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Article

Nonlinear Dependence and Spillovers between Currency Markets and Global Financial Market Variables

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Abstract: The widespread integration and growing dependence among currency, stock and commodity markets make these markets often very vulnerable to shocks and at risk of collapse at the same time. As a result, these trends threaten the sustainability of the entire financial system. In this study, we explore the spillovers and nonlinear dependences between the seven major foreign exchange rates, crude oil and gold prices, a global stock price index, and oil and stock implied volatility indices as proxy variables for global risk factors by employing directional spillover network approach. We also use multi-scale decomposition method and nonlinear causality test between these variables to capture multilevel relationships at short and long horizons. Major findings are summarized as follows. First, from the multi-scale decomposition analysis, we identify that Granger causality test results and the direction and strength of return spillovers change with the level of decomposition. Second, the results of nonlinear causality tests show variation in both the significance and direction of Granger causality relationships between the decomposed currency and other series at different timescales, especially for the decomposed oil, gold, and OVX series. Third, the measured directional spillover indices identify the EUR as the largest contributor of connectedness to the other series. The central role of the EUR is a net transmitter of connectedness to gold, oil, the GBP, JPY, and CHF.

Keywords: currency market; commodity market; stock market; risk factors; nonlinear dependence; spillover network

JEL Classifications: C58; D85; F36; G11; G15

1. Introduction

With globalization of the world economy, expansion in capital transactions, and increased financialization of commodity markets, the linkage between stock, foreign exchange, and commodity markets has been strengthened. As a result, global investors have come to consider the returns and risks of these markets together when composing their portfolios. Similarly, policy makers trying to stabilize these financial markets must consider their linkages when designing and implementing policy. Thus, for global investors, financial hedgers, portfolio managers, and policy makers, a clear understanding of return and volatility spillovers and the causality between these financial markets is essential.

Although there is a wide body of research related to the above end-users' needs, most preceding studies target and include only some of these financial markets. For this reason, prior studies only partially describe causal interrelationships and information transmission between these markets, but not the overall picture. Specifically, in studies analysing spillover effects between these financial markets, research where the foreign exchange market is a focus in the analysis is limited. Most studies that have analysed spillover effects of foreign exchange markets have examined the co-movement amongst major foreign exchange markets or information transmission between the foreign exchange and stock markets. Thus, there are few studies that can be used by foreign exchange market investors and policy makers to understand interdependence between the foreign exchange and other financial markets.

This study aims to identify the spillovers and nonlinear dependence between currency, commodity and stock markets, and global risk factors. The latter factors relate to stock and oil market price shocks. More concretely, we investigate the spillover effects and nonlinear causal dependence between seven major currency markets, commodity market (oil and gold), the global stock market, and proxy variables for global risk factors in the form of volatility indices (OVX and VIX). For this purpose, we employ three main methodologies: multi-scale decomposition analysis, nonlinear Granger causality testing, and a directional spillover network approach. This three-stage approach allows identification of the series that make major contributions to spillovers, interdependence properties (linear or non-linear Granger causality), and spillover network characteristics at different time horizons.

The contributions of this study are four-fold. First, we focus on the role of currency markets to uncover return relationships amongst the various financial markets. Moreover, we explore the role of global risk factors in these relationships. Second, we identify these relationships by applying both spillover network and directional spillover index approaches, using the spillover network graph to understand the 'big' picture. Third, most prior studies analyse relationships between variables only in the time domain, whereas we employ multi-scale decomposition analysis to reveal these relationships at short, medium, and long horizons (i.e., time and frequency domains). This method allows us a more thorough understanding of the relationships. Fourth, most prior studies assume linear relationships between variables, whereas we extend the analysis to nonlinear causality between variables to better capture relationships.

Our main findings are summarized as follows. First, from the multi-scale decomposition analysis, we find that the Granger causality results and the direction and strength of return spillovers changes with decomposition level. Second, the results of nonlinear Granger causality tests identify significant variations in both the significance and direction of Granger causality relationships between the decomposed currency and other series at different timescales, especially for the decomposed oil, gold, and OVX series. Third, from the directional spillover indices, the EUR is determined as the largest contributor of connectedness to other series, followed by the CHF. Spillover network figures of the original series highlight the primary role played by the stock market as a net transmitter of return connectedness, and the strong impact it has on the AUD, CAD, and GBP currencies. The central role that the EUR plays within the network is also identified, with it being a net transmitter of connectedness to gold, oil, the GBP, JPY, and CHF. Finally, the EUR shows its highest magnitude of net transmission to stock prices for long horizons and to the gold price and CHF for short horizons.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the sample data. Section 4 explains the methodology employed in this study. Section 5 summarizes and explains the empirical results. Section 6 provides conclusions.

2. Review of Related Literature

Globalization of markets and increases in international trade and capital flows have complicated the relationships between currency exchange rates and thus increased the importance of examining these relationships as a research topic. Most studies on this topic consider the return and volatility spillover relationships between major currencies' exchange rates but have failed to reach consensus on their characteristics. Bubák et al. (2011) discover intra-regional volatility spillovers among the Central European (CE) currency markets and no significant spillovers from the EUR/USD to the CE currency markets. Antonakakis (2012) identifies significant return and volatility connectedness between major foreign exchange rates, which are lower since the introduction of the euro. Sehgal et al. (2015) reveal the existence of return and volatility spillovers in exchange markets and that futures markets have important influence on these spillovers. Sehgal et al. (2017) investigate the currency market interdependency among South Asian countries and find that there is not much comovement in the currency market of this region. Salisu et al. (2018) provide statistical evidence to support return and volatility connectedness between major currencies. Kočenda and Moravcová (2019) identify that volatility transmission among EU currencies increases substantially during periods of distress. Huynh et al. (2020) provide evidence of asymmetric spillovers and connectedness amongst nine U.S. dollar exchange rates, and that volatility spillovers are stronger than the return linkages.

Many early currency market studies explore the linkage between currency exchange and stock markets in major economies. Amongst others, Aggarwal (1981) finds that appreciation of the U.S. dollar is positively correlated to U.S. stock returns, while Soenen and Hennigar (1988) identify a negative dependence between the value of the U.S. dollar and sector market returns. However, Chow et al. (1997) identify a lack of relationship between the U.S. dollar value and stock returns. Yang and Doong (2004) identify the asymmetric volatility linkage between currency exchange rates and stock prices of the G-7 countries.

Some studies devoted to examine the linkage between currency exchange and stock markets in Asian countries. Pan et al. (2007) explore the connectedness between the two market prices for seven East Asian countries. They identify evidence of a causality from exchange rates to stock prices for most countries during the Asian crisis. Lin (2012) finds the dependence from stock price shocks to the exchange rate, which is due to the capital account. Moore and Wang (2014) show that the trade balance

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is a major factor of the linkage in the emerging Asian markets. Jebran and Iqbal (2016) discover bidirectional asymmetric volatility spillovers between the two markets.

More recently, this strand of literature has extended to uncover the relationships between currency exchange rates and the prices of other diversifying assets such as precious metals and commodities. Amongst others, Bhar and Hammoudeh (2011) identify a positive dependence between silver and the exchange rate. Dimpfl and Peter (2018) reveal that oil and stock price volatilities are most influenced by past volatility of gold and currency markets. Antonakakis et al. (2020) investigate dynamic conditional correlations among fourteen implied volatility indices of some assets . Tian et al. (2021) determine that oil price shocks have positive influence on the volatility of the USD/RMB exchange rate and Chinese stock prices.

Studies on the connectedness between the oil and stock markets are also related to our research. Although many studies have analysed price and volatility transmission between these markets, no consensus has yet been reached. The empirical evidence in the literature on this relationship can be classified into four main strands as proposed by Zhu et al. (2011). The papers in the first strand reveal the existence of a significantly negative dependence between the two market returns. This strand of literature is in line with Jones and Kaul (1996), Sadorsky (1999), and Ciner (2001). Amongst others, Hammoudeh and Li (2005) find a negative bidirectional linkage between the two market indices. Basher and Sadorsky (2006), Chiou and Lee (2009), and Chen (2010), respectively, find strong evidence of the influence of oil price risk on stock market returns. The second strand in this categorization provides contradictory evidence in the form of positive interdependence between the two market returns. For example, El-Sharif et al. (2005) examine the linkage between the UK oil and gas sector equity prices. They find evidence that they are linked always positively. Narayan and Narayan (2010), Arouri and Rault (2012), and Luo and Qin (2017) also identify positive interlinkage between oil prices and stock prices of the Vietnamese, Gulf Cooperation Council (GCC), and Chinese markets, respectively. Studies in the third strand display that oil price shocks have a significant influence on stock market returns, but whether the influence is positive or negative is related to various determinants (Cong et al., 2008; Park and Ratti, 2008; Kilian and Park, 2009). For example, Kilian and Park (2009) show that the reaction of U.S. stock returns to an oil price shock can be positive or negative depending on the source of the oil shock. The final strand of studies demonstrates no significant linkage between the two markets (Chen et al., 1986; Wei, 2003; Apergis and Miller, 2009; Miller and Ratti, 2009; Al Janabi et al., 2010). For example, Apergis and Miller (2009) identify that stock returns of developed countries do not react to oil market shocks. Al Janabi et al. (2010) discover evidence no relationship between the oil and GCC stock markets.

