Examining the Long-term Dependency Structures of Crude Oil Prices and Borsa Istanbul Sector Indices Using Copulas

Tugay Karadag[1]
Yildiz Technical University

Gülhayat Gölbaşı Şimşek[2]
Yildiz Technical University

Abstract

In this study, we examine the interdependencies between West Texas Intermediate (WTI) crude oil prices and Borsa Istanbul (BIST) sector indices from 2005 to 2021, utilizing the copula approach. We conclude that bivariate copula analysis reveals varying correlations, with BIST Industrials and BIST Services sectors exhibiting the most significant negative and positive connections to WTI during financial shocks, respectively. Employing the vine copula method, we observe the dominance of BIST Industrials over other sectors, surpassing even WTI. We offer valuable insights for investors managing portfolios involving both crude oil and BIST firms.

Keywords: Borsa Istanbul; Copula; Oil Prices; Sector Indices; Tail Dependence

JELClassification: C10, G00, G10

Ham Petrol Fiyatları ve Borsa İstanbul Sektör Endekslerinin Uzun Vadeli Bağımlılık Yapılarının Kopulalar Kullanılarak İncelenmesi

Özet

Bu çalışmada 2005-2021 yılları arasında West Texas Intermediate (WTI) ham petrol fiyatları ile Borsa İstanbul (BIST) sektör endeksleri arasındaki karşılıklı bağımlılıkları kopula yaklaşımını kullanarak inceledik. İkili kopula analizi, finansal şoklar sırasında WTI ile en çok negatif ve pozitif korelasyona sahip olan sektörlerin sırasıyla BIST Sanayi ve BIST Hizmetler olduğunu ortaya koymaktadır. Vine kopula yöntemiyle BIST Sanayi sektörünün diğer sektörler ile WTI üzerinde baskın olduğu gözlenmiştir. Bu çalışmanın sonucunda, hem ham petrol hem de BIST firmalarını içeren portföyleri yöneten yatırımcılara yönelik önemli bulgular sunulmaktadır.

Anahtar Kelimeler: Borsa Istanbul; Kopula; Petrol Fiyatları; Sektör Endeksleri; Kuyruk Bağımlılıkları

JEL Sınıflandırması: C10, G00, G10

[1] Yildiz Technical University, Istanbul, Türkiye, 34220. E-mail: karadagt@yildiz.edu.tr, ORCID: 0000-0002-3579-7764

[2] Yildiz Technical University, Istanbul, Türkiye, 34220. E-mail: gulhayat@yildiz.edu.tr, ORCID: 0000-0002-8790-295X

Boğaziçi Journal Review of Social, Economic and Administrative Studies, Vol. 38, no. 2 (2024), pp. 68-90, doi: 10.21773/boun.2025.38.2.004 Research Article | Received: 23.09.2024 - Accepted: 04.12.2024

Introduction

Crude oil plays an important role in almost every market and it is one of the critical strategic commodities in the world. Hence, studying the dependencies between crude oil and stock market prices has been very popular recently (He et al., 2021; Ji, Wang, Zhong, et al., 2020; Mejdoub and Ghorbel, 2018; Shang and Hamori, 2023; Yu et al., 2020; Zhao et al., 2023). Commodity pricing, including crude oil, is determined by the balance between supply and demand, like the pricing mechanisms observed in stock markets.

An index, which is derived from the price movements of publicly listed companies selected based on specific criteria, expresses the primary value indicator of a country's stock market. Apart from this, index calculations can be made in many different ways. The best instance of these is sector indices. A sector index allows for inferences on a sectoral basis by showing the price fluctuations of a particular sector over the years. In this study, we aim to assess the dependence between crude oil prices and sectors within the Turkish stock market. To achieve this goal, we utilize the sector indices of the Istanbul Stock Exchange (Borsa Istanbul) for our analysis. Borsa Istanbul (BIST) is the only exchange foundation of Türkiye and its main index is defined as BIST100 Index, which represents the total market value of the free float shares of 100 public companies selected according to specific criteria. Besides this index, there are more than 20 sector indices in BIST that represent the price fluctuations of the sectors. There are plenty of studies measuring the dependencies between sector indices and crude oil prices in the literature (Kayalar et al., 2017; Mejdoub and Ghorbel, 2018; Mokni and Youssef, 2019; Sukcharoen et al., 2014; Zhao et al., 2023). In order to assess each existing sector index in the Turkish stock market, comprehensive research is a necessity. However, this issue seems to be highly limited in the literature. For this purpose, we take on an enlightening role as we embark on a long-term exploration of the historical dependency between BIST sector indices and crude oil prices.

In this study, we focus on West Texas Intermediate (WTI) as it's one of the primary benchmarks for global crude oil prices. We opt for WTI spot prices to represent crude oil prices in our analysis. Previous studies indicate significant interdependence between oil prices and sector indices (Çağlı et al., 2014; Zhao et al., 2023). The examination of the dependencies between crude oil prices and stock market indices is a sustained one and will continue to maintain its popularity in the future. One of the biggest reasons for this is that the data about these instruments are increasing day by day, that is, the data is constantly growing and being updated. Also, with the development of technology, the applicability of statistical methods is gaining momentum. On top of that, with the contribution of literature on the discovery of new methods or the improvement of existing methods, the relationships between variables can be examined from very different perspectives. Instead of examining dependencies in different periods such as pre-crisis, crisis, and post-crisis period, we aim to examine the dependencies from a broader perspective such as measuring the dependencies of the WTI crude oil prices and the BIST sector indices covering the period from 2005 to 2021, including both the 2008 global crisis and the COVID-19 outbreak.

Recently, researchers have widely applied the copula method in analyzing multivariate extremes and dependencies between variables. Due to its flexibility in asymmetric structures, its usability in financial data is quite high compared to correlation coefficients (Fenech and Vosgha, 2019). Therefore, we apply the copula method to measure the dependencies between variables. We first fit the most appropriate ARMA models to the variables before applying the copula approach. Then, we examine the dependencies between BIST sector indices and WTI via the bivariate copula method. Later, we apply the vine copula method, which can display

the multivariate dependencies, to examine whether the dependencies between WTI and BIST sector indices are dominant compared to the interdependency of the BIST sector indices. With this work, we fill the gap in the literature on assessing the dependencies of BIST sector indices with crude oil prices.

Literature

Studies, which examine the relationships between sector indices or sector-specific firms with various assets using the copula method, offer different perspectives. In their study, Mudiangombe and Muteba Mwamba (2023) investigate how the SP500 (Standard and Poor's 500) index affects top sector indices of the South Africa stock market during the COVID-19 pandemic and global crises. Similarly, Hanif, Hernandez, et al. (2020) employ bivariate and vine copulas to understand the relationships within the energy sectors of the United States and Canada. Moreover, Zhang et al. (2024) utilize a time-varying (TV) copula model to explore the dynamics and asymmetry in default interdependence between the insurance and banking sectors. Apergis et al. (2020) examine the dependence patterns of electric prices in the Australian national energy market over three time periods, considering the impact of the carbon tax. Hanif, Arreola-Hernandez, et al. (2020) explore regional dependencies among US and EU energy firms using vine copula. In a sector-specific study, Sukcharoen and Leatham (2016) use copulas to measure the dependencies among ten US sectors, revealing insights into how these sectors correlate. Lastly, Righi and Ceretta (2013) aim to estimate dependencies between seven sector indices in the Brazilian financial market, contributing to the understanding of financial interconnections in the region.

Researches in the literature have extensively explored the relationships between oil prices and various markets using diverse copula methodologies. Zhao et al. (2023) investigate the spillover risk effect of global oil prices on Chinese stock markets' sectors. Utilizing the GARCH-EVT-Copula-CoVaR approach, they uncover a significant positive risk spillover effect from the crude oil market to every sector. Shang and Hamori (2023), Ji, Wang, Zhong, et al. (2020), Yu et al. (2020), and Mejdoub and Ghorbel (2018) use WTI as the crude oil asset, while He et al. (2021) prefer Shanghai crude oil futures. Shang and Hamori (2023) employ a TV copula approach to scrutinize the interrelationships between the forex market and WTI oil prices, specifically focusing on TV tail dependence and TV linear correlation. Ji, Wang, Zhong, et al. (2020) introduce a wavelet-based vine copula approach to investigate multivariate dependencies involving WTI, stock markets, and safe-haven assets from the beginning of 2000 to the end of 2018. Yu et al. (2020) delve into the dynamic dependence among WTI, US, and China markets, spanning from 1991 to 2016. Their analysis encompasses not only identifying structural breaks in market dependence between these paired markets but also integrates these breakpoints into a comprehensive examination of market dependencies, employing a vine copula model. Mejdoub and Ghorbel (2018) aim to measure the dependence between WTI and renewable energy stock markets from 2003 to 2016. They employ a vine copula-based threshold GARCH (generalized autoregressive conditional heteroskedasticity) model for their analysis. He et al. (2021) adopt the GARCH-vine-copula method to investigate dependencies among Shanghai crude oil futures, gold, foreign exchange, and stock. These studies contribute valuable insights into the complex web of dependencies, shedding light on the nuanced interactions between oil prices and various markets.

Diverse perspectives emerge from studies which employ the copula approach to explore relationships among various assets. In a recent investigation, Zhao and Park (2024) try to understand bidirectional risk spillovers among the China stock market and eleven Asian stock markets. They employ a dynamic Copula-EVT-CoVaR model to reveal the intricate

dynamics of risk transmission. Evkaya et al. (2024) focus on estimating the interdependence structure of the BIST100 index using an r-vine copula approach. Considering 32 stocks from six sectors within BIST100, their study sheds light on the complex relationships within the Turkish stock market. Rašiová and Árendáš (2023) delve into the copula analysis to investigate the dependence between stock market volatility and technology in the US market. Chkir et al. (2020) explore the relationship between oil prices and exchange rates, utilizing vine copulas to figure out the intricate connections. Wu et al. (2020) examine the dependence structure between the Chinese stock market and the Renminbi exchange rate using the vine copula approach. Ji, Wang, Xu, et al. (2020) apply the ARIMA-GARCH (Autoregressive Integrated Moving Average- Generalized AutoRegressive Conditional Heteroskedasticity) skewed-t Vine Copula approach to study the changes in the dependency structure among seven major international stock markets during the 2008 global financial crisis. In a separate study, Chang et al. (2019) explore gold's safe haven property and US dollars against stocks using the vine copula approach. Finally, Song et al. (2019) undertake a comprehensive analysis, measuring and comparing risks across emerging countries' markets, developed countries' markets, and global markets. They contribute valuable insights into the risk landscape of diverse financial markets by applying vine copulas and factor copulas from May 1, 2003, to May 31, 2018.

