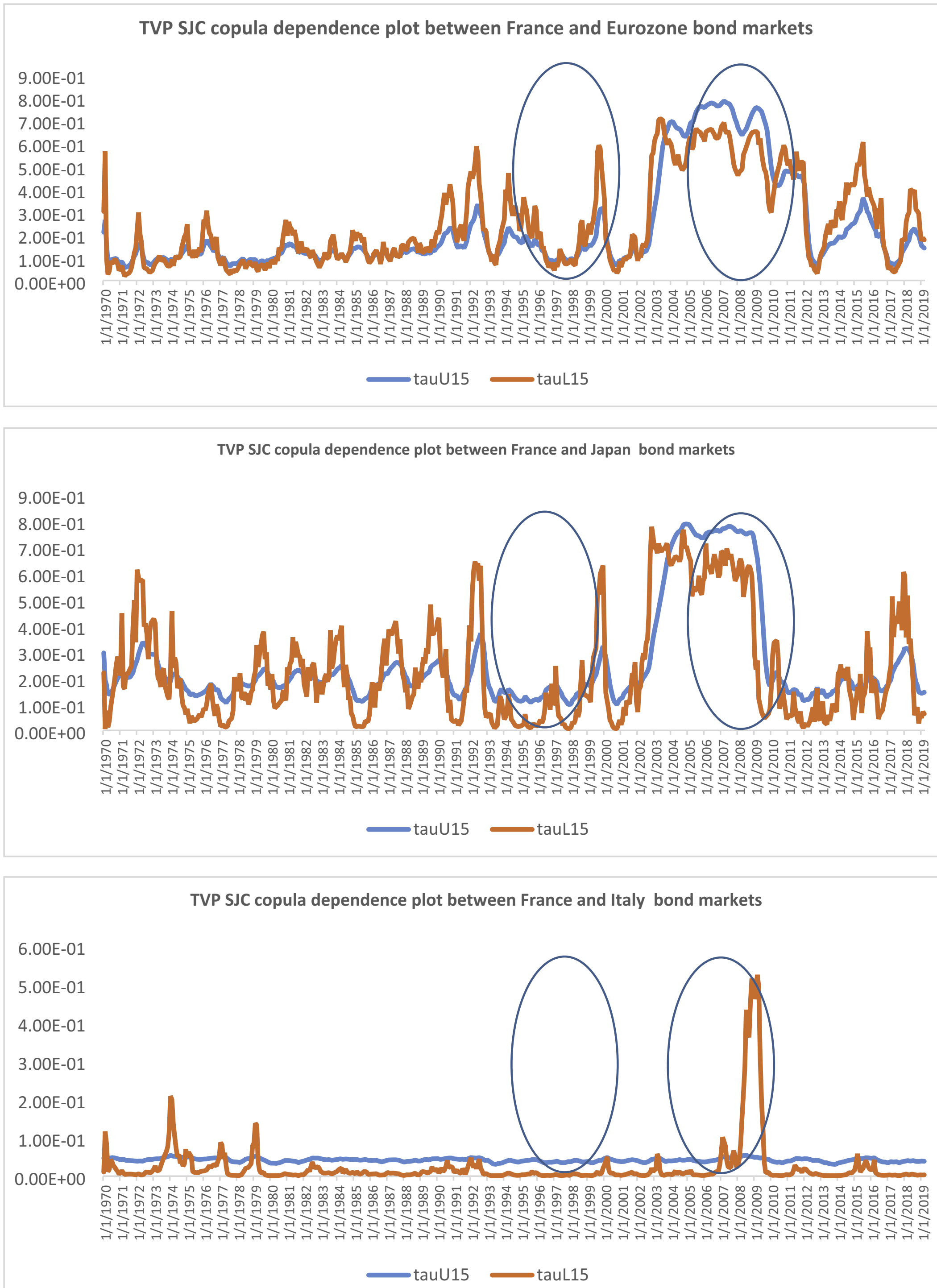
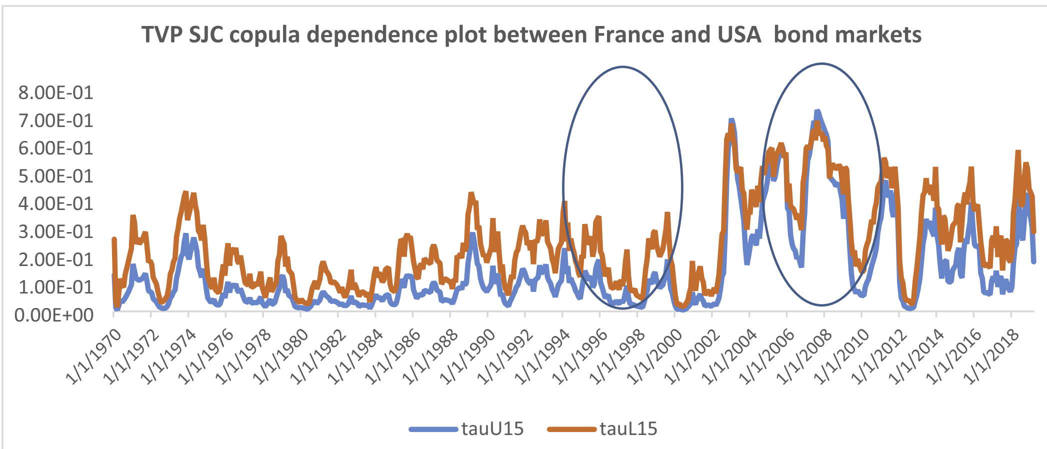


