Fear connectedness among asset classes

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Abstract

This study investigates the interconnection between five implied volatility indices representative of different financial markets during the period August 1, 2008-December 29, 2017. To this end, we first perform a static and dynamic analysis to measure the total volatility connectedness in the entire period (the system-wide approach) using a framework recently proposed by Diebold and Yilmaz (2014). Second, we make use of a dynamic analysis to evaluate both the net directional connectedness for each market and all net pairwise directional connectedness. Our results suggest that a 38.99%, of the total variance of the forecast errors is explained by shocks across markets, indicating that the remainder 61.01% of the variation is due to idiosyncratic shocks. Furthermore, we find that volatility connectedness varies over time, with a surge during periods of increasing economic and financial instability. Finally, we also document frequently switch between a net volatility transmitter and a net volatility receiver role in the five markets under study.

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1. Introduction

The global financial crisis ((hereafter, GFC) of 2008-2009 seems to trigger a prolonged worldwide fear spillover and cause a fundamental change in the linkages among international markets. In periods of market stress, the diversification benefits can vanish, resulting in a propagated crash and increase of their volatilities at once. In this sense, it provides a unique natural experiment for examining the dynamic interrelationships among alternative asset classes during a worldwide financial crisis.

Since volatility reflects the extent to which the market evaluates and assimilates the arrival of new information, capturing how perceptions of uncertainty about economic fundamentals are manifested in prices, the analysis of its transmission pattern might provide useful insights into the characteristics and dynamics of financial markets. Based on the theoretical papers of Demeterfi *et al.* (1999) and Carr and Madan (1998), the Chicago Board Options Exchange (CBOE) developed market volatility indices that are measures of implied volatility obtained from options markets, and constitute important indicators of financial markets risk[2]. They are often referred to as the "fear gauge" for asset markets (Whaley, 2000) because they represent the expectations of the investors about the future realized volatility of the underlying assets for 30 calendar days ahead. They are thought to reflect negative stock market psychology. Indeed, prior studies have provided support for the predictive ability of the Volatility Index (VIX, a measure of implied volatility of the Standard & Poor's 500 Index) with regard to stock return (see,

[2] For excellent primers on the VIX, see Whaley (2009) and Gonzalez-Perez (2015).

e. g., Giot, 2005; Guo and Whitelaw, 2006; and Banerjee *et al.,* 2007). Moreover, the forward-looking characteristic of volatility indices make them have a superiority of the information content over historical volatility measures as it has been extensively documented in the literature (Jorion, 1995; Xu and Taylor, 1995; Christenssen and Prabhala, 1998: Fleming, 1998; Blair, Poon, and Taylor, 2001; and Jiang and Tian, 2005; among others).[3]

Among the studies examining linkages in implied volatility indices, Nikkinen et al. (2006) analyze the connection between implied volatilities for the euro, the British pound and the Swiss franc (quoted against the U.S. dollar). These authors find that the implied volatility of the euro significantly affects the volatility expectations of the British pound and the Swiss franc. Äijö (2008) examines the implied volatility term structure linkages between the volatility indices for the German stock index (VDAX), the Swiss Market Index (VSMI) and the EURO STOXX 50 Index (VSTOXX). Badshah *et al.* (2013) investigate the contemporaneous spillover effects among the volatility indices for stocks (VIX), gold (GVZ), and the exchange rate (EVZ). The authors detect strong unidirectional spillover from VIX to GVZ and EVZ and bidirectional spillover between GVZ and EVZ. Liu *et al.* (2013) study the short- and long-term cross-market uncertainty transmission between the implied volatility index for crude oil (OVX), the VIX, the EVZ and the GVZ (gold price volatility index). They report that there are no strong long-run equilibrium relationships among these volatility indices and that the OVX is significantly influenced by other ones. Psaradellis and Sermpinis (2016) concentrate on modelling and trading of three daily market volatility indices: the VIX,

[3] Poon and Granger (2003) concluded that the VIX is the best predictor of realized volatility, although it may be a biased one.

the VXN (based on the Nasdaq-100 Index) and the VXD (based on the Dow Jones Industrial Average Index).

In this paper, we will focus on the interconnection between five volatility indices representative of different financial markets making use of Diebold and Yilmaz's (2014) measures of connectedness[4]. These volatility indices encompass the major asset classes such as equities, commodities, foreign exchanges and bonds, and accordingly, are able to measure the uncertainty or "fears" in the financial markets. Diebold and Yilmaz's (2014) connectedness framework is closely linked with both modern network theory (see Glover and Richards-Shubik, 2014) and modern measures of systemic risk (see Ang and Longstaff, 2013 or Acemoglu *et al*., 2015). This framework has been used by Diebold and Yilmaz (2015) for defining, measuring, and monitoring connectedness in financial and related macroeconomic environments (cross-firm, cross-asset, cross-market, cross-country, etc.). The degree of connectedness, on the other hand, measures the contribution of individual units to systemic network events, in a fashion very similar to the conditional value at risk (CoVaR) of this unit (see, e.g., Adrian and Brunnermeier, 2016).

Our study extends and complements the existing literature by providing a novel perspective on the interdependence among alternative asset classes. Although a substantial amount of literature has used different extensions of Diebold and Yilmaz's (2012) previous methodology to examine spillovers and transmission effects in different

[4] The connectedness methodology has several advantages over the alternative approach of focusing on contemporaneous correlations (corrected or not for volatility). First, while correlation is a symmetrical measure, connectedness is an asymmetrical one, so the procedure provides information on the direction and magnitude of the volatility transmission (from country *A* to country *B*, from country *B* to country *A*, or both). Second, by investigating dynamic connectedness through a rolling window, we can evaluate how the strength of the connectedness evolves over time, allowing us to detect episodes of sudden and temporary increases in volatility transmission.

financial markets[5], to the best of our knowledge, it has not been applied to explore volatility transmission between the volatility indices of different asset classes as representative of expected future market volatility. Since they are based on derivatives markets, where volatility plays a prominent role, market volatility indices are especially relevant for unraveling the connections between uncertainty, the dynamics of the economy, preferences, and prices.

Studies of the transmission of volatility shocks from one market to another are essential in finance, because they have many implications for international asset pricing and portfolio allocation. Indeed, a higher degree of connectedness between markets would reduce the diversification benefits. This would also imply that at least a partially integrated asset-pricing model is appropriate for modeling the risk-return profile of the different asset classes.

The rest of the paper is organized as follows. Section 2 presents Diebold and Yılmaz (2014)'s methodology for assessing connectedness in financial market volatility. Section 3 presents our data and a preliminary analysis. In Section 4 we report the empirical results (both static and dynamic) obtained for our sample of five market volatility indices (a system-wide measure of connectedness). Section 5 examines the evolution of net directional and net pairwise directional connectedness in each market. Finally, Section 6 summarizes the findings and offers some concluding remarks.

[5] Awartania *et al*. (2013), Lee and Chang (2013), Chau and Deesomsak (2014) and Cronin (2014) apply this methodology to examine spillovers in the United States' markets; Yilmaz (2010), Zhou *et al*. (2012) and Narayan *et al*. (2014) focus on Asian countries; Apostolakisa and Papadopoulos (2014) and Tsai (2014) examine G-7 economies; Demirer *et al.* (2015) estimate global bank network connectedness and Diebold and Yilmaz (2016) characterize equity return volatility connectedness in the network of major American and European financial institutions; McMillan *et al.* (2010), Antonakakis. (2012) and Bubák et al. (2014) examine interdependence and spillovers in exchange rate markets; and Antonakakis and Vergos (2013), Alter and Beyer (2014), Claeys and Vašícek (2014) and Fernández-Rodríguez *et al.* (2016) use connectedness analysis to assess financial stress transmission in European sovereign bond markets.

2. Methodology

The main tool for measuring the amount of connectedness is based on a decomposition of the forecast error variance, which we will now briefly describe.

Given a multivariate empirical time series, the forecast error variance decomposition is obtained from the following steps:

1. Fit a standard vector autoregressive (VAR) model to the series.

2. Using series data up to and including time t, establish an H period-ahead forecast (up to time $t + H$).

3. Decompose the error variance of the forecast for each component with respect to shocks from the same or other components at time t.

Diebold and Yilmaz (2014) propose several connectedness measures built from pieces of variance decompositions in which the forecast error variance of variable i is decomposed into parts attributed to the various variables in the system. This section provides a summary of their connectedness index methodology.

Let us denote by d^{H}_{ij} the ij-th H-step variance decomposition component (i.e., the fraction of variable i's H-step forecast error variance due to shocks in variable j). The connectedness measures are based on the "non-own", or "cross", variance decompositions, d^{H}_{ij}, $i, j = 1, \ldots, N$, $i \neq j$.

