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TVP-VAR FREQUENCY CONNECTEDNESS BETWEEN THE FOREIGN EXCHANGE RATES OF NON-EURO AREA MEMBER COUNTRIES

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Abstract

Research background: The main purpose of monetary integration between EU countries is to eliminate excessive fluctuations in exchange rates. High volatility in exchange rates can cause various negative economic and financial effects, especially during periods of economic shocks. In addition, estimating the volatility between currencies and their interactions is of great importance for effective portfolio management.
Purpose: The objective of this research is to scrutinize the transmission of volatility between the currencies of those European Union nations that do not participate in the EURO area, focusing on the exchange rate parity of the US Dollar with seven non-EURO zone currencies.
Research methodology: Daily volatility in exchange rates was calculated using the Garman-Klass-Yang-Zhang (GK-YZ) method. To investigate the connectedness between these volatilities, we used the Time-Varying Parameter Vector Autoregression (TVP-VAR) frequency connectedness approach.
Results: The Average Total Connectedness Index exhibits a significant degree of connectedness of approximately 71.84%. The Net Total Directional Connectedness Index indicates that the CZK, DKK and RON exchange rates are net beneficiaries in aggregate and in a longer term perspective, whereas the DKK, HUF and PLN exchange rates are net beneficiaries in a shorter term horizon. In the context of major global events such as the onset of the COVID-19 outbreak in March 2020 and the start of the Russia-Ukraine conflict in February 2022, it could be observed that the dynamic Total Connectedness Index

exhibited a substantial increase, both overall and from a long-term perspective, corroborating theoretical expectations. According to the Net Pairwise Directional Connectedness index, the highest bilateral connectedness overall and in the short run was between DKK and RON, while in the long run between BGN and DKK.
Novelty: Examining the connectedness of currencies is of great importance for investors doing business with foreign currency, international cooperation and policies, risk management and portfolio management. Determining the connectedness in different frequency (short and long-term) ranges provides important information for hedging risk. In addition, the bilateral connectedness between currencies is a guide for effective portfolio diversification.

Keywords: Garman-Klass-Yang-Zhang, FOREX markets, Non-Euro Area, Pairwise Connectedness Index, TVP-VAR Frequency Connectedness, Volatility transmission

JEL classification: C11, C22, E30, F31, G00

Introduction

The European Monetary System was established in 1979, and full monetary integration between countries was achieved with the signing of the European Union (EU) Agreement in 1991. With this agreement, the Economic and Monetary Union was established for the transition to a single and common currency, the Euro, among member countries. Convergence criteria were set among member countries for the use of a common currency, and permission to use a common currency was granted on the condition that these criteria were met. Initially, 11 member countries were designated for the transition, and then Greece changed to the Euro in 2001. As a result, the Euro entered into circulation as the physical currency of 12 countries from January 1, 2002. From July 1, 2002, the national currencies of those countries that joined the Euro monetary union were withdrawn from circulation, and they gained the status of a single legal currency in those countries. In the following years, participation in the monetary union increased, and as of today, the number of countries using the Euro has risen to 20. On the other hand, Bulgaria, Hungary, Poland, Romania, the Czech Republic, Sweden, and Denmark, despite being EU member countries, have remained outside the monetary union. While Denmark did not switch to the Euro based on the privileges included in the EU Agreement, the remaining countries could not join the monetary union due to their inability to meet the economic conditions (Indruchová, 2013).

The main objective of monetary integration among EU countries is to eliminate excessive fluctuations in exchange rates. High volatility in exchange rates, especially during periods of economic shocks, can cause various negative economic and financial effects. Moreover, the estimation of returns, volatility, and their interaction in financial instruments is of great importance for effective portfolio management. Therefore, volatility predictions are among the prominent topics in financial literature. With increasing integration between countries, interest in calculations of volatility measurements both nationally and internationally has been growing day by day. In this study, we focused on the volatility transmissions among the currencies of the group of countries we investigated, and their interconnections.

The aim of this research is to delve into the volatility transmission between the currencies of European Union countries that are not part of the Eurozone, specifically focusing on the exchange rate parity of the US Dollar with seven non-Euro currencies. To achieve this aim, daily volatility in exchange rates is calculated using the Garman-Klass-Yang-Zhang method. To further explore the interconnectedness among these volatilities, we utilize the Time-Varying Parameter Vector AutoRegression (TVP-VAR) frequency connectedness approach. This research takes into account significant global events such as the outbreak of the COVID-19 pandemic in March 2020 and the beginning of the Russia-Ukraine conflict in February 2022. Our analysis reveals that the dynamic Total Connectedness Index (TCI) displayed a substantial increase during these periods, both in the short term and long term, affirming theoretical predictions. Furthermore, we use the values derived from bilateral connectedness to pinpoint dominant currencies and thus inform the process of portfolio diversification. In this study, we have extended previous research by examining the volatility spillovers among the currencies of seven EU member countries that are not part of the Eurozone.

This research seeks to augment the existing body of scholarly work, particularly focusing on a group of non-Eurozone countries. The contributions of this study encompass: The application of the Time-Varying Parameter Vector Autoregressive (TVP-VAR) Frequency Connectedness approach to this specific network, marks the first instance of such a methodological approach. It is an inaugural study that analyzes the impacts of the COVID-19 pandemic and the Russia-Ukraine conflict on the interconnectedness among the volatilities of these countries' currencies. The study offers novel insights into short and long-run portfolio diversification, enlightened by the examination of the exchange rates volatility available within the network.

The remainder of this study is structured as follows: after the introduction we provide the literature part, then we introduce the Range-Based Volatility Estimators method and describe the collected volatility dataset. Following this, we outline the structure of the TVP-VAR

Connectedness Approach in both time and frequency domains, interpret the results of the analysis, and conclude the study with a summary of our findings and their implications.