Fig. 12. Time varying dependence parameter plots between France and other bond markets.



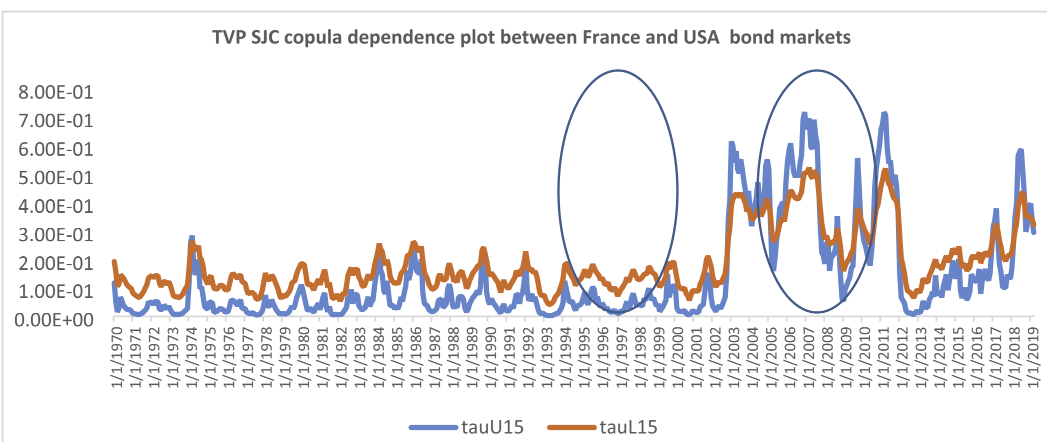


Fig. 12. (*continued*).

