Time-frequency information transmission among financial markets: Evidence from implied volatility

Muhammad Abubakr Naeem
School of Economics and Finance, Massey University, New Zealand
Email: m.naeem@massey.ac.nz

Fiza Qureshi
Institute of Business Administration, University of Sindh, Jamshoro, Pakistan
Email: fiza.qureshi@usindh.edu.pk

Saqib Farid
School of Business & Economics, University of Management & Technology, Lahore, Pakistan
Email: saqib.farid@umt.edu.pk

Aviral Kumar Tiwari
Rajagiri Business School, Rajagiri Valley Campus, Kochi, India
South Ural State University, Lenin Prospect 76, Chelyabinsk 454080, Russian Federation
Email: aviral.eco@gmail.com

Mohamed Elheddad
Lecturer in International Business,Department of Management

Huddersfield Business School

University of Huddersfield | Queensgate | Huddersfield | HD1 3DH

Email: *M.M.Elheddad@hud.ac.uk*

Abstract

In this paper, we utilize the Chicago Board Option Exchange (CBOE) implied volatility indices to estimate the time-frequency information transmission among financial markets from 01.08.2008 to 31.10.2019. In doing so, we utilize the rolling window wavelet correlation (RWWC), Diebold & Yilmaz (2012), and Barunik & Krehlik (2018). Our empirical findings suggest short-term and long-term dynamic connectedness between implied volatility indices of alternative assets. The long-term analysis findings suggest potential hedging and diversification opportunities that can be exploited by taking offsetting positions across volatility indices. The findings confirm heterogeneity between short-term and long-term connectedness results. Our findings also show superior out of sample hedging effectiveness of GVZ. The implications of the findings are further discussed in the paper.

Keywords: Implied volatility; time-frequency; rolling window wavelet correlation; hedging effectiveness

1. Introduction

Volatility transmission in global financial markets has imperative and inevitable implications for international portfolio investment and diversification. More importantly, the growing integration and financialization of the markets have compelled the practitioners and researchers to pay attention to the time-varying linkages among financial markets over the past few decades. In this backdrop, financial stability and process of financialization is central to debate as they are considered major source of systematic risk (Huynh et al., 2020). Some of the recent works on financial crises identify that risk transmission between financial markets is inevitable and significant due to monetary and financial amalgamation (for instance, Euro zone member countries), shared default risk, public debt policy, currency volatility and financialization (Ftiti et al., 2017). The information mechanisms entail that a lesser magnitude of spillover between financial markets augments the safe haven and diversification incentives. In other words, higher correlated asset classes are not a feasible model to optimize the risk-return policy of the portfolio of various assets (Andrada-Félix et al., 2018). Commonly, financial market volatility is determined by obtaining implied volatility from derivative securities. The pioneer works such as Demeterfi et al. (1999) assert that implied volatility indices established by Chicago Board Options Exchange (CBOE) are important representatives of market risk and proxies of realized volatility received from derivative financial markets. Moreover, the volatility indices are considered determinants of fear and negative market psychology for financial markets as they depict the investors' expectations about the uncertainty and future implied volatility of derivative securities for a month ahead (Whaley, 2000).

Understanding the causes and repercussions of economic uncertainty has become imperative for policy makers and economic managers since high uncertainty leads to challenges related to decision making and forecasting economic outlook and has significant implications on the financial markets and the whole economy (Huynh, et al 2020b). Nowadays, rising price fluctuations and contagious effects have increased the uncertainties in financial markets. Some of the culminating historical crises, such as the dot-com bubble crisis 2001, the Global Financial Crisis of 2007-08, the European Debt Crisis of 2011-12, and the Chinese Financial Crisis of 2015, have directed towards understanding the significance of financial contagion modes linked with untapped financial securities. Considering the growing risk and extreme jolts observed in the global financial markets, investors opt for different asset classes that compensate for market risk.

The sizeable empirical and theoretical literature on the connectedness between financial assets has focused on volatility spillovers between financial markets. The primary reason for investigating the volatility spillovers is to unravel the magnitude of integration and informational spillovers between the financial markets. The various theoretical linkages support the rationale of the transmission effect between multiple asset classes. Risk spillover and connectedness literature is intertwining with previous established theories like efficient market theory, modern portfolio theory and hedge and diversification hypotheses. Efficient market hypothesis by Fama (1965, 1970) asserts that securities prices reflect to all available information. In other words, market is called efficient if prices of financial instruments fully reflect complete and accessible information in the market. Thus, the reduced volatility transmission effect between two assets signals the market efficiency and quick dissemination of the information, which is also highly linked to the speed of market adjustment to recent information (Kyle, 1985; Inagaki, 2007). Ross (1989) argues that volatility in a specific financial market is directly connected to the degree of information transferred to other asset markets. Moreover, the recent empirical research work by

Jawadi et al. (2017) which tested the informational efficiency hypothesis on different classes of commodities conclude that in short term, commodity markets are inefficient in terms of information and vice versa in long term.

Further, the interlinkages and associations between various financial assets are elucidated under hedge and diversification hypotheses. Baur and Lucey (2010) concur that combination of either positively or negatively related financial assets makes up good diversifier or hedge portfolio in normal economic state. This specific theoretical argument is initiated and brought by modern portfolio theory originally conceptualized by Markowitz, H. (1959) which explains that to lessen and mitigate risk for given level of returns, the investors would opt for less risky portfolio than riskier one. Hence, this implies that risk diversion and aversion directs towards investing in various asset classes. Thus, the efficient portfolio and diversification strategies yield protection to the investors against risk and renders support to economic stability and optimal financialization. The theoretical underpinning on the interdependence of various financial assets is also apprehended under the cross-market re-balancing and portfolio re-adjusting mechanism in response to the financial market and economic shocks.

Following the notion, abundant research has investigated the association between various financial markets such as forex, gold, crude oil, and stock markets (see, e.g., Jain & Biswal, 2016; Akbar et al., 2019). More specifically, a large number of studies have also highlighted the volatility spillovers between different financial assets. For instance, Yaya et al. (2016) and Ftiti, Z et al. (2016) identify the spillover and co-movement between crude oil and gold during crises period. In the same vein, many others discover the volatility and return spillovers between oil, equities, and precious metals (see, e.g., Maghyereh et al., 2017; Awartani & Tziogkidis, 2017; Balli et al., 2019; Caporin et al., 2021; Farid et al., 2021).

Further, Dutta (2018) unveil implied volatility persistence between silver and gold by applying the VAR-GARCH model. Al-Yahyaee et al. (2019) explore implied risk and return spillovers between the precious metals and commodity futures of energy in the GCC equity markets. Likewise, An et al. (2020) analyze the significant volatility spillovers between mineral commodities using a network method. Also, Uddin et al. (2020) adopt the copula model to evaluate the dynamics of spillovers between the precious metals, oil, and equity market in the US. In short, time-varying interdependence and volatility spillovers between financial markets have been extensively explored.

On the contrary, limited studies have examined the volatility spillovers between the implied volatility indices (forward-looking measures of volatility in financial markets). Wherein, prior literature has also stressed the superiority of implied volatility indices over historical volatility indexes in terms of forecasting volatility in financial markets (Fleming, 1998; Blair et al., 2001; Jiang & Tian, 2005). In the same way, keeping in view the volatility transmission between implied volatility indexes, scarce research exists regarding the hedging and diversification benefits across different asset classes. Also, the existing literature on co-movement or spillover is largely unclear in providing the appropriate policy guidelines in countering hazardous spillover effects (Yoon et al., 2019). Thus, the reasons above necessitate enriching the extant empirical literature on the risk spillover between various asset classes.

This study adopts the spillover index methodology by Diebold and Yilmaz (2009, 2012). This study offers a novel methodology and mechanism for portfolio managers to compute the magnitude and size of the net transmitter and the contributor of implied volatility spillovers between different asset classes. Although the connectedness between these volatility indices has been partially investigated by Andrada-Felix et al. (2018) by using Diebold and Yilmaz (2012,

2014) framework, our study provides a more comprehensive illustration of the connectedness network between volatility indices using the frequency connectedness framework of Barunik and Krehlik (2018) and Polanco et al. (2018) frequency-based methodology of rolling window wavelet correlation. The resulting analysis will ascertain the risk transmission effects between equities, bonds, currencies, and energy and non-energy commodities in the time-frequency domains. The examination of this nature will allow market participants to understand the better frequency-based net transmission of volatility across alternative asset classes using implied volatility indices and shed light on potential hedging and diversification opportunities that can be exploited by taking offsetting positions across volatility indices.

The main contribution of this research falls into three areas. First, this study departs from the prior literature examining time-varying volatility spillovers between equities, bonds, currencies, and energy and non-energy commodities from the perspective of implied volatility spillovers. Although extensive research prevails on volatility spillovers between financial markets, there is still a gap regarding time-varying spillover effects between implied volatility indices and hedging strategies adopted among various asset classes to achieve portfolio diversification. Moreover, the assessment of extreme risk and volatility transmission between various financial assets will also give detailed insights into the diversification and hedging characteristics of each financial asset, respectively. Second, the study estimates the hedge ratios of each asset class to determine the optimal diversification strategies and hedging effectiveness and profitability. There is a growing need to diligently plan the diversification strategies by portfolio managers, given the mounting pressures investors confront in obtaining diversified portfolios and risk reduction. Third, in addition to analyzing information transmission, the study uses a novel methodology, the Rolling Window Wavelet Correlation framework, to detect the risk of extreme market fluctuations.

Our empirical findings suggest short-term and long-term dynamic connectedness between implied volatility indices of alternative assets. The long-term analysis findings suggest potential hedging and diversification opportunities that can be exploited by taking offsetting positions across volatility indices. The findings confirm heterogeneity between short-term and long-term connectedness results. Moreover, our findings indicate dynamic net-pairwise connectedness, which reveals various volatility transmission episodes where net propagators turn into net receivers. The rest of the paper is organized as follows. Section 2 presents a literature review. Section 3 explains the methodology. Section 4 presents the data details and obtained empirical findings, and finally, section 6 concludes and provides policy implications.