1. Literature review

In the literature, there are numerous studies which have been conducted using various methodologies related to volatility spillover (refer to: Baillie, Bollerslev 1990; Sosvilla-Rivero *et al.*, 1999; Hong, 2001; Inagaki, 2007; Cairns *et al.*, 2007). However, research focusing on the volatility interconnectedness among countries' currencies has seen an uptick in recent years. For instance, Diebold and Yilmaz (2015) analyzed the exchange rate volatility spillovers of nine major currencies against the US dollar, using data from January 1999 to June 2013. Their analysis found significant differences in volatility spillovers across these currencies. Particularly, they identified the Euro/US Dollar exchange rate as having higher volatility compared to other currencies. Greenwood-Nimmo *et al.* (2016) examined daily spillovers for G10 country currencies against the US dollar from January 1999 to October 2014, using an empirical network model derived from a generalization of Diebold and Yilmaz's (2009, 2014) connectedness methodology. Their results revealed an increase in spillover intensity among exchange rates during crisis periods and in response to deteriorating conditions in the US. Baruník *et al.* (2017) tested for asymmetric volatility connectedness among six currencies (Australian Dollar-AUD, British Pound-GBP, Canadian Dollar-CAD, Euro-EUR, Japanese Yen-JPY, Swiss Franc-CHF) using daily data from 2007 to 2015 and the volatility spillover index approach (Diebold, Yilmaz, 2012). They found that GBP and CAD were shock givers, AUD, JPY, and EUR were primarily shock receivers, while CHF was a balanced currency. Wen and Wang (2020) investigated both static and dynamic total and directional volatility connectedness among 65 major currencies for the period from November 29, 2000, to February 15, 2019. In their study using the volatility spillover index developed by Diebold and Yilmaz (2009, 2012, 2014) and the LASSO-VAR approach, they found that the US dollar and the Euro were major volatility transmitters, while other currencies like the Japanese Yen and British Pound were net volatility receivers. Bouri *et al.* (2020) examined the daily dynamic interconnectedness between the exchange rates of 11 Asia-Pacific regions from 1994 to 2019 using mean-based VAR models and quantile-based VAR models. Mean-based VAR model results revealed that there was a moderate level of connectivity between currencies, while the quantile-based VAR model results showed that the level of connectivity was much higher. The results further showed that the connectedness between currencies was much stronger, especially in cases of negative and positive shocks. Antonakakis et al (2021), examined the volatility of 6 currencies i.e. Australian dollar (AUD), British pound (GBP), Canadian dollar (CAD), Japanese yen (JPY), Swiss franc (CHF) and Euro (EUR) against the USD. They used data, started from January 2, 1975 to April 30, 2018, and analyzed it by dividing it into 5 different periods in terms of exchange rate regimes and crises. The study focused on the Euro's position as an international currency and its mobility with other currencies. Conditional volatility between currencies was determined with the DCC-GARCH-Copula model, and conditional volatility correlated with the Bayesian TVP-(Pseudo) FAVAR model. The results revealed that the interconnectedness of currencies was higher in a fixed exchange rate regime, while the currencies were independent in a flexible exchange rate regime. In addition, it was also observed that the Euro affected the volatility of other currencies in the pre-crisis periods, but this effect weakened during the crisis periods and strength of the Euro decreased. Gabauer (2021), used daily data from January 2, 1975 to October 23, 2001, to study whether the currencies of 14 countries which Joined the European common currency and Sweden faced symmetrical shocks. The purpose of the study was to determine which country could participate in the Optimum Currency Area (OCA). The analysis carried out with the TVP-VAR (Time-Varying Parameter Vector Autoregressions) model pointed to two OCAs. The first included the stable currencies of Germany, Austria and the Netherlands, and the second included the currencies of Belgium, Denmark, France and Luxembourg in addition to them. Wan and He (2021) examined the daily dynamic interconnectedness of five currencies used in the G7 countries for a period of 27 years. They analyzed the data by using the TVP-VAR model. The results revealed that the USD was a net transmitter, GBP and CAD were net recipients, and the EUR and JPY showed variability throughout the period. Anwer *et al.* (2022), used daily data from January 1995 to March 2021 to examine the interconnectedness between 11 Asia-Pacific currencies with a asymmetric time-frequency domain analysis. The results revealed that currencies are disconnected in normal periods and interconnected in crisis periods. In addition, it had been determined that the currencies of developed economies are net shock spreaders in extraordinary periods.

2. Materials and method

2.1. Data set

In this research, we undertake an examination of the volatility interconnections among the currencies of seven European Union member states that do not partake in the common currency system, specifically, those not encompassed within the Eurozone. To accomplish this, we employ daily exchange rate data spanning from January 02, 2019, to December 31, 2022, for the following currencies: Bulgarian Lev (BGN), Czech Koruna (CZK), Danish Krone (DKK), Hungarian Forint (HUF), Polish Zloty (PLN), Romanian Leu (RON), and the Swedish Krona (SEK). The dataset was obtained from the "Yahoo Finance" platform via the utilization of the 'quantmod' R package program (as per Ryan, Ulrich, 2020).

2.2. Range – based volatility

In the computation of volatility, intraday Open-High-Low-Close (OHLC) prices are frequently employed. A variety of volatility estimation approaches are present in the literature. The first of these is the volatility estimator based solely on high and low (HL) prices, developed by Parkinson (1980). Garman and Klass (1980), known as GK, expanded upon Parkinson's approach by including opening and closing prices in the development of a volatility estimator. Rogers and Satchell (1991), or RS, formulated an approach that allowed for non-zero drift in the volatility estimator. Lastly, Yang and Zhang (2000), or YZ, revised Garman and Klass's volatility estimator to account for opening jumps.

This study utilizes the Garman-Klass-Yang-Zhang (GKYZ) approach to estimate the volatility connection between the currencies of the countries. This approach utilizes returns of opening, high, low, and closing (OHLC) prices in calculating the volatility estimator and also considers the previous day's closing price. Moreover, the estimator presumes a zero-drift Brownian motion. However, when the drift is non-zero, it tends to overestimate volatility. Despite this, it is eight times more effective than the classic close-to-close volatility estimator (see (Ari, 2022) for details). The GK-YZ volatility estimator model is as follows:

$$\sigma_{GKYZ} = \sqrt{\frac{Z}{n}\sum_{i=1}^{n}\left(\left(\log\frac{O_i}{C_{i-1}}\right)^2 + \frac{1}{2}\left(\log\frac{H_i}{L_i}\right)^2 - \left(2\log 2 - 1\right)\left(\log\frac{C_i}{O_i}\right)^2\right)} \tag{1}$$

Figure 1 showcases the series of range-based volatility. The skewness and excess kurtosis metrics detailed in Table 1 suggest a significant skewness and excess kurtosis for all volatility series when compared to the normal distribution. The Jarque-Bera test statistics additionally affirm the non-normal distribution of the series, significant at the 1% level. Consequently, the Elliot-Rothenberg-Stock (ERS) test is applicable to verify the stationarity of these volatility series. The ERS figures confirm the stationarity of all of the volatility series.

