



MATTIA BEVILACQUA

**ASYMMETRIC VOLATILITY  
SPILLOVERS BETWEEN DEVELOPED  
AND DEVELOPING EUROPEAN  
COUNTRIES**

MNB WORKING PAPERS | 2

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MNB Working Papers 2018/2

**Asymmetric Volatility Spillovers between Developed and Developing European Countries**

(A részvénytársasági volatilitás asszimetrikus spillover hatásai fejlett és fejletlen pénzügyi piacokkal rendelkező uniós országokban)

Written by Mattia Bevilacqua \*

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\*Kent Business School, University of Kent, mb839@kent.ac.uk.

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# Abstract

This paper aims to examine the volatility spillovers among three asset classes, namely, equity, currency and credit among developed European countries and developing Central Eastern European countries in response to political, economic and financial events occurred in the Eurozone in the last decade. We use a different version of the Diebold-Yilmaz spillovers index in order to take into account the volatility asymmetry effect under both its leverage effect and, also, in relation to separated good or bad news. The first may be due to positive or negative shocks of identical size, whereas the latter may be due to good or bad news impacting separately. We find that the stock market is the main channel through which volatility spills over among these countries with a clear role as volatility transmitters for the developed EU stock markets. The volatility leverage effect is evident mainly for the equity market, while it emerges only after the Eurozone sovereign debt crisis for the credit market. The Brexit vote is found to be the main event contributing to volatility spillovers in the currency market with the British pound transmitting positive volatility to the system. The Italian CDS market is found to play a crucial role during the Eurozone sovereign debt crisis, while the German CDS market is found to be more stable and mainly transmitting positive volatility. The European Central Banks policies, such as, LTRO and QE result into a reduction of negative volatility spillovers and into an increase of positive volatility spillovers in the credit market. According to the considered asset classes and time period, we detect positive and negative volatility spillovers among the selected countries in Europe showing how different events might contribute to different, beneficial or harmful, reactions within the system.

**JEL:** C58, D53, F3, G15.

**Keywords:** Volatility Spillovers, Asymmetric Volatility, Stock Markets, Currency Market, Credit Markets.

## Összefoglaló

A papír azt vizsgálja, hogy az eurózána elmúlt egy évtizedében történt pénzpiaci vagy politikai történései milyen változást idéztek elő három eszközosztály árfolyamának a volatilitásában. A Diebold-Yilmaz index különböző verzióit használjuk arra, hogy számba vegyük a volatilitás aszimmetrikus természetét a tőkeáttétel illetve a kedvező/kedvezőtlen hírek tekintetében. Az előbbi azonos méret melletti pozitív és negatív sokkok hatását tükrözi, az utóbbi pedig a kedvező/kedvezőtlen hírekre való eltérő reakciót. Azt találjuk, hogy a részvénypiaci sokkok legfőbb közvetítője a pénzpiac a fejlett uniós országok esetében. A tőkeáttétel miatti volatilitás elsősorban a részvénypiacra jellemző és főként az európai szuverén adósságválságot követően jellemző. A Brexitet követően az angol font volatilitása az teljes pénzpiacon növelte a volatilitást. Az olasz CDS piac kitüntetett szerepet kapott a legutóbbi szuverén adósságválság során, míg a német CDS piac stabil maradt és inkább hűtötte a pénzpiacot. Az Európai Központi Bank nem-konvencionális politikái mint az LTRO vagy a QE csökkentette a negatív spillover hatásokat illetve pozitív spillover hatásokat generált a tőkepiacokon. A papírban vizsgált eszközosztályokra és időszakokra számos pozitív és negatív spillover hatást találunk, amely azt mutatja, hogy az egyes események különböző reakciókhoz vezethetnek az uniós országokban.

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# 1 Introduction

The study of volatility spillovers represents a topic that has always been of interest in the financial volatility literature. In light of the increase of the financial markets' uncertainty, integration and development in the European context in the last decade, the research about volatility spillovers in this area has been boosted. This paper focuses onto three asset classes' volatility, namely, equity, currency and credit markets in relation to two groups of countries. The first group includes developed European (EU) countries such as Germany, France, Italy and UK, while the other group includes developing countries in the Central and Eastern Europe (CEE) such as Poland, Hungary, Czech Republic and Slovakia also known as the Visegrad group. The literature about volatility spillovers between developed and developing countries is vast, but it has not fully covered, so far, the potential connectedness among these countries in response to the main recent events occurred in Eurozone in the last decade.

This paper represents a further step from Savva and Aslanidis (2010) who investigated the integration among CEE countries and also from Gjika and Horvath (2013) who focused on the same group of countries taking into account the potential asymmetry in the conditional variance and correlation dynamics. Following this path, we contribute to the existing literature merging these two intuitions together. We study the volatility spillovers asymmetry in conditional volatilities and, also, in realized volatilities among the developed EU and the developing CEE countries in response to events occurred in the Eurozone in the post global financial crisis. According to Baruník et al. (2016), there are events which impact more on the positive side of volatility, while some others impact more on the negative side. Thus, volatility spillovers can be classified, separately, as good or bad according to the perspective of the country we look at and according to the perspective of the asset class of interest.

Many studies about volatility spillovers in the stock market have conducted the analysis at the equity market returns level rather than at the volatility level (see Syriopoulos, 2004; Voronkova, 2004; Diebold and Yilmaz, 2009). However, according to Diebold and Yilmaz (2015), it is better to look at volatility spillovers, first, because volatility tracks investor fear and its connectedness provides an idea about the "fear connectedness" by market participants and, second, because volatility connectedness is of interest when studying economic, financial and political events which might potentially increase the level of countries' uncertainty. Furthermore, the high level of financial market volatility might have significant effect in increasing returns and in decreasing asset prices. It can lead to shock propagation and it can spread out risk averse investors and financial uncertainty especially across an integrated environment as the Euro area (see Horváth et al., 2017).

Thus, the choice of the developing CEE countries follows the researchers and policy-makers' interest in better diversification opportunities, attractive investments and deregulation (e.g. Fedorova and Saleem, 2010) as well as progress in liberalizing capital movements (e.g. Gelos and Sahay, 2001). An improvement in the understanding of the financial assets' volatility connectedness and integration among the selected countries is appealing both under a portfolio management and also under an asset allocation point of view. It might be also crucial for policy makers' decisions when credit or exchange rate volatilities are considered since they can potentially affect the stability of the financial system (see Savva and Aslanidis, 2010; Antonakakis, 2012). Additionally, CEE countries show one of the highest cycle correlation with the Eurozone that appears to be a specific financial integration for the European market rather than a world-wide phenomenon with different degrees of integration among countries (see Cappiello et al., 2006; Savva and Aslanidis, 2010; Reboredo et al., 2015).

*A look at the directional volatility network as of 31st August 2015 reveals that the European countries were the most important generators of volatility connectedness. Actually, European stock markets were generating connectedness towards each other more than the stock markets in other parts of the world. One can talk about the presence of a "European cluster". - Kamil Yilmaz.*

For the purpose of this paper, as definition of contagion, we rely on a mixture of two extracted from the literature<sup>1</sup>: contagion occurs when volatility of asset prices spills over from the crisis country to other countries (Pericoli and Sbracia, 2003) due to

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<sup>1</sup> An unique definition of contagion appears to miss in the financial literature. Forbes and Rigobon (2002) define contagion as a significant increase in cross-market links due to a shock happened in one country or asset. According to Bekaert and Harvey (2003), contagion is defined as a level of excess correlation, above what is expected from economic fundamentals. Exhaustive about contagion definition is Pericoli and Sbracia (2003) who

a significant increase in the asset linkages after a shock in one country asset (Forbes and Rigobon, 2002), where, in our case, shocks might be considered economic, financial and political events in the Eurozone with potential impact on the selected European financial markets.

The aims of this paper are threefold. First, it aims to detect the main channels through which the volatility spills over from the developed EU to developing CEE countries and, vice versa, assessing the following - *Which are the principal volatility channels and assets contributing to volatility spillovers between the developed EU countries and CEE countries?* Indeed, more recent studies found evidence of volatility spillovers in the exchange rates market among different currencies and by using different methodology for measuring their volatilities (see Pérez-Rodríguez, 2006; Fedorova and Saleem, 2010; Kitamura, 2010; McMillan and Speight, 2010; Bubák et al., 2011; Antonakakis, 2012). In recent years and, especially, in response to the Eurozone sovereign debt crisis, the study of credit volatility spillovers has also improved (Ehrmann et al., 2011; Calani et al., 2012; Caporin et al., 2013).

Moreover, it is clearly assessed in the literature how an increase in dynamic correlations is commonly found during crisis period (see Bekaert et al., 2014; Horváth et al., 2017) with decreasing diversification opportunities (see Gjika and Horvath, 2013; Reboredo et al., 2015). How this connectedness behaves during other circumstances such as in response to other events post-crisis has not been fully uncovered yet. Only recently, how volatility spillovers are influenced by financial, economic and political events has been started to be explored (see Belke et al., 2016; Baker et al., 2016b; Kelly et al., 2016; Gamba-Santamaria et al., 2017). Focusing on the post global financial crisis period and covering some of the main events contributing to increase in volatility in the Eurozone (e.g. sovereign debt crisis, Grexit and Brexit), this paper aims to detect whether or not volatility spillovers have been generating from those (e.g. Baker et al., 2016a). More specifically, the main focus of the paper is on the asymmetric effect that news and events might inject on the assets' volatility spillovers among the selected European countries. This is checked by applying a different version of the Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) spillovers index in which we input either conditional volatilities inferred from GARCH family models or model-free decomposed realized volatility measures as in Barndorff-Nielsen et al. (2010).<sup>2</sup>

Indeed, while the conditional volatilities inferred from GARCH models provide an idea about the volatility spillovers leverage effect, the decomposed realized volatility measures are considered in order to take into account the asymmetric volatility characteristics and separating the role of positive and negative volatilities in the spirit of Baruník et al. (2015); Baruník et al. (2016); Baruník et al. (2017). *How do volatility and, consequently, volatility spillovers react in response to good or bad news and events either of the same size or by turns?* - is asked both for the total volatility spillovers indexes analysis and also for the net directional spillovers indexes. With regards to the realized volatility measures, we define  $RV^+$  the positive realized volatility computed from assets' returns higher than zero, while  $RV^-$  the negative realized volatility computed from assets' returns lower than zero. This parallel - positive and negative - analysis is undertaken also for answering the previous questions in this paper and it allows us to compute also a spillovers asymmetry measure (SAM) computed as the difference between positive and negative spillovers indexes, namely  $SI^+$  and  $SI^-$ , both for the total and also for the net directional measures. The volatility asymmetric effect in spillovers has also been studied for currencies (e.g. Wang and Yang, 2009; Clements et al., 2015; Baruník et al., 2017), while, to the best of our knowledge, this is the first time that the CDS market' asymmetric volatility spillovers in response to different events is investigated.

According to Diebold and Yilmaz (2015), in some cases, volatility as a synonym or risk should not be avoided if we see it as a source of higher returns. There might be some events, in relation to the selected countries and assets, which can be considered harmful since increasing the "bad" volatility and some that can be considered beneficial since increasing the "good" volatility (e.g. Segal et al., 2015). The first might be due to decrease in economic growth, equity market value, increase in uncertainty and negative news; the latter might be due to positive specific or macroeconomic news, economic booms or end of recession periods (see Baruník et al., 2016; Feunou et al., 2017).

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provided five main definition of contagion. Mainly three of them are in line with the definition we adopt in this paper. First, contagion occurs when the volatility of asset prices spills over from the crisis country to other countries. Another definition stated that contagion is a significant increase in comovements of prices across markets, conditional on a crisis occurring in one market or group of markets. Lastly, they define *shift-contagion* as when the transmission channel intensifies or changes after a shock in one market.

<sup>2</sup> In recent studies, rather than multivariate GARCH models, the main methodology in order to study volatility spillovers or connectedness relies on Diebold and Yilmaz (2009); Diebold and Yilmaz (2012). They propose a spillovers index based on forecast error variance decomposition. The second version of the index manages to capture also the volatility spillovers directions since the variables are ordering invariant.

Another general trend in the volatility spillovers literature is that, most of the time, an unilateral volatility spillovers effect from main and mature financial markets to the emerging markets is found, while small markets do not affect bigger markets significantly (see Scheicher, 2001; Bhar and Nikolova, 2009; Moon and Yu, 2010; Le, Kakinaka, et al., 2010; Beirne et al., 2013). By considering the net directional spillovers indexes, we are able to check which are the countries which can be labeled as net positive or as net negative volatility transmitters or, conversely, receivers by answering the following - *Which are the net volatility transmitters and the net volatility receivers countries and between which of them is this link stronger?*

Main results of the paper show that, for the static analysis, the developed EU stock market indexes emerge as net volatility spillovers transmitters, while the CEE stock market indexes as net volatility spillovers receivers. In the dynamic framework, we find evidence of volatility spillovers asymmetry in the stock market, especially in relation to the events post sovereign debt crisis period with the  $RV^-$  dominating the  $RV^+$  generating a negative SAM. Brexit is found to be the main event contributing at the volatility spillovers increase and transmission within the currency market due to the depreciation of the British pound. The asymmetric volatility effect in the spillovers indexes emerges clearly for the equity and currency markets, while it intensifies only after the sovereign debt crisis for the credit market. Considering the realized volatility measures, we find that the spillovers index due to  $RV^-$  prevails the one due to  $RV^+$  in the stock market. The huge spike in the currency volatility spillovers index due to Brexit is caused by  $RV^+$  which is transmitted from the British pound to the system resulting in an appreciation for the other currencies against the euro. In the credit market, the sovereign debt crisis is found as the main event generating volatility spillovers with a key role played by the Italian CDS in transmitting negative volatility, while by German and French CDS in transmitting positive volatility. The presence of asymmetric effect strengthened due to the European Central Bank (ECB)'s LTRO programme and it was mainly due to an increase in positive and a decrease in negative volatility spillovers.

The remainder of this paper is organized as follows. Section 2 reports the literature about contagion and volatility spillovers and new trends in the volatility literature. Section 3 describes the methodology adopted in this paper. Section 4 illustrates the data and the descriptive statistics. Section 5 reports the static volatility spillovers analysis. Section 6 shows the dynamic volatility spillovers indexes analysis. Section 7 presents the results for the dynamic analysis with regards to the decomposed realized volatility measures whilst Section 8 concludes the paper.

## 2 Volatility Spillovers Overview

In this Section 2, we go through the literature about volatility spillovers in the stock market (Section 2.1), in relation to other assets (Section 2.2) and, lastly, about volatility spillovers asymmetry (Section 2.3). The events have been taken place in the Eurozone might, indeed, be seen as good or bad news according to the perspective of the country we look at and according to the asset class of interest.

### 2.1 STOCK MARKET VOLATILITY SPILLOVERS

In this Section, we focus on some of the studies about volatility spillovers in the stock market. With regards to the European countries selection, for instance, Savva and Aslanidis (2010) found that the integration between Eastern European countries and Eurozone has increased following the accession to EU with stronger evidence for Czech and Polish markets which are more correlated to the Eurozone than to the U.S. Syllignakis and Kouretas (2011) found an increase in the conditional correlation coefficients among countries as Germany, U.S. and Russia together with CEE countries due to and after the financial crisis. Reason why the study of these developing CEE countries next to the developed European countries deserves further analysis, especially when a more recent market time period is taken into account.

An increase in dynamic correlations is commonly found during crisis period (see Bekaert et al., 2014; Horváth et al., 2017). Gjika and Horvath (2013) applying a asymmetric DCC model, found that conditional variances and correlations increase during volatile periods and crisis in the central European stock market, decreasing diversification opportunities. This is also confirmed by Reboredo et al. (2015) examining more specifically the co-integration among the CEE stock markets themselves using dynamic copulas. While these studies have found that stock market co-movements intensified during the financial crisis, how this linkage behaves during other circumstances has not been completely uncovered.

Another general trend in the volatility spillovers literature is that, most of the time, an unilateral volatility spillovers effect from mature financial markets to the emerging markets is found, while small markets do not affect bigger markets significantly. Scheicher (2001) found that the emerging CEE stock markets are influenced by Central European and developed financial markets, but there is also a regional and local integration among the CEE countries. Bhar and Nikolova (2009) found, using a bivariate EGARCH model, that India has the highest level of integration within the BRIC countries with a negative relation with Asia-Pacific region countries opening up to portfolio diversification opportunities. Beirne et al. (2013) analysed volatility spillovers among a threefold groups of equity markets covering mature, regional emerging and local emerging countries applying a tri-variate GARCH-BEKK finding that volatility spills over, mostly, from mature markets to local emerging markets. Using a two stages GARCH-M models, Moon and Yu (2010) detected volatility spillovers from the U.S. S&P 500 to the Chinese Shanghai Stock Exchange index. On the same line, Le, Kakinaka, et al. (2010) found volatility spillovers effects from the U.S. and China to emerging markets as Indonesia and Malaysia. Using VARGARCH(1,1)-in-mean model, Caporale and Spagnolo (2011) found that volatility spillovers from Russia and UK impact on CEE countries stock market volatilities, but there is no linkage in the opposite way.

Rather than multivariate GARCH models, recently, the main methodology in order to study volatility spillovers or connectedness relies on Diebold and Yilmaz (2009); Diebold and Yilmaz (2012). They propose a spillovers index based on forecast error variance decomposition. The second version of the index manages to capture also the volatility spillovers directions since the variables are ordering invariant. By applying this methodology, for instance, Zhou et al. (2012) measured the directional volatility spillovers between the Chinese and world equity markets finding that the U.S. market shown a prevalent volatility impact on other markets during the sub-prime crisis, while the Chinese stock market volatility had an impact on other Asian markets since 2005. More recently, Gamba-Santamaria et al. (2017) improved the Diebold and Yilmaz (2012) spillovers index in the volatility factor measured through a DCC-GARCH model in order to better allow for a time varying asset pricing correlations and also for a better volatility clustering representation. By applying this methodology to the Latin American stock market they found Brazil as a net volatility transmitter, while Chile, Colombia and Mexico as net receivers.

## 2.2 OTHER ASSETS' VOLATILITY SPILLOVERS

Many studies on volatility spillovers have focused only on equity market without considering other important financial markets as foreign exchange and credit market (e.g. Soriano and Climent, 2006). The literature on the currency market volatility integration has probably started from the seminal paper by Ito et al. (1992) finding how news from adjacent regions (meteor shower) is to be preferred to local influences from the previous day (heatwave) as an explanation of the transmission of volatility in the foreign exchange market.

More recent studies as Pérez-Rodríguez (2006) used a DCC-GARCH finding a strong presence of volatility spillovers between Euro and Pound against U.S. dollar after the Euro introduction. Using a GARCH-BEKK model, Fedorova and Saleem (2010) focused on the volatility interdependence between emerging CEE countries and Russian stock market and currencies finding the presence of unilateral volatility spillovers from the latter to the stock market for Poland, Hungary and Russia. Kitamura (2010), applying a varying-coefficient MGARCH model, examined the intra-day volatility spillovers among the euro, the British pound and the Swiss franc finding that there is a volatility spillover transmitted from the euro to the other two currencies. McMillan and Speight (2010), using a realized variance method, found that the dollar rate dominates the Japanese Yen and the British pound in terms of volatility spillovers. Bubák et al. (2011) found presence of volatility spillovers among central European exchange rates increasing with market uncertainty in the central European currency market using model-free volatility measures. Antonakakis (2012) found that U.S. dollar's appreciation plays a crucial role for volatility spillovers.