2. Literature Review

The extant literature on volatility spillovers among different asset classes is divided into various research work strands. The first conduit on volatility spillovers investigates the spillovers across the same asset class markets. The inception of the literature in this direction started with evaluating exchange rate volatility after the events erupting due to the European Monetary System in the 1990 era (see, e.g., Rose & Svensson, 1994; Sosvilla-Rivero IV et al., 1999). Engle et al. (1990) first explored volatility transmission, which identifies volatility spillover in the foreign exchange market. Laopodis (1998) also confirms the evidence of strong volatility transmission and concludes that good news related to volatility spillover has a lesser effect than comparable bad news. In contrast, Baillie and Bollerslev (1991) identify slight or no evidence of volatility transmission between the US dollar exchange rate and other currencies. Few others also investigated the association among implied market volatilities. For instance, Nikkinen et al.

(2006) also examine the implied volatility term structure linkages between the British pound, euro, and the Swiss franc against the US dollar. In the same way, Huynh, et al., (2020b) also investigate return and volatility transmission effect among nine most traded international currencies and confirm the asymmetric relationship and spillover effect in currency markets specifically during times of trade policy uncertainty. Moreover, the researchers conclude that volatility spillover effect is more pronounced than return spillovers between currency rates and policy uncertainty.

The second conduit on volatility spillovers investigates the spillovers between stock markets. In this regard, Bonfiglioli and Favero (2005) found a lack of long-term linkages between the US and German stock markets. On the contrary, Caporale et al. (2006) unveil the interdependence of stock market returns among the US, Japanese, European, and Southeast Asian markets. Similarly, Chinzara and Aziakpono (2009) find evidence of both return and volatility spillover between major equity markets across the world. Some studies explore the volatility spillovers and interdependence between stock returns and exchange rates (see, e.g., Kanas, 2000; Beirne et al., 2013). The empirical findings confirm the rising financial integrations and interdependence of international markets. These researchers conclude the significant effect of the implied volatility of the currency market and stock market volatility's expectations on each other. Ftiti, Z et al. (2017) documented the effect of sovereign credit rating information on spillover effect and volatility of stock markets in fragile European countries.

Another strand of volatility spillover literature connects crude oil, equity, and the exchange rate market. Malik and Hammoudeh (2007) apply a multivariate GARCH model to determine the volatility spillover linkages between crude oil, US equity market, and stock markets of Gulf countries. The findings show strong volatility spillover effects among financial markets.

Similarly, Arouri et al. (2011) identify contagious volatility effects between oil and sectoral indices in the US and Europe. The empirical findings provide evidence on strong volatility transmission between sectoral stock market returns and oil. Badshah et al. (2013) document the concurrent transmission effects of volatility indices for gold, stock, and forex. Also, Liu et al. (2013) found significant short- and long-term equilibrium relationships between the implied volatility of gold, crude oil, and VIX.

Regarding commodity market spillovers, the majority of the coverage is related to the oil market. Pioneer studies in this subject matter investigate the association between oil price fluctuations and stock markets and conclude the significant impact of oil price fluctuations on stock market returns in developed and developing economies (Jones & Kaul, 1996; Huang et al., 1996; Sadorsky; Park & Ratti, 2008, among others). In other commodities, Büyüksahin et al. (2009) find insignificant interdependence between numerous commodity returns and US stock indices before the global financial crisis. Conversely, many other studies argue a strong relationship between commodity and stock markets (Silvennoinen & Thorp, 2013; Olson et al., 2014; Kang et al., 2015). Moreover, the recent studies assert that linkages between commodities and stock markets have strengthened after GFC 2007-08 due to the financialization of commodity markets. For instance, Delatte and Lopez (2013) and Büyükşahin and Robe (2014) document the time-varying co-movements between commodity and equity indices and confirm the evidence that significant surge and symmetrical interdependence is witnessed between equity and commodities returns in the aftermaths of financial turmoil. Also, Mensi et al. (2013) and Maghyereh et al. (2017) find strong volatility transmission linkages structure between oil and other commodities.

Another conduit in this direction reveals the linkages of time-varying dependence and co-movements between gold and other asset classes (e.g., Bouri et al., 2017; Biswal, & Roubaud, 2017; Schweikert, 2018; Yunus, 2020). Choudhry et al. (2015) and Reboredo and Ugolini (2017) found asymmetric causality linkage between gold, commodities, and stock prices. In the same vein, Bouri et al. (2018) explore the time-varying correlations and nonlinear quantile effects of gold and commodities index on Bitcoin. Schweikert (2018) document the long-term association between silver and gold, whereas Yunus (2020) identifies interdependence between real estate, gold, bond, and equity markets. Boukhatem, J. et al. (2020) conclude that the connectedness between bond market and macroeconomic variables is significant and pronounced in emerging economies during turmoil periods.

Our study is also a thread of literature that documents the effects of volatility transmission and spillovers on portfolio diversification strategies. For instance, Chang et al. (2011) estimate optimal hedge ratios for Brent and WTI crude oil spot and futures contracts from various multivariate conditional models. The empirical findings support multivariate conditional variance models, reducing the inconsistency between oil spot and futures portfolios. Similarly, Huynh et al. (2020c) determine the connectedness between commodity spot and futures prices of various financial variables (crude oil, corn, soya, gold, silver, and iron) and identify that commodities futures volatility significantly cause and effect the volatility in spot prices of major commodities in international financial markets. Mensi et al. (2015), Hammoudeh and Yoon (2015), and Basher and Sadorsky (2016) examine time-varying hedging strategies among various asset classes, e.g., exchange rate, crude oil, emerging market stock returns, the VIX, gold and bond prices. The results suggest time-varying phenomena among asset classes and identify oil as the best hedge against stock market volatilities. In the related works, Khalfaoui et al. (2015), Boutahar and Boubaker (2015), and Wang and Liu (2016) examine the hedge potentials and hedge ratios in various periods. Their findings manifest that hedge ratios are diverse across time and frequencies, and portfolio managers should hold more crude oil than stocks. Moreover, the evidence points towards cross-market hedging in the oil and stock markets. Recently, Huynh, et al (2020) examine risk spillover effects among 14 cryptocurrencies and find that risk transmission comes from small coins in cryptocurrency market and Bitcoin is apposite financial tool for hedging.

Despite ample research work in this line, a significant research gap exists in examining the time-varying interdependence and hedging strategies between equities, bonds, currencies, energy, and non-energy commodities' implied volatility indices. This study focuses on information transmission effects between five volatility indices, equities, bonds, currencies, and energy, and non-energy commodities. Moreover, the study makes use of Rolling- window wavelet correlation framework to detect extreme market fluctuations across different time intervals and to assess risk and volatility spillovers among implied volatility indices.

3. Methodology

3.1 Wavelet Correlation

The study determines the time and frequency coherency between equities, bonds, currencies, energy, and non-energy commodities by making use of the MODWT wavelet correlation (WC) following Gençay et al. (2001) and Tiwari et al. (2020) and rolling-window wavelet correlation (RWWC) approach by Polanco-Martínez et al. (2018). The MODWT WC could be elucidated as:

$$\tilde{\rho}AB = \frac{Cov\ (\grave{W}_{A,z,d}\ \widetilde{W}_{B,z,d})}{\sqrt{var\ \{\widetilde{W}_{A,z,d}\} var\ \{\widetilde{W}_{A,z,d}\}}} = \frac{\widetilde{\gamma}\ AB(\gamma Z)}{\acute{\sigma}A(\gamma Z)\widetilde{\sigma}\ B(\gamma Z)} \tag{1}$$

Whereas $\tilde{\gamma}\ AB(\gamma Z)$ signifies the wavelet covariance's unbiased estimates between the wavelet coefficients $\grave{W}_{A,z,d}$ and $\widetilde{W}_{B,z,d}$. $\acute{\sigma}^2 A(\gamma Z)\ \ and\ \tilde{\sigma}^2\widetilde{B(\gamma Z)}$ measure of the unbiased estimates, in accordance with scale γZ, the wavelet variance for A and B, correspondingly. The MODWT-based wavelet variance's unbiased estimate is represented as:

$$\tilde{\sigma}_A^2(\gamma Z) = \frac{1}{\tilde{N}}\ \sum_{d=\ L_{z-1}}^{N-1} \widetilde{W}_{zd}^2 \tag{2}$$

where $\grave{W}_{z,d}$denotes the jth level MODWT wavelet coefficients for the data series A, $L_z = (2^z - 1) + 1$ is the scale wavelet filter, γz, length, which denotes the sum of coefficients; the border does not cause a disturbance. In confirmation with Whitcher et al. (1999), the confidence intervals for the wavelet coherence chase the manifestation $100(1 - 2p)\%$.

Consequently, a confidence interval estimation for the wavelet coherence is represented as

$h\{h[\tilde{\rho}AB(\gamma z)] + \emptyset^{-1}(1-p)/\sqrt{\tilde{N}+3}\}$ where $\emptyset^{-1}(p)$ proxies the $100p\%$ percentage point for the standard normal distribution. The Fisher Z-transformation is explicated as by $h(\tilde{\rho}AB) = tanh^{-1}(\tilde{\rho}AB)$.

3.2 Rolling-window wavelet correlation

The study determines the time and frequency coherency between equities, bonds, currencies, energy, and non-energy commodities by making use of the rolling-window wavelet correlation (RWWC) approach by Polanco-Martínez et al. (2018). The RWWC is a dynamic approach that computes the sequential innovations of the wavelet correlation (WC). The study applies RWWC framework, which displays WCs between data series in which moving windows computations are required. It is a modern approach in the present literature that can grasp the different time intervals. The study assesses the pairwise RWWC where windows w = 120 data points. The study then rolls forward each series point positioned in a stated time following Polanco-Martínez et al. (2018).

