The spillover effect between central and eastern European financial markets

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Abstract
This paper investigates the return and volatility spillovers between EUR/RON, EUR/HUF and EUR/PLN exchange rates and S&P500 index, but also the spillover effect between the capital markets of these three countries and this index, using the methodologies of (Diebold & Yılmaz, 2012). The paper provides both a brief description of several scientific researches conducted by numerous authors in the field of literature, and a series of empirical and econometric results that support theoretical demonstrations. The main results highlight that the spread of volatilities (spillover) intensifies during periods of economic crisis, and the main transmitter of spillover on the foreign exchange market, both in terms of returns and volatilities, is the stock market index S&P500. This paper contributes to the field of spillover studies by analyzing the connection between Romanian currency and the geographic countries neighbors.

Keywords: directional spillover, exchange rates, dynamic conditional correlation, DCC-GARCH-VAR, COVID-19.

Introduction

The main economic aspect taken into account in choosing this subject of analysis is the importance of connections and contagion on the foreign exchange and capital markets in forecasting future movements of EUR / RON exchange rate and, respectively, of BET stock index. In the literature, the analysis of contagion (spillover) at the level of return, but also at the level of volatility, helps to optimize the process of making appropriate decisions to stabilize foreign exchange markets or investments during the effects of pronounced spillover.

This paper aims to determine the directional spillover based on calculating the forecast error variance decompositions in a generalized VAR framework of returns and volatilities between the exchange rate and the main stock indices of Romania, Hungary and Poland and S&P500 stock index.

The structure of the paper includes two major chapters, being presented from the general, to the purpose of the paper. The first chapter summarizes the literature review that presents the directional spillover between returns, but also between volatilities. And the second chapter, the most important, consists in presenting the research methodology, the database used in this analysis and the results obtained from the analysis. At the end of the paper are the conclusions, the related bibliography and the annexes.

The purpose of the first part of the paper is the analysis of the connection / contagion (spillover) between exchange rate returns, but also between the volatilities of Romania (EUR / RON), Hungary (EUR / HUF), and Poland (EUR / PLN), and the stock market index S&P500. Also in the first part, in order to better observe the effect of the spillover, I analyzed the spillover by time categories (before the 2007-2008 crisis; the 2007-2008 crisis; before the COVID-19 crisis and the COVID-19 crisis). And in the second part of the paper, the analysis of the spillover between the stock market indices S&P500 and BET (Romania), BUX (Hungary) and WIG20 (Poland) was followed in order to capture the connections between the capital markets.

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Literature review

Globalization and financial liberalization have allowed international financial markets to become more correlated and connected than ever before, an understanding of the correlations and interactions of different financial markets is crucial for investors, financial institutions and governments.

Studies in the literature that have focused on the correlations between developed financial markets have argued that these markets are interconnected and that the volatility of the US stock market is passed on to other developed markets. In the last decade, with the development of emerging financial markets, financial economists, including (Jayasuriya, 2011), (Neaime, 2012), (Bala & Takimoto, 2017), (Dash & Maitra, 2019) have become increasingly interested in the relationship between emerging and developed markets and sales implications for financial liberalization and global integration.

Eun & Shin (1989) have shown that the US stock market is the main source of international transmission of volatility that can, in turn, affect foreign stock markets. However, foreign exchange fluctuations cannot explain the fluctuations within the US market, implying a one-way effect. (Theodossiou & Lee, 1993) demonstrate that the US stock market has positive transmission effects on the stock markets of the United Kingdom, Germany, Canada and Japan. (Kearney, 2000) also notes that the change in most stock markets in the world is derived from stock changes in the US and Japan, which are then transferred to Europe. (Kasih, 2001) argues that, either in the long run or in the short term, the stock markets in the US, UK and Japan are world leaders, accounting for 75% of total global capital.

According to the authors Qunxing, et al. (2022) the integration of the global market has increased the transmission of shocks from one country to another, which has led to spillover effects. High spillover effects have increased the likelihood of a crisis. Therefore, capital flows in markets, the development of financial markets and the financial stability of the economy depend on the degree of spillover between economies.

The authors Zhang & Mao (2022) argued that the last twelve years have been marked by four major events, including the Global Financial Crisis (GSC) in 2007-2008, the European Sovereign Debt Crisis (ESDC) in 2010-2012, the collapse of the oil price in mid-2014 and the pandemic crisis of COVID-19, which are sources of contagion.