Consider an N-dimensional covariance-stationary data-generating process (DGP) with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \ldots$, $E(u_t, u_t') = I$. Note that Θ_0 need not be diagonal. All aspects of connectedness are contained in this very general representation. Contemporaneous aspects of connectedness are summarized in Θ_0 and dynamic aspects in $\{\Theta_1, \Theta_2, ...\}$. Transformation of $\{\Theta_1, \Theta_2, ...\}$ via variance decompositions is needed to reveal and compactly summarize connectedness. Diebold and Yilmaz (2014) propose a connectedness table such as Table 1 to understand the various connectedness measures and their relationships. Its main upper-left *NxN* block, which contains the variance decompositions, is called the "variance decomposition matrix," and is denoted by $D^H = [d_{ij}]$. The connectedness table increases D^H with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for $i \neq j$.

[Insert Table 1 here]

The off-diagonal entries of D^H are the parts of the N forecast-error variance decompositions of relevance from a connectedness perspective. In particular, the *gross pairwise directional connectedness* from *j* to *i* is defined as follows:

$$C^H_{i \leftarrow j} = d^H_{ij}.$$

Since in general $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}$, the *net pairwise directional connectedness* from *j* to *i,* can be defined as:

$$C^H_{ij} = C^H_{j \leftarrow i} - C^H_{i \leftarrow j}.$$

As for the off-diagonal row sums in Table 1, they give the share of the *H*-step forecast-error variance of variable x_i coming from shocks arising in other variables (all others, as opposed to a single other). The off-diagonal column sums provide the share of the H-step forecast-error variance of variable x_i going to shocks arising in other variables. Hence, the off-diagonal row and column sums, labelled "from" and "to" in the connectedness table, offer the total directional connectedness measures. In particular, total directional connectedness from others to i is defined as

$$C^H_{i\leftarrow\bullet} = \sum_{\substack{j=1\\ j\neq i}}^{N} d^H_{ij},$$

and *total directional connectedness* from j to others is defined as

$$C^H_{\bullet\leftarrow j} = \sum_{\substack{i=1\\ j\neq i}}^{N} d^H_{ji}.$$

We can also define *net total directional connectedness* as

$$C^H_i = C^H_{\bullet\leftarrow i} - C^H_{i\leftarrow\bullet}.$$

Finally, the grand total of the off-diagonal entries in D^H (equivalently, the sum of the "from" column or "to" row) measures *total connectedness*:

$$C^H = \frac{1}{N}\sum_{\substack{i,j=1\\ j\neq i}}^{N} d^H_{ij}.$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated as before, because the variance of a weighted sum is not an appropriate sum of variances. Methodologies for providing orthogonal innovations like traditional Cholesky-factor identification may be sensitive to ordering. Therefore, following

Diebold and Yilmaz (2014), a generalized VAR decomposition (GVD), invariant to ordering, proposed by Koop *et al.* (1996) and Pesaran and Shin (1998) will be used. The H-step generalized variance decomposition matrix is defined as $D^{gH} = \left[d_{ij}^{gH}\right]$, where

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e'_i\Theta_h\Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e'_i\Theta_h\Sigma\Theta'_h e_j\right)}$$

In this case, e_j is a vector with *j*th element unity and zeros elsewhere; Θ_h is the coefficient matrix in the infinite moving-average representation from VAR; Σ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, σ_{jj} being its *j*th diagonal element. In this GVD framework, the lack of orthogonality means that the rows of d_{ij}^{gH} do not have sum unity and, in order to obtain a generalized connectedness index $\tilde{D}^g = \left[\tilde{d}_{ij}^g\right]$, the following normalization is necessary: $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^{N} d_{ij}^g}$, where by construction $\sum_{j=1}^{N}\tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^{N}\tilde{d}_{ij}^g = N$

The matrix $\tilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ permits us to define similar concepts as defined before for the orthogonal case, that is, *total directional connectedness*, *net total directional connectedness*, and *total connectedness.*

3. Data and preliminary analysis

In this paper, we use close daily data on five market volatility indices representative of the main financial assets (equities, energy and non-energy commodities, currencies and bonds). As an indicator of stock market uncertainty, we employ the Volatility Index (VIX)[6]. VIX is a measure of the expected change in the Standard & Poor's 500 Index over the next 30 days calculated with reference to the price of options that allow investors to hedge against sharp increases or declines in prices[7]. As illustrative of non-energy commodity markets, we utilize the CBOE Gold exchange-traded fund (ETF) Volatility Index (GVZ).[8] GVZ measures market's expectation of 30-day volatility of gold prices, which based on the bid and ask prices of the SPDR Gold Shares. As indicator of energy commodity markets, we use the CBOE Crude Oil ETF Volatility Index (OVX). OVX is a measure of the market's expectation of 30-day volatility of crude oil prices United States Oil Fund, LP (Ticker-USO) options spanning a wide range of strike prices. As representative of foreign-exchange markets, we take the CBOE Euro Currency Volatility Index (EVZ) that measures market's expectation of 30-day volatility of the USD/Euro exchange rate, based on options on the Currency Shares Euro Trust. Finally, and as indicator of uncertainty in bond markets, we employ the CBOE/Chicago Board of Trade (CBT) 10-year U.S. Treasury Note Volatility Index (TYVIX). TYVIX measures a constant 30-day expected volatility of 10-year Treasury note futures prices, based on transparent pricing from CBOT's actively traded options

[6] Since its introduction in 1993, the VIX Index has been considered to be the world's premier barometer of investor sentiment and market volatility. The VIX has been utilized as a proxy for the level of investor risk aversion or market sentiment (see, e. g, Brunnermeier *et al*. 2008 or Bekaert *et al.* 2013),

[7] Recall that option prices provide a unique insight into the probabilities assigned by markets to various future outcomes for a particular economic variable.

[8] Note that gold is a precious and highly liquid metal, so it is categorized as a commodity and a monetary asset. Gold has possessed similar characteristics to money in that it acts as a store of wealth, medium of exchange and a unit of value (Goodman, 1956; Solt and Swanson, 1981). Gold has also played an important role as a precious metal with significant portfolio diversification properties (Ciner, 2001).

on the Treasury-note futures. All five indexes are calculated by the CBOE by applying the VIX methodology.[9] The data are collected from the CBOE website. Given that the GVD requires normality, and that volatilities tend to be distributed asymmetrically (with a right skew), we approximate normality by taking natural logarithms (see, e.g. Diebold and Yilmaz, 2015). Hence, we work with the logarithm of the daily implied-volatilities. Our sample spans from August 1, 2008 until December 29, 2017 (i.e., a total of 2,376 observations).

The Panel A of Table 2 reports the descriptive statistics for these series. The assets with the highest average log implied volatility in our sample are the two commodities, OVX (3.54) and GVZ (2.96), followed by VIX (2.90) and EZV (2.37). As expected, the TYVIX (1.81) has the lowest average implied volatility, given the well-known low risk of fixed income products. Otherwise, the logarithm of our market volatility indices are close to normal with skewness (positive but) close to zero and kurtosis close to 3. We report the pairwise correlations in the Panel B of Table 2. The correlations are high, being not lower than 0.58. Intuitively, these high correlations could shed light about the connections between these implied-volatilities, which we develop further below as the main goal of this paper.

[Insert Table 2 here]

Finally, Figure 1 shows the daily evolution in the logarithm of the implied volatilities. Note that the highest values of implied volatility occur when investors anticipate that huge moves in either direction are likely. In these graphs, we observe several well-known peaks in volatilities, which coincide with important events, such as:

i) the Lehman Bros. demise in September 2008;

[9] See http://www.cboe.com/micro/vix/vixwhite.pdf

ii) the European Debt crisis in May 2010;

iii) the debt ceiling crisis of August 2011, when the US Congress and White House clashed over raising the government borrowing limit, prompting a spike in economic policy uncertainty and a downgrading of US credit rating from AAA to AA+;

iv) the rapid fall in gold prices from the first months of 2013, following disappointing Chinese economic data and expectations of reduced inflation as consequence of a possible tighten of monetary policy by the Federal Reserve;

v) the collapse in oil prices and its impact on other assets in late 2014 to mid-2015;

vi) China's bursting equity bubble and the subsequent international stock market selloff in August 2015;

vii) the global financial turmoil after the UK voted to leave the European Union in June 2016; and

viii) the upsurge of political risk in August 2017, led by mounting US-North Korea tensions and terrorist attacks in Spain, triggering investor nerves and boosting volatility.

These spikes in volatility seem to affect at all the implied volatilities at some degree.