3.3 GFEVD and connectedness in the time-domain

Initially the study approximates a stationary VAR model

$$\mathbf{y}_t = \mathbf{\Phi}(L)\mathbf{y}_t + \boldsymbol{\varepsilon}_t = \mathbf{\Phi}_1 \boldsymbol{y}_{t-1} + \mathbf{\Phi}_2 \mathbf{y}_{t-2} + \cdots + \mathbf{\Phi}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t \tag{3}$$

where vector $\mathbf{y}_t$ is $n \times 1$, which comprises of all variables in system; $\mathbf{\Phi}(L)$ is a lag polynomial. The vector $\boldsymbol{\varepsilon}_t$ of random errors has zero mean, variance matrix $\mathbf{\Sigma}$, and no autocorrelation. As system of VAR is stationary, it has a moving average illustration with infinite order, or VMA(∞)

$$\mathbf{y}_t = \mathbf{\Psi}(L)\boldsymbol{\varepsilon}_t = \mathbf{\Psi}_0 \boldsymbol{\varepsilon}_t + \mathbf{\Psi}_1 \boldsymbol{\varepsilon}_{t-1} + \cdots + \mathbf{\Psi}_h \boldsymbol{\varepsilon}_{t-h} + \cdots \tag{4}$$

where $\mathbf{\Psi}_h$ is the moving average coefficient matrix that relates to the *h*-th lag; and when *h* is zero, $\mathbf{\Psi}_0$ diminishes to the unit diagonal matrix $\boldsymbol{I}$. Pesaran and Shin (1998) by making use of the generalized forecast error variance decomposition (GFEVD) depicted that the contribution of the *j*-th variable to the forecast error variance of the *i*-th variable *H*-steps ahead is

$$\theta_{ij}^H = \frac{\sum_{h=0}^{H-1} \left(\mathbf{e}_i' \mathbf{\Psi}_h \mathbf{\Sigma} \boldsymbol{e}_j\right)^2}{\mathbf{e}_j' \mathbf{\Sigma} \mathbf{e}_j \times \sum_{h=0}^{H-1} \mathbf{e}_i' (\mathbf{\Psi}_h \mathbf{\Sigma} \mathbf{\Psi}_h') \mathbf{e}_i} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{H-1} \left((\mathbf{\Psi}_h \mathbf{\Sigma})_{ij}\right)^2}{\sum_{h=0}^{H-1} (\mathbf{\Psi}_h \mathbf{\Sigma} \mathbf{\Psi}_h{}')_{ii}} \tag{5}$$

where σ_{jj} is the *j*-th diagonal matrix of $\mathbf{\Sigma}$; $\mathbf{e}_j$ represents a vector whose *j*-th component is one while all the other components are zero. The study can acquire the *pairwise* connectedness from variable j to variable i as $\tilde{\theta}_{ij}^H = \theta_{ij}^H / \sum_{ij}^H \theta_{ij}^H$ by standardizing the input of all variables ($j =$

$1, 2, \dots, n$). It is obvious that by definition, $\sum_{j=1}^{n} \tilde{\theta}_{ij}^{H} = 1$, $\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}^{H} = n$. And the *total connectedness* of the VAR system is

$$C^{H} = \frac{\sum_{i \neq j}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}^{H}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}^{H}} = \frac{1}{n} \sum_{i \neq j}^{n} \sum_{j=1}^{n} \tilde{\theta}_{ij}^{H} \tag{6}$$

The *net pairwise* connectedness is computed as

$$C_{ij,net}^{d} = \tilde{\theta}_{ij}^{H} - \tilde{\theta}_{ji}^{H} \tag{7}$$

The *from* connectedness and *to* connectedness are

$$C_{i \leftarrow \cdot}^{H} = \sum_{j \neq i}^{n} \tilde{\theta}_{ij}^{H}, C_{i \rightarrow \cdot}^{H} = \sum_{j \neq i}^{n} \tilde{\theta}_{ji}^{H} \tag{8}$$

The *net* connectedness of variable i is the difference between the *to* and *from* connectedness

$$C_{i,net}^{H} = C_{i \rightarrow \cdot}^{H} - C_{i \leftarrow \cdot}^{H} \tag{9}$$

3.4 GFEVD in the frequency domain

The discussion again begins with the VMA (∞) representation of the VAR(p) model. The lag operator is replaced L with $\mathrm{e}^{-\mathrm{i}\omega}$ to attain the Fourier transform for the lag polynomial $\boldsymbol{\Psi}(\mathrm{L})$ in Equation (10)

$$\boldsymbol{\Psi}\left(\mathrm{e}^{-\mathrm{i}\omega}\right) = \sum_{h=0}^{\infty} \mathrm{e}^{-\mathrm{i}\omega h} \boldsymbol{\Psi}_{h} \tag{10}$$

where ω is a definite frequency. The power spectrum of $\mathbf{y}_{t}$ is represented as

$$\mathcal{S}_y(\omega) = \sum_{h=-\infty}^{\infty} E[\mathbf{y}_t \mathbf{y}_{t-h}{}'] \, \mathrm{e}^{-\mathrm{i}\omega h} = \boldsymbol{\Psi}\left(\mathrm{e}^{-\mathrm{i}\omega}\right)\boldsymbol{\Sigma}\boldsymbol{\Psi}\left(\mathrm{e}^{\mathrm{i}\omega}\right) \tag{11}$$

The frequency version of the GFEVD is

$$\vartheta_{ij}(\omega) = \frac{1}{\sigma_{jj}} \times \frac{\left|\left(\boldsymbol{\Psi}\left(\mathrm{e}^{-\mathrm{i}\omega}\right)\boldsymbol{\Sigma}\right)_{ij}\right|^2}{\left(\boldsymbol{\Psi}(\mathrm{e}^{-\mathrm{i}\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(\mathrm{e}^{\mathrm{i}\omega})\right)_{ii}} = \frac{1}{\sigma_{jj}} \times \frac{\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}\left(\mathrm{e}^{-\mathrm{i}\omega h}\right)\boldsymbol{\Sigma}\right)_{ij}^2}{\sum_{h=0}^{\infty}\left(\boldsymbol{\Psi}(\mathrm{e}^{-\mathrm{i}\omega h})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(\mathrm{e}^{\mathrm{i}\omega h})\right)_{ii}} \tag{12}$$

The pairwise connectedness, after normalizing in the same way in the time-domain, from variable j to variable i is

$$\tilde{\vartheta}_{ij}(\omega) = \frac{\vartheta_{ij}(\omega)}{\sum_{j=1}^{n}\vartheta_{ij}(\omega)} \tag{13}$$

The *pairwise* connectedness within a frequency band (ω_1, ω_2) is explained as:

$$\tilde{\vartheta}_{ij}(\omega_1, \omega_2) = \int_{\omega_1}^{\omega_2} \tilde{\vartheta}_{ij}(\omega)\mathrm{d}\omega \tag{14}$$

And the *within net pairwise* connectedness is computed as

$$C_{ij,net}^{d}(\omega_1, \omega_2) = \tilde{\vartheta}_{ij}\,(\omega_1, \omega_2) - \tilde{\vartheta}_{ji}\,(\omega_1, \omega_2) \tag{15}$$

Then the *within total* connectedness over this frequency band (ω_1, ω_2) is

$$C^{(\omega_1,\omega_2)} = \frac{\sum_{i\neq j}^{n}\sum_{j=1}^{n}\tilde{\vartheta}_{ij}\,(\omega_1, \omega_2)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{\vartheta}_{ij}\,(\omega_1, \omega_2)} \tag{16}$$

The *within from* connectedness and *within to* connectedness are

$$C_{i\leftarrow\cdot}^{(\omega_1,\omega_2)} = \sum_{j\neq i}^{n} \tilde{\vartheta}_{ij}\,(\omega_1,\omega_2),\; C_{i\rightarrow\cdot}^{(\omega_1,\omega_2)} = \sum_{j\neq i}^{n} \tilde{\vartheta}_{ji}\;\,(\omega_1,\omega_2) \tag{17}$$

The *within net* connectedness is

$$C_{i,net}^{(\omega_1,\omega_2)} = C_{i\rightarrow\cdot}^{(\omega_1,\omega_2)} - C_{i\leftarrow\cdot}^{(\omega_1,\omega_2)} \tag{18}$$

A positive value *within net* connectedness in a given a frequency band suggests variable i is a net transmitter of spillover in the framework; else, if negative value is observed within connectedness then variable i is supposed to be net receiver of spillover in the framework.

And the *contribution* of connectedness over frequency band (ω_1,ω_2) is

$$c(\omega_1,\omega_2) = \frac{\sum_{i\neq j}^{n}\sum_{j=1}^{n}\tilde{\vartheta}_{ij}\,(\omega_1,\omega_2)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\tilde{\vartheta}_{ij}\;\,(-\pi,\pi)} = \frac{1}{n}\sum_{i\neq j}^{n}\sum_{j=1}^{n}\tilde{\vartheta}_{ij}\,(\omega_1,\omega_2) \tag{19}$$

3.5 Hedge Effectiveness

In the next stage, the study executes the out-of-sample hedging efficiency of variables for OVX, EVZ and TYNVI, which permits to match the hedging capability of variables. The study performs this by estimating the hedge efficacy of the hedged positions among variables for OVX, EVZ and TYNVI, and determine the extent of risk reduction by including VIX or GVZ in a shared portfolio. This technique and step are mostly applied by researchers for portfolio risk assessment. Assume $r_{hp,t}$ symbolizes the hedged portfolio's return that consists of a given style (industry) portfolio and variables position:

$$r_{hp,t} = r_{A,t} - \theta_t r_{B,t} \tag{20}$$

where $r_{A,t}$ represent the return on OVX, EVZ and TYNVI, and $r_{B,t}$ denotes the return on either VIX (GVZ), and the hedge ratio is symbolized by θ_t . Therefore, the variance of the hedged portfolio is dependent on the evidence accessible at the time I_{t-1}, and is represented as:

$$var(r_{A,t}I_{t-1}) = var(r_{B,t}I_{t-1}) + \emptyset_t^2\, var\,(r_{A,t}) - 2\emptyset_t cov(r_{sp,t}, r_{B,t}\, I_{t-1}) \qquad (21)$$

The calculation of the hedge ratios originates from the conditional-volatility and covariance estimation attained through the AGDCC-GARCH model. It is known as the asymmetric generalized dynamic conditional correlation form of the generalized autoregressive conditional heteroscedasticity model. This approach renders a robust estimation by determining the second moments of correlations and covariance. This facilitates in evaluating the hedge performance of variables on the style (industry) portfolios. Thus, a long position in a particular style (industry) portfolios can be hedged with a short position in variables from the underlying specification:

$$\frac{\theta_t^*}{I_t} = h_{A,B,t}/h_{B,t}$$

where $h_{A,B,t}$ signifies the conditional covariance between OVX, EVZ and TYNVI and either VIX (GVZ) and $h_{B,t}$ symbolizes the conditional variance of either VIX (GVZ). The hedge effectiveness is analyzed to determine and associate the performance of various hedge ratios attained by diverse GARCH models presented in the following equation

$$he = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \qquad (22)$$

In complete terms, a greater he indicates the higher hedge effectiveness. This implies that the he = 1 would show as a perfect hedge, and he = 0 suggests as a no hedge. A static-width rolling calculation for the hedge ratios yields forecast of 1,000 one step with model refitting is done every 10 observations. These hedge ratio projections further direct the creation of the hedged portfolio.