These authors state that during these periods, both commodity and foreign exchange assets fluctuate significantly in value. The movement of cross-border capital flows contributes to amplifying or mitigating price fluctuations and thus to the spillover of returns and volatility. Accurate information on the spread of risks from one market to another and the effects of directional spillovers can lead to optimal portfolio construction and hedging strategies. Understanding the effects of spillover and the connection between markets (why and how these effects occur) is essential for decision-makers to implement appropriate policies to stabilize foreign exchange and commodity markets, especially in times of crisis. Investors are more concerned with reducing risk exposure during turbulent times.

Several authors have found that financial market shocks in developed countries have had large spillover effects on emerging market economies (EMEs), some of these authors are: (Rogers, et al., 2014), (Gauvin, et al. , 2014), (Neely, 2015), (Bowman, et al., 2015), (Aizenman, et al., 2017), (Anaya, et al., 2017). In particular, the introduction of unconventional monetary policies and the eventual exit of these policies by advanced economies have sparked a heated and ongoing debate among policy makers and academia on the effects of propagation on EME.

According to the literature, due to the frequent episode of crisis (global financial crisis, European sovereign debt crisis, COVID-19 crisis) the importance of studying the contagion on the financial markets is further increased. The spread of the contagion between financial markets during the 2007-2008 crisis provides a good illustration of how a decline in one financial market can affect other financial markets.

From this point of view, Yıldırım, et al. (2022) they conducted a comparative analysis of "volatility spillover" between commodity markets and foreign exchange markets of emerging economies such as Mexico, Indonesia and Turkey. In this study it was shown that there is a two-way causal relationship between precious metals and the real exchange rate, and this relationship varies over time. This research also shows that in times of crisis, such as the COVID-19 pandemic, the transfer of volatility disappears.

Therefore, the topic "volatility spillover" has attracted the attention of many authors, and the corresponding literature can be divided into two components: the first component analyzes the spillovers between commodity markets and foreign exchange markets that vary over time. An example of this is the study of authors (Rogoff & Chen, 2003) who use different panel data models and find that commodity prices lead to exchange rate movements in the economies of Australia, Canada and New Zealand. And Meese & Rogoff (1983) use out-of-sample forecasting methods, and conclude that exchange rates serve as a predictor of economic fundamentals and as a result of commodity prices. In this section, the author provided the necessary framework literature for analyzing the state-of-the-art in the domain of the present research.

Methodology

The methodology of this paper is based on studies developed by (Diebold & Yilmaz, 2012) and (Engle, 2002) that analyze directional connections by measuring total, directional and net spillover indices based on forecast error variance decomposition in a model Generalized VAR framework.

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) multivariate models are an extension of GARCH univariate models and are used to capture correlations between several variables. GARCH models aim to analyze volatilities. The DCC-GARCH (Dynamic Conditional Correlation) model aims to analyze time-related correlations between variables. They have the flexibility of univariate GARCH models combined with parsimonious parametric models for correlations.

The first step in building the multivariate model DCC-GARCH (Dynamic Conditional Correlation) was the estimation of a generalized VAR model, and then the residues obtained are standardized using a univariate GARCH model suitable for modeling asymmetries in volatility and shock transmission, but also to take consider cross-correlations that vary over time between variables.

In the analysis we included five of the most common univariate models, namely GARCH, IGARCH, GJR-GARCH, TGARCH and EGARCH in order to choose the right model for waste standardization.

VAR (1) : X1,t = α1+β11,1X1t-1+β12,1X2,t-1+εt

εt ≈ Dist (0,Ht)

Ht=DtPtDt

Dt=diag{ √ h2t

- Ht is the conditional variance matrix of the DCC model,
- Dt is the diagonal matrix of ht of univariate GARCH models
- Pt is the correlation matrix that contains expressions from univariate GARCH models

Pt=Qt*-1 Qt Qt*-1

Qt=(1- αDCC - βDCC) Qt*)+ αDCC φ t−1 + βDCC Qt-1

- Qt is the conditional covariance matrix,
- Qt* is the unconditioned covariance matrix
- φt − 1 is the matrix of standardized residues.
- αDCC and βDCC involve the persistence of shocks. Their amount, which measures the persistence of volatility, must be less than 1.