The literature offers a wealth of studies examining specific BIST sectors using diverse analytical approaches. Kocaarslan (2020a), Kocaarslan (2020b), and Kamışlı et al. (2016) explore the volatility interactions within BIST sectors through the application of causality-in-variance tests. Kocaarslan (2020a) focuses on assessing volatility spillovers among BIST technology, industrials, services, and financials sector indices from January 3, 2011, to November 14, 2019, revealing significant volatility interconnections between these sectors. Kocaarslan (2020b) investigates the volatility dynamics among US economic policy uncertainty and three BIST sector indices— technology, industrials, and financials—spanning from 2011 to 2020. The findings document a notable sensitivity of BIST sector returns to shocks in US economic policy uncertainty. Kamışlı et al. (2016) delve into volatility spillovers among financial, industrial, and services sectors of BIST from February 2, 2001, to March 24, 2015, finding evidence of volatility transmissions from the industrial to services sector and from services to the financial sector. Tokat (2010) and Kamışlı and Sevil (2018) focus on financial shocks within BIST sectors. Tokat (2010) explores shock and volatility transmission among BIST industrial, service, finance, and technology sector indices from July 30, 2000, to August 27, 2009, revealing strong spillovers between these sectors. Kamışlı and Sevil (2018) investigate the impact of different shocks between January 2, 1997 and March 24, 2015 on volatility spillovers among 21 BIST sector indices, concluding that global, national, or sector-specific shocks have noticeable effects on spillovers. (Apan et al., 2019) utilize data envelopment analysis-window analysis to scrutinize the financial activities of 19 firms in the BIST textile leather index from 2008 to 2017, examining individual company financial performance. Eyüboğlu and Eyüboğlu (2019) explore relationships among technology, industrial, financial, and services sector indices of BIST using the Johansen cointegration test and Granger causality test for the period between 2014 and 2017. They find no cointegration relationship or causal links among the sector indices. Lastly, Korkmaz and Güngör (2018) explore the effect of global economic policy uncertainty on BIST chemical, electric, petroleum, plastic, industrial, and main metal sector indices, considering monthly data from 1997:1 to 2018:4. Based on the findings, they highlight a significant and positive effect of global economic policy uncertainty on these sector indices. Civcir and Akkoc (2021) investigate the impacts of oil prices on the BIST sector indices by using the non-linear autoregressive distributed lag approach. They conclude by showing the negative impact of oil prices on BIST sector indices in the short term.

There exist plenty of studies examining the dependencies among oil prices and stock market indices. The selected time period of the asset and the diversity of approaches cause the results to differ. Most studies involving BIST sector indices typically focus on specific sectors within their analysis. Moreover, we couldn't find such a copula study which investigates the long-term dependencies between a major global instrument (e.g. oil prices) and the BIST sectors in the literature.

Data and Methodology

We include the prices of WTI and 23 BIST sector indices in the study. Table 1 presents the names, market identifier codes, and abbreviations of variables. We obtain the daily dataset from the investing.com website. The data covers the period from January 3, 2005 to February 2, 2021. We remove the days when the markets are not open from the dataset. We convert the variables to US dollars except for WTI, which is already in US dollars. In this way, all variables in the data are in the same unit. Then we take the natural log-differences of all variables. Later, we apply the cumulative sum (CUSUM) test (Horváth et al., 2020) to investigate the existence of structural breaks for each index. Based on the test results, we don't reject the null hypothesis of parameter stability for each index, so there is no evidence of structural break for all variables. Thus, we set all the variables for further analyses.

Table 1. Names, market codes, and abbreviations of indices

Index	Market Identifier Code	Abbreviation
West Texas Intermediate Crude Oil Futures	WTI	WTI
BIST 100	XU100	xu100
BIST Banks	XBANK	banks
BIST Basic Metal	XMANA	bsmet
BIST Information Technology	XBLSM	inftech
BIST Electricity	XELKT	elect
BIST Financials	XUMAL	finance
BIST Real Estate Investment Trusts	XGMYO	reit
BIST Services	XUHIZ	service
BIST Holding & Investments	XHOLD	holding
BIST Chemical Petrol Plastic	XKMYA	chem
BIST Leasing Factoring	XFINK	leasing
BIST Non-Metal Mineral Product	XTAST	nonmetal
BIST Metal Products Machinery	XMESY	metal
BIST Wood Paper Printing	XKAGT	wood
BIST Industrials	XUSIN	indus
BIST Insurance	XSGRT	insur
BIST Sports	XSPOR	sport
BIST Technology	XUTEK	tech
BIST Textile and Leather	XTEKS	textile
BIST Telecommunication	XILTM	telecom
BIST Wholesale & Retail Trade	XTCRT	retail
BIST Tourism	XTRZM	tourism
BIST Transportation	XULAS	transpor
BIST Food Beverage	XGIDA	food

BIST: Borsa Istanbul

In recent times, researchers have widely embraced copulas, utilizing them to actively analyze multivariate extremes and understand the interdependence between variables (Hamma et al., 2018). Sklar (1959) introduced the copula theory and researchers have widely used this theory in finance applications for measuring tail dependencies. In addition, copulas serve as valuable alternative tools for handling situations involving multivariate extremes. Let $F(x_1, x_2)$ to be a bivariate joint cumulative distribution function of X_1 and X_2 random variables. Accordingly, we define the copula function as;

$$F(x_1, x_2) = C\big(F_1(x_1), F_2(x_2)\big) = C(u, v) \quad (1)$$

where $u = F_1(x_1)\ and\ v = F_2(x_2)$ in equation (1) are marginal distributions of the variables which have uniform distribution on [0,1].

In this section, we concentrate on copula families as the main focus of our study is copula analysis, particularly the vine copula method, which comprises pair copulas. Normal (Gaussian) and Student-t (t) copulas are extensively utilized in research and are part of the elliptical copula families (Evkaya et al., 2018). Additionally, Archimedean copulas, which are identified by their generator functions, find frequent application in various studies (Cheng et al., 2020). The most popular Archimedean copulas with different dependence forms are Frank, Joe, Clayton, Gumbel, BB1 (Clayton-Gumbel), and BB7 (Joe-Clayton). Table 2 presents the mathematical descriptions of these copula families.

Table 2. Mathematical descriptions of copula families with their parameter ranges

Copula Family	$\boldsymbol{C\ (u, v)}$	**Parameter Range**
Gaussian (Normal)	$\emptyset_{par1}\big(\emptyset^{-1}(u), \emptyset^{-1}(v)\big) = \int_{-\infty}^{\emptyset^{-1}(u)} \int_{-\infty}^{\emptyset^{-1}(v)} \frac{1}{2\pi\sqrt{1-par1^2}} \exp\left(-\frac{s^2 - 2par1st + t^2}{2(1-par1^2)}\right) dsdt$	par1 $\in (-1,1)$
t	$t_{par1,par2}\left(t_{par2}^{-1}(u), t_{par2}^{-1}(v)\right) = \int_{-\infty}^{t_{par2}^{-1}(u)} \int_{-\infty}^{t_{par2}^{-1}(v)} \frac{1}{2\pi\sqrt{1-par1^2}} \left(1 + \frac{s^2 - 2par1st + t^2}{par2(1-par1^2)}\right)^{-\frac{par2+2}{2}} dsdt$	par1 $\in (-1,1)$, par2 $\in (0, \infty)$
Frank	$\frac{-1}{par1} ln\left[1 + \frac{(e^{(-par1u)} - 1)(e^{(-par1v)} - 1)}{e^{(-par1)} - 1}\right]$	par1 $\in (-\infty, \infty)$
Joe	$1 - ((1-u)^{par1} + (1-v)^{par1} - (1-u)(1-v)^{par1})^{\frac{1}{par1}}$	par1 $\in [1, \infty)$
Clayton	$(u^{-par1} + v^{-par1} - 1)^{-\frac{1}{par1}}$	par1 $\in (0, \infty)$
Gumbel	$exp\left[-(u^{-par1} + v^{-par1})^{-\frac{1}{par1}}\right]$	par1 $\in [1, \infty)$
BB1	$\left\{1 + [(u^{-par1} - 1)^{par2} + (v^{-par1} - 1)^{par2}]^{\frac{1}{par2}}\right\}^{-\frac{1}{par1}}$	par1 $\in (0, \infty)$, par2 $\in [1, \infty)$
BB6	$1 - \left(1 - exp\left\{-\left[(-log(1-(1-u)^{par1}))\right]^{par2} + \left[(-log(1-(1-v)^{par1}))^{par2}\right]^{\frac{1}{par2}}\right\}\right)^{\frac{1}{par1}}$	par1 $\in [1, \infty)$, par2 $\in [1, \infty)$
BB7	$1 - (1 - [(1-(1-u)^{par1})^{-par2} + (1-(1-v)^{par1})^{-par2} - 1]^{-\frac{1}{par2}})^{\frac{1}{par1}}$	par1 $\in [1, \infty)$, par2 $\in [0, \infty)$
BB8	$par2^{-1}\left[1 - \{1 - [1-(1-par2)^{par1}]^{-1}[1-(1-par2u)^{par1}][1-(1-par2v)^{par1}]\}^{\left(\frac{1}{par1}\right)}\right]$	par1 $\in [1, \infty)$, par2 $\in [0, 1]$
Tawn	$(1-par2_1)\frac{\log(v)}{\log(uv)} - (1-par2_2)\left(1 - \left(\frac{\log(v)}{\log(uv)}\right)\right) + \left[\left(par2_1\left(1 - \left(\frac{\log(v)}{\log(uv)}\right)\right)\right)^{par1} + \left(par2_2\left(\frac{\log(v)}{\log(uv)}\right)\right)^{par1}\right]^{\frac{1}{par1}}$	par1 $\in [1, \infty)$, $par2_1 \in [0, 1]$, $par2_2 \in [0, 1]$
Independent	u.v, $u, v \epsilon (0,1)$	

par: parameter

Source: Cheng et al. (2020); Evkaya et al. (2018); Nagler et al. (2015); Czado (2019); Mendes et al. (2007); Joe (1997)

We don't directly define the dependence parameters of copulas by the functions. We acquire them through Kendall's Tau functions given in Table 3. The same is true for tail dependence parameters. We reveal a tail dependence parameter (if any) by the functions which are given in the last column of Table 3.