In the recent years and, especially, in response to the sovereign debt crisis in Europe, the studies about volatility propagation among countries have been rapidly moved towards the study of credit volatility spillovers. Hunter and Simon (2005) affirmed how the correlations between bond market returns are driven by macroeconomic and financial market events and Ehrmann et al. (2011) showed how the European Monetary Union has led to substantial convergence in the Eurozone sovereign bond markets. These studies use, mainly, CDS spread market in order to tackle this analysis<sup>3</sup>. For instance, Caporin et al. (2013) measured the sovereign risk contagion through CDS and bond spreads of selected countries in Europe. CDS contagion has been quite constant for the 2008-2011 period while bond spreads contagion increase in intensity from the pre and post crisis periods.

More recently, many studies have looked at volatility contagion by relying on the Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) spillovers index methodology. More specifically, Calani et al. (2012) investigated the relation between credit spread in sovereign debt and CDS spread concluding that there is no evidence of contagion during the first and second quarter of 2012 with a clear separation between two groups of countries: the first in which CDS spreads affect bond yield in a positive way, and the second in which the bond yields are independent to variation in CDS spreads (safe-havens). Evidence of a CDS volatility contagion from troubled countries on CDS on sovereign debt of not-troubled countries is also found. Alter and Beyer (2014) by extending the Diebold and Yilmaz (2012) methodology, measured spillovers between sovereign credit markets during the sovereign debt crisis between October 2009 and July 2012 in the euro area finding systemic effect among sovereigns and banks due to an unexpected shock to the creditworthiness of one of the two. Claeys and Vašíček (2014) found significant spillovers between EMU countries during the financial crisis by using a factor-augmented version of the Diebold and Yilmaz (2009) VAR model (FAVAR). Antonakakis and Vergos (2013) related the sovereign bond yield spread spillovers with the presence of news announcement and policy changes finding a strong spillovers effect from the periphery to the core of the Euro area especially in turbulent periods. Adam et al. (2013) focused on the sovereign credit default swaps (SCDS) spillovers with regards to developed and emerging economies during the recent sovereign debt crisis finding, for instance, that there is a significant time variation in spillovers and there is a strong commonality between global credit spreads. Lastly, Louzis (2012) studied the volatility spillovers among the money, stock, foreign exchange and bond markets in Euro-area between 2000 and 2012 finding that, on average, more than 50% of the forecast-error variance is explained by spillover effects with the stock market being the main volatility spillovers transmitter.

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<sup>3</sup> Using CDS spread allows us to directly interpret it as a default probability measure or premia impacting on the fixed income credit spread in relation to a sovereign risk-free asset mirroring, in our case, the selected country counterparty risk (see Calani et al., 2012). The advantage of using CDS spread data over bond spread is assessed also by Caporin et al. (2013). It is directly observable in the market while computing the bond spread might be subjective to the researcher. CDS capture the sovereign risk and therefore enable a more straightforward analysis while bond spreads might be conditioned to other factors as monetary policy and central bank and policymakers decisions.

## 2.3 VOLATILITY ASYMMETRY AND RESPONSE TO GOOD OR BAD NEWS

A recent stand of literature has seen some other extensions of the Diebold and Yilmaz (2009); Diebold and Yilmaz (2012) spillovers index which have been proposed in the literature in order to take into account the volatility asymmetry. For instance, Baruník et al. (2015); Baruník et al. (2016); Baruník et al. (2017) proposed an asymmetric version of the spillovers index computing the volatility series through the decomposed realized measure as in Barndorff-Nielsen et al. (2010). Thus, we anchor our paper in this new volatility spillovers branch of literature which takes into account the asymmetric volatility characteristics and the separate role of positive and negative volatilities. At the same time, other studies have started to look at the transmission of volatility spillovers among different assets and among different countries when news and macroeconomic announcements (e.g. Belgacem et al., 2015) or financial, economic and political events occur (e.g. Belke et al., 2016).

However, given that volatility spillovers respond in a different way to such events, these can be classified, separately, as good or bad. For instance, according to Baruník et al. (2016), there are events which impact more on the positive side of volatility, while some others impact more on the negative side. We look, according to Clements et al. (2015), at asymmetric transmission of volatility that can be either established as a leverage effect, when there is an asymmetric impact on assets' volatility due to positive or negative shocks or news of identical size, or that can be established as asymmetric volatility spillovers caused by good or bad news separately. There are two predominant theories on the first asymmetric volatility effect. The first one is the leverage effect by Black (1976) stating that after a decrease in an asset value, the leverage ratio of a firm holding that asset increases and so its volatility. Thus, negative news and shocks may have larger impacts on volatility compared to positive shocks of the same absolute value. An alternative theory, called volatility feedback (see Campbell and Hentschel, 1992), asserts that news that volatility will be higher in the future will induce risk-averse investors to sell positions today until they are compensated for that increase. Financial markets decrease in advance in order to already discount future volatility increases. However, after a negative return shock and an increase in volatility the increase in expected return will generate even more volatility (feedback). The first volatility feature is studied and incorporated in the spillovers indexes by computing GARCH models' conditional volatilities, while the second effect, depending on whether the volatility is due to good news or bad news, is captured by inputting the decomposed, positive and negative, realized volatility into the spillovers indexes as in Baruník et al. (2015); Baruník et al. (2016); Baruník et al. (2017).

The volatility asymmetric effect in spillovers has also been studied for the currency market (see Wang and Yang, 2009; Clements et al., 2015; Baruník et al., 2017), while, to the best of our knowledge, this is the first time that the CDS market' asymmetric volatility spillovers computed from the decomposed positive and negative volatility is investigated in the financial literature.

# 3 Volatilities and Spillovers Index Methodology

The methodology we use in this paper consists in computing the selected countries assets' conditional volatilities and the 23-day annualized model-free realized volatility series. The first are inferred from univariate GARCH models, such as, GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1)<sup>4</sup>. The last two models allow us to investigate the presence of volatility asymmetry and leverage effect. The second volatility series are computed model-free as in Barndorff-Nielsen (2002) and, then, decomposed into positive and negative components for taking into account the asymmetric effect as in Barndorff-Nielsen et al. (2010) (see Section 3.1). Both these volatility measures are, then, input in the Diebold and Yilmaz (2012) spillovers index as explained in Section 3.2.

We contribute to the existing volatility spillovers literature by replacing the standard methodology used in the original Diebold and Yilmaz (2012) spillovers index with the aim of taking into account the presence of two asymmetric effects in our financial assets' volatilities<sup>5</sup>. The first effect we want to check is whether or not conditional volatilities of such assets are sensitive to the sign of past innovations such as volatility increases more after a negative shock than after a positive shock of the same magnitude. The second is looking to how realized volatilities react to good or bad news in a separate framework. This allow us to link this study to a new and recent trend in the financial literature considering the asymmetrical behaviour of volatility in response to good or bad news and events.

## 3.1 REALIZED VOLATILITIES COMPUTATION AND DECOMPOSITION

In this Section, we present the model-free approach we use in order to compute the realized volatilities for all the EU countries' assets. Realized volatilities have been widely used in the financial literature (see Andersen and Bollerslev, 1998; Andersen et al., 2002; Barndorff-Nielsen, 2002; McAleer and Medeiros, 2008; Bennet and Gil, 2012). Nonparametric realized measures are, sometimes, considered as the most common way for looking at volatilities characteristics rather than using complicated volatility models (see Figlewski, 1997; Andersen and Bollerslev, 1998). We decide, for the purpose of this paper, to use daily annualized 23-days realized volatility measures from daily log-returns as in Barndorff-Nielsen (2002)<sup>6</sup>:

$$RV_{t,k} = \sqrt{\frac{252}{n} \sum_{i=1}^n (r_i)^2} \quad (1)$$

Where,  $r_i = \ln\left(\frac{P_t}{P_{t-1}}\right)$  are the daily stock index, CDS spread and currency returns computed from their difference in prices,  $k$  is indexed for EU countries according to the considered market. The volatility series we obtain for stock, currency and credit

<sup>4</sup> The volatility models we select are GARCH(1,1), EGARCH(1,1), GARCH-GJR(1,1) as the most common used in the empirical volatility literature. Moreover, according to Gjika and Horvath (2013), central European stock markets exhibit asymmetry in the conditional variances, but the asymmetry in the conditional correlations is less frequent. These results point to an importance of applying appropriately flexible modelling framework to assess the stock market co-movements accurately. That is why we decide to apply univariate GARCH model taking into account leverage effect in the conditional volatilities rather than models as ADCC (see Cappiello et al. (2006)) looking at asymmetry in conditional correlation.

<sup>5</sup> The volatility in Diebold and Yilmaz (2012) is computed using daily high and low assets' prices following Parkinson (1980) methodology: for the asset  $i$  on day  $t$  the daily variance is:  $\tilde{\sigma}_{it}^2 = 0.361[\ln(P_{it}^{max}) - \ln(P_{it}^{min})]^2$  where  $P_{it}^{max}$  is the high price on day  $t$  and  $P_{it}^{min}$  is the daily low price. The corresponding annualized daily percent volatility is  $\tilde{\sigma}_{it} = 100 \sqrt{365 \times \tilde{\sigma}_{it}^2}$ .

<sup>6</sup> However we are aware of the different volatility measures in the financial literature. For instance, high to low version by Parkinson (1980), the Garman-Klass formula (Garman and Klass (1980)) and its improvement by Yang and Zhang (2000) taking into account also opening price jumps and zero drifts.

market is directly comparable with the conditional volatilities obtained through GARCH models. Nonetheless, this model-free approach allows us to decompose the volatility measure into positive and negative components anchoring this paper in a growing strand of literature (see Ang et al., 2006; Barndorff-Nielsen et al., 2010; Patton and Sheppard, 2015). We are able, in this way, to take into account the asymmetric role that good and bad news play in influencing volatility series and, thus, volatility spillovers. Starting from formula (1), we decompose the realized volatility following Barndorff-Nielsen et al. (2010) in which the positive volatility measure considers only returns higher than 0, vice versa the negative volatility measure considers only returns lower or equal to 0:

$$RV_{t,k}^+ = \sqrt{\frac{252}{n} \sum_{i=1}^n (r_i)^2} \quad \text{if } 1_r(r_i) > 0 \tag{2}$$

$$RV_{t,k}^- = \sqrt{\frac{252}{n} \sum_{i=1}^n (r_i)^2} \quad \text{if } 1_r(r_i) \leq 0 \tag{3}$$

where  $1_r$  is the indicator function which is equal to 1 when the argument is true,  $r_i = \ln(\frac{P_t}{P_{t-1}})$  and  $P_i$  are stock index, CDS and currency daily prices with  $i$  going from time 1 to time  $n$  and  $k$  indexes one of the eight assets (stock indexes or CDS spreads) or five currencies.

### 3.2 VOLATILITY SPILLOVERS INDEX

In this section we present the methodology applied in this paper, namely, the Diebold and Yilmaz (2012) spillovers index. Previously, Diebold and Yilmaz (2009) proposed a simple methodology able to measure volatility linkages through forecast error variance decomposition from vector autoregressive (VAR) models (Sims, 1980). They further improved this index in Diebold and Yilmaz (2012) to take into account both total and directional spillovers. In this study we exactly need a more dynamic and flexible measure of volatility spillovers as the most recent methodology in Diebold and Yilmaz (2012) in a rolling window framework. This methodology allows us to obtain a dynamic connectedness measures not only with regards to the total volatility connectedness in the system, but also with regards to the contributions of each selected country’s asset to the others, from the others, net spillovers and pairwise net volatility linkages. We describe the Diebold and Yilmaz (2012) index following their notation. By using a generalized variance decomposition approach of Koop et al. (1996) and Pesaran and Shin (1998) we can understand also the direction of volatility spillovers across our countries assets since it is invariant to the ordering of variables<sup>7</sup>. First of all, a covariance stationary  $N$ -variable VAR ( $p$ ) is the following:

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t \tag{4}$$

where  $\varepsilon \sim (0, \Sigma)$  is an i.i.d vector of disturbances and  $x_t = (x_{1,t}, x_{2,t}, \dots, x_{p,t})$  with  $x$  that is a vector of volatilities and  $\Phi$  a  $N \times N$  matrix. A moving average (MA) representation is needed in order to employ the variance decomposition forecast error:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{5}$$

where the  $N \times N$  coefficient matrices  $A_i$  are expressed as:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p} \tag{6}$$

with  $A_0$  is a  $N \times N$  identity matrix and with  $A_i = 0$  for  $i < 0$ <sup>8</sup>.

Diebold and Yilmaz (2012) define the own variance shares as the fraction of the  $H$ -step-ahead error variances in forecasting  $x_i$  that are due to shocks to  $x_i$ , for  $i = 1, 2, \dots, N$  and, instead, they define spillovers as the fractions of the  $H$ -step-ahead error

<sup>7</sup> The limit of the Diebold and Yilmaz (2009) index is that it relies on Cholesky-factor identification of VAR model depending on variable ordering.

<sup>8</sup> The MA representation of the VAR in Diebold and Yilmaz (2009) is the following:  $x_t = \Theta(L)\varepsilon_t$  with  $\Theta(L) = (I - \Theta L)^{-1}$ . Rearranging we get:  $x_t = A(L)u_t$  where  $A(L) = \Theta(L)Q_t^{-1}$ ,  $u_t = Q_t \varepsilon_t$ ,  $E(u_t u_t') = I$  and  $Q_t^{-1}$  is the unique lower triangular Cholesky factor of the covariance matrix of  $\varepsilon_t$ .

variances in forecasting  $x_i$  that are due to shocks to  $x_j$ , for  $i, j = 1, 2, \dots, N$  and  $i \neq j$ . They denote KPPS the variance decomposition methodology of Koop et al. (1996) and Pesaran and Shin (1998). We keep this notation as well from now on. The KPPS H-step-ahead forecast error variance decomposition is denoted by  $\Theta_{ij}^g(H)$  for  $H = 1, 2, \dots, N$  and is equal to:

$$\Theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (7)$$

where  $\Sigma$  is the variance matrix for the error vector  $\varepsilon$ ,  $\sigma_{jj}$  is the standard deviation of the error term for the  $j$ th equation and  $e_i$  is the selection vector. They are the  $N \times (N - 1)$  forecast error variance decomposition in the  $N \times (N - 1)$  off-diagonal matrix entries in the upper-left matrix block. The total spillovers in this framework is simply given by the sum of these contributions which is, then, converted in the spillovers index (SI) in order to weight the total spillovers on the total forecast error variation<sup>9</sup>:

$$\widetilde{\Theta}_{ij}^g(H) = \frac{\Theta_{ij}^g(H)}{\sum_{j=1}^N \Theta_{ij}^g(H)} \quad (8)$$

By construction,  $\sum_{j=1}^N \widetilde{\Theta}_{ij}^g(H) = 1$  and  $\sum_{i,j=1}^N \widetilde{\Theta}_{ij}^g(H) = N$ . The total spillovers index (SI) is given as:

$$S^g(H) = \frac{\sum_{i,j=1 \neq j}^N \widetilde{\Theta}_{ij}^g(H)}{\sum_{i,j=1}^N \widetilde{\Theta}_{ij}^g(H)} \times 100 = \frac{\sum_{i,j=1 \neq j}^N \widetilde{\Theta}_{ij}^g(H)}{N} \times 100 \quad (9)$$

It measures the contribution of spillovers of volatility shocks across our assets over the total forecast error variance, thus measuring how much each asset contributes to the overall volatility spillovers in the considered system.

The Diebold and Yilmaz (2012) version of the index allows us to also measure the direction of volatility spillovers across assets and countries, detecting the net volatility *transmitters* when the volatility spillovers are transmitted by market  $i$  to all the others  $j$  and the net volatility *receivers* when the volatility spillovers are received by market  $i$  from all the other markets  $j$ . The directional volatility spillovers transmitted by market  $i$  TO all other markets  $j$  is:

$$S_{TO}^g(H) = \frac{\sum_{j=1 \neq j}^N \widetilde{\Theta}_{ji}^g(H)}{\sum_{i,j=1}^N \widetilde{\Theta}_{ji}^g(H)} \times 100 = \frac{\sum_{j=1 \neq j}^N \widetilde{\Theta}_{ji}^g(H)}{N} \times 100 \quad (10)$$

The directional volatility spillovers received by market  $i$  FROM all the other markets  $j$  is:

$$S_{FROM}^g(H) = \frac{\sum_{j=1 \neq i}^N \widetilde{\Theta}_{ij}^g(H)}{\sum_{i,j=1}^N \widetilde{\Theta}_{ij}^g(H)} \times 100 = \frac{\sum_{j=1 \neq i}^N \widetilde{\Theta}_{ij}^g(H)}{N} \times 100 \quad (11)$$

We can, now, compute the NET volatility spillovers from market  $i$  to all markets  $j$  that is equal to measure how much a specific single country's asset contributes for volatility spillovers to all the other markets. It is, basically, the difference between (10) and (11) as follow:

$$S_{NET}^g(H) = S_{TO}^g(H) - S_{FROM}^g(H) \quad (12)$$

What we are also interested is the net pairwise volatility spillovers defined as the difference between the gross volatility shocks transmitted from market  $i$  TO market  $j$  and these transmitted FROM  $j$  to  $i$  (or received) as:

$$S_{ij}^g(H) = \left( \frac{\widetilde{\Theta}_{ji}^g(H)}{\sum_{i,k=1}^N \widetilde{\Theta}_{ik}^g(H)} - \frac{\widetilde{\Theta}_{ij}^g(H)}{\sum_{j,k=1}^N \widetilde{\Theta}_{jk}^g(H)} \right) \times 100 = \left( \frac{\widetilde{\Theta}_{ji}^g(H) - \widetilde{\Theta}_{ij}^g(H)}{N} \right) \times 100 \quad (13)$$

Finally, in order to bring all these indexes in a dynamic framework, a 100 days rolling window has been performed tracking the behaviour of the spillovers indexes projected on our considered time period.