Then I analyzed the directional spillover effects of returns and volatilities of interest variables using the framework (Diebold & Yilmaz, 2012), which uses variance decompositions of predicted errors and a framework of generalized impulse response functions.

As a first step in this calculation, a VAR with p lags and then the decompositions of the variance allow the evaluation of the portion of the variation of the forecast error xi that is due to the shocks at xj, ∀j ≠ i, for each i. The variance decomposition matrix of the prediction error is calculated by the method developed by (Pesaran & Shin, 1998) which produces variance decompositions that do not take into account the order of introduction of the variables:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_h \Sigma A_h' e_i)}$$

In order to use the information available in the variance decomposition matrix in calculating the spillover index, each entry of the variance decomposition matrix was normalized by the sum of the rows (number of variables):

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{N}$$

Using the volatility contributions from the variance decomposition, Diebold and Yilmaz constructed the total volatility spread index as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$$

The spillover index is based on the “General Forecast Error Variance Descompotion” introduced by (Pesaran & Shin, 1998). This technique calculates the spillover effect table that has as inputs the variables ij and measures the contribution of return / volatility shocks to the variations of the forecast error. In addition to the spillover index, (Diebold & Yilmaz, 2012) they also build the directional spillover towards different asset classes. Two directional spillovers have been introduced and are known as: from (to) and to (to).

Directional spillovers allow us to know how much shock is transmitted to and from markets.

The directional spillovers received by market i from all other markets j are:

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1\\j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$$

The directional spillovers transmitted by market i to all other markets j are:

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1\\j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100$$

The net spillover can be calculated as the difference between the gross return / volatility shocks transmitted and received from all other exchange rate returns:

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$$

In this study were used daily data on the evolution of exchange rates and S&P500 stock index from Refinitiv Thomson Reuters platform. The analysis period covers the last two decades (from January 1, 2003 to March 16, 2022), this time horizon includes significant economic events, the most recent being the COVID-19 pandemic.

Results and discussions

The first step in study was the implementation of VAR(1) model. The numbers of the VAR model were chosen based on Shwartz informational criteria. The next step was to choose the optimum GARCH model to standardize VAR residuals.

Both the informational criteria and the Log-Likelihood function show that the most appropriate model for standardizing VAR (1) residues is EGARCH(1,1). The positive and statistically significant values of the αDCC and βDCC coefficients indicate that the volatilities are very persistent in market shocks (events). At the same time, βDCC is higher than αDCC, which means that past variations are dominant over current variations and in addition, conditional correlations are variable over time.

Tabel 1- Estimation of DCC-GARCH (1,1) parameters

	α DCC	β DCC	Log-Likelihood	AIC	BIC	HQ
GARCH	0.009452	0.976704	48122.76	-22.399	-22.328	-22.374
IGARCH	0.009608	0.976895	48115.95	-22.398	-22.332	-22.375
TGARCH	0.008903	0.966905	48119.6	-22.4	-22.334	-22.377
GJR-GARCH	0.008986	0.978856	48332.25	-22.493	-22.416	-22.466
EGARCH	0.009539	0.976772	**48424.32**	**-22.535**	**-22.458**	**-22.508**

Source: Author's own research

All ARCH and GARCH coefficients, namely α and β, respectively, are statistically significant, indicating that volatility reacts strongly to market movements and that shocks to conditional variation take time to disappear. High values of the β coefficient for all variables highlight a long-term persistence of the volatility spillover between the variables. The asymmetry term γ is significant in terms of all variables, indicating evidence of the asymmetric impact of bad and good news on conditional volatility. γ is negative, and this means that bad news (negative shocks) generates more volatility than good news.

In addition, it can be seen that all the coefficients related to the distribution of residues (Skew and ν) are statistically significant at a significance level of 1%, and this fact emphasizes that the distribution of Skew t-Student is the most suitable for residues.

