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Exchange Rate Dependency Between Emerging Countries-Case of Black Sea Countries

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Abstract: Research Question: This study tries to answer the following question, Does exchange rate shocks on one of the Black Sea countries affect the neighbour's countries' currencies. **Motivation:** Many different financial crises that afflicted the countries of the Black Sea region over different periods and thus affected their exchange rate. **Idea:** Hence, this study examines the existence of currency dependency in the form of a geographical pattern in the Black Sea countries and tests. The study measures the cross-market dependency by looking for significant dependency in the tails; any significant dependency reflects the co-movement in the market during the depreciation or appreciation period. **Data:** The study sample consists of daily observations of bilateral exchange rates against the US dollar for the countries of the Black Sea region (Russia, Romania, Ukraine, Turkey, Georgia, and Bulgaria); the total number of observations reached 7842, with 1307 views for each country during the period from 1st of Jan 2015 to the 26th of Feb 2020. **Method/Tools:** we employ the Regular Vine copula approach, which is multivariate copula functions; this approach deal with dependency between variables by using tail dependence coefficients to assess the interdependency of both positive and negative extreme cases. **Findings:** The results of the study indicate the existence of a strong geographical pattern of currency dependency between Black Sea countries as follow: First, The Russian Ruble affect all the countries of the Black Sea region in the of appreciation and depreciation periods except on Turkey, just in depreciation periods, there's no dependency in appreciation periods between Turkey and Russia. Second, the Turkish Lira effects on both Ukrainian Hryvnia and Bulgarian Leva in appreciation and depreciation periods. Third, Bulgarian Leva affects Ukrainian Hryvnia in appreciation and depreciation periods, and finally, Georgian Lari affects only Ukrainian Hryvnia in depreciation periods. **Contributions:** This study is considered the first study that discusses regional contagion in Black Sea countries, providing insight into how the exchange rate in one of these countries reacts to exchange rate crises in the others.

Keywords: Exchange rate, black sea countries, dependency, regular vine copula.
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1. Introduction

The need for a trusted estimator for investment optimization makes the exchange rate one of the crucial financial applications in international investing, where the exchange rate fluctuations impact the anticipated profitability and risk of financial assets. Traders, international companies, and policymakers need foreign policy evaluations and integration of international economic policy to make appropriate plans to control international investments (Cubillos-Rocha *et al.*, 2019). It is key to the risk-avoidance actions of investors holding positions in global capital systems, as well as to foreign policy evaluation and global economic policy planning (Loaiza-Maya *et al.*, 2015b). Thus, studying exchange rate correlation is considered one of the significant subjects of interest in terms of financial exposure.

Many studies have been conducted across different countries and periods about the exchange rate between nations. These studies have shown that the correlation between exchange rates in turmoil and financial crises differs significantly across time. For instance, Loaiza-Maya *et al.* (2015a) showed that the exchange rate contagion during a financial crisis has a greater correlation than other times. This significant correlation in financial crisis highlights the importance of studying exchange rate contagion across the world and its effects, especially when recalling the Asian financial crisis (1997), which had a geographical pattern, as well as the mortgage crisis in the United States, which caused a spillover effect around the world, and other separate crises that struck Argentina, Russia, Turkey, and others.

Many definitions and classifications for financial contagion have been introduced in the literature. Empirical studies have adopted various definitions of contagion based on their purpose. The present study follows Dornbusch *et al.*'s (1999) definition for dependency, which indicates the transfer and spillover of financial shocks, mostly negative shocks, from one market to another between countries. This phenomenon has been observed through co-movements of financial assets and exchanges rate in different markets with strong market interdependence.

Currency crises affect countries in geographic proximity. Several studies have investigated the existence of regional contagion across the world; Glick and Rose (1999) provided support empirically for how currency crises tend to be regional. They showed that the currency crisis tends to be regional and that international trading plays a crucial role in currency crisis spillover between regional countries. Tskhadadze (2019) tested the regional financial contagion between Russia and the soviet union and Turkey. Tskhadadze's (2019) findings supported the results of Glick and Rose (1999) and showed that trade openness played a crucial role in spreading the financial contagion. Loaiza-Maya *et al.* (2015b) investigated the existence of financial contagion in Latin American countries. The study found that the dependence between countries is significant periods of appreciation, whereas they found no evidence of financial contagion in periods of depreciation. Finally, a recent study was conducted by Cubillos-Rocha *et al.* (2019), which showed that exchange rate contagion takes place within countries in the same region. In this context, this study examines currency dependency in the form of a geographical pattern in the Black Sea countries; more precisely, we investigate whether exchange rate shocks on one of the Black Sea countries affect the neighbouring countries' currencies.