Lastly, this paper contributes to a better monitoring of the asymmetric volatility behaviour in relation to good and bad news and events separately by inputting the decomposed realized volatilities in our index and by computing spillovers asymmetry

<sup>9</sup> This is done since the sum of the elements in each row of the variance decomposition table is not equal to 1; thus each entry of this matrix has to be normalized by the row sum.

measure (SAM). Following Barunik et al. (2016) and Baruník et al. (2017), SAM measures the difference between the positive spillovers index ( $SI^+$ ) based only on positive realized volatility:

$$[S^g(H)]^+ = \frac{\sum_{i,j=1 \neq j}^N [\widehat{\Theta}_{ij}^g(H)]^+}{\sum_{i,j=1}^N [\widehat{\Theta}_{ij}^g(H)]^+} \times 100 = \frac{\sum_{i,j=1 \neq j}^N [\widehat{\Theta}_{ij}^g(H)]^+}{N} \times 100 \quad (14)$$

and the negative volatility spillovers index ( $SI^-$ ) based only on negative volatility:

$$[S^g(H)]^- = \frac{\sum_{i,j=1 \neq j}^N [\widehat{\Theta}_{ij}^g(H)]^-}{\sum_{i,j=1}^N [\widehat{\Theta}_{ij}^g(H)]^-} \times 100 = \frac{\sum_{i,j=1 \neq j}^N [\widehat{\Theta}_{ij}^g(H)]^-}{N} \times 100 \quad (15)$$

In a more compact notation we have:

$$SAM = SI^+ - SI^- \quad (16)$$

When the spillovers asymmetry measure is positive, it means that the volatility spillovers coming from  $RV^+$  are larger than the volatility spillovers coming from  $RV^-$ ; when SAM is negative the opposite is true. Moreover, having computed and decomposed the realized volatility series allows us to compute also the positive and negative directional spillovers asymmetric measure for each asset as:

$$SAM_{TO} = SI_{TO}^+ - SI_{TO}^- \quad (17)$$

for the directional spillovers from asset  $i$  TO all the assets in the system, where  $SI_{TO}^+$  is computed by considering only  $RV^+$ , while  $SI_{TO}^-$  by considering only  $RV^-$  in formula 10 and we get:

$$SAM_{FROM} = SI_{FROM}^+ - SI_{FROM}^- \quad (18)$$

for the directional spillovers received FROM asset  $i$  by the system, where  $SI_{FROM}^+$  is computed by considering only  $RV^+$ , while  $SI_{FROM}^-$  by considering only  $RV^-$  in formula 11. We, then, compute the positive and negative directional NET as the difference between positive and negative TO and between positive and negative FROM in order to shed light to the nature and sign of the transmitted or received volatility in the system:

$$NET^j = TO^j - FROM^j \quad j = TOT, +, - \quad (19)$$

## 4 Data and Assets Volatility Measures

This Section describes the data for the selected EU countries together with the descriptive statistics in relation to the conditional and realized volatility measures. Daily market data for each of the selected asset class for Germany, France, Italy and UK among the developed EU countries and for Poland, Czech Republic, Hungary, Slovakia among the developing Central Eastern Europe (CEE) countries are collected for the period spanning from 01-08-2008 to 30-06-2017<sup>10</sup>. For the equity market, eight nominal currency (expressed in the national currency) stock market indexes (see Diebold and Yilmaz, 2009), namely, DAX, CAC40, FTSEMIB and FTSE100, WIG20, PX, BUX and SAX are collected from Bloomberg. For the currency market, daily exchange rates euro based for British Pound, Polish Zloty, Czech Crown, Hungarian Forint and U.S. dollar are collected from Bloomberg. We control for the latter currency, U.S. dollar, given its important role on the ECB monetary policy which can be transmitted, in turn, on the other currencies. For the credit market, daily USD-denominated 5-year (tenor and senior debt type) sovereign CDS spreads for the eight EU countries are collected from both Bloomberg and Datastream. The considered time period is long enough to capture any volatility spillovers tendencies among the Eurozone and the CEE financial markets and it allows us to avoid bias and noise due to the euro introduction, 2004's EU enlargement and 2008 financial crisis period. This paper focuses, indeed, more on the volatility spillovers generated due to the recent economic, political and financial events which have been taken place in an already enlarged and integrated European Union.

Returns are calculated as daily, end of the day, log price changes for stationarity issues<sup>11</sup>. Their log returns time series show periods of high and low volatility often clustering together (heteroskedasticity). Thus, we test for presence of ARCH effect that has been detected for all the considered markets, equity, currency and credit: the Engle (1982) test showed presence of ARCH effect at 1% for all the series which motivates our choice of GARCH models. We model univariate GARCH models, namely, GARCH(1,1), EGARCH(1,1) and GJR-GARCH (1,1) for inferring conditional volatility, while we compute the realized volatility and the decomposed volatility components model-free. Overall, the volatility measures total eight volatility series for the stock and CDS markets, while five volatility series for the currency market. Following Diebold and Yilmaz (2012), log daily annualized conditional and realized volatilities are taken for the selected asset classes.

Starting with the equity market, Table 1 shows the descriptive statistics for the log daily annualized conditional volatilities computed through GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) for the EU countries' stock indexes. The Italian FTSEMIB is the most volatile index in our sample regardless of the model which is considered. The Czech PX shows the largest maximum-minimum spread presenting high standard deviation. All the indexes' volatilities are right skewed. Between the simple GARCH(1,1) and the other two GARCH models there is a difference in stock index volatilities maximum and minimum value, thus in standard deviation. It is not straightforward distinguishing between the EGARCH(1,1) and GJR(1,1) instead. The first seems to have lower minimum values, while the conditional volatility computed with the latter tends to spike more. In terms of standard deviation they are similar with a lower one for GJR(1,1), especially for the CEE countries. In terms of realized volatilities, the aggregate RV mean is higher than the corresponding positive or negative components for all the stock market indexes. The  $RV^+$  mean values are higher than the negative  $RV^-$  mean values for the majority of the indexes except for DAX, PX and SAX.  $RV^+$  presents also lower standard deviation compared to  $RV^-$  for all the indexes except for DAX. Maximum values are most of the time associated with negative realized volatility rather than with positive showing the downside risk and leverage effect in the stock market.

Table 2 shows the descriptive statistics for the log daily annualized conditional and realized volatilities for the currency market. When conditional volatilities are considered, the Czech Crown appears to have the lowest mean values, while, when realized volatility measures are considered, the Hungarian Forint is the currency presenting the lowest mean values. In terms of maximum and minimum values, GARCH models show higher values than the realized volatility measures, the only exception being

<sup>10</sup> This exact beginning of the time period is dictated by the CDS data availability for some of the selected countries. We focus on the post financial crisis period. Given that we select a 100 days rolling window for the dynamic analysis, the effect of the financial crisis does not affect our results.

<sup>11</sup> When daily data is not available for some countries it is replaced with the previous day's return, if at least half of the countries have data available in that day, otherwise that day's raw data is eliminated.

<b>Table 1</b>												
<b>Equity Market Descriptive Statistics - Conditional and Realized Volatilities</b>												
	Germany - DAX						France - CAC40					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	3.18	3.16	3.16	2.94	2.60	2.50	3.22	3.18	3.19	2.97	2.55	2.63
<b>Median</b>	3.12	3.13	3.12	2.91	2.57	2.53	3.17	3.16	3.14	2.95	2.56	2.60
<b>Max</b>	4.53	4.49	4.54	4.36	4.04	4.05	4.65	4.63	4.77	4.41	4.16	4.00
<b>Min</b>	2.50	2.22	2.44	1.79	1.21	0.06	2.51	2.25	2.47	1.87	1.00	1.43
<b>Std. Dev.</b>	0.36	0.39	0.40	0.44	0.42	0.58	0.37	0.40	0.41	0.44	0.55	0.43
<b>Skewness</b>	0.83	0.40	0.67	0.38	0.45	-0.23	0.88	0.47	0.78	0.43	0.09	0.40
<b>Kurtosis</b>	3.83	3.10	3.34	3.43	3.76	3.39	3.97	3.10	3.47	3.42	2.96	3.58
	Italy - FTSEMIB						UK - FTSE100					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	3.43	3.41	3.42	3.19	2.80	2.82	2.94	2.91	2.91	2.70	2.28	2.35
<b>Median</b>	3.36	3.38	3.35	3.11	2.77	2.78	2.86	2.86	2.83	2.63	2.25	2.30
<b>Max</b>	4.59	4.52	4.67	4.41	4.13	4.06	4.59	4.59	4.75	4.35	4.13	3.90
<b>Min</b>	2.92	2.76	2.90	2.37	1.29	1.85	2.24	1.87	2.16	1.59	-0.07	1.15
<b>Std. Dev.</b>	0.30	0.32	0.33	0.37	0.48	0.37	0.40	0.41	0.43	0.47	0.57	0.48
<b>Skewness</b>	1.07	0.58	0.92	0.74	0.17	0.54	1.10	0.69	1.06	0.67	0.18	0.50
<b>Kurtosis</b>	3.89	3.08	3.59	3.10	2.87	3.18	4.61	3.90	4.41	3.80	3.57	3.68
	Poland - WIG20						Czech - PX					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	3.17	3.16	3.16	2.93	2.53	2.55	3.05	3.05	3.05	2.81	2.42	2.42
<b>Median</b>	3.07	3.07	3.05	2.83	2.46	2.51	2.95	2.98	2.94	2.73	2.35	2.36
<b>Max</b>	4.34	4.44	4.44	4.23	4.10	3.82	5.01	4.98	5.07	4.78	4.56	4.28
<b>Min</b>	2.62	2.54	2.65	1.96	1.24	1.36	2.34	2.07	2.34	1.43	0.89	1.14
<b>Std. Dev.</b>	0.35	0.36	0.36	0.43	0.51	0.45	0.43	0.43	0.44	0.50	0.57	0.51
<b>Skewness</b>	0.98	0.90	1.04	0.68	0.51	0.32	1.43	1.01	1.44	0.97	0.69	0.83
<b>Kurtosis</b>	3.34	3.39	3.57	2.91	2.89	2.79	5.67	4.80	5.75	4.55	4.15	4.08
	Hungary - BUX						Slovakia - SAX					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	3.24	3.23	3.23	3.00	2.57	2.66	3.12	3.15	3.43	2.77	2.39	2.29
<b>Median</b>	3.15	3.17	3.15	2.93	2.52	2.58	3.09	3.13	3.40	2.78	2.36	2.33
<b>Max</b>	4.84	4.75	4.88	4.64	4.41	4.15	4.16	3.82	4.53	4.10	4.07	3.78
<b>Min</b>	2.61	2.30	2.56	2.02	0.99	1.53	2.89	3.09	2.52	1.52	0.47	-0.23
<b>Std. Dev.</b>	0.38	0.38	0.39	0.45	0.54	0.46	0.18	0.05	0.08	0.42	0.52	0.50
<b>Skewness</b>	1.12	0.78	1.11	0.74	0.34	0.65	1.79	3.57	4.32	0.24	0.18	-0.48
<b>Kurtosis</b>	4.31	3.87	4.49	3.49	3.44	3.22	7.42	8.64	8.07	3.34	3.97	4.45

*This table shows the main descriptive statistics regarding the log daily annualized conditional volatilities computed with GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models and the realized volatilities, namely total, negative (RV<sup>-</sup>) and positive (RV<sup>+</sup>) measures for the selected countries stock market indexes between 01-08-2008 to 30-06-2017.*

CZK. In some cases GARCH(1,1) shows higher maximum and lower minimum than the other two GARCH models considering volatility leverage effect.  $RV^-$  measures are slightly higher than the positive ones for the British Pound and U.S. Dollar. The positive  $RV^+$  values are always more volatile than the negative ones. The highest standard deviation is found with relation to EUR-CZK and EUR-HUF for conditional and realized volatility series, respectively.

Lastly, Table 3 shows the descriptive statistics for the log daily annualized volatilities for the CDS spreads for the developed EU and CEE countries. The most volatile CDS spreads are found for the developed EU countries in relation to all the considered measures. The only exception is Poland that shows also a high level of CDS conditional volatility. The highest maximum values are found with GJR(1,1) for Poland and Czech Republic CDS' volatility, while for the other countries the results are mixed. In some cases, CDS conditional volatility values computed by GARCH(1,1) are even higher than the ones computed with the other two GARCH models. For the minimum values, EGARCH(1,1) presents lower results compared with the other. The standard deviation for the credit market conditional volatilities is very similar between GARCH(1,1) and GJR(1,1) and even lower for EGARCH(1,1). It appears that the leverage effect is less present in the CDS market compared to the stock market. The  $RV^-$  mean values are, most of the time, higher than the positive volatility components' mean values. However, the  $RV^+$  measures have higher standard deviation compared to the aggregate and negative series.

Table 2 Currency Market Descriptive Statistics - Conditional and Realized Volatilities												
	British Pound - GBP						Polish Zloty - PLN					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	2.33	2.33	2.33	2.09	1.71	1.70	2.29	2.28	2.28	2.04	1.66	1.67
<b>Median</b>	2.33	2.35	2.33	2.09	1.71	1.70	2.23	2.24	2.22	2.02	1.63	1.62
<b>Max</b>	3.46	3.21	3.52	3.23	2.99	3.13	3.88	3.71	3.79	3.61	3.19	3.36
<b>Min</b>	1.63	1.55	1.63	1.16	0.54	0.30	1.44	1.28	1.46	0.75	0.41	-0.05
<b>Std. Dev.</b>	0.30	0.29	0.30	0.36	0.37	0.45	0.45	0.44	0.45	0.51	0.51	0.57
<b>Skewness</b>	0.60	0.16	0.63	0.32	0.05	0.03	0.80	0.61	0.85	0.46	0.39	0.34
<b>Kurtosis</b>	4.12	3.53	4.23	3.89	3.34	4.14	3.53	3.38	3.57	3.23	3.09	3.24
	Hungarian Forint - HUF						Czech Crown - CZK					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	2.33	2.33	2.32	1.23	0.83	0.85	1.63	1.63	1.62	2.09	1.69	1.74
<b>Median</b>	2.29	2.30	2.27	1.48	1.12	1.10	1.83	1.80	1.81	2.06	1.67	1.68
<b>Max</b>	3.77	3.63	3.85	3.22	2.91	2.86	3.67	4.47	3.70	3.62	3.01	3.44
<b>Min</b>	1.42	1.32	1.42	-2.90	-3.36	-3.20	-0.43	-0.59	-0.45	0.96	0.57	0.31
<b>Std. Dev.</b>	0.44	0.44	0.45	1.13	1.14	1.15	0.93	0.88	0.94	0.49	0.49	0.54
<b>Skewness</b>	0.45	0.30	0.52	-1.21	-1.13	-1.10	-0.60	-0.68	-0.57	0.31	0.20	0.26
<b>Kurtosis</b>	2.85	2.82	2.98	4.41	4.14	4.29	2.75	3.18	2.76	2.86	2.62	3.08
	U.S. Dollar - USD											
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>						
<b>Mean</b>	2.38	2.43	2.43	2.20	1.82	1.79						
<b>Median</b>	2.37	2.42	2.41	2.20	1.85	1.82						
<b>Max</b>	3.63	3.26	3.30	3.19	2.91	3.05						
<b>Min</b>	1.21	1.55	1.70	1.06	0.59	-0.14						
<b>Std. Dev.</b>	0.39	0.29	0.29	0.38	0.43	0.45						
<b>Skewness</b>	-0.04	-0.25	0.06	-0.27	-0.13	-0.42						
<b>Kurtosis</b>	3.01	3.23	3.03	3.30	2.51	3.62						

*This table shows the main descriptive statistics regarding the log daily annualized conditional volatilities computed with GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models and the realized volatilities, namely total, negative (RV<sup>-</sup>) and positive (RV<sup>+</sup>) measures for the selected countries currencies between 01-08-2008 to 30-06-2017.*

Table 3 Credit Market Descriptive Statistics - Conditional and Realized Volatilities												
	Germany CDS						France CDS					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	4.26	4.27	4.26	3.95	3.54	3.53	4.23	4.23	4.23	3.92	3.52	3.48
<b>Median</b>	4.20	4.27	4.21	3.97	3.55	3.55	4.19	4.23	4.19	3.93	3.46	3.53
<b>Max</b>	5.87	5.66	5.87	5.31	5.09	5.10	6.12	5.85	6.10	5.52	5.37	5.15
<b>Min</b>	3.61	3.31	3.62	2.10	1.77	1.61	3.28	3.12	3.29	2.30	1.25	1.16
<b>Std. Dev.</b>	0.37	0.34	0.36	0.49	0.51	0.62	0.50	0.47	0.50	0.58	0.59	0.73
<b>Skewness</b>	0.93	0.35	0.94	0.07	-0.02	-0.19	0.45	0.14	0.45	0.05	0.24	-0.45
<b>Kurtosis</b>	3.89	3.15	3.92	2.93	3.17	3.01	2.96	2.66	2.94	2.78	3.36	3.03
	Italy CDS						UK CDS					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	4.26	4.26	4.26	3.98	3.56	3.58	3.92	3.92	3.92	3.59	3.13	3.05
<b>Median</b>	4.19	4.19	4.19	3.96	3.58	3.58	3.83	3.89	3.82	3.55	3.22	3.15
<b>Max</b>	5.96	5.91	5.91	5.37	5.05	5.18	5.76	5.68	5.83	5.18	4.52	5.04
<b>Min</b>	3.72	3.73	3.73	2.71	1.87	1.00	3.32	3.12	3.33	0.97	-0.38	-0.82
<b>Std. Dev.</b>	0.35	0.35	0.35	0.47	0.51	0.59	0.42	0.39	0.42	0.57	0.75	0.85
<b>Skewness</b>	1.17	1.20	1.20	0.15	-0.19	-0.24	0.96	0.54	1.01	-0.18	-1.01	-0.89
<b>Kurtosis</b>	4.80	4.85	4.85	3.25	3.39	3.71	3.81	3.35	3.95	3.65	4.38	5.05
	Poland CDS						Czech CDS					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	4.24	4.26	4.24	3.39	2.94	2.79	3.99	4.03	3.99	2.91	2.40	2.27
<b>Median</b>	4.17	4.21	4.17	3.48	3.03	3.11	3.83	3.92	3.82	3.13	2.83	2.60
<b>Max</b>	6.38	7.43	6.58	6.17	5.46	6.03	6.32	7.36	6.41	6.03	5.45	5.86
<b>Min</b>	4.13	3.91	4.13	-1.91	-2.57	-2.81	3.74	3.73	3.74	-1.87	-2.32	-2.65
<b>Std. Dev.</b>	0.20	0.19	0.21	0.97	1.13	1.37	0.39	0.35	0.39	1.43	1.62	1.67
<b>Skewness</b>	4.92	6.26	5.34	-1.35	-1.91	-1.56	2.78	2.68	2.80	-0.96	-0.96	-0.66
<b>Kurtosis</b>	38.27	75.58	43.65	8.84	9.77	6.60	12.72	16.36	12.88	4.27	3.40	2.96
	Hungary CDS						Slovakia CDS					
	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>	GARCH	EGARCH	GJR	RV	RV <sup>-</sup>	RV <sup>+</sup>
<b>Mean</b>	3.74	3.74	3.74	3.38	2.95	2.73	3.62	3.61	3.62	3.00	2.49	2.25
<b>Median</b>	3.67	3.71	3.66	3.36	3.02	2.89	3.46	3.55	3.46	3.12	2.88	2.64
<b>Max</b>	5.90	5.74	5.98	5.51	4.87	5.34	5.71	5.46	5.71	5.45	4.95	5.28
<b>Min</b>	2.85	2.27	2.89	-2.04	-2.42	-2.76	2.81	2.47	2.81	-1.70	-5.64	-2.91
<b>Std. Dev.</b>	0.54	0.53	0.54	0.70	0.79	1.29	0.65	0.63	0.65	1.22	1.42	1.66
<b>Skewness</b>	0.92	0.26	1.01	-0.16	-0.79	-2.11	0.78	0.36	0.78	-1.13	-1.26	-0.98
<b>Kurtosis</b>	4.00	3.64	4.22	5.13	5.44	9.73	2.87	2.45	2.87	4.79	5.02	3.52

*This table shows the main descriptive statistics regarding the log daily annualized conditional volatilities computed with GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models and the realized volatilities, namely total, negative (RV<sup>-</sup>) and positive (RV<sup>+</sup>) measures for the selected countries CDS spreads between 01-08-2008 to 30-06-2017.*

# 5 Assets Volatility Spillovers: Static Analysis

After having computed our volatility series, we estimate the static forecast error variance decomposition table through Equation (7). In general this table contains the  $N \times (N - 1)$  forecast error variance decomposition in the  $N \times (N - 1)$  off-diagonal entries in the main matrix block representing the pairwise directional spillovers. The row and column sums, called *From Others* and *To Others* are the total directional connectedness measures, FROM and TO, respectively. The other row at the bottom labeled - Net - represents the difference for each asset's TO and FROM contributions. When positive, it means that the asset can be considered as a net volatility spillovers *transmitter*, while when negative, it means that the asset is a net volatility spillovers *receiver*. The bottom-right element is the total volatility spillovers index for all the considered asset classes in the system. For brevity we report only the forecast error variance decomposition table computed through GJR-GARCH(1,1) and decomposed realized volatilities ( $RV^+$  and  $RV^-$ )<sup>12</sup>. All the forecast error variance decomposition results refer to a 2-lag VAR model (as the minimum lags selected between AIC and BIC) with moving average forecasting horizon equal to 4<sup>13</sup>.