Recently, some research explored the linkage between oil market uncertainty and stock returns (Luo and Qin, 2017; Bašta and Molnár, 2018; Dutta, 2018; Xiao et al., 2019; Alqahtani and Chevallier, 2020; Mensi et al., 2021). Amongst others, Dutta (2018) reveals that there exists a long-run dependence between the implied volatility indexes of oil and the U.S. energy stock market. Mensi et al. (2021) reveal that OVX index impacts the

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predictability of stock prices in top oil producing and oil consuming countries.

Although the currency market is not included, there are studies that explore the connectedness between the oil price (and/or its volatility) and precious metal prices. For example, Ji and Fan (2012) reveal that the oil market volatility has spillover effects on non-energy commodity markets. Bouri et al. (2017) find evidence to support the presence of cointegration relationships and nonlinear causality amongst the oil, gold, and Indian stock markets. Alqahtani (2019) finds that global gold volatility can transmit positive shocks to the UAE stock market and that the OVX and VIX can influence on the GCC stock markets. Dutta et al. (2019) identify the presence of cointegration between oil and precious metal prices and nonlinear causality between oil and gold markets. Kang et al. (2021) discover that the VIX has the strongest influence on the U.S. sector equity ETFs. Löwen et al. (2021) find Granger causality between VIX, GVZ, and OVX indices during the COVID-19 pandemic.

A review of the above studies raises the following crucially important questions: Does a stable relationship between currency and other markets exist? If so, what are the correct magnitude and sign of this linkage? If present, is the relationship constant or time-varying? In this study, we investigate the linkage between currency and other markets in order to address these questions.

3. Sample Data

We use daily frequency data on the foreign exchange (FX) rates of seven major currencies: the euro (EUR), Chinese Yuan (CNY), Japanese Yen (JPY), British Pound (GBP), Swiss Franc (CHF), Canadian Dollar (CAD), and Australian Dollar (AUD). We also consider a representative global stock index (STOCK); two important commodity prices, the WTI crude oil spot price (OIL) and gold futures price (GOLD); and two oil and stock risk variables, the CBOE Crude Oil Volatility Index (OVX) and CBOE Volatility Index (VIX). We use the MSCI (Morgan Stanley Capital International) ACWI (All Country World Index) as a global stock index, which tracks about 3,000 stocks in 23 developed countries and 26 emerging markets (for more details, see https://www.msci.com). All the data that support the findings of this study are downloaded from Thomson Reuters Eikon (these data are available at https://eikon.thomsonreuters.com with the permission of Thomson Reuters Eikon).

The data spans from 10 May 2007 to 31 January 2020, providing a sample with 3,205 observations of daily data. Daily return series for currency exchange rates, commodity prices, and the stock index, are calculated by taking logarithmic differences. Changes in the OVX and VIX indices are derived as daily differences.

Table 1 displays descriptive statistics on each of the return/change series. GOLD exhibits the highest average daily returns (0.025), while OIL exhibits the highest level of daily volatility as measured by standard deviations (2.398). Overall, the commodity, stock and volatility index series display much higher volatility than currency series. All series display leptokurtosis, with this being highest for currency exchange rates and the implied volatility indices, as well as all series displaying varying levels of skewness. Normality hypothesis of returns/changes is rejected for all series, with the Jarque-Bera test statistic for each being significant at the 1% level.

Table 1. Descriptive statistics of returns/changes.

Variable	μ	Median	Max.	Min.	σ	K	SK	J-B
EUR	0.006	0.000	2.473	-3.483	0.603	5.209	-0.092	656.5***
GBP	0.016	0.013	8.440	-2.996	0.607	16.746	1.054	25825.1***
AUD	0.006	-0.023	7.311	-8.270	0.851	13.830	0.340	15724.3***
CHF	-0.007	0.008	9.089	-19.383	0.733	163.843	-5.303	3469795.0***
JPY	-0.004	-0.009	5.504	-3.782	0.643	8.009	-0.017	3351.1***
CAD	0.006	0.007	3.254	-3.998	0.612	5.815	0.105	1064.3***
CNY	-0.003	0.000	1.833	-1.195	0.164	16.773	0.640	25552.5***
OIL	-0.006	0.057	16.414	-12.827	2.398	7.787	0.138	3070.8***
GOLD	0.025	0.000	8.625	-9.821	1.125	9.378	-0.249	5464.9***
STOCK	0.007	0.053	8.903	-7.371	1.035	12.417	-0.496	11974.4***
OVX	0.005	-0.100	23.930	-24.600	2.156	25.481	0.566	67661.8***
VIX	0.001	-0.090	20.010	-17.360	1.889	21.471	0.965	46059.7***

Notes: The abbreviations μ, σ, K, and SK stand for the mean, standard deviation, kurtosis, and skewness, respectively. J-B stands for the Jarque-Bera test statistic. The symbol *** indicates significance at the 1% level.

4. Methodology

To ensure a thorough analysis of mechanisms linking the currency (EUR, JPY, AUD, CAD, CNY, GBP, and CHF) exchange rates and related global variables, i.e., commodity (OIL and GOLD) and stock (STOCK) prices, and global risk factors measured using implied volatility indices (OVX and VIX), the framework in this paper combines three main methodologies: a multi-scale analysis, a nonlinear Granger causality test, and a spillover network approach. The multi-scale analysis utilizes an Ensemble Empirical Mode Decomposition (EEMD) approach. The EEMD methodology is employed to decompose the original time series data of currency, commodity, and stock returns, and implied volatility changes, into sets of modes matched on different timescales (short, medium, and long horizons), which relate to different features in the related markets. Both linear and nonlinear Granger causality tests are employed to both the original data and to decomposed data matched on timescale (or frequency band) to determine causal relationships between the currency exchange rate and related global commodity and stock prices and implied volatility indices. The Diebold-Yilmaz (DY) spillover network approach is then used to analyse information spillovers and find the direction and magnitude of spillover effects between the variables being studied. This three-stage approach allows identification of the series that make major contributions to spillovers, linkage properties (linear or nonlinear Granger causality), and spillover network characteristics on different timescales.

4.1. Decomposition of Currency and Commodity Returns

From the perspective of multi-scale methodology, the EEMD analysis affords a method to avoid the underlying time-frequency features inherent in the original signal. The EEMD analysis can decompose an original time series into different timescales. This can figure out the hidden characteristics of these returns/changes fluctuation at different timescales. In particular, the economic meaning of different fluctuation modes can be analysed using the investigation of decomposed components at different timescales (Zhang et al., 2008).

The EEMD approach, suggested by Huang et al. (1998) and enhanced by Wu and Huang (2009), is then applied to decompose the sample return/change series. In this method, returns/changes series $x(t)$ can be written by the intrinsic mode functions (IMF) and residual term as follows,

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{1}$$

where $c_i(t)$ means the i^{th} IMF component; n denotes the number of the decomposed IMF components; and $r(t)$ represents the residual term. In this way, different timescale series are obtained for the considered return/change series.

4.2. Nonlinear Linkage Analysis Model

In this study, we employ linear and nonlinear Granger causality tests to investigate possible causal relationships between the currency and each of the commodity, stock, and implied volatility index returns/changes. The nonlinear Granger causality test of Diks and Panchenko (2006) introduces a nonparametric approach to effectively alleviate the over-rejection problem of the Hiemstra and Jones (1994) approach.

