A copula function investigation of the external dependence and contagion of Romanian financial asset prices

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Introduction

Introduction

Thesis proposal and objectives

- ❑ European economies have started to stabilize in the aftermath of the 2007-2008 financial crisis and the Great Recession that followed. International influences and systemic risks are still intensely-debated issues of renewed interest in building investment strategies on the one hand and safeguards against simultaneous market crashes, on the other;

- ❑ The research carried out an investigation into the linkages between Romania and similar markets from Central and Eastern Europe, on two types of financial assets – **equities and exchange rates against the Euro** – :

Poland, **Hungary** and the **Czech Republic**:

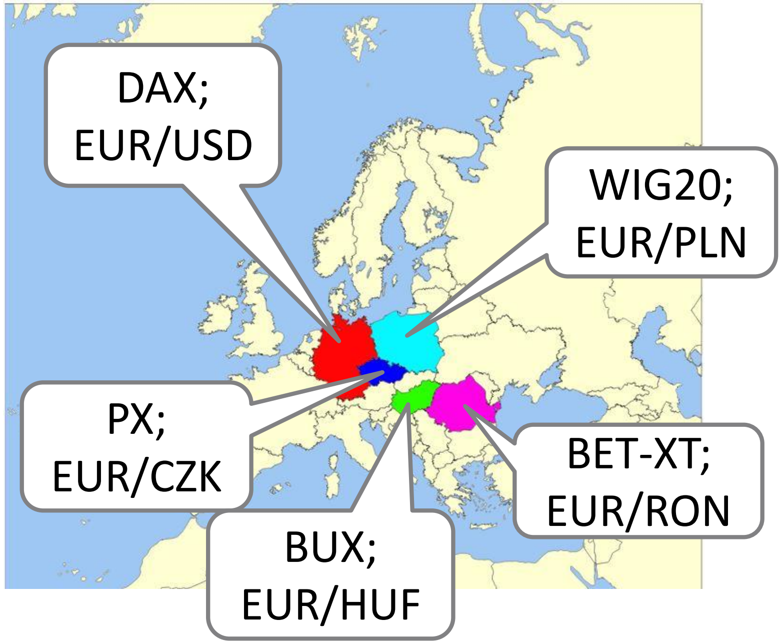
- common history; emerging markets (acc. to the IMF and Dow Jones);
- comparable attractiveness for investors in Eastern European equities;
- important economic relationships, i.e. non-Eurozone imports and exports (BoP for 2012).

Germany was added due to Romania's large exposure to the German economy:

- Romania's largest trading partner – 18.7% exports; 17.6% imports; 11% FDI;

4% of Medium and Long- Term debt (acc. to the Balance of Payments for 2012);

- proxy for contagion from the Eurozone and the EUR/USD exchange rate.



"**Romania** has surpassed **Hungary** among the most attractive countries for foreign investments in CEE in 2014, ranking **third** after **Poland** and **the Czech Republic**."

(Ernst and Young's attractiveness survey Europe 2014)

Introduction

Thesis proposal and objectives – Literature review

- Pericoli and Sbracia (2003) describe **financial contagion** as the probability of a crisis in one country (or asset) conditional on a crisis in another;

- Copula functions, introduced by Sklar in 1959, are increasingly used to model correlation, as they exhibit a series of improvements over traditional measures of correlation and concordance (Patton, 2009);

- Spearman and Kendall concordance measures have great advantages over Pearson correlation, as they are invariant with regard to increasing linear or non-linear transformations, but, still, tail dependence coefficients, as a property of copula functions, offer more precise information (Necula, 2012);

- Most studies involving copulae concentrate on one single type of asset:
  - **equity markets** are the most studied for dependence (Jondeau and Rockinger, 2002, or Aloui et al., 2011), along with **currencies** (Patton, 2006, Benediktsdóttir and Scotti, 2009, Dias and Embrechts, 2010);
  - **bond markets** are the least approached due to lesser correlations.

- Garcia and Tsafack (2011) undertake a study of bond and equity markets, investigating inter-market and inter-asset dependence using a regime-switching copula model, whereas Markun et al., 2013 study dependence on all of the above financial assets in the case of Poland;

- The present research applies the method set forth by Genest and Rivest (1993) and reviewed in Genest, Remillard and Beaudoin (2009) for approaching the goodness-of-fit of copula functions in an endeavour to **describe the correlation and dependence structure** of equities and exchange rates from Romania and abroad.

Introduction

Thesis proposal and objectives – An explanatory endeavour

Shmueli (2010) discusses the main differences between the explanatory and predictive approach to modelling.

Explanatory modelling

- Seeks to describe and diagnose
- Emphasis on significance, goodness-of-fit and well-specified models
- Does not explore out-of-sample effects
- The Bayesian Information Criterion (BIC) is appropriate, because it penalizes for extra parameters for a better fit
- Multicollinearity must be accounted for in explaining the process

vs.

Predictive modelling

- Concerned with forecasting behaviour
- Caution with regard to overfitting
- In-sample fit does not always translate into out-of-sample gains
- The Akaike Information Criterion (AIC) is used more often for model selection
- Multicollinearity is not a serious issue as long as the predicted values lie within the prediction intervals

Applied Methods and Models

Applied Methods and Models

Data collection

Variable	Data source	Input into R via	Start date	End date	No. of observations
BET-XT	Thomson Reuters; BSE	directly	3 January 2007	30 April 2014	1738; daily data
DAX	Thomson Reuters	Quandl.com API	2 January 2007	30 April 2014	
BUX	Thomson Reuters	Quandl.com API	2 January 2007	30 April 2014	
PX	Prague Stock Exchange	Quandl.com API	2 January 2007	30 April 2014	
WIG20	Thomson Reuters	directly	2 January 2007	30 April 2014	
EUR/RON	European Central Bank	directly	2 January 2007	30 April 2014	1875; daily data
EUR/USD	European Central Bank	directly	2 January 2007	30 April 2014	
EUR/HUF	European Central Bank	directly	2 January 2007	30 April 2014	
EUR/CZK	European Central Bank	directly	2 January 2007	30 April 2014	
EUR/PLN	European Central Bank	directly	2 January 2007	30 April 2014	

Applied Methods and Models

Exploratory analysis – Stylized facts

Stylized facts on financial market returns are observed properties have important implications for assessing whether the risk model chosen is appropriate or not:

a) **Not i.i.d.**: Time series data of returns – in particular, daily return series – are not independent and identically distributed;

b) **Non-constant volatility**: Return processes exhibit time-varying volatility;

c) **Volatility clustering**: Extreme returns cluster together in time, as do ‘calm periods’;

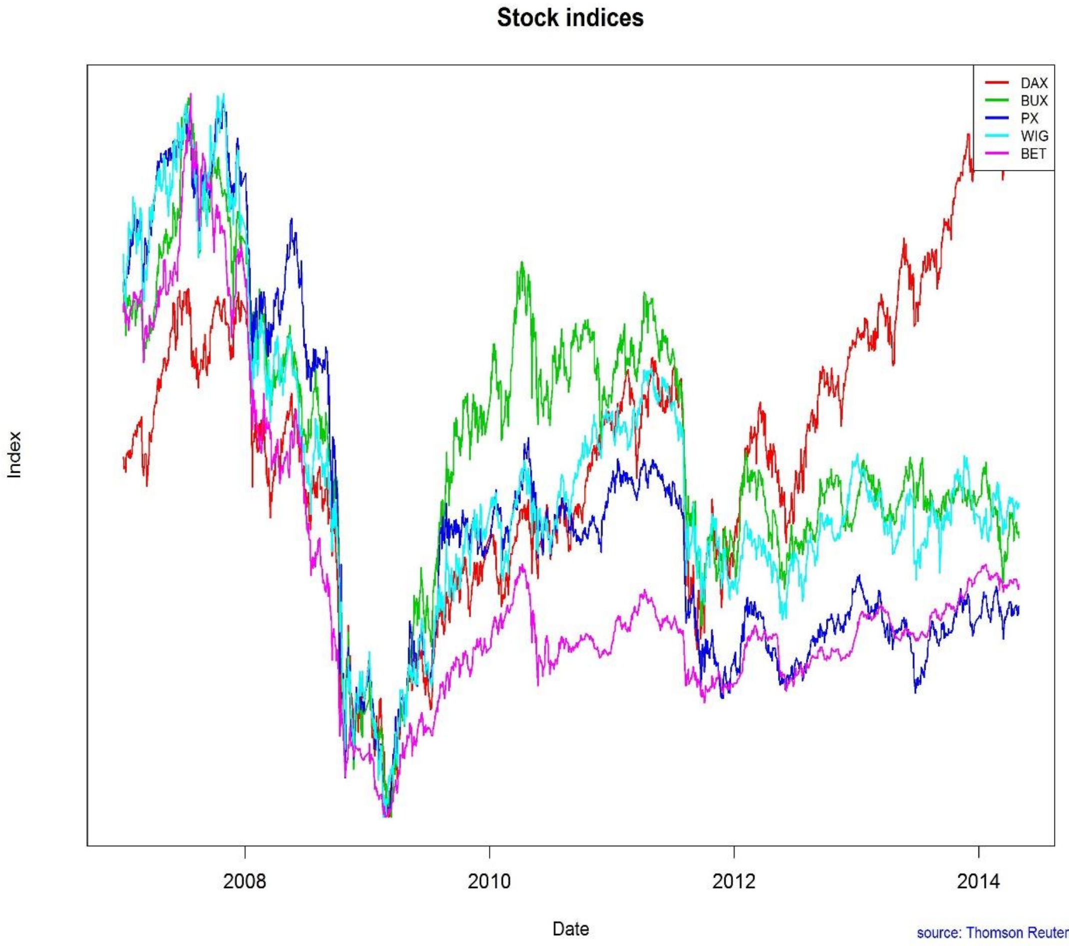
d) **Serial correlation** in the absolute or squared returns;

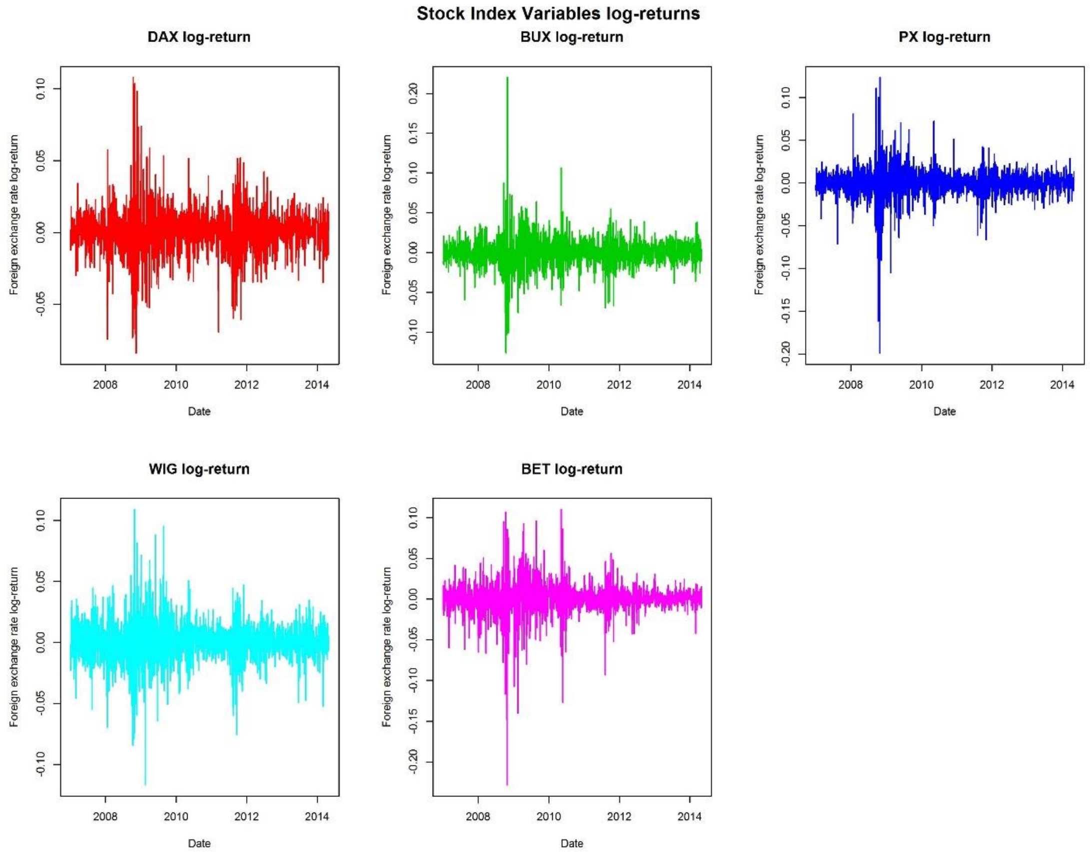
e) **Fat tails**: The distribution of financial market returns is leptokurtic;

f) **Asymmetry**: The empirical distribution of returns is negatively skewed; extreme negative returns are more likely to occur than extreme positive returns.