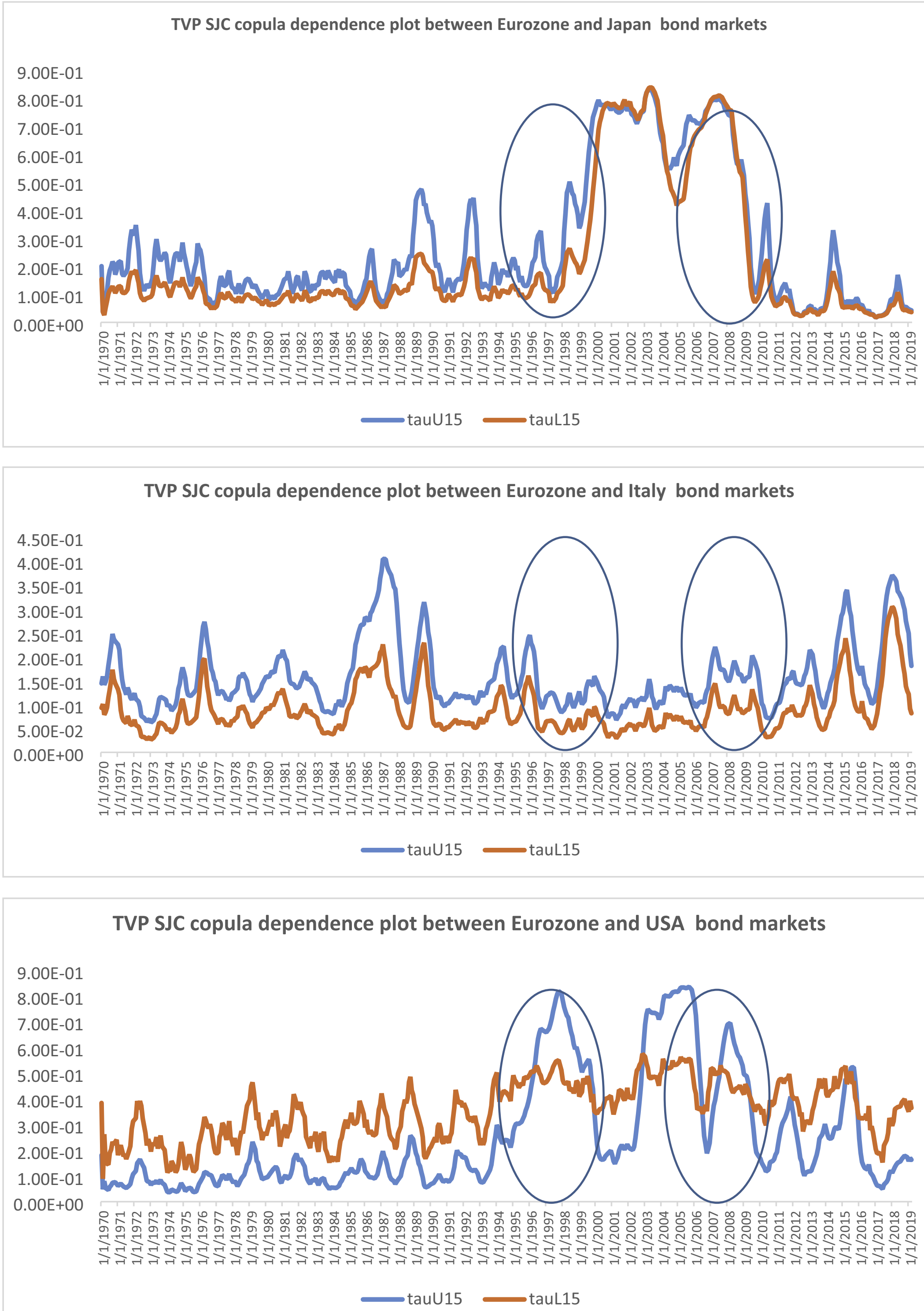


Fig. 13. Time varying dependence parameter plots between Eurozone and other bond markets.

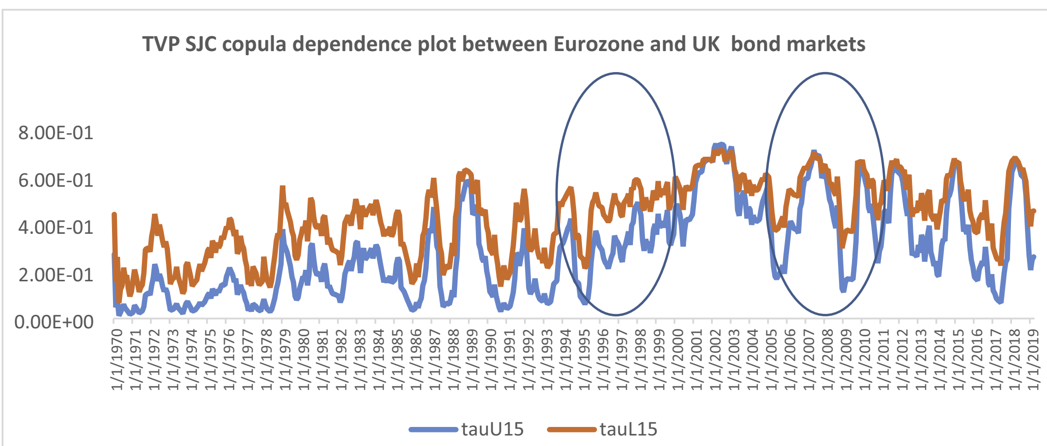


Fig. 13. (*continued*).

