Resources Policy 74 (2021) 102263

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Multiscale spillovers and connectedness between gold, copper, oil, wheat and currency markets

Ramzi Nekhili[a], Walid Mensi[b,c,*], Xuan Vinh Vo[d]

[a] College of Administrative Sciences, Applied Science University, Bahrain
[b] Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman
[c] Institute of Business Research, University of Economics Ho Chi Minh City, Vietnam
[d] Institute of Business Research and CFVG, University of Economics Ho Chi Minh City, Vietnam

ARTICLE INFO

Keywords:
Commodity futures
Currencies
Uncertainty index
Spillover
Frequency
JEL classification: G14
G15

ABSTRACT

This paper examines the time-frequency return and volatility spillovers between major commodity futures (copper, crude oil, gold, and wheat) and currency markets (British pound, Canadian dollar, Euro, Japanese yen, Swedish krona, and Swiss franc) using the methodologies by Diebold and Yılmaz (2012) and Baruník and Křehlík (2018). The results show that the spillover between markets under investigation is time-varying, asymmetric, and crisis-sensitive. Furthermore, short-term return spillovers dominate the intermediate- and long-term spillovers. In contrast, long-term volatility spillovers constitute the principal proportion of the total volatility spillovers. COVID-19 and GFC intensify more the long-term volatility spillovers than short- and medium-terms. Wheat is the better portfolio diversfier among the four commodities irrespective of the investment horizons. Liquidity shocks show a stronger impact on the return and volatility spillover strengths than the economic policy uncertainty and volatility index. The effect of liquidity shocks on return is a sizable increase in connectedness in the short-term than in both medium- and long-terms. Our findings have significant implications for currency investors and policymakers.

1. Introduction

The global market integration has increased the transmission of shocks from one country to another, leading to contagion effects. The high spillover effects have increased the likelihood of crisis. Therefore, the capital flows across markets, the development of commodity and financial markets, and the economy's financial stability depend on the degree of spillovers among economies. The last twelve years have been marked by four important events, including the global financial crisis (GFC) in 2008–2009, the European sovereign debt crisis (ESDC) in 2010–2012, the oil price crash in mid-2014, and the COVID-19 pandemic crisis, which constitute sources of contagion. During these periods, both commodity and currency assets experience large swings in value. The movements of capital flows across borders contribute to amplify or alleviate the price swings and, as a result, the spillover of returns and volatility. Accurate information on the risk propagation from one market to another and the directional spillovers may result in optimal portfolio construction and hedging strategies.

Understanding the spillover and connectedness among markets (why and how these effects occur) is crucial for policymakers to implement the appropriate policies to stabilize the currency and commodity markets especially during crisis periods. Investors are more concerned about cutting risk exposure during turbulent periods. Therefore, the analysis of both return and volatility spillover strengths and directions between commodity and currency markets provides valuable information on hedging strategies and financial risk management. Practically, assessing the spillovers across different markets helps optimize the investment decision-making process during upward spillovers and undertake the appropriate decisions. Holding a short or long position depends on the frequency spillovers strengths and directions. During bearish market conditions, commodity investors may face important losses and thus taking a short position to avoid extreme losses. Policymakers strive to reduce the currency depreciation due to commodity price shocks and implement the appropriate regulations to ensure the financial stability.

The heterogeneity in the business cycles of commodity and foreign exchange (forex) markets has essential implications in hedging and diversification strategies. Commodity prices are driven not only by their shocks but also by the appreciation and depreciation of U.S. dollars as all

* Corresponding author. Department of Economics and Finance, College of Economics and Political Science, Sultan Qaboos University, Muscat, Oman
E-mail addresses: Ramzi.Nekhili@asu.edu.bh (R. Nekhili), walidmensi1@gmail.com (W. Mensi), vxvinh@yahoo.com (X.V. Vo).

https://doi.org/10.1016/j.resourpol.2021.102263
Received 14 September 2020; Received in revised form 18 July 2021; Accepted 19 July 2021
Available online 27 July 2021

commodities are quoted in US dollars. Qian et al. (2019) showed that a fall in the US dollar index is an indication that the dollar-priced commodity has appreciated. Therefore, connectedness between commodity and forex exchange markets can be a useful indicator of price direction. The knowledge of price spillover from commodity to currency can help traders understand market movements, contagion effects better and seek alternative portfolio risk management purposes. We notice that the role of commodity markets in portfolio management and hedging strategies has significantly increased especially following the financialization.

Despite the complexity of existing trading strategies, previous studies support evidence on the nexus between commodity markets and forex markets (see Fratzscher et al., 2014; Ferraro et al., 2015). There are currencies from which traders express a view on commodity prices. Some major commodity prices act as a leading indicator for forex markets (Baruník and Kočenda, 2019). For example, the price of crude oil and the Canadian dollar has displayed a solid long-term correlation. Being one of the largest oil producers, Canada's proximity to the U.S. makes it a convenient place from which the U.S. can import oil. Japan displays a particular sensitivity to oil prices at an extreme geographical side due to a lack of energy resources. Other commodities like gold are a leading indicator for the Swiss franc currency. Hence and from a seasoned trader perspective, looking at other currencies as a supplemental instrument to trading commodities could be beneficial.

This study aims to examine the time-frequency return and volatility spillovers between global commodity futures, namely gold, wheat, copper, West Texas Intermediate (WTI) crude oil, and main foreign exchange markets, namely the Euro (EUR), Japanese yen (JPY), British pound (GBP), Canadian dollar (CAD), Swiss franc (CHF), and Swedish krona (SEK). These currencies are the constituents of the U.S. dollar index (USDX), listed on the Intercontinental Exchange (ICE). Further, we examine the impacts of liquidity shocks, volatility uncertainty index (VIX), and economic policy uncertainty index (EPU) on return and volatility spillover strengths among markets under investigation.

This paper contributes to the existing literature on three main fronts. First, it examines the magnitude and the directional of dynamic return and volatility spillovers among foreign exchange and commodity futures markets using the spillover index of Diebold and Yılmaz (2012) [DY thereafter]. The DY method is based on variance decomposition of vector auto-regression to explore the spillover direction and size among the considered markets. The main advantage of this empirical method compared with the related literature is to account for dynamic, size, and directional (Hung and Vo, 2021). It is therefore flexible to identify the source of contagion and differentiates between markets that are net receivers and net transmitters of return and volatility. Besides, returns measure, in financial markets, the general market level while volatilities are considered to measure market risk. According to the investment theory, the risk–return trade-off is evaluated using the first and second moments (He and Hamori, 2021). Overall, understanding the risk propagation between markets under study is crucial for portfolio risk management.

Second, we examine the time-frequency return and volatility spillovers between commodity and currency markets using the multiscale spillover index of Baruník and Křehlík (2018) [BK thereafter]. It is worth noting that the investor's anticipations and reactions are heterogeneous as traders, speculators, and arbitragists are concerned by short-term investments whereas others regulators and institutional investors are interested in the long-term spillovers. Again, the motivation behind this decomposition of the aggregate return and volatility spillover into distinct parts, that when summed give the original aggregate spillovers, is that different traders use different time scales and, therefore, different heterogeneous expectations and trading mechanisms (Dacorogna et al., 2001; Nekhili et al., 2002). The currency markets are more vulnerable to negative shocks (Wang and Li, 2021). BK model can assess the extent of information spillover and interrelatedness across markets at any particular date and across different frequencies. Thus, disentangling between short-, medium-, and long-term investment horizon provides new insights into the commodity-currency nexus. We follow BK to decompose the total spillover into different frequency spillovers. Specifically, The total spillover is computed on a moving window with a length of 300 days. The short-term spillover ranges between 1 and 5 days, the intermediate-term spillover varies between 5 and 20 days whereas the long-term spillover oscillates between 20 and 300 days. Therefore, analyzing the frequency connectedness (direction and size) among the considered markets is suitable for our study. The dynamic frequency spillovers are due to heterogeneous expectations and different perceptions of risk, making financial investors more cautious about their investment decision over investment horizons (Baruník et al., 2016).

Third, it is fundamental for market participants to identify the drivers of spillover size and direction between currency and commodity markets. To do so, we examine the impacts of the volatility uncertainty index (VIX), economic policy uncertainty index (EPU), and liquidity shocks on returns and volatility spillover strengths at short-, intermediate- and long-terms. We notice that the last few years have been marked by an increase in uncertainty that is captured by the fear index VIX. Baruník and Kočenda (2019) show that liquidity and uncertainty shocks are the main drivers of volatility spillovers between oil and forex markets. They further reveal that long-term connectedness between oil and forex markets is affected by economic uncertainty. Krol (2014) and Abid (2019) document that EPU increases the volatility of exchange rates during bad times and explains the movements of currencies in the short- and long-runs. This analysis is fundamental to better understand the factors that increase/reduce that linkage risk and return between currency and commodity markets. Therefore, our control variables may improve the forecasting purpose, hedging strategies, portfolio diversification of investments, the investment decision-making process, and risk management for global investors.

It is worth noting that these three factors proxy both economic and financial system health. They are used as barometers for investors. Due to the existence of heterogeneous expectations, investors differ in perceiving the financial system's stability and therefore trigger differences in the connectedness of financial assets over time. The literature has revealed that there exist economic factors that drive the scope of connectedness between financial assets. Fratzscher et al. (2014) studied the long-term connectedness between exchange rates and oil and found evidence that these two markets displayed strong negative correlations during the GFC and ESDC.

The choice of the commodity and currency markets is justified by different reasons. Crude oil, gold, copper, and wheat commodities are attractive assets and represent an alternative investment for commodity investors and currency investors especially following the commodity financialization (Daskalaki and Skiadopoulos, 2011). Oil is a vital commodity for the world economy. It is a crucial input for industry activity. As for gold, it is commonly accepted as a safe haven asset during crisis periods for financial markets (Baur and Lucey, 2010; Baur and McDermott, 2010), currency markets (Reboredo, 2013), and periods of high inflation (Gorton and Rouwenhorst, 2006). The copper market plays a vital role in industrial manufacturing and economic activities worldwide (Todorova et al., 2014). It is the world's third most widely used metal after gold and silver. The global copper demand experiences an annual growth rate of approximately 9.9% in 2020Q1. The copper price movements are not affected by only the law of supply and demand, leading to a sharp price instability creating a price bubble (Guo et al., 2020). The non-ferrous price is related to the industrial economic systems. Wheat is a strategic commodity for each economy because it is the most significant contributor to human food supplies globally. World wheat trade is forecast at an all-time high of 178.7 million tons in 2020/21, up 1.5 million tons) from 2019/20, based on anticipated larger export supplies, particularly on the expectation of strong production recoveries in Australia and Canada.[1] This market is influenced

[1] http://www.fao.org/worldfoodsituation/csdb/en/.

by many factors, including, among other climate concerns, crude oil prices, and imports. Moreover, the high instability in global wheat demand makes the wheat prices more and more volatile. It is important to notice that a large proportion of transaction is executed in futures markets characterized by high volume trading and high liquidity level. Financial and commodity futures markets explain the trading behavior of hedgers and speculators (Chen and Yang, 2021).[2] The Chicago Mercantile Exchange (CME) is ranked as the top futures exchange in the world. The average volume amounts to more than 19.2 million contracts per day in 2019.[3] The occurrence of financial and economic crises has increased the demand for hedging risk through commodity futures (Cagli et al., 2019).

The remainder of this paper is organized as follows. Section 2 presents an overview of the literature. Section 3 discusses the methodology. Section 4 presents the data and the descriptive statistics. Section 5 discusses the empirical results. Section 6 concludes.