Applied Methods and Models

Exploratory analysis – Plots for equities

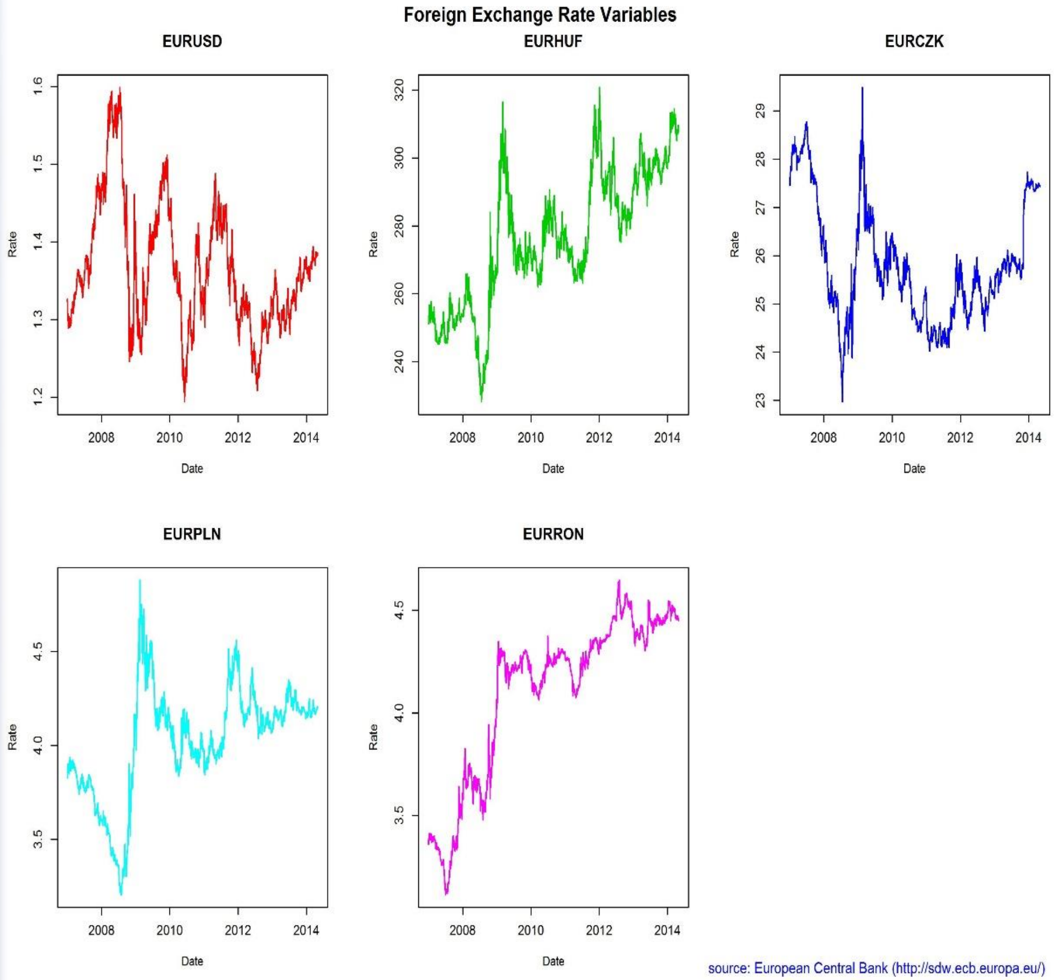


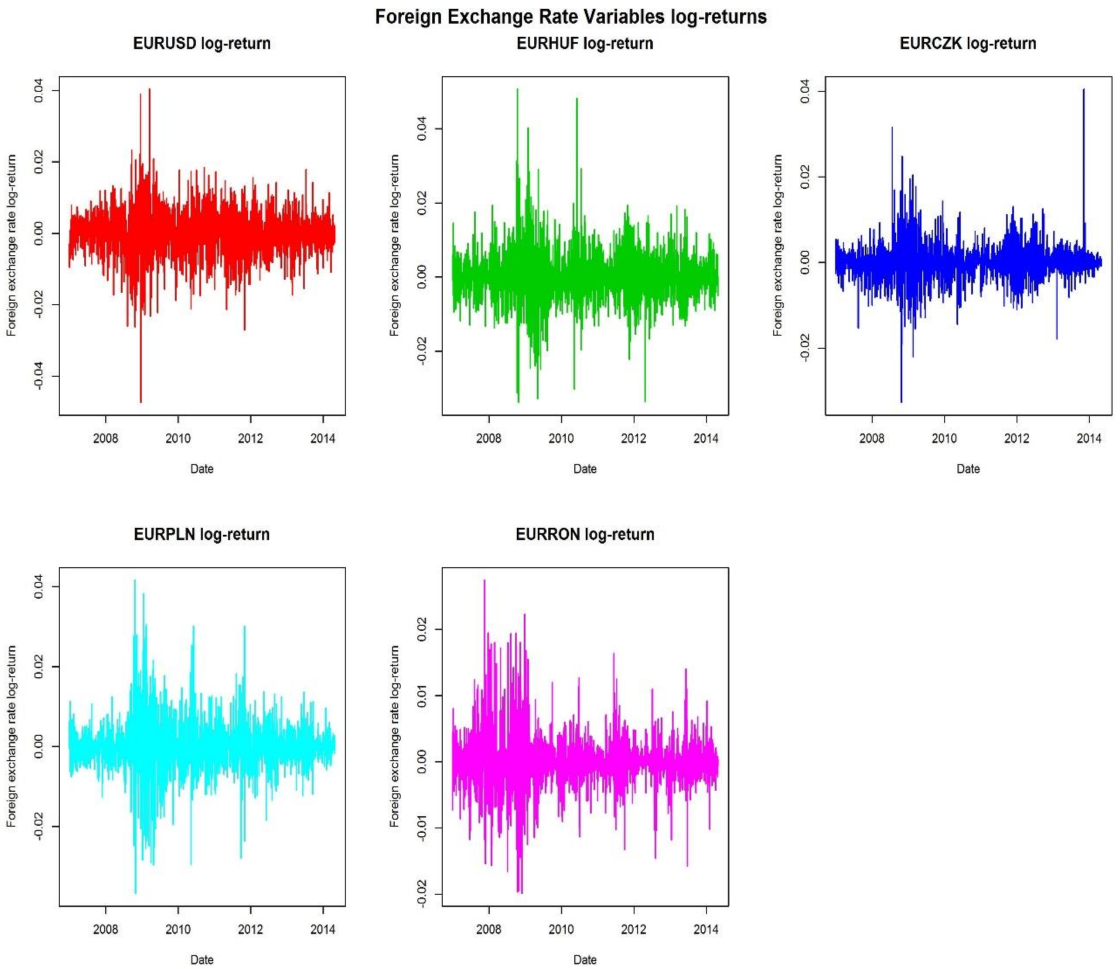


source: Thomson Reuters Eikon

Applied Methods and Models

Exploratory analysis – Plots for foreign exchange rates





source: European Central Bank (http://sdw.ecb.europa.eu/)

Applied Methods and Models

Exploratory analysis – Descriptive statistics and tests

	Mean	St. Dev.	Min	Max	Skewness	Kurtosis	Std. Err.	JarqueBera	JB.pV	ShapiroWilks	SW.pV	ARCH-LM(10)	ARCH.pV	LjungBox(20)	LB.pV
DAX	0.000208	0.0159	-0.084	0.108	0.03	6.09	0.00038	2693.874	0	0.924548	1.11E-28	358.0566	0	1372.5033	0
BUX	-0.0002	0.0186	-0.126	0.22	0.533	15.7	0.000446	17974.74	0	0.8988296	2.16E-32	329.7599	0	722.7396	0
PX	-0.00027	0.0176	-0.199	0.124	-1.158	19.84	0.000423	28970.91	0	0.8413307	1.52E-38	514.4578	0	1588.8698	0
WIG20	-0.00018	0.0172	-0.117	0.109	-0.134	5.08	0.000412	1878.626	0	0.9441866	4.06E-25	183.4598	0	668.839	0
BET-XT	-0.00035	0.0205	-0.228	0.11	-1.213	15.05	0.000492	16882.464	0	0.861545	1.27E-36	218.9502	0	630.5982	0
EUR/USD	2.28E-05	0.00657	-0.0474	0.0404	-0.199	3.69	0.000152	1078.184	0	0.9669422	2.56E-20	253.056	0	637.1652	0
EUR/HUF	0.000108	0.00709	-0.0339	0.0507	0.4	4.97	0.000164	1986.623	0	0.9511852	1.65E-24	212.2181	0	659.5499	0
EUR/CZK	-1.4E-06	0.00445	-0.0327	0.0405	0.556	9.22	0.000103	6759.774	0	0.9110588	8.74E-32	171.7161	0	509.3537	0
EUR/PLN	4.97E-05	0.00651	-0.0368	0.0416	0.309	6.01	0.00015	2856.102	0	0.9148905	3.23E-31	357.3236	0	1660.5968	0
EUR/RON	0.000146	0.00424	-0.0199	0.0274	0.514	5.09	0.000098	2117.618	0	0.9140746	2.44E-31	325.7041	0	1237.264	0

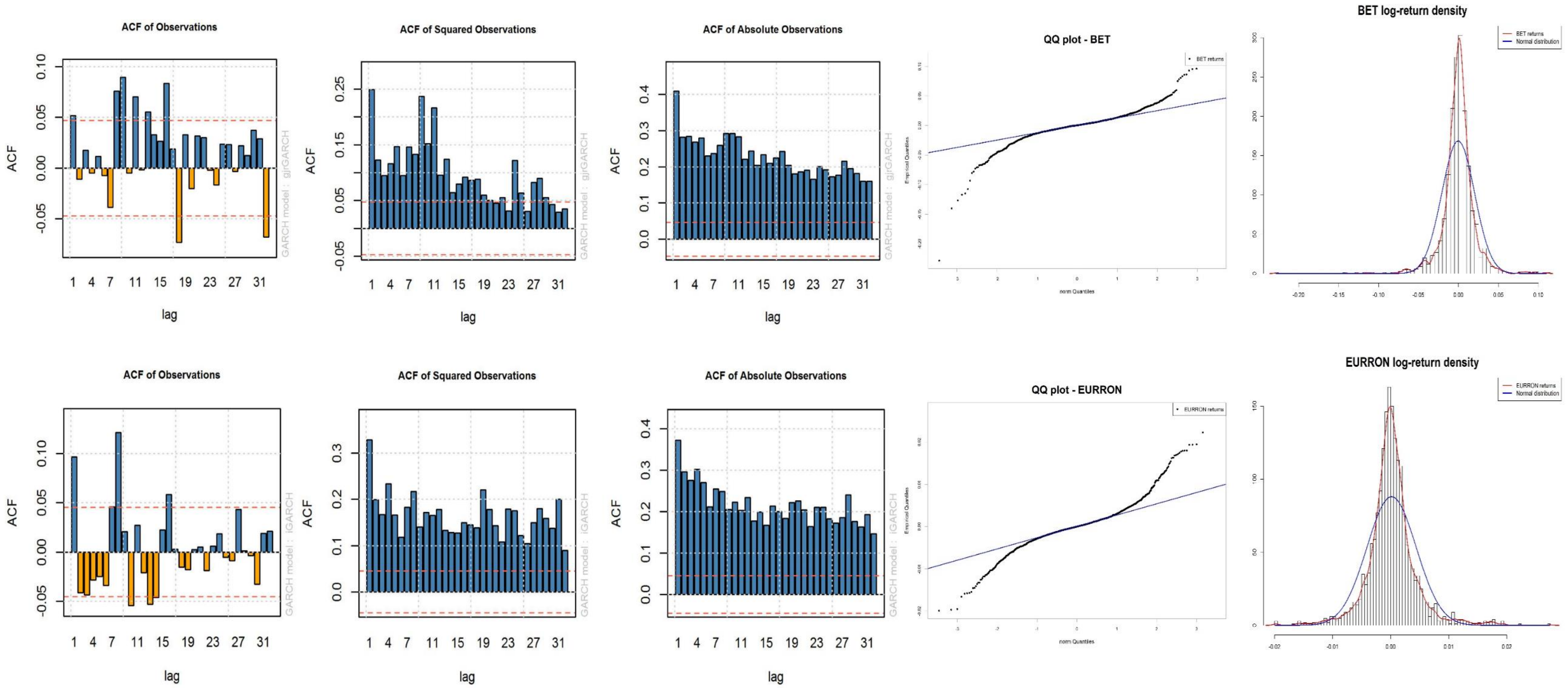
	DAX	BUX	PX	WIG20	BET-XT	EUR/USD	EUR/HUF	EUR/CZK	EUR/PLN	EUR/RON	1% critical value	5% critical value	10% critical value
ADF	-30.9689*	-31.6942*	-33.078*	-31.7544*	-29.1042*	-30.5205*	-31.598*	-29.7968*	-30.3941*	-30.6024*	-3.96	-3.41	-3.12
KPSS	0.046	0.0703	0.063	0.0653	0.1036	0.0482	0.0233	0.0335	0.0585	0.0438	0.216	0.146	0.119

All transformed variables (log-returns) exhibit the following:

- ❑ Skewness;
- ❑ High kurtosis;
- ❑ Non-normal distribution (JB & SW tests);
- ❑ ARCH effects (ARCH-LM test);
- ❑ Autocorrelation (LjungBox test);
- ❑ Stationarity (ADF & KPSS tests).