Given two strictly stationary bivariate time series $\{X_t, Y_t\}$, $\{X_t\}$ does Granger-cause $\{Y_t\}$ if predictions of the value of $\{Y_t\}$ based on the past values of $\{X_t, Y_t\}$ are better than predictions of $\{Y_t\}$ based only on the past values of $\{Y_t\}$. Let $F_{X,t}$ and $F_{Y,t}$ represent the information sets included in the past values of $\{X_t\}$ and $\{Y_t\}$, and symbol ´$\sim$´ denotes equivalence in distribution. Then, $\{X_t\}$ does not Granger-cause $\{Y_t\}$ if, for some $k \geq 1$,

$$(Y_{t+1}, \cdots, Y_{t+k}) | (F_{X,t}, F_{Y,t}) \sim (Y_{t+1}, \cdots, Y_{t+k}) | F_{Y,t} \tag{2}$$

Following Diks and Panchenko (2006), the null hypothesis in the nonlinear causality test is written as follow,

$$q = E\left[f_{X,Y,Z}(X,Y,Z) f_Y(Y) - f_{X,Y}(X,Y) f_{Y,Z}(Y,Z)\right] = 0 \tag{3}$$

where $f(\cdot)$ denotes probability density function.

The test statistics is suggested as follow,

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_{i}^{n} \left(\hat{f}_{X,Y,Z}(X_i, Y_i, Z_i) \hat{f}_Y(Y_i) - \hat{f}_{X,Y}(X_i, Y_i) \hat{f}_{Y,Z}(Y_i, Z_i)\right) \tag{4}$$

For a sequence of bandwidths $\varepsilon_n = Cn^{-\beta} \left(C > 0, \frac{1}{4} < \beta < \frac{1}{3}\right)$, Diks and Panchenko (2006) proved that $T_n(\varepsilon_n)$ satisfies the following,

$$\sqrt{n} \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{5}$$

weher the symbol $' \xrightarrow{D} '$ means convergence in distribution, and S_n is an estimator of the asymptotic variance of $T_n(\cdot)$.

4.3. DY Spillover Network Approach

The DY spillover network approach has been widely applied to analyze directional spillover effects among financial markets or energy markets, allowing identification of the magnitude of directional spillover effects. The level of influence is measured using the generalized variance decomposition (Diebold and Yilmaz, 2009, 2012, 2014). Therefore, θ_{ij}^{H} can be used to represent the level to which the variable j^{th} contributes to the H-period forecast variation in i^{th} variable. Thus, the sum of the impact of other variables on variation in i^{th} variable can be written as $From_i = \sum_{j=1}^{k} \theta_{ij}^{H}$, for $j \neq i$, whereas the total influence of i^{th} variable to variation in the other variables can be represented as $To_i = \sum_{j=1}^{k} \theta_{ji}^{H}$ for $j \neq i$. Based on contributions $From_i$ and To_i, the total spillover index can be expressed as $Total = \frac{\sum_{i=1}^{k} From_i}{k} = \frac{\sum_{i=1}^{k} To_i}{k}$

The net total directional spillover measure (NDC) for i^{th} variable can then be measured as follow,

$$NDC_i = \sum_{j=i}^{k} \theta_{ji}^{H} - \sum_{j=i}^{k} \theta_{ij}^{H}, \quad \text{for} \quad i \neq j \tag{6}$$

Thus, the net directional pairwise connectedness (Net) from j^{th} variable to i^{th} variable can be calculated as $Net_{ij} = \theta_{ij}^{H} - \theta_{ji}^{H}$.

5. Empirical Results

Figure 1 identifies the set of independent IMF associated with the daily returns for the EUR, illustrating the approach to timescale breakdown undertaken for each of the return/change series. IMF1 and IMF2 are associated with higher frequency, short-term timescale components. IMF3 and IMF4 are associated with medium-term timescale components, and IMF5 and IMF6 with lower frequency, longer-term timescale components. Finally, the residual (Res) identifies the underlying (moving) trend, or long-term deterministic component (Huang et al., 1998), in the growth rate of the EUR exchange rate.

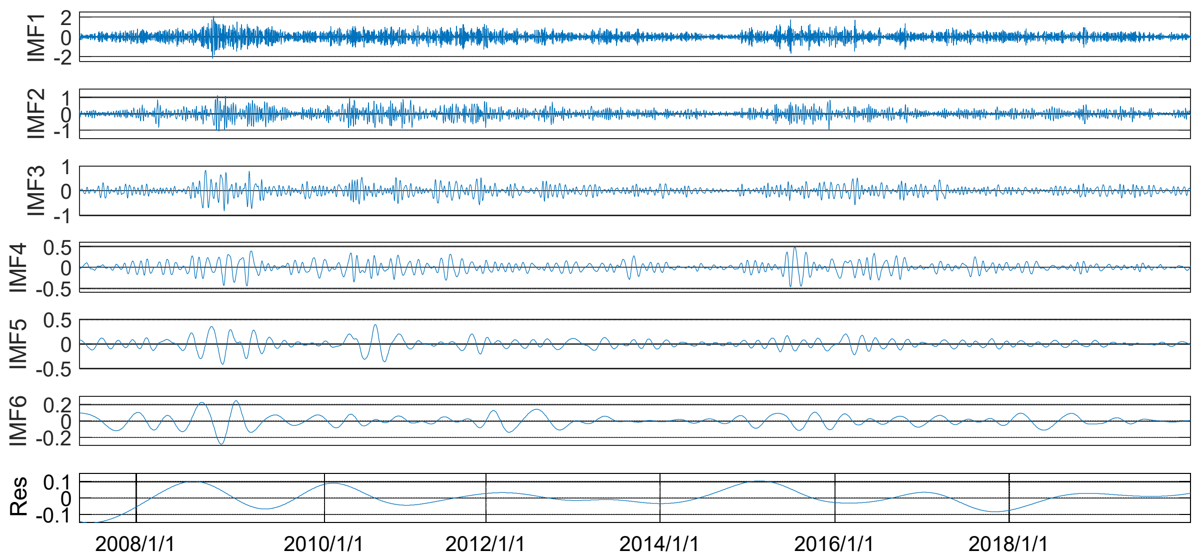

Figure 1. Decomposition results of the daily returns of the EUR.

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The decomposition shown in Figure 1 allows identification of the dominance of short-term modes in generating variation in the observed data on EUR returns, with IMF1 having a range within -2 to 2, and that of IMF2 a range of just over -1 to 1. The medium-term and longer-term modes, and the residual, make a relatively smaller contribution to variability in the EUR return series. For example, the residual has a relatively small range, being within the range of -0.1 to 0.1, and thus makes a significantly smaller contribution to overall variability.

The conclusion that short-term modes dominate variation in the observed data on returns/changes is supported for each series by the data presented in Table 2. Variances in IMF1 for each return/change series account for between 35.13 and 41.71 percent of the summed variances of the IMF and the residual, whereas the residual accounts for only 2.89 to 8.32 percent of this total variability. In the case of crude oil (OIL), our findings are different from those of Zhang et al. (2008), who suggest that longer-term modes, especially the residual, dominate in determining volatility. However, their result is based on use of monthly data on the price level itself, and ending in the mid-2000s, rather than the more recent daily data on returns/changes used in this study. Our data covers a more recent and, potentially, volatile period, covering such events as the global financial crisis (GFC), European debt crisis (EDC), and the beginnings of the COVID-19 crisis periods. In the case of oil, our findings are consistent with those of Yu et al. (2015) who also use daily data.

Table 2. Proportion of the variance of IMF and Res for the decomposed series.

	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	Res
EUR	38.22%	20.14%	14.28%	9.85%	7.85%	5.43%	4.24%
GBP	37.74%	22.64%	13.67%	8.97%	7.04%	3.61%	6.33%
AUD	39.20%	20.48%	14.03%	10.21%	6.36%	4.52%	5.20%
CHF	36.57%	19.24%	17.45%	10.39%	8.10%	4.51%	3.73%
JPY	37.50%	21.48%	14.31%	9.40%	6.79%	3.97%	6.55%
CAD	41.19%	21.28%	13.24%	9.58%	5.32%	5.09%	4.31%
CNY	36.65%	19.93%	13.87%	9.35%	6.86%	5.02%	8.32%
OIL	38.85%	20.48%	15.30%	8.95%	6.13%	4.19%	6.09%
GOLD	36.60%	20.46%	15.57%	10.79%	6.76%	5.09%	4.73%
STOCK	35.13%	22.92%	15.44%	9.70%	6.07%	4.79%	5.94%
OVX	40.49%	22.43%	14.93%	8.54%	5.39%	4.11%	4.11%
VIX	41.71%	21.98%	14.61%	9.11%	6.15%	3.54%	2.89%

Note: Mode importance is measured using the proportion of the variance of each component that accounts for the total variances of IMF and the residual (Res) series.