The Black Sea region comprises six countries: Bulgaria, Georgia, Romania, Russia, Turkey, and Ukraine. Two leading countries of these six, Russia and Turkey, have recently faced crucial financial shocks to their exchange rates during the study period, 2015-2020. For example, the Russian crisis, which began in the second half of 2014 and its effects appeared on the Russian economy since the beginning of 2015, which caused the decline of the Russian ruble (Hartley, 2015), and the Turkish crisis that began in 2018 and caused high inflation and a depreciation of the Turkish currency (Goujon, 2018).

Since there are a limited number of studies that tested regional contagion, this study is considered an addition to the literature concerned about regional contagion. Also, this study is considered the first study that discusses regional contagion in Black Sea countries which provides an insight into how the exchange rate in one of these countries reacts to exchange rate crises in the others.

Different tools were employed in the literature to test regional exchange rate dependency. In this study, we employ the Regular Vine copula approach, which is multivariate copula functions; this approach can overcome the cons of regular correlation and deal with dependency between variables by using tail dependence coefficients to assess the interdependency of both positive and negative extreme cases (Loaiza-Maya *et al.*, 2015a). Regular Vine copula is considered one of the most recent trusted and development types of the Copula; it allows for very flexible dependency and can measure linear and nonlinear correlation. We model Multivariate Copula between the variables by following Dissmann *et al.* (2013); the marginal distribution is modelled using GARCH (1,1) with t student innovation.

The study measures the cross-market dependency by looking for significant dependency in the tails; any significant dependency reflects the co-movement in the market during the depreciation or appreciation period. Our main finding shows that the exchange rate movement during the appreciation (depreciation) of the Russian exchange rate with other countries' exchange rates is faster than at normal times. For this, the opportunity for traders to diversify by investing in these pairs that include Russia is riskier, especially between Russia and Georgia (RUB_GEL), which have 78% tail dependence. Some cases, like Turkey and Georgia (TRY_GEL) and Romania with Georgia (RON_GEL), are independent of each other. The other pairs, which have a lower tail coefficient, have no risk of diversification using these currencies. This finding of the strongest dependency during the appreciation period is consistent with Cubillos-Rocha *et al.* (2019), Dimitriou *et al.* (2017), Dimitriou and Kenourgios (2013) and Loaiza-Maya *et al.* (2015b). The strongest dependence between Russia and other countries is in line with Tskhadadze (2019) finding that the Russian crisis spread geographically into neighboring countries like Ukraine, Turkey, Georgia, and other Soviet Union countries.

This paper is structured as follows: the literature review and previous studies are included in Section 2. Sections 3 demonstrate the methodology used in the study. Section 4 describes the data and discusses the result. Our conclusion is in Section 4.

2. Methodology

2.1 Model for The Marginal Distributions

As financial data are heavily reliant on past values and have many features that linear models cannot capture, GARCH (1,1) is employed as it is effective at capturing such volatility (Brooks, 2019), copula-based models have to consider this by employing the GARCH model. (for more see: Liu, 2011) Considering the dependency of financial markets is key to trading options and predicting market returns, Copula has employed in this field for a long time. However, the absence of tail dependence with Copula was credited to the global financial crisis in 2008 (Czado, 2019). This study utilizes semi-parametric IFM by considering two-step estimation. First, the standardized residuals are determined by using the conditional variance GARCH (1,1) model for the marginal distributions and then define copula data based on the standardized residual of GARCH. The first step involves the GARCH (1,1) modeling. It is known that the original assumption GARCH builds based on the normality of the disturbance term, which does not go with financial data that have fat tails. Typically, Student's t-distribution is employed in this field as follows:

$$Y_t = \sigma_t Z_t \tag{1}$$

$$\sigma_t = \omega + \alpha Y^2{}_{t-1} + \beta \sigma^2{}_{t-1} \tag{2}$$

where $\sigma_t = var(Y_t | Y_1, \dots, Y_{t-1})$ and the innovation Z_t is assumed to follow student t-distribution. The second step is to define the copula data based on the standardized residual obtained from the previous GARCH (1,1) model. This step generates pseudo observations that will subsequently be used in estimating the Copula. The following equation performs the generation of pseudo observation:

$$u_{it} = F(\frac{y_{it}}{\hat{\sigma}_{it}}; \hat{v}_i) \tag{3}$$

where $\hat{\sigma}_{it}^2$ is estimated conditional variance for market i= 1,2,..,6, $\hat{\nu}_i$ is degree of freedom, and t refers to time 1,2,…,T.