Table 4 shows the forecast error variance decomposition matrix for the equity market according to GJR-GARCH(1,1) model,  $RV^-$  and  $RV^+$  measures. First of all, what is emerged is that the main countries contributing to volatility spillovers in the considered system are the ones from the developed EU countries. This result is also evident when looking at the own volatility contribution values in the matrix main diagonal which are, indeed, lower for these countries, while increasing with respect to the CEE countries counting almost for the total in the case of the Slovakian SAX. CAC40 and DAX lead the ranking of the stock market indexes transmitting more volatility spillovers to the others in the system. They are followed by FTSE100 and FTSEMIB, while the Polish WIG20 plays a mixed role between CEE and developed EU countries. With regards to the FROM others contributions side, we have a more lined up picture with values ranging from the highest of CAC40 to the lowest of SAX accounting for less than 1%, regardless to the volatility measure. While the developed EU countries' role is predominant in this system, CEE countries, on the other hand, appear to absorb volatility every time there is a shock within the system. Having a look at the net row, the developed EU countries can be labeled as net volatility spillovers transmitters, while the CEE countries are net volatility spillovers receivers, in line with the findings in Moon and Yu (2010) and Le, Kakinaka, et al. (2010). The stock index that seems to transmit more volatility in this system is the French CAC40 followed by the German DAX. The stock market indexes which, instead, seem to receive more volatility shocks in this system from the other countries are PX and BUX. The role of SAX as volatility receiver is also really marginal. In terms of pairwise spillovers, the highest values are between DAX and CAC40 in pair between each other and also between FTSEMIB, FTSE100 and WIG20. The pairwise spillovers for the CEE countries' stock indexes is, instead, less evident when paired both with the developed EU stock markets and also with the CEE stock markets. The bottom right cell of this matrix shows the single static total volatility spillovers index that accounts for 55.93% when computed with GJR(1,1), for 59.58% with  $RV^-$  and for 61.77% with  $RV^+$ . On average, across our stock indexes system in the selected market period, more than half of the volatility forecast error variance for the eight EU stock market indexes is due to volatility spillovers and this is even greater when positive volatility spillovers are considered.

Table 5 shows the forecast error variance decomposition for the currency market. The role of the currencies as net receivers or transmitters in the system varies according to the measure of volatility chosen. The Polish Zloty emerges as the main volatility transmitter regardless to the volatility measure, however this is not true in terms of net values given that, in this case, the Polish Zloty is a net transmitter when GJR(1,1) and  $RV^+$  are considered, while net receiver when  $RV^-$  is considered. Also the other currencies invert their role according to the volatility input measure. On average, the Hungarian Forint is the only net negative realized volatility spillovers transmitter, while it is a net positive volatility spillovers receiver together with the U.S. dollar. The total volatility spillovers index in this system, highlighted in the bottom right corner, is not really high and equal to 20.86% for GJR(1,1), 18.69% for  $RV^-$  and 16.51% for  $RV^+$ . Only this small percentage of volatility forecast error variance for the five

<sup>12</sup> The forecast error variance decomposition matrix with regards to the other volatility measures is available from the authors upon request.

<sup>13</sup> We have computed also the other forecast error variance decomposition tables for the other volatility measures, for a number of VAR model lags from 1 to 4 and for a different MA forecast horizons (2,4,6,10). All the other tables are available from the authors upon request.

**Table 4**  
**Forecast Error Variance Decompositions Table - Equity Market**

Forecast Error Variance Decomposition: GJR(1,1)									
	DAX	CAC40	FTSEMIB	FTSE100	WIG20	PX	BUX	SAX	From Others
DAX	28.11	23.79	17.22	17.40	5.85	3.90	3.70	0.03	71.89
CAC40	22.96	27.06	18.49	18.34	5.27	4.40	3.46	0.01	72.94
FTSEMIB	19.17	20.79	29.76	14.64	6.08	5.30	4.23	0.03	70.24
FTSE100	18.64	20.33	14.20	32.03	6.05	4.74	3.99	0.01	67.97
WIG20	10.44	9.57	9.52	9.91	43.35	8.17	8.97	0.09	56.65
PX	8.94	9.76	10.06	9.72	10.70	43.32	7.50	0.00	56.68
BUX	8.84	8.46	8.37	8.03	9.20	7.17	49.83	0.10	50.17
SAX	0.14	0.08	0.18	0.08	0.06	0.30	0.02	99.14	0.86
To Others	89.14	92.78	78.04	78.12	43.21	33.98	31.87	0.27	Tot.Index
Net	17.26	19.84	7.80	10.15	-13.44	-22.70	-18.30	-0.60	<b>55.93</b>
Forecast Error Variance Decomposition: $RV^-$									
	DAX	CAC40	FTSEMIB	FTSE100	WIG20	PX	BUX	SAX	From Others
DAX	26.12	22.08	16.95	16.30	7.34	5.64	5.55	0.01	73.88
CAC40	21.19	24.52	18.58	16.78	6.95	6.22	5.74	0.02	75.48
FTSEMIB	18.75	21.37	28.75	12.71	6.40	6.20	5.81	0.01	71.25
FTSE100	17.93	19.02	12.34	29.32	8.07	7.09	6.12	0.11	70.68
WIG20	11.30	11.12	8.83	11.50	38.42	10.46	8.37	0.00	61.58
PX	10.86	11.31	9.87	12.09	12.90	33.70	9.18	0.08	66.30
BUX	10.63	10.12	8.59	9.78	9.48	8.56	42.75	0.09	57.25
SAX	0.00	0.00	0.00	0.04	0.05	0.11	0.02	99.77	0.23
To Others	90.67	95.03	75.16	79.20	51.19	44.28	40.80	0.32	Tot.Index
Net	16.79	19.55	3.91	8.52	-10.39	-22.01	-16.45	0.09	<b>59.58</b>
Forecast Error Variance Decomposition: $RV^+$									
	DAX	CAC40	FTSEMIB	FTSE100	WIG20	PX	BUX	SAX	From Others
DAX	27.64	20.19	15.87	16.67	6.72	7.56	5.34	0.01	72.36
CAC40	18.32	22.87	18.07	18.12	6.40	8.88	7.34	0.00	77.13
FTSEMIB	15.85	19.49	25.47	14.87	5.71	10.28	8.32	0.00	74.53
FTSE100	16.41	19.39	14.78	25.95	7.18	9.14	7.14	0.01	74.05
WIG20	11.79	10.50	8.00	11.16	37.22	11.12	10.21	0.00	62.78
PX	11.51	12.42	12.49	11.63	8.53	30.79	12.61	0.00	69.21
BUX	10.29	11.31	10.80	9.55	9.34	12.47	36.23	0.01	63.77
SAX	0.04	0.01	0.03	0.18	0.01	0.01	0.05	99.68	0.32
To Others	84.22	93.32	80.04	82.19	43.89	59.46	51.00	0.03	Tot.Index
Net	11.86	16.19	5.51	8.15	-18.89	-9.75	-12.77	-0.30	<b>61.77</b>

This table contains the  $N \times (N - 1)$  forecast error variance decomposition for the equity market computed with GJR(1,1) model,  $RV^-$  and  $RV^+$ .  $d_{ij}$  elements in the  $N \times (N - 1)$  off-diagonal entries are the pairwise directional connectedness. The  $2 \times N$  off-diagonal row and column sums, To Others and From Others, are the  $2 \times N$  total directional spillovers and the Net row is the difference between them. The bottom-right element is the total spillovers index. Selected VAR lags = 2 and Forecast Horizon = 4.

exchange rates in the system is, then, caused by volatility connectedness. This is lower compared to what has found by Diebold and Yilmaz (2015) who found that the total volatility connectedness of the major exchange rates was even higher than the one among global stock and bond markets. This is however justifiable from the choice of our currencies, time period and, also, from the fact that the spillovers level is positively related with the number of variables in the system.

Lastly, we show the results for the forecast error variance decomposition static analysis for the CDS market in Table 6. In this case there is not a clear separation between developed EU and CEE eight economies as found in the stock market, but their roles are found to be more balanced and depending more on the volatility measure which is input. For the TO others volatility contribution, France, Italy and Poland CDS markets emerge, overall, as the predominant. Germany CDS market transmits more positive volatility spillovers and, when  $RV^+$  is considered, Germany emerges as net volatility transmitter. Hungary CDS market is found to be a net negative volatility spillovers transmitter, while it receives positive volatility spillovers. France and Czech Republic CDS are net negative volatility spillovers receivers, but net positive volatility spillovers transmitters. Slovakia CDS market is found to be a net volatility spillovers receivers regardless of the volatility measure. With regards to the pairwise spillover measures, we observe that the German and French CDS markets are the most connected within each other and the Italian CDS has also high linkage with the German and French CDS. The UK CDS market is linked with the developed EU countries CDS even if the UK is not a member of the European Monetary Union (EMU) (see Diebold and Yilmaz, 2015). The total spillovers index in the system is quite high and equal to 35.84% with  $GJR(1,1)$ , 45.89% with  $RV^-$  and 43.99% with  $RV^+$ . It is, however, lower than the one found in the stock market, such a finding being in line with Hunter and Simon (2005).

**Table 5**  
**Forecast Error Variance Decompositions Table - Currency Market**

Forecast Error Variance Decomposition: GJR(1,1)						
	EURGBP	EURPLN	EURHUF	EURCZK	EURUSD	From Others
EURGBP	82.11	3.32	0.72	0.40	13.43	17.88
EURPLN	3.39	69.99	17.35	4.50	4.74	30.00
EURHUF	1.05	17.82	76.47	2.36	2.27	23.52
EURCZK	0.92	5.95	3.04	88.81	1.25	11.18
EURUSD	12.73	5.49	2.69	0.76	78.31	21.68
To Others	18.11	32.59	23.83	8.03	21.71	Tot.Index
Net	0.23	2.58	0.30	-3.15	0.02	<b>20.86</b>
Forecast Error Variance Decomposition: $RV^-$						
	EURGBP	EURPLN	EURHUF	EURCZK	EURUSD	From Others
EURGBP	84.04	0.93	0.00	0.03	14.98	15.95
EURPLN	0.62	73.44	13.15	12.60	0.16	26.55
EURHUF	0.10	9.35	85.83	4.46	0.23	14.16
EURCZK	0.03	13.88	7.02	78.90	0.13	21.09
EURUSD	14.82	0.01	0.09	0.73	84.33	15.66
To Others	15.59	24.19	20.28	17.83	15.52	Tot.Index
Net	-0.36	-2.35	6.12	-3.26	-0.14	<b>18.69</b>
Forecast Error Variance Decomposition: $RV^+$						
	EURGBP	EURPLN	EURHUF	EURCZK	EURUSD	From Others
EURGBP	92.28	1.41	0.10	0.15	6.04	7.71
EURPLN	1.88	70.26	7.30	20.48	0.06	29.73
EURHUF	0.07	9.67	86.22	3.99	0.03	13.77
EURCZK	0.18	19.52	3.62	76.58	0.07	23.41
EURUSD	7.07	0.19	0.43	0.21	92.08	7.91
To Others	9.21	30.81	11.47	24.84	6.21	Tot.Index
Net	1.49	1.08	-2.29	1.42	-1.70	<b>16.51</b>

*This table contains the  $N \times (N - 1)$  forecast error variance decomposition for the currency market computed with GJR(1,1) model,  $RV^-$  and  $RV^+$ .  $d_{ij}$  elements in the  $N \times (N - 1)$  off-diagonal entries are the pairwise directional connectedness. The off-diagonal row and column sums, To Others and From Others, are the  $2 \times N$  total directional spillovers and the Net row is the difference between them. The bottom-right element is the total spillovers index. Selected VAR lags = 2 and Forecast Horizon = 4.*

**Table 6**  
**Forecast Error Variance Decompositions Table - Credit Market**

Forecast Error Variance Decomposition: GJR(1,1)									
	Germany	France	Italy	UK	Poland	Czech Rep	Hungary	Slovakia	From Others
Germany	63.42	16.63	11.03	3.68	0.62	0.90	2.36	1.36	36.58
France	14.49	63.48	12.66	3.83	0.77	0.85	2.33	1.59	36.52
Italy	8.94	14.18	64.68	4.78	1.67	1.18	3.15	1.42	35.32
UK	6.25	6.42	7.92	68.88	2.55	1.64	4.07	2.28	31.12
Poland	0.89	0.96	2.47	2.41	62.24	22.82	6.13	2.08	37.76
Czech Rep	1.15	1.09	1.39	0.75	25.23	57.23	6.65	6.51	42.77
Hungary	2.05	3.36	4.47	1.97	10.19	7.64	64.21	6.11	35.79
Slovakia	1.94	2.48	2.74	1.72	5.66	7.87	8.48	69.10	30.90
To Others	35.71	45.13	42.66	19.14	46.68	42.90	33.17	21.35	Tot.Index
Net	-0.87	8.61	7.34	-11.98	8.92	0.14	-2.62	-9.54	<b>35.84</b>
Forecast Error Variance Decomposition: $RV^-$									
	Germany	France	Italy	UK	Poland	Czech Rep	Hungary	Slovakia	From Others
Germany	62.52	12.90	10.91	6.12	3.77	0.46	2.73	0.61	37.48
France	13.66	64.06	12.64	4.15	2.55	0.45	2.18	0.31	35.94
Italy	8.43	10.20	55.52	8.11	5.80	1.28	8.76	1.91	44.48
UK	6.63	5.17	8.94	51.20	10.75	5.16	8.15	4.00	48.80
Poland	2.51	2.23	5.33	9.86	47.21	16.31	11.82	4.73	52.79
Czech Rep	1.45	1.73	4.13	4.89	17.79	45.24	10.65	14.12	54.76
Hungary	2.16	2.05	8.59	6.02	11.38	6.69	53.60	9.50	46.40
Slovakia	1.91	1.57	5.20	3.63	5.87	14.40	13.88	53.54	46.46
To Others	36.75	35.85	55.74	42.77	57.92	44.75	58.17	35.18	Tot.Index
Net	-0.74	-0.10	11.26	-6.04	5.13	-10.01	11.77	-11.28	<b>45.89</b>
Forecast Error Variance Decomposition: $RV^+$									
	Germany	France	Italy	UK	Poland	Czech Rep	Hungary	Slovakia	From Others
Germany	54.30	24.70	11.70	2.55	0.23	0.56	3.36	2.60	45.70
France	22.16	54.58	13.52	2.24	0.40	0.66	3.97	2.48	45.42
Italy	12.76	15.12	62.37	3.68	0.47	0.35	3.04	2.21	37.63
UK	7.84	7.72	7.23	62.60	1.47	1.39	7.12	4.63	37.40
Poland	0.66	0.59	0.77	1.25	57.39	32.70	4.12	2.51	42.61
Czech Rep	0.19	0.14	0.23	0.60	34.14	53.00	4.53	7.18	47.00
Hungary	2.20	2.84	2.91	1.73	18.37	14.58	47.65	9.72	52.35
Slovakia	3.12	2.21	2.39	3.31	7.48	12.34	12.96	56.18	43.82
To Others	48.94	53.32	38.74	15.35	62.57	62.58	39.10	31.33	Tot.Index
Net	3.24	7.89	1.11	-22.05	19.97	15.57	-13.25	-12.49	<b>43.99</b>

This table contains the  $N \times (N - 1)$  forecast error variance decomposition for the credit market computed with GJR(1,1) model,  $RV^-$  and  $RV^+$ .  $d_{ij}$  elements in the  $N \times (N - 1)$  off-diagonal entries are the pairwise directional connectedness. The  $2 \times N$  off-diagonal row and column sums, To Others and From Others, are the  $2 \times N$  total directional spillovers and the Net row is the difference between them. The bottom-right element is the total spillovers index. Selected VAR lags = 2 and Forecast Horizon = 4.

# 6 Dynamic Conditional Volatility Spillovers

In this Section, we show the results for the volatility spillovers dynamic analysis computed by inputting the conditional volatility measures inferred from GARCH models for all the three asset classes among the selected European countries. The results for the equity market are reported in Section 6.1, for the currency markets in Section 6.2 and for the credit market in Section 6.3. For each asset class the total volatility spillovers index, the net total volatility spillovers contributions and the net pairwise volatility spillovers are reported<sup>14</sup>. The plots in this sections show comparatively the results we find for the volatility spillovers indexes computed with all the three conditional volatility measures, namely, GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1), with 2-lag vector autoregressive model and 4 days forecast horizon moving average in a 100-day rolling window. As a common result among all the three asset classes, the total spillovers indexes decline immediately after the 2008 global financial crisis. However, in this paper, by starting our sample in mid-2008, we are mainly interested in showing how these spillovers indexes react to other financial, politic and economic events which occurred in the Eurozone from the post financial crisis until the first half of 2017.

## 6.1 EQUITY MARKET CONDITIONAL VOLATILITY SPILLOVERS

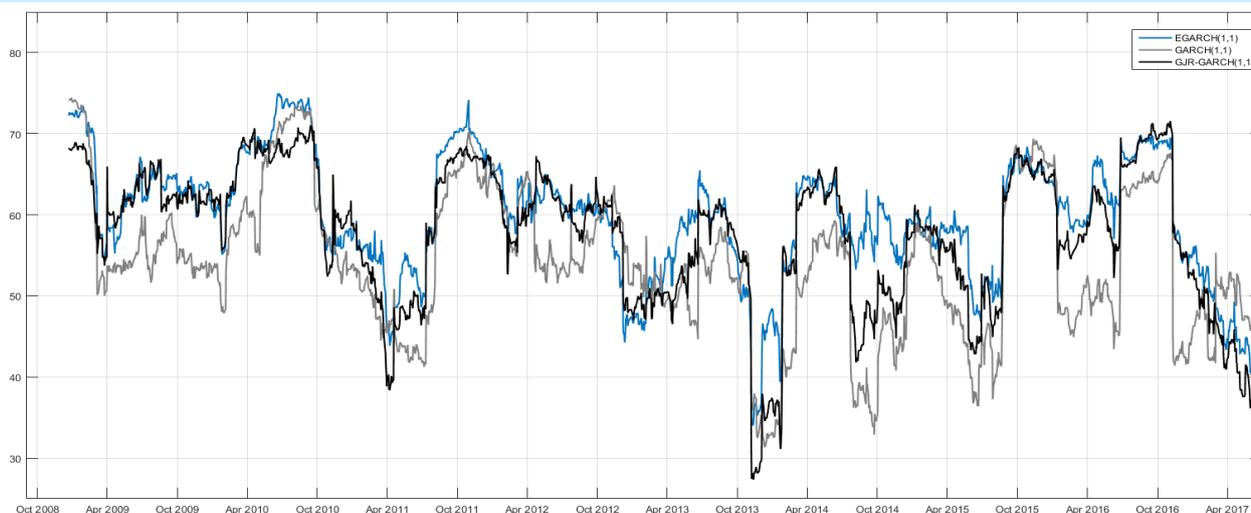
Figure 1 shows the dynamic total volatility spillovers index for the eight stock market indexes in the system with a 100-day rolling window. The figure takes into account all the three GARCH-family models and it covers the period from 01-08-2008 to 30-06-2017.