4. Data and Empirical Findings

4.1 Data

This study uses daily data of five volatility indices representing five major financial asset classes, including equities, bonds, currencies, energy, and non-energy commodities. We use the VIX index for stock market volatility, which expresses the expected change in the S&P 500 index over the next 30 days. It is calculated with respect to option prices that allow investors to hedge against sharp price movements. As illustrative of the bond market, we utilize the CBOE/Chicago Board of Trade (CBOT) 10-year US Treasury-Note, known as (TYNVI). Based on the prices from CBOT's actively traded options contracts on Treasury-Note futures, TYNVI measures the expected volatility of the next 30-days for 10-year Treasury-Note futures. Further, we take CBOE Euro Currency VIX (EVZ) as an indicator of foreign exchange markets. Based on the option of Currency Shares Euro Trust, the indicator computes the expected volatility of the USD/EURO exchange rate for the next 30-days. Furthermore, as representative of the energy market, we utilize CBOE crude oil price ETF VIX (OVX). OVX estimates the next 30-day volatility of crude oil prices by using LP (Ticker- USO) options with a wide range of strike prices of the United States Oil Fund. Finally, as an indicator of non-energy commodities, CBOE Gold exchange-traded fund (ETF) VIX (GVZ) is employed. Based on the bid and ask prices of SPDR gold shares, the GVZ computes the 30-day volatility of the gold prices. The data for all of the indicators are taken from the CBOE website. The period of our study spans from 01/08/2008 to 31/10/2019.

4.2 Descriptive Analysis

Panel A of Table 1 displays the descriptive statistics of volatility indices utilized in the study. Not surprisingly the statistics show that the highest mean implied volatility in our sample is reported for OVX (36.23) depicting extreme oil price movements. In addition, in terms of implied volatility, OVX is followed by VIX (19.27) and GVX (18.96). This also showcases that in the post-financial crisis era, non-energy commodities are also vulnerable to increasing price volatilities due to the financialization of the commodity markets (Balli et al., 2019). Also, as expected in our sample volatility indices, TYNVI (6.04) has the lowest average implied volatility (low volatility of fixed income securities is well documented by Houweling & Zundert, 2014; Carvalho et al., 2014). Additionally, the skewness, kurtosis, and Jarque Bera tests reveal that volatility indices are not normally distributed. Finally, the results of the Augmented Dickey-Fuller test illustrate that all series are stationary.

Panel B of Table 1 also reports the pairwise correlations between the volatility indices. Opposite to Andrada-Felix et al. (2018) we find low correlations among implied volatility indices. The low correlations highlight the case for using alternative asset for diversification and hedging. We further develop this idea in the empirical analysis section.

<< Table 1 about here >>

Fig. 1 displays the daily evolution of volatility for sample implied volatility indices. It is to be noted that the values of volatility indices correspond with important events (when investors anticipate significant moves in either direction). Large volatility spikes correspond to events such as default of Lehman Bros. in September 2008, European debt crisis 2010-2012, oil price collapse in 2014 that lasted till mid-2015, financial turmoil in June 2016 after the UK voted to leave European Union and the most recent in September 2019 when finally Brexit happened. The results showcase significant influence of economic and financial conditions on the volatility of implied volatility indices. The findings illustrate market sentiment and risk-averse behavior of investors in periods with high market volatility (Tversky & Kahneman, 1991; Hwang & Satchell, 2010).

<< Figure 1 about here >>

4.3 Rolling Window Wavelet Correlation Analysis

Unlike normal correlation matrix, the rolling window wavelet correlation analysis reveals interesting additional information about the co-movement between implied volatility indices. The correlation coefficients for the four wavelet scales, from D1 to D4, imply time horizons associated with changes of 1 to 8 days and intra-week to monthly periods. The results showcase the correlations structure among volatility indices is frequency-dependent and the degree of correlation between the implied volatility indices is not constant over time.

<< Figure 2 about here >>

Fig. 2 illustrates the rolling window wavelet correlations for volatility indices. First, in the case of VIX, we found maximum pairs of correlations for VIX-OVX followed by VIX-GVZ, VIX-EVZ, whereas least pairs are detected for VIZ- TYNVI. Regarding VIX-OVX, we observe high correlations during GFC, European debt crisis, oil price slump in 2014, and Brexit. The high correlations are spread across all wavelet scales but more evident in the longest wavelet scales D3 and D4. The findings highlight the strong linkages between the implied volatility of the stock and crude oil markets, which are more pronounced during financial instability periods. Moving on to VIX-GVZ, we note various high correlation episodes during the sample that correspond to the longest wavelet scales. However, the episodes of high correlation are brief and do not persist for a long period. Instead, the findings reinforce the earlier evidence that suggests strong properties of gold as a diversifier and safe-haven asset for stock markets, in particular during periods of the economic downturn (e.g., Baur & Lucey, 2010; Baur & McDermott, 2010; Ratner & Klein, 2008; Bekiros et al., 2017; Naeem et al., 2020; Naeem et al., 2021, among others). Next, about VIX-EVZ, we found high correlations during the first half of the sample spread across all wavelet scales. On the contrary, we note very few pairs of high correlations for the second half of the sample. From investor point view the findings imply that market participants can capitalize on the recent weak linkages between the stock and exchange market to create successful hedging and diversification opportunities. Finally, among the volatility indices least pairs of high correlations are reported between VIX- TYNVI. Moreover, only time persistent higher co-movement between stock and bond market is observed around 2018 when the bond market volatility was considerably high.

As shown in Fig.4 we found only a few pairs of high and moderate correlation among OVX-GVZ. In addition, we note a few episodes of negative correlations that highlight the functional role of gold as hedger and diversifier for other asset classes. Nevertheless, the highest correlation between the implied volatility of gold and crude oil is seen during 2016 due to collapse of commodity markets and subsequent rebound. Also, concerning OVX-EVZ we detect few high pairwise correlations corresponding to GFC and the European debt crisis. More importantly, we also observe various negative correlations between the underlying implied volatility indices spread across all wavelet scales. The findings highlight the strong prospects of cross-market hedging for investors. Furthermore, we note weak volatility linkages among OVX- TYNVI as weak and negative correlations dominate the underlying association and only few instances of high correlations are reported. Hence, Once again findings suggest strong cross-market diversification possibilities for investors and portfolio managers.

Next we detect moderate correlations between gold and foreign exchange market during the sample period corresponding to all wavelet scales. The high correlations are found in the longest wavelet scale D4. The findings somewhat again suggest the use of precious metal to diversify foreign exchange risk as found for other alternative asset classes. Additionally, once again we found weak co-movement between implied volatility indices of bond and gold market. In fact, similar results can are also reported for EVZ- TYNVI during our sample time. The findings confirm our earlier evidence that suggests weak association and connectedness of the fixed-income market with other alternative assets. Moreover, the results highlight the stable and less volatile nature of the fixed-income market.

Overall, the findings of this section suggest time-varying relationship between the co-movement of the volatility indices. The findings highlight the frequency-dependent nature of the underlying markets. The findings validate the use of frequency-based methods to analyze and understand the risk transmission among implied volatility indices. Moreover, visual depiction of co-movement between the implied volatility indices offers important implications for market participants as it provides specific information related to risk management, asset allocation and cross-market hedging.

4.4 Static Connectedness Analysis

First, we estimate time-frequency connectedness among implied volatility indices to analyze the static volatility linkages. Table 2 reports the volatility spillovers between the volatility indices, where total static connectedness is estimated using Diebold and Yilmaz (2012) time-domain approach and frequency-based connectedness follows Barunik and Krehlik (2018) frequency-domain approach. The off-diagonal components in the table measure the connectedness between the volatility indices.

<< Table 2 about here >>

Panel A displays the total connectedness among the implied volatility indexes. The results show that own connectedness values are reported to be highest, ranging from 65.12% to 79.28%. In fact, own connectedness for all of the implied volatility indices is greater than any directional connectedness FROM and TO. The findings somewhat suggest that implied volatility indices of alternative assets are independent of each other to an extent. Also, the risk transmission due to shocks in a particular asset does not strongly transmit to other implied volatility indices. In the same vein, the total static connectedness between volatility indices is only recorded around 25.96%[1], whereas 74.04% of the variation is driven by idiosyncratic risk. The findings indicate that the level of connectedness among implied volatility indices is less as compare to other financial markets. In contrast, Diebold and Yilmaz (2012, 2014) report much higher value of connectedness among financial markets. In the same way, Maghyereh et al. (2016) also found that the total connectedness between crude oil and stock markets around the globe is 51.60% and Fernández-Rodríguez and Sosvilla-Rivero (2016) report a connectedness value of 48.75% among foreign exchange and equity markets for the seven largest economies of the world.

Now concerning the pairwise connectedness, the highest level of connectedness is among VIX, GVZ, and OVX. The findings reinforce the recent evidence that stresses strong linkages among equities and commodities due to financialization of commodity market, especially post global

[1] Where Felix et al. (2018) report total connectedness for volatility indices is 38.99%.

financial crisis (Balli et al., 2019). Also, many researchers also suggest that nowadays institutional investors recognize commodities as an alternative investment class (Büyükşahin & Robe, 2014; Singleton, 2014; Junttila, 2018). On the other hand, the bond market has low pairwise connectedness values with other financial markets except VIX. This once again highlights the independent and stable nature of the fixed-income securities market. Moreover, the findings second the evidence that indicates weak connectedness between bonds and other financial markets (e.g., Maghyereh & Awartani, 2016; Champagne et al., 2017; Wang & Wang, 2018; Tiwari et al., 2018). Additionally, the net-connectedness results unveil that VIX is the net transmitter of volatility shocks to other implied volatility indices. The results indicate that shocks in stock market strongly influence the volatility in other financial markets. In fact, the results corroborate a thread of literature that suggests the leading role of equities in transmitting volatility shocks to other financial markets (Ferrer et al., 2018; Yoon et al., 2019). Therefore, our findings also recognize the functional importance of VIX as the world's major indicators of volatility and investor sentiment.