A notable autocorrelation is evident in all of the series, including the square series, leading to time-dependent changes in the mean and variance of each series. Consequently, the TVP-VAR model that contains a time-varying variance-covariance structure is a suitable econometric framework to encapsulate all of these variables. Additionally, Table 1 displays the unconditional correlation matrix across the range-based volatility series for the currencies during the sample period. The Pearson correlations indicate a significant positive correlation between the volatilities. Despite the presence of a notably high and statistically significant correlation among all exchange rates, it is observed that the least correlation value, amounting to 0.742, exists between BGN and CZK. The most substantial correlation is evident between the volatilities of BGN and DKK. We can interpret these results as initial hints that there might be a variable structure in volatility transmissibility between BGN and other exchange rates.

Table 1. Summary statistics of the GK-YZ volatility series

	BGN	CZK	DKK	HUF	PLN	RON	SEK
Statistics							
Mean	0.119	0.141	0.099	0.171	0.149	0.106	0.158
Variance	0.001	0.004	0.002	0.006	0.005	0.002	0.007
Skewness	1.507	1.898	1.385	1.465	1.865	1.284	2.926
Ex.Kurtosis	3.466	6.726	2.045	1.989	5.049	1.535	12.684
JB	907.528	2,564.974	509.614	539.457	1,694.357	385.028	8,390.434
ERS	–3.301	–4.665	–3.233	–4.195	–4.825	–2.988	–5.677
Q(20)	6,945.731	7,176.561	7,651.310	7,574.429	6,652.446	7,865.362	5,486.585
$Q^2(20)$	6,233.274	5,705.890	6,873.779	6,427.699	5,422.600	7,414.374	4,105.741
Spearman							
BGN	1.000						
CZK	0.742	1.000					
DKK	0.929	0.835	1.000				
HUF	0.820	0.881	0.889	1.000			
PLN	0.803	0.872	0.860	0.884	1.000		
RON	0.913	0.789	0.966	0.855	0.817	1.000	
SEK	0.799	0.786	0.849	0.819	0.863	0.803	1.000

Notes: all statistics are significant at 1% levels. Skewness: The D'Agostino (1970) test examines the skewness of a distribution to identify if it significantly deviates from a normal distribution. Ex. Kurtosis: The test by Anscombe and Glynn (1983) assesses the kurtosis of a distribution, which helps ascertain if the data exhibit heavier or lighter tails compared to a normal distribution. JB: The Jarque and Bera (1980) normality test investigates whether a dataset follows a normal distribution by considering both skewness and kurtosis. ERS: The unit-root test by Elliott *et al.* (1996) examines the presence of a unit root in a time series, assisting in determining if the data is stationary or non-stationary. Q(20) and $Q^2(20)$: The weighted portmanteau test by Fisher and Gallagher (2012) serves as a diagnostic instrument to identify autocorrelation in the residuals of a time series model.

Source: own elaboration.

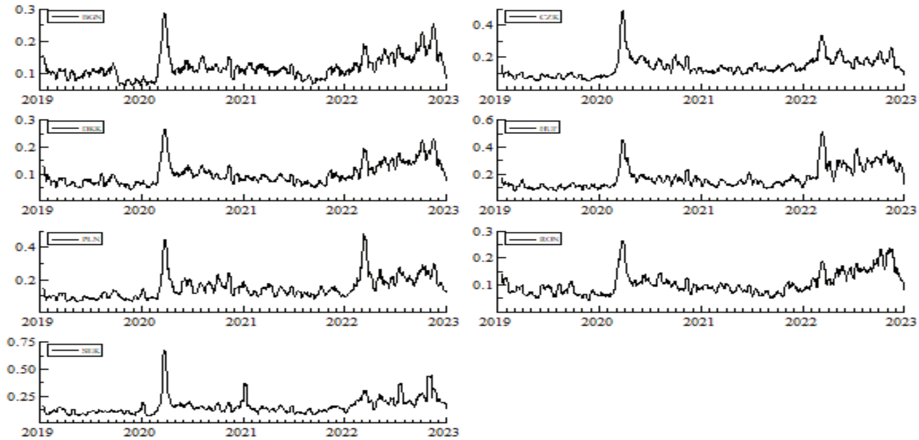


Figure 1. Time series plots of range-based volatility series

Source: own elaboration.

It can be observed that nearly all currency exchange rate fluctuations exhibit a similar trend. This could be attributed to a convergence effect, which is a result of financial integration. Another noteworthy observation in the volatility series, as presented in Figure 1, is that volatility reached its highest level in March 2020, which is typically recognized as the beginning of the COVID-19 pandemic. Volatility also reached high levels in February 2022, coinciding with the onset of the Russia-Ukraine conflict in some countries. The highest volatility value, in other words, the highest standard deviation, is observed in the SEK. Indeed, according to the summary statistics given in Table 1, the highest average volatility is again in the SEK.