Prior to assessing linear and nonlinear causality, the Phillips and Perron (PP) (1988) unit root test is performed to check the stationarity of the return/change series and the decomposed IMF components. Table 3 displays the results of the PP unit root test. The test results determine rejection of the hypothesis in both the original and IMF return/change series. Thus, we conclude that all considered return/change series are stationary.

Table 3. The results of Phillips and Perron (1988) unit test.

	Original	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	Res
EUR	-56.19***	-115.73***	-30.60***	-6.75***	-15.90***	-6.63***	-7.78***	-2.98***
GBP	-23.37***	-121.54***	-23.89***	-6.14***	-15.71***	-6.41***	-7.99***	-3.24***
AUD	-15.04***	-130.71***	-33.58***	-7.11***	-15.71***	-6.44***	-7.94***	-3.62***
CHF	-13.01***	-94.19***	-24.96***	-6.01***	-13.91***	-5.90***	-7.94***	-2.96***
JPY	-12.23***	-108.70***	-30.51***	-7.32***	-15.00***	-5.46***	-7.87***	-3.92***
CAD	-10.83***	-118.85***	-37.93***	-7.05***	-15.49***	-5.95***	-7.64***	-2.96***
CNY	-7.77***	-110.16***	-33.65***	-4.07***	-10.86***	-6.85***	-7.58***	-3.00***
OIL	-14.76***	-135.30***	-33.24***	-6.71***	-13.44***	-5.71***	-7.78***	-3.62***
GOLD	-16.10***	-119.53***	-36.30***	-6.54***	-15.27***	-6.57***	-7.89***	-4.54***
STOCK	-13.36***	-128.80***	-24.70***	-4.76***	-13.59***	-6.78***	-7.95***	-3.19***
OVX	-14.77***	-125.95***	-34.42***	-8.24***	-9.81***	-5.82***	-7.95***	-3.94***
VIX	-13.46***	-101.36***	-45.59***	-8.02***	-6.78**	-5.97***	-8.01***	-2.61***

Note: *** denotes rejection at the 1% significance level.

Tables 4, 5 and 6 present results for both linear and nonlinear Granger causality tests on the original and (multi-scale) decomposed series. In each case we test for causality and reverse causality between each of the currency exchange rate, and, respectively, the commodity, stock, and implied volatility index returns/changes.

Turning first to the results for the original return series in Table 4. Comparison of the results of the linear and nonlinear causality tests is highly informative. The results of the nonlinear causality tests indicate a higher occurrence of reverse causality, with respect to commodity, stock, and implied volatility index returns/changes, for all currency returns except that of China's Yuan (CNY). This likely reflects capture of non-linearities for most of the currencies (EUR, GBP, AUD, CHF, JPY and CAD) (e.g., Serletis et al., 2012) and other assets, both individually and in the dynamic dependence structures between the original currency, and commodity, stock, and implied volatility index return/change series. In the case of the CNY, which displays limited evidence of Granger causality, China's use of exchange rate targets, capital controls, and monetary policy interventions to sterilize foreign currency inflows, suggest that its exchange rate system is essentially a form of currency peg (Tong and Yang, 2021). This means that rather than being partly absorbed through shifts in the exchange rate, it will be reflected in shifts in both monetary and real variables (e.g., inflation and GDP growth).

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Table 4. Linear and nonlinear Granger causality test on original returns

X-variables	OIL		GOLD		STOCK		OVX		VIX	
	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$
Panel A: Linear Granger causality test										
EUR			***	***	***	***	***		***	**
GBP			***	***	***	***	**	*		**
AUD	***	***	***	***	***	***	***	***	***	***
CHF	**		***	**	***	***	*	**	*	
JPY	***	***	***			***				***
CAD	**	***	***	***	***	***	***	***	**	***
CNY	*			***		***		*		
Panel B: Nonlinear Granger causality test										
EUR	***	***	***	***	***	***	***	***	***	***
GBP	***	***		***	***	***	***	***	**	*
AUD	***	***	***	***	***	***	***	***	***	***
CHF	***	***	***	***	***	***	***	***	*	***
JPY	**	**	***	***	***	***	**	**	*	
CAD	***	***	***	***	***	***	***	***	***	***
CNY		*					**			

Notes: Y means the commodity, stock, and implied volatility index returns/changes and X means the currency exchange rate returns. The test is performed in two directions; $X \nLeftarrow Y$ implies that Y does not Granger-cause X; and $Y \nLeftarrow X$ implies that X does not Granger-cause Y. The optimal lag order is determined based on the AIC criterion. *, ** or *** denote rejection of null hypothesis at the 10%, 5% or 1% significance levels, respectively.

Tables 5 and 6 provide similar information to that in Table 4 but identify the distinct characteristics for Granger causality related to each of the different timescales associated with the six IMF modes determined for each return/change series. Table 5 provides this information for the linear Granger causality test, while Table 6 provides this information for the nonlinear test.

Like the results discussed for Table 4, the nonlinear Granger causality tests (Table 6) identify a greater number of causality and reverse-causality relationships between the decomposed currency (X), and commodity, stock, and implied volatility index (Y) return/change series than is the case for the linear Granger causality tests (Table 5). This identifies that, as with the original series, there are significant nonlinearities at each of the different modes, both individually and in the dynamic dependence structures. Again, as for the original returns, the CNY is associated with evidence of limited linear or nonlinear Granger causality relationships between its decomposed series, and the decomposed series for the commodity, stock, and implied volatility index returns/changes. Exceptions relate mainly to the oil (OIL) and oil volatility (OVX) markets, with no evidence for the CNY series Granger-causing changes in the gold (GOLD) series as suggested in Table 4.

Examination of the results presented in Tables 5 and 6 highlight the significant variation in both the significance and direction of causality relationships between the decomposed currency, and commodity, stock, and implied volatility index returns/changes series at different time-scales. This is most apparent for the oil, gold, and OVX decomposed series, with a decline in the number of significant causality and reverse causality relationships being identified at lower time-scales. In the case of oil,

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the number of decomposed currency series evidencing significant linear Granger causality from oil (Y) to currency (X) declines, in general, at lower frequencies. This effect is, however, less clear when considering nonlinear Granger causality, with a higher number of currencies being identified as being impacted by oil at most timescales. A similar, but more obvious, pattern holds for gold. Although declining the set of currencies to which this result applies varies by mode (IMF). For example, in the case of linear Granger causality, significance for the EUR is evident for IMF1, IMF2, IMF4 and IMF6, whereas for the JPY it is evident for IMF1, IMF3, IMF4 and IMF5. In the case of linear causality from currency (X) to oil (Y), the EUR appears to have a more important influence on oil at medium and longer-term timescales, rather than at shorter-term timescales, with significant causality being identified at IMF3, IMF5 and IMF6. Again, a similar result holds for gold. Examination of the nonlinear Granger causality results support these conclusions for oil and gold.

However, in the case of the relationships between the decomposed series of exchange rate and the VIX, specifically, the results in Table 6 suggests a lower prevalence of the VIX decomposed series impacting the currencies' decomposed series at intermediate timescales (IMF3 and IMF4). With respect to the decomposed series for the stock market, both the linear and nonlinear causality results, generally, show high levels of causality and reverse causality between the decomposed currency, and commodity and implied volatility index series across the different timescales, with the CNY being the exception currency. Overall, our results highlight the need to identify and understand the specific timescale that is applied to in the Granger causality test, and whether linear or more complex nonlinear processes underlay these results. These will flow to the relationships likely to be identified in the spillover analysis that follows.

Tables 7 to 13 report the total static return connectedness index matrices across the currency, and commodity, stock, and implied volatility index series for both the original time series and for each of the different timescales. In Table 7, the average value of the total return connectedness index is 32.66%, implying a moderate level of connectedness among the currency, and commodity, stock, and implied volatility index series. With respect to directional spillovers transmitted to other series (To_i), the EUR is determined as the largest average contributor of spillovers to the other series (73.48%), followed by the CHF (51.52%).

The EUR (59.48%) is the largest recipient of return spillovers, with the average contribution from other series ($From_i$), followed by the AUD (56.47%) and CAD (53.85%). In the case of these currencies, especially the AUD, this result reflects a high level of sensitivity to trade and global financial market forces. In terms of net directional spillovers (NDC_i), the stock market is the largest net transmitter of return spillovers, providing a net contribution of 37.52%, followed by the EUR (14.00%). The largest net recipients of return connectedness are the CAD and CNY, respectively, at -11.02 and -9.54 percent.