Tabel 2. Estimation of univariate GARCH parameters

Source:Author's own research

		ω	α	β1	γ	Skew	ν
dl_ron	EGARCH	0.00000	0.10488***	0.85167***	-0.14048	1.01130***	1.10318***
dl_huf	EGARCH	0.00000	0.04421**	0.93361***	-0.66080***	1.00215***	1.69813***
dl_pln	EGARCH	0.00000	0.08981***	0.89640***	-0.28700***	0.98474***	1.51762***
S&P500	EGARCH	0.0000**	0.27352***	0.70547***	-0.22505***	0.98834***	1.27839***

Figure 1. Dynamic conditional correlations between exchange rates

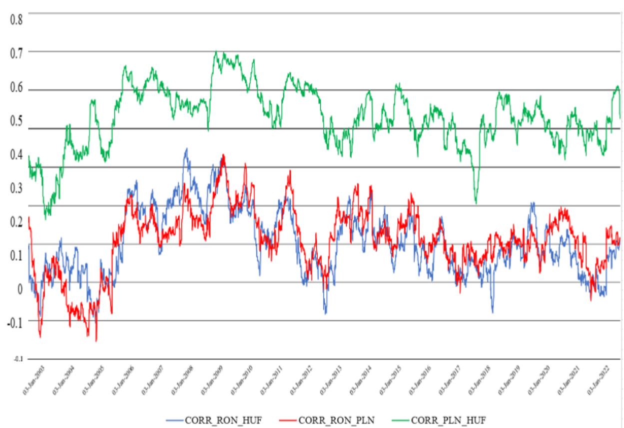
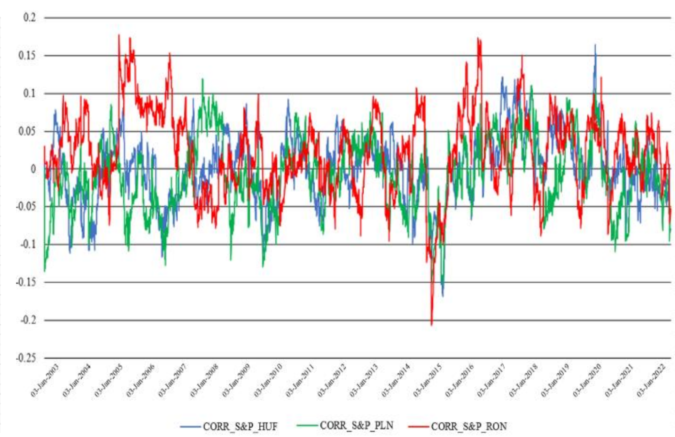