2. Literature review

The spillover topic attracts special attention with the occurrence of crisis (e.g., 2008–2009 GFC, 2010–2012 ESDC, 2014–2015 oil price crash, and the COVID-19 pandemic crisis) given its importance in terms of asset allocation and portfolio risk management. The first strand of literature analyzes the spillovers between commodity and foreign exchange markets in the time domain. For example, Chen and Rogoff (2003) use different panel models and find that commodity prices lead to exchange rate movements of Australia, Canada, and New Zealand economies. Using out-of-sample forecasting accuracy methods, Meese and Rogoff (1983) conclude that exchange rates serve as a predictor of economic fundamentals and as a result the commodity prices. These results are in line with the findings of Zhang et al. (2016) who use a multi-horizon causality method and find significant bidirectional causalities between commodity (gold, copper, Brent crude oil, and West Texas Intermediate [WTI] crude oil) and foreign exchange rates of Canada, Norway, Australia, and Chile. The authors conclude that the causality strength from commodity prices to currency markets is stronger than vice versa. The causality is more significant at short horizons than long horizons. Finally, the macroeconomic/trade-based mechanism affects the exchange-rate dynamics.

Using a VARMA-DCC model, Hammoudeh et al. (2010) examine the spillover volatilities and time-varying conditional correlations between precious metals and the US dollar/Euro exchange rate. The results show a strong volatility sensitivity of precious metals to the exchange rate and that the performance of hedging precious metals against each other is limited. In time-domain connectedness, the study of Huang et al. (2012) examines the spillover effects of the U.S. dollar and oil on the Chinese precious metals (gold, silver, and copper). Using a vector autoregressive (VAR) framework, the authors show that the U.S. dollar exchange rate mainly drives Chinese gold and silver prices. Antonakakis and Kizys (2015) explore the dynamic return and volatility spillover among a portfolio of commodities and forex markets. The authors show that precious metals (gold, silver, and platinum) drive the returns and volatilities of the GBP and CHF currencies. Furthermore, they reveal that CHF and gold are net transmitters of return and volatility spillovers to other currencies, such as the Euro, and other commodities, such as palladium. Moreover, they attribute the change in the dynamics of return and volatility spillovers to economic events. In the same vein, Fernandez-Perez and FrijnsTourani-Rad (2017) use a structural vector autoregressive model (SVAR) to study the spillover effects among gold, silver, platinum, palladium, oil, and U.S. dollar rates. They show that there is a strong asymmetric connectedness between the U.S. exchange rates and commodities. Analyzing the linkages among forex markets, Baruník et al. (2017) find significant asymmetric connectedness primarily dominated by negative volatility. They show that bad volatility is due to the ESDC, while positive spillovers due to the US subprime mortgage crisis. Hence, they document that net positive spillovers are caused by a combination of monetary and real-economy events, while net negative spillovers come from fiscal factors. Tian and Hamori (2016) use a time-varying SVAR model with a stochastic volatility model and the spillover index of Diebold and Yılmaz (2012). The authors show evidence of time-varying volatility spillovers between foreign exchange, bond, equity, and commodity (agriculture, energy, industrial metals, and precious metals) markets. The magnitude of spillover effects rises after the Lehman shock, ESDC, and the recent expectation of the monetary shock in the United States.

By accounting for lower and upper tail dependence, Wu et al. (2012) use copula functions to analyze the dependence structure between U.S. dollar exchange rates and WTI oil prices. They show evidence of an asymmetric dependence between oil and the U.S. dollar, which they explained by the dynamics of demand for oil by non-U.S. dollar consumers. They further argue that oil could be a substitute commodity for foreign investors seeking diversification. Recently, Shahzad et al. (2019) examine the return connectedness between oil prices and a portfolio of precious metals, namely gold, silver, platinum, palladium, and titanium. Using both VAR for VaR and the cross-quantilogram approaches, the authors show greater downside spillover effects exist from oil returns to precious metal returns. More importantly, precious metals returns had greater exposure to downside risk than upside risk. The authors conclude a higher spillover and risk exposure during the GFC. Gold, silver, platinum, palladium, and titanium could be safe-haven assets against extreme oil price movements. More recently, Fasanya et al. (2021) apply both the spillover index of Diebold and Yılmaz (2012) and the nonparametric Causality-in-Quantiles approach to examine the effects of U.S. EPU on the connectedness of crude oil and global foreign exchange pairs. The authors find strong spillover effects between crude oil and foreign exchange markets and the EPU affect the oil-currency nexus at both lower and middle quantiles.

The limitation of these studies is to assume that market participants have the same reactions, risk appetite, anticipations, and investment strategies. They also assume that the spillover effects are similar in the short- and long-terms (same spillover size across different time scales). In reality, investors exhibit heterogeneous behaviors. Thus, the second strand of literature that provides additional insight by integrating a frequency factor to consider the heterogeneous market anticipations and reactions. In the medium to long term, an increase in foreign investment in the local commodity sector leads to a further appreciation of the local currency as dollars are sold off (see Kohlscheen et al., 2017). This heightened interest is driven by its importance for investors, regulators, and policymakers, including risk management. Wang et al. (2020) examine the dynamic frequency return connectedness among four global commodity futures markets — gold, wheat, WTI crude oil, and copper. They document that the connectedness on the short-term frequency band (one to five days) contributes most to total ones, signifying that shocks get transmitted very quickly across commodity markets.

Using high-frequency data, Baruník and Kočenda (2019) analyze the time-frequency connectedness on oil and forex markets. The authors find that negative shocks explain the asymmetries in forex volatility connectedness whereas positive shocks explain the connectedness between both oil and currency markets. Furthermore, the authors find that short- and long-term connectedness constitute the major components of total connectedness between oil and forex markets. They attribute these dynamics to the difference in investment horizons and investment preferences. They further argue that liquidity and uncertainty shocks drive the frequency connectedness. Using Hierarchical Vector Autoregression (HVAR) model, Bagheri and Ebrahimi (2020) show that stock, commodity (Brent crude oil, gold, and WTI crude oil), bond (US 10-Year

[2] For further details, see The 'hedging pressure' theory of Keynes (1930) and Hicks (1939).

[3] http://investor.cmegroup.com/news-releases/news-release-details/cme-group-reports-2019-annual-volume-and-monthly-market.

Bond Yield and US 30-Year Bond Yield), currency (EUR/USD, GBP/USD and Dollar Index futures), and cryptocurrency (Bitcoin, Ethereum and Litecoin) markets are highly connected, especially during GFC. WTI crude oil — Brent crude oil, 30-Year bond and 10-Year bond, Dollar Index futures-EUR/USD have significant connections. Gold and cryptocurrencies serve as good hedge assets during GFC.

From the above literature, modeling the linkages among leading commodity and the most traded currency assets enhances our understanding of the dynamic nonlinear relationships between the markets under investigation. Besides, modeling frequency connectedness behavior and the determinants of the spillover strengths and directions respond to investors' concerns.

To the best of our knowledge, this is the first paper to examine the return and volatility connectedness between four global commodity futures markets and forex markets at both time and frequency domains. More specifically, we first employ the DCC-AR(1)-EGARCH(1,1) model to examine the time-varying conditional correlations between commodity and currency price returns. Second, we apply the spillover index of DY to investigate the time domain return and volatility spillover strengths and directions for a currency portfolio as well as for commodity-currency portfolios. Third, we carry out the time-frequency spillover index of BK to examine the evolving spillovers in returns and volatility at short, intermediate-, and long-terms. Finally, we use the ordinary least square to investigate the impacts of volatility uncertainty, liquidity shocks, and EPU on the return and volatility spillover magnitude at different time horizons.

3. Empirical method

This paper's methodology is based on the time and frequency domain spillover frameworks proposed by Diebold and Yilmaz (2009, 2012) and Baruník and Křehlík (2018). The first framework is applied to analyze the directional connectedness by measuring the total, directional, and net spillover indexes based on forecast error variance decomposition from a generalized VAR model. Whereas, the second framework is used to study the strength of spillovers based on a spectral representation of variance decomposition at short, medium, and long frequencies. Both methods are applied to the return and volatility of the variables of interest using a multivariate GARCH-type filtering technique, which constitutes the start of the analysis.

Let us consider an autoregressive (AR) model for conditional mean, considering any presence of autocorrelation of p order, and the DCC-EGARCH(mn) model of Nelson (1991) for conditional volatility. This model is suitable for modeling asymmetries in volatility and transmission of shocks and accounting for time-varying cross-correlations between variables (e.g. Mensi et al., 2014). Let R_t be a vector of return series of N assets, and the model is represented as follows:

$$R_t = A_0 + \sum_{j=1}^{p} A_j R_{t-1} + \mathscr{E}_t,\ \mathscr{E}_t \sim Dist(0, H_t)$$

$$H_t = D_t Corr_t D_t \tag{1}$$

where A_0 and A_j are a constant term and autoregressive term in the mean equation, respectively. with $\mathscr{E}_t$ being the error terms $\varepsilon_{it},\ i = 1, \dots, N$, $H_t$is the conditional variance matrix, $D_t$is a NxNdiagonal matrix having conditional volatility $\sqrt{h_{i,t}}$, $i = 1, \dots, N$, on its diagonal, and $Corr_t$ is a time-varying correlation matrix. For each asset i, the conditional variance ($h^2_{i,t}$) is estimated using EGARCH(mn) as follows:

$$Log\ h^2_{i,t} = w + \sum_{j=1}^{n} \alpha_j \left[\frac{e_{t-j}}{h_{t-j}} - E\left\{ \frac{e_{t-j}}{h_{t-j}} \right\} \right] + \sum_{j=1}^{n} \gamma_j \left(\frac{e_{t-j}}{h_{t-j}} \right) + \sum_{j=1}^{m} \beta_j h^2_{i,t-j} \tag{2}$$

In this model, the parameters α_j and β_j are respectively the ARCH and GARCH coefficients, the parameter $\gamma_j$captures the leverage effect of the returns. Positive values of $\gamma_j$would imply that negative innovations increase the conditional volatility by a larger magnitude than positive innovations. The distribution$Dist$, of shocks follows a skewed Student-t (with ν degree of freedom) distribution to accommodate fat tails and skewness in the returns. The correlation dynamics, $Corr_t$, is a conditional correlations matrix given by $Corr_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$, and where $Q_t$are symmetric semi-positive matrices containing the unconditional covariance of the standardized residuals of univariate EGARCH model, $u_t = D_t^{-1/2} \mathscr{E}_t$, and represented by

$$Q_t = (1 - \vartheta_1 - \vartheta_2)\overline{Q} + \vartheta_1 u_{t-1} u_{t-1}^{'} + \vartheta_2 Q_{t-1} \tag{3}$$

$\overline{Q}$denotes the unconditional covariance matrix of $u_t$and the parameters $\vartheta_1$and $\vartheta_2$are the correlation persistence parameters of the DCC-EGARCH model.

Next, we analyze the directional spillovers of both return and volatilities of the variables of interest using the spillover framework ofy Diebold and Yılmaz (2012) utilizes variance decompositions (VDCs) and a framework of generalized impulse response functions. The DY model does not require any particular ordering of the futures prices to measure spillovers in the present context. The VDCs, in percentage terms, measure the forecast error variance of a dependent variable that is partly due to its own shocks (heatwave) and partly due to innovations of other explanatory variables (meteor shower). Briefly, the p^{th} order vector autoregressive (VAR) system for a portfolio of N assets' returns or volatilities $X_t = (X_{t,1}, X_{t,2}, \dots, X_{t,N})^{'}$can be written as:

$$X_t = c + \sum_{i=1}^{p} B_i X_{t-i} + \varepsilon_t \tag{4}$$

where c is a constant, B_i are $N \times N$ autoregressive coefficients matrices, and $\varepsilon \sim (0,\ \Sigma)$ is a vector of independently and identically distributed errors. The moving average of system (1) may be written as:

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

where the $N \times N$ coefficients matrices follow the recursion process $A_i = B_1 A_{i-1} + B_2 A_{i-2} + \dots + B_p A_{i-p}$, with A_0being the identity matrix. The total and directional spillovers are produced by the generalized forecast-error variance decompositions of the moving average representation equation (2). The VDCs define the 'own variance shares' as a fraction of H-step-ahead variance in forecasting X_i, for $i = 1, \dots, N$, and 'cross variance shares' as a fraction of H-step-ahead variance in forecasting X_j, for $j = 1, \dots, N$, such that for $i \neq j$. Using the notion of the H-step-ahead generalized forecast error variance decomposition, we may write the VDCs as:

$$\Theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma A_h^{'} e_i \right)} \tag{6}$$

where $\Theta_{ij}(H)$ is an estimate of the contribution of market j to of market i, $\sigma_{jj} = (\Sigma)_{jj}$ denotes the standard deviation of the errors of the j^{th} equation and e_i is an $N \times 1$ vector, whose i^{th} element is 1 and other elements are 0. The own variance and cross variance shares are contained in the main diagonal and off-diagonal elements of $\Theta(H)$ matrix, respectively. The sum of the rows normalizes each entry of the VDC matrix, and the own and cross-variance shares contributions do not sum to one under the generalized decompositions:

$$\Theta_{ij}(H) = \frac{\Theta_{ij}(H)}{\sum_{j=1}^{N} \Theta_{ij}(H)} \tag{7}$$

with $\sum\limits_{j=1}^{N} \Theta_{ij}(H) = 1$ and $\sum\limits_{i,j=1}^{N} \Theta_{ij}(H) = N$ by construction.