[Insert Figure 1 here]

4. Empirical results

In this section, we report the empirical results of the volatility connectedness. First, we show the static or full-sample GVD table. Second, we analyze the dynamic connectedness.

4.1 Static (full-sample, unconditional) analysis

In the Table 3, we report the full-sample connectedness table where the off-diagonal elements measure the connectedness between the implied-volatility indices. As mentioned in Section 2, the *ij*th entry of the upper-left 5x5 market submatrix gives the estimated *ij*th pair-wise directional connectedness contribution to the forecast error variance of market *i*'s implied volatility coming from innovations to market *j*. Hence, the off-diagonal column sums (labelled TO) and row sums (labelled FROM) gives the total directional connectedness to all others from *i* and from all others to *i*, respectively. The bottom-most row (labelled NET) gives the difference in total directional connectedness (TO minus FROM). Finally, the bottom-right element (in boldface) is total connectedness, which is calculated as the sum of the non-diagonal elements of the connectedness matrix, divided by number of assets[10].

[Insert Table 3 here]

As can be seen, the diagonal elements (own connectedness) are the largest individual elements in the table, ranging from 55.27% (VIX) to 65.56% (TYVIX). Interestingly, the own connectedness is also larger than any total directional connectedness FROM and TO others, reflecting that these implied volatilities are relatively independent of each other. Namely, news shocks that affect to the implied volatility of a particular asset do not fully spread on the implied volatilities of the other assets. Accordingly, the total connectedness of implied volatilities is merely a 38.99%, indicating that 61.01% of the variation is due to idiosyncratic shocks. This result sharply contrasts with the value of 78.3% obtained by Diebold and Yilmaz (2014) for the total connectedness between US

[10] All results are based on vector autoregressions of order 2 and generalized variance decompositions of 10-day ahead volatility forecast errors. To check for the sensitivity of the results to the choice of the order of VAR, we also calculate the spillover index for orders 2 through 4, as well as for forecast horizons varying from 4 days to 10 days. The main results of our paper are not affected by these choices. Detailed results are available from the authors upon request.

financial institutions and with the value of 97.2% found by Diebold and Yilmaz (2012) for international financial markets. Our result is more closed to the values of 31.3% found Antonakakis (2012) for exchange rates in the post-euro period and 48.75% found by Fernández-Rodríguez and Sosvilla-Rivero (2016) for the stock and foreign exchange markets of the seven major world economies.

Regarding to the net (TO minus FROM) contribution, our results suggest that the VIX is net trigger of implied volatility, 15.19%, being OVX, EVZ, GVZ and TYVIX net volatility receivers (-6.81%, -3.53%, -1.34% and -3.52%, respectively). Finally, the highest observed pairwise connectedness is from VIX to the crude oil's implied volatility, OVX, about 18%. This may be due to phenomenon known as the financialization in commodity futures. This states that the equity and commodity markets have been integrating in such a way that news shocks that affect the volatility in the equity markets, at some degree, spread to commodity markets. Indeed, an emerging literature on financialization of commodities attributes this behaviour to the appearance of commodities as an asset class, which has become widely held by institutional investors seeking diversification benefits (see, Büyükşahin and Robe, 2014; or Singleton, 2014, among others).

4.2 Dynamic (rolling-sample, conditional) analysis

The previous section provides a snapshot of the "unconditional", or full-sample, aspects of the connectedness measure among the implied volatility indices. However, the dynamics of the connectedness measures remains covered. The appeal of connectedness methodology lies in its use as a measure of how quickly volatility shocks spread across assets as well as within the same asset class. Following the literature, we carry out an analysis of dynamic connectedness, which relies on rolling estimation windows.

Specifically, we focus on a 200-day rolling-sample windows and using 10 days as the predictive horizon for the underlying variance decomposition.

In the Figure 2, we report the evolution of the total connectedness between the five implied volatility indices. Figure 2 also highlights several cycles of connectedness where the total connectedness is higher or lower than the full sample average. As expected, the connectedness index shows a time-varying pattern over the sample period. Interestingly, during our subsample corresponding to the GFC (May 2009-April 2010), the degree of connectedness is relatively low (35% on average). This low degree of connectedness may be due to this period encompasses the worst of the GFC, such as the Lehman Bros. demise, and a period of recovery or decrease in implied volatilities. We observe several spikes in the evolution of the total connectedness, reaching figures of over 50% in several periods of our sample. The first spike appears after the stress observed in financial markets from May 2010, reflecting the Eurozone sovereign debt crisis, which ended in February 2011 with a second Greek bailout[11]. A second episode of increase in connectedness comes after the heavy losses registered in stock exchanges worldwide in August 2011. This was due to the fears of contagion of the Eurozone sovereign debt crisis and the credit rating downgraded because of the debt-ceiling crisis of the United States. These tensions were intensified in 2012 due to a growing concern about the weak US recovery and political uncertainty around the world. After some ups and downs, the connectedness among implied volatility indices experienced an important reduction. The stabilizing actions by central banks and the Cyprus bailout that boosted investor confidence in financial markets was possibly the cause of this

[11] During this period, there was the May 6, 2010 Flash Crash, one of the most turbulent periods in the history of financial markets.

reduction. From July 2013, coinciding with a geopolitical risk in Arab countries, the connectedness indicator registers a gradual rise until April 2014 as the conflict in eastern Ukraine escalated in the course of 2014, in a context of the considerable uncertainty triggered by the crisis and the fall in energy prices. After a temporary reduction, a renewed impulse is observed from October 2014. The world stock markets slide as bad news mounts up fears of a global economic slowdown, tensions in the Middle East and the spread of the Ebola virus weighed on world shares. Another increase in connectedness is found coinciding with slumping commodity prices, China's bursting equity bubble, and pressure on exchange rates registered from July 2015 leading to the devaluation of the yuan on August 11, 2015. Investors world-wide took the yuan devaluation as a sign that China's economy was performing worse than thought, originating an intense correction in stock markets and wild fluctuations in bonds. In a year marked by volatility and political upheaval, financial markets in 2016 endured an escalation of negative interest rates, the collapse and subsequent rebound in commodity prices, and fluctuating stock market valuations. The effects were especially intensified after the UK's vote on whether to remain a member of the EU and the unexpected results of the US presidential election. Finally, during 2017 low interest rates, an improved economic outlook, and increased risk appetite boosted asset prices and suppressed volatility.

Therefore, the "unconditional", or full-sample, total connectedness of 38.99% that we report in the previous section actually undervalues the potential connectedness of the implied volatilities indices, which seem to be more connected in periods of high market stress, making them most vulnerable to contagion. Our findings are consistent with earlier literature in that the linkage between markets intensifies during periods of increasing economic and financial instability (see, e. g., Kolb, 2011), implying a loss of diversification just when it is needed most.

5. Net directional connectedness

5.1. Rolling-sample net directional volatility connectedness plots

The net directional connectedness index provides information about how much each market's volatility contributes in net terms to other market's volatilities. As the full sample dynamic measure presented in Section 4.1, it also relies on rolling estimation windows. Figures 3a to 3e display the rolling net connectedness (shaded grey area).

[Insert Figures 3a to 3e here]

In contrast with Table 2 where we report the static net contribution, Figures 3a to 3e show how the volatility indices have switched from generators to receivers of volatility, and *vice versa*, throughout the sample.

As can be seen in Figure 3a (black line), VIX is net generator of volatility in our sample. Indeed, 70% of the computed values are positive, indicating that during most of the sample period, VIX influenced the rest of markets. This is consistent with the general knowledge that VIX is the fear index of the US economy and the main gauge of broad market performance. This is remarkable from 2009 to early 2010 (GFC), August 2011 until the beginning of 2013, and from the end of 2015 to early 2016, being the VIX the strongest volatility generator. In this sense, shocks that affect the VIX are spread all over the other asset classes. Nevertheless, VIX is net receiver of volatility in the second half of 2010 and spring 2013 (a time of real turbulence in EMU sovereign debt markets). It is also net receiver during some months of 2013 and 2014, which coincides with sudden positive increase in the net contribution of GVZ. In this episode, slowing economies in Europe and Asia provoked a wider flight from gold after a panic selling that triggered the biggest gold price drop in 30 years in April 2013. Finally, a further surge is observed during the 2015–16 stock market selloffs, initiated in the United States instigated by global financial events. In this later episode, we detect the maximum value of the net connectedness index (89.58 in September 2015).