Figure 2-Dynamic conditional correlations between S&P index and exchange rates



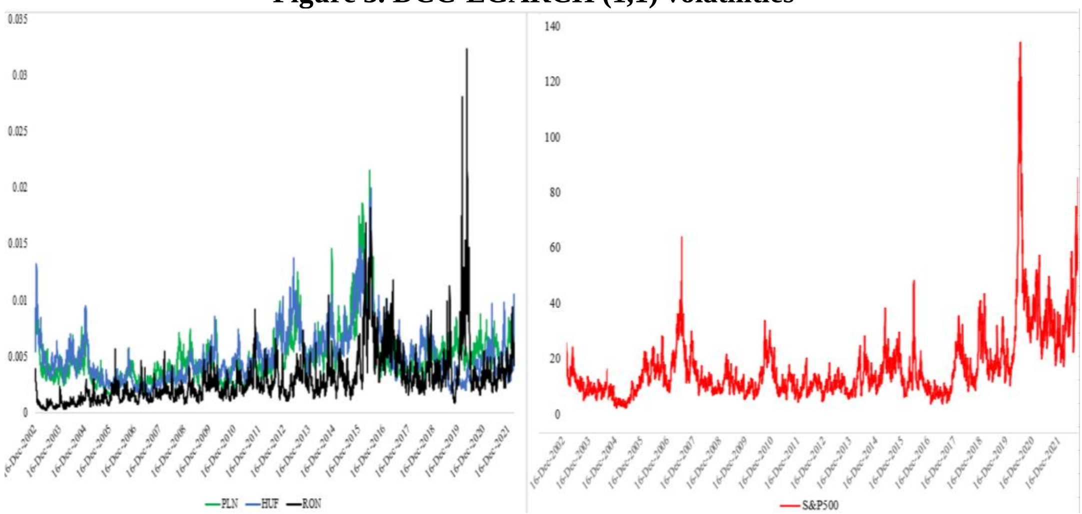
Source:Author's own research

The graphical evidence presented in Figure 1 shows that the correlations between exchange rates, respectively *PLN-HUF*, *RON-HUF* and *RON-PLN*, are not constant, but are intensified during major events, especially during the global financial crisis of 2008. In addition, the graph shows periods of positive and negative correlations. One aspect that should be mentioned is that all pairs they seem to move in the same way over the years, the difference being given by the intensity of the movement, which underlines the connection between the variables. As for the correlation between the other two exchange rates, PLN and HUF, it can be stated that of all the pairs analyzed, their correlation is the strongest. Its evolution over time does not include negative values. This is explained by the geographical position of these countries, but more importantly, by the close trade relationship between them.

In Figure 2 it can be seen that as in the case of the analysis of the correlation between RON and the other two exchange rates, both negative and positive correlations are present here. Also, they are not constant but are intensified during the significant events that marked the analyzed period. It is obvious that unlike the correlation between exchange rates, the volatility index correlates with lower fluctuations with the other two currencies. This aspect highlights the closer connection of the index with the other exchange rates than with the Romanian leu. In addition, we see weak correlations that decrease during major events, indicating that a currency that is depreciating is associated with a jump in the volatility index. The highest values of the correlations in figure 3 are registered around the years 2010-2014, and the graphical representations indicate the presence of two correlation regimes.

The first regime is approximately stable, starting in 2009 to 2013, and the second regime is a more volatile one, which highlights correlations at a lower level. During the Brexit of UK and the presidential elections in the United States of America in 2016 there is an increase in the correlations of time series, and in 2015 when the most prosperous year for the European Union economy is observed the weakest correlation between series.

Figure 3. DCC-EGARCH (1,1) volatilities



Source:Author's own research

As it can be seen in Figure 3, the volatilities of the three exchange rate series move in the same direction, following the same pattern of evolution. The highest volatility values are recorded by EUR / RON exchange rate at the beginning of the COVID-19 pandemic when the value of the exchange rate reached 4.8650 on March 18, 2020, and then continuing the upward trend. Another aspect that needs to be mentioned is the obvious synchronous movement of S&P500 index and EUR / HUF and EUR / PLN exchange rates. These three series show increases in volatility at the same chronological points. The most obvious increase in volatility is observed in 2016, when S&P500 index fluctuated significantly due to the presidential election period. Therefore, it can be stated that S&P500 stock index had a greater influence on the two exchange rates, respectively EUR / HUF and EUR / PLN, than in the case of the Romanian leu exchange rate.

Table 3. Return spillovers between exchange rate and S&P 500

Return Spillover					
	S&P500	**dl_ron**	**dl_huf**	**dl_pln**	**C. from others**
S&P500	24.97	0.01	0.01	0.01	0.03
dl_ron	0.01	21.92	1.57	1.51	3.08
dl_huf	0.03	1.25	16.88	6.85	8.12
dl_pln	0.01	1.20	6.49	17.30	7.70
C. to others(spillovers)	0.05	2.46	8.06	8.37	18.99
C.to others including own	25.01	24.38	24.94	25.67	100.00
Total spillover index(%)	**4.66**				

Source:Author’s own research

Table 4. Volatility spillovers between exchange rate and S&P 500

Volatility Spillover					
	S&P500	**dl_ron**	**dl_huf**	**dl_pln**	**C. from others**
S&P500	25.97	0	0.01	0	0.01
dl_ron	0.98	17.91	2.44	2.51	4.95
dl_huf	0.99	2.25	15.45	7.65	9.91
dl_pln	0.98	2.32	5.39	16.8	7.71
C. to others(spillovers)	2.95	4.57	7.84	10.16	25.52
C.to others including own	28.92	22.48	24.29	25.96	101.65
Total spillover index(%)	**5.72**				

Source:Author’s own research

The diagonal of the table shows the estimated contribution to the forecast error variance of its own returns due to the shocks of its own return/volatility. Both in the case of return spillovers and in the case of volatility spillovers (Table 3 and Tale 4), S&P500 index registers the highest value on the diagonal. This means that the share of own shocks is not as strong for each variable. Spillovers sent by exchange rates to S&P500 index are very low, but in case of volatility it is a bit higher. The explanation behind this is that financial markets are interconnected, and S&P500 stock index is a factor with a high decision-making impact.