2.2 Copula

The concept of copulas refers to a particular joint distribution produced by a given marginal, and it can be constructed based on the following (Sklar, 1959) theorem: let $X = (X_1, \dots, X_n)$ a n-dimensional random vector with F, which is a univariate marginal continuous distribution function $F_1, \dots F_n$ on the interval [0,1], The joint distribution function can then be represented as:

$$F(X_1, \dots, X_d) = C(F_1(X_1), \dots, F_n(X_n)) \tag{4}$$

2.3 The Pair Copula Decompositions and Constructions (PCCs)

Conditioning is the best method for building multivariate distributions using only bivariate structures to achieving such a building was offered by (Joe, 1996) through constructing the first pair of copulas to create a multivariate copula in terms of distribution functions. Independently, Bedford and Cooke (2001, 2002) built new constructions of Copula represented in terms of density. In fact, they established a general structure for the definition of all potential constructions. The Pair-Copula Decomposition is given by $f(x_1, \dots,\ x_n)$; this density function can be factorized as:

$$f(x_n).f(x_{n-1}|x_n).f(x_1|x_2, \dots x_n) \tag{5}$$

Now, we can write the marginal distribution of the previous equation as follows:

$$f(x_i|k) = c_{x_i v_l | v-l}(f(x_i|k_{-l}), F\big(k_j\big|k_{-l}\big)).f(x_i|k_{-l}) \tag{6}$$

where $f(x_i|k)$ is the bivariate density copula and the marginal density function product of x_i. $k = x_{i+1}, \dots, x_n$ and represent $x_i{}'s$ marginal distribution, k_l is a variable of k set. The rest of the variable that remains in k after extracting k_l is denoted by k_{l-1}, i refers to {1,….,(n-1)} and the density function c is defined as:

$$\frac{\partial C(u_1, u_2)}{\partial u_1 \partial u_2} \tag{7}$$

Among several types of Pair Copula Decompositions and Constructions (PCCs), an interesting one is the regular vine copula, which calculates c as a product of bivariate Copula $\frac{n(n-1)}{2}$. This technique is helpful for modeling dependency as it allows for asymmetry and flexible upper and lower tail dependence (Loaiza-Maya *et al.*, 2015a). The description of the R-vine Copula introduced by Bedford and Cooke (2001, 2002) is as follows:

$$f(x) = \prod_{k=1}^{n} f_k(x_k) \prod_{i=1}^{n-1} \prod_{j=1}^{n-i} c_{(mi,i,mj,i|m_j+1,i,\dots,m_n,i)}\left(f_{(mi,i|mj+1,i,\dots m_{n,i})}\right)', F_{(mj,i|mj+1,i,\dots,m_{n,i})}\left(x_{(mj,i|mj+1,i,\dots,m_{n,i})}\right) \quad (8)$$

where the matrix element m matrix in R-vine is denoted by $m_{n,i}$. The tail dependence demonstrates how bivariate variables rely on each other in extreme cases. In other words, the tail dependence shows the possibility that a given variable exceeds a specific threshold, given that the other variable exceeds a specific threshold (Loaiza-Maya *et al.*, 2015a). The study follows Joe (1997) definition in estimating the upper and the lower dependence tails as follow:

$$\lambda_u = \lim_{u\to 1^-} p\left(X_1 > F_1^{-1}(u) \middle| X_2 > F_2^{-1}(u)\right) = \lim_{u\to 1^{-1}} \frac{1-2u+C(u,u)}{1-u} \quad (9)$$

$$\lambda_m = \lim_{u\to 0^-} p\left(X_1 < F_1^{-1}(u) \middle| X_2 > F_2^{-1}(u)\right) = \lim_{u\to 0^{+1}} \frac{1-2u+C(u,u)}{1-u} \quad (10)$$

3. Data and Result

This study is focused on testing the geographical pattern of tail dependence in the Black Sea region, which includes countries that have recently faced financial turmoil, such as Turkey and, Russia. The study uses the exchange rate for six countries located in this region for testing tail dependency in the Black Sea region, namely Bulgaria (BGN), Georgia (GEL), Romania (RON), Russia (RUB), Turkey (TRY), and Ukraine (UAH). Bulgaria and Romania are members of the European Union. The study period covers five years, and it extends from the 1st of Jan 2015 to the 26th of Feb 2020. The number of observations for each variable is 1307 after standardizing the market calendars by removing non-mutual observations that occurred during the holidays of other countries. The data is in the form of daily observations and obtained from investing websites. Figure 1 exhibits the exchange rate behaviour for the series. Bulgaria and Romania show appreciation around 2018 and depreciation after that. It is clear that Turkey experienced currency depreciation during the study period while Russia showed depreciation until around 2016 and appreciation after that. The financial data are considered as noisy data. Consequently, the data are converted to continuous daily returns by taking the first difference of the natural logarithms of the exchange rate. The bilateral exchange rate of domestic currency against the US dollar was employed for each country.