The total volatility spillovers index for the equity market begins with one of the highest level of the series due to the 2008 global financial crisis and collapse of Lehman Brothers which injected and transmitted fear and uncertainty also in the European stock markets. We can observe how the GARCH(1,1) spillovers index is, most of the time, lower than the spillovers indexes computed with EGARCH(1,1) and GJR-GARCH(1,1) models. This is due to the fact that the latter reflect the asymmetric volatility characteristic and leverage effect which are transmitted, in turn, to the volatility spillovers measures. EGARCH(1,1) and GJR-GARCH(1,1) spillovers indexes show a high level also after the financial crisis since the possibility of bad news and events was still in the financial investors' minds. The total volatility spillovers indexes computed with the leverage models spike above the simple GARCH(1,1) spillovers index throughout 2010 (Greek debt crisis) and from June 2011 onwards due to the second stage of the sovereign debt crisis involving also countries, such as, Italy and Spain see Diebold and Yilmaz (2015). The asymmetric effect in volatility spillovers indexes is mostly detected with regards to events characterized by the possibility of an increase in the investors' future uncertainty regarding the financial markets. Among these events we can list the global economic slowdown coming from the U.S., the Ukraine-Russia conflict, the tensions in the Middle East, the ISIS escalation, the Grexit referendum and, eventually, the Brexit vote in June 2016. Especially Brexit represents the event due to which the spillovers indexes computed through leverage GARCH models reach their widest spread from the GARCH(1,1) spillovers index. It is quite clear from Figure 1 how volatility spillovers indexes taking into account the leverage volatility effect spike more in reaction to events which transmit fear and uncertainty among the European countries increasing, consequently, the volatility contagion.

However, we also detect points in time during which a *reverse asymmetric effect* is found, being the GARCH(1,1) volatility spillovers measure at higher level compared to EGARCH(1,1) and GJR(1,1) volatility spillovers, as, for instance, during 2013, in the first half of 2017 and, interestingly, at the very end of the 2008 financial crisis. These might be periods characterized by optimistic expectations being a synonym of economies and financial market recovery with, consequently, less volatility caused by leverage effect and contagion. The total volatility spillovers index provides an overview of how the volatility contagion among the eight stock market indexes spreads in the total system, but it does not tell us much about the role of each single selected European stock market index within the system.

<sup>14</sup> In this paper we left out the TO others and FROM others plots for brevity. These results and plots are available from the authors upon request.

**Figure 1**  
**Total Spillovers Index - Equity Market**



*Notes: This figure shows the volatility total spillovers index for the stock market computed through Equation (15) having as input daily annualized conditional volatilities computed through GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) for the developed EU and developing CEE stock market indexes. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

Thus, Figure 2 shows the results of the analysis regarding the net directional volatility spillovers in order to distinguish between countries that can be labeled as equity volatility spillovers receivers (negative net spillovers index) or equity volatility spillovers transmitters (positive net spillovers index). The net directional volatility spillovers indexes provide also a better understanding of the different roles of the three GARCH models during the study period. While GJR(1,1) and EGARCH(1,1) follow, most of the time, a similar trend, GARCH(1,1) model appears to follow, in some particular cases, a volatility spillovers counter-trend.

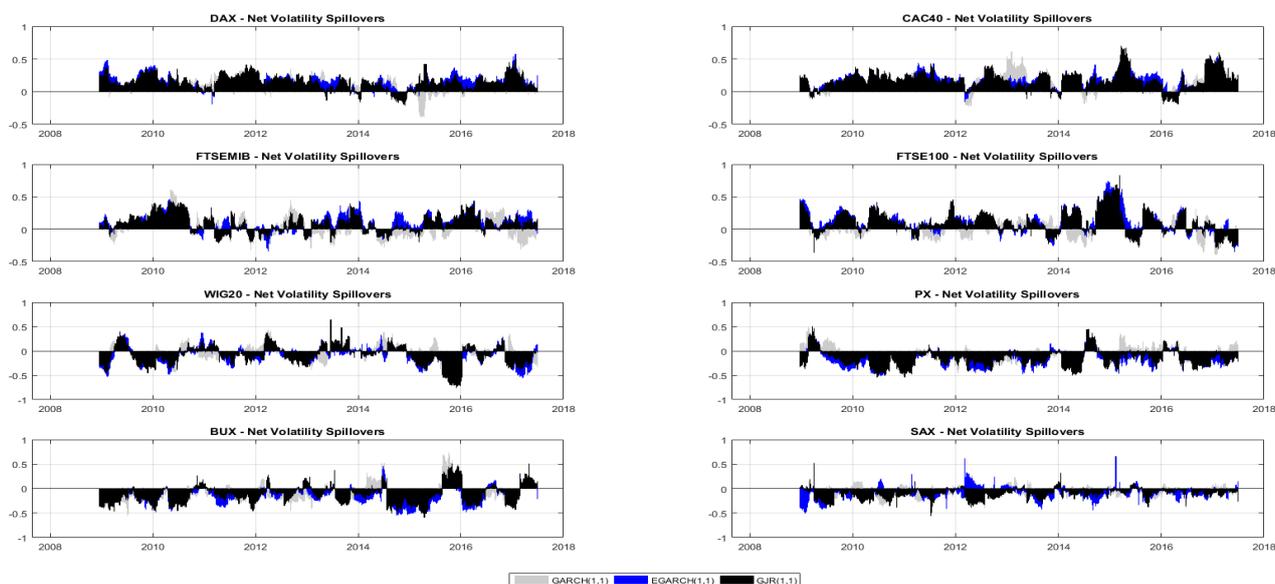
As expected, the developed EU countries' stock indexes inject the main part of the volatility in the considered system and they appear to be volatility spillovers net transmitters. This means that for them the level of FROM others volatility spillovers is lower than the one we observed for the TO others<sup>15</sup>. This is found to be true, especially, for DAX and CAC40 indexes during almost the entire time period. For FTSEMIB and FTSE100, this trend is weaker since they alternate periods of positive volatility spillovers with period of negative volatility spillovers. However, they can be classified, overall, as net volatility spillovers transmitters with some exceptions in which the two equity markets behave as volatility spillovers absorbers, such as, during the second half of 2011 in correspondence to the Eurozone sovereign debt financial crisis or during Grexit and Brexit.

In terms of volatility leverage effect, many differences emerge among these countries' volatility spillovers indexes. For instance, while FTSEMIB is found to be a volatility spillovers net receiver in the first half of 2017, when GARCH(1,1) model is applied, it is found to be a volatility spillovers net transmitter when the other leverage GARCH models are used. In general, a prevalent role for GJR(1,1) is found in terms of amount of volatility spillovers transmitted in the system. In only few cases, this level is overcome by EGARCH(1,1) and, even more rarely, by GARCH(1,1) as, for instance, in 2013 for CAC40 and during Brexit for FTSEMIB. These results further confirm what is shown in the total volatility spillovers index in Figure 1.

For the CEE countries, the three different models play a less clear role alternating their trend especially with regards to SAX and PX. The Polish WIG20 index is found to be the most prevalent volatility spillovers transmitter among the CEE countries and its role may be seen as a mixture between the net volatility transmitters developed EU and the net volatility receivers CEE countries. This may be due to the fact that it is the principal CEE stock market and it has linkages with both the developed and also developing CEE financial markets. In periods such as the global financial crisis and the sovereign debt crisis, the Polish financial market is found to be more stable compared to the other financial markets, in line with the findings by Gjika and Horvath (2013). The Polish stock market index reaches its highest level of volatility received from the system in correspondence

<sup>15</sup> According to Diebold and Yilmaz (2015), the total volatility "to" connectedness of an asset is high, for either it is a very central asset among the selected system or it has been subject to frequent volatility shocks over the period, or both.

**Figure 2**  
**Total NET Volatility Spillovers - Equity Market**



*Notes: This figure shows the total net volatility spillovers for the 8 stock market indexes. This is computed as a difference between To Others and From Others volatility spillovers through Equation (12) and plotted for all the stock indexes in a dynamic framework. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar) for the developed EU and developing CEE stock market indexes. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

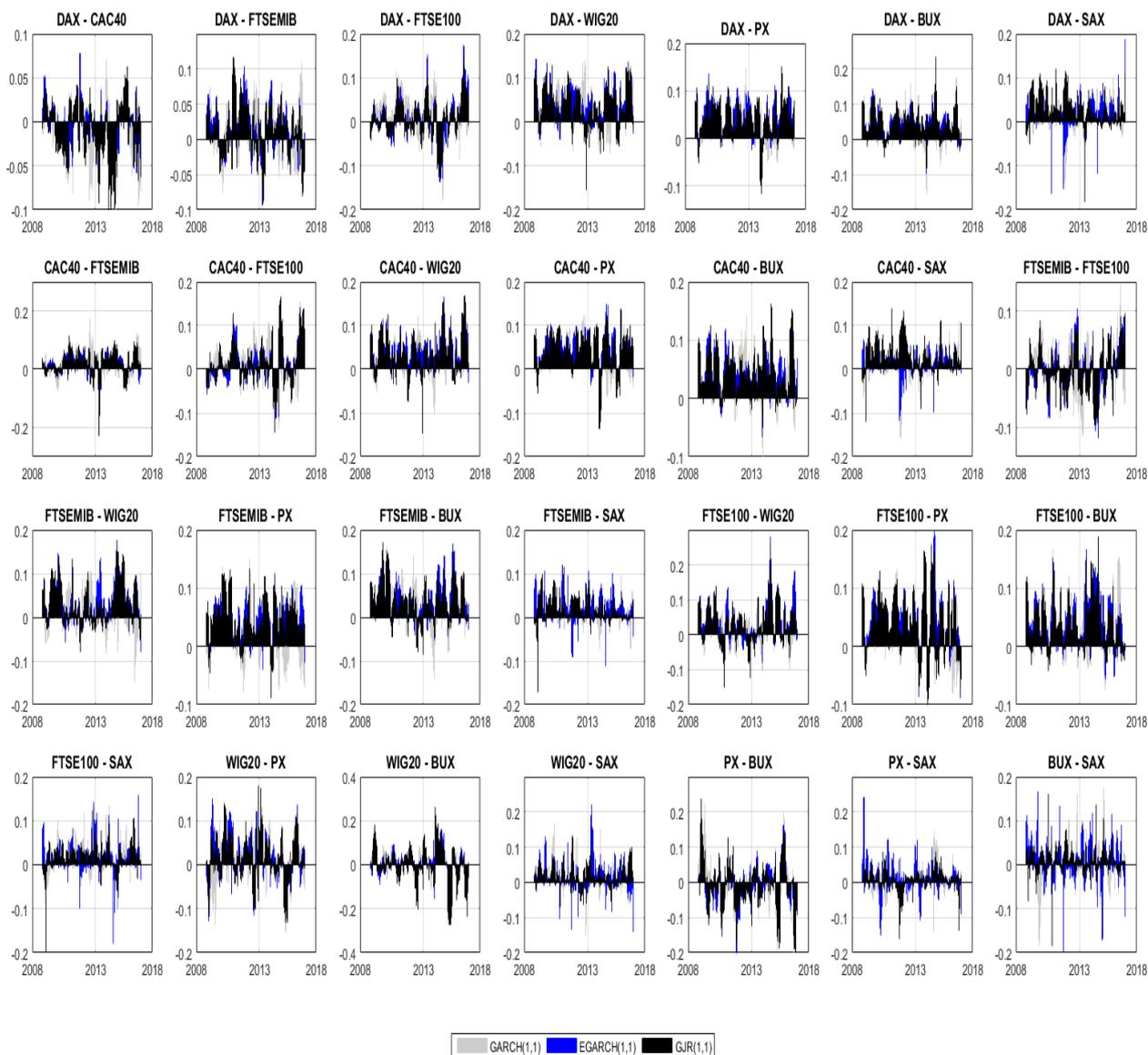
of the political election in 2015 with the victory of a conservative and Euro-skeptical party. For the other CEE stock indexes, namely, PX, BUX and SAX, we find a clear net volatility receivers role. The level of volatility spillovers received by these indexes in the system is higher than the one transmitted. This trend is reversed only in rare circumstances, such as, at the end of 2015 for BUX, in mid 2015 for SAX and at the beginning of 2009 and at the end of 2014 for PX. In the case of Hungary, it had experienced several debt downgrades during the crisis that might have also impacted on its position with respect to the developed EU and CEE countries (Gjika and Horvath, 2013). Slovakia is, mainly, found to have the weakest role in the system being able only to absorb volatility from the other countries (see Reboredo et al., 2015).

Figure 3 reports the net pairwise spillovers analysis in order to show the volatility spillovers channels among the selected countries. For most of the time, CAC40 transmits volatility to DAX, while the relationship between DAX and FTSEMIB is not entirely clear with the first transmitting volatility to the second, except in 2013 and in 2017.

The German DAX is a clear net pairwise volatility spillovers transmitter in relation to all the other developed EU stock market indexes. The French CAC40 emerges as the main volatility spillovers transmitter in relation to all the CEE stock market indexes, however receiving volatility from FTSEMIB during 2013 and from FTSE100 during Brexit. The relationship between FTSEMIB and FTSE100 appears to change direction along the time period with the first being, clearly, a net volatility transmitter in relation to the CEE countries' stock markets, while FTSE100 absorbing volatilities from PX and BUX after 2014. With regards to the CEE countries, WIG20 is found to be the main net volatility transmitter especially towards PX and SAX. The relationship between WIG20 and BUX is, on the other hand, mixed experiencing a trend inversion of the first from net transmitter to net receiver in the recent years. It might reflect the growing of the Hungarian financial market combined with the political election in Poland in 2015. The pairwise relationships among PX, BUX and SAX are periodic without a clear trend. The interdependence among CEE countries is higher, especially, in volatile periods as, for instance, after the 2008 financial crisis, during the sovereign debt crisis and during Brexit. Such a finding is in line with other studies as Reboredo et al. (2015), Cappiello et al. (2006) and Gjika and Horvath (2013). Moreover, as found in Reboredo et al. (2015), different degrees of integration between CEE countries with developed EU countries are detected.

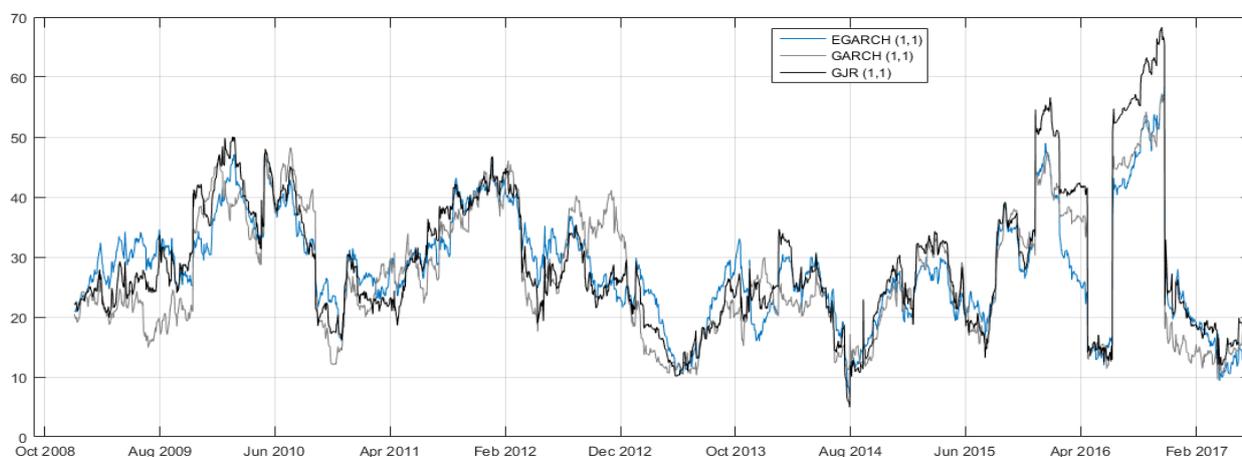
While stock markets, such as, the Polish, Czech and Hungarian do co-move and share volatility and uncertainty with the developed EU stock markets, the same result is not found for the Slovak stock market showing less integration within the system

**Figure 3**  
**NET Pairwise Volatility Spillovers - Equity Market**



*Notes: This figure shows the net pairwise volatility spillovers among the 8 stock market indexes for a total of 28 combinations. This expresses the volatility that has been transmitted from and received by a specific countries' stock index pair in a dynamic time period. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar) for the developed EU and developing CEE stock market indexes. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

**Figure 4**  
**Total Spillovers Index - Currency Market**



*Notes: This figure shows the volatility total spillovers index for the currency market. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) for the 5 currencies, namely, GBP, PLN, HUF, CZK and USD against EUR. Spillovers index computed through Equation (15) with VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

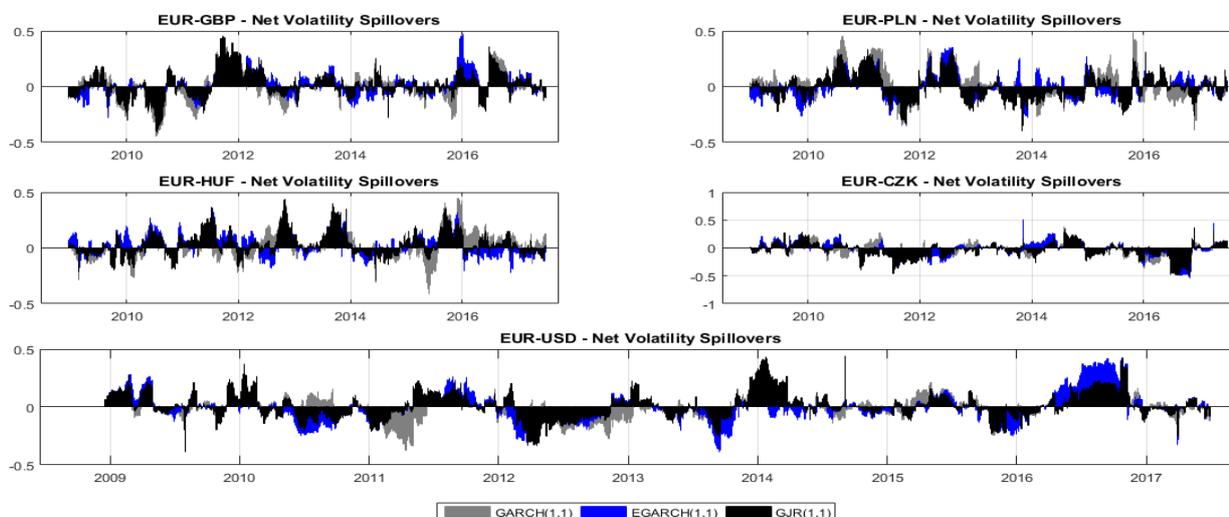
also due to its small stock market capitalisation. Thus, in line with Scheicher (2001), we find that developed EU stock markets influence the CEE stock markets, but, also, that there are regional and internal linkages within the Visegrad group. Especially BUX, WIG20 and PX indexes can be considered as an unique investment portfolio rather than three completely separate assets. WIG20 and PX indexes have a stronger connectedness together with the Eurozone countries (e.g. Savva and Aslanidis, 2010), while weaker is the linkage found for BUX and SAX due to their smaller stock market capitalization, especially for the latter.

## 6.2 CURRENCY MARKET CONDITIONAL VOLATILITY SPILLOVERS

In this Section 6.2, we present the dynamic volatility spillovers analysis with regards to the five selected currencies' conditional volatilities, namely, British Pound (GBP), Polish Zloty (PLN), Hungarian Forint (HUF), Czech Crown (CZK) and U.S. Dollar (USD), all taken against the Euro. We estimate and report in Figure 4 the total currency volatility spillovers index using a 100-day rolling window.