The fact that the variables send and receive stronger spillovers between volatilities is also underlined by the total spillover index, in case of volatilities this index is about 5.7% and in case of returns is about 4.6%. The two tables suggests that the largest gross spillover transmitter is PLN currency. Respectively, a shock of 1% of the return of EUR / PLN impact impacts 8.37% of the variation of the forecast error of the other variables, and a shock of 1% of the volatility of EUR / PLN impacts 10.16% of the variation of the forecast error of the other variables. The explanation for this is the strong economic situation of Poland.

The graphs below (Figure 4) show the representations of the evolution over the analyzed period of the net volatility spillover index for each of the four variables.The four charts highlight the fact that of the four variables, the largest spillover transmitter over time was S&P500 stock index and the biggest spillover receiver was the Romanian leu, but also the Hungarian forint.The three exchange rates are obviously higher spillover receivers in crisis periods (2007-2008 financial crises, COVID-19 pandemic).

Figure 4. Net volatilities spillover between exchange rates and S&P 500

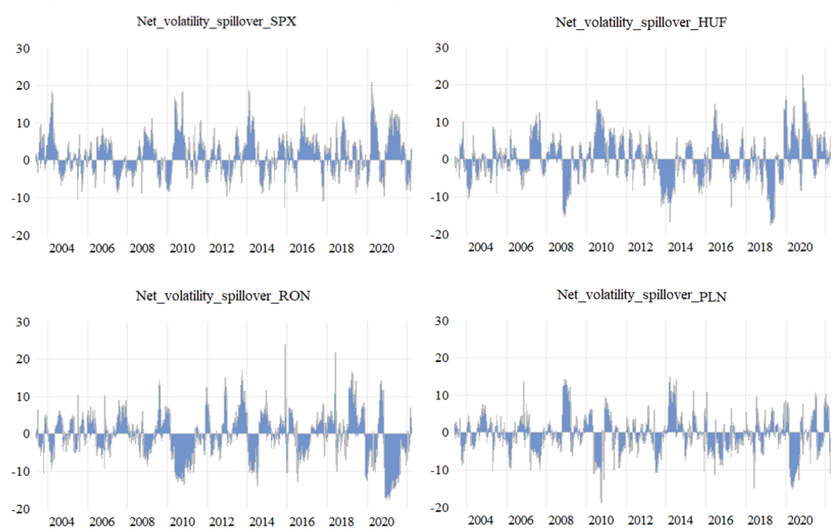
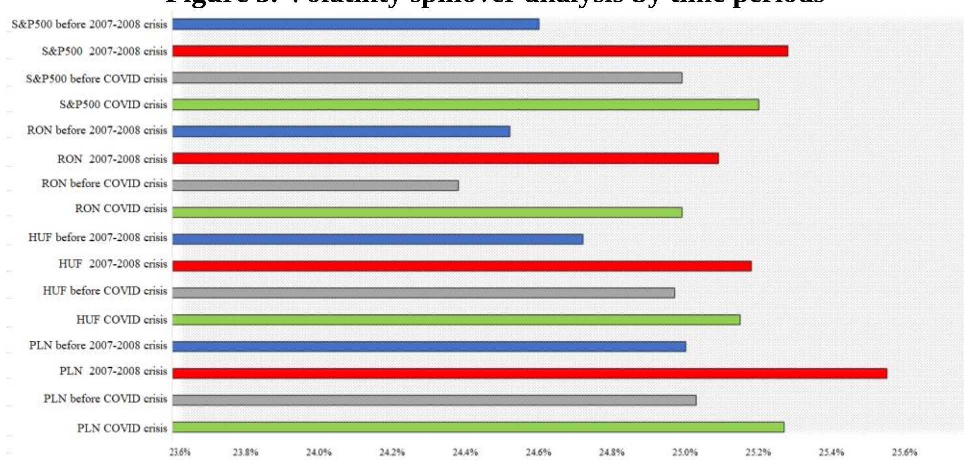


Figure 5 highlights what is also demonstrated in the studies of specialized authors. The fact that in times of crisis the spillover is the most pronounced, and of the two periods of crisis caught in this analyze, the financial crisis of 2007-2008 had the strongest impact on variables. As for the volatility spillover during the COVID-19 crisis, it can be stated that again there are high values in the table, but lower than in the case of the financial crisis of 2007-2008. Another aspect that is highlighted here is the fact that the total gross spillover index is lower than in the case of the financial crisis, which means that of all the four subperiods analyzed, during the 2007-2008 crisis the strongest spread of spillover occurred. volatility between the four variables analyzed.