Regarding EVZ (Figure 3c, red line), it is net generator of volatility in 74% of the sample. Instead, it is net receiver of volatility at the beginning of the sample and between the months of April to October 2015. Note, the increase in total connectedness that we observe Figure 2 around May 2010 is mostly generated by EVZ which is its net generator, being the other volatility indices net receivers of volatility. This could reflect rising concerns about the sovereign debt situation in some euro area countries due to high government deficits, rapidly increasing government debt-to-GDP ratios and rising contingent liabilities because of guarantees for banks set the stage for a re-intensification of the financial crisis. During this episode, there was a mounting tension in Eurozone sovereign bond markets in a context of fear of contagion (see, for instance, Constâncio, 2012). This was not only because there was a sudden loss of confidence among investors (see Beirne and Fratzscher, 2013), but also because several European Union banks had a particularly high exposure to Greece (see Gómez-Puig and Sosvilla-Rivero, 2013 or Vuillemey and Peltonen, 2015). It is worth to notice a further significant intensification in the underlying uncertainty transmission in the first months of 2013. This coincides with financial market tensions originated by the escalation in the conflict in eastern Ukraine, the fall in energy prices and the doubts about the resilience and pace of the global recovery. EVZ also was a strong volatility generator from the second half of 2014, when the euro depreciated with respect to the US dollar in a context of a continuously declining outlook for growth and inflation in the euro area. The political uncertainty that followed the outcomes of the UK referendum on EU membership in June and the US presidential election in November 2016 reinforced this effect of net volatility propagator.

As seen in Figure 3d, GVZ (yellow line) is net receiver of volatility along the sample, since 75% of the computed values are negative. Nevertheless, there are episodes of uncertainty transmission at the beginning of the sample (May-August 2009), in a context of a re-intensification of the adverse feedback loop between the real and financial sectors. Further episodes of volatility transmission are detected in the central part of the sample (April 2013 –January 2014). This is explained in a context of falling global inflation (reducing gold's value as a hedge against rising prices) and of gold undermining its status as a safe haven markets regaining confidence in the US dollar. The latter coincides in time with all the other volatility indices as net receivers of volatility. Gold is often identified as a store of wealth during periods of economic and political instability (Aggarwal and Lucey, 2007) and as a volatile monetary asset commodity (Batten et al., 2010 and Lucey *et al.*, 2013). These characteristics seemed to play a role during the first months of 2013 before the sudden revision of expectations by market participants in April 2013. At the beginning of 2014, GVZ became volatility propagator when gold recorded its first annual price decline since 2000. At that time, speculative investors ran down their holdings in response to Fed Quantitative Easing (QE, hereafter) tapering and an outlook for still soft inflation. After that, there is a subperiod where GVZ is net receiver of volatility in a context of low volatility despite heightened economic, political, and monetary uncertainty. Finally, following the outcomes of the UK referendum and the US election, GVZ turned out to be net transmitter of volatility as investors flew to Gold, once again due to its status as a safe haven asset.

Finally, TYVIX and OVX are net receivers of volatility during large periods of the sample (Figures 3e and 3b, green and blue lines, respectively), being 74% and 68% of the computed values negative, respectively. Regarding the TYVIX, this behaviour could be related with being perceived by market participants as safe haven assets (together with Gold), being driven by “flight-to-safety” movements whenever there is concern about the macroeconomic and financial environment. As for the OVX, the surge in net directional connectedness observed in 2010 could be reflecting downside risks related to renewed increases in oil prices after OPEC production cuts. It is worth noting also that, from late 2014 until mid-2015, when the crude oil prices down sharply, the OVX was net generator of volatility. We interpret this result as the market could understand this sudden drop in crude oil prices as a slowdown in the world economy, mainly due to a possible recession in China, which spread the fear over other asset classes. The evolution of net connectedness of TYVIX and OVX during 2016 and 2017 was influenced by the escalation of negative interest rates, the collapse and subsequent rebound in commodity prices and fluctuating stock market valuations.

5.2. Rolling-sample net pair-wise directional volatility connectedness plots

So far, we have discussed the behavior of the total connectedness and total net directional connectedness measures for the five implied volatility indices. However, we have also examined their net pairwise directional connectedness during the financial turmoil periods experienced in the sample period. By construction, the net directional connectedness from implied volatility *i*-th to others is equal to the sum of all the net pair-wise connectedness from implied volatility *i*-th to implied volatility *j*-th, for all *j* with $i \neq j$. Having this relationship in mind, in Figures 3a to 3e, the dynamics of the net pairwise directional connectedness with respect to the other asset markets under study are added to the net directional connectedness (grey area) explained before. This decomposition of the dynamics of net directional connectedness into their pairwise directional connectedness is appealing since it allows a deeper understanding how the transmission of volatility works for each implied volatility index.

As can be seen in Figure 3a, VIX was net trigger of volatility to all other implied volatility indices most of the sample. Interestingly, the two episodes where VIX was net receiver of volatility are link to EVZ (spring 2010) and GVZ (2013), coinciding with subperiods where these markets were volatility generators as commented before. Note also that the VIX was a net transmitter of volatility to the TYVIX whose net pair-wise volatility from VIX was increasing gradually after the 2014 stock market crash. This finding is in line with previous research documenting that perception of uncertainty in the Treasury market tends to rise during stock market crashes (see, e.g. López, 2015). During 2015, we observe a stronger net volatility transfer to the remainder financial asset classes, which can be taken as a symptom of herding and search-for-yield behaviour. This trend reverted in the last part of the sample, being the VIX net receiver from to EVZ. The latter might be reasonably interpreted as reflecting the different cyclical positions and monetary policy stances across USA and the euro area.

Figure 3b reports the results for OVX. As can be seen, OVX was net receiver of volatility during much of the sample, which is mostly due to the VIX and EVZ transmitting volatility to OVX. It is interesting to note that in the two episodes when OVX is net trigger of volatility (beginning of 2010 and from late 2014), the main net pair-wise directional connectedness is with TYVIX. This result suggests that during turbulent periods in crude oil market there is common information that simultaneously affects the perception of uncertainty in the Treasury market. Remarkably, OVX received strong transmission of volatility from GVZ in the period April 2013-January 2014, which was also transmitted indirectly to VIX through OVX. This result highlights how there may exist indirect mechanisms of volatility transmission among the implied volatility indices. Finally, although OVX carried on generating volatility to all the implied volatility indices after late 2014, VIX was turning from receiver to generator of volatility to OVX in that particular period and during the August 2015 turmoil.

In Figure 3c, EVZ shows swing in net volatility where periods of net generator of volatility to all the other implied volatility indices are followed by periods where this is net receiver of volatility. The biggest net pairwise connectedness is from EVZ to GVZ and from EVZ to TYVIX, which may be due to the usage of these assets and their safe-haven properties in a context of heightened economic, political, and monetary uncertainty.

GVZ (Figure 3d) is net receiver of volatility from VIX and EVZ but net generator of volatility to OVX and TYVIX. This result indicates that linkages between the equity and foreign exchange markets and between oil and Treasury markets with respect to uncertainty are closer. Nevertheless, GVZ was a substantial generator of volatility over OVZ and VIX during the period April 2013-January 2014. This episode coincides with a fall in global inflation, and evidence of gold undermining its status as a safe haven markets regaining confidence in the US dollar. Latter GVZ became net receiver from all other assets until Nov 2016, net giver from November 2016 until October 2017 for VIX and OVX, and net receiver from EVZ, in a context marked by the escalation of negative interest rates, the collapse and subsequent rebound in commodity prices and fluctuating stock market valuations. Finally, our results suggest that GVZ turned into net receiver from EVZ between October 2017 and the end of the sample.

Finally, Figure 3e plots the results for TYVIX. This is mostly a net receiver of volatility from all the implied volatility indices but overall from VIX and EVZ. There are few periods where TYVIX was net generator of volatility. At the beginning of our sample in 2009, ~~where~~ TYVIX was a strong net generator of volatility to OVX, EVZ and GVZ, reflecting the intensification of financial tensions and a substantial increase in uncertainty and investors' risk aversion. Likewise, TYVIX was a net generator of volatility from 2014, mainly, to GVZ and OVZ, as the US Federal Reserve System began to phase out its QE programme. Diverging monetary policies between the European Central Bank and Fed marked the evolution of the net connectedness between TYVIX and EVZ at the end of the sample. Uncertainty and geopolitical risks also influenced the net volatility transmission from TYVIX to GVZ during 2016.

In summary, Figures 3.a to 3.e have shown how the dynamics of the net pair-wise connectedness between all the volatility indices are not constant but switch from net pair-wise generator to net receiver of volatility to other, depending on either market-wide as asset-specific effects.