We now analyze the transmission of shocks among the variables under investigation by measuring the total connectedness index, the

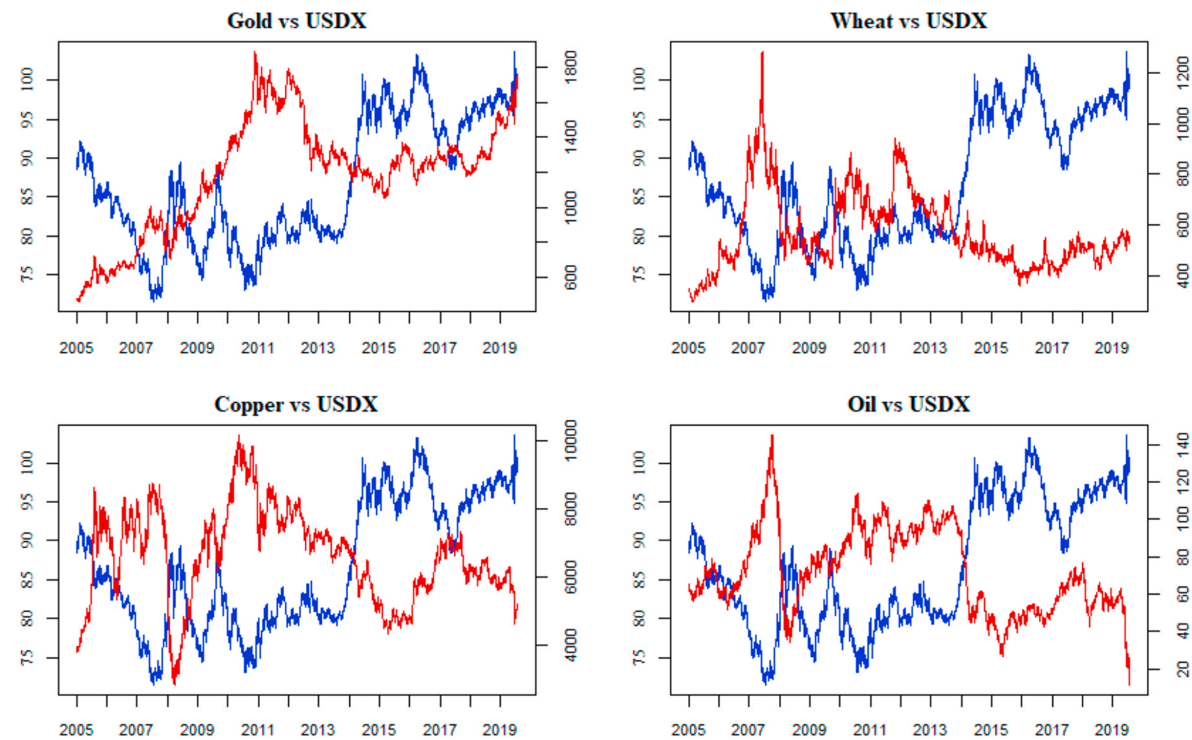

Fig. 1. Forex prices (blue line and left axis) and commodity prices (red line and right axis). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

total directional connectedness to and from others, and then deriving the net total directional connectedness. Using equations (3) and (4), the total spillover index can be calculated as:

$$TS(H)=\frac{\sum_{i,j=1,\ i\neq j}^{N}\Theta_{ij}(H)}{\sum_{i,j=1}^{N}\Theta_{ij}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\Theta_{ij}(H)}{N}\times 100 \tag{8}$$

This index also serves to get the directional return/volatility spillovers received by market i from the market j, and the reverse direction of transmission, from market i to the market j , as follows:

$$TS_{i\leftarrow *}(H)=\frac{\sum_{j=1,\ j\neq i}^{N}\Theta_{ij}(H)}{\sum_{i,j=1}^{N}\Theta_{ij}(H)}\times 100=\frac{\sum_{j=1,\ j\neq i}^{N}\Theta_{ij}(H)}{N}\times 100 \tag{9}$$

and

$$TS_{i\rightarrow *}(H)=\frac{\sum_{j=1,j\neq i}^{N}\Theta_{ij}(H)}{\sum_{i,j=1}^{N}\Theta_{ij}(H)}\times 100=\frac{\sum_{j=1,j\neq i}^{N}\Theta_{ij}(H)}{N}\times 100 \tag{10}$$

The calculation of the net return/volatility spillovers from market i to all other markets is performed by:

$$TS_i(H)=TS_{i\rightarrow *}(H)-TS_{i\leftarrow *}(H) \tag{11}$$

Finally, we examine the connectedness in the frequency domain following Baruník and Křehlík (2018). The previous DY spillovers are now decomposed at different frequencies using a spectral representation that could be described as follows: the procedure starts with decomposing the generalized impulse response function of the series X_t as follows:

$$\sum_{h=0}^{\infty}E(X_tX_{t-h})e^{-ihf}=\Psi\left(e^{ihf}\right) \tag{12}$$

where $\Psi(e^{-ihf})=\sum_{h=0}^{\infty}\Psi_h e^{-ihf}$is the Fourier transform of the impulse response Ψ, f denotes the frequency, and $i=\sqrt{-1}$. Then, the generalized forecast error variance decomposition (GFVED) over frequencies $f\in(-\pi,\pi)$ is found as:

$$(\Theta(f))_{ij}=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{\infty}\left(\Psi(e^{-ihf})\Sigma\right)_{i,j}^{2}}{\sum_{h=0}^{\infty}\left(\Psi(e^{-ihf})\Sigma\Psi(e^{ihf})\right)_{i,i}} \tag{13}$$

where $(\Theta(f))_{ij}$ represents the portion of the spectrum of j^{th} variable at frequency f due to shocks in i^{th}variable. At any given frequency, this quantity gives the within frequency causation in the cross-spectral density of X_t. Taking an arbitrary frequency band $d=(a,b)$, with $a<b\in(-\pi,\pi)$, we can generate a connectedness table expressed as:

$$(\Theta_d)_{ij}=\int_a^b(\Theta(f))_{ij}df \tag{14}$$

We follow by calculating the total frequency connectedness at the frequency band d as

$$TS^d=\frac{\sum_{i=1,i\neq j}^{N}(\Theta_d)_{ij}}{\sum_{i,j}(\Theta_d)_{ij}}\times 100 \tag{15}$$

which is applied to the DY total spillovers. We finally proceed with measuring the directional frequency return/volatility spillovers received by market i from the market j at frequency band d, and the reverse direction of transmission, from market i to the market j at frequency band d, which can be expressed as:

$$TS_{i\leftarrow *}^{d}=\sum_{j=1,i\neq j}^{N}(\Theta_d)_{ij}\times 100 \tag{16}$$

and,

$$TS_{i\rightarrow *}^{d}=\sum_{j=1,i\neq j}^{N}(\Theta_d)_{ji}\times 100 \tag{17}$$

Table 1
Descriptive statistics for currency and global commodity returns.

	EUR	JPY	GBP	CAD	CHF	SEK	Gold	Wheat	Copper	Oil
Mean	−2.85E-05	−1.45E-05	−9.62E-05	−5.36E-05	7.77E-05	−7.10E-05	3.63E-04	1.24E-04	8.25E-05	−3.79E-04
Median	0.00E+00	0.00E+00	−5.04E-05	0.00E+00	−9.61E-05	9.36E-05	4.02E-04	−4.50E-04	0.00E+00	7.50E-04
Minimum	−0.030	−0.051	−0.081	−0.037	−0.088	−0.053	−0.098	−0.0997	−0.104	−0.568
Maximum	0.032	0.040	0.033	0.051	0.156	0.049	0.086	0.0884	0.118	0.258
Std.Dev	0.005	0.006	0.006	0.005	0.007	0.007	0.011	0.020	0.017	0.027
Skewness	−0.034	−0.221	−1.045	−0.095	2.7312	−0.1392	−0.299	0.127	−0.003	−2.503
Kurtosis	5.168	7.841	15.063	7.631	84.976	6.529	8.568	4.765	7.306	65.795
Normality tests										
A-D	16.646*	24.681*	23.791*	27.435*	46.288*	20.817*	42.289*	13.195*	42.047*	85.436*
p-value	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24	3.70E-24
S–W	0.97*8	0.95*5	0.935*	0.957*	0.841*	0.965*	0.942*	0.981*	0.947*	0.80*6
p-value	3.61E-23	5.09E-32	4.51E-37	2.29E-31	3.16E-51	1.49E-28	1.35E-35	2.06E-21	4.18E-34	1.13E-54
Unit Root test										
ADF	−42.063*	−42.860*	−41.380*	−41.339*	−42.975*	−43.903*	−43.086*	−44.080*	−44.468*	−44.288*

Note: This table reports summary statistics for log-returns of global commodity futures and forex markets futures. The Anderson-Darling (A-D) and Shapiro-Wilk (S–W) statistic tests and their p-values are for the null hypothesis of normality for the distribution of the series. ADF is the t-statistics for Augmented Dickey-Fuller test. * indicates the rejection of the null hypothesis at the 1% level.

Table 2
DCC-EGARCH parameters for commodity and forex futures markets.

	A_0	A_1	w	α	β	γ	skew	ν
EUR	−2.2E-05	0.002	−0.050*	0.032*	0.961*	0.087**	0.972*	9.322*
	(8.2E-05)	(0.016)	(0.002)	(0.005)	(0.001)	(0.009)	(0.022)	(1.095)
JPY	2.8E-05	−0.022	−0.205*	0.044*	0.931*	0.147*	0.977*	5.898*
	(8.7E-05)	(0.017)	(0.004)	(0.004)	(0.005)	(0.016)	(0.022)	(0.684)
GBP	−6.1E-05	0.003	−0.061*	0.027*	0.963*	0.074**	0.957*	7.675*
	(8.5E-05)	(0.016)	(0.001)	(0.005)	(0.002)	(0.006)	(0.024)	(0.900)
CAD	−1.1E-04	−0.004	−0.073*	0.033*	0.952*	0.108*	0.960*	7.929*
	(7.9E-05)	(0.017)	(0.015)	(0.003)	(0.005)	(0.014)	(0.020)	(6.158)
CHF	6.7E-05	−0.011	−0.086*	0.054*	0.945*	0.081*	1.064*	6.434*
	(8.9E-05)	(0.016)	(0.002)	(0.001)	(0.004)	(0.012)	(0.024)	(0.638)
SEK	−1.3E-04	−0.024	−0.042*	0.024*	0.963*	0.076*	0.951*	9.151*
	(1.0E-04)	(0.017)	(0.001)	(0.004)	(0.002)	(0.006)	(0.023)	(1.059)
Gold	3.7E-04	−0.031*	−0.042*	0.017*	0.995	0.096*	0.956*	4.529*
	(1.5E-04)	(0.014)	(0.009)	(0.008)	(0.001)	(0.045)	(0.021)	(0.683)
	ϑ_1	ϑ_2	Log-Lik	AIC	Q (10)	Q^2 (10)		
	0.023*	0.975*	100336.7	−55.10	1.855*	6.231*		
	(0.001)	(0.001)						
Wheat	3.3E-05	−0.009	−0.081*	0.021*	0.989*	0.104*	1.096*	8.530*
	(3.1E-04)	(0.017)	(0.003)	(0.009)	(0000)	(0.008)	(0.028)	(1.052)
	ϑ_1	ϑ_2	Log-Lik	AIC	Q (10)	Q^2 (10)		
	0.021*	0.977*	97445.68	−53.51	1.672*	3.976*		
	(0.001)	(0.001)						
Copper	−7.5E-05	−0.078*	−0.045*	0.029**	0.951*	0.035*	0.990*	6.079*
	(1.4E-04	(0.015)	(0.011)	(0.014)	(0.018)	(0.003)	(0.019)	(1.082)
	ϑ_1	ϑ_2	Log-Lik	AIC	Q (10)	Q^2 (10)		
	0.023*	0.975*	98826.7	−54.27	1.942*	5.989*		
	(0.001)	(0.001)						
Oil	−2.0E-04	−0.048*	−0.048*	0.016	0.948*	0.064*	0.889*	8.035*
	(3.1E-04	(0.018)	(0.006)	(0.021)	(0.030)	(0.007)	(0.021)	(1.533)
	ϑ_1	ϑ_2	Log-Lik	AIC	Q (10)	Q^2 (10)		
	0.022*	0.976*	97800.4	−53.70	1.059*	8.469**		
	(0.001)	(0.001)						