Applied Methods and Models

Exploratory analysis – Graphical diagnostics – BET-XT (equities) & EUR/RON (FX)



Applied Methods and Models

Exploratory analysis - Linear and rank correlation

	DAX	BUX	PX	WIG20
BET-XT (Pearson)	0.51	0.51	0.65	0.52
BET-XT (Kendall)	0.31	0.28	0.35	0.30
BET-XT (Spearman)	0.45	0.40	0.49	0.42
	EUR/USD	**EUR/HUF**	**EUR/CZK**	**EUR/PLN**
EUR/RON (Pearson)	-0.11	0.35	0.14	0.32
EUR/RON (Kendall)	-0.10	0.26	0.13	0.26
EUR/RON (Spearman)	-0.14	0.38	0.18	0.38

Pearson's $\rho_{X,Y} = \frac{Cov(X,Y)}{\sqrt{\sigma_X^2 \sigma_Y^2}}$

Kendall's $\tau_{X,Y} = \frac{2}{n(n-1)} \sum_{i<j} sign[(X_i - X_j)(Y_i - Y_j)]$

Spearman's $\rho_{X,Y} = \frac{12}{n(n^2-1)} \sum_{i=1}^{n} \left(rank(X_i) - \frac{n+1}{2}\right)\left(rank(Y_i) - \frac{n+1}{2}\right)$

- The objective of the research is to explain dependence between the variables in times of crisis;
- The simple **Pearson correlation coefficient is inadequate** for this task:
  - it is suited to describe dependence for multivariate normal distribution (or other elliptical distributions);
  - our variables are not normally distributed.
- **Concordance measures,** i.e. Kendall's τ, or Spearman's ρ (rank correlation coefficients) may apply better:
  - they capture non-linear relations between distributions;
- They provide monotone dependence, offering no information about the dependence structure and tail behaviour.
- Full dependence can be modeled with copulas

Applied Methods and Models

Modelling correlation with copula functions – The IFM method

- Following Sklar (1959), there exists a unique function C, such that for continuous random variables $X_1, \dots, X_n$ with distribution functions $F_1(x_1), \dots, F_n(x_n)$:

$$\Pr(X_1 \leq x_1, \dots, X_n \leq x_n) = C\big(F_1(x_1), \dots, F_n(x_n)\big)$$

Parametric estimation of copulae:
- Exact Maximum Likelihood (EML);
- Inference Functions for Margins (IFM);
- Canonical Maximum Likelihood (CML).

- Consequently, multivariate distributions can be decomposed into marginal distributions and a dependence function by which they are linked (a n-copula), uniquely determined for any $u \in [0,1]$ if the margins are continuous:

$$C(u_1, \dots, u_n) = H\left(F_1^{-1}(u_1), \dots, F_n^{-1}(u_n)\right)$$

- **The IFM estimation method**: Joe and Xu (1996) suggest, based on the form of the joint log-likelihood, a two-step estimation of the copula function:
  i. the **independent** estimation of the parameters of the marginal distribution and
  ii. estimation of the copula parameter conditionally on the margins' parameters.
- This is a more computationally efficient approach than joint estimation by maximum likelihood (ML).

$$log\big(h(x,\alpha,\theta)\big) = \sum_{t=1}^{T}\sum_{i=1}^{n} log\big(f_i(x_{it},\alpha_i)\big) + \sum_{t=1}^{T} log\left(c_\theta\big(F_1(x_{1t},\alpha_1), \dots, F_n(x_{nt},\alpha_n)\big)\right)$$

- The present analysis implements the IFM estimation method for bivariate copula functions.

Applied Methods and Models

Modelling volatility – ARMA-GARCH models

- **IFM method first step – parametric specification of the marginal distributions**

- ARMA-GARCH models are known to capture the observed stylized facts;

- Modelling the conditional mean – ARMA model: $x_t = \mu + \sum_{i=1}^{r} \phi_i x_{t-i} + \varepsilon_t + \sum_{j=1}^{m} \theta_j \varepsilon_{t-j}$

- Modelling the conditional variance – Three flavours of GARCH(p,q)
  - **Standard GARCH(p,q)** - symmetric: $\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$
  - **EGARCH(p,q)** - asymmetric: $\ln \sigma_t^2 = \omega + \sum_{j=1}^{q} \left(\alpha_j z_{t-j} + \boldsymbol{\gamma_j} \left(\left| z_{t-j} \right| - E \left| z_{t-j} \right| \right) \right) + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2$
  - **GJR(p,q)** - asymmetric: $\sigma_t^2 = \omega + \sum_{j=1}^{q} \left(\alpha_j \varepsilon_{t-j}^2 + \boldsymbol{\gamma_j} \boldsymbol{I_{t-j}} \varepsilon_{t-j}^2 \right) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$

Applied Methods and Models

Modelling volatility – ARMA-GARCH models – minimizing misspecification

- Conditional variance residual distributions: **Normal**, **t-Student**, **generalised error distribution (GED)** and their **skewed** alternatives;

- Model selection according to the **BIC**;

- Tests to check for misspecification:
  - Significance of parameters;
  - Ljung-Box test on standardised residuals;
  - ARCH-LM tests;
  - Nyblom stability test;
  - Sign bias test;
  - Pearson Goodness-of-Fit test;
  - Berkowitz test.

- The BIC favours parsimonious models; **no GARCH models were estimated to have orders higher than 2**. The search was limited to a maximum of 2 for the orders of the models;

- High persistence in the conditional variance suggested that **IGARCH(p,q)** could be viable.

Using the cdf of the selected model, the standardised residuals of the conditional variance model are transformed to **pseudo-variables** $u, v \sim U(0,1)$ to serve as inputs for the **second step of the IFM**.

Applied Methods and Models

Modelling dependence structure – Copula functions – 32 copula families

Copula Family	Function $C(u,v)$	Lower TDC λ_L	Upper TDC λ_U
Independence copula	uv	0	
Gaussian	$\phi_\rho(\phi^{-1}(u),\phi^{-1}(v))$ ϕ_ρ = std Gaussian cdf, ρ = Pearson corr coeff	0	
Clayton	$(u^{-\alpha}+v^{-\alpha}-1)^{-\frac{1}{\alpha}}$ $\alpha > 0$	$2^{-\frac{1}{\alpha}}$	0
Frank	$\frac{1}{\alpha}\ln\left(1+\frac{(e^{\alpha u}-1)(e^{\alpha v}-1)}{e^{\alpha}-1}\right)$ $\alpha \neq 0$	0	
Gumbel	$\exp\left(-((-\ln u)^{\alpha}+(-\ln v)^{\alpha})^{\frac{1}{\alpha}}\right)$ $\alpha > 1$	0	$2-2^{\frac{1}{\alpha}}$
t-Student	$t_{v,r}(t_v^{-1}(u),t_v^{-1}(v))$ $t_{v,r}$= t-Student cdf with parameter r and v degrees of freedom	$2t_{v+1}\left(-\sqrt{\frac{(v+1)(1-r)}{1+r}}\right)$	
Joe	$1-\left((1-u)^{\alpha}+(1-v)^{\alpha}-(1-u)^{\alpha}(1-v)^{\alpha}\right)^{1/\alpha}$ $\alpha \geq 1$	0	$2-2^{\frac{1}{\alpha}}$

Other copula types:

- Mixed families: BB1 (Clayton-Gumbel), BB6 (Joe-Gumbel), BB7 (Joe-Clayton), BB8 (Joe-Frank) – **asymmetric tail dependence**;
- Rotated Clayton/Gumbel/Joe/BB1/BB6/BB7/BB8 – 90 degrees / 180 degrees (survival) / 270 degrees

Initial copula selection according to **BIC**.

Applied Methods and Models

Copula functions – Testing for goodness-of-fit via parametric bootstrapping

- $H_0\colon C \in C_0 = \{C_\theta\colon \theta \epsilon \Theta\}$, i.e. the copula C linking the marginal distributions belongs to a chosen family of copulae C_0;
- Let $U_t = (U_{t1}, \ldots, U_{td})$, be pseudo-observations deduced from the ranks, with $U_{ij} = \frac{R_{ij}}{T+1}$ and rescaled by means of the "empirical copula", as $V_t = C_T(U_t)$ ("Kendall's transform")
- Compare the distance between the estimated parametric Kendall distribution and the "empirical Kendall distribution":

$$K_T(v) = \frac{1}{T}\sum_{i=1}^{T} \mathbf{1}(V_i \leq v)\,, v \in [0,1]$$

- The test statistic is based on the empirical process $\mathbb{K}_T = \sqrt{T}\left(K_T - K_{\hat{\theta}}\right)$ and it is based on the **Cramér-von-Mises statistic**:

$$S_T^{(K)} = \int_0^1 \mathbb{K}_T(v)^2 dK_{\hat{\theta}}(v)$$

- The **bootstrap procedure** introduced in Genest and Rivest (1993) and reviewed in Genest, Remillard and Beaudoin (2009)
  1. Compute K_T and estimate $\hat{\theta}$;
  2. Compute $S_T^{(K)}$;
  3. For a large B repeat the below procedure taking $b = 1, \ldots, B$:
     - Generate a random sample from the distribution $C_{\hat{\theta}}$;
     - Using the random sample compute $K_{T,b}^*(t)$ and estimate $\hat{\theta}^*$;
     - Compute $S_{T,b}^{(K)*} = \int_0^1 \left\{K_{T,b}^*(t) - K_{\hat{\theta}^*}(t)\right\}^2 dK_{\hat{\theta}^*}(t)$.
  4. Approximate *p-value* with $p = \frac{1}{B}\sum_{b=1}^{B} \mathbf{1}\left(S_{T,b}^{(K)*} > S_T^{(K)}\right)$
- Large values of the statistic imply the rejection of H_0. Hence, the best fitting copula is the one with the **lowest $\boldsymbol{S_T^{(K)}}$** and a ***p-value*** greater than the chosen level of significance **0.05**.

Applied Methods and Models

Modelling correlation with copula functions – Tail dependence

Lower TDC: $\lambda_L = \lim_{t \to 0^+} P\left(Y \leq F_Y^{-1}(t) \mid X \leq F_X^{-1}(t)\right)$

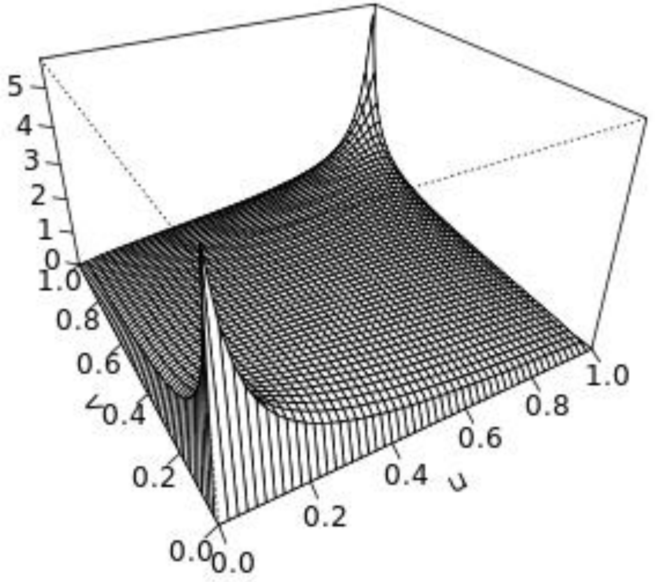
Upper TDC: $\lambda_U = \lim_{t \to 1^-} P\left(Y > F_Y^{-1}(t) \mid X > F_X^{-1}(t)\right)$

Example: **BB1 copula family (Clayton – Gumbel)**

Parameters: (0.32,1.2)