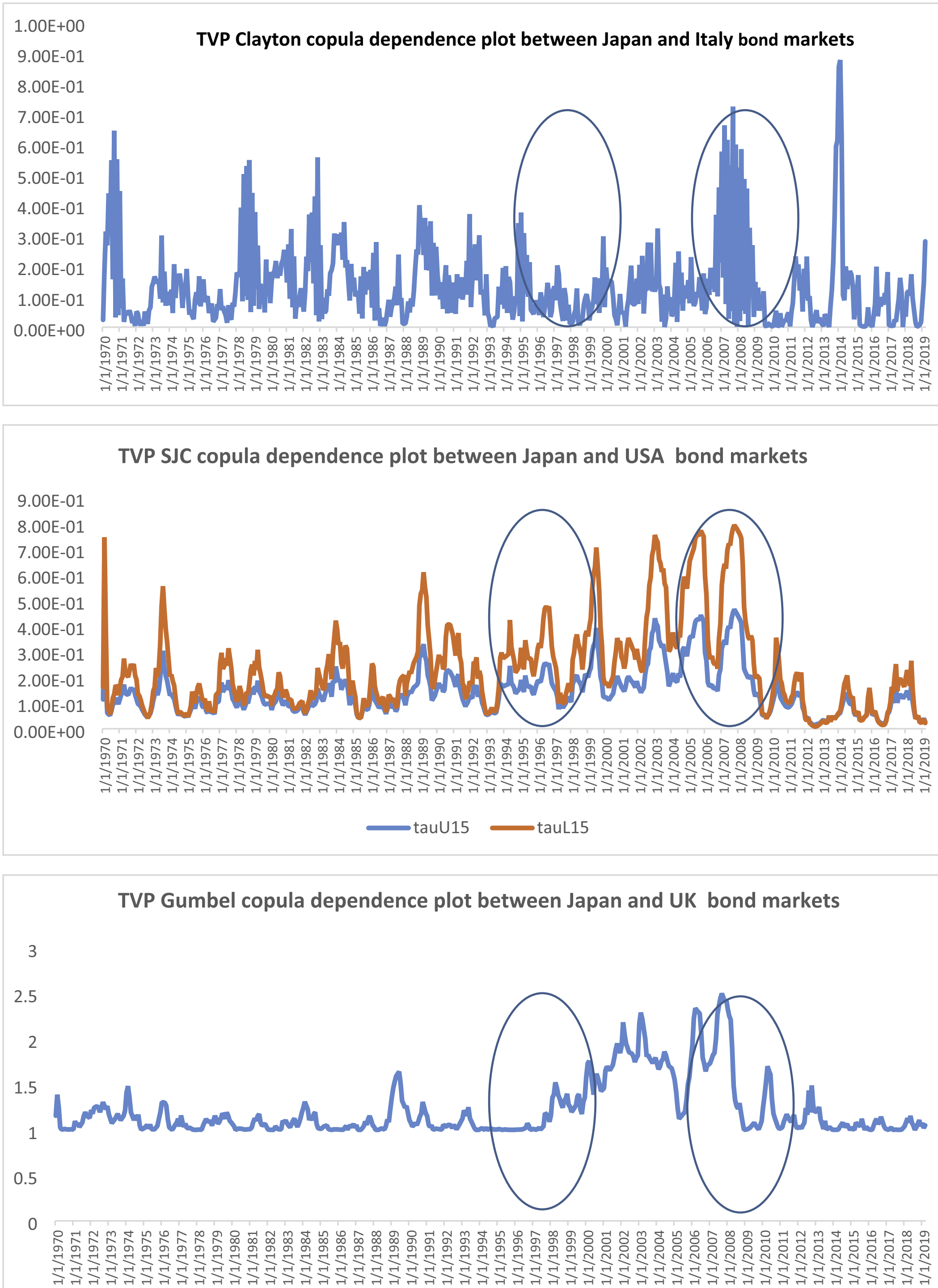


Fig. 14. Time varying dependence parameter plots between Japan and other bond markets.