The level of the total volatility spillovers in the currency market is, overall, lower than the one found in the equity market (see Figure 1). It is also worth noting that this index appears to be less volatile than the stock market spillovers index, but it still follows and reacts to the main events occurred or impacted the Eurozone along our time period. As shown in Figure 4, the currency volatility spillovers index among the developed EU currencies increases substantially in the post global crisis period and in periods of uncertainty. This finding is in line with Bubák et al. (2011) who, by using the dynamic version of the Diebold-Yilmaz spillovers index, found that the magnitude of the FX spillovers index increased during periods of market uncertainty. For instance, the index spikes at the end of 2009 due to the beginning of the Greek debt crisis and it increases again in May 2010 and in mid 2011 due to the intensification of the Eurozone sovereign debt crisis as also found in Diebold and Yilmaz (2015). However, interestingly, while Diebold and Yilmaz (2015) found that the FX volatility connectedness decreased in the first half of 2009 due to the fade of the financial crisis, our findings show the same only when GARCH (1,1) is considered, while the EGARCH(1,1) and GJR(1,1) spillovers indexes are still high, probably reflecting the investors' concern in other future losses. However, the volatility spillovers index spikes again due to the Chinese Yuan crisis in mid 2015 and, impressively, during Brexit in June 2016. The second effect is in line with Belke et al. (2016) who found that Brexit impacted more on the currency market compared to the equity market. Thus, currencies appear to be the main volatility spillovers channel during the Brexit vote in spreading volatility among the developed EU and developing CEE countries. Euro based currency volatilities increase their connectedness when turbulent and uncertain periods impact on the Eurozone financial stability with GJR(1,1) and EGARCH(1,1) volatility spillovers indexes found above the GARCH(1,1) volatility spillovers index for most of the time. The reverse is true when the currency volatility

**Figure 5**  
**Total NET Volatility Spillovers - Currency Market**



*Notes: This figure shows the total net volatility spillovers for the currency market for the five currencies, namely, GBP, PLN, HUF, CZK and USD against EUR. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar). Net directional spillovers computed through Equation (12) with VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

spillovers index is in a downward period, such as, when the volatility in the currency market decreases and the linkages among the selected countries relax.

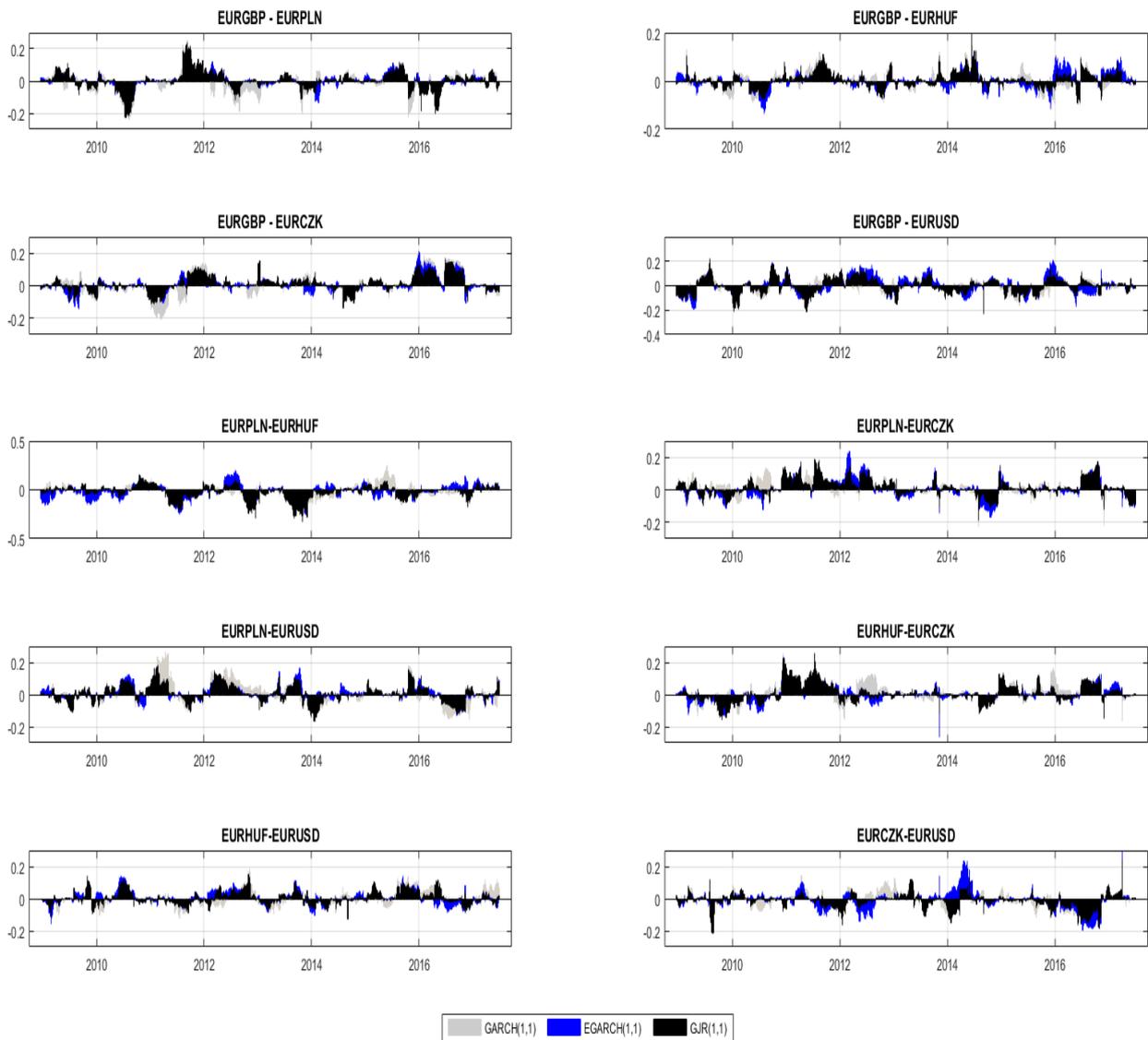
Figure 5 shows the total net volatility spillovers as the difference between TO others and FROM others currency volatility spillovers. The British pound transmits volatility towards the other currencies mostly during the Brexit period, but also throughout the sovereign debt crisis. Conversely, at the beginning of the time period and after the sovereign debt crisis, it behaves as a net volatility receiver. This appears to be in line with Antonakakis (2012) who found that the British pound is the dominant currency in receiving volatility from all other markets in the post euro period.

The Polish-PLN is also found to act as a net volatility spillovers receiver during the same periods of the British pound and also during the sovereign debt crisis. The Hungarian Forint is, most of the time, found to be a net volatility spillovers transmitter, however its role during Brexit really depends on the GARCH model that we consider. The Czech Crown appears to be a net volatility receiver, especially during the second stage of the sovereign debt crisis and during Brexit. A volatility spillovers peak is found in correspondence to November 2013, when an exchange rate floor for the EUR-CZK has been introduced from the Czech Central Bank. We investigate better the nature of this volatility spillovers peak when positive and negative realized volatility measures will be considered (Section 7). The U.S. Dollar volatility spillovers contribution appears cyclical, alternating periods in which it received volatility from the European currencies, such as, during the sovereign debt crisis, in the second half of 2014 and during the Chinese Yuan crisis and periods in which it transmitted volatility to the European currencies as, mainly, in the aftermath of the global financial crisis and during Brexit.

Figure 6 shows the net pairwise volatility spillovers for the five euro crosses. We observe that the Polish Zloty affects the volatility of the British Pound during 2010 and, surprisingly, during Brexit, while, on the other hand, it receives the volatility spillovers coming from the British currency during the sovereign debt crisis.

However, we find a prevalent position as a net volatility transmitter for the British pound against HUF and CZK, while an alternating behaviour against the U.S. Dollar. Mixed results are found between the CEE currencies themselves: the Polish Zloty receives rather than transmits volatility in relation to the Hungarian currency, while it is a clear net volatility transmitter with regard to the Czech Crown. The same direction is found from HUF to CZK with the latter identified as the least correlated within the system. The U.S. Dollar receives a small part of the volatility from the Polish Zloty and from the Hungarian forint, while it transmits volatility to the Czech Crown which appears to be the currency suffering external shocks in volatility within our system the most.

**Figure 6**  
**Pairwise NET Volatility Spillovers - Currency Market**



*Notes: This figure shows the pairwise net volatility spillovers among the five currencies for a total of ten combinations. This expresses the volatility that is transmitted from and received by a specific currency pair in a dynamic framework. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar) for the five exchange rates, namely, GBP, PLN, HUF, CZK and USD against EUR. Spillovers are computed through Equation 13 with VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

**Figure 7**  
**Total Spillovers Index - Credit Market**



*Notes: This figure shows the total net volatility spillovers for the credit market for the eight selected countries CDS spreads. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1). Spillovers index computed through Equation (15) with selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

### 6.3 CREDIT MARKET CONDITIONAL VOLATILITY SPILLOVERS

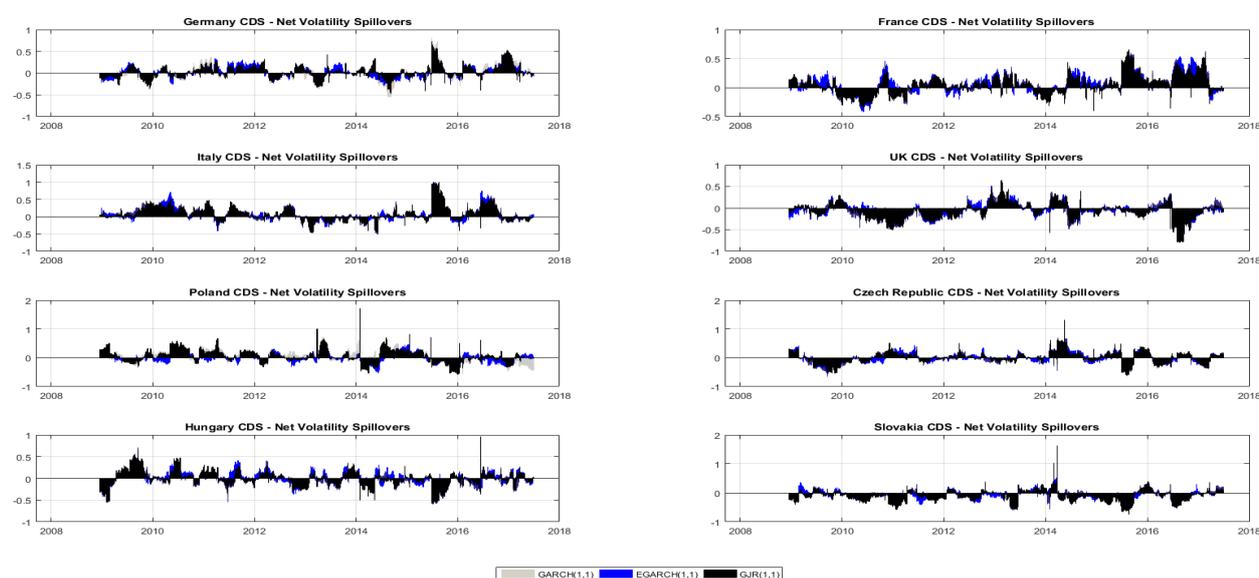
The dynamic volatility spillovers index with regards to the eight CDS spreads in the selected European countries is shown in Figure 7.

We confirm how the level of the credit market volatility spillovers index spikes throughout the Eurozone sovereign debt crisis. Indeed, at the end of 2009, Greece's sovereign debt reliability was started to vacillate scaring the EU that was forced to suddenly react in order to deal with the Greek debt crisis. Additionally, from the beginning of 2010 to half 2010, the total volatility spillovers in the European context increases until the end of 2010 and, again, in the second half of 2011 due to the Spanish and Italian bonds market uncertainty (see Diebold and Yilmaz, 2015). We find that the presence of volatility leverage effect and asymmetry is weak in the first part of our time period, while it starts to increase substantially after the second stage of the Eurozone sovereign debt crisis. Since that moment, the volatility spillovers indexes computed through GJR(1,1) and EGARCH(1,1) models are found to be above the one computed through GARCH(1,1), conversely to what is found for the currency and stock market (see Figures 1 and 4). After the sovereign debt crisis, the credit market volatility spillovers index decreases in 2012 due to the intervention of the European Central Bank (ECB) with the long-term refinancing operation (LTRO). However, the index spikes again in the second half of 2013, second half of 2014, during Grexit and it reaches its peak during the more recent Brexit vote.

The total net CDS volatility spillovers is shown in Figure 8 for the eight countries' CDS spreads. The level of volatility spillovers transmitted by the German, French and Italian CDS is high during the Eurozone sovereign debt crisis and it spikes again in reaction to the Grexit and Brexit. We find the German, French and Italian CDS spreads to be net volatility spillovers transmitters. Interesting is the result we find with regards to the CDS market in the UK. British CDS appears to receive volatility rather than to give it away especially during high volatile and turbulent times such as the European sovereign debt crisis and Brexit. The first result is justifiable from the fact that the sovereign debt crisis developed in the Eurozone and the UK CDS market was impacted absorbing the credit volatility generated in there. During the Brexit period, the result might depend on the underway negotiations among UK and the EU with regards to the decision about the UK-exit from the EU.

For the CEE countries, the Polish and Hungarian CDS markets alternate periods in which they act as net volatility spillovers transmitters and periods in which they, instead, receive volatilities from other countries. The Polish CDS is found to be a net volatility spillovers transmitter during the sovereign debt crisis, whilst a net receiver during Grexit and Brexit. The Hungarian

**Figure 8**  
**Total NET Volatility Spillovers - Credit Market**



*Notes: This figure shows the total net volatility spillovers for the credit market for the eight selected countries CDS spreads. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar). Net directional spillovers computed through Equation (12) with selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

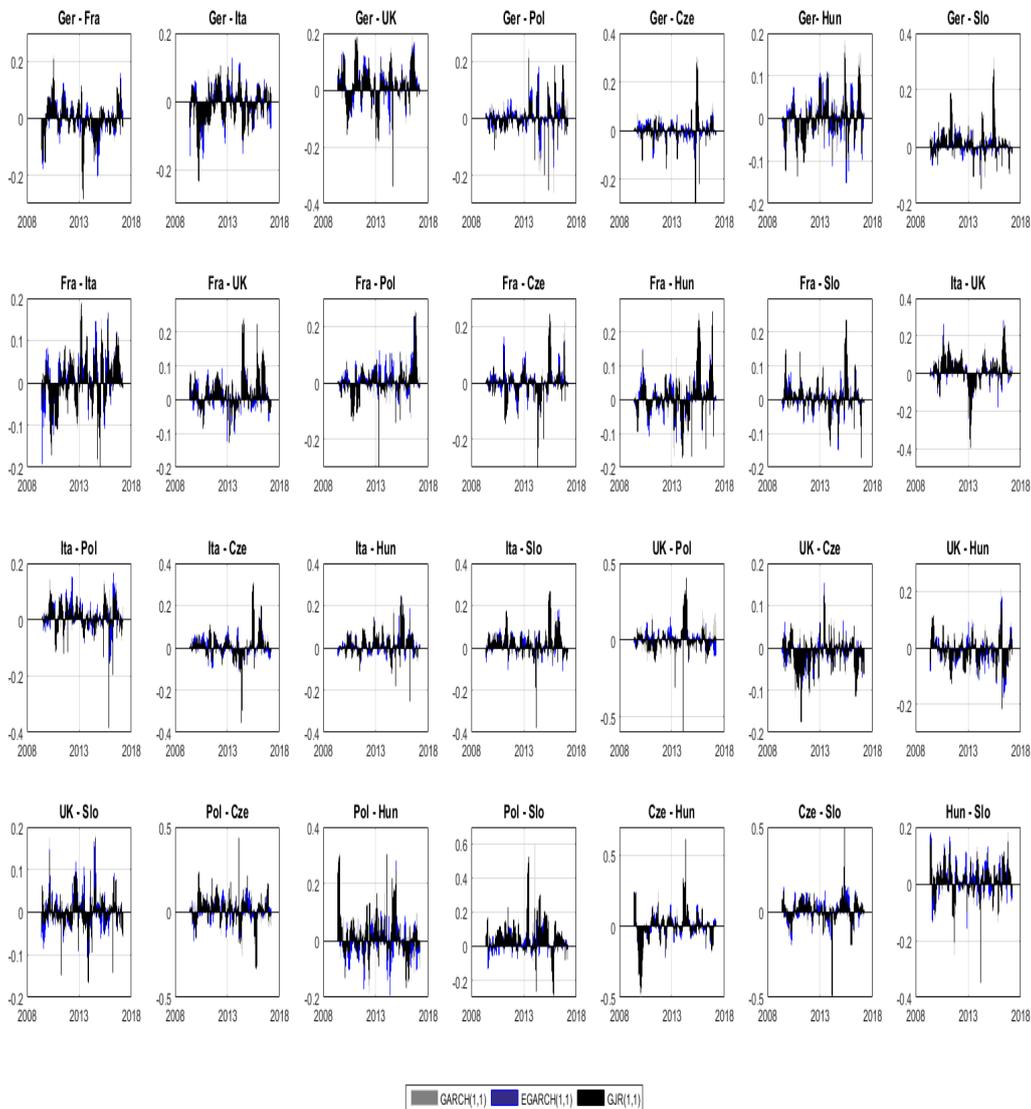
CDS market is found to transmit volatility during the sovereign debt crisis, while to receive volatility during Grexit. The Czech and Slovak CDS appear to behave as volatility spillovers absorbers.

We detect the prevalent role of the volatility leverage effect in Figure 8. GARCH(1,1) model volatility spillovers index is rarely higher than the volatility spillovers index computed through GJR(1,1) model. The same is found to be true for EGARCH(1,1) in relation to GJR(1,1). This further confirms the intuition behind this analysis pointed towards a better understanding of the asymmetric behaviour of volatilities and, consequently, of their spillovers indexes.

Figure 9 reports the net pairwise volatility spillovers for the eight countries' CDS spreads. The German CDS is found to be a net total credit volatility transmitter in relation to the British CDS and CEE countries' CDS. Interestingly during Brexit the German credit market transmitted volatility to the UK credit market and not viceversa. The relationship between the German CDS and the Italian and French CDS is mixed. During the sovereign debt crisis, the German CDS appears to transmit volatility to the French CDS, while the opposite is true in the afterwards of the crisis. Conversely, the Italian CDS market, due to the main role played by Italy in the sovereign debt crisis, transmits volatility to Germany during that period. The Italian credit market confirms its main role as a net credit volatility spillovers transmitter also after 2011, when its role in the sovereign debt crisis intensified and, also, during Grexit. More precisely, during the sovereign debt crisis, the Italian CDS market is found to transmit volatility to all the other countries' CDS markets in the system, including French and British credit markets. These findings further confirm the study by Blatt et al. (2015) who found that the European sovereign debt crisis has negatively affected countries, such as, Italy, Portugal and Spain, while country such as Germany has experienced less severe impact. Same result is found in Beirne et al. (2013) reporting how countries in the core of Euro area such as Germany and France under-priced the sovereign risk and the actual yields remained substantially below those pre-crisis conversely to emerging countries where they were over-priced.