Tables 8 to 13 indicate that return spillovers between decomposed series are strongest at both the highest and lowest timescales, with IMF1 associated with the highest level of total return spillovers (25.75%) and IMF6 the next highest (24.71%). Total return spillovers decline in level from IMF1 to IMF5, with these being 18.98, 13.95, 9.56, and 5.92 percent, for IMF2 to IMF5, respectively. This contrasts with the general lessening in statistically significant causality at longer timescales observed for several of the decomposed series in Tables 5 and 6.

Considering individual series, the pattern for total return spillovers identified above appears to hold for both return spillovers To_i and $From_i$ other series. Thus, spillovers transmitted and received initially decline in level, then increase at the lowest timescale. Return spillovers "To others" and "From others" are generally highest for IMF1, with those for IMF6 being next highest. The exception is for stock returns, where the lowest levels of spillovers To_i and $From_i$ other series occur at IMF2 and IMF5, while the highest levels of spillovers To_i and $From_i$ other series occur at IMF6.

Table 5. Multi-scale linear Granger causality tests

X-variables	OIL		GOLD		STOCK		OVX		VIX	
	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$
IMF1										
EUR	**		***	***	***	***	***	**	***	*
GBP			***	***	***	***	*			**
AUD	***	***	***	***	***	***	***	***	***	***
CHF	**		***	***	***	**	***			
JPY	**	***	**	***	***	***	**			***
CAD	**	***	***	***	***	***			*	***
CNY		*				**	***			
IMF2										
EUR	***		***	***	***	***				***
GBP	**	*	***	***	***	***	***		***	
AUD	***	***	*	***	***	***	***	***	***	***
CHF		**	***	***	***	***				
JPY		**	***	***	*	***	***	***	**	***
CAD	***			**	***	***	**	***	***	***
CNY	***	**								
IMF3										
EUR		**	***	***	***	***	**	***		***
GBP			***	***	*	***	***			***
AUD	**	***	***	***	***	***		***	***	***
CHF		**	*	*		***	***	***		***
JPY	***	***	***		*	***		***	**	***
CAD	**			*	***	***	***	***		***
CNY		***					*			
IMF4										
EUR	**					***	**	**	***	**
GBP	***	***	***		***	***	***	***		*
AUD		***		***	***	***		***	***	**
CHF	***	***	*		***	***	***	***	***	***
JPY	***	***	***	***				*		***
CAD	*	***	*	***	***	***		***		
CNY	***							*		
IMF5										
EUR		***			***	***		***	**	***
GBP	***	***	**		***	***		***	***	***
AUD	***	***			***	***	*	***	***	***
CHF	***	***			***	***	***	***	***	***
JPY	*	***	***	***	***	**	***	***	**	***

CAD		**			***	***	***	***		
CNY										
IMF6										
EUR	***	***			***	***	***	***		***
GBP		*				***		*		***
AUD	***	***			***	***		**		***
CHF	***	***			***	***	****	***		***
JPY			***		*	*	**	**	***	***
CAD					***	***	***	***		
CNY		***								

Note: See note of Table 4.

Table 6. Multi-scale nonlinear Granger causality tests.

X-variables	OIL		GOLD		STOCK		OVX		VIX	
	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$	$X \nLeftarrow Y$	$Y \nLeftarrow X$
IMF1										
EUR	***	***	***	***	***	***	***	***	***	***
GBP	**	***	***	***	***	***	***	***	**	*
AUD	***	***	***	***	***	***	***	***	***	***
CHF	***	**	***	***	***	***	***	**	*	***
JPY	**		***	***	***	***	***	*	**	
CAD	***	***	***	***	***	***	**	***	***	***
CNY		*					***			
IMF2										
EUR	**		***	***	***	***	**	***	**	***
GBP	***	**	***	**	***	***	**	***	***	***
AUD	**	**	***	***	***	***	**	**	***	***
CHF	***		***	***	***	***	***	*	**	**
JPY	**	**	***	***	***	***	**	**		
CAD	***	***		**	***	***	***	*	***	**
CNY		*					*			
IMF3										
EUR	***	***	***	***	***	***	***	***	**	**
GBP	***	***	***	***	***	***	**	***		
AUD	**	*	***	***	***	***	*			**
CHF	***	**	***	***	***	***	***	***		
JPY			***	***	***	***	**	**		
CAD	***	***	***	***	***	***	***	***	**	
CNY	*	*					**	***		***
IMF4										
EUR	***	***	***	***	***	***	***	***	***	***
GBP	***	**	***	***	***	***	***	***	***	**
AUD	***	***	***	***	***	***	***	***	***	**
CHF	***		***	***	***	***	***	***	**	
JPY	***	***	***	***	***	**	***	***		
CAD	***		***	***	***	***	*	**		
CNY		*						**		
IMF5										
EUR		**	***	***	***	**	*		*	*
GBP	***	***	***	**	***	**	***	*	***	**
AUD	***	***	**	***	***	***	***	**	**	***
CHF	***	**	***	***	***	***	***		***	**
JPY	**	*	***	***	***	***	*			
CAD	***	**	***	***	***	***	***	*	***	**
CNY		*								
IMF6										
EUR	***	***		***	***	***	***	***	***	***
GBP				**	***	**				
AUD			***	***	**	***			**	***
CHF	***	***	*		***	***	***	***	***	***
JPY		*	***	***	***		***	***	***	*
CAD		***	**	***	***	***	***		***	***
CNY	**						**			

Note: See note of Table 4.

Table 7. The connectedness matrix for original returns

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	40.52	12.39	10.09	16.73	3.76	7.57	0.66	0.07	4.17	3.84	0.09	0.11	59.48
GBP	15.18	50.16	9.37	6.72	0.84	7.56	0.99	0.24	2.68	5.82	0.12	0.32	49.84
AUD	10.38	7.86	43.53	4.11	0.20	15.96	0.95	0.24	3.04	13.23	0.25	0.24	56.47
CHF	20.63	6.69	4.98	50.21	7.46	3.63	0.37	0.08	5.09	0.58	0.20	0.07	49.79
JPY	6.74	1.19	0.57	10.83	71.77	0.54	0.44	0.23	4.66	2.78	0.03	0.21	28.23
CAD	8.74	7.24	17.97	3.46	0.09	46.15	0.46	0.24	3.48	11.96	0.09	0.12	53.85
CNY	2.92	2.29	1.99	1.38	1.59	1.05	84.98	0.04	1.82	1.51	0.34	0.09	15.02
OIL	0.22	0.14	0.51	0.19	0.21	0.11	0.21	89.40	0.31	0.96	3.39	4.34	10.60
GOLD	6.85	3.53	4.72	6.93	4.54	5.19	1.06	0.50	65.47	0.60	0.18	0.42	34.53
STOCK	0.67	0.03	0.59	0.60	0.47	0.81	0.15	0.35	0.61	95.23	0.26	0.24	4.77
OVX	0.53	0.21	0.24	0.22	0.09	0.10	0.12	0.70	0.49	0.68	85.48	11.15	14.52
VIX	0.61	0.23	0.20	0.34	0.20	0.30	0.08	0.40	0.34	0.32	11.81	85.16	14.84
To others	73.48	41.80	51.21	51.52	19.45	42.82	5.49	3.10	26.71	42.29	16.77	17.31	**32.66**
Net	**14.00**	**-8.05**	**-5.26**	**1.73**	**-8.78**	**-11.02**	**-9.54**	**-7.51**	**-7.82**	**37.52**	**2.25**	**2.48**	

Notes: The number of lags for VAR models is selected using the AIC and the optimal lag for original returns is 5. The forecast horizon H is set to 10.