Moreover, there are 180 degrees rotated versions of Archimedean copula families which have the opposite tail dependency feature. For instance, in the BB7 copula family the magnitude of lower tail dependency is lower than the magnitude of upper dependency while in the survival BB7 copula family the magnitude of lower tail dependency is higher than the upper tail dependency. In order to give visual examples of the structures of the bivariate copulas, we obtain an example dataset for each copula family as a result of the simulation. We graph scatter and density plots of some copula families with their parameters in Figure 1.

Table 3. Kendall's Tau and tail dependence coefficients of copula families

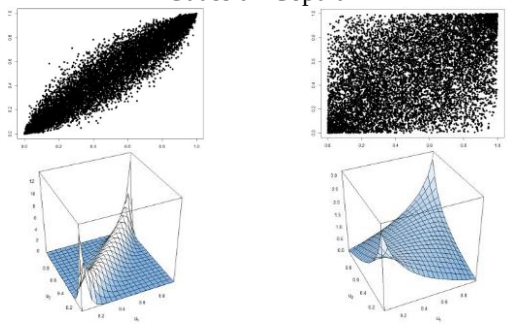
Copula Family	**Kendall's Tau**	**Lower Tail Dependence**	**Upper Tail Dependence**
Gaussian (Normal)	$\frac{2}{\pi}arcsin(par1), \in [-1,1]$	0	0
t	$\frac{2}{\pi}arcsin(par1), \in [-1,1]$	$2t_{par2+1}\left(-\sqrt{par2+1}\sqrt{\frac{1-par1}{1+par2}}\right)$	$2t_{par2+1}\left(-\sqrt{par2+1}\sqrt{\frac{1-par1}{1+par2}}\right)$
Frank	$1-\frac{4}{par1}+4\frac{\int_0^{par1} x/par1}{par1}\frac{dx}{e^x-1}, \in [-1,1]$	0	0
Joe	$1+\left(\frac{-2+2\gamma+2\ln(2)+\psi\left(\frac{1}{par1}\right)+\psi\left(\frac{2+par1}{2par1}\right)+par1}{-2+par1}\right), \in [0,1]$ Euler constant $\gamma=\lim_{n\to\infty}\left(\sum_{i=1}^{n}\frac{1}{i}-\ln(n)\right)\approx .5772157$ Digamma function $\psi(x)=\frac{d}{dx}\ln\left(\Gamma(x)\right)=\frac{\frac{d}{dx}\Gamma(x)}{\Gamma(x)}$	0	$2-2^{\frac{1}{par1}}$
Clayton	$\frac{par1}{par1+2}, \in [0,1]$	$2^{-\frac{1}{par1}}$	0
Gumbel	$1-\frac{1}{par1}, \in [0,1]$	0	$2-2^{\frac{1}{par1}}$
BB1	$1-\frac{2}{par2(par1+2)}, \in [0,1]$	$2^{\frac{-1}{(par1par2)}}$	$2-2^{\frac{1}{(par2)}}$
BB7	$1-\frac{2}{par2(2-par1)}+\frac{4}{par1^2par2}B\left(\frac{2-2par1}{par1}+1, par2+2\right), \in [0,1]$ for 1 < par1 < 2 with beta function $B(x,y)$ $B(x,y)=\int_0^1 t^{x+1}(1-t)^{y-1}dt$	$2^{-\frac{1}{par2}}$	$2-2^{\frac{1}{par1}}$
Independent	-	0	0

par: parameter

Source: Cheng et al. (2020); Nagler et al. (2015); Czado (2019); Mendes et al. (2007); Joe (1997)

Figure 1. Examples for copula families with their scatter and density plots

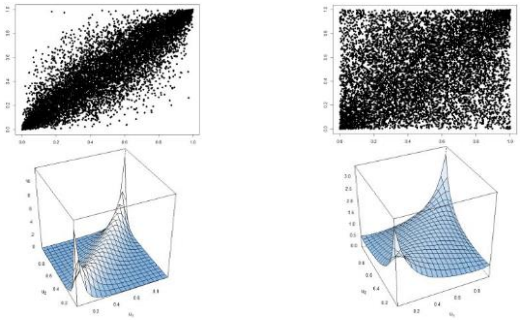
Gaussian Copula



par1= .95, par2= n.a., Tau= .80 (Lower,Upper) TD=(0,0)

par1= .50, par2= n.a., Tau= .33 (Lower,Upper) TD=(0,0)

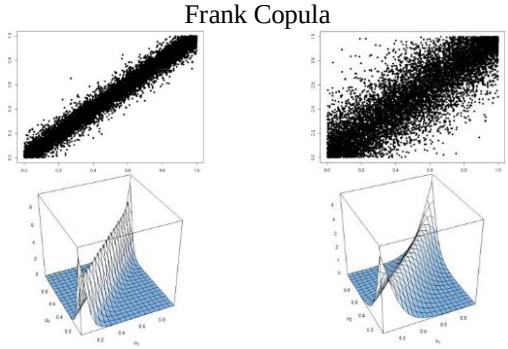
t Copula



par1=.90, par2=4.72, Tau=.71 (Lower,Upper) TD=(.60, .60)

par1=.39, par2=3.89, Tau=.26 (Lower,Upper) TD=(.21, .21)

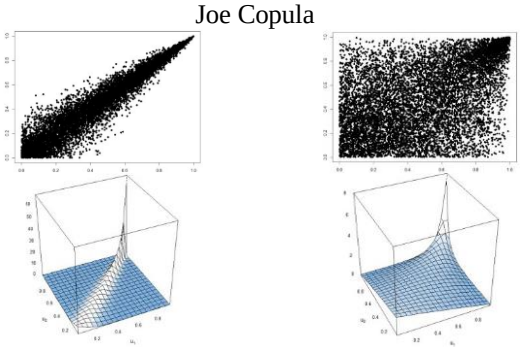
Frank Copula



par1=34.8, par2=n.a., Tau=.89 (Lower,Upper) TD=(0, 0)

par1=10.1, par2= n.a., Tau=.67 (Lower,Upper) TD=(0, 0)

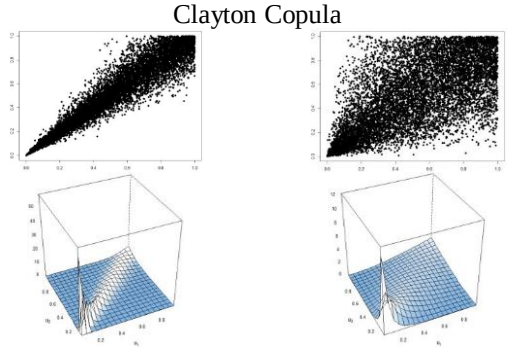
Joe Copula



par1=12.13, par2= n.a., Tau=.85 (Lower,Upper) TD=(0, .94)

par1=1.98, par2= n.a., Tau=.35 (Lower,Upper) TD=(0, .58)

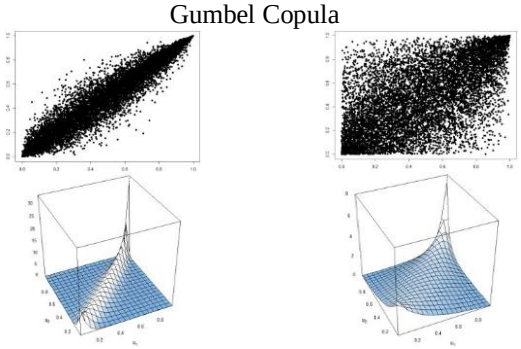
Clayton Copula



par1= 9.86, par2= n.a., Tau=.83 (Lower,Upper) TD=(.93, 0)

par1= 2, par2= n.a., Tau=.50 (Lower,Upper) TD=(.70, 0)

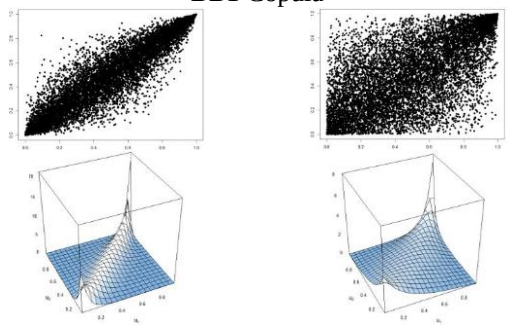
Gumbel Copula



par1= 6.01, par2= n.a., Tau=.83 (Lower,Upper) TD=(0, .88)

par1= 1.89, par2= n.a., Tau=.47 (Lower,Upper) TD=(0, .56)

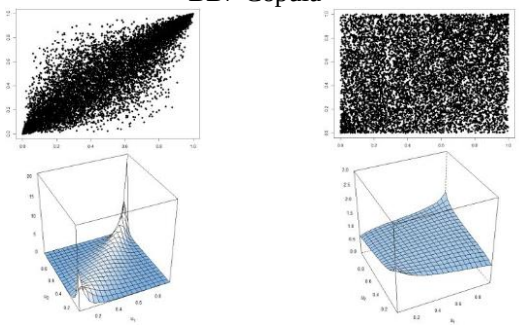
BB1 Copula



par1=.24, par2=3.98, Tau=.78 (Lower,Upper) TD=(.48, .81)

par1=.04, par2=1.91, Tau=.49 (Lower,Upper) TD=(0, .56)

BB7 Copula



par1=4.06, par2=2.02, Tau=.70 (Lower,Upper) TD=(.71, .81)

par1=1.06, par2=0.14, Tau=.10 (Lower,Upper) TD=(.0, .08)

TD: Tail Dependence; par: Parameter

Source: Authors' calculations

Joe (1997) introduced the vine copula method to expand the scope of application of the copula method in higher dimensions. Initially, c-vine and d-vine structures emerged, and later, researchers developed the regular vine (r-vine) structure. The c-vine structure designates one variable as the root node, connecting all remaining variables to that root, while d-vine structure connects the variables as pairs in respect to the order between variables. The r-vine structure combines the features of both c-vine and d-vine, making it a hybrid and more effective method, especially in scenarios with a high number of variables (Wu et al., 2020).

For the copula method to work properly, it is essential that the time series data are both stationary and continuous. Once we confirm the stationarity of the variables, we identify the most suitable ARMA model for each variable before applying the copula approach. Utilizing the "auto.arima()" function in the R package "forecast" (Hyndman et al., 2020), we employ Akaike (AIC) and Bayesian (BIC) information criteria values to determine the best model for each variable.