Kendall's τ: 0.28

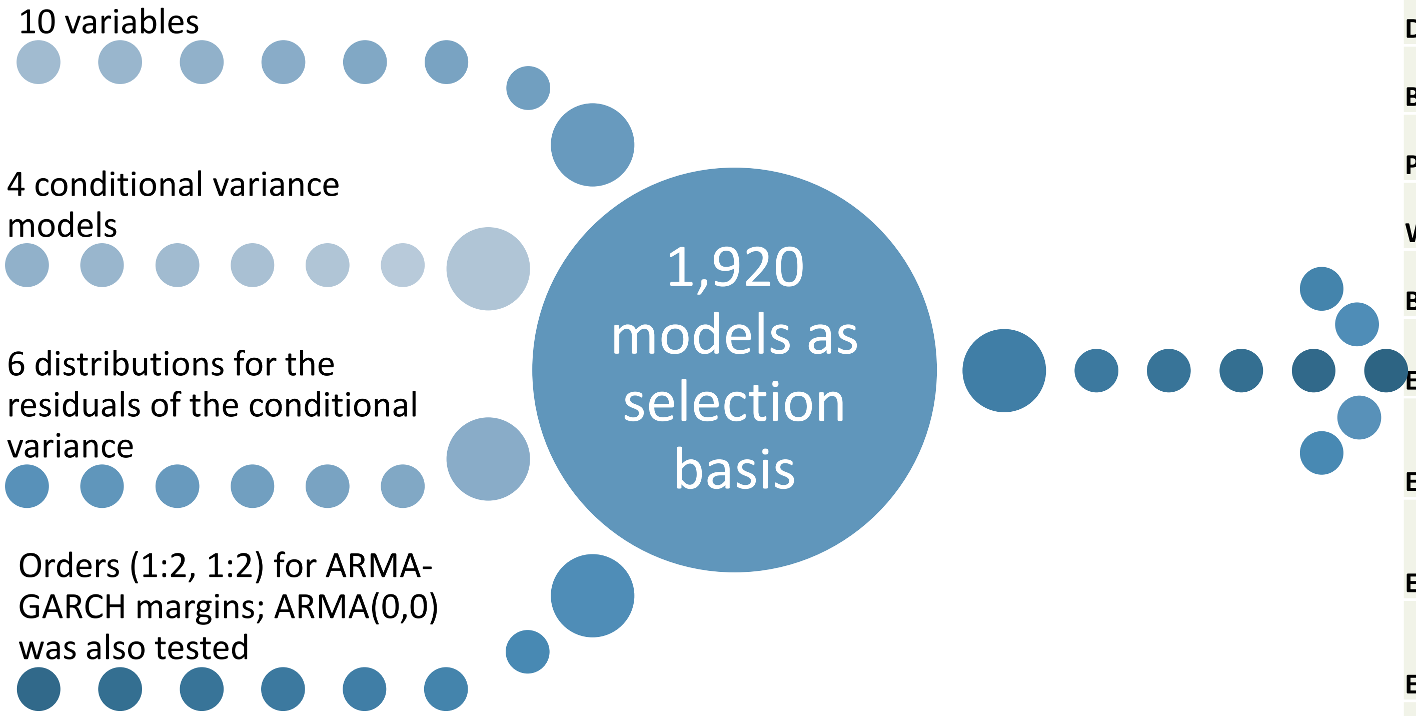
$\lambda_L = 0.16; \lambda_U = 0.22$



Results

Results

Conditional mean and conditional variance modelling - Summary



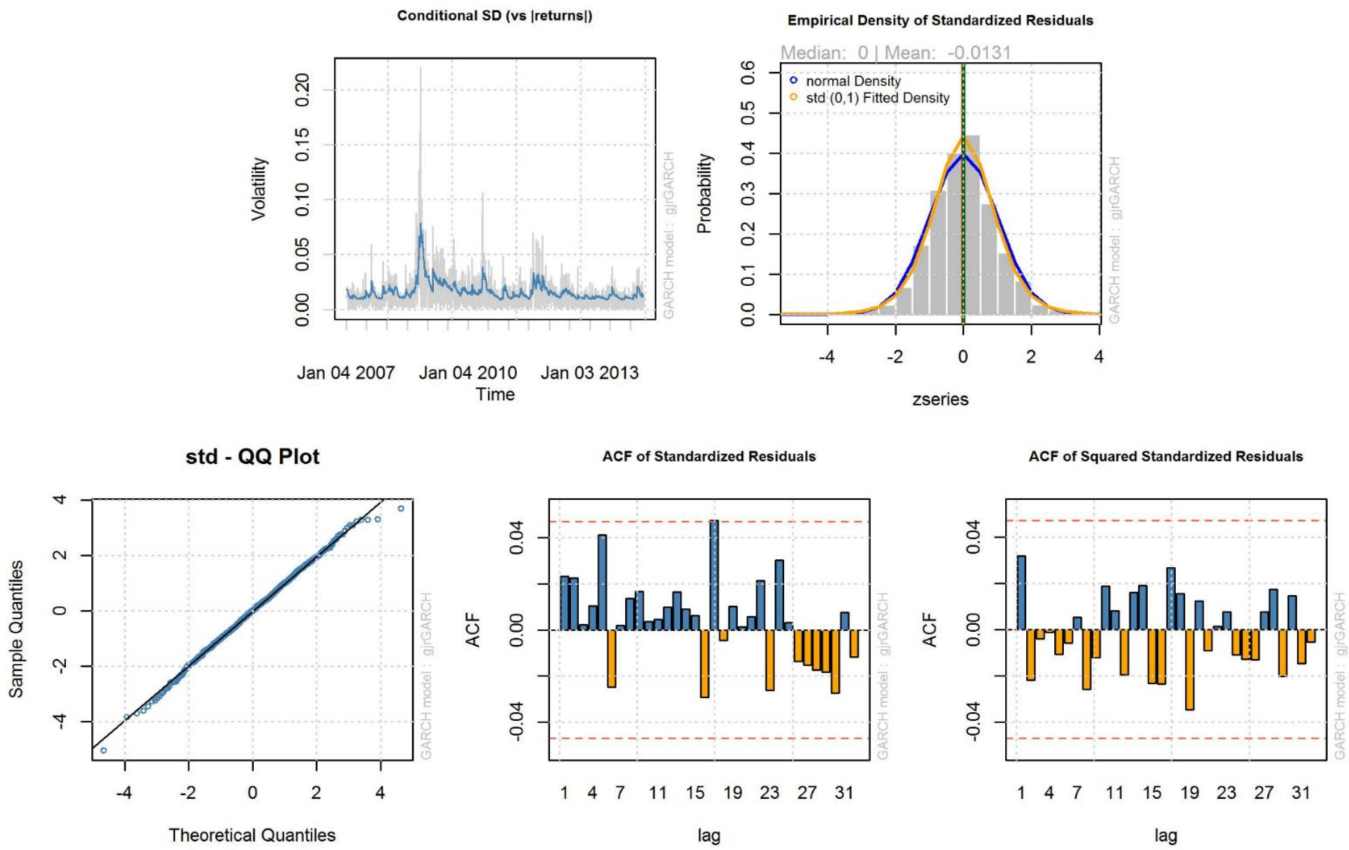
	Conditional Mean	Conditional Variance	Residual distribution
DAX	MA(2[2])	EGARCH(2,1)	Skewed t-Student
BUX	AR(2[2])	GJR(1,1)	t-Student
PX	ARMA(0,0)	IGARCH(1,1)	t-Student
WIG20	ARMA(0,0)	EGARCH(1,1)	t-Student
BET-XT	MA(1)	GJR(1,2)	t-Student
EUR/USD	ARMA(2[2],2[2])	IGARCH(1,1)	Skewed GED
EUR/HUF	ARMA(0,0)	GJR (1,1)	Skewed t-Student
EUR/CZK	AR(1)	EGARCH(1,1)	t-Student
EUR/PLN	ARMA(0,0)	IGARCH(1,1)	t-Student
EUR/RON	ARMA(2[2],2[2])	IGARCH(1,1)	t-Student

Results

Conditional mean and conditional variance modelling – Selection

The final selected models were required to (example for **BUX**):

- ❑ have coefficients as significant and as stable as possible;
- ❑ eliminate ARCH and leverage effects;
- ❑ eliminate most of the serial correlation in the standardised and squared standardised residuals
- ❑ model the distribution of the standardised residuals well.



Results

Conditional mean and conditional variance modelling - Observations

- Parsimonious models obtained: orders rarely exceeded 2; most models have only one descriptive lag for all of the ARMA and GARCH terms;
- None of the models with normal distributions (standard or skewed) passed the goodness-of-fit tests at 5% significance;
- All of the variables were best fitted by an asymmetric or integrated ‘flavour’ of GARCH - no variable was estimated as a standard GARCH;
- The Polish variables, WIG20 and EUR/PLN were selected as pure GARCH models, as well as the Czech PX index and EUR/HUF rate;
- Models are highly persistent; the IGARCH model was the best fit for 4 of the margin functions.

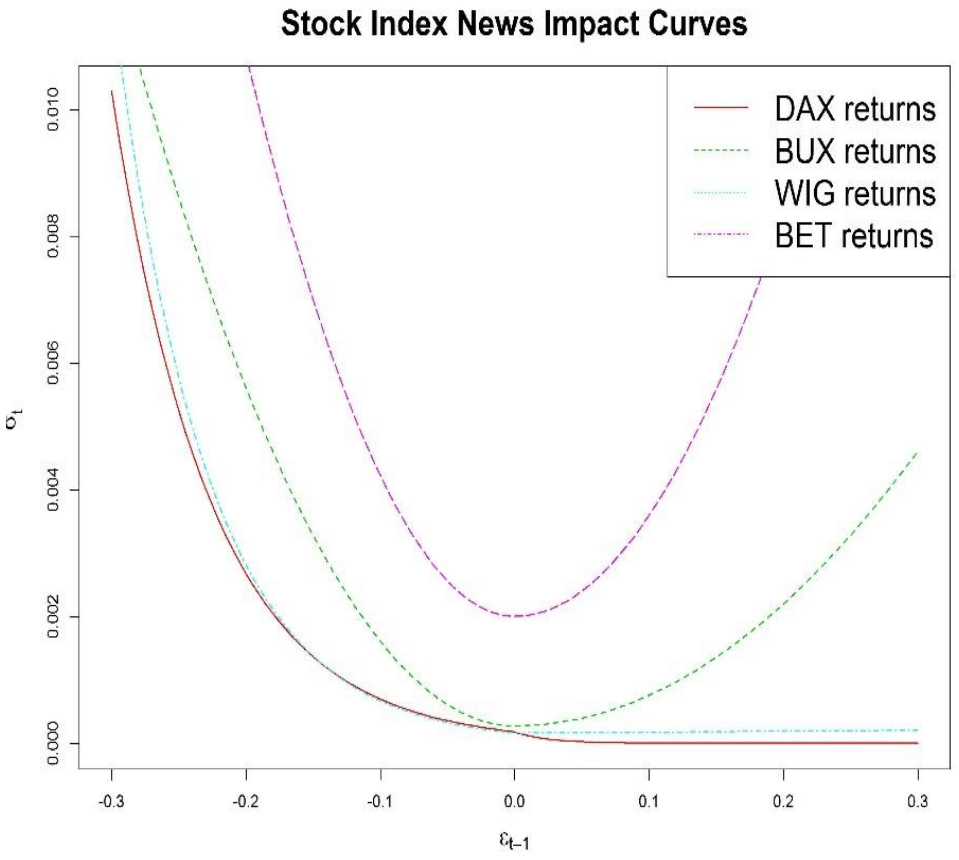
	Persistence	Half-life
DAX	0.979214	32.99918
BUX	0.983561	41.81743
PX	1	-Inf
WIG	0.989601	66.30895
BET	0.998998	691.7194
EURUSD	1	-Inf
EURHUF	0.987109	53.42299
EURCZK	0.99597	171.6505
EURPLN	1	-Inf
EURRON	1	-Inf