6. Concluding remarks

The recent GFC has again brought the interdependencies of alternative asset classes to the fore. This has underlined that the cross-market transference of shocks can be rapid and powerful where ~~confidence~~ the "fears" play~~s~~ an important transmission mechanism. Eichengreen (2016) contend that macroeconomic and financial volatility is likely to remain a fact of twenty-first century economic life; therefore, good understanding of international spillovers is essential for policy coordination and design.

We have analyzed the connectedness of the implied volatility indices of several asset classes, known as the “fear indices”. Although the interactions among some of these volatility indices have been previously partially examined in the empirical literature. To the best of our knowledge, we are the first to systematically analyse their nexus applying the framework proposed by Diebold and Yilmaz (2012, 2014). Such framework allows us to examine the directional spillovers emanating from each market to another under both, static and dynamic settings.

The main findings of our research can be summarized as follows. In the first step, we found a system-wide value of 38.99% for the total connectedness between the VIX, OVZ, EVZ, GVZ and TYVIX implied volatility indices under study for the full sample period. This level is much lower than that obtained by Diebold and Yilmaz (2012, 2014) for international financial markets and US financial institutions, respectively. In the second step, we studied the dynamic nature of total net connectedness, obtaining evidence of volatility connectedness showing large variation over time and supporting the literature documenting that volatility across markets increases during unstable periods. In a third step, we examined the time-varying net spillovers across markets, observing in all cases that the variables frequently switch between a net transmitting and a net receiving role depending on either market-wide as asset-specific effects. Finally, when analyzing net pairwise directional volatility connectedness, our results suggest that there exists common information (i.e., news about economic fundamentals and unexpected events) that direct or indirectly affects uncertainty about the future development of the segment markets under study.

The results presented in this paper should be of value to macro-prudential and monetary policymakers, as they provide evidence on the time-varying volatility transmission among different asset classes, incorporating information for signaling systemic events. Our findings may also provide useful insight into the file of volatility forecasting, option pricing and futures hedging strategies, among other, that could be useful to portfolio managers, risk strategists and insurers.

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The authors wish to thank two anonymous referees and the editor for their helpful comments and suggestions on a previous draft of this article, which have enabled us to introduce substantial improvements. Julián Andrada-Félix gratefully acknowledges warm hospitality and financial support of the Department of Finance at the Auckland University of Technology during his research visit. Simón Sosvilla-Rivero thanks the members of the Department of Economics at the University of Bath for their warm hospitality during his research visit.

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Table 1: Schematic connectedness table

	x_1	x_2	…	x_N	Connectedness from others
x_1	d_{11}^H	d_{12}^H	…	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	…	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H, j \neq 2$
.	.	.	.		
.	.	.	.		
.	.	.	.		
x_N	d_{N1}^H	d_{N2}^H	…	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H, j \neq N$
Connectedness to others	$\sum_{i=1}^N d_{i1}^H$ $i \neq 1$	$\sum_{i=1}^N d_{i2}^H$ $i \neq 2$	…	$\sum_{i=1}^N d_{iN}^H$ $i \neq N$	**Total connectedness =** $\frac{1}{N}\sum_{i,j=1}^N d_{iN}^H$ $i \neq N$

Table 2: Descriptive statistics and contemporaneous correlations of implied volatilities

	VIX		OVX		EVZ		GVZ		TYVIX	
Panel A: Descriptive statistics										
Mean	2.8956		3.5439		2.3697		2.9549		1.8069	
Std. Dev.	0.4050		0.3666		0.3227		0.3192		0.2927	
Min	2.2127		2.6741		1.5454		2.2439		1.1663	
Median	2.8127		3.5176		2.3726		2.9145		1.7561	
Max	4.3927		4.6094		3.4230		4.1671		2.6892	
Skewness	0.9940		0.1660		0.2350		0.8804		0.7419	
Kurtosis	3.8001		2.9902		3.1350		4.1653		3.2049	
Observations	2376		2376		2376		2376		2376	
Panel B: Matrix correlations										
	VIX		**OVX**		**EVZ**		**GVZ**		**TYVIX**	
VIX	1									
OVX	0.6981	***	1							
EVZ	0.8057	***	0.7556	***	1					
GVZ	0.8379	***	0.5835	***	0.7110	***	1			
TYVIX	0.8322	***	0.6283	***	0.7892	***	0.7393	***	1	

Notes: All the series are in logs.
Daily data from August 1, 2008 to December 29, 2017.
*** indicates significance at the 1% level.

Table 3: Full-sample connectedness

	VIX	OVX	EVZ	GVZ	TYVIX	Directional *FROM* Others
VIX	55.2670	11.7807	10.3603	12.5200	10.0721	44.7330
OVX	17.5813	63.6472	5.9591	7.8877	4.9247	36.3528
EVZ	13.4766	6.1621	60.8753	10.4953	8.9907	39.1247
GVZ	15.7181	7.2408	10.3883	59.7199	6.9329	40.2801
TYVIX	13.1500	4.3575	8.8924	8.0380	65.5621	34.4379
Directional *TO* Others	59.9260	29.5412	35.6002	38.9409	30.9204	**Total connectednes s =38.9857**
Net Contribution (To – From) Others	15.1929	-6.8116	-3.5245	-1.3393	-3.5175	-

Figure 1: Daily financial market volatilities (in logs)

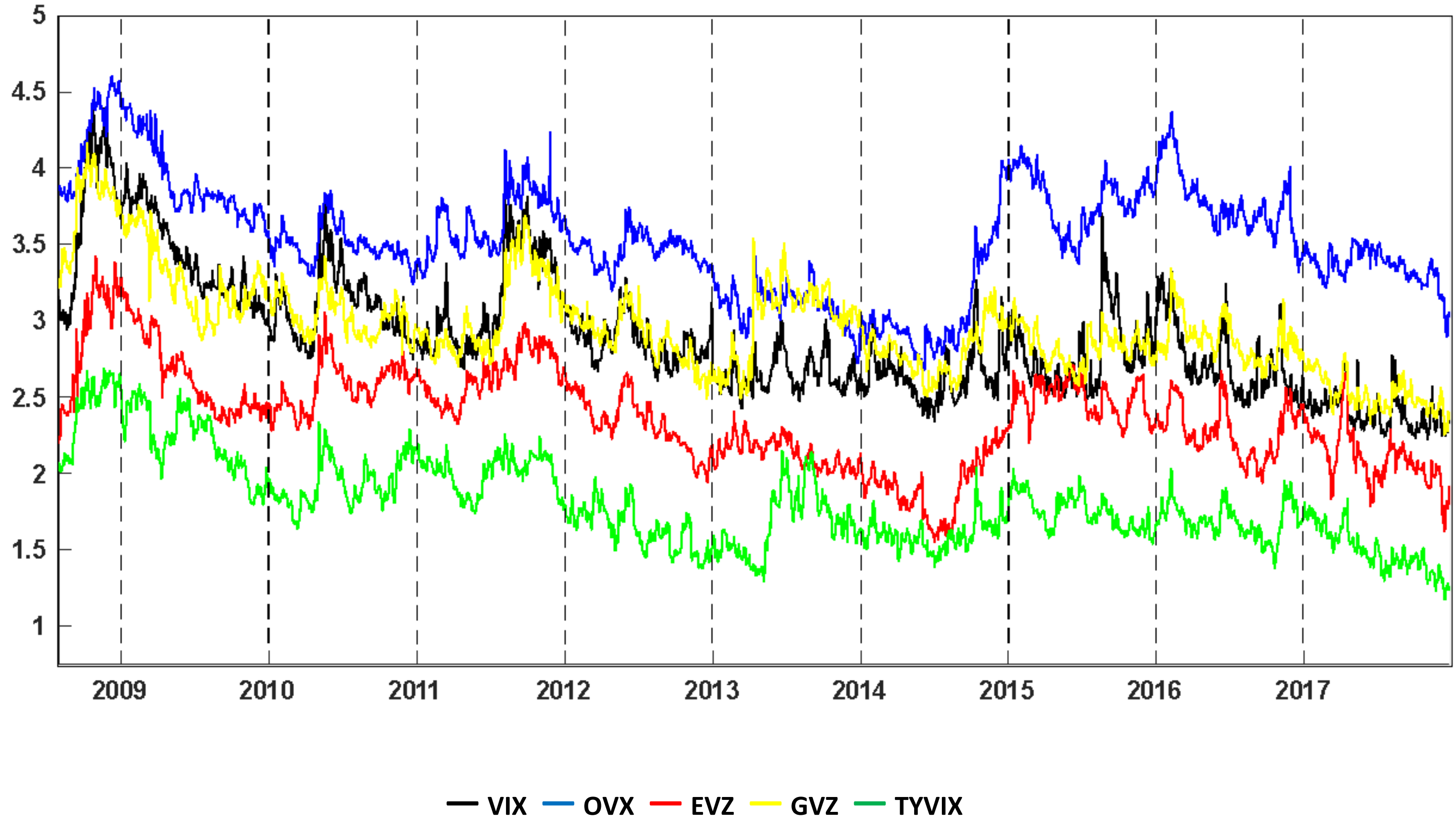
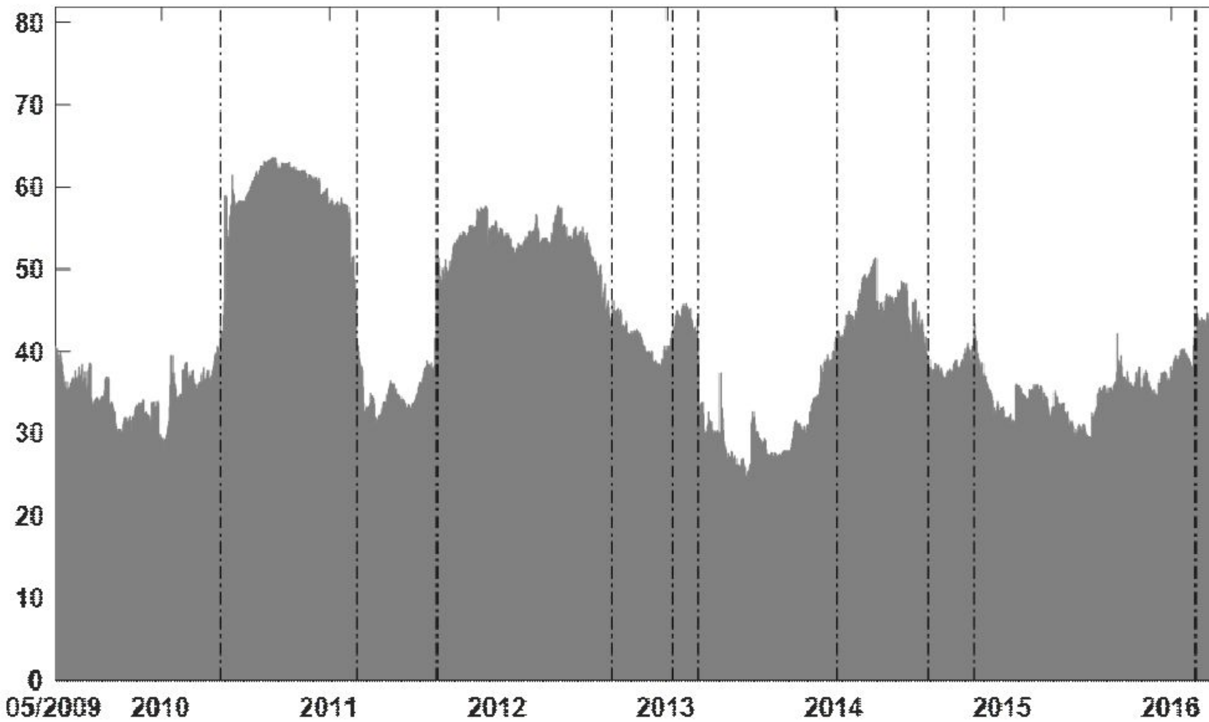