Table 1 and Table 2 show the descriptive statistics and Pearson correlation of the variables, respectively. The descriptive table shows that the Russian exchange rate fluctuated the most, as it has the most significant standard deviation of 4.9 with a range of 33.6, which reflects the volatility of the Russian exchange rate during the study period. The Bulgarian exchange rate is the most stable as its standard deviation is 0.06 with a mean of 1.7 and a range of 0.31. From the descriptive statistics table, it appears that is not all countries' exchange rates except Ukraine have evidence for the fat tail, which shows the risk of the opportunity of loss occurring if the kurtosis excess 3 and a negative skew with -1.54. The kurtosis for Georgia and Romania is negative, with values -0.27 and -0.86, respectively. In Bulgaria, the mean equals the median, which is 1.74, and the skew is negative with a value of -0.4. It is clear that the currencies of Russia and Ukraine fluctuated the most according to the study variables as they have standard deviations of 4.95 and 2.30, respectively. They were followed by Turkey, which has a standard deviation of 1.23.

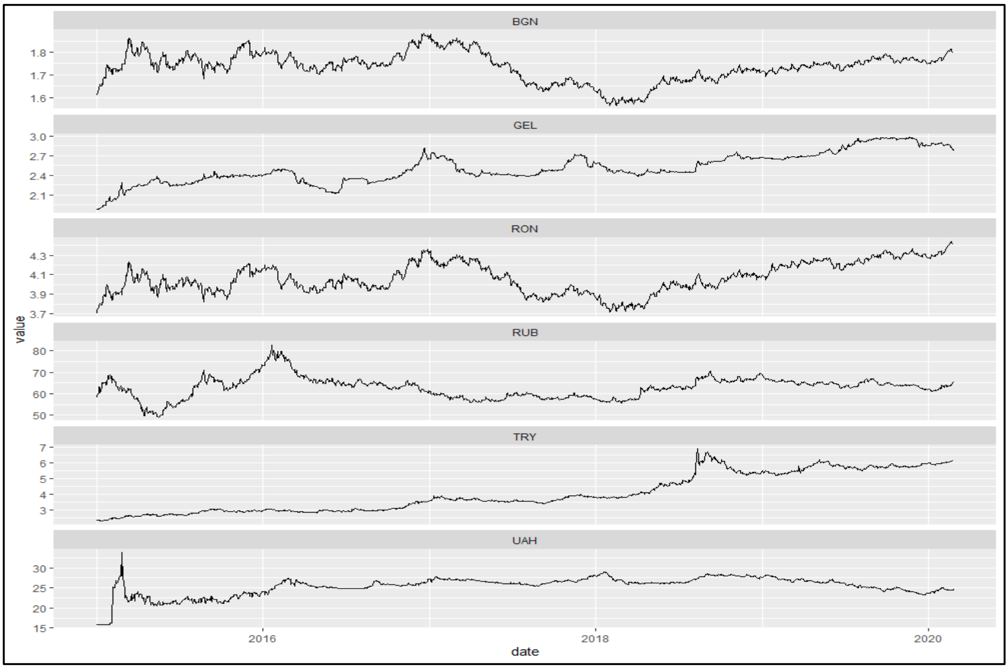

Figure 1: Bilateral exchange rate against the US dollar

Table 1: Descriptive statistics

	Mean	SD	Median	Min	Max	Range	Skew	Kurtosis
BGN	1.74	0.06	1.74	0.05	1.56	0.32	-0.40	0.01
GEL	2.51	0.23	2.46	0.23	1.88	1.10	0.22	-0.27
RON	4.07	0.16	4.06	0.18	3.70	0.74	0.04	-0.86
RUB	62.80	4.95	63.51	4.10	49.07	33.61	0.29	1.24
TRY	4.03	1.23	3.64	1.15	2.28	4.60	0.50	-1.26
UAH	25.37	2.30	26.02	1.57	15.80	17.95	-1.54	3.87