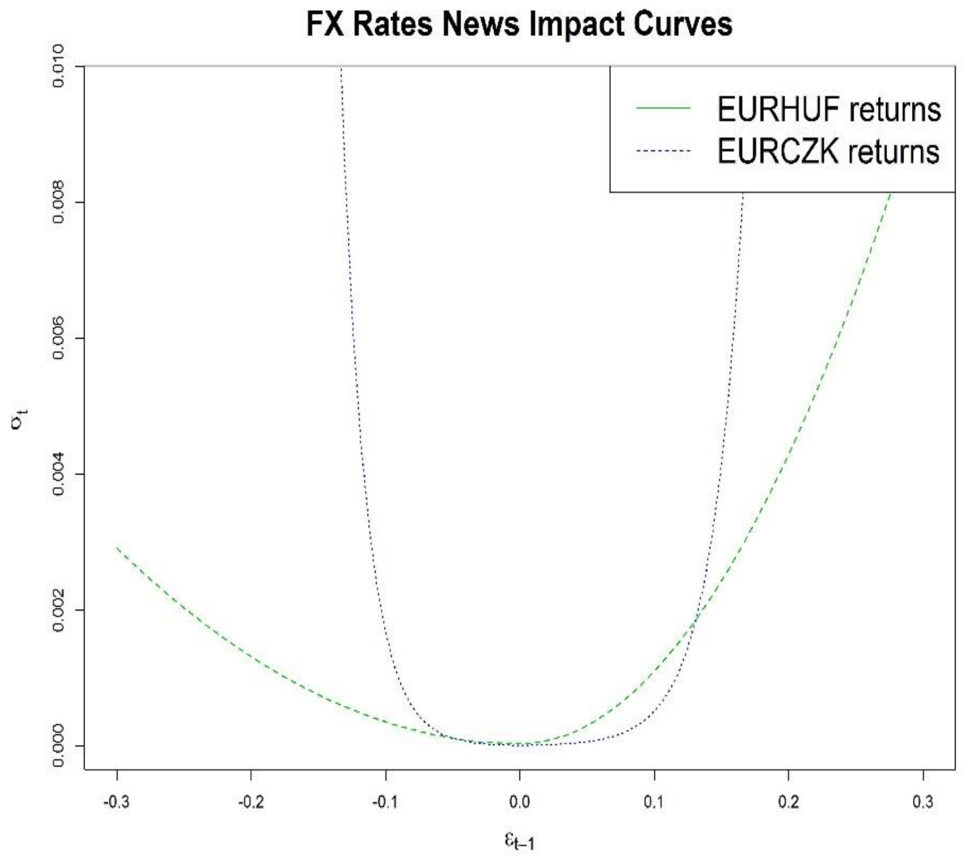
Coefficient	DAX	BUX	PX	WIG20	BET-XT	EUR/USD	EUR/HUF	EUR/CZK	EUR/PLN	EUR/RON
μ	0.00034	0	0	0	0.000409	0	0	-3.589E-06	0	0
ϕ_1		0				0		0.07289924		0
ϕ_2		-0.05558				0.883126				-0.8305
θ_1	0				0.0563692	0				0
θ_2	-0.04378					-0.86983				0.782383
ω	-0.18175	4.98E-06	3.9E-06	-0.09009	5.228E-06	0	0	-0.047018	1.84E-07	2.89E-07
α_1	-0.34156	0.048186	0.136956	-0.08878	0.1593976	0.035199	0.106555	-0.017288	0.088458	0.182141
α_2	0.216913									
β_1	0.979214	0.892798	0.863044	0.989601	0.3829586	0.964801	0.919242	0.99597	0.911542	0.817859
β_2					0.4254988					
γ_1	-0.17164	0.085155		0.099669	0.0622869		-0.074601	0.1399899		
γ_2	0.311									
skew	0.875818					0.913845	1.110441			
shape	6.418464	8.57325	6.166121	8.39419	4.880484	1.483294	8.282833	4.865494	6.725946	4.471322

Results

Conditional mean and conditional variance modelling - Observations

- The News Impact Curves reveal the leverage effects (except EUR/HUF);
- IGARCH models do not have a News Impact Curve.





Results

Selecting the copula function **based on the BIC**

Tested pair		Copula function	λ_L	λ_U
BET-XT	DAX	Gaussian copula (0.453)	0	0
BET-XT	BUX	BB1 copula (0.198, 1.235)	0.0588124	0.2475121
BET-XT	PX	Student t-copula (0.5076, 11.05)	0.07051488	0.07051488
BET-XT	WIG20	Survival BB1 copula (0.252, 1.233)	0.2453416	0.03354712
EUR/RON	EUR/USD	Rotated BB8 copula (270 degrees) (-1.29 , -0.939)	0	0
EUR/RON	EUR/HUF	Gaussian copula (0.397 , 0)	0	0
EUR/RON	EUR/CZK	Frank copula (1.064, 0)	0	0
EUR/RON	EUR/PLN	Gaussian copula (0.390 , 0)	0	0

- Opposite tail dependence of BET-XT with BUX and WIG20 does not seem an economically-sound conclusion;
- No tail dependence between EUR/RON and the other FX rates;
- Further investigation is required.

Results

Goodness-of-fit testing via the parametric bootstrap

The parametric bootstrap brief
8 copula functions to be checked
32 copula models were assessed
B = 300 random sampling iterations
76,800 trials were accomplished

The parametric bootstrap goodness-of fit test revealed **four copula functions** that were poorly selected by the BIC (red): the dependence structure is different with regard to DAX, WIG20, EUR/CZK and EUR/PLN. Selected copulae in bold.

		Gaussian copula	**Student t-copula**	**Frank copula**	**Joe copula**	**BB1 copula**	**BB7 copula**	**BB8 copula**	**survival Joe copula**	**survival BB1 copula**	**survival BB7 copula**	**rotated BB8 copula (270 degrees)**
BET-XT	**DAX**	**0.453 (0.057)**	0.454; 25.952 (0.177)									
BET-XT	**BUX**	0.413 (0.059)	0.408; 10.385 (0.04621)			**0.198; 1.235 (0.034)**	1.3; 0.345 (0.078)			0.293; 1.183 (0.0513)	1.2258; 0.4309 (0.0823)	
BET-XT	**PX**	0.509 (0.0999)	**0.5076; 11.051 (0.0579)**			0.322; 1.284 (0.066)				0.278; 1.308 (0.0933)		
BET-XT	**WIG20**	0.4333 (0.1161)	0.428; 8.0408 (0.1456)			**0.2583; 1.2274 (0.02944)**	1.291; 0.4123 (0.06428)			0.2517; 1.2328 (0.0679)	1.2924; 0.4153 (0.0821)	
EUR/RON	**EUR/USD**	-0.1417 (0.1786)	-0.149; 13.1285 (0.0896)	-0.9307 (0.0535)								**-1.2891; -0.9389 (0.0388)**
EUR/RON	**EUR/HUF**	0.397 (0.1863)	**0.399; 16.99 (0.1457)**									
EUR/RON	**EUR/CZK**	**0.1632 (0.0414)**	0.1715; 14.1876 (0.0643)	1.0638 (0.0458)	1.1205 (2.6816)	0.0813; 1.0719 (0.0932)	1.0796; 0.1255 (0.1413)	3.0208; 0.3816 (0.0552)	1.1186 (2.4775)	0.0929; 1.0656 (0.0769)	1.0709; 0.1342 (0.116)	
EUR/RON	**EUR/PLN**	0.39 (0.1012)	0.3923; 30 (0.16996)	2.559 (0.0892)				**5.872; 0.3872 (0.0876)**				

Results

Contagion and dependence explained: tail dependence coefficients

	DAX		BUX		PX		WIG20	
BET-XT	0	0	0.0588	0.247512	0.07051	0.070515	0.112373	0.241055
	EUR/USD		EUR/HUF		EUR/CZK		EUR/PLN	
EUR/RON	0	0	0.01244	0.01244	0	0	0	0

- **Asymmetric dependence** of the BET-XT index with **BUX** and **WIG20**: positive shocks “spill over” into the Romanian stock market with a greater probability than negative shocks – **approx. 24%**;
- **Symmetric**, relative weak dependence of the BET-XT on the Czech **PX** index, with a **7%** chance of positive or negative shocks influencing the Romanian market, as well;
  - Foreign investment funds (e.g. Franklin Templeton, East Capital) and foreign brokers acting on the stock market (e.g. KBC Securities NV, Wood & Co. Prague (>50% BVB)) could be the carriers of such spill-overs.
- On the FX market, there seems to not be any tail dependence with any other currencies, except a **low, 1.24% dependence with the Hungarian Forint**; could be due to the National Bank of Romania’s watchful position over the exchange rate and interventions in the market.

Results

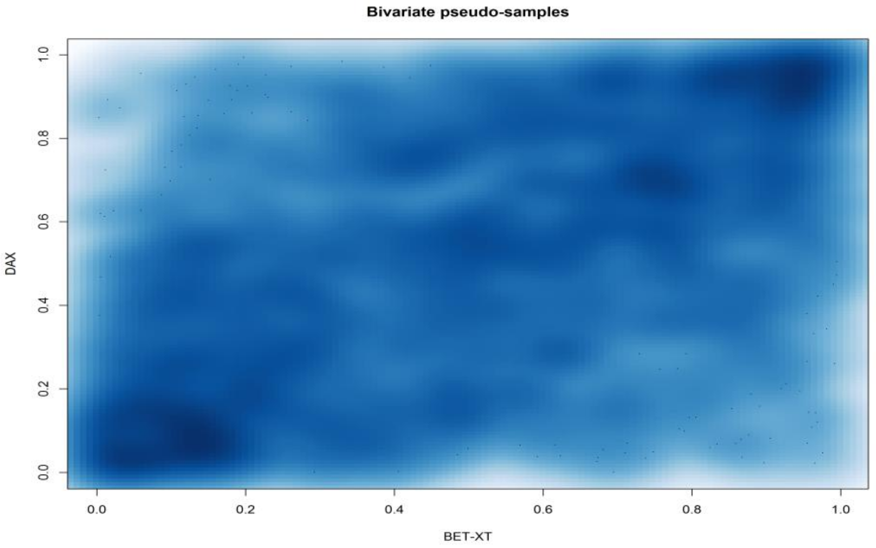
Contagion and dependence at CEE level: copulae & TDCs

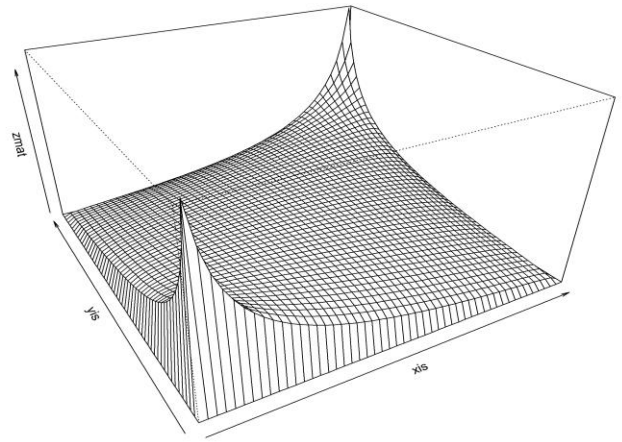
	EUR/HUF		EUR/CZK		EUR/PLN		EUR/USD
EUR/HUF	-		Survival BB1 copula (0.21 , 1.162)		Student t-copula (0.65 , 10.7)		Student t-copula (-0.35 , 8.07)
EUR/CZK	0.18	0.022	-		Survival BB1 copula (0.202 , 1.185)		Rotated BB1 copula (90 degrees) (-0.16,-1.04)
EUR/PLN	0.1414	0.1414	0.2053	0.0171	-		Frank copula (-2.228)
EUR/USD	0.0018	0.0018	0	0	0	0	-

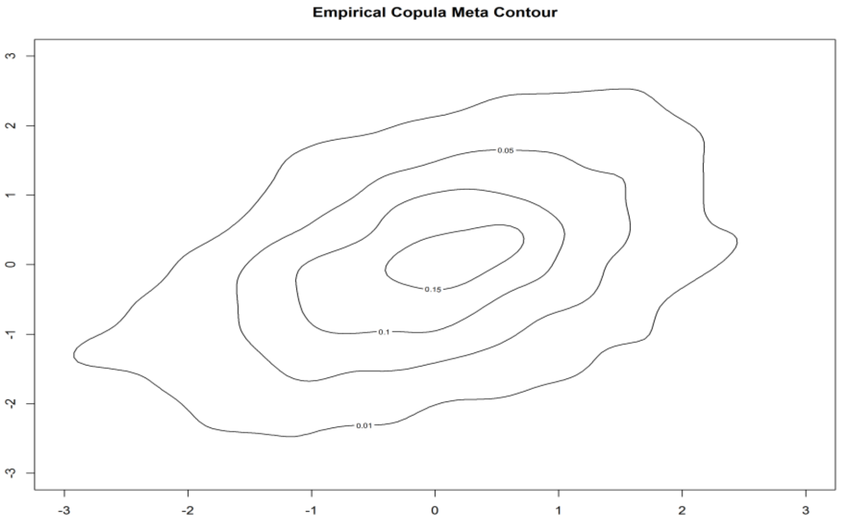
- **Important tail dependence** between the Hungarian, Czech and Polish currencies:
  - **Asymmetric tail dependence** of the CZK with both HUF and PLN: the exchange rates crash together with a probability of **20%**, while upper tail dependence is rather weak, approximately 2%.
  - EUR/HUF-EUR/PLN: extreme volatility in one will spill over to the other with a symmetric probability of **14%**.
- **Tail independence** with regard to the EUR/USD exchange rate seems unanimous;
- The evidence from these estimations support the conclusion that the managed floating exchange rate regime of Romania determines the EUR/RON's imperviousness to shocks from abroad: the Romanian leu does not incorporate these foreign influences into its exchange rate volatility.