Note: The table reports the estimation results of the AR(1)-DCC-EGARCH(1,1) with skewed Student-t error distribution. A_0 and A_1 refer respectively to the intercept and the autoregressive coefficient in the mean equation. w, α β, and γ stand for intercept, ARCH effect, GARCH effect, and the leverage effect, respectively. Skew and ν indicates the skewness and fat tails in the distributions. The values between parenthesis stand for the standard errors. The asterisks * and ** denote significance at the 1% and 5% levels, respectively. The significance of the Ljung-Box tests for serial correlation with ten lags in the standardized residuals and squared standardized residuals indicate acceptance of the null hypothesis of no serial correlation.

4. Data and preliminary analysis

We use daily futures contracts of commodities traded in the London Mercantile Exchange (LME), and main foreign exchange markets. The commodities are gold, wheat, copper, and WTI crude oil futures contracts. The currency futures are the EUR, JPY, GBP, CAD, CHF, and SEK, and are all quoted against the U.S. dollar. These currencies constitute a basket of developed market currencies for the U.S. dollar index USDX. This latter is listed on the Intercontinental Exchange (ICE) and indirectly tradable using spot and futures on component currencies. The futures data represent the most active continuous contracts based on CME prices, rolling to the next contract seven days before expiration with no adjustments on roll dates. The sample period spans from October 4, 2005, to April 23, 2020, covering different economic events, including

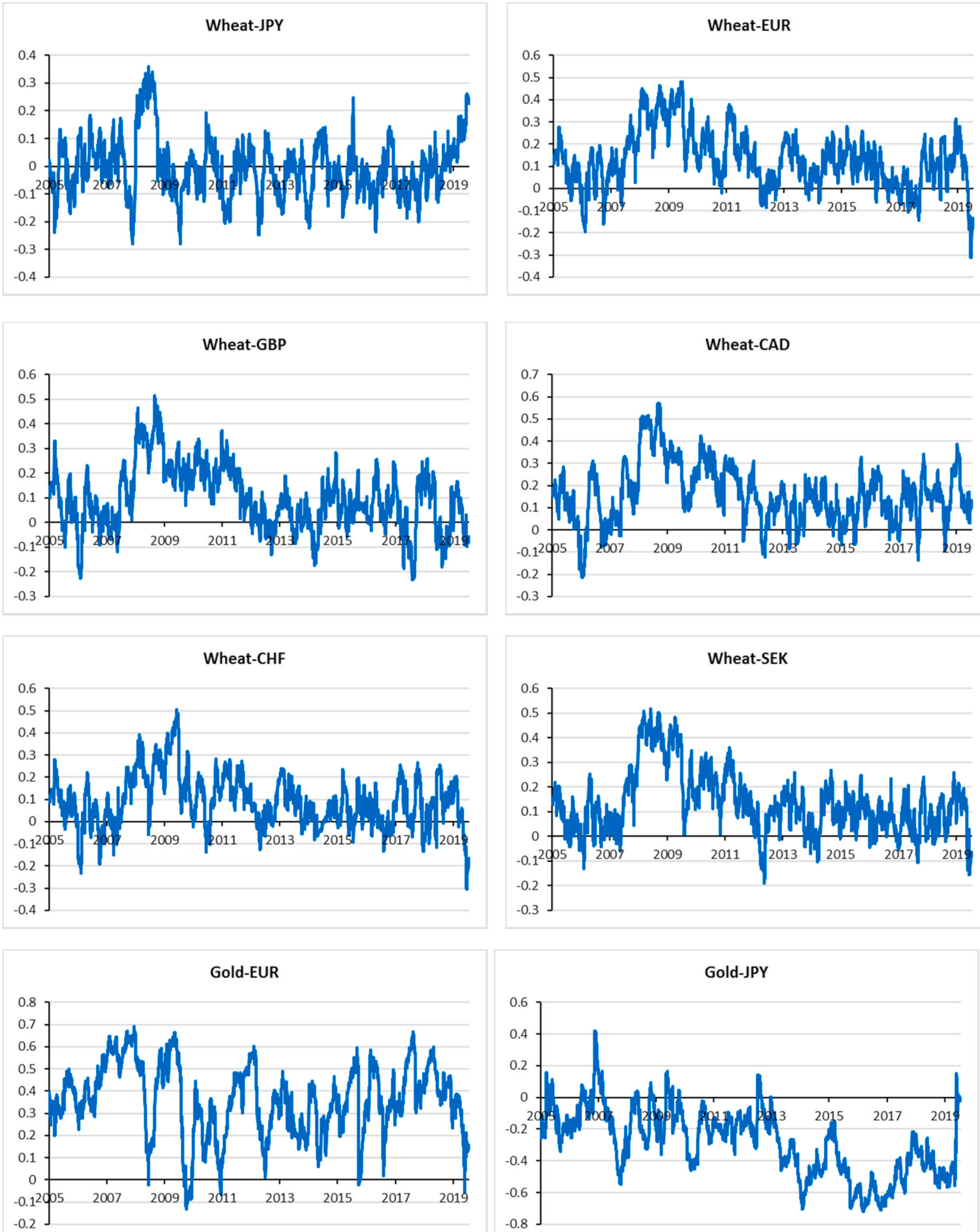

Fig. 2. Time-varying conditional correlations between commodity and currency markets.

the 2005–2006 food crisis, 2008–2009 GFC, 2010–2012 ESDC, the 2004 great oil bust, and the COVID-19 pandemic crisis. The data are compiled from the Bloomberg terminal.

Fig. 1 displays the time series of the commodities plotted against the U.S. dollar index. While most commodities are negatively correlated with the dollar index, surprisingly, there is evidence that recent days' correlation may turn positive. This is true for the U.S. dollar and gold. Since 2017, the two markets appear to be trending in the same direction, suggesting that diversification opportunities using gold and USDX may not be feasible due to a positive correlation between them. Moreover, a pattern shows that an appreciation (depreciation) of the U.S. Dollar is associated with a drop (rise) in wheat prices. The reason for such a pattern is that for non-U.S. buyers of U.S. wheat, commodity prices rally on a drop in the value of the U.S. dollar. This is also valid for most bilateral exchange rates, and therefore we can assert a strong link between the wheat and forex markets.

In contrast, copper, wheat, and oil show a similar pattern against the U.S. dollar index around major economic downturns. More importantly,

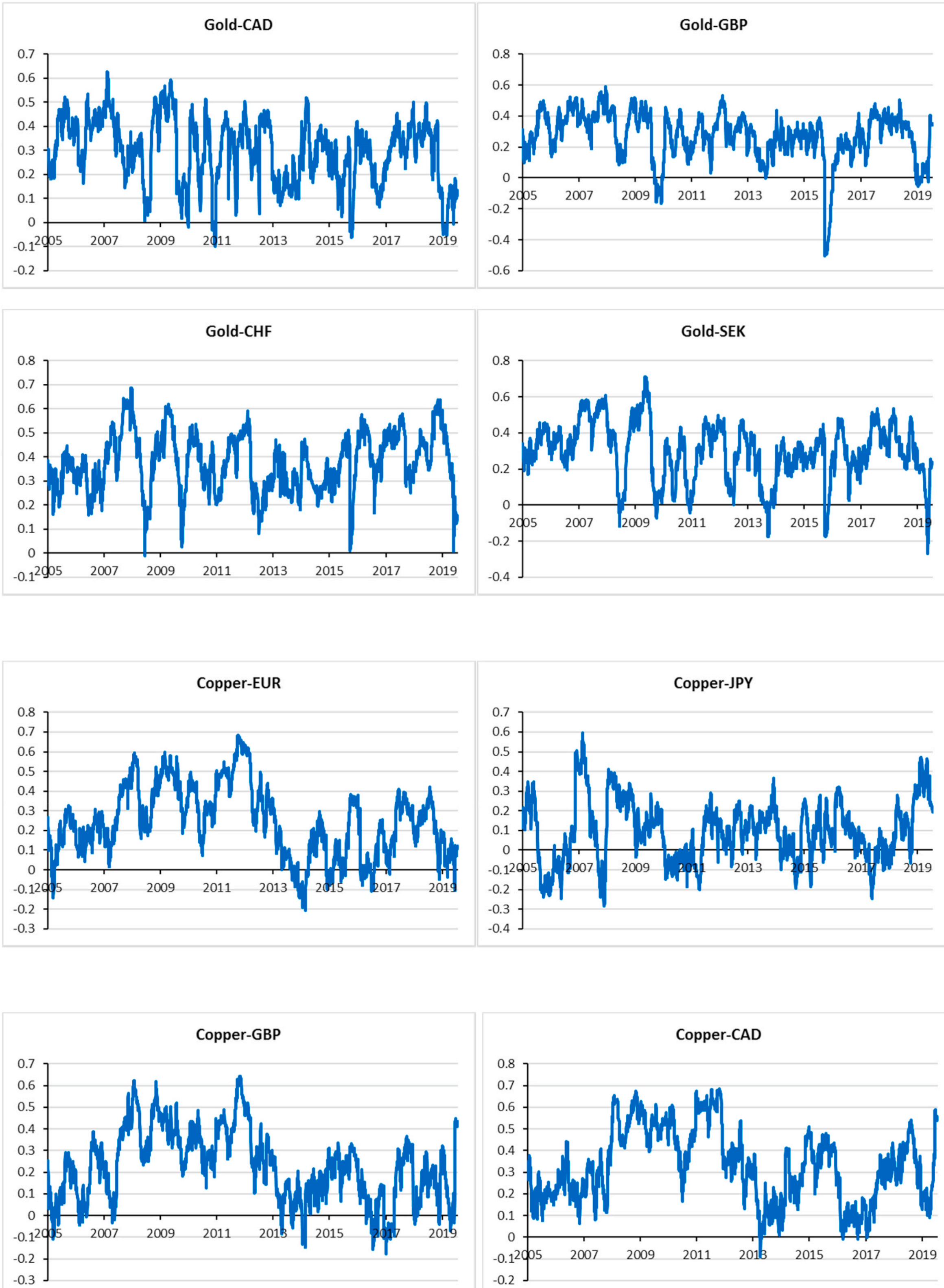

Fig. 2. (*continued*).

we observe that the demand for these commodities has slowed down because of the global financial crisis of 2008, the recession fear in September 2011, and the growth slowdown in emerging economies, which has sparked rapid sell-off of these commodities. Such a pattern corroborates the findings of Ferraro et al. (2015) and Baruník and Kočenda (2019). The recent consequence of the COVID-19 pandemic has significantly slowed down the demand for major global commodities as the currency markets and gold.