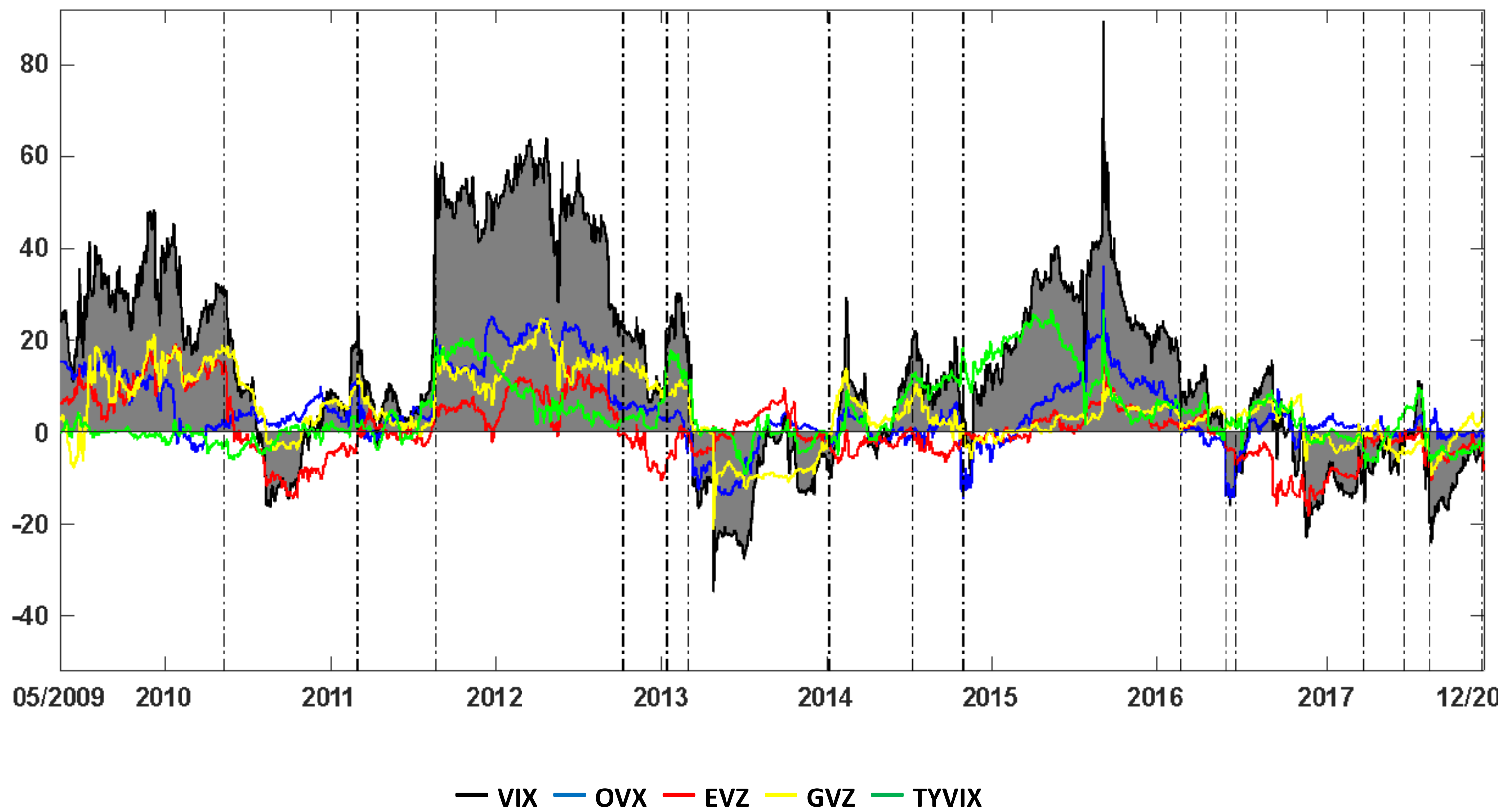
Figure 2: Rolling total connectedness



ertical lines delimit the following episodes: I: May 2009-May 2010, II: May 2010-March 2011, III: March 2011-August 2011, IV: August 2011-Oc
tober 2012-January 2013, VI: January 2013-March 2013, VII: March 2013-January 2014, VIII: January 2014-July 2014, IX: July 2014-Octobe
er 2014-October 2014, XI: November 2014-February 2016, XII: February 2016-June 2016, XIII: June 2016-June 2016, XIV: June 2016-April 2017
May 2017, XVI: May 2017-August 2017, and XVII: August 2017-December 2017.