For preliminary testing of the dependency, the study evaluates the unconditional Pearson correlation between the study variable. Table 2 shows the Pearson's correlation coefficients between the exchange rate of the variables. It appears that the highest correlation coefficient is between Turkey and Georgia, with a correlation coefficient of 0.84, whereas between Bulgaria and Romania, the coefficient value is 0.77. Also, a high correlation coefficient can be observed between Romania and Georgia of 0.63. All correlation coefficients are positive except for negative correlations between the exchange rates of Turkey and Bulgaria exchange rate with a correlation coefficient of -0.13 and between Ukraine and Bulgaria with a correlation coefficient of -0.21. The weakest correlation coefficients are between Ukraine - Romania and Ukraine - Russia with values of 0.07 and 0.08, respectively.

Table 2: Pearson correlation

	BGN	GEL	RON	RUB	TRY	UAH
BGN		0.10	0.77	0.16	-0.13	-0.21
GEL	0.10		0.63	0.14	0.84	0.41
RON	0.77	0.63		0.21	0.48	0.07
RUB	0.16	0.14	0.21		0.19	0.08
TRY	-0.13	0.84	0.48	0.19		0.44
UAH	-0.21	0.41	0.07	0.08	0.44	

We can notice that most exchange rate pairs, regardless of correlation coefficient value, move together in the same direction. Since they have a positive correlation, while some of them, such as Turkey and Bulgaria exchange rate and Ukraine and Bulgaria exchange rate, have a negative correlation, they move in the opposite direction, and this means if one of them is an appreciation to USD, the second pair will be depreciation. Figure 2 exhibits the Pearson correlation between the variables.

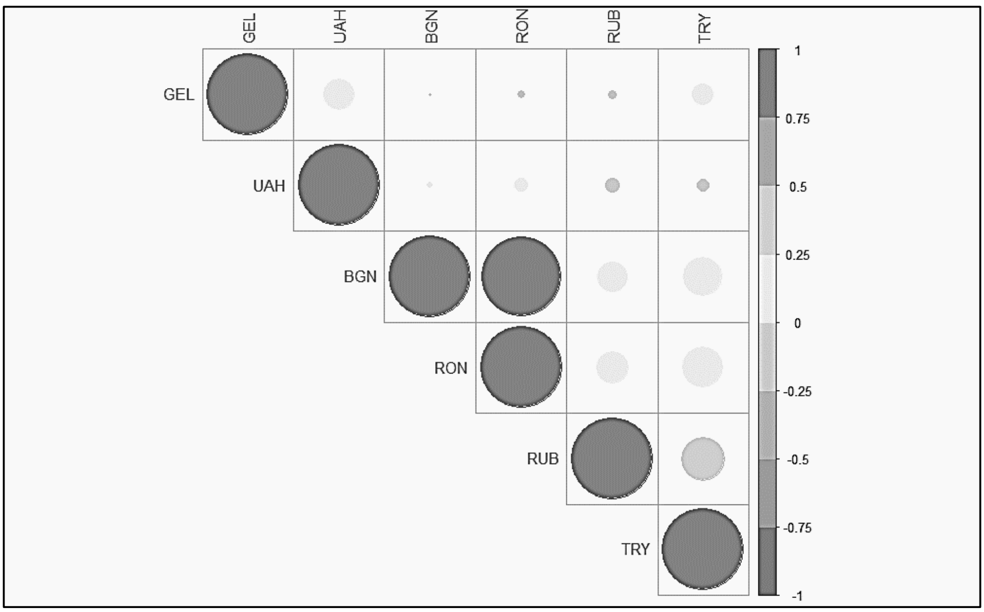

Figure 2: Pearson correlation between the variables.

It is important to note that there is a significant limitation of using unconditional correlations in that it can be challenging to determine whether the associations in regular times and in times of significant market fluctuations are different. Also, due to the high frequency of the observations, it is difficult to determine the effect size of these coefficients. Consequently, the copula approach is considered the best function to overcome this limitation by considering these limits (Cubillos-Rocha *et al.*, 2019). Based on this, we construct multivariate Copula. We employ the Regular Vine copula, which has a feature that enables it to deal with dependency between variables by using the tails dependence coefficients to assess the dependency between exchange rates. For constructing the regular vine copula, we start by adopting GARCH (1,1) with t innovation to eliminate the serial correlation and allow for a dependence structure between the standardized residual of the variable (Czado, 2019). The multivariate specification test and univariate specification test for the standardised residual are shown in Table 3 and Table 4, respectively.