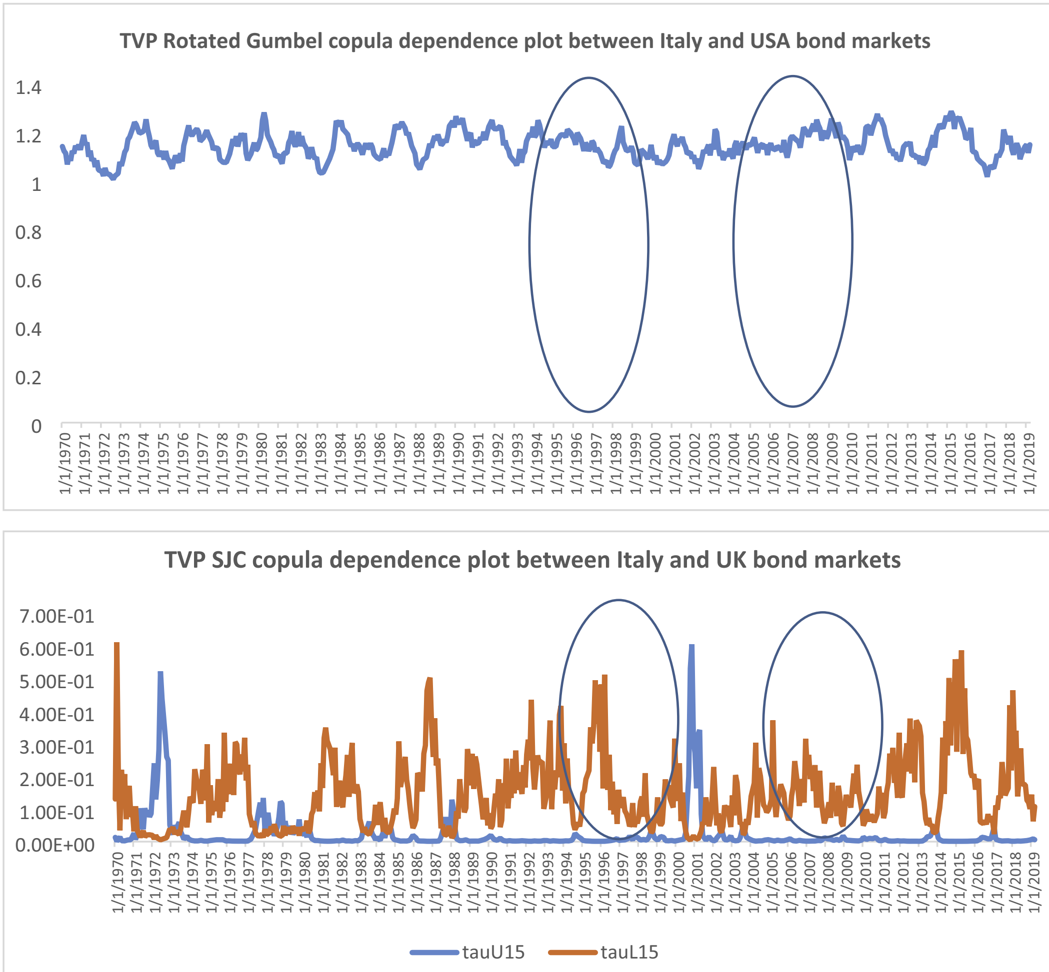


Fig. 15. Time varying dependence parameter plots between Italy and other bond markets.

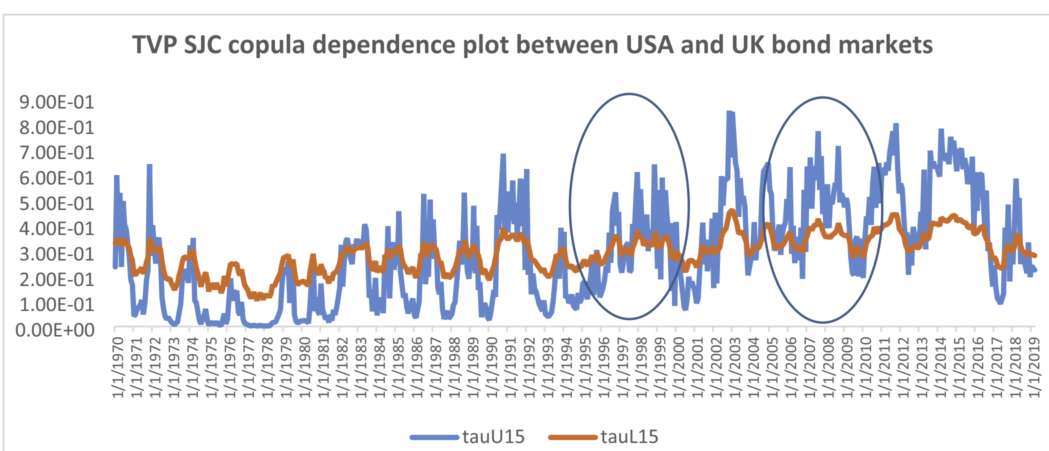


Fig. 16. Time varying dependence parameter plots between USA and UK bond markets.