Table 8. The connectedness matrix for IMF1

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	48.00	12.75	11.37	12.70	2.14	8.27	0.47	0.13	2.19	1.78	0.11	0.08	52.00
GBP	14.31	58.58	9.80	4.33	0.63	6.77	0.77	0.15	1.82	2.24	0.20	0.40	41.42
AUD	11.03	8.35	53.34	2.65	0.46	16.35	1.00	0.43	1.57	4.44	0.14	0.25	46.66
CHF	18.61	4.75	3.65	60.77	5.76	2.23	0.24	0.16	2.76	0.64	0.28	0.16	39.23
JPY	3.62	0.87	0.45	6.57	80.83	0.81	0.21	0.62	3.81	1.46	0.25	0.48	19.17
CAD	9.47	7.23	20.31	2.16	0.35	54.18	0.48	0.28	1.51	3.78	0.13	0.12	45.82
CNY	1.35	0.82	1.34	0.47	0.54	0.67	92.34	0.19	0.73	0.80	0.53	0.23	7.66
OIL	0.64	0.15	0.87	0.36	0.61	0.12	0.22	91.16	0.35	1.12	1.32	3.08	8.84
GOLD	3.76	1.90	2.95	2.80	3.07	2.52	0.67	0.65	80.10	0.70	0.30	0.59	19.90
STOCK	0.94	0.35	0.65	1.10	0.25	0.17	0.30	0.54	1.05	93.85	0.59	0.24	6.15
OVX	1.00	0.45	0.75	0.19	0.69	0.14	0.61	0.96	0.91	0.76	88.49	5.05	11.51
VIX	0.82	0.19	0.25	0.24	0.21	0.29	0.21	0.68	0.24	0.83	6.61	89.42	10.58
To others	65.54	37.81	52.40	33.57	14.69	38.33	5.17	4.79	16.95	18.55	10.45	10.67	**25.75**
Net	**13.54**	**-3.61**	**5.73**	**-5.66**	**-4.47**	**-7.48**	**-2.49**	**-4.04**	**-2.94**	**12.40**	**-1.07**	**0.10**	

Notes: The optimal lag for IMF1 is 7. See also the note of Table 7.

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Table 9. The connectedness matrix for IMF2.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	65.76	6.20	3.93	12.61	1.58	4.03	0.26	0.09	1.56	3.39	0.36	0.23	34.24
GBP	5.20	76.24	4.30	2.51	0.45	4.48	0.39	0.23	0.38	5.61	0.08	0.13	23.76
AUD	7.73	4.36	60.18	1.40	0.49	10.97	0.62	0.39	0.78	11.11	0.69	1.27	39.82
CHF	13.91	2.49	1.21	74.74	3.30	1.90	0.10	0.51	0.91	0.54	0.31	0.08	25.26
JPY	2.62	0.15	0.46	4.34	87.80	0.83	0.16	0.22	1.09	1.41	0.07	0.84	12.20
CAD	7.18	2.55	8.89	1.80	0.23	64.50	0.44	0.11	1.25	11.95	0.51	0.58	35.50
CNY	2.19	0.75	0.29	0.47	0.89	0.71	92.67	0.32	0.92	0.41	0.32	0.05	7.33
OIL	0.42	0.09	0.87	0.32	1.11	0.31	0.19	93.39	0.07	0.34	1.04	1.86	6.61
GOLD	5.09	0.85	0.45	3.67	3.27	2.44	0.47	0.05	82.32	0.66	0.19	0.54	17.68
STOCK	0.58	1.22	1.08	0.59	0.31	1.30	0.29	0.71	0.49	90.89	0.68	1.85	9.11
OVX	0.40	0.29	0.24	0.13	0.49	0.14	0.17	0.80	0.75	0.25	91.74	4.59	8.26
VIX	0.61	0.30	0.18	0.18	0.51	0.25	0.42	0.85	0.29	0.54	3.91	91.96	8.04
To others	45.93	19.26	21.91	28.00	12.63	27.35	3.51	4.29	8.49	36.23	8.16	12.03	**18.98**
Net	**11.70**	**-4.50**	**-17.91**	**2.74**	**0.44**	**-8.15**	**-3.82**	**-2.33**	**-9.19**	**27.12**	**-0.10**	**4.00**	

Note: The optimal lag for IMF2 is 12. See also the note of Table 7.

Table 10. The connectedness matrix for IMF3.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	71.35	6.19	4.60	10.55	2.16	1.42	0.52	0.10	1.17	1.39	0.23	0.32	28.65
GBP	3.34	81.68	0.61	1.32	1.00	2.29	1.25	0.13	1.60	6.42	0.12	0.23	18.32
AUD	1.07	2.12	79.59	0.53	0.04	4.90	0.07	0.86	0.71	9.89	0.20	0.03	20.41
CHF	7.90	1.78	1.44	82.42	2.57	1.69	0.32	0.39	0.49	0.78	0.15	0.05	17.58
JPY	0.51	0.29	0.26	1.95	91.55	0.38	0.51	0.10	0.31	3.77	0.08	0.30	8.45
CAD	2.01	0.67	7.58	1.06	0.26	75.85	0.31	0.00	0.95	11.22	0.04	0.07	24.15
CNY	0.70	0.31	0.41	0.14	0.67	0.52	94.26	0.64	0.85	0.88	0.44	0.19	5.74
OIL	0.17	0.23	0.39	0.58	0.39	0.18	0.11	92.43	1.06	0.30	2.54	1.60	7.57
GOLD	2.56	0.97	0.22	2.04	2.30	0.92	0.34	0.12	88.86	1.56	0.07	0.04	11.14
STOCK	0.08	0.64	5.11	0.03	0.72	1.01	0.34	0.21	0.32	91.35	0.07	0.12	8.65
OVX	0.59	0.78	0.33	0.58	0.09	0.25	0.60	0.65	0.15	0.30	90.56	5.11	9.44
VIX	0.17	0.53	0.16	0.13	0.22	0.07	0.12	0.77	0.47	0.02	4.59	92.74	7.26
To others	19.11	14.51	21.10	18.91	10.43	13.64	4.49	3.98	8.08	36.51	8.54	8.06	**13.95**
Net	**-9.54**	**-3.81**	**0.69**	**1.34**	**1.98**	**-10.51**	**-1.25**	**-3.59**	**-3.06**	**27.86**	**-0.90**	**0.80**	

Note: The optimal lag for IMF3 is 14. See also the note of Table 7.

Table 11. The connectedness matrix for IMF4.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	83.64	3.49	1.28	3.40	2.14	0.27	0.24	0.42	0.30	3.65	0.67	0.51	16.36
GBP	2.48	86.83	1.26	0.66	0.14	1.20	0.07	0.01	1.79	5.06	0.13	0.37	13.17
AUD	0.96	1.45	74.21	0.14	0.57	4.29	0.03	0.06	0.10	17.84	0.02	0.33	25.79
CHF	4.37	1.82	0.04	88.99	2.13	0.10	0.88	0.12	0.54	0.80	0.12	0.08	11.01
JPY	0.98	0.04	0.18	0.66	96.90	0.00	0.71	0.03	0.29	0.12	0.02	0.06	3.10
CAD	0.09	0.22	5.87	0.04	0.03	87.10	0.03	0.28	0.09	6.15	0.10	0.00	12.90
CNY	0.26	0.71	0.16	0.11	0.13	0.06	97.64	0.22	0.65	0.01	0.00	0.05	2.36
OIL	0.18	0.08	0.55	0.66	0.84	0.14	3.00	89.74	1.24	0.45	1.67	1.45	10.26
GOLD	0.52	0.30	0.26	0.11	0.05	0.48	0.10	2.33	94.71	1.12	0.02	0.01	5.29
STOCK	0.20	0.37	0.40	0.60	0.10	0.71	0.11	0.04	0.91	96.38	0.17	0.01	3.62
OVX	0.89	0.48	0.62	0.02	0.04	0.02	0.19	0.12	0.04	1.30	94.04	2.24	5.96
VIX	0.09	0.02	0.18	0.59	0.30	0.06	0.09	2.49	0.22	0.19	0.66	95.12	4.88
To others	11.02	8.97	10.80	6.99	6.47	7.33	5.45	6.13	6.15	36.68	3.59	5.11	**9.56**
Net	**-5.33**	**-4.20**	**-14.99**	**-4.02**	**3.37**	**-5.57**	**3.09**	**-4.14**	**0.86**	**33.06**	**-2.37**	**0.23**	

Note: The optimal lag for IMF4 is 35. See also the note of Table 7.