Table 1 presents the descriptive statistics for the log returns of the commodity and forex return series. Among the considered currencies,

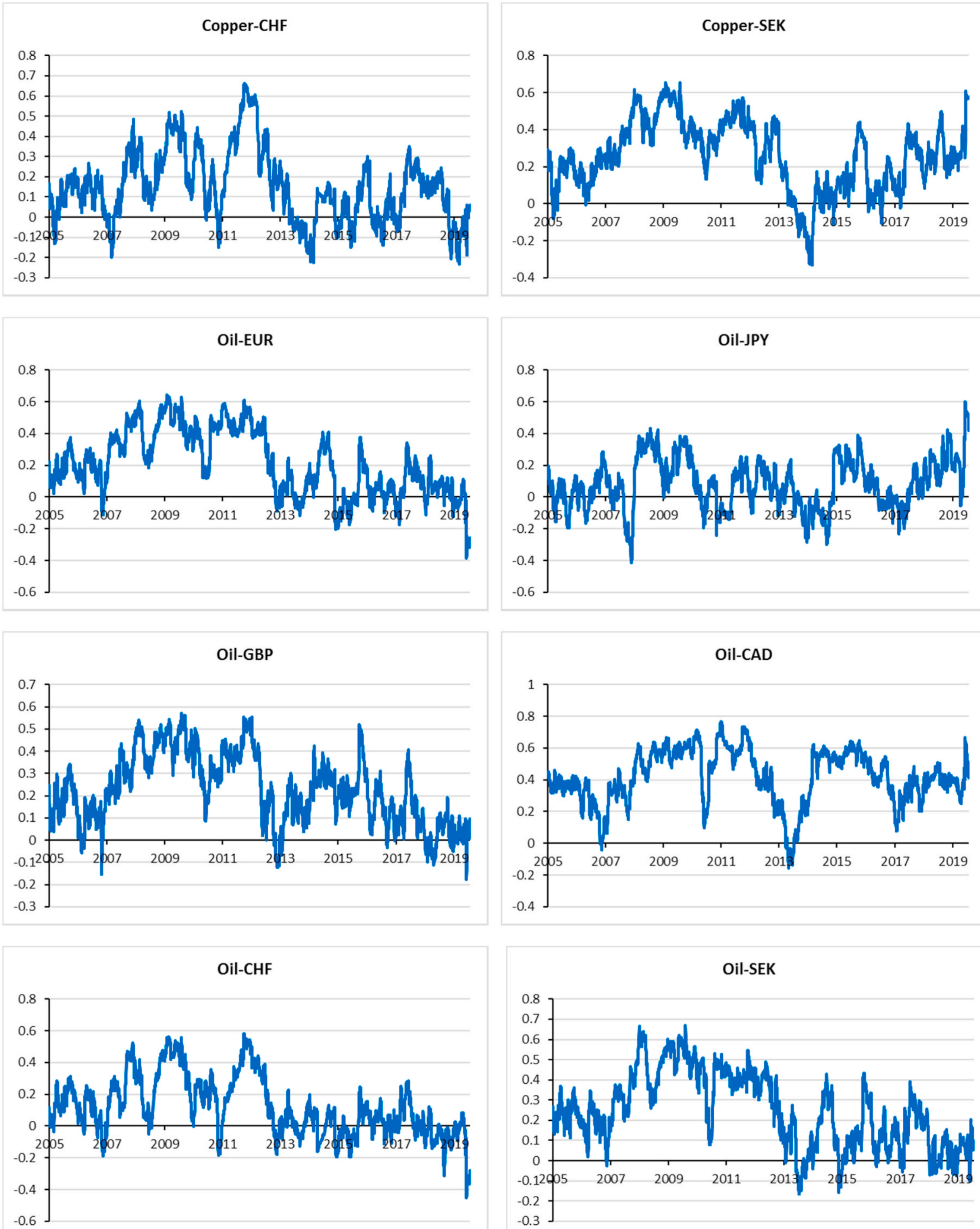

Fig. 2. (*continued*).

the Euro has the highest mean, and the Swedish krona has the highest standard deviation (risk). As for commodities, gold has the highest mean returns, and oil is the most volatile. All return series display a departure from normality distributions as showed by skewness and kurtosis values and confirmed by Anderson-Darling and Shapiro-Wilks statistic tests. We ensure the stationarity of all VAR components because of Dickey and Fuller's unit root test.

5. Empirical analysis

5.1. Volatility and dynamic conditional correlation analysis

It is interesting to consider the stylized facts of the return series highlighted in the previous section. Unlike the traditional approach used in the literature, we estimate a volatility model for each pair of commodity and currency futures returns using multivariate dynamic conditional correlations exponential generalized autoregressive conditional heteroscedasticity (DCC-EGARCH) model, which accounts for asymmetric behavior (leverage effects).[4] Table 2 displays the estimation results of the DCC-AR(1)-EGARCH(1,1) model. As shown in this table, we show that the autoregressive parameter (A_1) for all currency futures markets is insignificant, whereas for the commodity futures markets is significant at a conventional level, except the wheat futures market. This result suggests no possible one-step ahead predictability of the returns of currency futures returns as opposed to commodity futures returns. All ARCH and GARCH coefficients, namely α and β, respectively, are statistically significant, indicating that the volatility is intensively reacting to market movements and that shocks to the conditional variance take time to die out. The leverage effect γ is positive and statistically significant at the conventional level for all markets, indicating evidence of the asymmetric impact of bad and good news on conditional volatilities. All commodities react more to bad news (negative returns) than good news (positive returns). Besides, the stylized facts of all return distributions are reflected from the significance of the skewness (skew) and shape (ν) parameters at the 1% significance level. These distributions are skewed and fat-tailed, underlying that the skewed Student-t distribution is the best fit for the residuals based on the dynamic conditional correlations. ϑ_1 coefficients are positive and statistically significant at the 1% level, indicating the importance of shocks between the commodity and currency markets. ϑ_2 coefficients are also positive, statistically significant, and very close to one. This result shows the higher volatility persistence between commodity and currency markets. It is worth noting that the significance of these parameters confirms the appropriateness of our model.

According to diagnostic tests, there were no remaining autocorrelations in both the standardized residuals and the squared standardized residuals for most of the futures, as indicated by the Ljung-Box statistics. This result exhibits evidence against misspecification.

Fig. 2 illustrates the dynamic conditional correlations between commodity and currency markets. The graphical evidence shows that the correlations among markets under study are not constant and are intensified during major events, particularly during the 2008 GFC. In addition, all commodity-currency pairs exhibit periods of positive correlations and negative correlations. The correlations between gold and Euro vary from - 0.13 in July 2010 to 0.7 in September 2008. The correlations between wheat and most currencies (except for JPY rate) have declined during COVID-19. As for gold, we show a negative correlation between the yellow metal and JPY currency for almost all sample periods. This result is important for currency traders. In addition, for the remaining assets, we observe weak correlations which decline during major events, indicating that a depreciation currency is associated with a gold price jump. The conditional correlations between copper and both Euro and SEK currencies show a decrease following the ESDC. The degree of correlations shows a significant increase during the GFC for all currencies. Another upside trend is observed during the COVID-19 crisis, except for the CHF currency. The relationships between currencies and oil prices are positive for almost all the sample periods except Euro and GBP currencies during the pandemic crisis. Table A1 reports the minimum and the maximum of the conditional correlations and their corresponding date for each commodity currency pair. As shown, the highest correlation is influenced by the main events, particularly the GFC. To sum up, the correlations between currencies and commodities show time- and event-specific patterns.

[4] This is the best fitting model among other volatility models (GARCH, GJR-GARCH, and TARCH) that we have tested, and based on the Akaike Information Criterion (AIC) and log-likelihood.

Table 3
Estimate results of total spillovers among forex futures markets.

Return spillovers							
	EUR	JPY	GBP	CAD	CHF	SEK	From
EUR	36.53	2.33	13.39	8.62	17.75	21.39	10.58
JPY	5.09	80.83	0.54	0.41	12.24	0.88	3.19
GBP	17.73	0.39	48.29	11.14	8.63	13.84	8.62
CAD	13	0.25	12.39	55.23	4.96	14.18	7.46
CHF	22.35	6.91	8.25	4.18	45.97	12.34	9.01
SEK	24.28	0.46	11.84	10.62	11.14	41.65	9.73
To	13.74	1.72	7.74	5.83	9.12	10.44	
Net	3.16	−1.47	−0.88	−1.63	0.11	0.71	48.58
Volatility spillovers							
	EUR	JPY	GBP	CAD	CHF	SEK	From
EUR	42.05	13.33	4.37	12.38	13.85	14.01	9.66
JPY	10.91	66.03	8.16	9.29	1.26	4.34	5.66
GBP	13.45	21.42	42.48	12.81	1.31	8.54	9.59
CAD	11.42	25.87	4.04	45.28	8.37	5.03	9.12
CHF	12.29	7.07	0.53	2.14	71.71	6.26	4.71
SEK	21.98	20.07	6.55	14.64	5.68	31.09	11.49
To	11.67	14.63	3.94	8.54	5.08	6.36	
Net	2.01	8.97	−5.65	−0.58	0.37	−5.13	50.29

5.2. Spillover analysis

As a preliminary picture, we estimate the total return and volatility spillovers across currencies (see Table 3).[5] The total aggregate return spillover is 48.58%. The results reveal that shocks to the Euro and Swedish krone currencies impact these two currencies more than the other currencies. In terms of return spillovers, the euro currency is the largest net transmitter to the other currency markets, with a net transmission of 3.16%. As for volatility spillovers, the Japanese yen currency is the largest transmitter to the other currencies. This shows that the yen is no longer a safe haven, and rather the British pound is the calmest of all currencies in the portfolio of the U.S. dollar index. The interesting result reveals that the pound is a net receiver of both returns and volatility spillovers. This result is not in line with the recent findings of Baruník and Kočenda (2019), where the authors find that GBP is a net contributor of spillover to both the Australian dollar, Canadian dollar, Euro, Japanese yen, and Swiss currencies during the period January 2, 2007, to December 31, 2017. This result is explained by two factors. First, unlike our study, the authors used 5-min intraday prices. Second, the authors did not consider two important events, including Brexit and COVID-19 pandemic crisis. We note that the CHF and SEK currencies are net transmitters of return spillovers to the rest of the currencies, whereas CAD and JPY are net receivers of return spillovers in the system.

Looking at the volatility spillovers, the total volatility spillover is 50.29%. More importantly, we find that Euro, JPY, and CHF currencies are net contributors of volatility spillovers whereas GBP, CAD, and SEK are net receivers of volatility in the system. JPY is the highest contributor of volatility spillovers, and CHF is the least one. SEK currency is the highest receiver of volatility spillovers, and CHF currency is the least one. It is worth noting that Euro, GBP, and CAD currencies receive nearly the same proportion of volatility spillovers. More importantly, all currencies are mainly influenced by their own returns and volatility (see the diagonal of the matrix).

We proceed with the analysis of the magnitude and the directional spillovers of foreign currency futures and commodity futures. Table 4 reports the estimated results of total return and volatility spillovers between currencies and commodities. As we can see, we show that the

[5] The dynamic net return spillover index is calculated by subtracting directional 'to' spillovers from directional 'from' spillovers. For Net raw, the positive (negative) values indicate a source (recipient) of return and volatility to (from) others.

Table 4
Total spillovers: forex and global commodities.