Subsequently, we fit the variables based on the selected ARMA models. Then we conduct KPSS (Kwiatkowski-Phillips-Schmidt-Shin) (Kwiatkowski et al., 1992), ADF (augmented Dickey–Fuller) (Dickey and Fuller, 1979), and PP (Phillips Perron) unit root (Peter and Perron, 1988) tests to check the stationarity. We present the stationary tests results in Table 4. Based on the KPSS tests, we observe no rejection of the null hypothesis of stationarity for all variables. Additionally, based on the ADF and PP tests, we reject the null hypotheses of the existence of a unit root for all indices. From these results, we confirm that the variables are stationary.

We provide the best-fitted ARMA models and their selection criteria values in Table 5. To determine the most appropriate copula family for each pair, we utilize the "BiCopSelect()" function in the "VineCopula" R package (Nagler et al., 2015). This function employs maximum likelihood estimation to fit all probable copulas for a given pair, and it computes AIC and BIC values to identify the most suitable family among all available copula families.

Table 4. Stationary tests results

	KPSS test results			**ADF test results**			**PP test results**		
Variable Name	**KPSS Statistic**	**Truncation Lag Parameter**	**p value**	**ADF Statistic**	**Lag Order**	**p value**	**PP Statistic**	**Truncation Lag Parameter**	**p value**
WTI	.03	9	.10	-14.74	15	.01	-1679.531	9	.01
xu100	.02	9	.10	-15.12	15	.01	-3596.241	9	.01
banks	.02	9	.10	-15.24	15	.01	-5767.385	9	.01
bsmet	.03	9	.10	-14.65	15	.01	-3772.507	9	.01
inftech	.05	9	.10	-14.65	15	.01	-1979.154	9	.01
elect	.05	9	.10	-15.30	15	.01	-5057.551	9	.01
finance	.02	9	.10	-15.11	15	.01	-3653.221	9	.01
reit	.04	9	.10	-13.88	15	.01	-3581.213	9	.01
service	.02	9	.10	-15.48	15	.01	-3564.939	9	.01
holding	.02	9	.10	-14.80	15	.01	-2267.217	9	.01
chem	.02	9	.10	-15.66	15	.01	-2786.672	9	.01
leasing	.03	9	.10	-13.08	15	.01	-3349.589	9	.01
nonmetal	.08	9	.10	-13.91	15	.01	-4568.629	9	.01
metal	.04	9	.10	-14.10	15	.01	-3042.735	9	.01
wood	.09	9	.10	-14.84	15	.01	-3688.151	9	.01
indus	.03	9	.10	-14.78	15	.01	-3503.135	9	.01
insur	.04	9	.10	-13.99	15	.01	-3507.784	9	.01
sport	.07	9	.10	-16.56	15	.01	-2983.950	9	.01
tech	.04	9	.10	-14.52	15	.01	-2582.512	9	.01
textile	.05	9	.10	-14.35	15	.01	-2934.866	9	.01
telecom	.01	9	.10	-16.16	15	.01	-1618.005	9	.01
retail	.03	9	.10	-15.19	15	.01	-3699.209	9	.01
tourism	.09	9	.10	-14.84	15	.01	-1833.915	9	.01
transpor	.04	9	.10	-14.81	15	.01	-1607.158	9	.01
food	.03	9	.10	-15.45	15	.01	-3531.965	9	.01

Table 5. The best fitted ARIMA models and their selection criteria values

Variable	Model	Sigma Squared	Log-L	AIC	BIC
WTI	ARIMA(4,1,0)	0.0008279	8253.37	-16496.75	-16465.43
xu100	ARIMA(1,1,0)	0.0005008	9225.76	-18447.52	-18435.00
banks	ARIMA(3,1,2)	0.0007748	8382.67	-16751.33	-16707.50
bsmet	ARIMA(0,1,1)	0.0006404	8749.41	-17494.81	-17482.29
inftech	ARIMA(2,1,3)	0.0005699	8977.19	-17942.39	-17904.81
elect	ARIMA(5,1,0)	0.0006361	8764.53	-17517.05	-17479.48
finance	ARIMA(1,1,0)	0.0006383	8755.87	-17507.74	-17495.21
reit	ARIMA(1,1,0)	0.0005123	9181.79	-18359.57	-18347.05
service	ARIMA(1,1,0)	0.0003971	9675.53	-19347.06	-19334.54
holding	ARIMA(1,1,1)	0.0005310	9112.98	-18219.96	-18201.17
chem	ARIMA(3,1,2)	0.0004877	9279.14	-18546.28	-18508.70
leasing	ARIMA(1,1,0)	0.0007864	8351.44	-16698.89	-16686.36
nonmetal	ARIMA(0,1,4)	0.0003979	9672.91	-19335.83	-19304.52
metal	ARIMA(1,1,2)	0.0004823	9299.80	-18591.60	-18566.55
wood	ARIMA(1,1,0)	0.0005361	9093.78	-18183.56	-18171.04
indus	ARIMA(1,1,0)	0.0003915	9702.83	-19401.66	-19389.13
insur	ARIMA(1,1,0)	0.0005281	9123.03	-18242.06	-18229.54
sport	ARIMA(3,1,2)	0.0007588	8422.64	-16833.29	-16795.71
tech	ARIMA(3,1,2)	0.0005683	8982.63	-17953.25	-17915.68
textile	ARIMA(0,1,4)	0.0004762	9324.90	-18639.80	-18608.49
telecom	ARIMA(3,1,2)	0.0005833	8932.21	-17852.42	-17814.85
retail	ARIMA(0,1,1)	0.0004672	9360.12	-18716.25	-18703.72
tourism	ARIMA(1,1,1)	0.0007335	8486.76	-16967.51	-16948.73
transpor	ARIMA(1,1,1)	0.0007511	8440.93	-16875.85	-16857.07
food	ARIMA(1,1,2)	0.0004712	9344.91	-18681.82	-18656.77

ARIMA: Autoregressive Integrated Moving Average

Results and Discussion

Bivariate Copula Results

We graph the best-fitted bivariate copula graphs in Figure 2 depicting the relationships between BIST sector indices and WTI, along with their respective copula family names, Kendall's tau values, parameter 1 and parameter 2 values, and lower and upper tail dependence coefficients. In Figure 2, parameter 1 is the association parameter in determining Kendall's Tau value and parameter 2 represents the degree of tail dependency (Czado, 2019). Based on the information in Figure 2, we find that the bivariate copula family of WTI with Food Beverage, Information Technology, Leasing Factoring, Non-Metal Mineral Product, Wholesale & Retail Trade, and Sports sectors is t copula. In addition, we determine that WTI exhibits a BB7 copula with Financials, Real Estate Investment Trusts, Services, Holding & Investments, Wood Paper Printing, Insurance, Textile and Leather, and Telecommunication sectors. Likewise, we observe that WTI forms a survival BB7 copula family with Banks, Basic Metal, Chemical Petrol Plastic, Electricity, Industrials, Metal Products Machinery, Technology, Tourism, and Transportation sectors, indicating a 180-degree rotated BB7

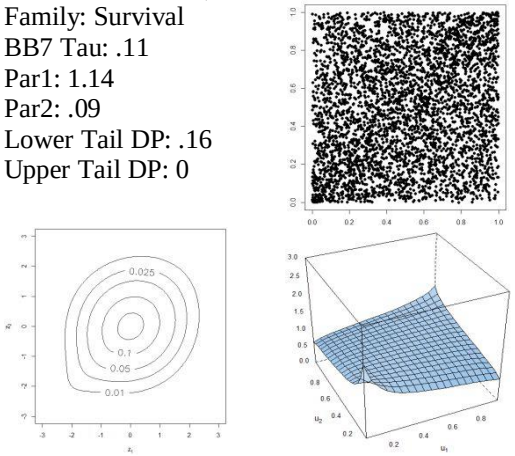
copula. We don't observe any independent copula family which indicates that dependency is not significant. Therefore, we show the existence of a significant dependence for all copula pairs. Although we observe a significant dependence in each pair, we find that the strength of the dependencies is quite weak. Among all indices, we determine that the sector with the highest dependency value with WTI is Industrials with the value of .14. It is noteworthy that the lower tail dependency value of the WTI-Industrials pair (.18) is the highest among other pairs, suggesting a higher dependence between Industrials and WTI during negative extreme events compared to other sector indices.

Based on the upper tail dependency results, we find that the dependence between BIST Services and WTI in positive extreme price movements is the highest among others with .10 coefficient value. We also find that BIST Banks, BIST Basic Metal, BIST Electricity, BIST Chemical Petrol Plastic, BIST Metal Products Machinery, BIST Industrials, BIST Technology, BIST Tourism, and BIST Transportation indices have no upper tail dependency with WTI. It means that there is no significant correlation between these nine sector indices and WTI in positive extreme movements throughout the research period. On the contrary, we detect that these nine sector indices have the highest lower tail dependency values with WTI. Based on these findings, we conclude that in negative extreme movements BIST Banks, BIST Basic Metal, BIST Electricity, BIST Chemical Petrol Plastic BIST Metal Products Machinery, BIST Industrials, BIST Technology, BIST Tourism, and BIST Transportation indices are more dependent on WTI than the others.

Figure 2. Family names of each pair with their estimated coefficient values, pair plots, contour plots, and density plots of the variables

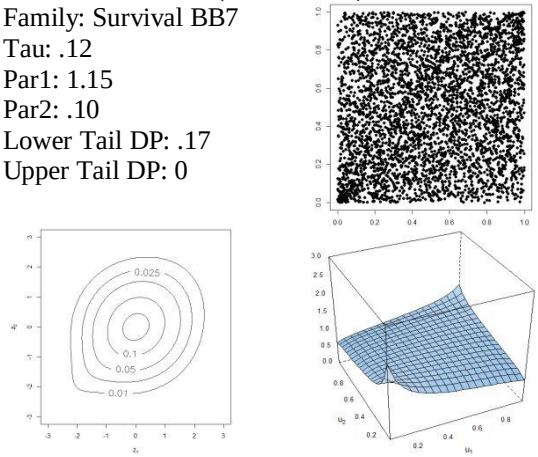
(WTI,banks)

Family: Survival
BB7 Tau: .11
Par1: 1.14
Par2: .09
Lower Tail DP: .16
Upper Tail DP: 0



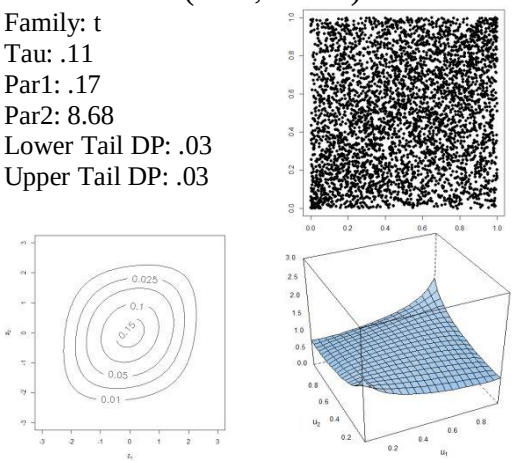
(WTI,bsmet)