Figure 5. Volatility spillover analysis by time periods



Source:Author's own research

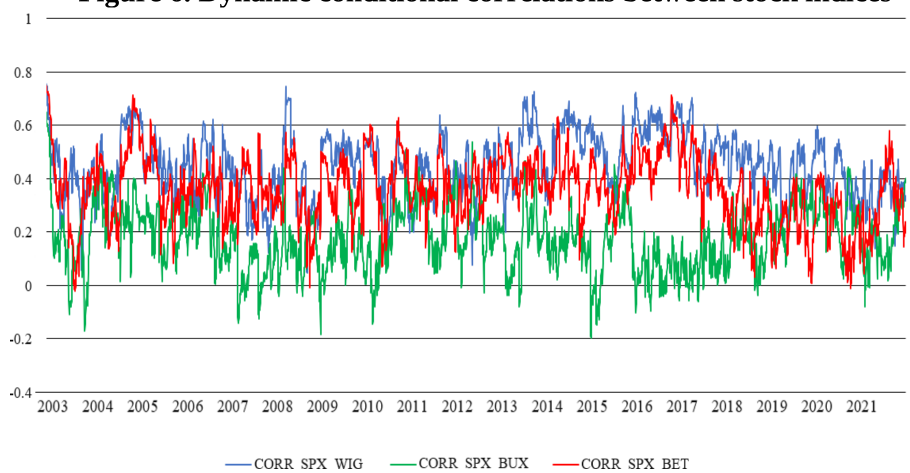
Effective policy actions implemented by monetary and economic authorities have helped to improve conditions on international financial markets. Unprecedented measures have also been implemented at European level. In financial terms, the European Commission adopted, in April 2020 and later in July 2020, two packages of measures on the regulatory and supervisory framework for the banking sector and capital markets to support the financing of the economy, the recapitalization of companies and investment.

They complement the exceptional measures taken by central banks to provide liquidity to the banking sectors, both through measures to reduce monetary policy interest rates and through quantitative easing measures.

Figure 6 shows the conditional correlations over time between S&P 500 index and BET, BUX and WIG20 stock indices. As can be seen, the closest correlation with S&P index is BET stock index, and the weakest is WIG20 index. Similar to the evolutions of the correlations studied in the first part between the exchange rates and S&P500 index, here too it is obvious the change of the correlation frequency in the periods of crisis and during significant economic events.

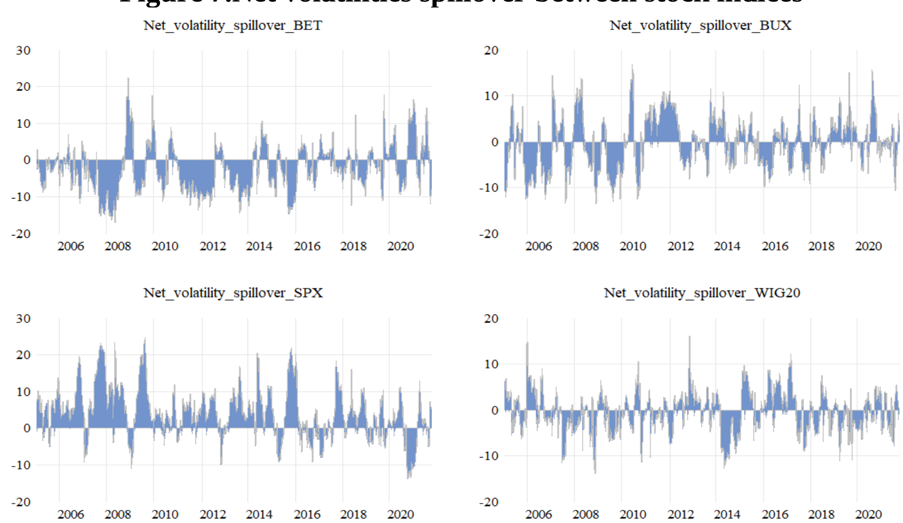
The biggest discrepancy is highlighted in 2014 and 2015, when after in mid-2014 the price of oil registered a sudden shock and this was felt in the increase of correlations between variables, 2015 had the effect of decreasing the correlations due to the increase of the economic situation in the entire European Union.