Currencies and Gold – Return spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Gold	From
EUR	35.06	2.25	12.79	8.24	17.01	20.46	4.18	9.28
JPY	4.93	77.81	0.52	0.38	11.81	0.85	3.69	3.17
GBP	17.11	0.37	46.84	10.77	8.31	13.33	3.28	7.59
CAD	12.38	0.23	11.82	52.8	4.72	13.5	4.56	6.74
CHF	21.24	6.59	7.81	3.96	43.78	11.69	4.93	8.03
SEK	23.45	0.46	11.39	10.25	10.74	40.34	3.38	8.52
Gold	7.76	3.23	4.45	5.79	7.51	5.32	65.95	4.86
To	12.41	1.88	6.97	5.63	8.59	9.31	3.43	
Net	3.13	−1.29	−0.62	−1.11	0.56	0.79	−1.43	48.21

Currencies and Gold – Volatility spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Gold	From
EUR	40.67	12.70	3.99	11.39	11.89	12.18	7.18	8.48
JPY	8.97	61.72	7.45	8.85	0.75	4.13	8.14	5.47
GBP	12.05	20.79	39.46	11.32	0.73	8.67	6.99	8.65
CAD	10.36	24.90	3.36	40.38	6.43	4.68	9.88	8.52
CHF	10.23	5.35	0.29	1.69	73.03	4.16	5.25	3.85
SEK	20.39	18.99	6.49	13.34	4.08	28.96	7.75	10.15
Gold	5.08	19.96	1.89	2.96	1.81	2.46	65.84	4.88
To	9.58	14.67	3.35	7.08	3.67	5.18	6.46	
Net	1.10	9.20	−5.30	−1.44	−0.18	−4.97	1.58	49.99

Currencies and Wheat – Return spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Wheat	From
EUR	36.11	2.31	13.26	8.53	17.56	21.14	1.1	9.13
JPY	5.10	80.75	0.55	0.41	12.23	0.88	0.08	2.75
GBP	17.57	0.38	47.8	11.01	8.55	13.71	0.98	7.46
CAD	12.65	0.24	12.03	53.71	4.83	13.8	2.73	6.61
CHF	22.23	6.87	8.21	4.16	45.71	12.27	0.53	7.76
SEK	23.9	0.46	11.67	10.47	10.97	41.00	1.52	8.43
Wheat	2.56	0.07	1.71	4.32	1.06	3.23	87.05	1.85
To	12.00	1.48	6.78	5.56	7.89	9.29	0.99	
Net	2.87	−1.27	−0.68	−1.05	0.13	0.86	−0.86	43.98

Currencies and Wheat – Volatility spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Wheat	From
EUR	40.22	12.14	4.69	12.16	11.49	12.87	6.42	8.54
JPY	9.39	64.14	8.33	10.40	0.85	4.70	2.19	5.12
GBP	12.87	21.95	40.95	12.89	0.95	9.55	0.83	8.44
CAD	9.91	24.33	4.13	42.53	6.12	5.22	7.76	8.21
CHF	9.85	4.85	0.44	2.04	74.45	4.50	3.87	3.65
SEK	20.38	18.94	7.32	14.58	4.07	30.52	4.19	9.93
Wheat	1.12	0.67	0.13	10.36	0.19	0.71	86.82	1.88
To	9.07	11.84	3.58	8.92	3.38	5.36	3.61	
Net	0.53	6.72	−4.86	0.71	−0.27	−4.57	1.73	45.77

Table 4. (*continued*)

Currencies and Copper – Return spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Copper	From
EUR	35.53	2.28	13.01	8.37	17.3	20.8	2.71	9.21
JPY	5.05	79.51	0.55	0.39	12.05	0.88	1.58	2.93
GBP	17.06	0.38	46.51	10.72	8.33	13.31	3.69	7.64
CAD	11.92	0.22	11.37	50.71	4.54	12.99	8.26	7.04
CHF	22.11	6.83	8.18	4.12	45.42	12.2	1.13	7.8
SEK	23.21	0.45	11.31	10.13	10.67	39.82	4.41	8.6
Copper	5.15	1.28	5.17	10.94	1.74	7.47	68.25	4.54
To	12.07	1.63	7.08	6.38	7.8	9.66	3.11	
Net	2.86	−1.3	−0.56	−0.66	0.00	1.06	−1.43	47.75

Currencies and Copper – Volatility spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Copper	From
EUR	41.16	13.04	4.02	12.26	12.47	12.74	4.32	8.41
JPY	9.71	63.63	7.49	9.21	0.95	4.39	4.62	5.20
GBP	12.67	21.43	39.78	11.06	0.89	8.79	5.39	8.60
CAD	10.61	24.50	3.05	37.67	6.59	4.48	13.09	8.90
CHF	11.08	5.86	0.43	2.98	72.56	5.37	1.71	3.92
SEK	20.84	19.16	6.29	13.10	4.42	28.89	7.31	10.16
Copper	7.19	17.89	0.54	9.14	1.36	3.70	60.17	5.69
To	10.30	14.56	3.12	8.25	3.81	5.64	5.21	
Net	1.89	9.36	−5.48	−0.65	−0.11	−4.52	−0.48	50.88

Currencies and Oil – Return spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Oil	From
EUR	36.11	2.31	13.23	8.51	17.54	21.13	1.17	9.13
JPY	5.01	79.24	0.54	0.4	12.02	0.86	1.93	2.97
GBP	17.23	0.38	46.96	10.83	8.38	13.45	2.77	7.58
CAD	11.95	0.23	11.39	50.79	4.55	13.03	8.06	7.03
CHF	22.28	6.9	8.22	4.16	45.85	12.29	0.29	7.74
SEK	23.67	0.45	11.54	10.35	10.85	40.61	2.52	8.48
Oil	2.36	1.73	4.35	11.82	0.38	4.59	74.77	3.60
To	11.78	1.72	7.04	6.58	7.67	9.34	2.39	
Net	2.65	−1.25	−0.54	−0.45	−0.07	0.86	−1.21	46.52

Currencies and Oil – Volatility spillovers

	EUR	JPY	GBP	CAD	CHF	SEK	Oil	From
EUR	22.38	9.18	1.93	9.60	4.97	7.74	44.20	11.09
JPY	9.70	62.90	7.60	10.86	1.01	4.78	3.15	5.30
GBP	3.34	10.44	15.31	6.77	0.11	3.59	60.45	12.10
CAD	6.42	19.60	2.07	33.22	3.41	3.74	31.53	9.54
CHF	4.28	3.85	0.09	2.02	38.19	2.29	49.28	8.83
SEK	8.58	11.80	2.75	9.70	0.80	15.64	50.73	12.05
Oil	0.10	1.24	0.46	0.84	0.72	0.09	96.56	0.49
To	4.63	8.01	2.13	5.69	1.57	3.17	34.19	
Net	−6.46	2.71	−9.97	−3.85	−7.26	−8.88	33.70	59.40

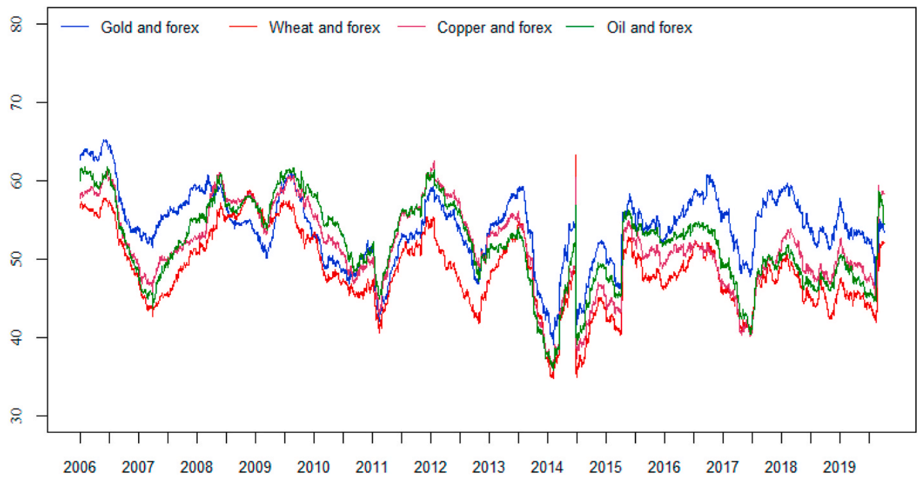

Fig. 3. Dynamic total return spillover between major commodities and forex markets.

magnitude of total return spillovers decreases when commodity futures are added to the currency portfolio. The same result is obtained for volatility spillovers except for oil and copper cases. More precisely, the estimated lowest return and volatility spillovers happen when the wheat asset is added to the currency portfolio (43.98% and 45.77%, respectively). In addition, the four commodities' own volatilities are dominating in comparison to the currencies. The GBP currency is the largest net receiver of volatility spillover from gold, wheat, copper, and gold. It remains not on par with the EUR and JPY, as they are net transmitters of volatility to oil.

The extent of return spillover of shocks to the four commodities is less than the shocks to currencies to the same commodities. However, the volatility spillover shows different pictures. The own volatility for crude oil (96.56%) is much larger than that of gold (65.84%), wheat (86.82%), and copper (60.17%). This indicates that crude oil prices are significantly affected by oil's own shocks, which can be mainly from shocks in the demand and supply as well as OPEC decisions. The bidirectional spillover reveals that oil is the largest contributor and source of volatility to other currency markets compared to the other commodity futures. More precisely, oil transmits 34.19% of volatility spillover to other currencies while receiving a negligible percentage of volatility from currencies (0.49%). The estimation results indicate that, among the global commodities, copper is the only net receiver of volatility.

Looking at some specific cases, JPY currency transmits much more volatility shocks to gold and copper than the remaining currencies. It is worth noting that the yen currency is the third most traded currency in the foreign exchange market, after the greenback and the Euro. In addition, it is the second most widely held currency by the Bank of Japan, after the U.S. dollar. The yen is one of the most important alternatives to the U.S. dollar among fiat currencies, explaining thus the positive relationship between the yen and gold. We notice that both gold and yen currency are negatively correlated with the greenback and both are considered safe havens. On the other hand, the electrolytic copper demand in Japan amounted to 53.94 thousand tons in 2019, an increase from about 44.2 thousand tons in 2015.[6] Japan is planning to ramp up government control over strategic reserves of 34 ″rare metals" and increase inventories of some strategically vital metals as measures to monitor potential supply risks from geopolitical instability or future pandemics.

GBP and CHF are resistant to shocks to all commodities, and their returns and volatilities do not transmit to all commodities, as opposed to the other currencies. The wheat market receives a large portion of return and risk from CAD currency rather than the rest of the currencies. It is worth noting that Canada is one of the large wheat producers. We also notice that there are weak or insignificant volatility spillovers from currencies to crude oil. In contrast, we find evidence of volatility shocks from oil to currency markets except for JPY. This result reveals a strong link between crude oil prices and EUR, GBP, CAD, CHF, and SEK rates and that JPY serves as a safe haven currency. There is a balanced bidirectional return spillover between gold, Euro, and Swiss franc from another angle. In contrast, return shocks from CAD affect largely copper and oil, which Canada's major commodity-exporting country could drive. CAD has a tight correlation with commodities like copper and oil, whereas JPY is affected by gold and copper commodity prices.

Fig. 3 displays the dynamic return spillovers among forex markets and commodity markets. As we can see, the total return spillovers are time-varying along the whole sample period.[7] Moreover, the evolving return spillovers show event-specific patterns. We observe that the dynamics of spillovers of each pair of commodity-forex portfolios are evolving and follow the same pattern. Besides, the graphical evidence shows the presence of short-run trends and large levels of spillovers. The return spillover ranges between low values (around 32%), associated with the pair wheat-forex, and higher values (around 60%) associated with the pair gold-forex. Obviously, the GFC, oil price crash, and COVID-19 pandemic have intensified the return spillover index. Along with the forex markets, the four commodities have witnessed an increase in connectedness during the 2012 ESDC and a decrease between 2013 and mid-2014, corresponding to the economic recovery period. The same levels continued until the end of 2015 when the spillover indices jumped dramatically. This could have been the consequence of the black Monday in China and the great oil bust between mid-2014 and 2016. At the beginning of 2018Q2, the trade war and tariffs hike has driven the connectedness between commodities and forex markets to another increase. More interestingly, we observe a new jump in spillover strengths in the early break of the COVID-19 pandemic crisis, and where both return and volatility spillovers between major global commodities and forex markets recorded a sudden jump.