Further confirmation of this result is also shown in Diebold and Yilmaz (2015) who affirmed how the Italian credit market had very little TO connectedness with others and high FROM connectedness with the European bond markets being affected from the latter and not vice versa. However, during the Eurozone debt crisis in 2011 the Italian market's TO connectedness increased substantially transforming it to a net volatility spillovers transmitter. The French CDS market is found to give away volatility in the direction of Italy, UK and CEE countries especially after 2011. UK CDS market absorbs volatility spillovers from France during Brexit as well. Interesting how, also the UK CDS receives volatilities from CEE countries' CDS such as Hungary and, especially,

**Figure 9**  
**NET Pairwise Volatility Spillovers - Credit Market**



*Notes: This figure shows the total net volatility spillovers for the credit market for the eight selected countries CDS spreads for a total of 28 combinations. This expresses the volatility that has been transmitted from and received by a specific countries' CDS spread in a dynamic framework. Volatilities are computed as daily annualized conditional volatilities through GARCH(1,1) (grey bar), EGARCH(1,1) (blue bar) and GJR-GARCH(1,1) (black bar). Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

Czech Republic, while it mostly transmits volatility to Slovakia and Poland. Among the CEE countries' credit markets the volatility spillovers move, mainly, from the Polish CDS market to the other three. Differences between the conditional volatilities spillovers indexes according to the selected GARCH model arise, especially, for the French CDS market which counter-trends the volatility spillovers indexes computed with leverage GARCH in relation to the German CDS in 2013 and to the Hungarian and Slovak CDS during Brexit. For the other CDS volatility spillovers indexes, the differences we detect are, mostly, in the size of the peaks and drops due to the downside risk and leverage effect of the credit market volatilities in response to some of the events in the Eurozone.

However, we contribute to the financial volatility and contagion literature showing that presence of leverage effect is found also in the credit market for the selected European countries. The asymmetric volatility effect impacts on the level of dynamic volatility spillovers indexes within the selected countries changing their roles as net receivers or net transmitters in the system. This should be taken into account from policy makers and central banks, but also from portfolio managers in terms of a diversification point of view. Indeed, asymmetric volatility features might be considered as more prudent measures compared to the simple measure as GARCH(1,1) model that is found to predict, overall, lower levels of volatility spillovers within the system. The next Section 7 contributes even more to the volatility spillovers literature by looking at the volatility asymmetry effect which is translated into asymmetric volatility spillovers, when the separate role of good or bad news and events is considered in impacting the selected financial assets' volatility.

# 7 Asymmetric Realized Volatilities Spillovers: Results

So far in the paper we have shown how the volatility leverage and asymmetric effect is emerged affecting the volatility spillovers indexes for the developed EU and developing CEE financial assets in the last decade. However, only the first type of volatility asymmetry, namely, the leverage effect in response to good and bad news of identical size (see Clements et al., 2015) has been considered. It is found that the results in relation to some particular countries or asset classes vary according to the selected conditional volatility model. In order to overcome this modelling selection, in this Section 7, we input the model-free realized decomposed measures in the Diebold and Yilmaz (2012) spillovers index in place of the conditional volatility measures. This allows us to consider the different impact that bad and good news might have, in turn, on the selected asset classes volatility spread in a separate framework. We look at events influencing the Eurozone and due to which the selected countries' total positive volatility spillovers index ( $SI^+$ ) and total negative volatility spillovers index ( $SI^-$ ) have changed the most. We also check in relation to which asset class and due to which event the volatility asymmetric behaviour is stronger. After having computed the  $SI^-$  and the  $SI^+$  measures, we compute the *Spillovers Asymmetry Measure (SAM)* as the difference between  $SI^+$  and  $SI^-$  (see Baruník et al., 2016; Baruník et al., 2017). Every increase in either  $RV^+$  or  $RV^-$  corresponds to an increase in  $SI^+$  or  $SI^-$ , respectively and it affects, consequently, the SAM that will turn to be higher or lower than zero accordingly. When the SAM is negative, it means that  $SI^-$  impacts more on the aggregate volatility spillovers, while when SAM is positive it means that  $SI^+$  is the main component of the aggregate volatility spillovers. In the next sections, we show the total volatility spillovers index and the net directional volatility spillovers index according to the total, positive and negative realized volatility measures together with the spillovers asymmetry measure (SAM), both for the total index, but also for the net directional in relation to all the three asset classes for the developed EU and developing CEE countries.

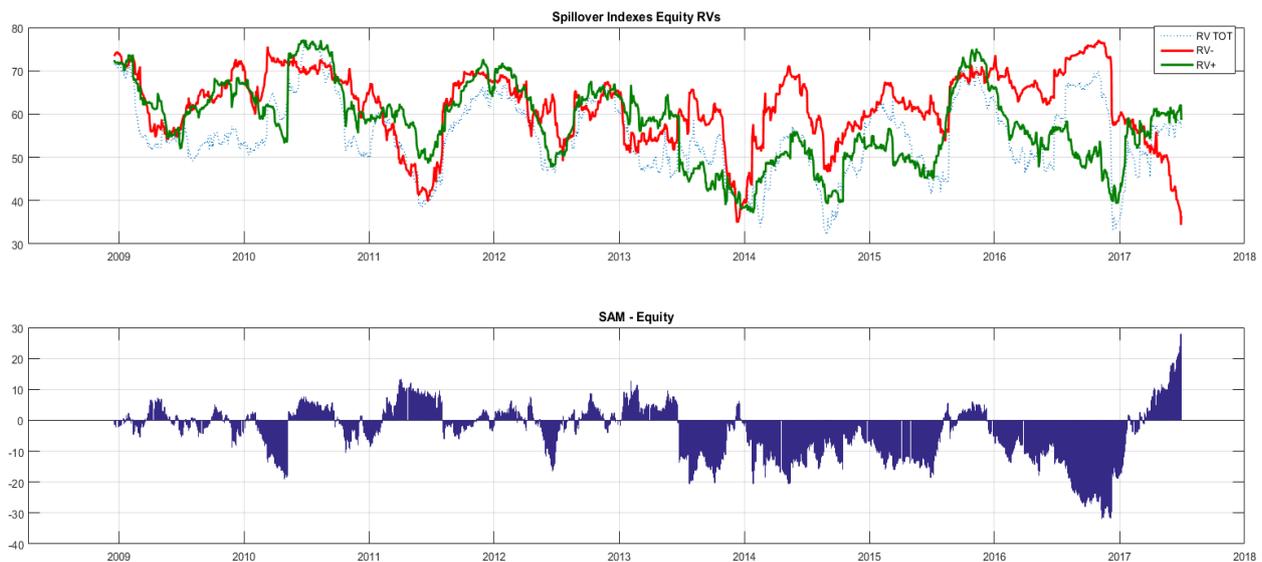
## 7.1 ASYMMETRIC REALIZED VOLATILITIES SPILLOVERS IN THE EQUITY MARKET

Starting with the equity market, we show in Figure 10 the comparison between the total volatility spillovers indexes computed with the total, positive and negative realized volatility measures (upper panel) and the spillovers asymmetry measure, SAM, as in Equation (16) (bottom panel).

As already shown in Section 6.1, all the volatility spillovers indexes in the equity market present a high level in the immediate post global financial crisis due to the uncertainty this injected in the European stock markets. However, in the years after the global financial crisis, the positive and negative spillovers indexes alternate reflecting the different investors' reactions to news. Many investors were speculating on the post global financial crisis market re-bounce, while others were still experiencing negative returns and fear in future financial market collapse. Similar results are found in Baruník et al. (2016) who stated that since 2009 the pattern of alternating positive and negative asymmetries prevails. This is a synonym of a mixture of investors positions making the SAM oscillating between the positive and negative domain for few years<sup>16</sup>. During the European sovereign debt crisis, this alternating trend appears to prevail as well. Conversely, after the the sovereign debt crisis, in the first half of 2013 we find a long period where  $SI^-$  dominated  $SI^+$  for most of the time until the first half of 2017 dragging the SAM below zero (Figure 10 bottom panel). This means that volatility spillovers in the system during the post sovereign debt crisis were mainly due to negative volatilities and investors negative expectations about the stock market. Thus, the asymmetric effect in response to good or bad news and events is clearly detected with relation to the stock market. This effect is mainly evident in relation to events which increased the investors' future uncertainty such as the economic slowdown coming from the U.S., the Ukraine-Russia conflict, the tensions in the Middle East, the ISIS escalation and, eventually, the Grexit referendum in July 2015 and the Brexit vote in June 2016. During the Brexit period,  $SI^-$  reaches its highest level reflecting it in the widest spillovers asymmetry measure in the last decade.

<sup>16</sup> In fact, according to Baruník et al. (2016), SAM can be also seen as an approximation of optimistic or pessimistic investors' expectations and beliefs in relation to the future market trends.

**Figure 10**  
**Total Realized Volatilities Spillovers Indexes and SAM - Equity Market**



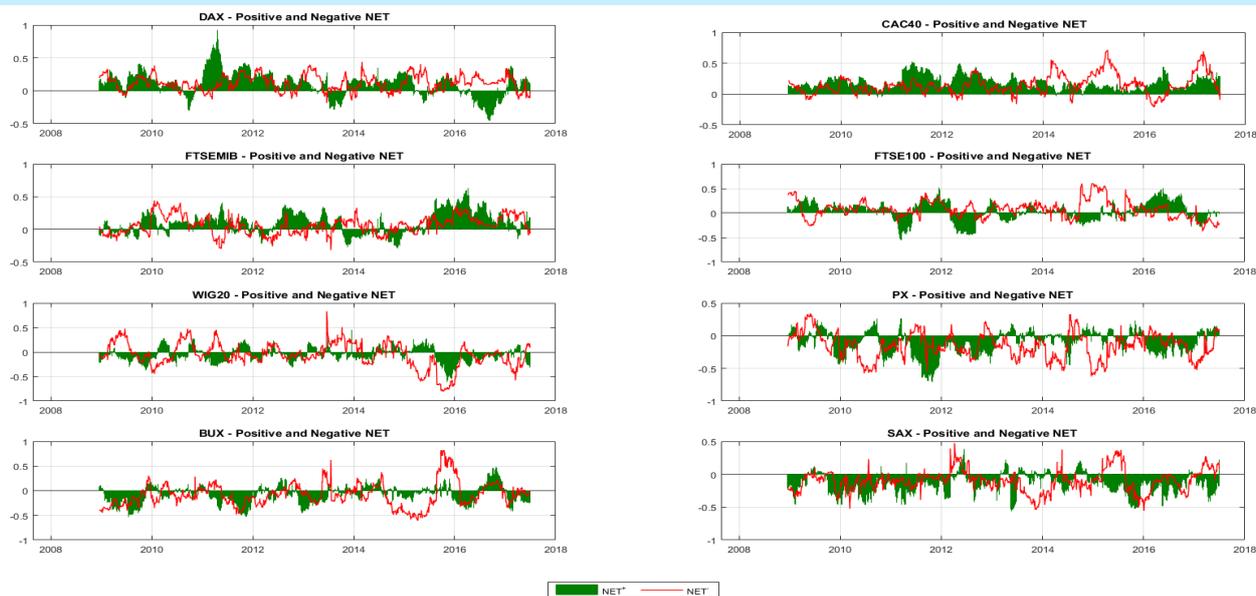
*Notes: This figure shows the comparison between the total volatility spillovers indexes computed through equation (15) in relation to the selected equity markets with inputs the decomposed realized volatilities and the total volatility series (upper panel). In the bottom panel is shown the spillovers asymmetric measure (SAM) as a difference between  $SI^+$  and  $SI^-$ . Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

Figure 11 shows the positive and negative directional net volatility spillovers for the equity market according to the positive and negative realized volatilities as computed in Equation (19). It illustrates, at the same time, whether the specific asset can be labeled as positive volatility spillovers transmitter or receiver and also whether the asset can be labeled as negative volatility spillovers transmitter or receiver. In other words, the NET directional is the difference between TO and FROM directional spillovers indexes for both the positive and also the negative volatility spillovers indexes computed by inputting  $RV^+$  and  $RV^-$  in (19), respectively.

As already found for the conditional volatility measures (see Figure 2), the developed EU countries spread the main part of the volatility in the system and they clearly appear to be volatility spillovers net transmitters for both the net positive and also for the net negative volatility spillovers. DAX and CAC40 indexes appear to be both positive and negative volatility spillovers transmitters during almost the entire time period, with asymmetry in volatility spillovers which increases especially after mid 2013. During Brexit, the German DAX behaves as net positive volatility spillovers receiver and net negative volatility spillovers transmitter appearing to benefit from the UK vote to leave the EU. The French CAC40 can be classified as positive volatility transmitter in the system from the post global financial crisis onwards, however this trend changes during the Grexit and Brexit votes. During the first, CAC40 transmits three times more negative volatility compared to the positive and, during Brexit, it transmits almost double negative volatility compared to the positive. The Italian FTSEMIB is, mainly, a positive volatility transmitter in the system, however it receives negative volatility during the sovereign debt crisis, especially during the phases of it in which Italy was more involved. Interestingly, we find that the UK FTSE100 can be, overall, seen as negative volatility transmitter presenting a huge spike at the end of 2014. However, the British stock market index inverts this trend during Brexit becoming a negative volatility spillovers receiver and a positive volatility transmitter especially in direction to the German and to the CEE stock market indexes. FTSE100 also receives positive volatility in the two main phases of the sovereign debt crisis being a useful diversifying asset for European investors during those times.

Among the CEE stock market indexes, WIG20 appears to have the most prevalent role as volatility spillovers transmitter, mostly negative, showing a mixed behaviour between the developed EU and the other CEE countries. This might be due to the fact that the Polish is the principal CEE stock market and it is linked in trades both with the developed EU stock markets and also with the CEE financial markets and investors. However, it receives mainly negative volatility from the system due to the political election and situation in Poland at the end of 2015. For the other CEE stock indexes, namely PX, BUX and SAX, we find a clear

**Figure 11**  
Positive and Negative NET SI - Equity Market



Notes: This figure shows the positive and negative net directional spillovers indexes according to the positive  $RV^+$  and negative  $RV^-$  measures and computed through Equation (19) for all the eight stock market indexes. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.

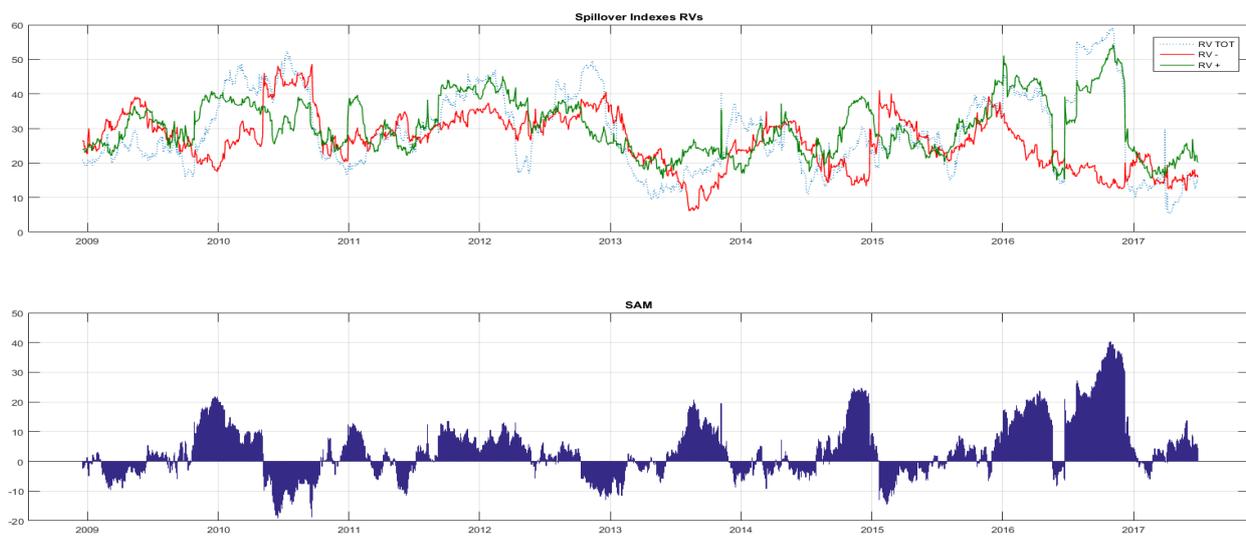
net receiver role, positive or negative. This trend is reversed only in rare circumstances such as in 2012 and mid 2015 for SAX, at the beginning of 2009 and at the end of 2014 for PX and at the end of 2015 for BUX. In the last case, Hungary experiences several debt downgrades during the crisis that might also impact on its position with regards to the other countries transmitting negative volatility to the system (see Gjika and Horvath, 2013). The CEE stock markets are related to news and events occurring in the Eurozone absorbing, most of the time, volatility from the developed EU countries. However, they show, in some circumstances, a counter trend during some volatile and turbulent periods as Brexit and sovereign debt crisis during which they present better diversification opportunities compared to the developed EU countries. For Slovakia the level of volatility asymmetry is, however, lower than the one detected for the other CEE markets. Overall, we show a clear evidence of volatility asymmetry with regards to the net directional spillovers indexes in the stock market for all the eight countries with positive or negative spread of volatility according to the considered event.

## 7.2 ASYMMETRIC REALIZED VOLATILITIES SPILLOVERS IN THE CURRENCY MARKET

In this Section, we present the dynamic volatility spillovers analysis for the currency market in relation to the five selected currencies' volatility, namely, British Pound (GBP), Polish Zloty (PLN), Czech Crown (CZK), Hungarian Forint (HUF) and U.S. Dollar (USD) all taken against the Euro.

Figure 12 shows the comparison between the total volatility spillovers indexes computed with the aggregate, positive and negative realized volatilities (upper panel) and the total SAM measure for the currency market (bottom panel) using a 100-day rolling window. Also within this market, we find evidence of volatility asymmetries in response to positive or negative news. The bottom panel in Figure 12 shows how SAM is, most of the time, in the positive domain of the x-axis meaning that volatility spillovers due to  $RV^+$  dominate the ones coming from  $RV^-$ . Similar results are found by Baruník et al. (2017): periods as after the 2008 global financial crisis and calm period as 2014–2015 present more volatility spillovers due to positive volatility. Conversely, between these two periods, during 2010–2013 and, mainly, due to the beginning and ending of the Eurozone sovereign financial crisis, the asymmetry due to negative news coming from  $RV^-$  dominate the positive one. These negative spillovers appear to be dictated by the uncertainty that was surrounding the European markets at that time. Moreover, we find two main peaks of positive volatility spillovers in the considered system and time period: the first is mainly due to the Chinese

**Figure 12**  
**Total Realized Volatilities Spillovers Indexes and SAM - Currency Market**



*Notes: This figure shows the comparison between the total volatility spillovers indexes computed through equation (15) in relation to the five currencies where the input are the decomposed realized volatilities and the total volatility series (upper panel). In the bottom panel is shown the spillovers asymmetric measure (SAM) as a difference between  $SI^+$  and  $SI^-$ . Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

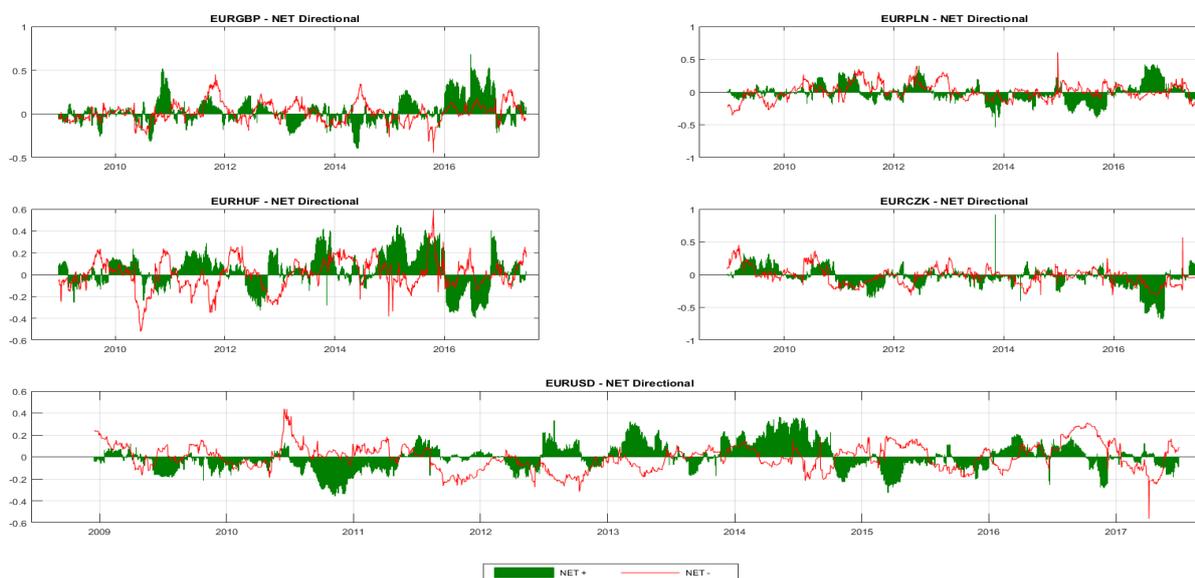
Yuan crisis, while the second is found in correspondence of the Brexit vote. In both cases the asymmetries in volatility due to these events have been generated from a spread of good volatility in the system in which some currencies appreciated mainly due to the decline of the Chinese Yuan and British Pound.