2.3. TVP-VAR based volatility connectedness approach in the time domain

The methodology of Antonakakis *et al.* (2020) enhances the connectedness approach proposed by Diebold and Yilmaz (2014, 2015) through the utilization of the Time-Varying Parameter Vector Autoregressive (TVP-VAR) method. This approach facilitates the variance-covariance matrix's adaptability by employing a Kalman filter estimation fortified with forgetting factors. The study derives its methodology from the research conducted by Koop and Korobilis (2013, 2014) for the determination of the Vector Autoregressive (VAR) and Exponential Weighted Moving Average (EWMA) forgetting factors. Antonakakis *et al*. (2020) stated that the TVP-VAR connectedness approach effectively mitigates the issues associated with the arbitrary selection of rolling window size, which can often lead to inconsistent or overly generalized parameters, and circumvents the discarding of crucial observations. Consequently, this technique could also be utilized to investigate dynamic connectedness measures for datasets characterized by low-frequency or limited temporal scope. In order to scrutinize the time-variant interrelationship amidst the price volatilities of foreign exchange rates, the most suitable model, as determined by the Bayes Information Criteria (BIC), is the TVP-VAR (2) model. This model is subsequently estimated as follows:

$$y_t = \mathrm{A}_t z_{t-1} + \epsilon_t \qquad \epsilon_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(A_t) = vec(A_{t-1}) + \upsilon_t \qquad \upsilon_t \sim N(0, S_t) \tag{3}$$

In the aforementioned model, y_t and z_{t-1} are designated as $k \times 1$ and $2k \times 1$ vectors, respectively. The matrix A_t is characterized by the dimensionality of $k \times 2k$, while ϵ_t and υ_t are represented as $k \times 1$ and $2k^2 \times 1$ dimensional vectors, correspondingly. The matrices Σ_t and S_t, which are time-varying variance-covariance matrices, possess dimensions of $k \times k$ and $2k^2 \times 2k^2$, respectively. Lastly, the vector $vec(\mathrm{A}_t)$ is quantified as a $2k^2 \times 1$ dimensional vector.

The methodology employed by Diebold and Yilmaz hinges on the Generalized Forecast Error Variance Decomposition (GFEVD) analysis. To transform the TVP-VAR into a TVP-VMA representation, the formula $y_t = \sum_{h=0}^{\infty} A_{ht} \int_{t-h}$ is used, where $A_0 = I_k$. Hence, the impact of a shock in variable j on variable i is quantified via the following calculation:

$$\tilde{\phi}_{ij,t}^{g}(H) = \frac{\sum_{h=0}^{H-1} \left(\int_i^T A_{ht} \Sigma_t \int_j \right)^2}{\left(\int_i^T \Sigma_t \int_j \right) \sum_{h=0}^{H-1} \left(\int_i^T A_h \Sigma_t A_{ht}^T \int_i \right)} \tag{4}$$

where $\sum_{j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}^{g}(H) = k$. Consequently, the measures of connectedness as proposed by Diebold and Yilmaz (2012, 2014) through the use of GFEVD are computed in the following manner:

Total Directional Connectedness to Others – TO

$$TO_{jt}(H) = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) \tag{5}$$

Total Directional Connectedness from Others – FROM

$$FROM_{jt}(H) = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) \tag{6}$$

Net Total Directional Connectedness – NET

$$NET_{jt}(H) = \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H) - \sum_{i=1, i\neq j}^{k} \tilde{\phi}_{ji,t}^{g}(H) = TO_{jt} - FROM_{jt} \tag{7}$$

Total Connectedness Index – TCI

$$TCI_t(H) = k^{-1}\sum_{j=1}^{k} TO_{jt} \equiv k^{-1}\sum_{j=1}^{k} FROM_{jt} \tag{8}$$

Net Pairwise Directional Connectedness – NPDC

$$NPDC_{ij,t}(H) = \tilde{\phi}_{ij,t}^{g}(H) - \tilde{\phi}_{ji,t}^{g}(H) \tag{9}$$

2.4. TVP-VAR based volatility connectedness in the frequency domain

In this study, we apply the novel TVP-VAR frequency connectedness approach, as proposed by Chatziantoniou *et al.* (2021). This methodology adeptly harnesses the core principles previously laid out in the works of Baruník and Krehlík (2018) and Antonakakis *et al.* (2020). Furthermore, we adhere to the methodology proposed in the research conducted by Huang *et al.* (2023), which includes a meticulously structured appendix that provides a comprehensive guide for this approach. The TVP-VAR frequency connectedness approach facilitates the segmentation of volatility connectedness into short-term and long-term components while concurrently considering the time-varying coefficient and the variance-covariance structure. Remarkably, it accomplishes this without the loss of observations attributed to the unnecessary use of an arbitrary rolling-window, thus eliminating the need for concerns about outliers or inconsistent parameters.

Utilizing the frequency response function, denoted as $\Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h}\Psi_h$, where i signifies the imaginary unit (square root of –1) and ω symbolizes the frequency, we can proceed with the spectral density of y_t at frequency ω. The spectral density of y_t over ω may be characterized as a Fourier transformation of the Time-Varying Parameter Vector Moving Average of order infinity (TVP-VMA(∞)).

$$S_y(\omega) = \sum_{h=-\infty}^{\infty} E\left(y_t y_{t-h}'\right) e^{-i\omega h} = \Psi\left(e^{-i\omega}\right)\Sigma_t \Psi'\left(e^{i\omega h}\right) \tag{10}$$

Thus, we can calculate the Generalized Forecast Error Variance Decomposition (GFEVD) which is a fusion of the spectral density and the GFEVD in the frequency domain, as follows:

$$\phi_{ij,t}^{g}(\omega)=\frac{(\Sigma_t)_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi\left(e^{-i\omega h}\right)\Sigma_t\right)_{ij,t}\right|^2}{\sum_{h=0}^{\infty}\left[\Psi\left(e^{-i\omega h}\right)\Sigma_t\Psi'\left(e^{i\omega h}\right)\right]_{ii}} \tag{11}$$

$$\tilde{\phi}_{\mathrm{ij,t}}^{\mathrm{g}}(\omega)=\frac{\phi_{ij,t}^{g}(\omega)}{\sum_{\mathrm{i=1}}^{\mathrm{k}}\phi_{ij,t}^{g}(\omega)} \tag{12}$$