Family: Survival BB7
Tau: .12
Par1: 1.15
Par2: .10
Lower Tail DP: .17
Upper Tail DP: 0



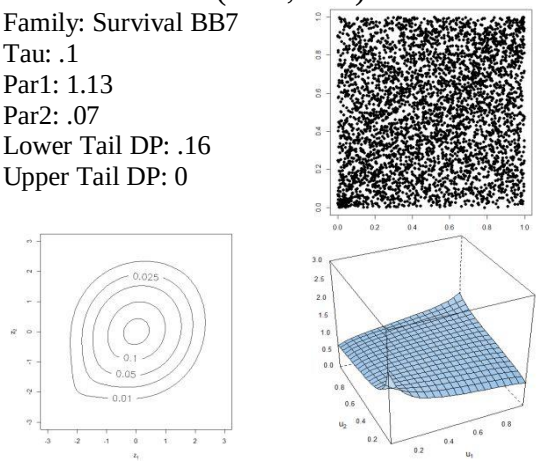
(WTI,inftech)

Family: t
Tau: .11
Par1: .17
Par2: 8.68
Lower Tail DP: .03
Upper Tail DP: .03



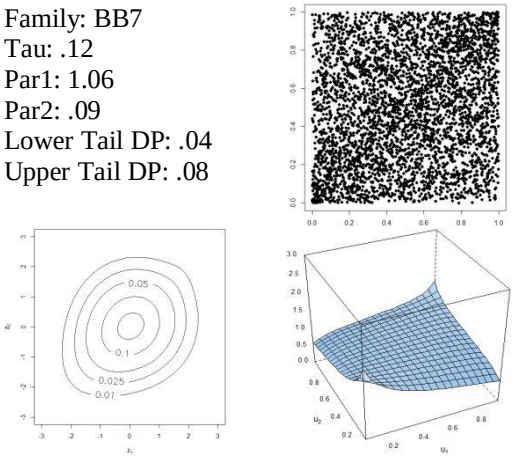
(WTI,elect)

Family: Survival BB7
Tau: .1
Par1: 1.13
Par2: .07
Lower Tail DP: .16
Upper Tail DP: 0



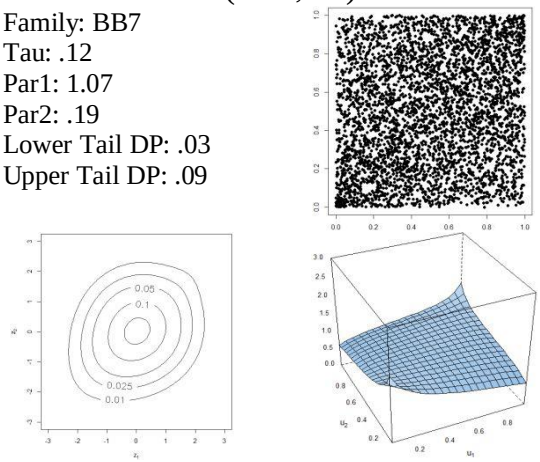
(WTI,finance)

Family: BB7
Tau: .12
Par1: 1.06
Par2: .09
Lower Tail DP: .04
Upper Tail DP: .08



(WTI,reit)

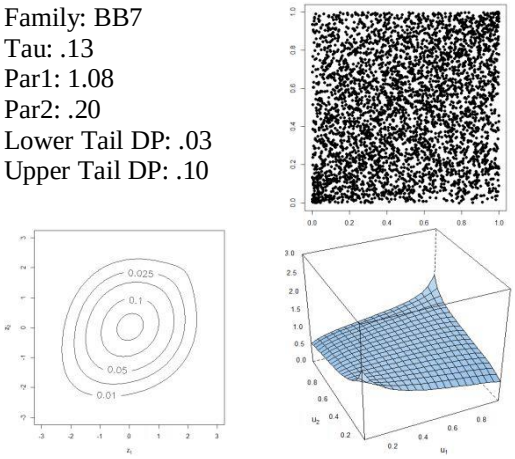
Family: BB7
Tau: .12
Par1: 1.07
Par2: .19
Lower Tail DP: .03
Upper Tail DP: .09



Par: Parameter, Tail DP: Tail Dependence

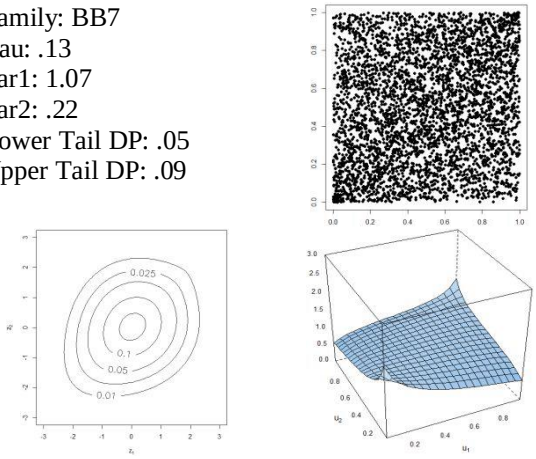
(WTI,service)

Family: BB7
Tau: .13
Par1: 1.08
Par2: .20
Lower Tail DP: .03
Upper Tail DP: .10



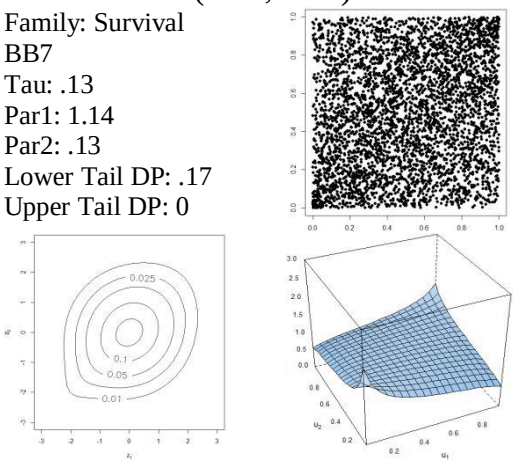
(WTI,holding)

Family: BB7
Tau: .13
Par1: 1.07
Par2: .22
Lower Tail DP: .05
Upper Tail DP: .09



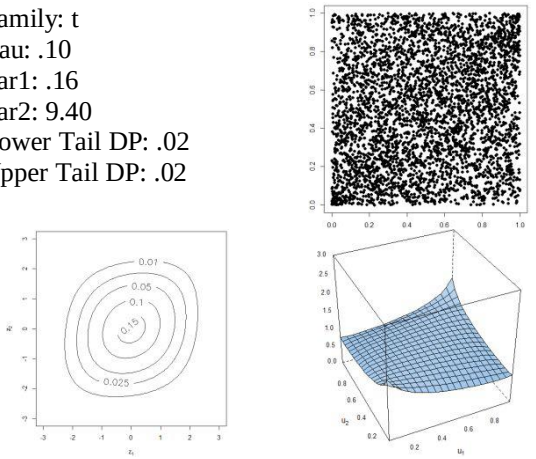
(WTI,chem)

Family: Survival BB7
Tau: .13
Par1: 1.14
Par2: .13
Lower Tail DP: .17
Upper Tail DP: 0



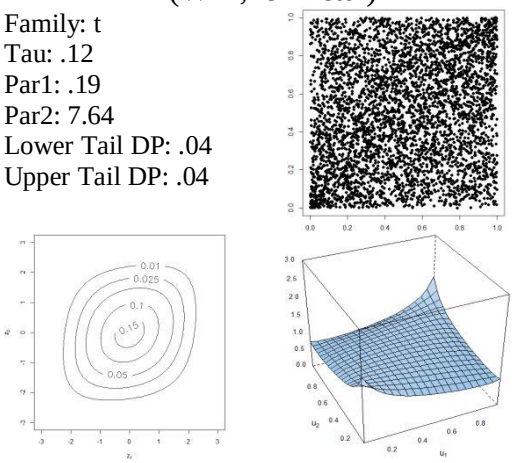
(WTI,leasing)

Family: t
Tau: .10
Par1: .16
Par2: 9.40
Lower Tail DP: .02
Upper Tail DP: .02



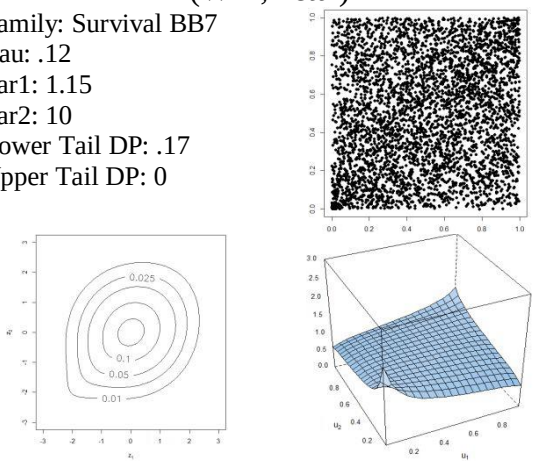
(WTI,nonmetal)

Family: t
Tau: .12
Par1: .19
Par2: 7.64
Lower Tail DP: .04
Upper Tail DP: .04



(WTI,metal)

Family: Survival BB7
Tau: .12
Par1: 1.15
Par2: 10
Lower Tail DP: .17
Upper Tail DP: 0

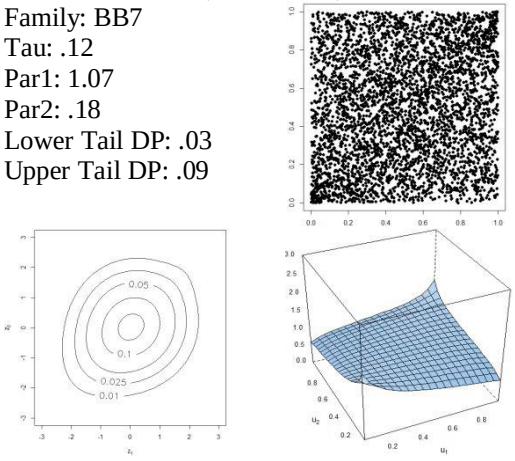


Par: Parameter, Tail DP: Tail Dependence

Figure 2 (continued)