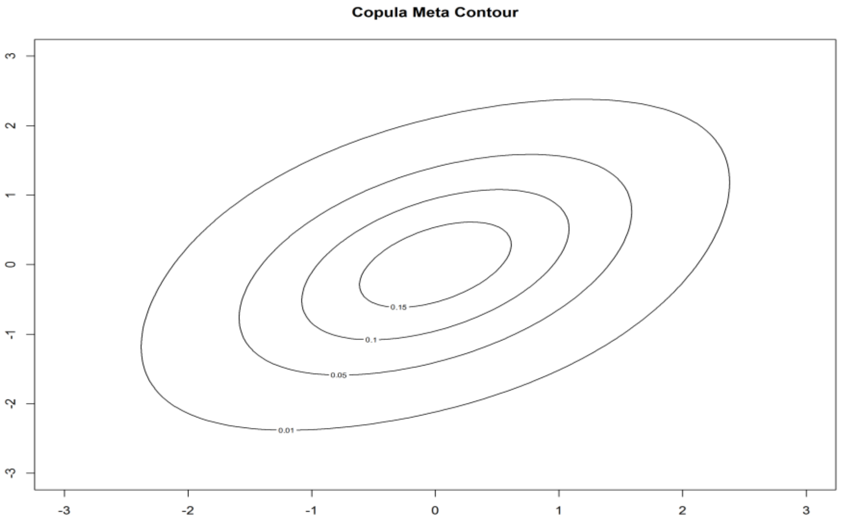
Results

Dependence and contagion in perspective – BET-XT & DAX Gaussian copula



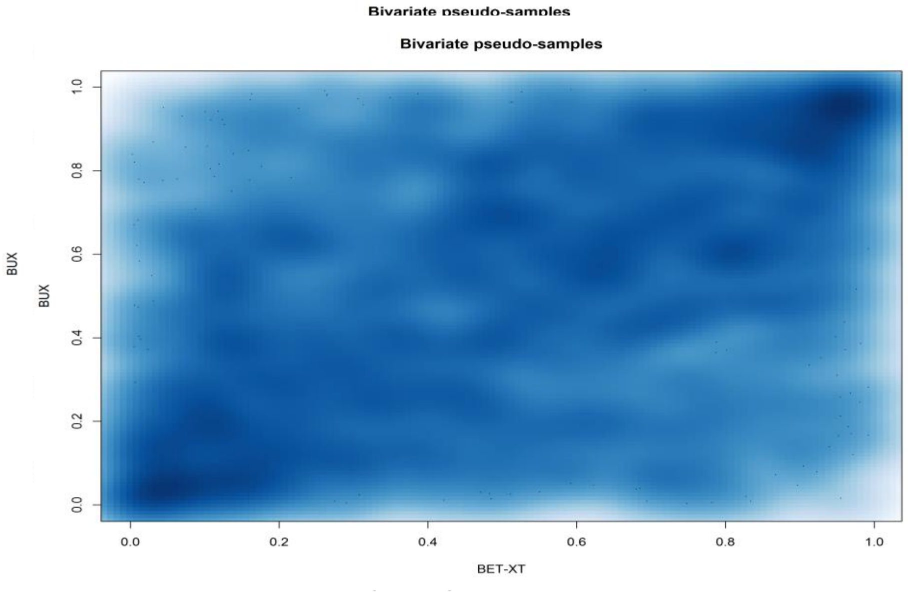


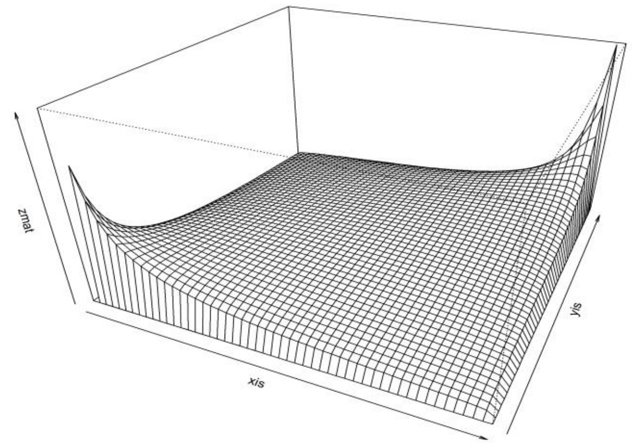


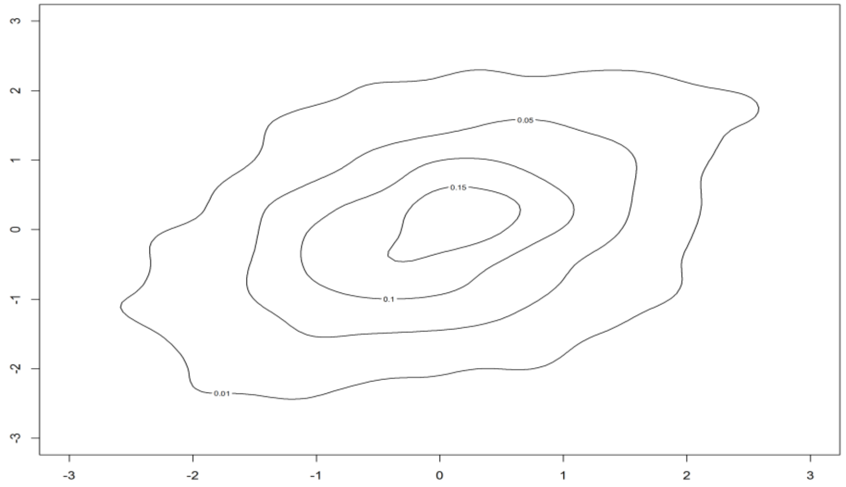


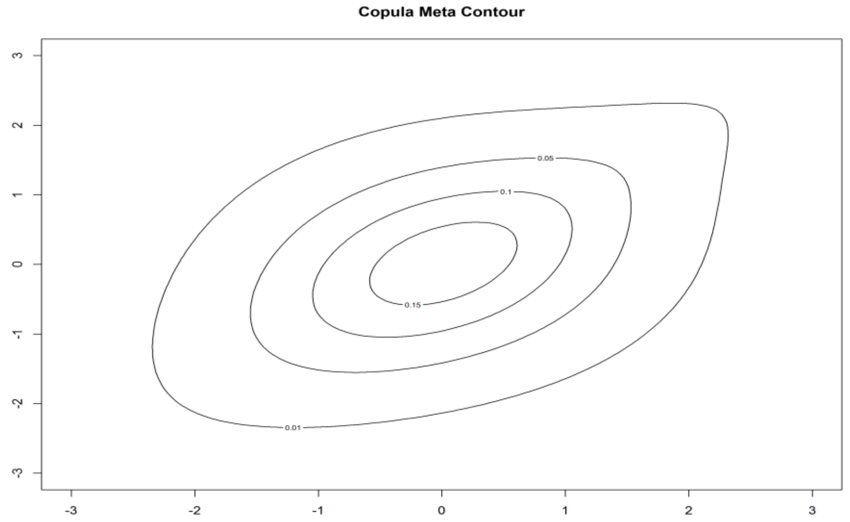
Results

Dependence and contagion in perspective – BET-XT & BUX BB1 copula



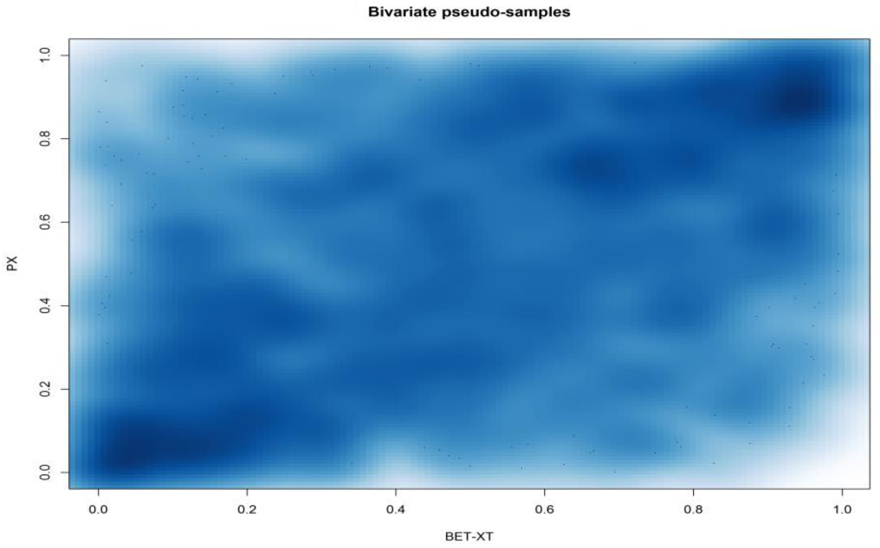


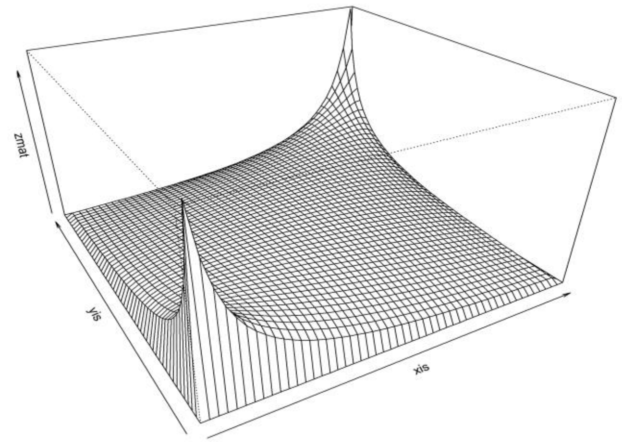


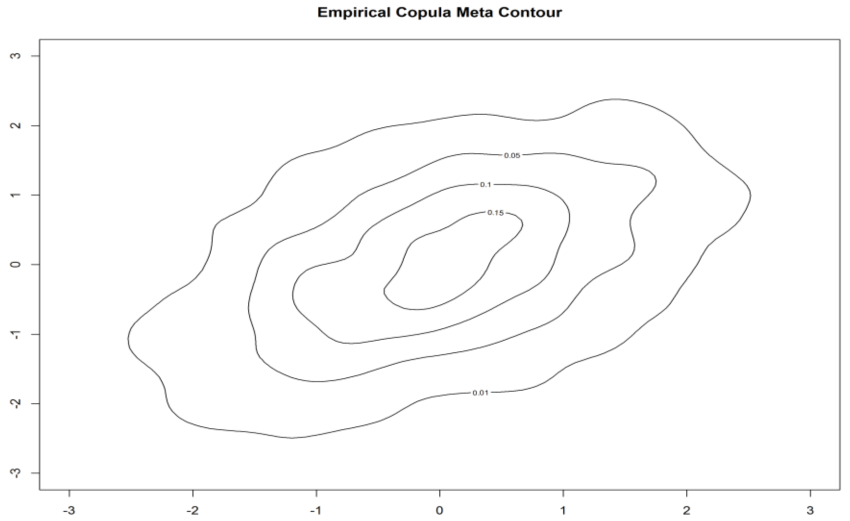


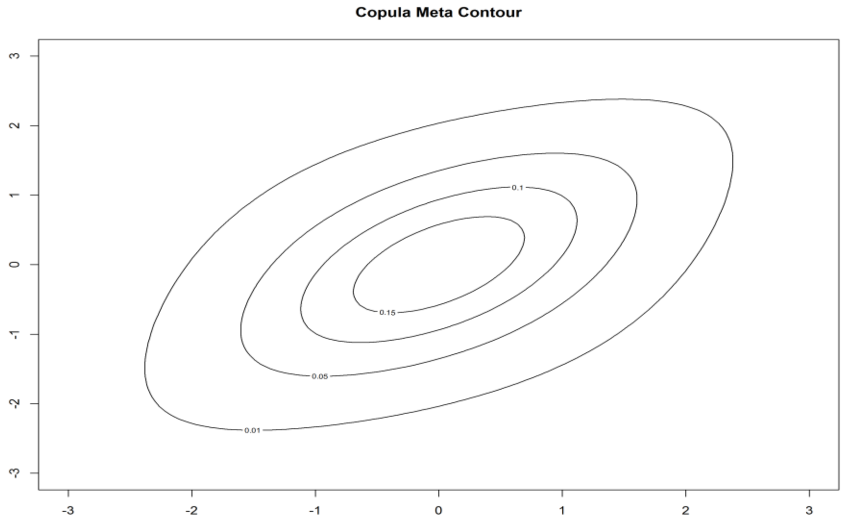
Results