Table 12. The connectedness matrix for IMF5.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	94.85	1.76	0.31	1.80	0.11	0.29	0.02	0.04	0.00	0.16	0.12	0.55	5.15
GBP	5.98	89.04	0.55	0.05	0.72	0.46	1.81	0.05	0.00	0.08	1.10	0.17	10.96
AUD	0.31	0.30	85.57	0.05	0.43	3.45	0.22	0.07	0.01	9.40	0.00	0.17	14.43
CHF	3.40	0.09	0.23	92.96	0.17	0.21	0.17	1.18	0.97	0.14	0.01	0.48	7.04
JPY	0.01	0.82	0.09	0.01	96.12	0.05	1.80	0.09	0.29	0.02	0.01	0.68	3.88
CAD	0.90	0.47	1.36	0.00	0.01	95.65	0.18	0.10	0.39	0.84	0.02	0.08	4.35
CNY	0.02	2.02	0.31	0.06	1.90	0.20	94.28	0.55	0.00	0.32	0.11	0.24	5.72
OIL	0.01	0.02	0.10	0.23	0.00	0.36	1.07	96.44	0.11	0.80	0.05	0.81	3.56
GOLD	0.02	0.30	0.02	0.25	0.24	0.30	0.00	0.01	98.41	0.20	0.00	0.26	1.59
STOCK	0.76	0.05	0.73	0.01	1.50	1.26	0.04	0.03	0.04	95.41	0.15	0.01	4.59
OVX	0.27	0.08	0.02	0.04	0.02	0.00	0.02	0.01	0.03	0.50	98.46	0.53	1.54
VIX	0.05	0.04	0.19	0.03	1.46	0.06	0.08	2.25	0.12	0.02	1.54	94.15	5.85
To others	11.74	5.94	3.93	2.53	6.57	6.64	5.42	4.38	1.97	12.47	3.10	3.99	**5.72**
Net	**6.58**	**-5.03**	**-10.50**	**-4.51**	**2.69**	**2.29**	**-0.30**	**0.82**	**0.38**	**7.88**	**1.56**	**-1.86**	

Note: The optimal lag for IMF5 is 45. See also the note of Table 7.

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Table 13. The connectedness matrix for IMF6.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY	OIL	GOLD	STOCK	OVX	VIX	*From others*
EUR	60.30	5.13	5.82	16.02	0.50	2.02	0.15	0.20	0.00	8.79	0.37	0.69	39.70
GBP	7.78	77.35	1.52	1.96	1.17	0.48	3.19	0.01	0.12	5.44	0.17	0.83	22.65
AUD	4.73	1.15	63.66	3.30	0.09	12.76	0.91	2.49	0.27	10.54	0.08	0.02	36.34
CHF	17.83	1.02	3.80	65.30	3.63	0.94	0.49	0.02	1.58	4.21	0.89	0.29	34.70
JPY	1.38	0.87	0.10	3.66	84.18	1.50	0.97	0.08	3.51	0.76	2.95	0.03	15.82
CAD	1.69	0.08	13.66	0.66	2.29	69.09	0.10	0.27	1.14	10.61	0.26	0.15	30.91
CNY	0.12	3.70	0.89	0.46	1.06	0.14	90.83	1.90	0.11	0.21	0.04	0.55	9.17
OIL	0.14	0.03	2.20	0.01	0.02	1.04	2.21	84.20	0.74	1.18	6.79	1.44	15.80
GOLD	0.13	0.04	0.05	1.77	4.45	1.41	0.08	0.74	90.32	0.16	0.83	0.03	9.68
STOCK	10.83	3.20	10.53	3.44	1.02	8.55	0.20	0.97	0.08	60.90	0.24	0.03	39.10
OVX	0.69	0.35	0.18	1.76	4.73	0.06	0.00	6.42	0.67	0.26	75.96	8.90	24.04
VIX	1.45	0.81	0.01	0.91	0.85	0.16	0.76	1.62	0.31	0.28	11.52	81.33	18.67
To others	46.76	16.39	38.76	33.95	19.81	29.06	9.05	14.71	8.53	42.44	24.13	12.97	**24.71**
Net	**7.07**	**-6.27**	**2.42**	**-0.74**	**3.99**	**-1.85**	**-0.11**	**-1.09**	**-1.15**	**3.34**	**0.09**	**-5.70**	

Note: The optimal lag for IMF6 is 8. See also the note of Table 7.

Figure 2 presents the system-wide connectedness network based on the return spillover index data in Table 8. The red (green) colour of a node represents the net transmitter (recipient) of connectedness (i.e., the difference between To_i and $From_i$ other series). The thickness of the lines and colors indicate the magnitude of the pairwise connectedness, while arrows identify the direction of net spillover. Figure 2 shows the main role played by the global stock market as a net transmitter of return connectedness, and the strong impact it has, on average, on the AUD, CAD, GBP, and, to a lesser extent, the EUR and JPY. The central role that the EUR plays within the network, again on average, is also shown in Figure 2, with it being a net transmitter of connectedness to gold, oil, the GBP, JPY, and CHF. The latter also plays a net transmitter role, especially with respect to the JPY. Although identified as net transmitters of connectedness, the magnitude of signals from the OVX and VIX is identified as being small.

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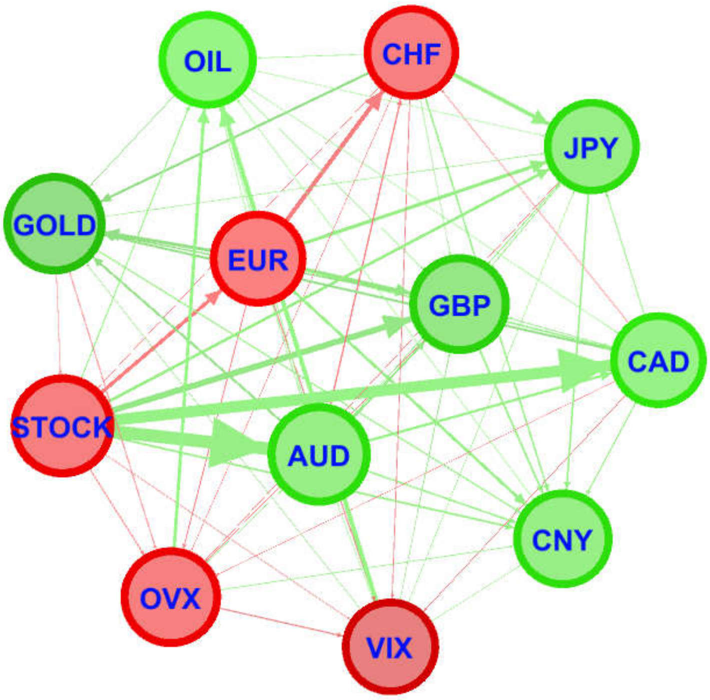

Figure 2. Connectedness spillover network for original returns.

Notes: The red circles denote the information transmitter, and the green circles denote the information receivers. The thickness of the arrows represents the magnitude of spillover index between the currency and the global variables considered.

Examination of Figure 3 allows identification of important differences in net connectedness at the different timescales (modes IMF1 to IMF6) associated with each of the decomposed series. Specifically, the JPY is shown to be an overall weak net transmitter of connectedness for modes IMF2 to IMF6, exceptions being moderate net transmission to the stock market for mode IMF5, and a relatively high magnitude of net transmission to the OVX for mode IMF6. In the case of the EUR, its highest magnitude of net transmission is to the stock price for mode IMF6, to gold price for modes of IMF1 and IMF2, and to CHF for mode IMF1. Additionally, the AUD is shown to provide a low magnitude of net transmission at some timescales (IMF1, IMF3 and IMF6), with its major impact being on the CAD (IMF1, IMF3 and IMF6) and VIX (IMF3 and IMF6). Differences are also apparent with respect to the net connectedness characteristics of the decomposed series of the two implied volatility indexes. Specifically, the VIX is a net transmitter of connectedness for modes IMF1 to IMF4, the high-frequency and medium-frequency modes, while it is a net receiver for modes IMF5 and IMF6. However, the OVX is a net receiver of connectedness for modes IMF1 to IMF4, while it is a net transmitter only for IMF5 and IMF6, the lower-frequency modes. That noted, it is a moderate net transmitter to the VIX for modes IMF1 and IMF5, with stronger effects being observed for mode IMF6. These results highlight the important of the volatility of the oil price for volatility in the stock market. Finally, both gold and the CNY, although net receivers of connectedness on average (Figure 2), are shown to be low net transmitters of connectedness at longer timescales; IMF4 for the CNY, and IMF4 and IMF5 for gold.