Panel B and C of Table 2 exhibits the results of frequency (short- and long-term) connectedness among the implied volatility indices. The findings uncover that for all of the implied volatility indexes own connectedness is greater than directional connectedness FROM and TO in both short-run and long-run. The findings somewhat stress weak transmission of volatility shocks across implied volatility indices in the frequency-domain. The findings showcase that majority of the variation in implied volatility indices are caused by idiosyncratic risk. The findings also imply that investors can take advantage of the weak volatility linkages among implied volatility indices by taking off-setting positions across alternative assets to shield against volatility shocks.

As anticipated the volatility connectedness among implied volatility indices varies across frequencies. For Instance, the total connectedness estimated among the implied volatility indexes is 21.48 % in the short-run, whereas the value significantly decreases to 4.48 % in the long-run. The results clearly depict that the volatility transmission among the underlying markets significantly changes at different frequencies. Moreover, the decomposition of total connectedness into short- and long-term frequencies unveils that volatility connectedness among the implied volatility indexes is more pronounced in the short-term period and otherwise there is weak risk transmission among the indices in the long-run period. The findings are in line with a thread of literature that suggests frequency-based volatility connectedness among different financial markets (e.g., Luo & Ji, 2018; Baruník & Kocenda, 2019; Tiwari et al., 2020). In this way, the results validate the use of frequency based methods to evaluate volatility connectedness among the implied volatility indexes. The findings have crucial implications for investors with heterogeneous interests in investment time horizons. For example, some investors (such as individual trades and hedge funds) focus on short-term performance of the financial assets, while others (large institutional investors) are more concerned about the long-run performance. Further, the findings of this section confirm earlier obtained evidence as we again note volatility spillovers among the indices swell during periods of financial turmoil. Furthermore, the results also stress leading role of VIX as volatility transmitter to other implied volatility indexes.

4.5 Time-Varying Connectedness Analysis

The previous section illustrated the static time and frequency connectedness among the implied volatility indices. Although, the static analysis reveals the effective design of spillovers among the volatility indices, still the effectiveness of the connectedness framework lies in understanding the time-varying nature of volatility shocks across time and alternative asset markets (Diebold &

Yilmaz, 2012, 2014). This section presents time-varying volatility connectedness among the implied volatility indices based on a 120-day rolling window with a predictive horizon of 100 days. Fig. 2 displays the time-varying total, short-, and long-term connectedness of the implied volatility indices. The findings point towards strong evidence of time-varying volatility connectedness among the implied volatility indexes financial markets, wherein we trace several high connectedness cycles among implied volatility indices. The findings corroborate the earlier evidence that indicates time-varying volatility connectedness among different financial assets (e.g., Antonakakis et al., 2017; Rehman et al., 2018; Elsayed et al., 2020). In addition, once again we observe that volatility connectedness among the implied volatility indices is a short-run phenomena. The results somewhat stress that volatility linkages among the underlying markets are largely influenced by investor sentiments, which are more pronounced in the short-run.

<< Figure 3 about here >>

We detect several high connectedness cycles (large spikes) corresponding with important global financial events. The first spike is observed during the European Debt crisis 2010 when total connectedness reaches around 60%, while the cycle ends at the beginning of 2011 with the Greek bailout. The second connectedness cycle appears close to the end of the year 2011 after heavy losses encountered by investors in stock markets due to volatility linked with contagion of European Debt crisis and US debt ceiling crisis. Also, the cycle reaches its peak at the start of 2012 due to economic and political uncertainties surrounding the events experienced in the previous year. Nevertheless, after the Cyprus bailout and stabilizing measures taken by central banks the volatility connectedness among the implied volatility indices decreases. The third large spike is noted around mid-2013, which corresponds to rise of geopolitical risk in Arab countries. Further, the volatility connectedness again rises in 2014 due to conflict in eastern Ukraine and the fall in energy prices. The next spike in volatility connectedness is reported at the end of 2014 when stock markets crash as adverse news related to the economic slowdown and political instabilities in Arab countries reach the markets.

In the same manner, another episode of high volatility connectedness is seen around mid-2015, which corresponds to slump in commodity prices and the Chinese Financial Crisis of 2015. Next, volatility connectedness swells among implied volatility indices in 2016 due to political turmoil, the collapse of commodity markets, subsequent rebound, and the effects of negative interest rates on financial markets. More importantly, the situation gets further intensified due to the US presidential elections' results and the uncertainty surrounding the UK's vote to stay or leave the European Union. In contrast, during the year 2017 the volatility indices are reported close to their lowest due to stable economic outlook, low-interest rates, and a rise in asset prices. Once again, the rise in connectedness is observed close to mid-2018, which corresponds to U.S-China trade war and political upheaval due to Iran's sanctions. Finally, the last connectedness spike in our sample reflects September 2019 when Brexit finally happened.

Overall, the findings stress that static connectedness analysis underestimates the total connectedness among the volatility indices. While, the time-varying analysis uncovers that implied volatility indices are more connected, especially during high-stress periods. Moreover, the findings are in line with the literature that indicates high connectivity among financial markets during the high contagion periods (Kolb, 2011). From the investors' perspective the findings imply that high contagion effects in financial distress periods destroy the diversification benefits.

Fig. 3 illustrates time-varying short-term and long-term connectedness among implied volatility indices of alternative assets. The connectedness pattern detected for both of the frequencies is similar to total period analysis as almost same connectedness cycles are noted. In accordance with our earlier static analysis we found that connectedness between implied volatility indices reduces when we move from short-run to long-run. More importantly, the finding of the long-run analysis highlights potential hedging and diversification opportunities that can be exploited by taking offsetting positions across implied volatility indices. In fact, given the low connectivity and risk transmission in the long-run, investors can use a particular market to hedge or diversify risk in the other markets.

4.6 Dynamic Net-pairwise Connectedness

In this section we report dynamic net pairwise connectedness among implied volatility indices based on the frequency-connectedness method of Barunik and Krehlik (2018). The analysis uncovers insightful information about how a particular market transmits (receives) volatility shocks to (from) the other market. Fig. 4 presents the dynamic net pairwise connectedness among the five implied volatility indices. The green area indicates connectedness at the higher frequency band (up to five days). In contrast, the red area reflects the connectedness at the lower frequency band (from six to one hundred and twenty days).

<< Figure 4 about here >>

First, concerning VIX and OVX it is noted that VIX is the net transmitter of volatility shocks to OVX. The findings here reinforce the evidence that stock markets transmit shocks to the oil market, while oil price volatility does not significantly impact stock markets, instead large oil price shocks matter for stock markets (Zhang, 2017). Accordingly, we find that OVX is net transmitter of volatility to stock markets during GFC and late 2014 when oil prices fell drastically. The findings stress sharp reduction in oil prices is an indicator of global economic slowdown causing volatility in the stock markets. Regarding VIX and GVZ the findings unveil bi-directional volatility spillovers. In fact, GVZ is a net transmitter of volatility during GFC, European debt crisis, fall of gold prices in 2014, and during 2019 when the gold prices rapidly increased. Here the findings somewhat differ from the evidence that indicates volatility trasnmission from gold to equities is weak and insignificant (Maghyereh et al., 2017), whereas our findings suggest otherwise for implied volatility indexes. On the contrary, we also detect various episodes when VIX is net-transmitter of volatility shocks to GVZ. The findings are supported by a common notion that suggests equities are net-transmitter of volatility shocks to precious metals, especially during periods of the economic downturn (Mensi et al., 2017). Next, we note VIX is the net transmitter of volatility to EVZ. The rise in volatility transmission is noted during periods of financial instability, in particular during the European debt crisis. Oppositely, EVZ is a volatility transmitter for limited period of time such as at the start of GFC. Similarly, Fernández-Rodríguez and Sosvilla-Rivero (2016) also found that the foreign exchange market was a strong transmitter of volatility to stock markets during GFC period. Finally, it is observed that VIX is a net transmitter of volatility to TYNVI starting from 2009 to the start of 2015. The findings are in line with the evidence that indicates strong volatility transmission from equities to bond indices (Ahmad et al., 2018). However, volatility trasnmission from TYNVI to VIX is high during 2016 and the start of 2018, when volatility in the bond market accelerated.

The findings showcase bi-directional volatility transmission between OVX-GVZ. Wherein, OVX is a net generator of volatility in the first half of the sample, whereas GVZ is the net contributor of volatility shocks in the second half of the sample. Here, the results differ from few earlier studies such as Awartani et al. (2016) who show volatility spillovers from oil to precious metals increased post-oil price crash in July 2014. Also, we find no evidence of strong volatility transmission from the oil to gold market during GFC as suggested by a few other studies (see, e.g., Rehman et al., 2018). As far as OVX-EVZ we observe moderate bi-directional volatility trasnmission, which spiked in 2014 during the crude oil crisis. In the same way like Andrada-Felix et al. (2018) we also note that EVZ is a net transmitter of volatility during the GFC period. Lastly, we note OVX is a net-transmitter of volatility to TYNVI. The dominant role of crude oil in volatility transmission soars after the oil price crash in 2014. However, similar to the currency market TYNVI is also net propagator of volatility to OVX during the GFC period.

Our findings also unveil bi-directional volatility transmission between GVZ-EVZ. GVZ is the net transmitter to the foreign exchange market during periods of financial instability like the GFC, European debt crisis, and Chinese financial crisis of 2015. In contrast, we also detect few episodes when EVZ is a net propagator of volatility to gold market. Next, GVZ is net transmitter of volatility shocks to TYNVI. The volatility spillovers from GVZ to the bond market correspond to important financial events like GFC and European debt crisis. Finally, we also observe volatility transmission among EVZ- TYNVI. The findings show that EVZ is a net transmitter of volatility in the first half of the sample and a receiver from TYNVI in the second half.