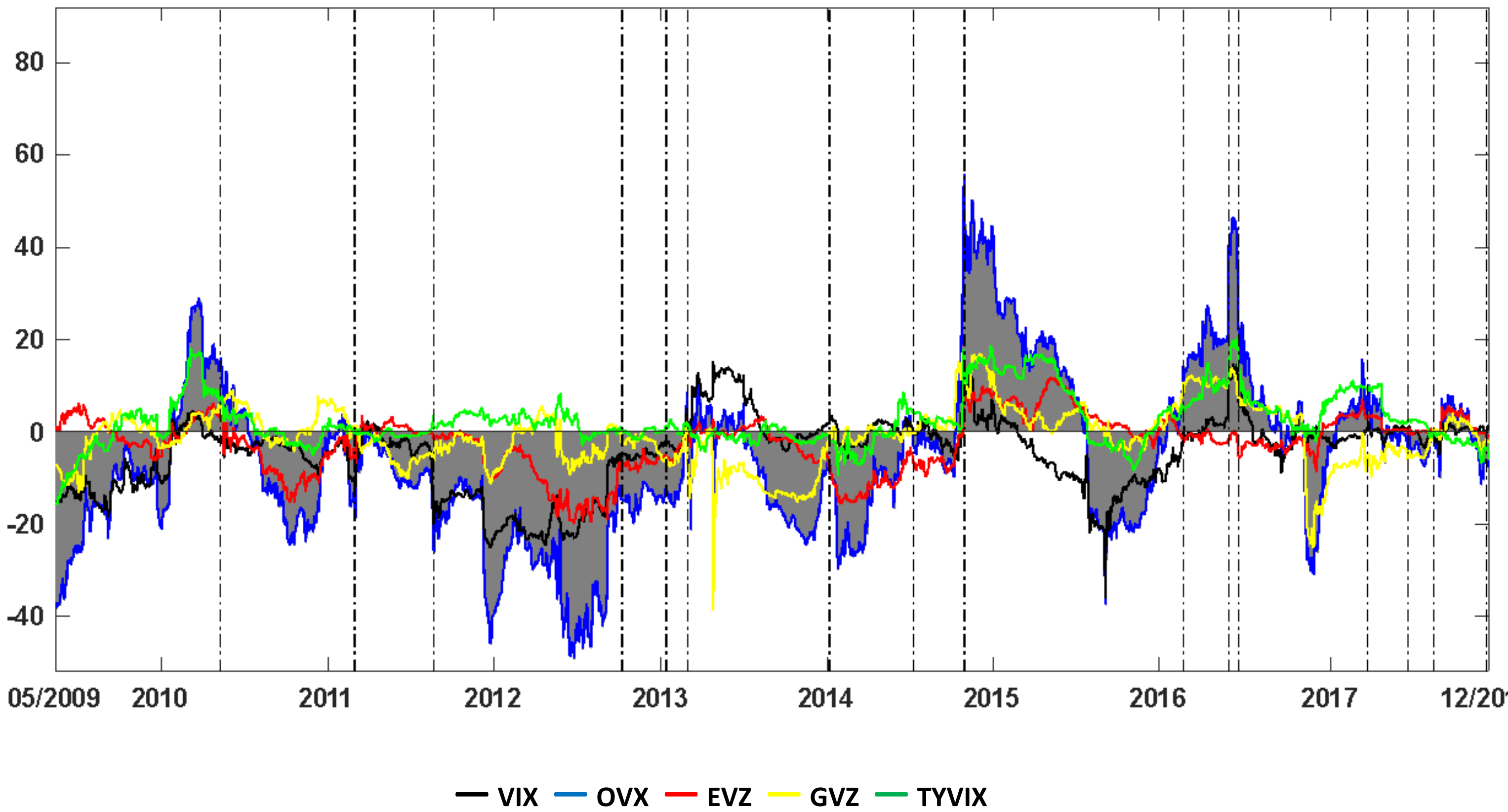
Figure 3a: Net directional connectedness and net pair-wise directional connectedness:

CBOE Volatility Index (VIX)



ertical lines delimit the following episodes: I: May 2009-May 2010, II: May 2010-March 2011, III: March 2011-August 2011, IV: August 2011-Oc tober 2012-January 2013, VI: January 2013-March 2013, VII: March 2013-January 2014, VIII: January 2014-July 2014, IX: July 2014-Octob er 2014-October 2014, XI: November 2014-February 2016, XII: February 2016-June 2016, XIII: June 2016-June 2016, XIV: June 2016-April 2017 May 2017, XVI: May 2017-August 2017, and XVII: August 2017-December 2017.

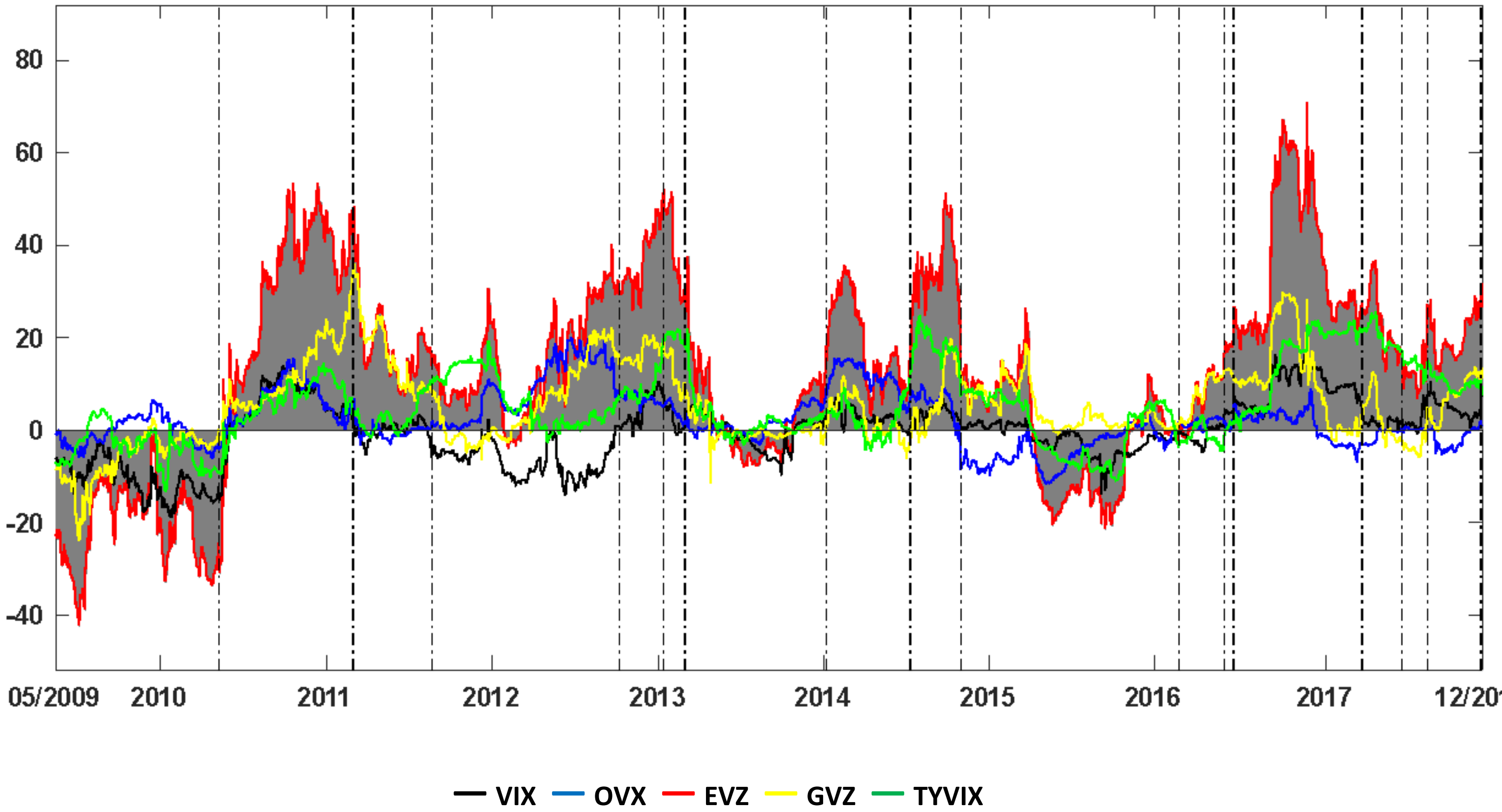
Figure 3b: Net directional connectedness and net pair-wise directional connectedness: CBOE Crude Oil ETF Volatility Index (OVX)



ertical lines delimit the following episodes: I: May 2009-May 2010, II: May 2010-March 2011, III: March 2011-August 2011, IV: August 2011-Oc tober 2012-January 2013, VI: January 2013-March 2013, VII: March 2013-January 2014, VIII: January 2014-July 2014, IX: July 2014-Octobe er 2014-October 2014, XI: November 2014-February 2016, XII: February 2016-June 2016, XIII: June 2016-June 2016, XIV: June 2016-April 2017 May 2017, XVI: May 2017-August 2017, and XVII: August 2017-December 2017.