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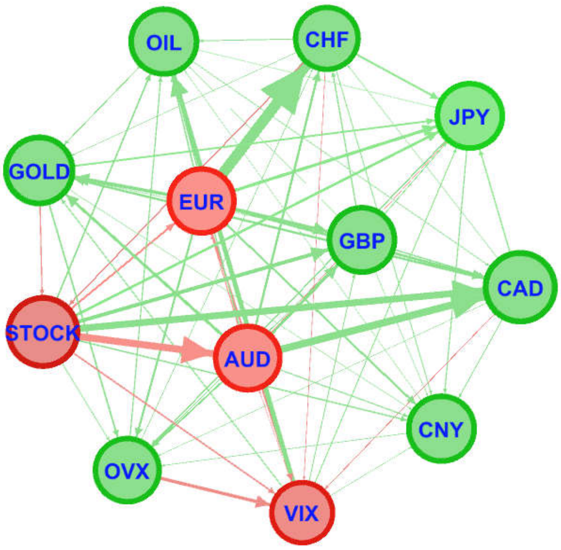

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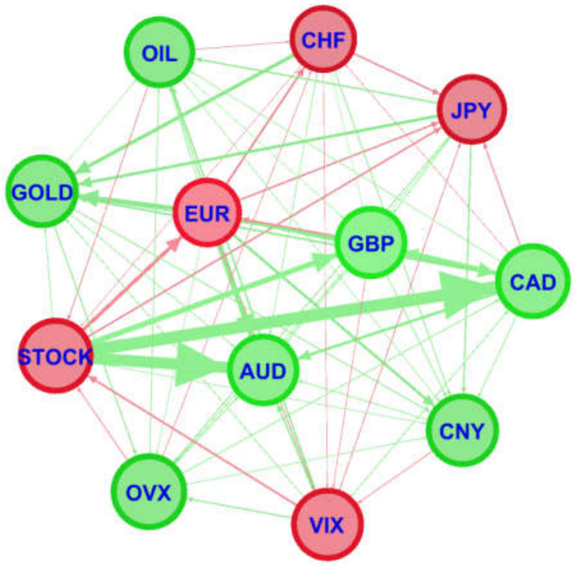

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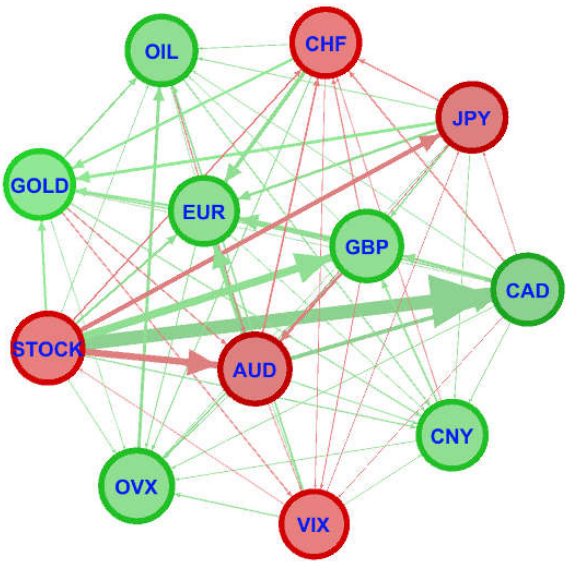
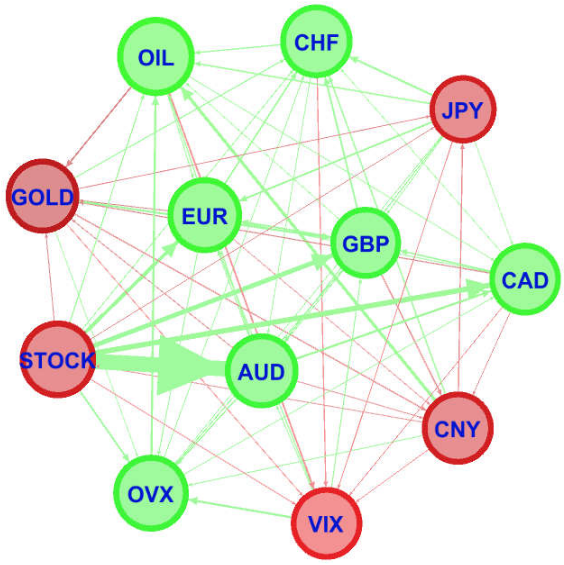


IMF3



IMF4

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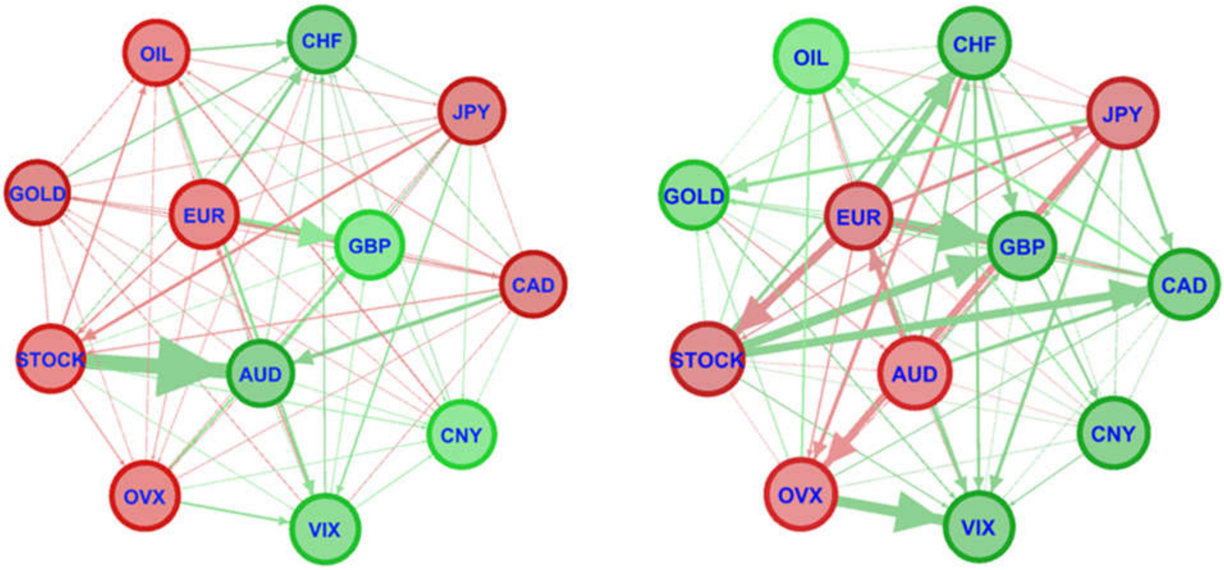

IMF5 **IMF6**

Figure 3. Directional net spillover connectedness network for each IMF.

Note: See the note of Figure 2.

6. Conclusion

The aim of this study is to explore the spillover and nonlinear interdependence between the major currency markets (CHF, JPY, AUD, CNY, CAD, EUR, and GBP), commodity markets (OIL and GOLD), stock market (MSCI ACWI), and global risk factors (OVX and VIX) due to stock and oil market price shocks. For this purpose, we used daily data spanning from 10 May 2007 to 31 January 2020 and employed three main methodologies: multi-scale decomposition analysis, nonlinear Granger causality testing, and a directional spillover network approach.

The main findings are summarised as follows. First, from the multi-scale decomposition analysis, we find that short-term modes (timescales) dominate variation in sample returns/changes for all series considered. We find the Granger causality and the direction and strength of return spillovers change with the level of timescale decomposition. Second, the results of nonlinear Granger causality tests identify a greater number of bi-directional causality relationships between the decomposed currency and other asset return series than for the linear Granger causality tests. We find significant variation in both the significance and direction of Granger causality relationships between the decomposed currency and other series at different timescales, especially for the decomposed oil, gold, and OVX series. Third, from the measured directional spillover indices, the EUR is determined as the largest average contributor of connectedness to other series, followed by the CHF. Spillover network analysis of the original series demonstrates the primary role played by the stock market as a net transmitter of return connectedness, and the strong impact it has on the AUD, CAD, and GBP currencies. The central role that the EUR plays within the network is also identified, with it being a net transmitter of connectedness to gold, oil, the GBP, JPY, and CHF. Although identified as net transmitters of connectedness, the magnitude of signals from the OVX and VIX are found to be small. Finally, the EUR shows its highest magnitude of net transmission to the stock price at long horizons and to gold price and CHF at short horizons.

As this study focuses on the interdependence between key currency exchange rates and stock and commodity market returns, whose prices fluctuate frequently, our empirical results are important for enhancing portfolio performance, managing risk and stabilizing financial markets. Thus, the interdependence between these markets, and their relationship with global risk factors, should be fully understood and closely monitored by relevant stakeholders. These include global investors, portfolio and risk managers, market analysts, and government and policy makers. And more emphasis should be placed on the stability and sustainability of the overall financial system.

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