Overall our findings once again confirm heterogeneity between our short-term and long-term connectedness results. Various cases of pairwise connectedness demonstrate that volatility spillovers among the implied volatility indices are a short-term phenomenon which does not persist in the long-run. Given this investors can take a hedging position in the long-run across implied volatility indices to create meaningful hedging and diversification opportunities. Also, our findings showcase various instances where net propagators of volatility switch to net receivers of volatility. Hence, even though connectedness among volatility indices exists, still such connectivity is still time and event dependent. The findings are critical for the success of portfolio managers seeking hedging and diversification opportunities across alternative asset classes since we provide a detailed visual demonstration of the time-varying connectedness network of implied volatility indices.

<< Table 3 about here >>

4.7 Hedge Ratio and Hedge Effectiveness

Our previous findings clearly showcase the connectedness network of implied volatility indices and its importance for cross-market hedging. In Table 3, we report summary statistics of hedge ratios and hedging effectiveness. First, in case of VIX the average values of hedge ratios are positive except for TYNVI. The positive hedge ratio indicates that a long position in any of the implied volatility indices can be hedged by taking a short position in VIX. In contrast, inverse relationship between VIX and TYNVI implies that hedge can be created by either taking a long or short position. In addition, among the three implied volatility indices lowest average hedge ratio is reported for EVZ which indicates that one dollar long position in EVZ can be hedged by taking short position of (0.04) cents in VIX. As far as hedging effectiveness results, we see that highest value of (0.1620) is recorded for TYNVI. Furthermore, in case of GVZ all the estimated hedge ratios are positive and highest value of (0.2149) hedging effectiveness is noted for EVZ. The findings indicate that GVZ is superior hedger as compare to VIX.

5. Conclusions

The knowledge of co-movement and spillovers between alternative asset classes has important implications for asset allocation, portfolio diversification, and cross-market hedging. The value of such information is becoming increasingly relevant for portfolio managers as increasing connectedness spillovers and high contagion effects between financial markets drive out portfolio diversification benefits. Given the increasing difficulties in diversification, one needs specific information on volatility connectedness among financial markets to intelligently plan hedging strategies. In fact, better understanding of volatility transmission process across financial markets is essential for effective policy design to reduce the negative effects of connectedness spillovers.

In this study, we estimate time-frequency based risk transmission across financial markets using implied volatility indices. For this purpose, we utilize the rolling window wavelet correlation (RWWC), Diebold and Yilmaz (2012) time-domain and Barunik and Krehlik (2018) frequency-domain approaches. Further, considering the increasingly volatile environment in the financial markets and mounting pressures confronted by investors and portfolio managers in obtaining portfolio diversification and risk reduction; we compute hedge ratios and hedging effectiveness for each of the implied volatility indices to determine the optimal hedging and diversification strategies. The findings of the study uncover some interesting facts regarding risk transmission process among major financial markets. For instance, the empirical findings confirm dynamic short-term and long-term dynamic connectedness among implied volatility indices of alternative assets. Also, the findings reinforce that volatility connectedness between financial markets is time and event dependent, as the results exhibit heterogeneity between short-term and long-term connectedness results. The findings validate the use of time-frequency approach, since the dynamic interaction among volatility indices varies across time and frequencies. In addition, the findings of long-term connectedness analysis suggest potential hedging and diversification opportunities for market participants that can be exploited by taking offsetting positions across volatility indices. Finally, the findings also showcase superior out of sample hedging effectiveness of GVZ among volatility indices.

The findings of the study are crucial for broad range of stakeholders including portfolio managers, investors and financial regulators as they hold useful implications in terms of portfolio strategies and policymaking. First, the high risk dependence among implied volatility indices stresses that investors should carefully study the volatility linkages among financial markets to safeguard investments and diversify portfolio risk. Moreover, investors can utilize the findings of the study to improve their risk management practices and hedging strategies. In fact, in light of the findings investors and portfolio managers in the financial markets can better position themselves to shield against the negative shocks arising from volatility spillovers, especially during the periods of economic and financial meltdown. Second, the evidence presented in the study is useful for policy makers to formulate appropriate policy tools and mechanisms to absorb negative shocks arising from contagion effects among financial markets. In this way, they will be able to implement suitable strategies and optimal policies to mitigate unfavorable effects of risk connectedness among alternative assets.

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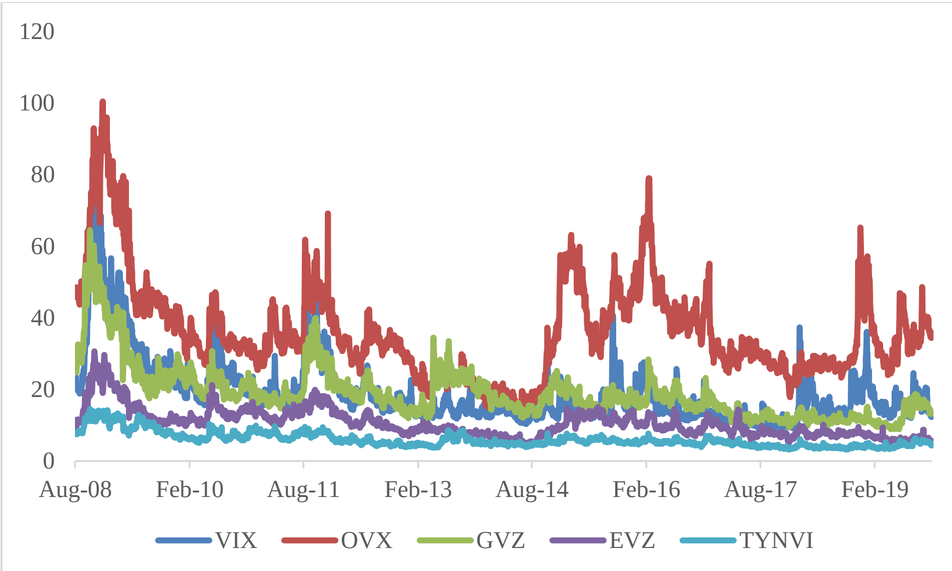
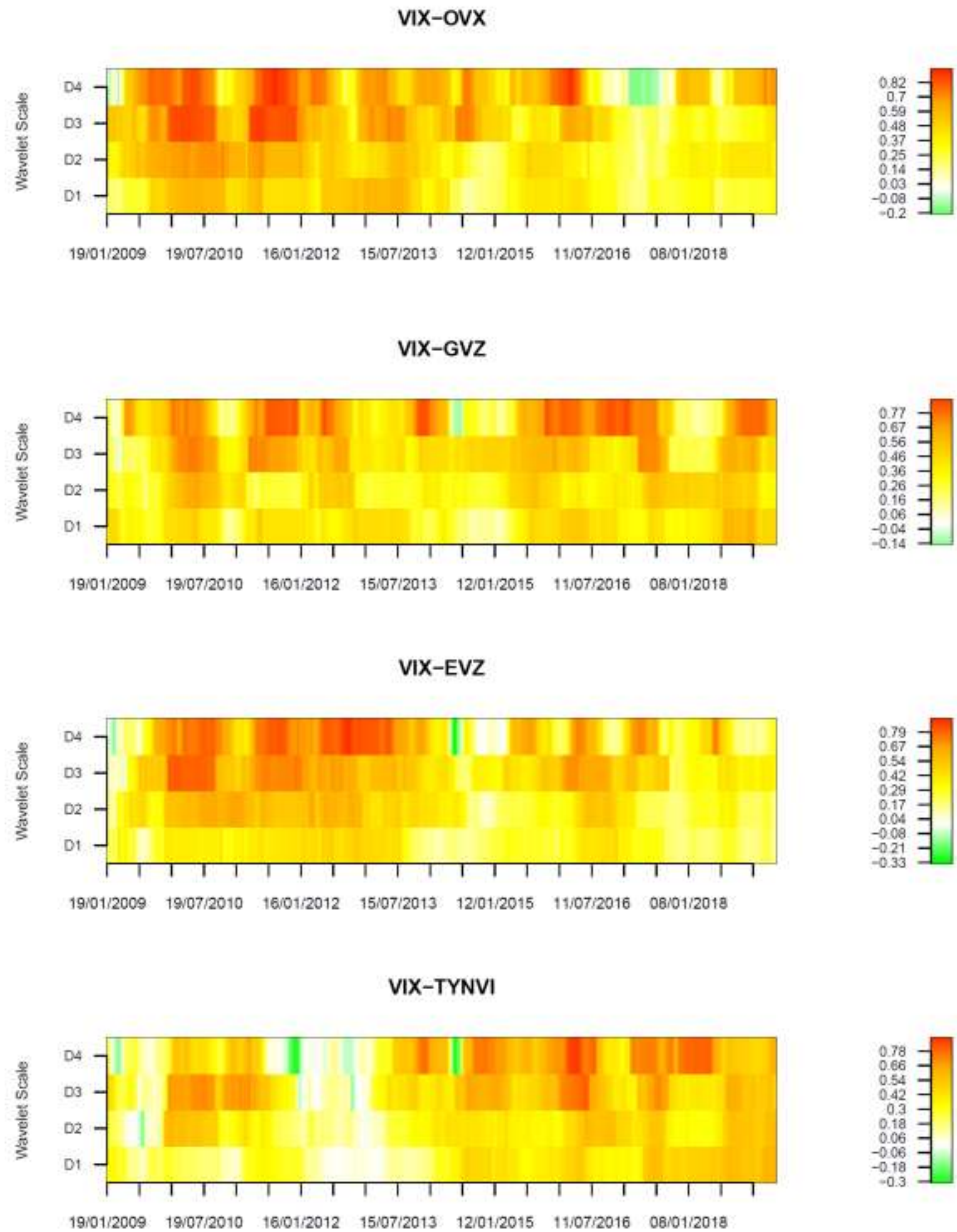
Figure 1. Daily financial market volatilities