Figure 6. Dynamic conditional correlations between stock indices



Source:Author's own research

Figure 7.Net volatilities spillover between stock indices



Source:Author's own research

Regarding the net volatility spillover (figure 7), we observe a fluctuation of the asymmetry over the entire time horizon analyzed. All four stock indices are both net volatility receivers and transmitters. On the other hand, we can conclude that in periods of declining price indices, the spread of volatility increases. For example, in March 2020 S&P 500 index collapsed in the stock market, and this is reflected in the charts above by the fact that it was a net receiver of volatility. This result confirms the findings that volatility-conditioned spillovers between stock indices are asymmetric and bidirectional.

Another conclusion that can be drawn is that although Bucharest Stock Exchange is one of the most volatile in the region, the short-term movements of market indices are not chaotic, but follow exactly the evolution globally, especially the American market, which it makes it more predictable and reduces the risks to which investors who decide to invest in the structure of BET index are exposed.

An explanation for the close correlation of the Romanian Stock Exchange with the American one is the high degree of uncertainty regarding the evolution of the companies listed on Bucharest Stock Exchange, so investors prefer to take as a reference the global evolution, especially of the largest economy, the American one.

Conclusion

This study analyzes the spillover effect between EUR/RON, EUR/HUF and EUR/PLN exchange rates and S&P500 stock index, as well as the spillover between the capital markets of these three countries.

The high correlations of currencies with the stock market index were obviously observed in times of crisis, and also during major events it was observed that a currency that is depreciating is associated with a decrease in S&P500 index. The stock index has stronger correlations with EUR / PLN and EUR / HUF exchange rates than with EUR / RON currency pair. Both in the case of exchange rates and in the case of stock indices, their volatility is very persistent in shocks, past variations are dominant compared to current variations, and conditional correlations are variable over time.

In addition, the volatility of variables reacts intensely to market movements, and shocks need time to disappear. Another important aspect highlighted in the paper is the fact that bad news (negative shocks) generates a higher volatility of variables than good news. EUR/RON pair is the one that receives the lowest amount of spillover, and this fact is due to the interventions of the Romanian Central Bank to keep the exchange rate as stable as possible. Also, about this currency pair it was found that it does not influence the other exchange rates nor S&P500 index.

About BET index of Romania, it was highlighted that it has a strong connection with S&P500 index, BET having the highest correlation with S&P500 among the indices included in the analysis. A stronger spillover transmission was observed on the capital market than in the case of the foreign exchange market, and the influence of S&P is felt differently on the two financial markets, being a transmitter of spillover on the foreign exchange market, and on the capital market. spillover transmitter position, the transmitted values being significantly higher.

The close correlation between S&P and BET has led to another important conclusion, namely that although Bucharest Stock Exchange is one of the most volatile in the region, the short-term movements of market indices are not chaotic, but follow global developments, especially the US market, which makes it more predictable and reduces the risks to investors who decide to invest in the structure of BET index. The high spillover between the two indices is also due to the high degree of uncertainty regarding the evolution of the companies listed on BVB, so that investors prefer to take as a benchmark the global evolution, especially of the largest economy, the American one.

As highlighted in the analysis by time periods, all three countries included in the analysis managed to recover from the two major events that affected economies. The connections between the exchange rates, but also between the exchange rates and S&P500 decreased immediately after the financial crisis of 2007-2008 and after the economic-sanitary crisis caused by the COVID-19 pandemic.

A recommendation for future analysis of the spillover between exchange rate returns/ volatility and stock market indices can be represented by researching the impact of a period of geopolitical tensions. Specifically, this study can be extended by including in the analysis the period of the war between Russia and Ukraine, which began in the second half of March 2022. At the same time, such a study in the case of Romania could highlight the stability of the economy, taking into account the geographical location of this country, with two neighboring countries, one in open conflict (Ukraine) with one of the world's largest powers and one in of uncertain conflict (Republic of Moldova).

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