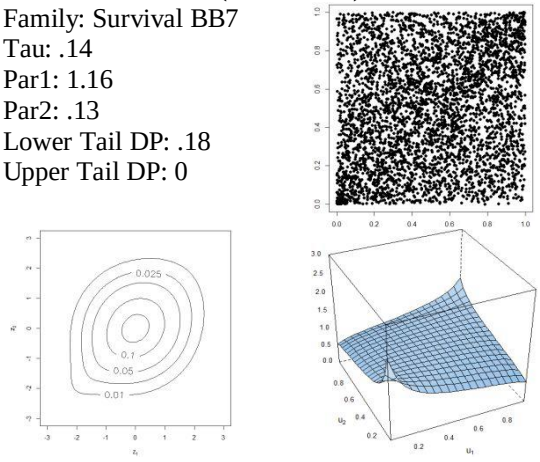
(WTI,wood)

Family: BB7
Tau: .12
Par1: 1.07
Par2: .18
Lower Tail DP: .03
Upper Tail DP: .09



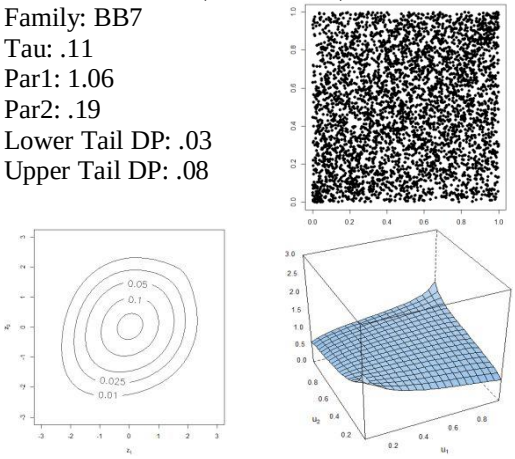
(WTI,indus)

Family: Survival BB7
Tau: .14
Par1: 1.16
Par2: .13
Lower Tail DP: .18
Upper Tail DP: 0



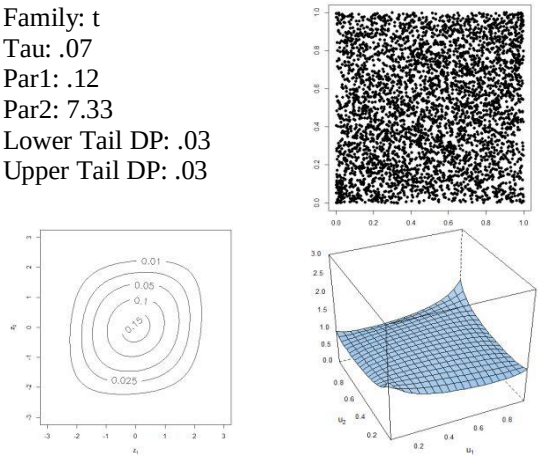
(WTI,insur)

Family: BB7
Tau: .11
Par1: 1.06
Par2: .19
Lower Tail DP: .03
Upper Tail DP: .08



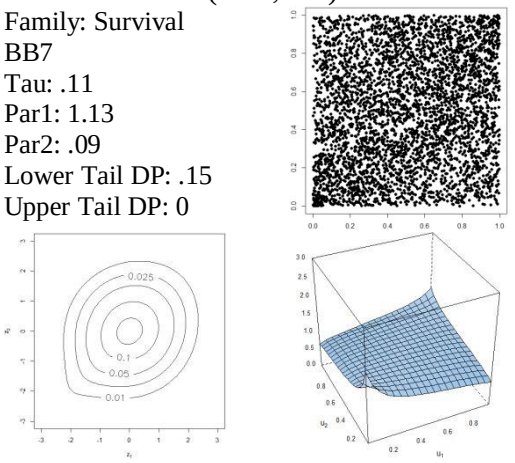
(WTI,sport)

Family: t
Tau: .07
Par1: .12
Par2: 7.33
Lower Tail DP: .03
Upper Tail DP: .03



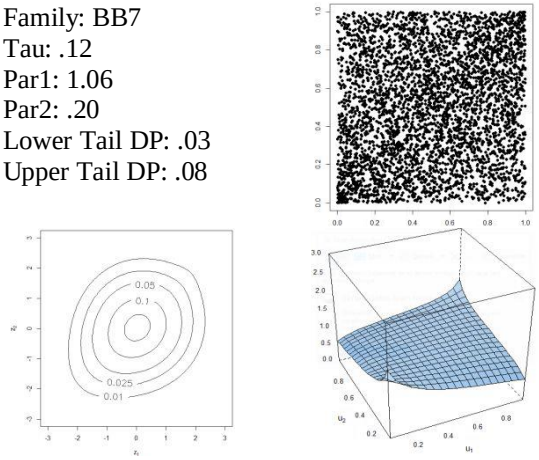
(WTI,tech)

Family: Survival BB7
Tau: .11
Par1: 1.13
Par2: .09
Lower Tail DP: .15
Upper Tail DP: 0



(WTI,textile)

Family: BB7
Tau: .12
Par1: 1.06
Par2: .20
Lower Tail DP: .03
Upper Tail DP: .08

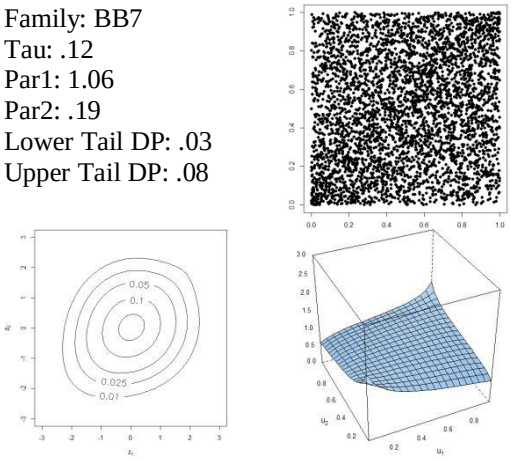


Par: Parameter, Tail DP: Tail Dependence

Figure 2 (continued)

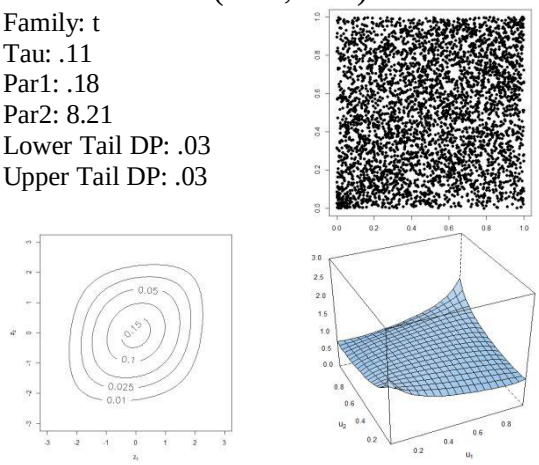
(WTI,telecom)

Family: BB7
Tau: .12
Par1: 1.06
Par2: .19
Lower Tail DP: .03
Upper Tail DP: .08



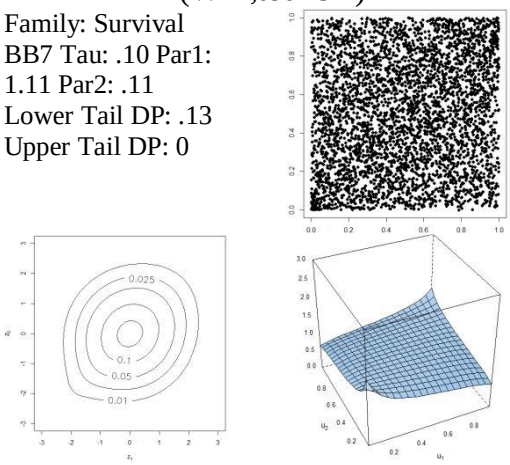
(WTI,retail)

Family: t
Tau: .11
Par1: .18
Par2: 8.21
Lower Tail DP: .03
Upper Tail DP: .03



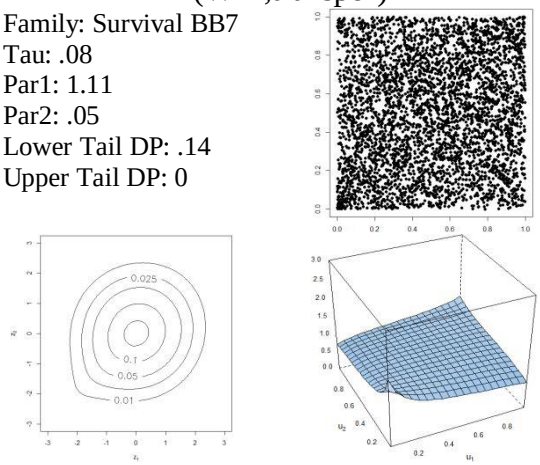
(WTI,tourism)

Family: Survival BB7 Tau: .10 Par1: 1.11 Par2: .11
Lower Tail DP: .13
Upper Tail DP: 0



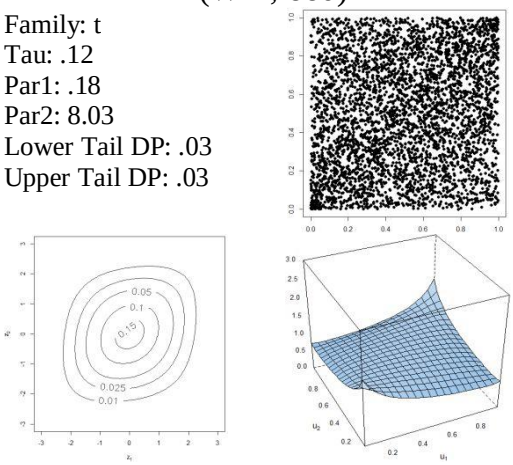
(WTI,transpor)

Family: Survival BB7
Tau: .08
Par1: 1.11
Par2: .05
Lower Tail DP: .14
Upper Tail DP: 0



(WTI,food)

Family: t
Tau: .12
Par1: .18
Par2: 8.03
Lower Tail DP: .03
Upper Tail DP: .03



Par: Parameter, Tail DP: Tail Dependence

Tau: Kendall's Tau value; Par: Parameter; DP: Dependency Coefficient

Figure 2 (continued)

R-Vine Copula Results

We measure the dependencies between WTI and BIST sector indices in bivariate dimensions in the previous subsection. What conclusions do we get if we display the dependencies between all included variables in higher dimensions? We use the vine copula approach to identify the dependencies in higher dimensions. The "RVineStructureSelect()" function in the "VineCopula" package in R gives the most appropriate vine copula structure (either r-vine copula or c-vine copula) based on AIC, BIC, and corrected-AIC. We draw the tree of the vine copula structure in Figure 3 which is called as first tree. The names in the edges describe the abbreviations of the indices. The texts on the straight lines linking the edges are the family names and the magnitude of dependence. For example, the most significant bivariate copula family for BIST Insurance-BIST Financials is BB1 copula with .58 correlation coefficient, which is on the top left of Figure 3. We conclude that the index which is most correlated with BIST Insurance is the finance index, considering that BIST Insurance has no other connection with any variable. Likewise, as we have no connection to WTI rather than BIST Industrials, we induce that the most correlated index with WTI is BIST Industrials. We find that the family of the bivariate copula pair of WTI-BIST Industrials is survival BB7 copula with .14 correlation coefficient according to the r-vine copula. These arguments coincide with the results that we give in the previous bivariate copula results subsection. Here, we argue that one of the biggest reasons why WTI is not in the center is due to the fact that other variables in the analysis are in the same market and therefore are more correlated with each other.