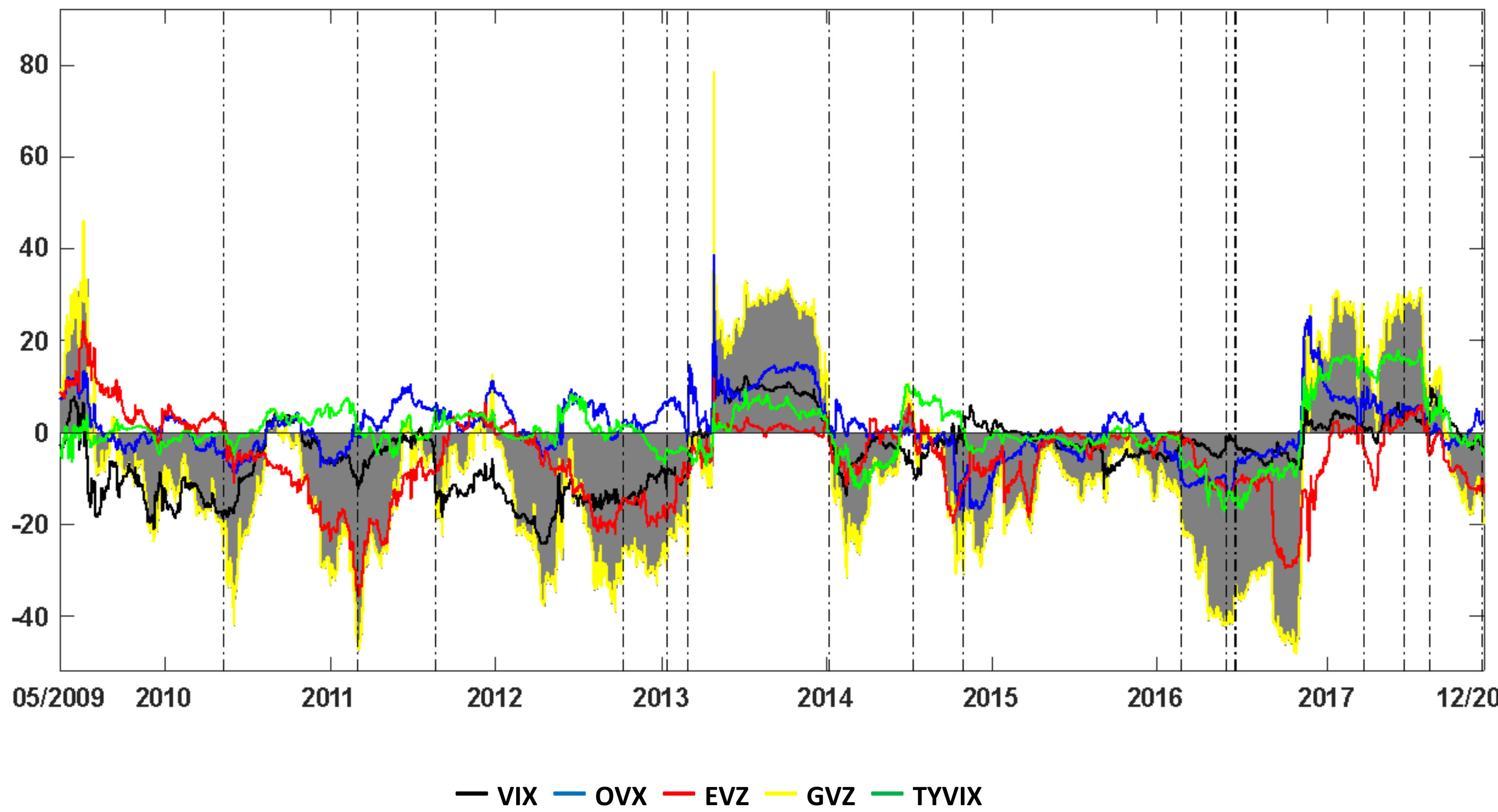
Figure 3c: Net directional connectedness and net pair-wise directional connectedness:

CBOE EuroCurrency Volatility Index (EVZ)



ertical lines delimit the following episodes: I: May 2009-May 2010, II: May 2010-March 2011, III: March 2011-August 2011, IV: August 2011-Oc tober 2012-January 2013, VI: January 2013-March 2013, VII: March 2013-January 2014, VIII: January 2014-July 2014, IX: July 2014-Octob er 2014-October 2014, XI: November 2014-February 2016, XII: February 2016-June 2016, XIII: June 2016-June 2016, XIV: June 2016-April 2017 May 2017, XVI: May 2017-August 2017, and XVII: August 2017-December 2017.

Figure 3d: Net directional connectedness and net pair-wise directional connectedness: CBOE Gold ETF Volatility Index (GVZ)



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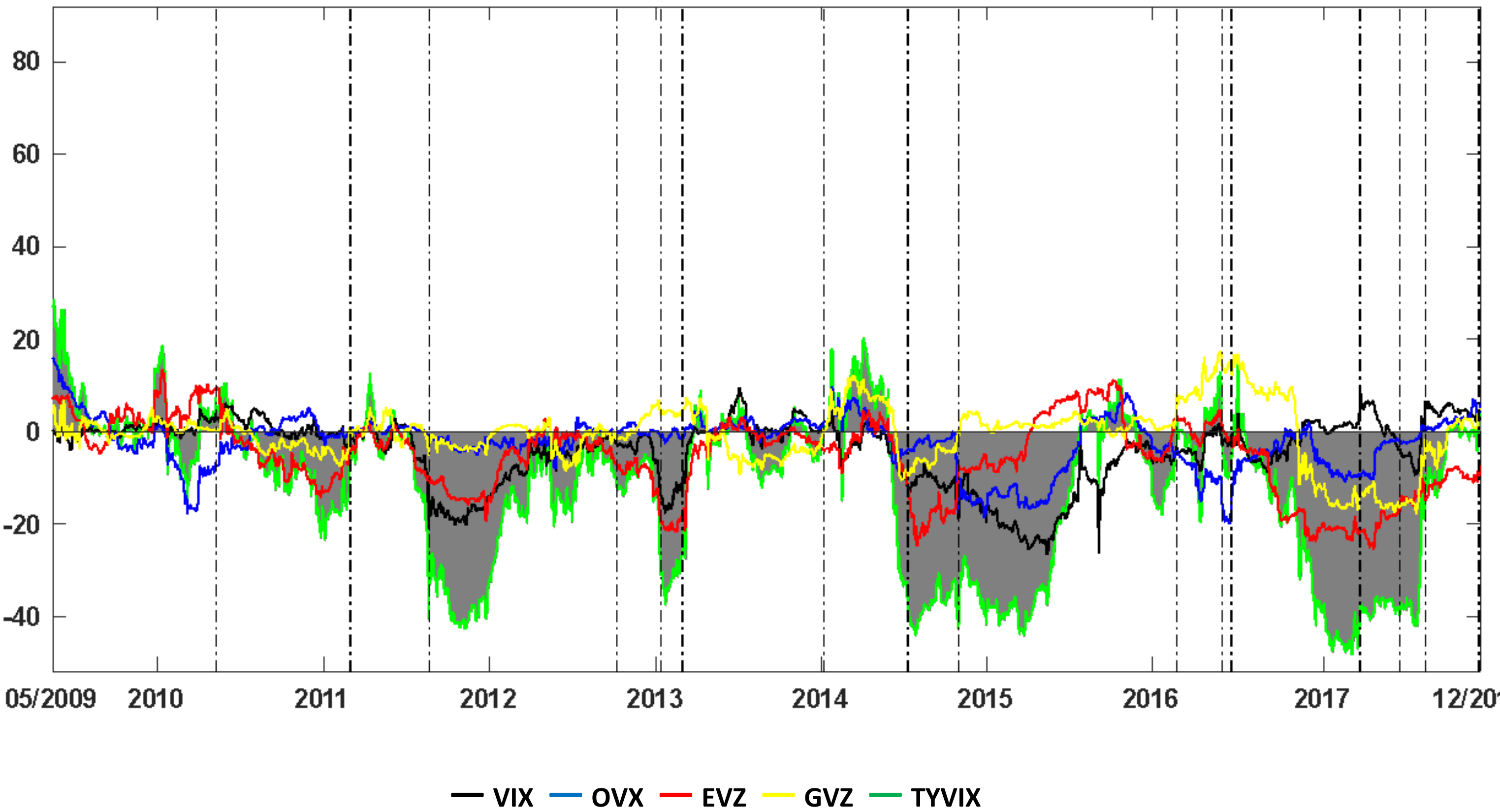
er 2014-October 2014, XI: November 2014-February 2016, XII: February 2016-June 2016, XIII: June 2016-June 2016, XIV: June 2016-April 2017
May 2017, XVI: May 2017-August 2017, and XVII: August 2017-December 2017.

Figure 3e: Net directional connectedness and net pair-wise directional connectedness:

CBOE/CBOT 10-year U.S. Treasury Note Volatility Index (TYVIX)



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