Table 3: Multivariate specification tests for the standardized residuals

Tests	Lags	Statistic	P-Value
Portmanteau*	100	3576.088	0.440
LM**	100	3621.559	0.855

Notes: * indicates null hypothesis: no autocorrelation and ** indicates null hypothesis: no multivariate GARCH effect.

Table 4: Univariate specification tests for the standardized residuals

Variable	ARCH (LM) (lag=100)	Portmanteau (lag=100)
BGN	0.9625	0.9129
GEL	0.1134	0.0353
RON	0.9660	0.9520
RUB	0.8403	0.5313
TRY	0.3540	0.2705
UAH	0.1057	0.2680

Notes: Null hypothesis: No arch effect.

The procedures of Dissmann *et al.* (2013) were followed in constructing the vine copula for the pair of exchange rates by employing the algorithm suggested by Prim (1957) to maximize the sum of absolute empirical Kendall correlation coefficients to choose the tree structure then select the copula family for each pair using the "goodness of fit test" via minimizing AIC. Then, the ML method is used to estimate the parameter. Figure 3 shows the plot of regular Vine copula trees and its estimated parameters are reported in Table 5.

There is a vast family of Copula that can be employed. For exchange rate pairs, the copula family has been chosen based on goodness fit test among 39 types of Copula, namely (Gaussian, Student t, Clayton, Survival Clayton, Rotated Clayton (90 degrees), Rotated Clayton (270 degrees), Gumbel, Survival Gumbel, Rotated Gumbel (90 degrees), Rotated Gumbel (270 degrees), Frank, Joe, Survival Joe, Rotated Joe (90 degrees), Rotated Joe (270 degrees), Clayton-Gumbel, Survival Clayton-Gumbel, Rotated Clayton-Gumbel (90 degrees), Rotated Clayton-Gumbel (270 degrees), Joe-Gumbel, Survival Joe-Gumbel, Rotated Joe-Gumbel (90 degrees), Rotated Joe-Gumbel (270 degrees), Joe-Clayton, Survival Joe-Clayton, Rotated Joe-Clayton (90 degrees), Rotated Joe-Clayton (270 degrees), Joe-Frank, Survival Joe-Frank, Rotated Joe-Frank (90 degrees), Rotated Joe-Frank (270 degrees), Tawn type 1, Survival Tawn type 1, Rotated Tawn type 1 (90 degrees), Rotated Tawn type 1 (270 degrees), Tawn type 2, Survival Tawn type 2, Rotated Tawn type 2 (90 degrees) and Rotated Tawn type 2 (270 degrees).

Table 5: Regular vine specification

Pairs	Copula family	Par1	Par2
RUB_UAH	Student t	0.1221	2.0001
RUB_BGN	Student t	-0.0232	2.6904
RUB_GEL	Student t	0.9589	3.1758
RUB_RON	Student t	0.4151	6.1243
RUB_TRY	Gumbel	1.5417	0.0000
TRY_UAH	Student t	0.0024	4.9907
TRY_BGN	Student t	0.0486	11.4020
TRY_GEL	Independence copula	0.0000	0.0000
TRY_RON	Frank	0.7161	0.0000
RON_UAH	Rotated Joe copula (270 degrees)	-1.0359	0.0000
RON_BGN	Rotated Tawn type 2 (270 degree)	-1.1181	0.0940
RON_GEL	Independence copula	0.0000	0.0000
GEL_UAH	Clayton	0.0646	0.0000
GEL_BGN	Rotated Joe copula (90 degrees)	-1.0339	0.0000
BGN_UAH	Student t	-0.0068	12.0718