Understanding such market movements, magnitude, and directional spillovers is important for both currency and commodity traders to allocate weights to their portfolios better and adjust their position against risk exposure. Fig. 4 illustrates the evolving volatility spillovers between currencies and commodities. The graphical evidence shows that, by combining oil to a set of currencies, the total volatility

[6] https://www.statista.com/statistics/819832/japan-electrolytic-copper-consumption-volume/.

[7] To be consistent with the existing literature (Diebold and Yılmaz, 2012; and Baruník et al., 2017), we have selected a 200-day rolling window and 10-day forecasting horizon for the construction of spillover indices.

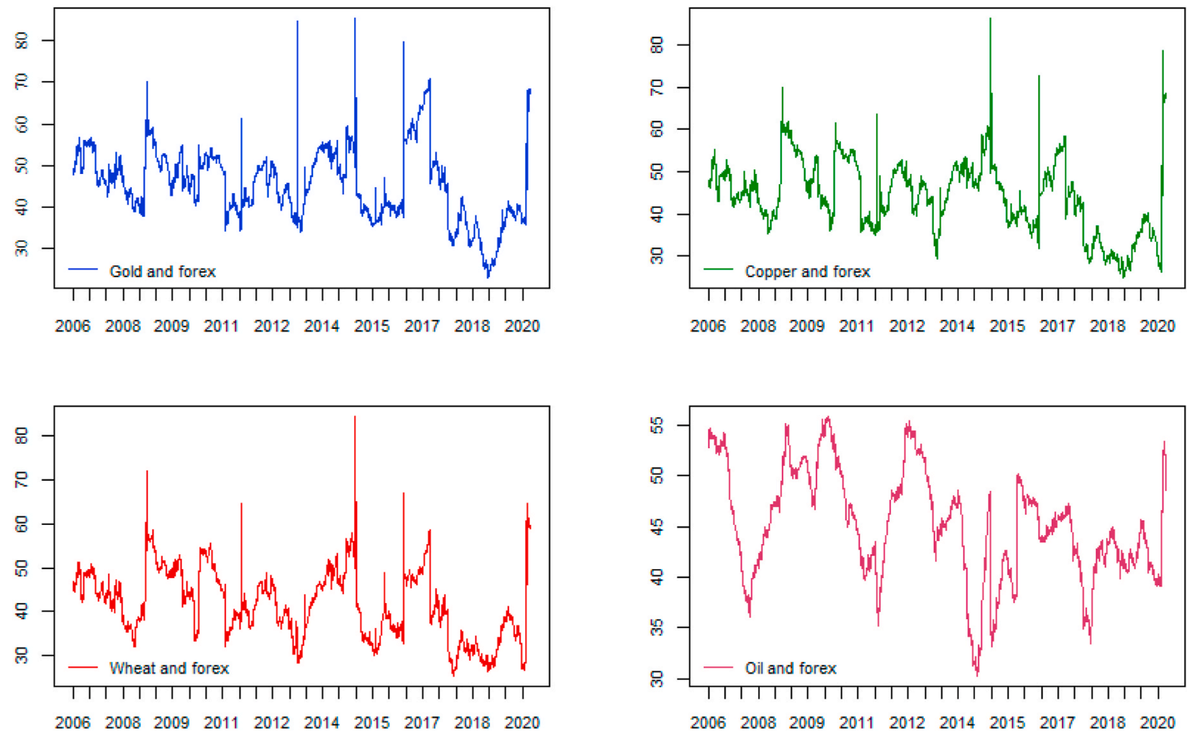

Fig. 4. Dynamic total volatility spillover between major commodities and forex markets.

connectedness dynamically evolves within a lower band than that by combining other commodities with currency markets. There is an increase in volatility spillovers during times of GFC, ESDC, oil price crash, and COVID-19, indicating that the dynamic volatility spillovers are crisis-sensitive. The results show that adding wheat to the forex markets provides a lower total connectedness along the sample period compared to gold, copper, and crude oil. This result indicates that wheat brings stability to a currency portfolio. Therefore, investors would look at a mix of wheat commodity and forex portfolio that provides stability in dynamically revising their portfolio weights.

We now examine the role of adding commodities to a currency portfolio and check whether they are net transmitters or receivers of returns (Panel a of Fig. 5) and volatility (Panel b of Fig. 5).[8] Looking at panel a of Fig. 5, we observe an asymmetric return spillover between each commodity and the forex markets. This asymmetry is due to positive as well as negative shocks from commodities to forex markets. However, there is clear evidence that positive shocks have the largest asymmetric effects on return spillovers between commodities and forex markets than negative shocks. We also identify a visible pattern of negative spillovers between each commodity and the forex markets between 2012 and mid-2014, indicating that gold, wheat, copper, and oil are net receivers of return spillover in the commodity-forex nexus. Additionally, a large negative spike can be observed in the return spillovers between all commodities and the forex markets, which is due to the large drop in oil prices. During GFC and COVID-19 outbreak, we observe that commodities are net contributors to return spillovers.

As for net volatility spillovers (Panel b of Fig. 5), we observe more negative asymmetry dominance than a positive one. Commodities are net receivers of volatility from currency markets. For instance, there is a similar asymmetries pattern in volatility spillover in all commodity-forex portfolios to the oil price bust in 2014. This result confirms the findings that the conditional volatility spillovers in commodity-currency nexus are asymmetric and bidirectional. It is also interesting to observe that oil is a net receiver of volatility from currency markets along the sample period except when the oil price dropped in 2014 and 2020. This suggests that sudden drops in oil prices have an immediate impact on increasing the volatility spillover. This result is consistent with Baruník and Kočenda (2019) who conclude that oil contributes to lower asymmetry in volatility spillover in forex markets.

5.3. The impact of frequency, uncertainty, and liquidity on directional and extent of spillovers

The time horizon is a key factor when designing trading strategies (Mensi et al., 2021). Specifically, traders and arbitrageurs are interested in short-term spillovers, whereas institutional investors are concerned by long-term spillovers. To provide accurate information to different market participants, it is thus interesting to examine the spillovers between commodities and currencies at multiple frequencies (or time investment horizons) using the methodology by Baruník and Křehlík (2018). We notice that the selected frequencies represent different time horizons for investors, namely the short-term horizon, from one to 5 days, medium-term horizon, from 5 to 20 days, and long-term horizon, from 20 to 300 days. Both return and volatility frequency spillovers between each commodity and forex markets are displayed in Fig. 6 a and Fig. 6 b, respectively.

Looking at the return spillovers, we show that the dynamics of medium- and long-term return spillovers are the lowest compared to their short-term spillovers counterpart and for all commodity-forex portfolios. This result reveals that the short-term return spillover constitutes the major part of the total return spillovers, whereas the medium- and long-term form the minor parts of the total return spillovers. For the oil-forex portfolio, the graphical evidence reveals a sharp increase in the long-term connectedness relative to both the medium- and short-term during the spark of the COVID-19 outbreak. The pandemic has undermined the global oil demand, and there was a big sell-off of the crude oil

[8] The total volatility spillover is decomposed into two directions: the first is for transmitters (to others) and the second for receivers (from others). The net directional volatility spillover is obtained by deducting the spillover 'to others' from the spillover 'to others'. Negative estimates indicate that the commodity in question is a net receiver of volatility spillover, and positive estimates indicate the opposite.

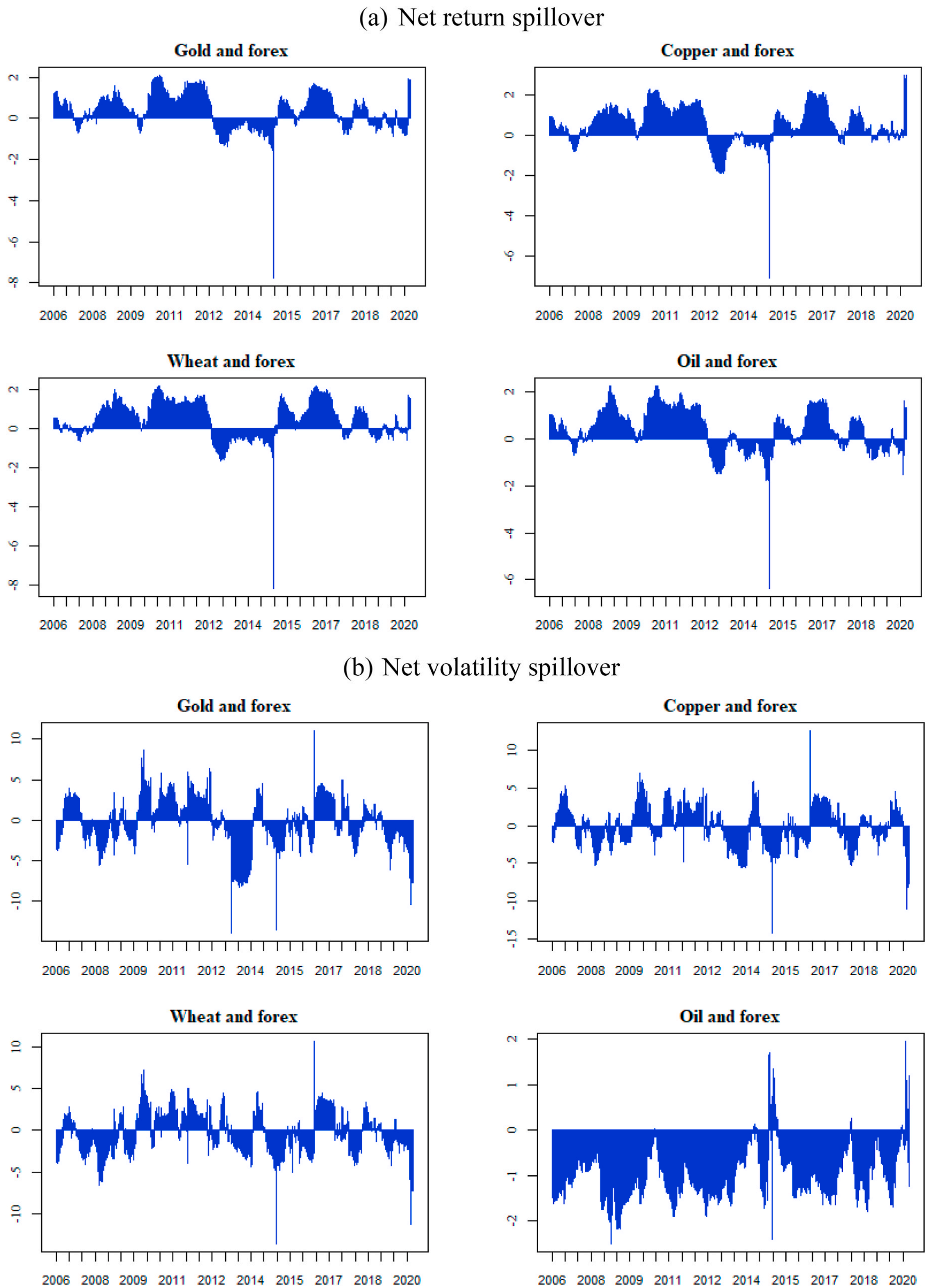

Fig. 5. Dynamic net return and volatility spillovers between major commodities and forex markets.

futures. Similarly, we observe a jump in long-term return spillovers for the copper-forex portfolio during the GFC and oil crash. In contrast, the medium-term return spillovers show an upside trend during the COVID-19 pandemic crisis for both gold-forex and wheat-forex portfolios.