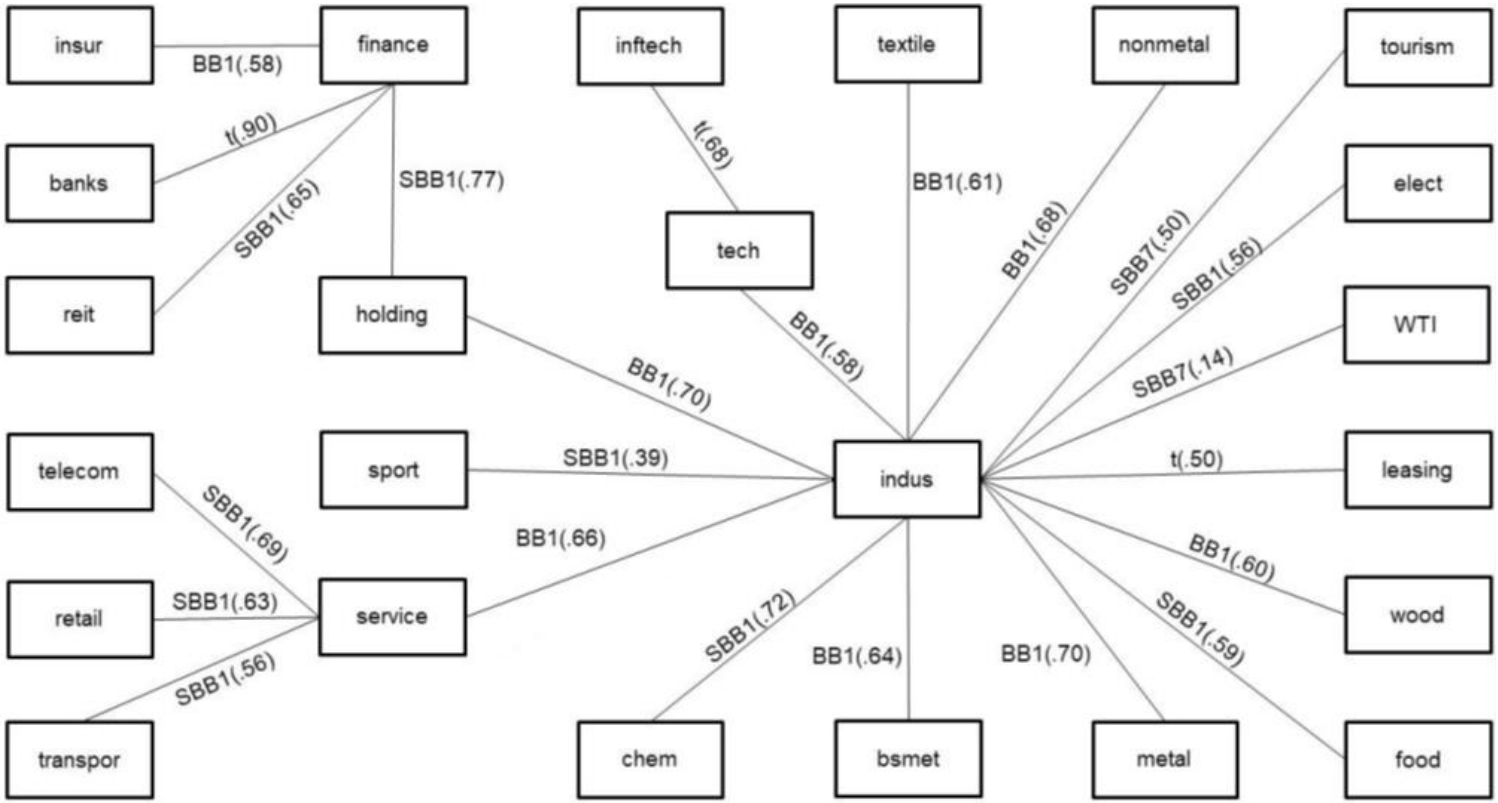


Figure 3. First tree of R-vine model

Conclusions

We aim to assess the dependencies between WTI and BIST sector indices through the copula approach. Initially, we utilize the bivariate copula model to gauge the upper and lower tail dependencies between WTI and other indices. Subsequently, we construct a multivariate model using the r-vine copula to examine dependencies in higher dimensions.

From the bivariate copula model outcomes, we identify a t copula family between WTI and BIST Information Technology, BIST Leasing Factoring, BIST Non-Metal Mineral Product, BIST Sports, BIST Wholesale & Retail Trade, and BIST Food Beverage indices, indicating significant dependency with symmetric upper and lower tail dependency. Similarly, we find a BB7 copula family between WTI and BIST Financials, BIST Real Estate Investment Trusts, BIST Services, BIST Holding & Investments, BIST Wood Paper Printing, BIST Insurance, BIST Textile and Leather, and BIST Telecommunication indices, demonstrating significant dependency with asymmetric upper and lower tail dependency. Additionally, we observe a 180-degree rotated BB7 copula family between WTI and BIST Banks, BIST Basic Metal, BIST Electricity, BIST Chemical Petrol Plastic, BIST Metal Products Machinery, BIST Industrials, BIST Technology, BIST Tourism, and BIST Transportation indices, also indicating significant dependence with asymmetric lower and upper tail dependency.

We determine industrials as the sector index that is most correlated with WTI, with a dependency value of 0.14. Moreover, holding & investments, services, and chemical petrol plastic sector indices exhibit a dependency value of 0.13 with WTI. Conversely, the sports sector index has the lowest dependency value with WTI, standing at 0.07 Kendall's Tau value. When examining the upper tail dependency structures of the sector indices with WTI, we observe that the services sector index has the highest dependency value at 0.10. Compared to others, the services sector and WTI show a stronger positive correlation in extreme price movements. We also identify nine indices whose dependence with WTI is not significant in positive shocks, namely transportation, electricity, technology, banks, metal products machinery, basic metal, tourism, chemical petrol plastic, and industrials. We don't find any significant correlation between these nine sector indices and WTI in positive extreme movements throughout the research period. Regarding the lower tail dependency results, we conclude that transportation, electricity, technology, banks, financials, metal products machinery, basic metal, tourism, chemical petrol plastic, and industrials sectors exhibit greater dependency on WTI than others in negative extreme movements. With a coefficient of 0.02, leasing factoring, wood paper printing, and telecommunication sector indices have the lowest tail dependency with WTI, suggesting the lowest dependency with WTI in negative price movements for these three sectors.

Based on the vine copula results, we conclude that the sole index connected to WTI among all industry indices is the BIST Industrials index. The family of the WTI-BIST Industrials pair is survival BB7 copula with .14 correlation coefficient according to the r-vine copula. This aligns with our earlier bivariate copula results. Çağlı et al. (2014) highlight the significant interdependence between WTI prices and sector indices, a finding consistent with ours. When analyzed in pairs, we reveal significant dependence between WTI crude oil prices and BIST sector indices, albeit with weak strength. For a long-term perspective, we provide important implications in terms of giving ideas to portfolio managers or individual investors who asset WTI and BIST sectors together in their portfolio, especially in hedging or making decisions about their portfolios.

References

Apan, M., Alp, İ., & Öztel, A. (2019). "Determination of the Efficiencies of Textile Firms Listed in Borsa İstanbul by Using DEA-Window Analysis". *Sosyoekonomi, 27*(42), 107-128. https://doi.org/10.17233/sosyoekonomi.2019.04.06

Apergis, N., Gozgor, G., Lau, C. K. M., & Wang, S. (2020). "Dependence Structure in the Australian Electricity Markets: New Evidence from Regular Vine Copulae". *Energy Economics, 90*, 104834. https://doi.org/10.1016/j.eneco.2020.104834

Chang, M.-S., Yuan, J., & Xu, J. (2019). "Could Holding Multiple Safe Havens Improve Diversification in a Portfolio? The Extended Skew-t Vine Copula Approach". *Journal of Risk, 21*(4). https://doi.org/10.21314/JOR.2019.407

Cheng, Y., Du, J., & Ji, H. (2020). "Multivariate Joint Probability Function of Earthquake Ground Motion Prediction Equations Based on Vine Copula Approach". *Mathematical Problems in Engineering, 2020*, 1-12. https://doi.org/10.1155/2020/1697352

Chkir, I., Guesmi, K., Brayek, A. B., & Naoui, K. (2020). "Modelling the Nonlinear Relationship between Oil Prices, Stock Markets, and Exchange Rates in Oil-Exporting and Oil-Importing Countries". *Research in International Business and Finance, 54*, 101274. https://doi.org/10.1016/j.ribaf.2020.101274

Civcir, I., & Akkoc, U. (2021). "Non-linear ARDL Approach to the Oil-Stock Nexus: Detailed Sectoral Analysis of the Turkish Stock Market". *Resources Policy, 74*, 102424. https://doi.org/10.1016/j.resourpol.2021.102424

Czado, C. (2019). *Analyzing Dependent Data with Vine Copulas* (Vol. 222). Springer Cham. Springer Nature Switzerland AG 2019. https://doi.org/10.1007/978-3-030-13785-4

Çağlı, E. Ç., Taşkın, F. D., & Mandacı, P. E. (2014). "The Interactions between Oil Prices and Borsa Istanbul Sector Indices". *International Journal of Economic Policy in Emerging Economies, 7*(1), 55-65. https://doi.org/10.1504/IJEPEE.2014.05989

Dickey, D. A., & Fuller, W. A. (1979). "Distribution of the Estimators for Autoregressive Time Series with a Unit Root". *Journal of the American statistical association, 74*(366a), 427-431. https://doi.org/10.2307/2286348