Dependence and contagion in perspective – BET-XT & PX t-Student copula



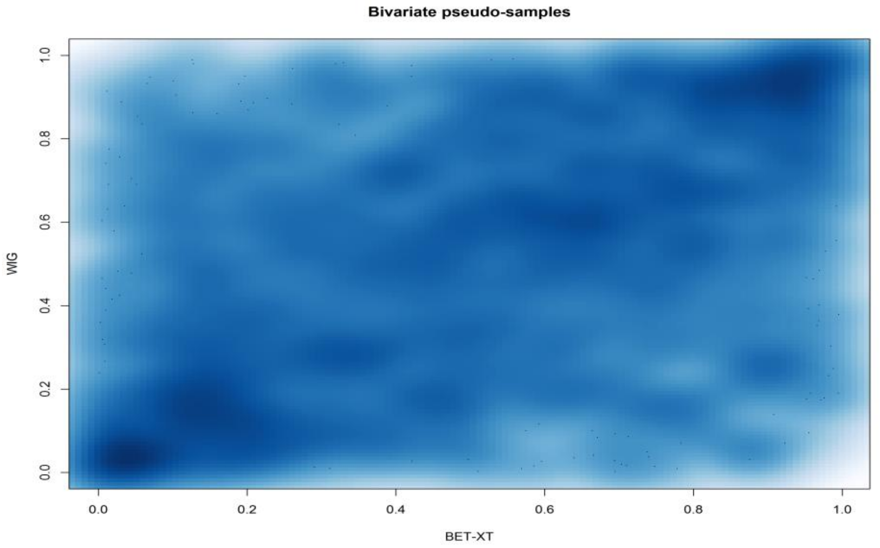


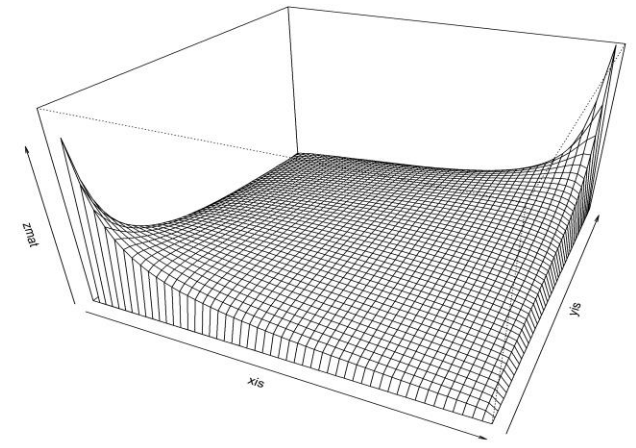


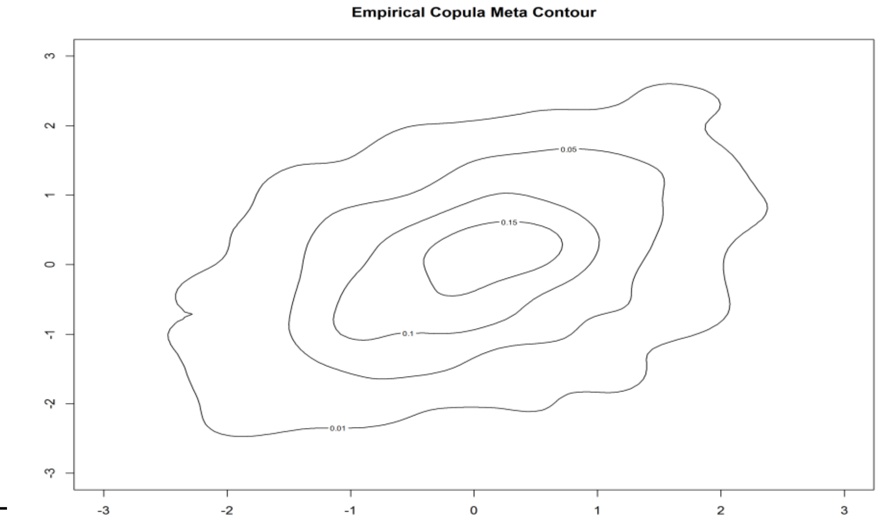


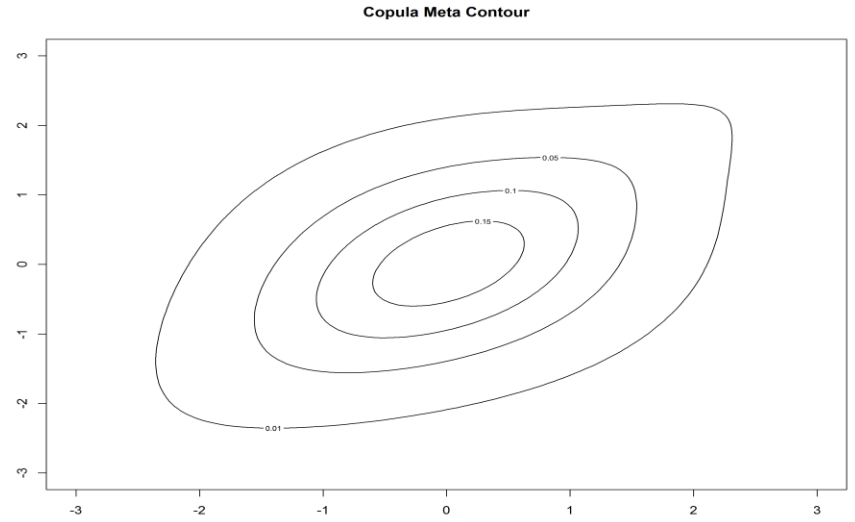
Results

Dependence and contagion in perspective – BET-XT & WIG BB1 copula



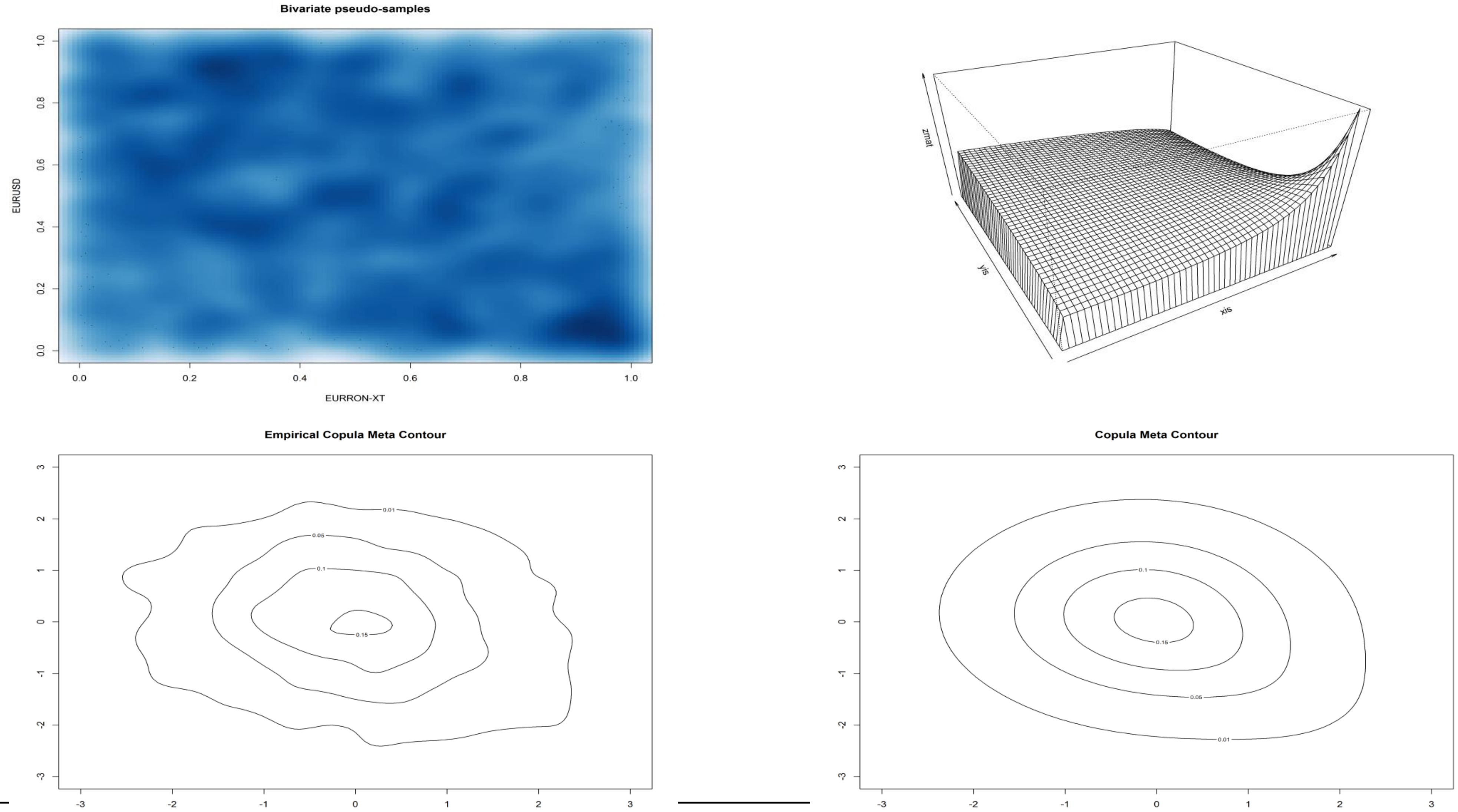






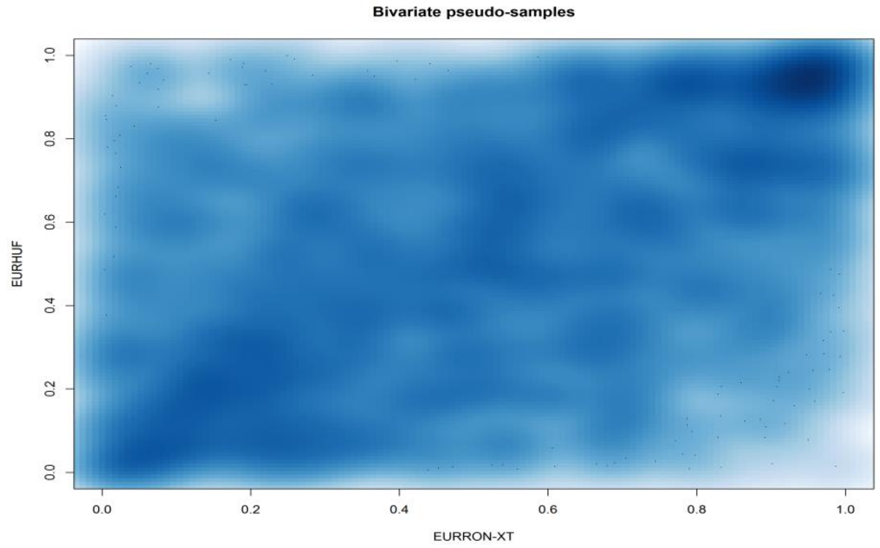
Results

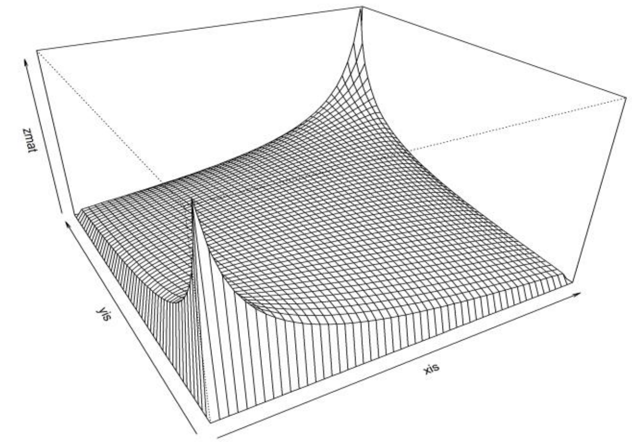
Dependence and contagion in perspective – EUR/RON & EUR/USD rotated 270⁰ BB8 copula