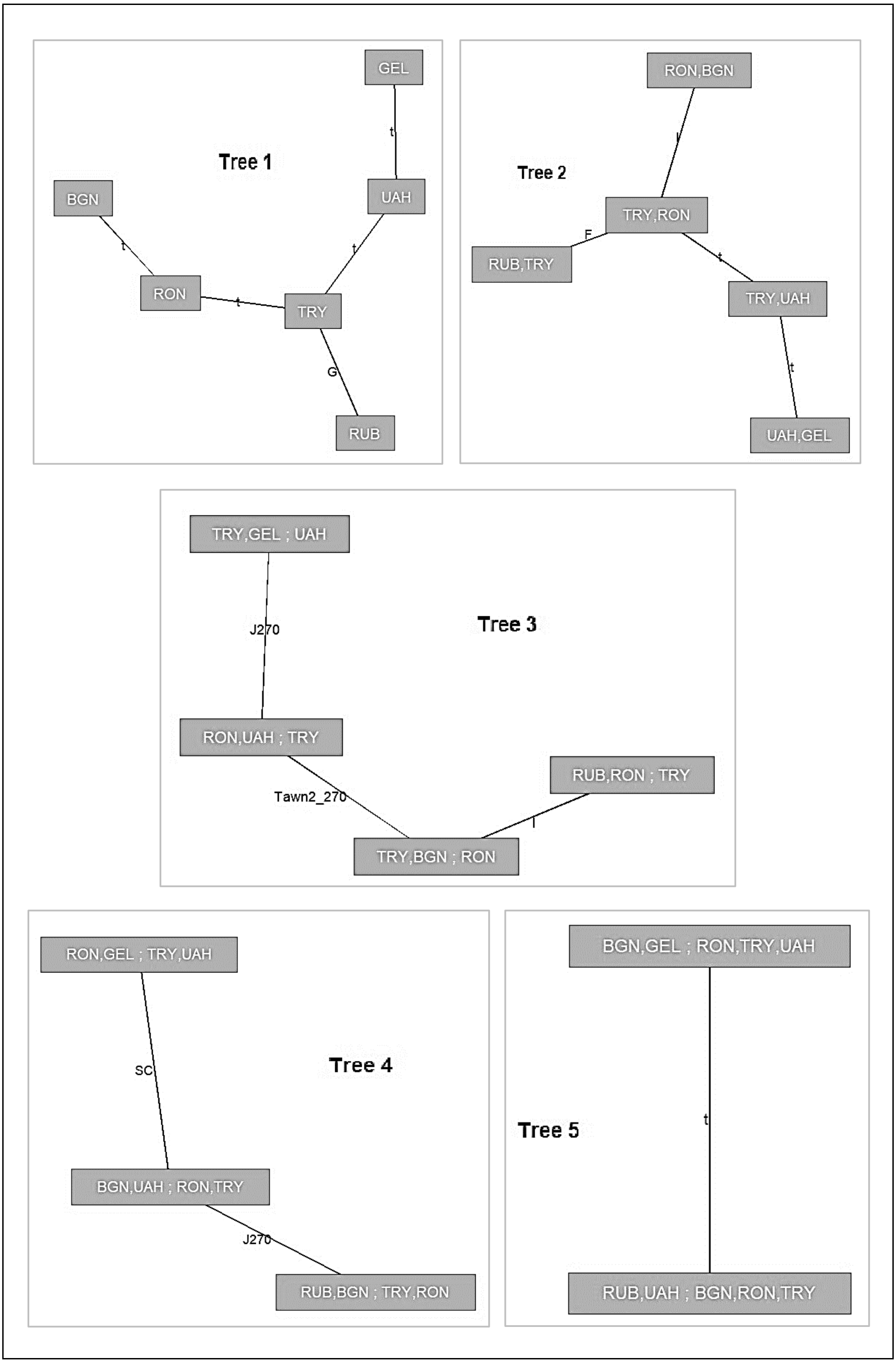

Figure 3: The plot of regular Vine copula trees

From Table 5. we can see that each pair of Romania with Georgia (RON_GEL) and Turkey with Georgia (TRY_GEL) are independent, which means that the Romanian leu and Georgian lari are independent of each other, and the same applies to the second pair (Turkish Lira and Georgian lari).

Table 6 shows the upper and lower tail dependence coefficients of the bivariate exchange rate pairs. The coefficient of the tails indicates how the pairs are asymptotically dependent on their tails (upper or lower or both tails) and the strength of this dependence between them. The upper tail coefficients are linked with exchange rate movements through extreme depreciation. The table shows that Russia has the strongest tail dependence with other countries, followed by Turkey, which has a tails dependence with Ukraine, while the others have a negligible tails coefficient. The strongest upper tail dependence is between Russia and Georgia (RUB_GEL), with a tail dependence coefficient of 78%. This indicates that currencies co-move considerably faster than in usual times across cycles of intense currency appreciation with regard to the US dollar. A strong upper tail follows this between Russia and Turkey (RUB_TRY) with a 43% tail dependence coefficient. For RUB_UAH, RUB_BGN, RUB_RON and TRY_UAH, the upper tail dependence coefficients are 22%, 12.6%, 12.9% and 5%, respectively. The rest of the pairs have either small coefficients or independence.