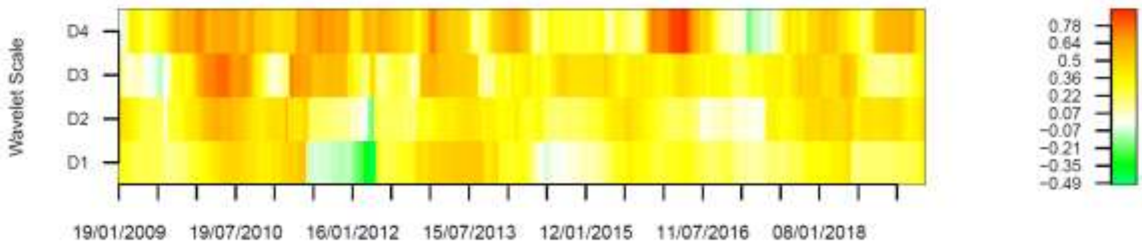


Note: The sample period is from 01.08.2008 to 31.10.2019

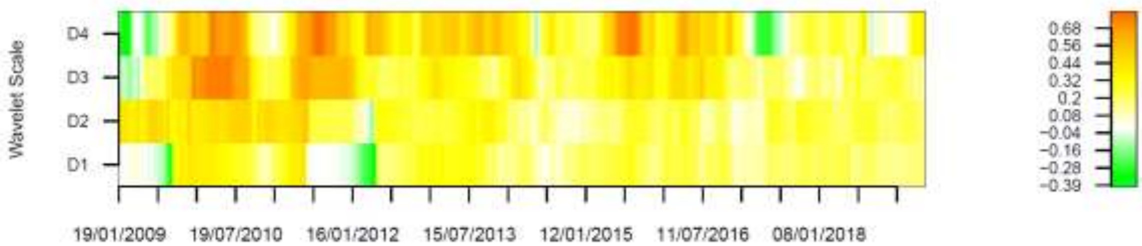
Figure 2. Rolling window wavelet correlation



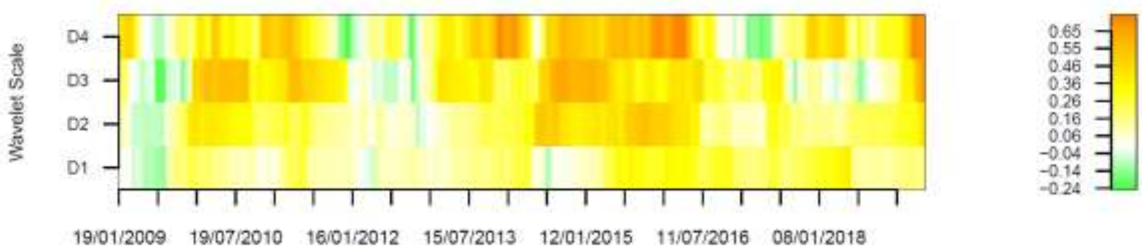
OVX-GVZ



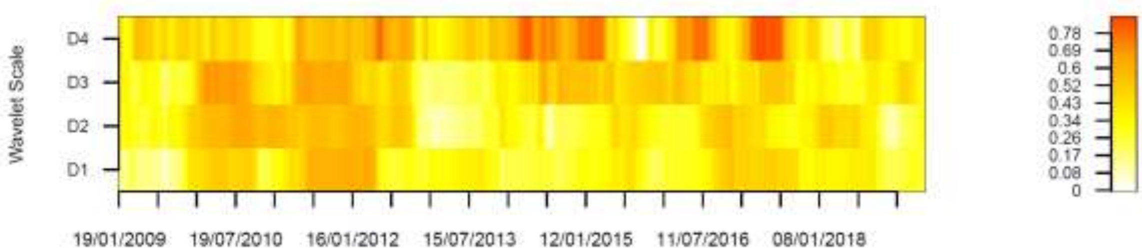
OVX-EVZ

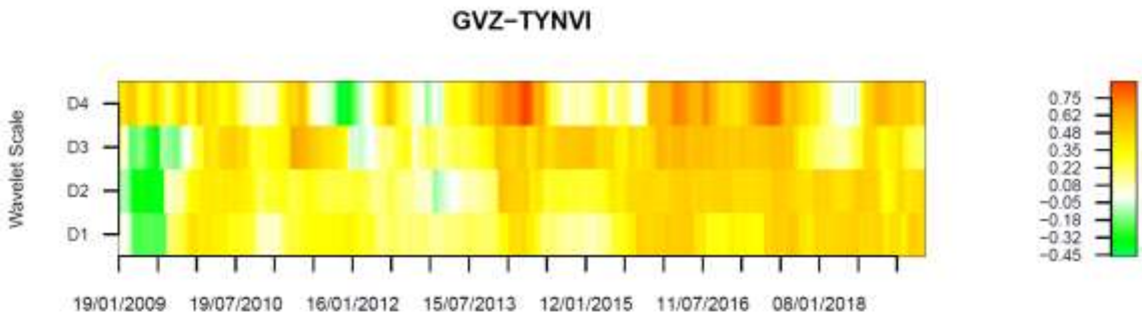


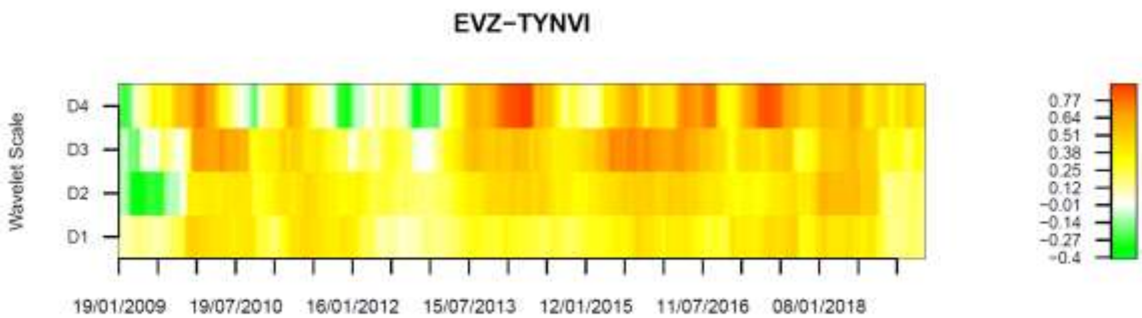
OVX-TYNVI



GVZ-EVZ

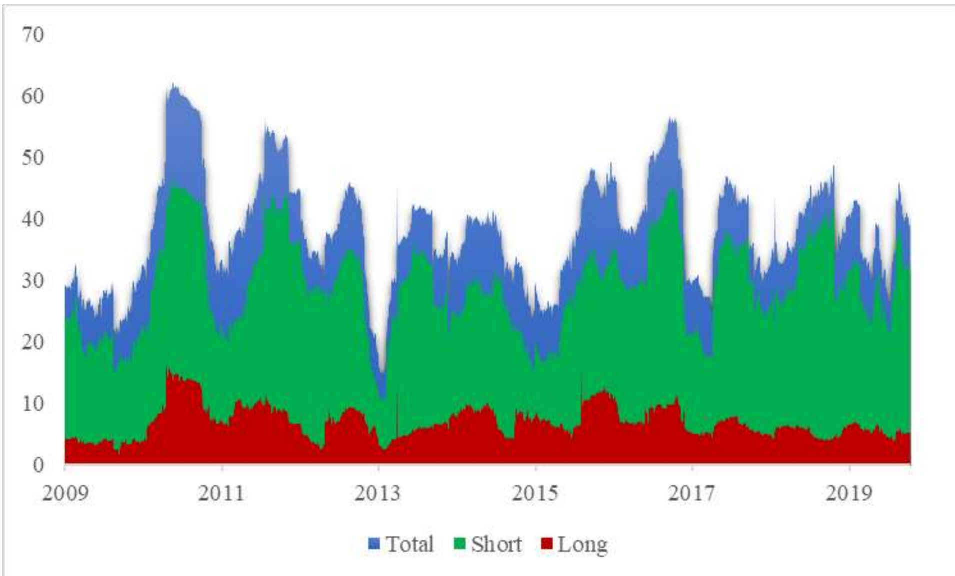






Note: Rolling window for the pairwise wavelet correlation coefficients for the financial market volatilities under study. The colour bars represent the wavelet correlations, where the red and blue colours correspond to the highest and lowest wavelet correlation values respectively. The correlation coefficients for the four wavelet scales, that is, from D1 to D4, imply time horizons associated with changes of 1 to 8 days and intraweek to monthly periods. The wavelet coefficients are within of the 95% confidence interval for each wavelet scale.

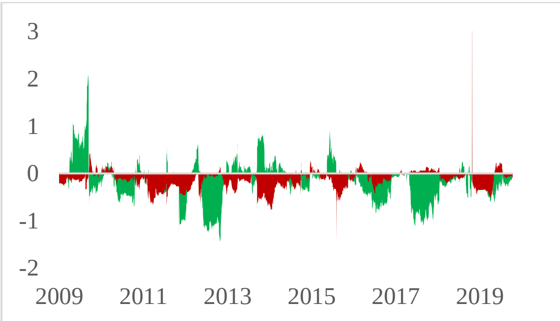
Figure 3. Time-varying total, short-, and long-term connectedness of stock markets.



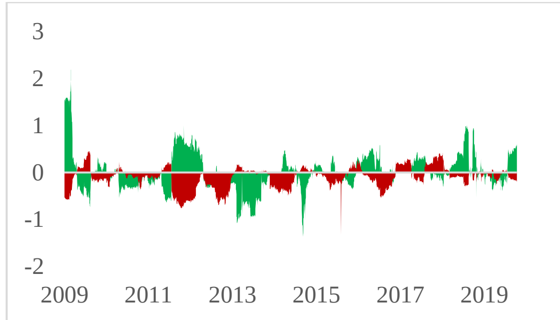
Notes: FEVD is based on 5-variate VAR with two lags and a 120-day rolling window with a predictive horizon of 100 days. The sample period is from 01.08.2008 to 31.10.2019; short, and long-term connectedness of implied volatility indexes, respectively.

Figure 4. Dynamic net pairwise connectedness based on the time-frequency method of Barunik and Krehlik (2018).