Appendix C. The density functions of all copulas. Reproduced from Nelsen (2006) and Joe (1996)

Table C1
Characteristics of bivariate copulas.

Copula name	Formula	Parameter	Tail Dependence
Gaussian Copula	$\Phi_2\ \{\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta\}$	$\theta = \rho$	$\tau(\theta) = \frac{2}{\pi arcsin(\theta)}$
Clayton Copula	$[max\{{u_1}^{-\theta} + {u_2}^{-\theta} - 1; 0\}]^{-1/\theta}$	$\theta \in [(-1, \infty)\backslash\{0\}]$	$\tau(\theta) = \frac{\theta}{\theta + 2}$
Rotated Clayton Copula	$u - [max\{{u_1}^{-\theta} + {u_2}^{-\theta} - 1; 0\}]^{-1/\theta}(u, 1-v; -\theta)$	$\theta < 0$	Asymmetric tail dependence
Placket Copula	$\frac{1}{2(\theta-1)}\left(1 + (\theta-1)(u+v)) - \sqrt{(1+(\theta-1)(u+v)}\right)^2 - 4\theta(\theta-1)uv$	θ	Zero tail dependence
Frank Copula	$-\frac{1}{\theta}log\left[1 + \frac{(exp(-\theta u_1) - 1)(exp(-\theta u_2) - 1)}{exp(-\theta) - 1}\right]$	$\theta \in [-1, 1]$	$\tau(\theta) = 1 - \frac{4}{\theta}\left(1 - \frac{1}{\theta}\int_0^\theta \frac{a}{e^a - 1}da\right)$
Gumbel Copula	$exp[-((-log(u_1))^\theta) + (-log(u_2)^\theta)]^{1/\theta}$	$\theta \in [1, \infty]$	$\tau(\theta) = 1 - \theta^{-1}$
Rotated Gumbel Copula	$u + v - 1 + \left(exp[-((-log(u_1))^\theta) + (-log(u_2)^\theta)]^{1/\theta}\right)(1-u, 1-v; \theta)$		Upper tail dependence and lower tail dependence.
Student-*t* Copula	$(t_v^{-1}(u_1), \ldots, t_v^{-1}(u_d))$	$\theta = \rho$	$\tau(\theta) = \frac{2}{\pi arcsin(\theta)}$
Survival Joe Copula	$1 - [(1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta]$	$\theta \in [1, \infty]$	$\tau(\theta) = 1 + \frac{4}{\theta^2}\int_0^1 xlog(x)(1-x)^{2(1-\theta)/\theta}dx$
Joe Copula	$1 - [(1-u)^\theta + (1-v)^\theta - (1-u)^\theta(1-v)^\theta]$	$\theta \in [1, \infty]$	$\tau(\theta) = 1 + \frac{4}{\theta^2}\int_0^1 xlog(x)(1-x)^{2(1-\theta)/\theta}dx$
Survival Clayton Copula	$[max\{{u_1}^{-\theta} + {u_2}^{-\theta} - 1; 0\}]^{-1/\theta}$	$\theta \in [(-1, \infty)\backslash\{0\}$	$\tau(\theta) = \frac{\theta}{\theta + 2}$
Survival Gumbel Copula	$exp[-((-log(u_1))^\theta) + (-log(u_2)^\theta)]^{1/\theta}$	$\theta \in [1, \infty]$	$\tau(\theta) = 1 - \theta^{-1}$
Tawn Copula	$exp(logu_1 u_2)A\left(\frac{logu_2}{log(u_1, u_2)}\right)$	A ∈ [0,1]	$\tau(A) = \int_0^1 \frac{t(1-t)}{A(t)}dA'(t)$

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