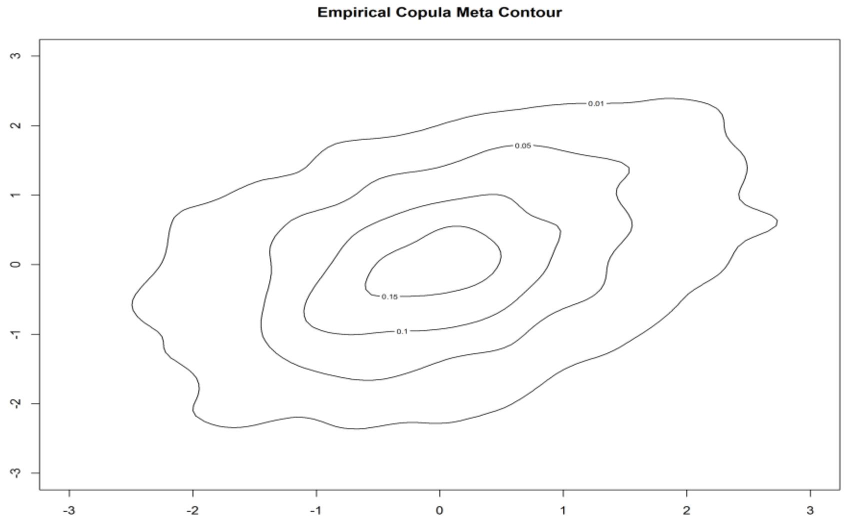


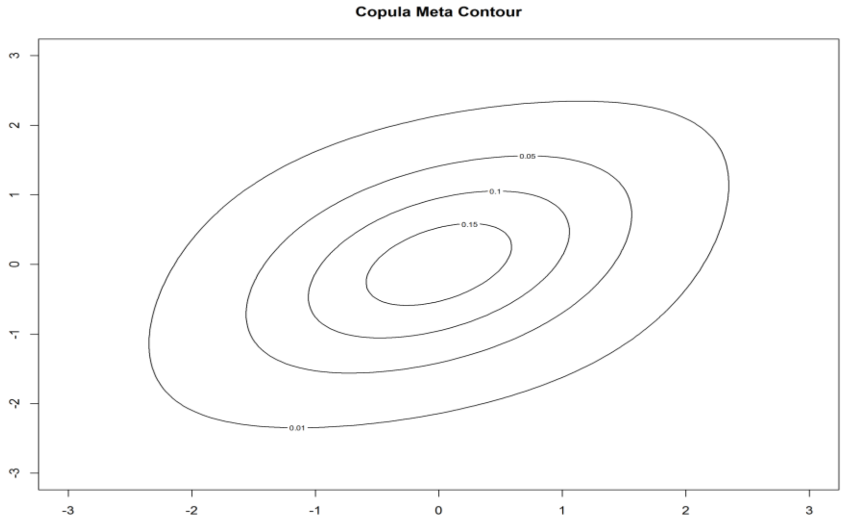
Results

Dependence and contagion in perspective – EUR/RON & EUR/HUF t-Student copula



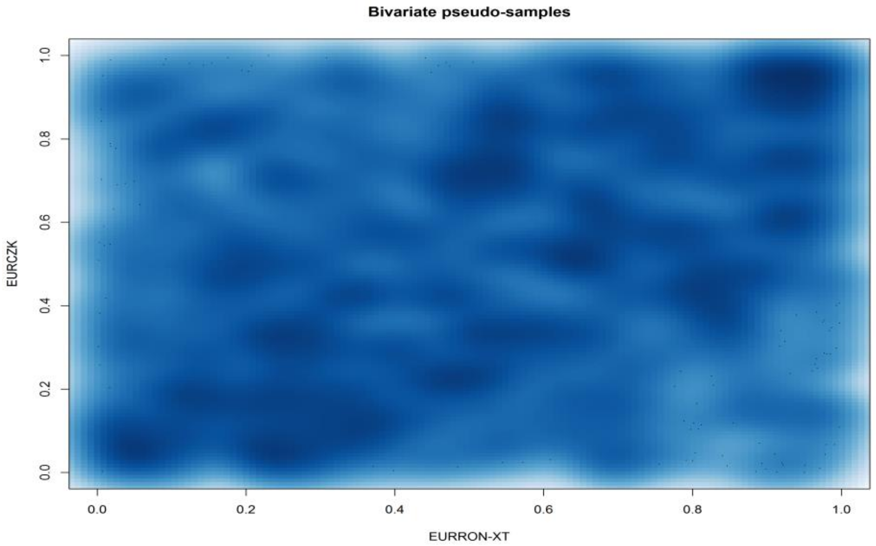


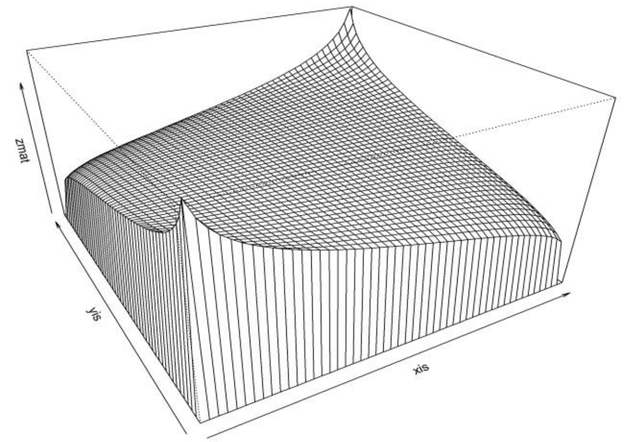


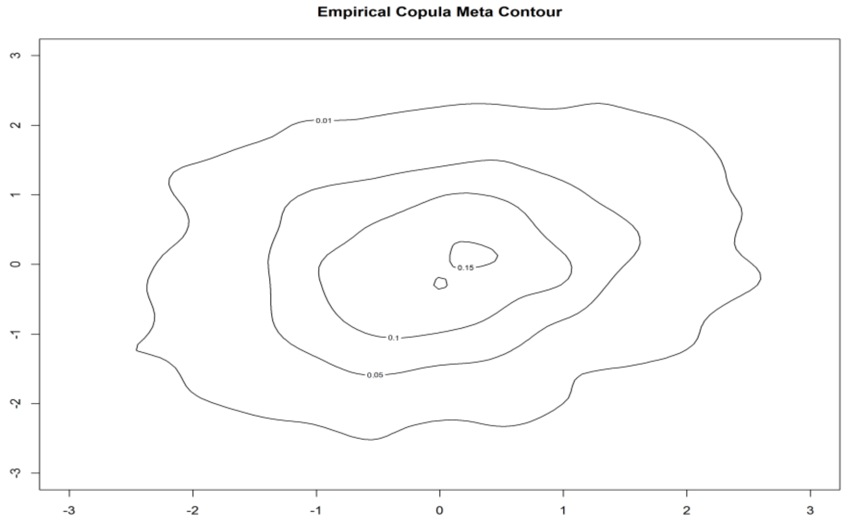


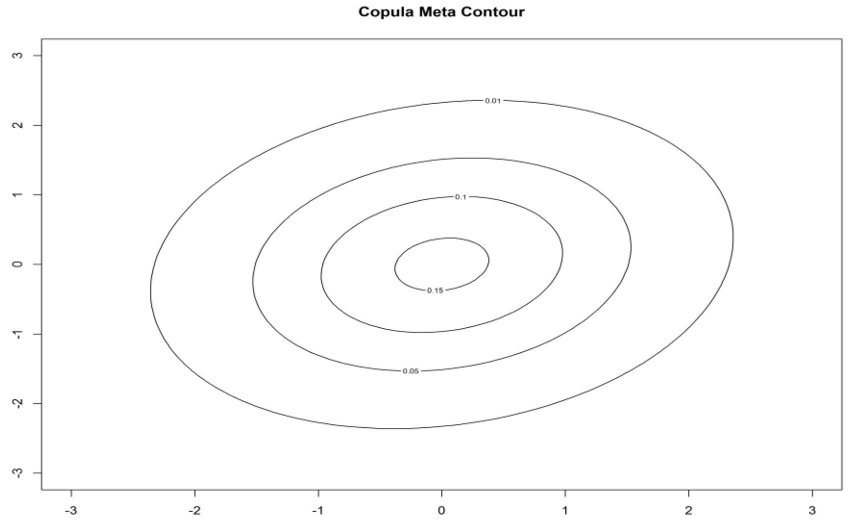
Results

Dependence and contagion in perspective – EUR/RON & EUR/CZK Gaussian copula



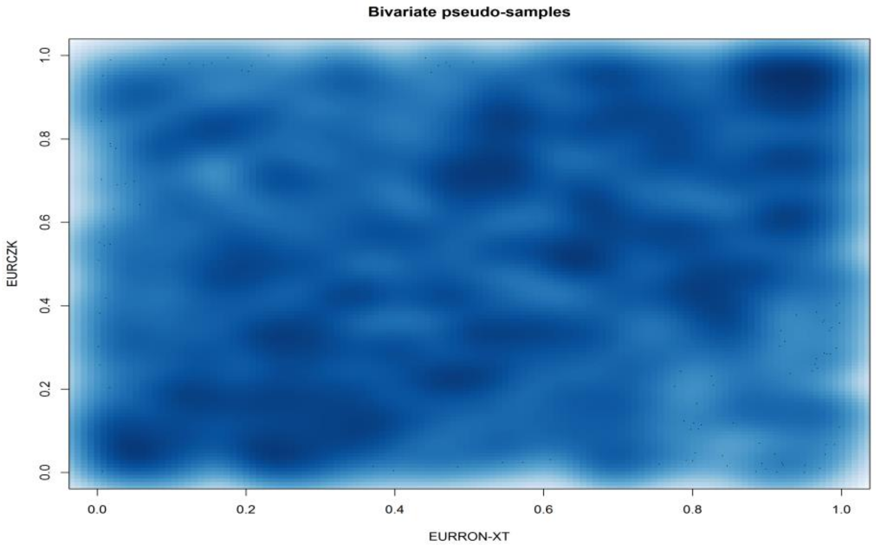


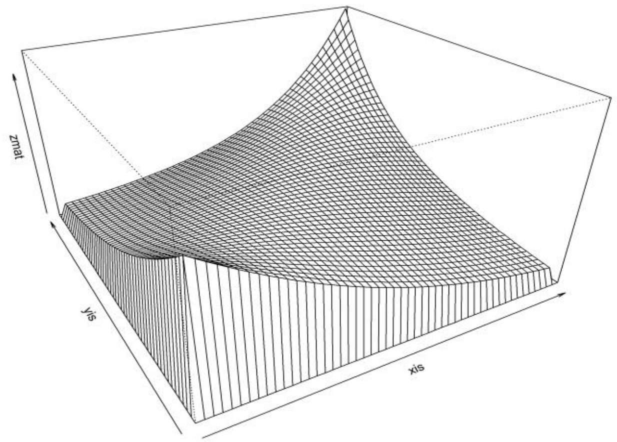


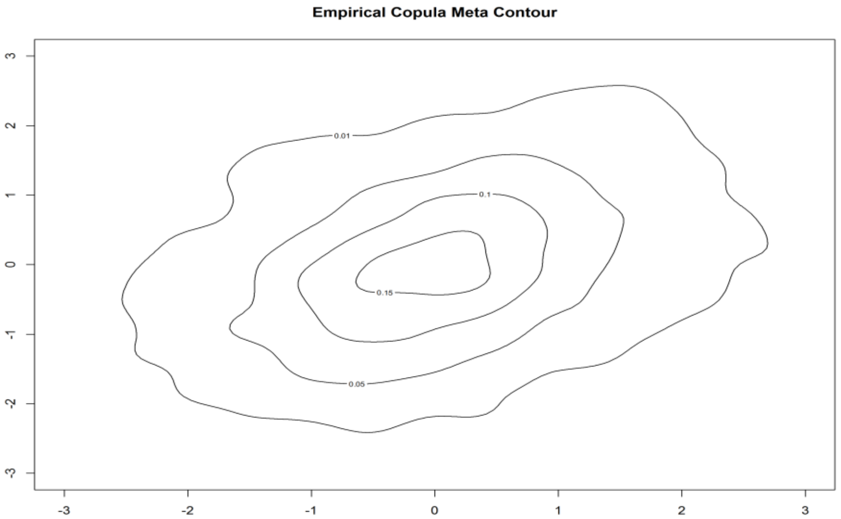


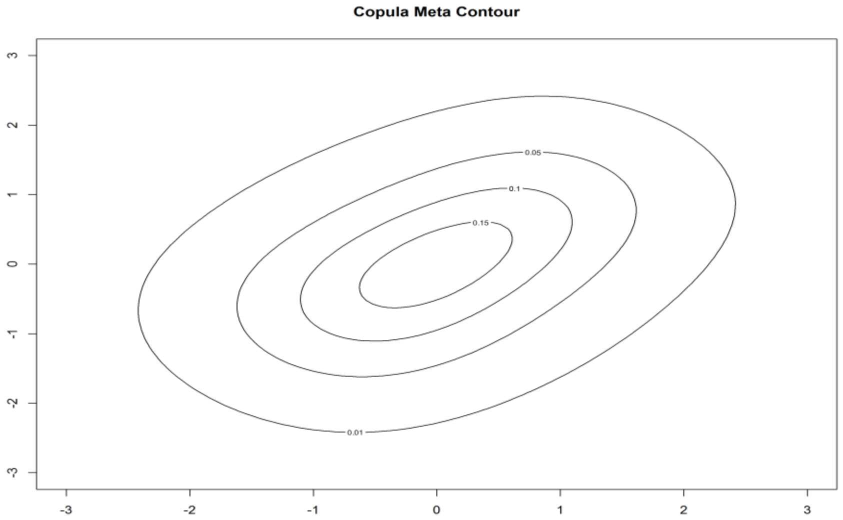
Results

Dependence and contagion in perspective – EUR/RON & EUR/PLN BB8 copula









Conclusions

Concluding remarks

- By analysing daily data from 2007 to 2014, the present research has undertaken an explanatory analysis of the dependence and contagion between equity prices and foreign exchange rates. The study emphasized the **importance of goodness-of-fit and good model selection techniques** for both margins and copulae, with the aim of comparing the evolution in crisis situations of return volatility in Romania and other four countries which are either large trade partners, or similar markets, or both.
- **Minor evidence of exchange rate contagion** of the EUR/RON with regard to other countries. This supports the appropriate management of the exchange rate's volatility by the National Bank of Romania, since significant extremal behaviour is discovered in the relationships between the other currencies' exchange rates;
- While there is no contagion risk on the equity market from Germany, on the other hand, Hungary, the Czech Republic and Poland were discovered to have significant tail correlations – both asymmetric and symmetric – with the Romanian stock market. There is a **24% chance with both Hungary and Poland of positive shocks** spilling over in Romanian stock returns , while **on the negative side**, the tail correlation with **Hungary is approx. 6%,** while with **Poland it is approximately double**. Dependence on the **Czech** market is symmetric: **7% chance of contagion for both positive and negative shocks**.
- Further areas of research could involve analysing **multivariate copula models** to study the joint dependence of, for example, Romania, Hungary, and Poland. Moreover, the marginal distributions could be estimated with the **FIEGARCH** model, as opposed to only IGARCH, or EGARCH, to account for both integration and asymmetry.

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