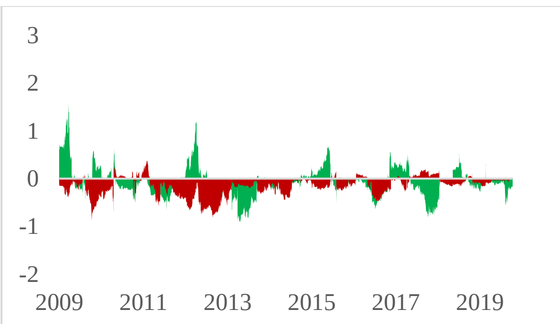
a. VIX-OVX



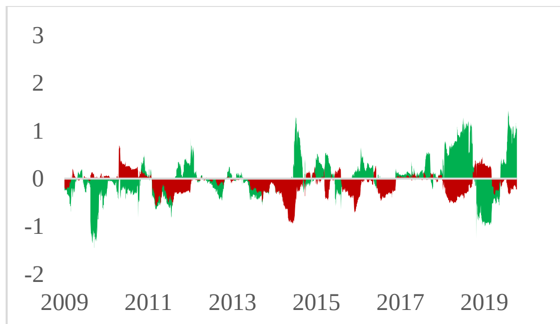
b. VIX-GVZ



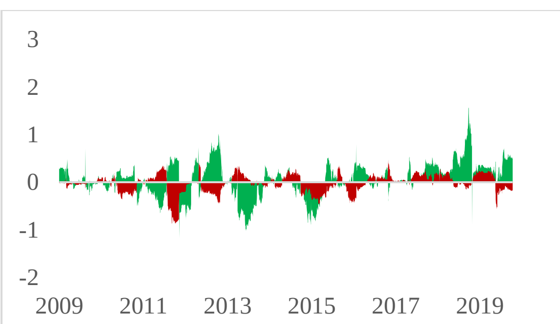
c. VIX-EVZ



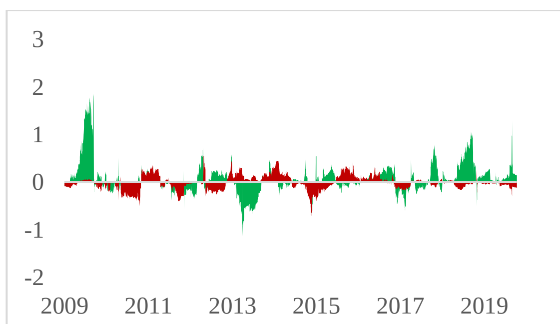
d. VIX-TYNVI



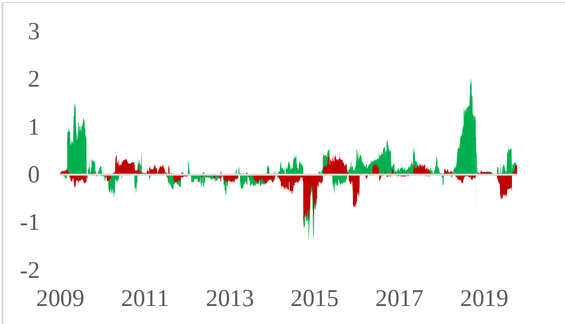
e. OVX-GVZ



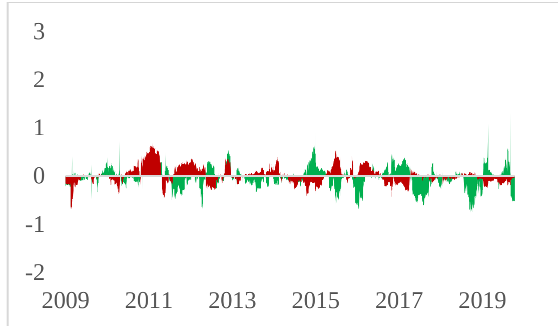
f. OVX-EVZ



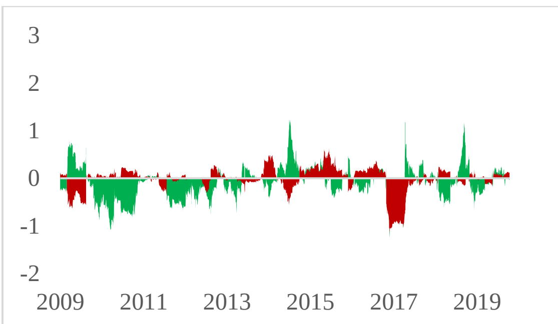
g. OVX-TYNVI



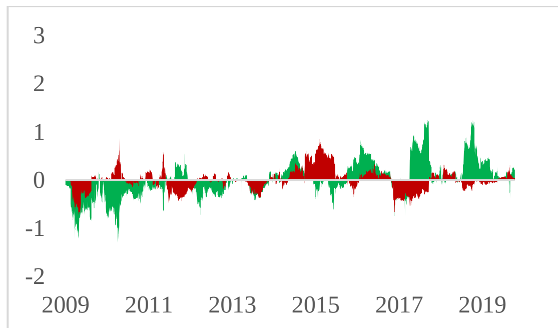
h. GVZ-EVZ



i. GVZ-TYNVI



j. EVZ-TYNVI



Note: This figure displays the time-frequency dynamics of the net pairwise connectedness across the five implied volatility indexes under study estimated using the method of Barunik and Krehlik (2018). The green area indicates the connectedness at the higher frequency band (up to five days). In turn, the red area reflects the connectedness at the lower frequency band (from six to one hundred and twenty days).

Table 1: Descriptive statistics and correlation between financial market volatilities

Panel A: Descriptive statistics

	Mean	Std. Dev.	Skewness	Kurtosis	J-B	ADF
VIX	19.2712	9.5495	2.4915	10.9453	10756.4400***	-25.6945***
OVX	36.2304	13.7882	1.4592	5.9169	2082.0910***	-36.0220***
GVZ	18.9686	7.7386	2.0812	8.9172	6400.5650***	-46.8793***
EVZ	10.5901	3.9231	1.3807	5.6909	1817.9790***	-36.7414***
TYNVI	6.0405	2.0958	1.5078	5.2980	1757.9250***	-27.1968***

Panel B: Correlations

	VIX	OVX	GVZ	EVZ	TYNVI
VIX	1				
OVX	0.3653***	1			
GVZ	0.3901***	0.2656***	1		
EVZ	0.3007***	0.1655***	0.3304***	1	
TYNVI	0.3392***	0.1621***	0.2133***	0.2309***	1

Note: Panel A of this table presents the descriptive statistics and unit root tests of the daily series over the period from 01.08.2008 to 31.10.2019. ADF is the statistic of the ADF (Augmented Dickey-Fuller) unit root test. *** indicates statistical significance at the 1% level.

Panel B of this table reports the unconditional correlation coefficients between all possible pairs of the daily series over the whole sample period from 01.08.2008 to 31.10.2019.
As usual, *** indicates statistical significance at the 1% level.

Table 2: Full-sample connectedness

Panel A: Total

	VIX	OVX	GVZ	EVZ	TYNVI	FROM	
VIX	65.1155	9.5147	11.0651	6.5920	7.7128	6.9769	
OVX	11.3050	77.5233	5.7329	2.8467	2.5922	4.4953	
GVZ	10.9957	5.3704	71.5312	8.3106	3.7921	5.6938	
EVZ	7.6871	2.8758	8.7318	76.7322	3.9731	4.6536	
TYNVI	9.5420	2.4304	4.4642	4.2895	79.2740	4.1452	
TO	7.9059	4.0382	5.9988	4.4078	3.6140		**25.9648%**
NET	0.9290	-0.4571	0.3050	-0.2458	-0.5312		

Panel B: Short-term

	VIX	OVX	GVZ	EVZ	TYNVI	FROM	
VIX	56.5578	8.0455	10.1003	5.8786	6.4491	6.0947	
OVX	8.9037	67.1546	4.8881	2.4587	1.8510	3.6203	
GVZ	8.9356	4.4315	62.6044	7.1393	2.8979	4.6809	
EVZ	5.9690	2.2114	7.1347	66.2069	3.2202	3.7071	
TYNVI	7.6165	1.8634	3.7067	3.7137	66.6859	3.3801	
TO	6.2850	3.3104	5.1660	3.8381	2.8836		**21.4830%**
NET	0.1903	-0.3099	0.4851	0.1310	-0.4964		

Panel C: Long-term

	VIX	OVX	GVZ	EVZ	TYNVI	FROM	
VIX	8.5577	1.4692	0.9648	0.7134	1.2636	0.8822	
OVX	2.4013	10.3687	0.8448	0.3881	0.7412	0.8751	
GVZ	2.0600	0.9389	8.9268	1.1713	0.8942	1.0129	
EVZ	1.7181	0.6644	1.5971	10.5253	0.7530	0.9465	
TYNVI	1.9255	0.5669	0.7575	0.5757	12.5881	0.7651	
TO	1.6210	0.7279	0.8328	0.5697	0.7304		**4.4818%**
NET	0.7388	-0.1472	-0.1801	-0.3768	-0.0347		

Note: This table reports the static total and frequency connectedness among the financial market volatilities from 01.08.2008 to 31.10.2019. FEVD is based on 5-variate VAR with two lags and hundred days predictive horizons. 'FROM' denotes total directional spillovers from all others i.e., off-diagonal row sums whereas 'TO' denotes total directional spillovers to all others i.e., off-diagonal column sums. 'Net' spillovers are the difference between the contribution TO others and the contribution FROM others.

Table 3
Hedge ratio summary statistics and hedging effectiveness (HE)

	VIX				**GVZ**			
	Mean	**Min**	**Max**	**HE**	**Mean**	**Min**	**Max**	**HE**
OVX	0.9701	0.2194	2.5570	0.1231	0.2591	-0.4367	0.8816	-0.0042
EVZ	0.0410	-0.1754	0.3795	0.0008	0.2274	-0.0625	0.4285	0.2149
TYNVI	-0.2017	-0.4434	0.0017	0.1620	0.1093	0.0140	0.2229	0.1239

Notes: The forecasts are calculated from the fixed width rolling analysis which produces 1000 one step forecasts. The models are refit every 10 observations. ADCC are estimated using a multivariate t (MVT) distribution. All specifications include a constant and an AR (1) term in the mean equation.