The process of accumulating all frequencies within a designated range of interest is represented by the equation $\tilde{\phi}_{ij,t}^{g}(d)=\int_a^b\tilde{\phi}_{ij,t}^{g}(\omega)d\omega$, where d is defined as the interval (a, b), and both a and b belong to the spectrum (–π, π). Additionally, it is necessary that $a < b$. So, the frequency connectedness metrics are as follows:

$$TO_{jt}(d)=\sum_{i=1,i\neq j}^{k}\tilde{\phi}_{ij,t}^{g}(d) \tag{13}$$

$$FROM_{jt}(d)=\sum_{i=1,i\neq j}^{k}\tilde{\phi}_{ji,t}^{g}(d) \tag{14}$$

$$NET_{jt}(d)=\sum_{i=1,i\neq j}^{k}\tilde{\phi}_{ij,t}^{g}(d)-\sum_{i=1,i\neq j}^{k}\tilde{\phi}_{ji,t}^{g}(d)=TO_{jt}-FROM_{jt} \tag{15}$$

$$TCI_t(d)=k^{-1}\sum_{j=1}^{k}TO_{jt}\equiv k^{-1}\sum_{j=1}^{k}FROM_{jt} \tag{16}$$

$$NPDC_{ij,t}(d)=\tilde{\phi}_{ij,t}^{g}(H)-\tilde{\phi}_{ji,t}^{g}(H) \tag{17}$$

Subsequently, it is feasible to compute all the frequency connectedness metrics which yield information pertaining to spillovers within a particular frequency range denoted by d. This can be expressed as:

$$\phi(H)=\sum_{d}\phi(d) \tag{18}$$

In this context, the symbol $\phi(\cdot)$ is representative of a set of connectedness measures [NPDC, TO, FROM, NET, TCI], all of which have been previously discussed. This signifies that the total accumulation of all frequencies pertaining to the frequency connectedness measure is equivalent to the corresponding connectedness within the time domain.

For those interested in a more exhaustive exploration of the employed methodology, we recommend referring to the works of Diebold and Yilmaz (2009, 2012, 2014, 2015), Baruník and Krehlík (2018), Antonakakis *et al.* (2020), Chatziantoniou *et al.* (2021), and Huang *et al.* (2023). These resources should provide a comprehensive insight into the research techniques employed in our study.

3. Empirical findings

In their 2020 research, Antonakakis *et al.* chose to employ fixed values for forgetting factors associated with the VAR and Exponential Weighted Moving Average (EWMA) models. Specifically, the forgetting factor for the TVP-VAR was set at 0.99, and for the EWMA, it was set at 0.97. This decision significantly diminished the computational load of the Kalman filter algorithm. Furthermore, their simulations demonstrated that these decay factors engendered the least amount of error. Antonakakis *et al.* (2020) undertook a simulation study to explore the repercussions of varying forgetting factors. In this study, both forgetting factors were adjusted independently and at random between the values of 0.96 and 0.99. They found that a VAR forgetting factor of 0.99 and an EWMA decay factor between 0.96 and 0.99 yielded relatively superior performance. Given that the TVP-VAR model is estimated using Bayesian methodology, which necessitates prior knowledge. To scrutinize the sensitivity of the results to the chosen prior, Antonakakis *et al.* (2020) performed a prior sensitivity analysis using non-informative, informative, and 500 randomly chosen Minnesota priors. The outcome of this analysis revealed that the effect of the prior was negligible after approximately 50 updates of the coefficients. In our analysis, the average was TCI derived from the TVP-VAR(2) model, incorporating the Minnesota Prior, and employing the GFEVD with a forecast horizon of 10 days.

3.1. Total Connectedness Index

The average TCI displayed in Table 2 suggests that a moderate proportion of the forecast error variance in the variables can be attributed to the transitions and interconnections between these variables. The diagonal elements of the 7×7 matrix presented in the table depict the forecast error variance instigated by the variables themselves, whereas the remaining elements delineate the decomposition of the error variances. Essentially, the diagonal elements expose the volatility spillovers that are self-inflicted, while all the off-diagonal elements reveal the rates of spillover. The entry at the i-th and j-th position of the matrix signifies the estimated contribution to the forecast error variance of stock i, which results from disturbances to stock j. The columns labelled "TO" represent the variance decompositions of spillovers to other variables, while the elements in the rows marked "FROM" indicate the shocks originating from other variables.

Table 2 presents the static TCI, encompassing the indices of interconnectedness for total, short-term (spanning 1–5 days), and long-term durations (extending from 5 days to the end of the period under consideration). In accordance with the data, the total connectedness index stands at 71.84%, while the short-run index is comparatively lower at 4.64%, and the long-run index demonstrates a substantial figure of 67.20%. The Swedish Krona (SEK) exhibits the highest self-induced GFEVD both in the short and long term, signifying its volatility is primarily self-derived. Consequently, it represents the currency least susceptible to transmissions arising from the network's interconnectedness-induced spread. Overall, the currency exchange rate that experiences the highest degree of spillover caused by the network is the DKK, showing a spread of 79.23% (FROM), while the RON transmits the highest shock spillover at 91% (TO). This pattern remains consistent over a longer duration with the DKK at 74.07% (FROM) and RON at 87.12% (TO). On the other hand, in the short term, RON is the most vulnerable to network-originated shocks with a 5.95% rate (FROM), while the PLN exhibits the greatest spillover at 5.46% (TO).

3.2. Net Total Directional Connectedness

NET provides a statistical measure to ascertain whether a given variable functions as a primary shock transmitter or receiver within a network. This is calculated by deducting the impact of a specific variable j on all other variables from the influence of all other variables on the same variable j as Equations 7 and 15. If the NET value is positive, it signifies that variable j exerts a more substantial impact on the other variables within the network than they impose on it. Consequently, variable j is identified as a net transmitter of shocks, thereby driving the dynamics of the network. In contrast, if the NET value is negative, it suggests that the other variables within the network have a more pronounced impact on variable j than its influence on them. In this situation, variable j is designated as a net receiver of shocks and is primarily influenced by the network's dynamics. The NET measure serves as an instrumental tool for evaluating the role of a variable within a network, its influence on or sensitivity to other variables, and for identifying pivotal variables that are central to the network's operation. It also facilitates tracking variations in the connectedness of a network over time.