Evkaya, O., Gür, İ., Yıldırım Külekci, B., & Poyraz, G. (2024). "Vine Copula Approach to Understand the Financial Dependence of the Istanbul Stock Exchange Index". *Computational Economics*, 1-46. https://doi.org/10.1007/s10614-023-10544-7

Case". *Gazi University Journal of Science, 31*(4), 1284-1296. https://dergipark.org.tr/en/download/article-file/584947

Eyüboğlu, S., & Eyüboğlu, K. (2019). "Borsa İstanbul Sektör Endekslerinin Karşılıklı Bağımlılıklarının Test Edilmesi (Testing the Interdependence of Borsa İstanbul Sector Indices)". *Erciyes Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*(53), 246-260. https://doi.org/10.18070/erciyesiibd.345786

Fenech, J.-P., & Vosgha, H. (2019). "Oil Price and Gulf Corporation Council Stock Indices: New Evidence from Time-Varying Copula Models". *Economic Modelling*, *77*, 81-91. https://doi.org/10.1016/j.econmod.2018.09.009

Hamma, W., Ghorbel, A., & Jarboui, A. (2018). "Copula Model Dependency between Oil Prices and Stock Markets: Evidence from Tunisia and Egypt". *American Journal of Finance and Accounting*, *5*(2), 111-150. https://doi.org/10.1504/AJFA.2018.10011612

Hanif, W., Arreola-Hernandez, J., Hussain Shahzad, S. J., Hoang, T. H. V., & Yoon, S.-M. (2020). "Regional and Copula Estimation Effects on EU and US Energy Equity Portfolios". *Applied Economics*, *52*(49), 5311-5342. https://doi.org/10.1080/00036846.2020.1763244

Hanif, W., Hernandez, J. A., Sadorsky, P., & Yoon, S.-M. (2020). "Are the Interdependence Characteristics of the US and Canadian Energy Equity Sectors Nonlinear and Asymmetric?". *The North American Journal of Economics and Finance*, *51*, 101065. https://doi.org/10.1016/j.najef.2019.101065

He, C., Li, G., Fan, H., & Wei, W. (2021). "Correlation between Shanghai Crude Oil Futures, Stock, Foreign Exchange, and Gold Markets: a GARCH-Vine-Copula Method". *Applied Economics*, *53*(11), 1249-1263. https://doi.org/10.1080/00036846.2020.1828566

Horváth, L., Miller, C., & Rice, G. (2020). "A New Class of Change Point Test Statistics of Rényi Type". *Journal of Business & Economic Statistics*, *38*(3), 570-579. https://doi.org/10.1080/07350015.2018.1537923

Hyndman, R. J., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., Petropoulos, F., Razbash, S., & Wang, E. (2020). Package 'forecast'. https://cran.r-project.org/web/packages/forecast/forecast.pdf

Ji, H., Wang, H., Xu, J., & Liseo, B. (2020). "Dependence Structure between China's Stock Market and Other Major Stock Markets before and after the 2008 Financial Crisis". *Emerging Markets Finance and Trade*, *56*(11), 2608-2624. https://doi.org/10.1080/1540496X.2019.1615434

Ji, H., Wang, H., Zhong, R., & Li, M. (2020). "China's Liberalizing Stock Market, Crude Oil, and Safe-Haven Assets: A Linkage Study Based on a Novel Multivariate Wavelet-

Vine Copula Approach". *Economic Modelling, 93,* 187-204. https://doi.org/10.1016/j.econmod.2020.07.022

Joe, H. (1997). *Multivariate Models and Multivariate Dependence Concepts*. CRC press.

Kamışlı, M., Kamışlı, S., & Sevil, G. (2016). "The Effects of Crises on Volatility Spillovers between Borsa Istanbul Sector Indexes". *Advances in Economics and Business, 4*(7), 339-344. https://doi.org/10.13189/aeb.2016.040703

Kamışlı, M., & Sevil, G. (2018). "Borsa İstanbul Alt Sektör Endeksleri Arasındaki Oynaklık Yayılımlarının Analizi (Analysis of the Volatility Spillovers among Borsa Istanbul Sub-Sector Indices)". *Business & Management Studies: An International Journal, 6*(4), 1015-1032. https://doi.org/10.15295/bmij.v6i4.381

Kayalar, D. E., Küçüközmen, C. C., & Selcuk-Kestel, A. S. (2017). "The Impact of Crude Oil Prices on Financial Market Indicators: Copula Approach". *Energy Economics, 61*, 162-173. https://doi.org/10.1016/j.eneco.2016.11.016

Kocaarslan, B. (2020a). "Volatility Interaction Between BIST (Borsa Istanbul) Technology Index And Other Main Sector Indices". *Business & Management Studies: An International Journal, 8*(1), 458. https://doi.org/10.15295/bmij.v8i1.1392

Kocaarslan, B. (2020b). "Volatility Transmission Between US Economic Policy Uncertainty and BIST (Borsa Istanbul) Major Sector Indices". *Business & Management Studies: An International Journal, 8*(3), 3221-3238. https://doi.org/10.15295/bmij.v8i3.1572

Korkmaz, Ö., & Güngör, S. (2018). "Küresel Ekonomi Politika Belirsizliğinin Borsa İstanbul'da İşlem Gören Seçilmiş Endeks Getirileri Üzerindeki Etkisi (The Impact of Global Economic Policy Uncertainty on Stock Returns of Selected Index Traded on Istanbul Stock Exchange)". *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi, 6*(ICEESS'18), 211-219. https://doi.org/10.18506/anemon.452749

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). "Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root?". *Journal of econometrics, 54*(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Mejdoub, H., & Ghorbel, A. (2018). "Conditional Dependence between Oil Price and Stock Prices of Renewable Energy: A Vine Copula Approach". *Economic and Political Studies, 6*(2), 176-193. https://doi.org/10.1080/20954816.2018.1463600

Mendes, B. V., de Melo, E. F., & Nelsen, R. B. (2007). "Robust Fits for Copula Models". *Communications in Statistics—Simulation and Computation®, 36*(5), 997-1017. https://doi.org/10.1080/03610910701539708

Mokni, K., & Youssef, M. (2019). "Measuring Persistence of Dependence between Crude Oil Prices and GCC Stock Markets: A Copula Approach". *The Quarterly Review of Economics and Finance, 72*, 14-33. https://doi.org/10.1016/j.qref.2019.03.003

Mudiangombe, B. M., & Muteba Mwamba, J. W. (2023). "Impacts of US Stock Market Crash on South African Top Sector Indices, Volatility, and Market Linkages: Evidence of Copula-Based BEKK-GARCH Models". *International Journal of Financial Studies, 11*(2), 77. https://doi.org/10.3390/ijfs11020077

Nagler, T., Schepsmeier, U., Stoeber, J., Brechmann, E. C., Graeler, B., Erhardt, T., Almeida, C., Min, A., Czado, C., & Hofmann, M. (2015). *Package 'VineCopula'*. In *R package version*

Peter, C. B. P., & Perron, P. (1988). "Testing for a Unit Root in Time Series Regression". *Biometrika, 75*(2), 335-346. http://www.jstor.org/stable/2336182 https://doi.org/10.2307/2336182

Rašiová, B., & Árendáš, P. (2023). "Copula Approach to Market Volatility and Technology Stocks Dependence". *Finance Research Letters, 52*, 103553. https://doi.org/10.1016/j.frl.2022.103553

Righi, M. B., & Ceretta, P. S. (2013). "Analyzing the Dependence Structure of Various Sectors in the Brazilian Market: A Pair Copula Construction approach". *Economic Modelling, 35*, 199-206. https://doi.org/10.1016/j.econmod.2013.06.012

Shang, J., & Hamori, S. (2023). "Differential Tail Dependence between Crude Oil and Forex Markets in Oil-Importing and Oil-Exporting Countries during Recent Crisis Periods". *Sustainability, 15*(19), 14445. https://doi.org/10.3390/su151914445

Sklar, M. (1959). Fonctions de Répartition à N Dimensions et Leurs Marges. Annales de l'ISUP, *8*(3), 229-231. https://hal.science/hal-04094463

Song, Q., Liu, J., & Sriboonchitta, S. (2019). "Risk Measurement of Stock Markets in BRICS, G7, and G20: Vine Copulas versus Factor Copulas". *Mathematics, 7*(3), 274. https://doi.org/10.3390/math7030274

Sukcharoen, K., & Leatham, D. J. (2016). "Dependence and Extreme Correlation among US Industry Sectors". *Studies in Economics and Finance, 33*(1), 26-49. https://doi.org/10.1108/SEF-01-2015-0021

Sukcharoen, K., Zohrabyan, T., Leatham, D., & Wu, X. (2014). "Interdependence of Oil Prices and Stock Market Indices: A Copula Approach". *Energy Economics, 44*, 331-339. https://doi.org/10.1016/j.eneco.2014.04.012

Tokat, E. (2010). "İMKB Sektör Endeksleri Arasındaki Şok ve Oynaklık Etkisi (Shock and Volatility Interaction Between The Sector Indexes of Istanbul Stock Exchange)". *BDDK Bankacılık ve Finansal Piyasalar Dergisi*, *4*(1), 91-104. https://dergipark.org.tr/en/download/article-file/1352398

Wu, X., Zhu, S., & Wang, S. (2020). "Research on Information Spillover Effect of the RMB Exchange Rate and Stock Market Based on R-Vine Copula". *Complexity*, *2020*. https://doi.org/10.1155/2020/2492181

Yu, L., Zha, R., Stafylas, D., He, K., & Liu, J. (2020). "Dependences and Volatility Spillovers between the Oil and Stock Markets: New Evidence from the Copula and VAR-BEKK-GARCH Models". *International Review of Financial Analysis, 68,* 101280. https://doi.org/10.1016/j.irfa.2018.11.007

Zhang, X., Kim, M., Yan, C., & Zhao, Y. (2024). "Default Dependence in the Insurance and Banking Sectors: A Copula Approach". *Journal of International Financial Markets, Institutions and Money*, *91*, 101911. https://doi.org/10.1016/j.intfin.2023.101911

Zhao, J., Cui, L., Liu, W., & Zhang, Q. (2023). "Extreme Risk Spillover Effects of International Oil Prices on the Chinese Stock Market: A GARCH-EVT-Copula-CoVaR Approach". *Resources Policy*, *86,* 104142. https://doi.org/10.1016/j.resourpol.2023.104142

Zhao, M., & Park, H. (2024). "Bidirectional Risk Spillovers between Chinese and Asian Stock Markets: A Dynamic Copula-EVT-CoVaR Approach". *Journal of Risk and Financial Management*, *17*(3), 110. https://doi.org/10.3390/jrfm17030110