Table 6: Tail dependence coefficient

Pairs	Upper tail	Lower tail
RUB_UAH	0.223021200	0.223021186
RUB_BGN	0.126614647	0.126614647
RUB_GEL	0.781254000	0.781254000
RUB_RON	0.129112700	0.129112700
RUB_TRY	0.432326100	0.000000000
TRY_UAH	0.050411240	0.050411241
TRY_BGN	0.005495005	0.005495005
TRY_GEL	0.000000000	0.000000000
TRY_RON	0.000000000	0.000000000
RON_UAH	0.000000000	0.000000000
RON_BGN	0.000000000	0.000000000
RON_GEL	0.000000000	0.000000000
GEL_UAH	0.000022000	0.000000000
GEL_BGN	0.000000000	0.000000000
BGN_UAH	0.002967000	0.002967386

Notes: The dependency in tails ranges between zero and one, zero indicates no dependency, one indicates 100% dependency.

The coefficient of the lower tails dependence is linked to exchange rate movement during the appreciations of the exchange rate of the pairs of the exchange rate. The lower tail dependence coefficient has almost the same result as the upper tail coefficient except for Russia and Turkey, which has no dependence on the lower tail, thus indicating no correlation between the Russian ruble and Turkish Lira during the period of appreciation. These results are consistent with those of Cubillos-Rocha *et al.* (2019), Dimitriou *et al.* (2017), Dimitriou and Kenourgios (2013), Eduardo *et al.* (2013) and Loaiza-Maya *et al.* (2015b).

The pairs TRY_GEL, TRY_RON, RON_UAH, RON_BGN, RON_GEL, and GEL_BGN, have no dependency in appreciation and depreciation periods since the lower and upper tails have a zero value. The increase in international capital flows and trade liberalization worldwide has led to significant co-movement between exchange rates. Russia is considered the main oil and gas producer in the Black Sea area, making Russia a prominent partner for this region. The result indicates that the exchange rate movement during periods of appreciation (depreciation) of the Russian exchange rate with other countries' currencies is faster than at regular times. Consequently, the opportunity for traders to diversify by investing in these pairs that include Russia is riskier, especially the pair of Russia and Georgia (RUB_GEL) that has a tail dependence of 78%. In some cases, like Turkey and Georgia (TRY_GEL) and Romania with Georgia (RON_GEL), which are independent with no risk, and other pairs with lower tail coefficients, there is no risk of diversification these currencies. The strongest dependence between Russia and other countries is in line with Tskhadadze (2019) findings who found that the Russian crisis spread geographically into neighboring countries such as Ukraine, Turkey, Georgia, and other former Soviet Union countries.

4. Conclusion

This study investigates the existence of a geographical pattern of dependency in exchange rates among Black Sea countries (Russia, Romania, Ukraine, Turkey, Georgia, and Bulgaria) by constructing a multivariate copula by using regular vine copula and GARCH (1,1) with t-innovation during the period from the 1st of Jan 2015 to 26th of Feb 2020. The data used were in the form of continuous daily returns. The bilateral exchange rate of the domestic currency against the US dollar was employed for each country.

The results reveal the existence of a strong geographical pattern of dependency between Russia and other countries. The upper tail shows that Russia has the strongest tail dependence with other countries, followed by Turkey, which has a tails dependence with Ukraine, while the others have negligible tails coefficients. The strongest upper tail dependence is between Russia and Georgia (RUB_GEL), with a tail dependence coefficient of 78%. This indicates that currencies co-move considerably faster than in usual times across cycles of intense currency appreciation with regard to the US dollar. A strong upper tail follows this between Russia and Turkey (RUB_TRY) with a tail dependence coefficient of 43%. The lower tail dependence coefficient has almost the same result as the upper tail coefficient, apart from the fact that Russia and Turkey have no dependence in the lower tail, which means that there is a correlation between the Russian ruble and the Turkish Lira during the appreciation time. These results are consistent with Cubillos-Rocha *et al.* (2019), Dimitriou *et al.* (2017), Dimitriou and Kenourgios (2013), Loaiza-Maya *et al.* (2015b). The strongest dependence between Russia and other countries in line with Tskhadadze (2019) findings who found that the Russian crisis spread geographically into neighboring countries as Ukraine, Turkey, Georgia, and other former Soviet Union countries. Generally, the results indicate that the exchange rate movement during the appreciations (depreciation) of the Russian exchange rate with other countries' exchange rates is faster than normal time. Consequently, the opportunity for traders to diversify by investing in these pairs that include Russia is riskier.

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