The NET values in Table 2 indicate that the exchange rates for CZK, DKK, and RON predominantly act as net transmitters, while BGN, HUF, PLN, and SEK primarily serve as net receivers both overall and in the long run. During both these timeframes, the RON emerges

Table 2. Total, short-run, and long-run average TCI

Total	BGN.Total	CZK.Total	DKK.Total	HUF.Total	PLN.Total	RON.Total	SEK.Total	FROM.Total
BGN	24.11	12.17	17.23	8.85	8.38	20.09	9.18	75.89
CZK	9.65	32.93	13.13	12.08	11.02	12.74	8.45	67.07
DKK	15.52	14.35	20.77	9.94	9.49	20.83	9.11	79.23
HUF	10.90	15.52	13.67	25.03	12.46	14.30	8.12	74.97
PLN	10.52	14.87	13.87	12.48	24.92	13.45	9.89	75.08
RON	14.52	13.51	18.46	9.29	8.94	26.23	9.05	73.77
SEK	9.07	10.35	10.29	6.65	10.26	10.25	43.13	56.87
TO	70.18	80.77	86.65	59.30	60.54	91.64	53.80	502.89
Inc.Own	94.28	113.70	107.42	84.33	85.46	117.88	96.93	**TCI**
Net	–5.72	13.70	7.42	–15.67	–14.54	17.88	–3.07	**71.84**
NPDC	2	6	4	1	1	5	2	
Short-run	BGN.1–5	CZK.1–5	DKK.1–5	HUF.1–5	PLN.1–5	RON.1–5	SEK.1–5	FROM.1–5
BGN	1.64	0.68	1.25	1.01	0.9	1.05	0.73	5.62
CZK	0.70	1.27	0.83	0.81	0.90	0.67	0.50	4.40
DKK	0.96	0.65	1.32	0.97	1.01	0.98	0.60	5.16
HUF	0.57	0.58	0.62	1.34	0.81	0.60	0.60	3.78
PLN	0.50	0.56	0.57	0.74	1.74	0.54	0.59	3.49
RON	1.04	0.72	1.28	1.05	1.09	1.37	0.77	5.95
SEK	0.64	0.64	0.69	0.68	0.75	0.69	2.93	4.07
TO	4.40	3.84	5.24	5.24	5.46	4.52	3.78	32.49
Inc.Own	6.04	5.10	6.56	6.59	7.20	5.89	6.72	**TCI**
Net	–1.21	–0.57	0.08	1.46	1.97	–1.43	–0.29	**4.64**
NPDC	1	2	4	5	6	1	2	
Long-run	BGN.5–Inf	CZK.5–Inf	DKK.5–Inf	HUF.5–Inf	PLN.5–Inf	RON.5–Inf	SEK.5–Inf	FROM.5–Inf
BGN	22.47	11.48	15.98	7.85	7.48	19.04	8.45	70.28
CZK	8.95	31.66	12.30	11.27	10.12	12.08	7.95	62.67
DKK	14.56	13.7	19.45	8.98	8.48	19.85	8.51	74.07
HUF	10.33	14.95	13.05	23.69	11.65	13.69	7.52	71.19
PLN	10.02	14.31	13.30	11.74	23.17	12.91	9.30	71.59
RON	13.48	12.79	17.18	8.25	7.84	24.86	8.28	67.81
SEK	8.43	9.71	9.60	5.97	9.52	9.56	40.20	52.79
TO	65.77	76.94	81.41	54.05	55.08	87.12	50.01	470.40
Inc.Own	88.24	108.60	100.86	77.74	78.25	111.98	90.21	**TCI**
Net	–4.50	14.27	7.34	–17.13	–16.51	19.31	–2.78	**67.20**
NPDC	2	6	4	1	1	5	2	

Notes: The findings are derived from a TVP-VAR model with a lag length of order 2 (as suggested by the Bayesian Information Criterion, BIC) and a 10-step-ahead generalized forecast error variance decomposition. The estimation process was conducted utilizing the R programming software, specifically employing the “Connectedness Approach” package developed by Gabauer (2022). “Inc. Own” refers to the inclusion of own contributions, “TCI” stands for the Total Connectedness Index, “NET” represents the Net Total Connectedness, and “NPT” denotes the Net Pairwise Total Connectedness. Short run: 1–5 days. Long run: 5-inf.

Source: own elaboration.

as the most powerful shock transmitter, with NET index values of 17.88% and 19.31% respectively, while the HUF is the main shock receiver, with NET values of –15.67% and –17.13% respectively. Intriguingly, in the short term, the PLN, HUF, and DKK take the roles of net transmitters. The PLN stands out as the most potent short-term shock transmitter, having a NET value of 1.97%.

3.3. Dynamic Total Connectedness Index

In the realm of connectedness literature, it is widely accepted that dynamic Total Connectedness Index (TCI) serves as a robustness check for the analysis. The validity of the results obtained is reinforced by the occurrence of abrupt shifts in the dynamic structure, which can be attributed to specific events. However, this study does not intend to provide an exhaustive explanation of every peak and trough in the dynamic structure with reference to specific historical events. The most salient aspect of the connectedness theory lies in the significant amplification of interconnectedness among the variables constituting the network during periods of crisis. As illustrated in Figure 2, the dynamic TCIs exhibit considerable variations over time. Certain spikes in the dynamic Total Connectedness Index (TCI) chart can be accounted for by specific events. The initial impact of Brexit at the start of February 2020, the first COVID-19 case detected in France on January 24, 2020, and the official declaration of the pandemic in March 2020 all contributed to a rise in total connectedness beyond the average level. On March 13, 2020, the World Health Organization declared Europe as the new epicenter of the epidemic. This announcement significantly increased the spillover of exchange

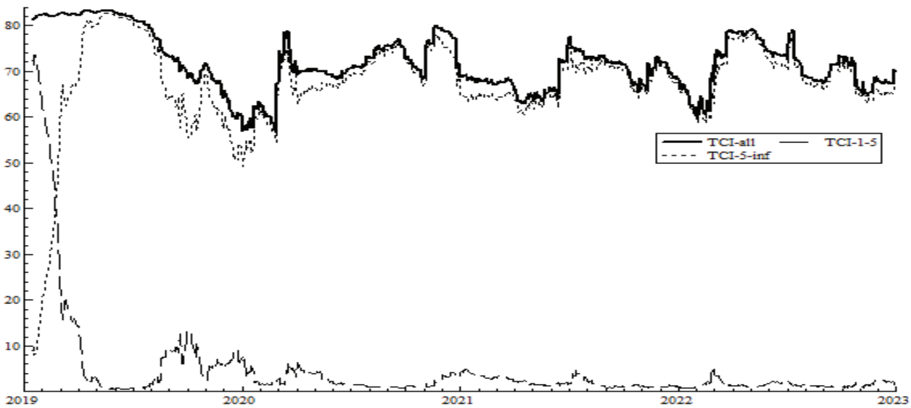


Figure 2. Dynamic TCI Plots

Source: own elaboration.