Figure 13 shows the positive and negative directional NET spillovers for each currency. A spread of negative volatility in relation to one of the currency in the system might be associated with a decrease of its price. Considering that the currencies for the purpose of this paper have been taken against euro, a negative effect on one of the currency's price might also be associated with a depreciation of the base currency with respect to the euro.

Figure 13 shows the net positive and net negative directional spillovers indexes with regards to the selected five currencies. The British pound is found to be a clear diversifying asset afterwards the global financial crisis and during the sovereign debt crisis receiving positive volatility. It transmits positive volatility and it receives negative volatility during Grexit and Chinese Yuan crisis as a synonym of uncertainty in relation to other countries and currencies. Interestingly, during Brexit, the British pound transmits both positive and also negative volatility with the first being almost double compared to the second. Indeed, during Brexit the British pound gives away positive volatility to the system with euro and the other CEE currencies which benefit from it appreciating against the British pound. On the other hand, the UK currency depreciates due to the negative effect of the Brexit outcome on the UK economy.

The Polish Zloty behaves similar to the British Pound during the sovereign debt crisis and during Brexit being a positive volatility transmitter. Conversely, the Czech Crown and the Hungarian Forint behave as positive volatility receivers during Brexit showing more diversifying opportunities for the European investors. Indeed, they benefit from the Brexit receiving, mainly, positive volatility from the British pound. PLN and CZK receive negative volatility spillovers during the post global financial crisis, while PLN and HUF receive positive volatility during the sovereign debt crisis. These currencies have been shelters against the Euro uncertainty. Interestingly, we notice a spike in transmitted volatility in November 2013 for the Czech Crown. This is due to the imposition from the Czech National Bank of a lower limit on the CZK-EUR exchange rate in order to prevent the euro from depreciating under 27 CZK. This reflects with a positive volatility spillovers transmission from the CZK to the system. After that the CZK level of volatility spillovers has been really low, however reacting to the other CEE currencies and receiving positive volatility from GBP during Brexit. In April 2017 we notice a peak in negative volatility transmitted from CZK to the system in

**Figure 13**  
Positive and Negative NET SI - Currency Market



Notes: This figure shows the positive and negative net directional spillovers indexes according to the positive  $RV^+$  and negative  $RV^-$  measures and computed through Equation (19) for the five currencies. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.

correspondence to the decision of the Czech National Bank to remove the floor after three and a half years. Another peak in transmitted negative volatility is found, this time, for the Polish Zloty in correspondence of the uncertainty that the 2015 Polish political situation spread within the system. In the bottom plot in Figure 13, we notice how the U.S. dollar has shown an alternating behaviour. It is found to be a positive volatility receiver and negative volatility transmitter during the sovereign debt crisis with the dollar appreciating against euro. It, mainly, receives negative volatility while transmitted positive from 2012 to 2015 and vice versa during mid 2015. During Brexit, it receives positive volatility due to the appreciation of the U.S. dollar against the British Pound, while it transmits negative volatility to the system. Overall, also in relation to the currency market, we find evidence of a not symmetric transmission of volatility spillovers according to different events of interest, this behaviour being impressively emphasized during Brexit.

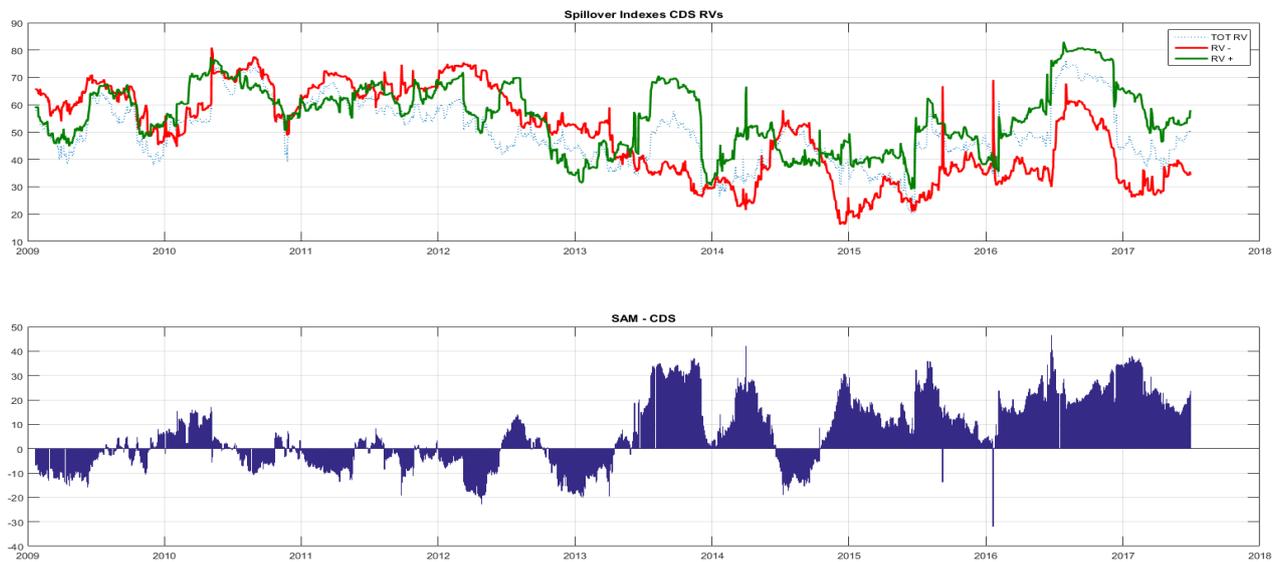
### 7.3 ASYMMETRIC REALIZED VOLATILITIES SPILLOVERS IN THE CREDIT MARKET

Figure 14 illustrates the comparison between the decomposed realized volatility spillovers indexes for the credit market. We find the Eurozone sovereign debt crisis as the main event contributing in injecting negative volatility spillovers in the CDS market.

After the sovereign debt crisis, an increase in positive volatility spillovers is detected due to the ECB long-term refinancing operation (LTRO) and the ECB Quantitative Easing (QE)<sup>17</sup>. This is in line with the definition of bailout program that is, overall, undertaken in order to avoid contagion spread. While Alter and Beyer (2014) found that the LTRO program had a mitigating effect on the contagion in the Euro area, in Figure 14 we show that is exactly the negative volatility spillovers index which is, indeed, reduced after the ECB' policies. Thus, having decomposed the volatility spillovers indexes allows us to contribute to the previous literature by showing how a bailout can be either interpreted as a negative contagion decrease or as a positive volatility contagion increase. The negative volatility spillovers present a downturn in correspondence of the end of the sovereign debt crisis until the first quarter of 2014 showing how volatility spillovers caused in the system due to negative volatility reduced by

<sup>17</sup> What turned the tide in favor of tranquility was the intervention of the ECB, under the leadership of its new president Mario Draghi. On December 12, the ECB announced that it would make 500 billion euros available to Eurozone banks through a program called a long-term refinancing operation (LTRO). The ECB added that there might be further rounds of LTROs in the near future. Once the news came out, all financial markets in the Eurozone and beyond became calm with a decline in the bond market volatility connectedness in the second half of December and even less by the end of May 2012.

**Figure 14**  
**Total Realized Volatilities Spillovers Indexes and SAM - Credit Market**

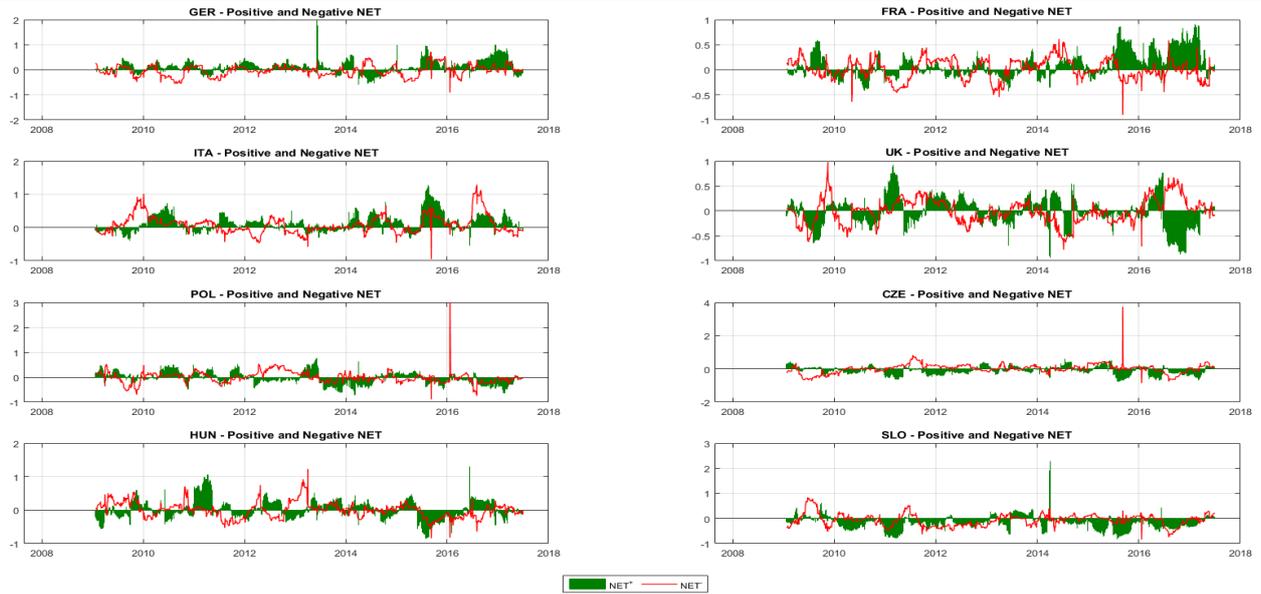


*Notes: This figure shows the comparison between the total volatility spillovers indexes computed through equation (15) in relation to the eight credit markets where the input are the decomposed realized volatilities and the total volatility series (upper panel). In the bottom panel is shown the spillovers asymmetric measure (SAM) as a difference between  $SI^+$  and  $SI^-$ . Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.*

almost 60%. A period characterized by positive volatility spillovers is also found in correspondence of Brexit. For the SAM, we find a negative measure before the LTRO and a positive SAM post LTRO, specifically during the ECB QE, during Grexit and during Brexit.

Figure 15 shows the net directional volatility spillovers for the CDS markets according to the positive and negative volatility measures. Germany CDS markets is found to be the prevalent positive volatility transmitter in the system representing the most stable country among our credit markets. A huge spike of positive volatility spillovers is found in correspondence of 2013 Merkel's election. On the other hand, Germany CDS market receives for good part of the sample negative volatilities from the other developed EU and CEE credit markets. This can also be interpreted as a sign of stability of the Germany credit system compared to the other countries. It, actually, shows its role as negative volatility absorber in relation to the bad credit news and events which might have occurred in other markets especially during the sovereign debt crisis. France credit market gave away positive volatility spillovers, especially during the post 2008 global financial crisis and during the last few years due to Grexit and Brexit. The role of Italy reflected more the widespread of a negative economic performance after the 2008 global financial crisis and due to the uncertainty in relation to the political situation in 2016, transmitting negative volatility spillovers into the system. It, instead, absorbed negative volatility from the system during the sovereign debt crisis in which it played a key role, but also during Grexit. These findings are in line with Beirne et al. (2013) showing how Germany and France credit markets can be considered, overall, stable in the Eurozone system since they were not affected much by the sovereign debt crisis which, in turn, impacted on countries such as Greece, Spain, Portugal and Italy. The same appears to be true during Grexit and Brexit. The UK CDS market behaved in a fully asymmetric way during Brexit: positive volatility is received by British CDS coming from the more stable developed EU and developing CEE countries, while negative volatility is transmitted since it is caused by negative UK CDS returns. In relation to the CEE countries, we find that the Polish credit markets transmits, mainly, positive volatility before 2012 and during the sovereign debt crisis since its role as an outsider in the crisis. During 2015 and 2016 the Czech and Polish CDS markets shown a huge negative volatility spike, respectively. Hungarian CDS received, mainly, negative volatility during the sovereign debt crisis and during Brexit reflecting the, overall, instable credit situation in the Eurozone. Slovakia credit market is mainly classifiable as a positive volatility receiver, however presenting less asymmetry compared to the other markets.

**Figure 15**  
**Positive and Negative NET SI - Credit Market**



Notes: This figure shows the positive and negative net directional spillovers indexes according to the positive  $RV^+$  and negative  $RV^-$  measures and computed through Equation (19) for the eight CDS spreads. Selected VAR lags = 2 and forecast horizon = 4. The selected time period is from 01-08-2008 to 30-06-2017 with a 100-day rolling window.

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## 8 Conclusion

In this paper we have shown that volatilities of assets, such as, stock indexes, currencies and CDS spreads spill over asymmetrically among the developed EU and the developing CEE countries in response to some of the main economic and political events which have interested the Eurozone and increased its uncertainty in the last decade.

This paper has contributed to the volatility spillovers literature in several ways. First of all, we have applied the Diebold-Yilmaz spillovers index methodology to a new geographical context and in a more recent post-crisis period in light of the fact that uncertain and turbulent times have been characterising the Eurozone in the last decade. This has made the study of the potential volatility connectedness among these two groups of countries in reaction to some of the most meaningful events more of interest. In addition, we have conducted our analysis with regards to three different asset classes, namely, stock market, currencies and credit market showing how different channels contribute to volatility spillovers in different ways.

Lastly, our contribution is placed mainly in the new version of the volatility spillovers index we compute: we have input a different set of volatility measures with the aim of checking the potential volatility leverage and asymmetry effect. The first measures are within the GARCH models family, namely GARCH(1,1), EGARCH(1,1) and GJR(1,1) models, while the second measure is the model-free realized volatility. The latter has decomposed into positive and negative volatility components, namely,  $RV^+$  and  $RV^-$ . These different measures considered in the spillovers index framework allowed us to test, not only, the volatility asymmetry effect in relation to positive and negative shocks of identical size, but, also, in relation to asymmetric effect caused by positive and negative news of events, separately.

We have shown that not all the selected European countries have reacted in the same way to economic, financial and political situations occurred in the last decade. For some countries these events might result in a spread of positive volatility being beneficial in affecting assets returns, while for other countries they might be seen as negative events due to a spread of negative volatility from the system to their assets.

In the stock market, we found that the volatility spillovers index computed with leverage GARCH methodologies such as EGARCH(1,1) and GJR-GARCH(1,1) are, most of the time, higher than the one computed with the simple GARCH(1,1) reflecting the investors' concern of a possible future financial crisis. In the credit market, however, this asymmetric volatility effect, although present, appeared to emerge only throughout and afterwards the sovereign debt crisis. For the currency market, the connectedness level computed through asymmetric volatility models dominated the GARCH(1,1) model for most of the sample, reverting its trend only in upward times for all the currencies in the system.

We have further confirmed that the more developed EU stock markets are, most of the time, volatility spillovers transmitters towards the other stock markets in the developing CEE countries. Overall, the two groups of countries appeared to be strictly connected through the stock market channel with the only exception of the Slovak economy. Poland shown a rapid growth in its stock market being placed in a middle position between the developed EU and developing CEE economies. These findings might bring some new insights on the diversification opportunities which the CEE countries might still offer to European investors.

Furthermore, we have found that many events in the Eurozone in the recent years, have, not only, shown their effect among the most developed EU countries, but also by transmitting volatility among the CEE markets. Thus, even when uncertainty generated and occurred in the midst of the Eurozone, CEE economies are still affected and this happened mostly through the equity market channel. With regards to the currency market we have detected the British pound as the main net volatility transmitter during Brexit. In relation to the credit market, a weak presence of volatility leverage after the 2008 global financial crisis is found. However it started to increase after the second stage of the sovereign debt crisis. The Italian CDS spreads emerged to play a crucial role as net credit volatility spillovers transmitter when the Italian role in the sovereign debt crisis intensified. The German CDS volatility spillovers index remained, overall, stable and it is found not to be affected much from the sovereign debt crisis. The CEE countries confirmed their role as net volatility spillovers absorbers in the credit market volatilities as well.

When decomposed realized volatility measures are considered, some results are confirmed. However, we have been able to shed new light by considering, this time, volatility asymmetry due to good and bad events and news impacting, in turn, the three asset classes in the developed EU and CEE countries. In the stock market, volatility spillovers are characterized mainly by  $RV^-$  which prevailed over the positive  $RV^+$  since the post Eurozone sovereign debt crisis, reflecting the period of uncertainty in Europe. In the currency and credit market, volatility spillovers are characterized mainly by  $RV^+$ . The peak of positive volatility spillovers in the currency market is due to the Brexit vote due to the fact that the event has generated an appreciation for the other currencies in the system against euro. The British pound has found to be a clear diversifying asset during the sovereign debt crisis receiving positive volatility from the system, while it transmitted positive volatility during Brexit since other currencies appreciated. Lastly, in the credit market, the total negative spillovers index has decreased in mid 2012 due to the ECB's LTRO bailout program, while the positive spillovers index has increased. Moreover, we have found the Germany CDS market as a positive volatility transmitter in the system as synonym of stability compared to the other CDS spreads.

This paper has aimed to follow the opening and new strand of literature investigating whether or not financial assets volatility contagion might also be considered as desirable by investors and portfolio managers willing to share the risk, entering in the channel or directly make a profit from the increase in financial markets volatility. In general, measuring the volatility connectedness among countries might assess the level of integration they are experiencing within each other. Measuring the asymmetric volatility connectedness among them gives also additional insight on the side, positive or negative, beneficial or harmful, of this integration. On the other hand, the question would be to understand whether diversification is always beneficial or not. As we have seen, especially for the equity market, the European countries are getting too integrated and these diversification opportunities might be easier to find abroad, such as, for instance, in Asian or Latin American markets. Furthermore, since a more integrated environment has found among the developed EU and developing CEE stock markets, while less within the credit and forex markets, investors should start taking more in consideration portfolio diversification opportunities provided by these other assets in the European market in replacement of the standard stock indexes.

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