rate volatility, affecting both long-run and short-run projections. The contraction of the global economy in September 2020 led to a new peak in the TCI values. Furthermore, several factors in 2021 appear to have contributed to a rise in TCI values in July 2021. These factors include the widespread distribution of vaccines, a return to normality and economic recovery, high post-pandemic inflation rates in the USA, a deceleration in European economic growth, and a global increase in demand inflation. We can add the escalating tensions between Ukraine and Russia towards the end of 2021 and the Ukraine-Russia conflict that started in late February 2022 as other factors contributing to a rise in the connectedness index. The dynamic TCI values create peak values due to numerous factors not mentioned here. This is indicative of the analysis aligning with the theory of network connectedness.

3.4. Net Pairwise Directional Connectedness

NPDC provides insight into the bilateral relationship between two variables (i and j). This is achieved by computing the difference between the impact of variable j on variable i and the influence of variable i on variable j as in Equations 9 and 17. If the NPDC value is positive, it denotes that variable j has a dominating influence over variable i. Conversely, a negative NPDC value suggests the opposite, indicating that variable i exerts a greater influence over variable j. The examination of pairwise volatility connectedness measures is vital for understanding the transmission of volatility shocks among commodities across the entire dataset, particularly during periods of crisis. This form of analysis can aid in discerning how the interconnectedness among commodities fluctuates over time, and how volatility shocks contribute to changes in this connectedness.

Given that the NPDC did not sufficiently portray the intensity of bilateral interconnectedness, Gabauer (2021) introduced the Pairwise Connectedness Index (PCI) by decomposing the TCI. Whereas the TCI quantifies the overall interconnectedness of a system, the PCI measures the interconnectedness specifically between pairs of variables within the system. The PCI ranges between 0 and 1, where a value of 1 denotes a robust connection between the two variables, and a value of 0 signifies a lack of connection. One can determine the PCI as follows:

$$PCI_{ij,t} = 2\left(\frac{\tilde{\phi}^{g}_{ij,t}(H) + \tilde{\phi}^{g}_{ji,t}(H)}{\tilde{\phi}^{g}_{ii,t}(H) + \tilde{\phi}^{g}_{ij,t}(H) + \tilde{\phi}^{g}_{ji,t}(H) + \tilde{\phi}^{g}_{j,t}(H)} \right) \tag{19}$$

Table 3 presents NPDI and PCI values for pairwise connectedness between foreign exchange rates. Overall, the highest bilateral connectedness is observed between the DKK and the RON, with PCI values of 91.03%. Based on an NPDCI value of –2.37%, the DKK acts as a net volatility receiver relative to the RON. In the short run, the most potent bilateral connectedness is again seen between DKK and RON, with PCI and NPDCI values of 91.33% and 0.30%, respectively. In this short-term scenario, the DKK operates as a net transmitter and exerts dominance over the RON. The lowest PCI values both overall and in the short term occur between the Swedish Krona (SEK) and the Hungarian Forint (HUF). The minimal NPDCI and PCI values between these two exchange rates suggest they could both be effectively utilized for portfolio diversification purposes. In the long-run frequency band, PCI values decrease. According to the long-run results, the strongest bilateral connectivity is between BGN and DKK, while the weakest correlation is between CZK and SEK. Therefore, CZK and SEK may be used for portfolio diversification in the long-run period because of the weak volatility transmission.

Table 3. Total, short-run, and long-run NPDCI and PCI

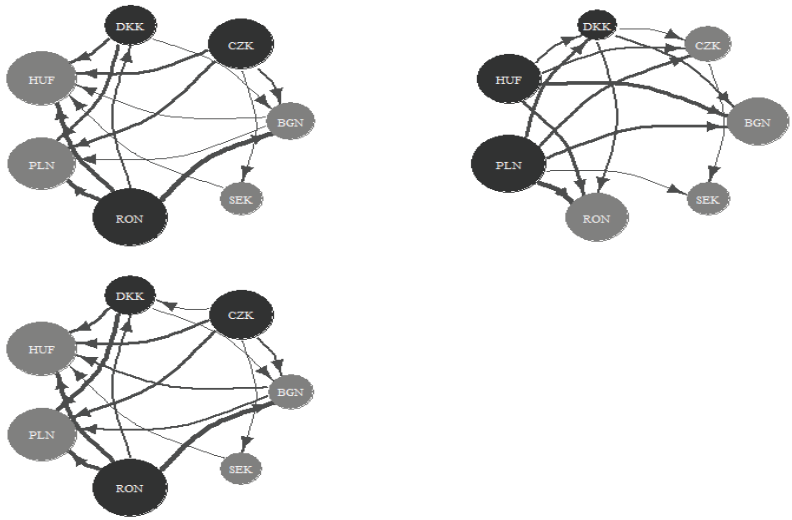
Time domain	CZK	DKK	HUF	PLN	RON	SEK
BGN	–2.52 (56.24)	–1.71 (84.56)	2.05 (57.92)	2.14 (56.57)	–5.57 (81.41)	–0.11 (45.85)
CZK		1.22 (68.66)	3.44 (65.95)	3.86 (63.77)	0.77 (62.59)	1.90 (41.81)
DKK			3.73 (68.23)	4.39 (68.39)	–2.37 (91.03)	1.18 (49.06)
HUF				0.02 (67.44)	–5.00 (63.35)	–1.47 (38.51)
PLN					–4.51 (61.73)	0.37 (47.66)
RON						1.20 (46.44)
Frequency domain short-run (1–5 days)						
BGN	0.02 (56.59)	–0.29 (84.80)	–0.44 (58.43)	–0.40 (57.13)	–0.01 (81.79)	–0.09 (46.56)
CZK		–0.18 (69.03)	–0.23 (66.53)	–0.34 (64.22)	0.06 (63.10)	0.14 (42.66)
DKK			–0.34 (68.85)	–0.44 (68.83)	0.30 (91.33)	0.09 (49.84)
HUF				–0.07 (67.68)	0.44 (64.03)	0.08 (39.26)
PLN					0.56 (62.36)	0.16 (48.52)
RON						–0.08 (47.21)
Frequency domain long-run (5 – inf days)						
BGN	–2.53 (3.99)	–1.42 (6.13)	2.48 (4.86)	2.54 (4.41)	–5.56 (5.71)	–0.02 (3.83)
CZK		1.40 (4.06)	3.68 (3.75)	4.19 (3.89)	0.71 (3.91)	1.76 (2.99)
DKK			4.07 (4.95)	4.82 (5.05)	–2.67 (5.90)	1.09 (3.69)
HUF				0.09 (4.42)	–5.45 (4.85)	–1.55 (3.52)
PLN					–5.06 (4.87)	0.21 (3.41)
RON						1.28 (4.03)

Notes: PCIs are presented in parentheses.

Source: own elaboration.

3.5. Network Plots

To clarify the concept of pairwise connectedness, we use network plots, as depicted in Figure 3. These plots serve as graphical depictions of the dynamic interplay among variables in a TVP-VAR based frequency connectedness analysis. They help visualize the strength and directionality of causal relationships among variables over time. In these diagrams, variables are represented as nodes, with connecting lines (or edges) indicating the presence and extent of causal connections. The weights of these edges represent the strength of the relationship, and their orientation signifies the direction of causality. Additionally, the color of the edges can represent the nature of the relationship. Network plots are useful for identifying the key influences in a system over time, as well as uncovering potential feedback mechanisms or complex interactions among variables. In Figure 3, dark-gray nodes represent volatility transmitters, while gray nodes represent volatility receivers. Network plots, in total and in the long run, exchange rates of CZK, RON and DKK have dominant volatility in the network, and they drive the network. Interestingly, we can observe that the most dominant currency in the short run is PLN, while HUF and DKK are the other two dominant currencies that serve as net transmitters.



Notes: Time-domain Network (up-left), Short-run Network (up-right), Long-run Network (bottom left)

Figure 3. Network Plots

Source: own elaboration.

Conclusions

This study utilizes the innovative TVP-VAR frequency connectedness approach to examine the volatility transmission between the currencies of non-Euro European Union countries. The approach segments volatility connectedness into short-term and long-term components, considering time-varying coefficients and the variance-covariance structure. The total connectedness index is 71.84%, with the short-run index at 4.64% and the long-run index at 67.20%. The Swedish Krona (SEK) has the highest self-induced Generalized Forecast Error Variance Decomposition (GFEVD) in both short and long terms, suggesting its volatility is mostly self-derived. The Danish Krone (DKK) shows the highest volatility spread from the network, while the Romanian Leu (RON) transmits the highest shock spillover. This pattern is consistent in the long term. In the short term, RON is most exposed to shocks originating from the network, while the Polish Złoty (PLN) shows the highest spillover. Global events like Brexit, the onset of the COVID-19 pandemic, and the Russia-Ukraine conflict have caused significant changes in total connectedness. The study also notes that currencies such as DKK and RON act as net transmitters while others like SEK and the Hungarian Forint (HUF) are net receivers. The most potent short-term shock transmitter is PLN. When it comes to bilateral connectedness, DKK and RON have the highest values, suggesting a strong relationship, while SEK and HUF have the lowest, indicating potential for portfolio diversification. In the long run, the strongest connectivity is between the Bulgarian Lev (BGN) and DKK, while the weakest is between the Czech Koruna (CZK) and SEK. The elevated degree of interconnectedness amongst these exchange rates implies a substantial level of risk transmission. Market perturbations or disturbances within this network exert nearly equivalent impacts on each respective exchange rate. A pronounced degree of interconnectedness is indicative of extensive integration, thereby suggesting the operational effectiveness of the convergence theory. Consequently, these exchange rates are typically not advisable for portfolio allocation in a long-term perspective. However, by considering short-term bilateral volatility transmissions, they may serve as viable options for portfolio diversification.

The countries of Bulgaria, Czechia, Hungary, Poland, Romania, and Sweden represent non-Eurozone countries that have yet to adopt the Euro but will do so upon meeting the requisite conditions. They predominantly comprise member states that joined the Union subsequent to the Euro's inception in 2002. Occasionally, member states may negotiate an exemption from specific European Union legislation or agreements, electing not to participate in certain policy domains. This exemption, in the context of the single currency, pertains to Denmark, which retained its prior currency upon Union accession. This retention of national currency can be viewed as a potential barrier to grouping Denmark and other nations within the same network. Nevertheless, the implementation of shared policies and joint projects among these countries has facilitated a level of structural and economic integration. Such countries exhibit parallel responses to external economic shocks. This pattern is affirmed by our discovery of substantial connectedness between currencies within the network scrutinized in our study. Our volatility findings further revealed that these countries share similar structural characteristics. These outcomes are congruent with the theory of economic integration.

The primary objective of this research was to elucidate the impact of the COVID-19 pandemic and the Russia-Ukraine conflict on the economies of seven EU member countries that do not partake in the common currency. As such, we relied on data spanning from January 2019 through to December 2022, a time frame that allows for the investigation of the dynamic effects these two events imposed on economic connectivity. Moreover, given the dynamic character of our chosen approach, an expansion of the time frame would yield numerous peak values in TCI that would necessitate explanation, thereby potentially diverting the focus of our research. Consequently, we have chosen to confine our data period to the post-2019 era, ensuring that our study remains concentrated on its original intent. For future studies that aim to reveal the ramifications of pre-existing external shocks, the data set could be expanded to encompass a more extensive period. Moreover, these subsequent inquiries could utilize alternative methodologies such as the quantile connectedness approach or quantile-frequency connectedness, and could also apply varying volatility models to diversify analytical perspectives.

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