The previous findings are reversed when we look at the time-varying volatility spillovers (panel b of Fig. 6). The long-term connectedness constitutes the major part of the total volatility connectedness, compared to the short- and medium-term spillovers. The long-term

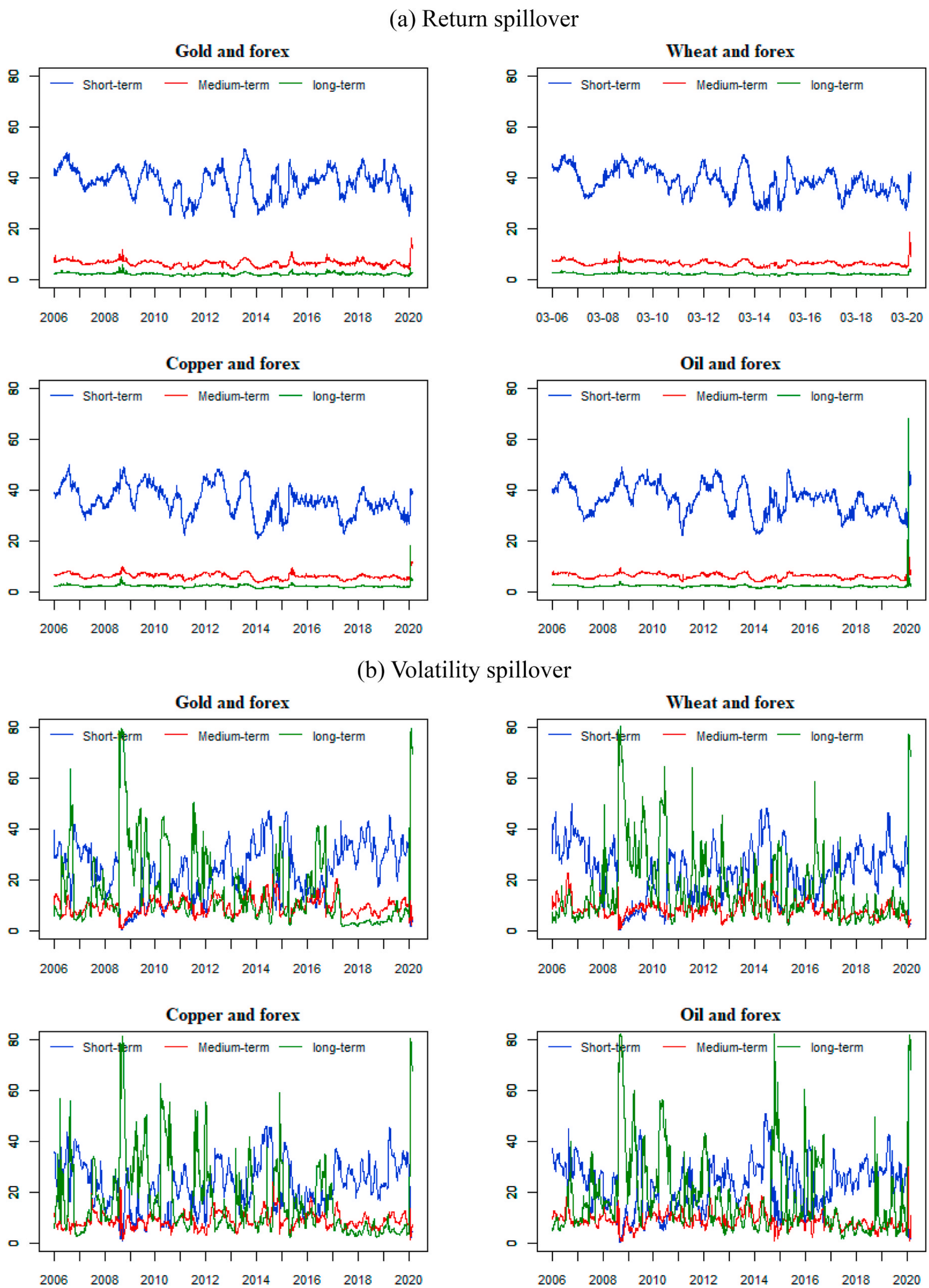

Fig. 6. Dynamic frequency spillovers in return and volatility between commodity and currency markets.

spillover makes 86% of the total spillover for the gold-forex portfolio, 67% for the wheat-forex portfolio, 56.7% for the copper-forex portfolio, and 82.5% for the crude oil-forex portfolio. In addition, we observe that the long-term connectedness dramatically increases during turmoil periods, such as the 2008–2009 GFC, the 2014 oil price bust, and the COVID-19 pandemic crisis. During tranquil market periods, we observed a prevalence of short-term volatility connectedness. It is, therefore, obvious that investors have heterogeneous expectations, perceptions,

Table 5
Volatility uncertainty shocks and frequency spillovers estimation.

Return spillover												
	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	VIX	R^2	Const.	VIX	R^2	Const.	VIX	R^2	Const.	VIX	R^2
Short-term	39.117*	**−0.043***	0.056	36.215*	**0.129***	0.056	32.839*	**0.159***	0.068	33.175*	**0.172***	0.083
	(0.207)	(0.009)		(0.190)	(0.008)		(0.213)	(0.010)		(0.206)	(0.009)	
Medium-term	6.224*	0.019*	0.023	5.872*	0.039*	0.117	5.325*	0.039*	0.124	5.505*	0.033*	0.099
	(0.045)	(0.002)		(0.039)	(0.002)		(0.037)	(0.001)		(0.035)	(0.001)	
Long-term	2.071*	0.015*	0.138	2.071*	0.015*	0.138	1.714*	0.024*	0.188	1.685*	0.027*	0.047
	(0.014)	(0.000)		(0.014)	(0.000)		(0.018)	(0.000)		(0.044)	(0.002)	
Volatility spillover												
	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	VIX	R^2	Const.	VIX	R^2	Const.	VIX	R^2	Const.	VIX	R^2
Short-term	36.171*	−0.662*	0.373	34.697*	−0.604*	0.321	32.128*	−0.496*	0.274	32.136*	−0.496*	0.261
	(0.309)	(0.014)		(0.317)	(0.015)		(0.291)	(0.014)		(0.301)	(0.014)	
Medium-term	12.085*	−0.118*	0.118	10.326*	−0.075*	0.030	9.748*	−0.047*	0.023	9.507*	−0.045*	0.021
	(0.117)	(0.005)		(0.124)	(0.005)		(0.110)	(0.005)		(0.114)	(0.005)	
Long-term	−3.759*	**1.028***	0.453	−1.781*	**0.942***	0.305	−1.162*	**0.930***	0.374	−0.505*	**0.962***	0.373
	(0.407)	(0.018)		(0.389)	(0.018)		(0.434)	(0.020)		(0.449)	(0.020)	

Notes: This table presents the estimation results of return and volatility spillovers (short-, medium-, and long-term) on uncertainty shocks represented by VIX, the volatility index. In parenthesis are reported the standard errors. * denotes significance at 1% level. Numbers highlighted in bold indicate the highest effect (in absolute terms).

Table 6
Liquidity shocks and frequency spillovers estimation.

Return spillover												
	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	TED	R^2	Const.	TED	R^2	Const.	TED	R^2	Const.	TED	R^2
Short-term	37.409*	**1.912***	0.024	37.954*	**1.643***	0.020	35.126*	**1.712***	0.017	36.033*	**1.007***	0.006
	(0.130)	(0.202)		(0.123)	(0.191)		(0.139)	(0.215)		(0.137)	(0.212)	
Medium-term	6.329*	0.600*	0.048	6.514*	0.261*	0.011	5.932*	0.331*	0.019	6.053*	0.184*	0.007
	(0.028)	(0.044)		(0.026)	(0.040)		(0.025)	(0.039)		(0.023)	(0.037)	
Long-term	2.230*	0.279*	0.076	2.294*	0.165*	0.035	2.087*	0.202*	0.029	2.177*	0.066*	0.006
	(0.010)	(0.016)		(0.009)	(0.014)		(0.012)	(0.019)		(0.028)	(0.044)	
Volatility spillover												
	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	TED	R2	Const.	TED	R2	Const.	TED	R2	Const.	TED	R2
Short-term	25.495*	−4.451*	0.037	24.009*	−2.009*	0.007	23.958*	−2.956*	0.021	24.257*	−3.614*	0.030
	(0.244)	(0.378)		(0.243)	(0.377)		(0.215)	(0.333)		(0.219)	(0.340)	
Medium-term	10.305*	−1.072*	0.021	9.029*	−0.316*	0.001	8.835*	0.010	0.000	8.840*	−0.454*	0.004
	(0.078)	(0.120)		(0.080)	(0.005)		(0.071)	(0.110)		(0.073)	(0.113)	
Long-term	12.399*	**7.822***	0.058	14.307*	**4.348***	0.020	13.665*	**6.608***	0.042	14.844*	**6.813***	0.041
	(0.340)	(0.527)		(0.325)	(0.504)		(0.341)	(0.529)		(0.353)	(0.548)	

Notes: This table presents the estimation results of return and volatility spillovers (short-, medium-, and long-term) on liquidity shocks represented by TED spread, the difference between the interest rate on short-term U.S. government debt and the interest rate on interbank loans. In parenthesis are reported the standard errors. * denotes significance at 1% level. Numbers highlighted in bold indicate the highest effect (in absolute terms).

and risk appetites. These results are in line with the findings of Baruník and Kočenda (2019). This may suggest that investors and portfolio managers link their long-term investments with perspectives on economic indicators.

To better understand the differences in the frequency return and volatility spillovers, we analyze the key factors that may drive the magnitude of connectedness. Traders' and investors' perceptions of financial and economic stability and perspectives are heterogeneous. We looked at three major economic barometers: the Chicago Board Options Exchange (CBOE) volatility index (VIX), the credit risk indicator Treasury-Euro Dollar (TED), and the US economic policy uncertainty index (EPU).[9] These indicators contain pertinent information for a wide range of decision-makers. The VIX index represents the market's expectations for the relative strength of the S&P 500 index's near-term price changes. The VIX index affects the movement of the US stock market price and the US Dollar index (Fratzscher, 2009; Ma et al., 2018) as well as commodity prices (Dutta et al., 2021). The EPU exerts a significant effect on currency and commodity returns and volatilities (Al-Yahyaee et al., 2020; Jiang et al., 2021; Ma et al., 2019). In addition, the rise in EPU reduces investment (Suh and Yang, 2021). The TED spread is a proxy of credit risk. It acts as a leading 'fear' indicator and adjusts to new information rapidly during the crisis (Cheung et al., 2010).

Table 5, 6, and 7 report the estimation results of the impacts of volatility uncertainty, liquidity, and economic policy uncertainty on the frequency connectedness between the global major commodities and forex markets, respectively. We show that the effect of liquidity shocks is stronger than the EPU and VIX indexes for both return and volatility spillovers. Strikingly, the effect of liquidity shocks on return is a sizable increase in connectedness in the short-term than in both medium- and long-terms. This joins the earlier observation that the total return spillovers are mainly driven by short-term connectedness. We also observe that long-term volatility connectedness is highly affected by

[9] The daily news-based EPU index uses newspaper archives from Access World News Bank service. It is developed by Baker *et al.* (2016) to measure the degree of uncertainty in the US economy. The data comes from the website: www.policyuncertainty.com, and is expressed in logarithmic terms.

Table 7
Economic policy uncertainty shocks and frequency spillovers estimation.

Return spillover	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	EPU	R^2	Const.	EPU	R^2	Const.	EPU	R^2	Const.	EPU	R^2
Short-term	34.243*	**0.887***	0.009	32.538*	**1.355***	0.024	35.205*	**1.033***	0.011	30.721*	**1.268***	0.017
	(0.714)	(0.155)		(0.668)	(0.145)		(0.755)	(0.164)		(0.737)	(0.160)	
Medium-term	4.325*	0.501*	0.059	4.471*	0.475*	0.065	4.334*	0.384*	0.045	4.762*	0.302*	0.032
	(0.154)	(0.033)		(0.139)	(0.030)		(0.136)	(0.029)		(0.127)	(0.027)	
Long-term	1.827*	0.116*	0.023	1.743*	0.137*	0.042	1.213*	0.212*	0.056	1.055*	0.253*	0.016
	(0.058)	(0.012)		(0.050)	(0.011)		(0.067)	(0.014)		(0.153)	(0.033)	
Volatility spillover												
	Gold and forex			Wheat and forex			Copper and forex			Oil and forex		
	Const.	EPU	R^2	Const.	EPU	R^2	Const.	EPU	R^2	Const.	EPU	R^2
Short-term	29.908*	−1.417*	0.006	25.752*	−0.586*	0.011	29.879*	−1.598*	0.011	24.954*	−0.516*	0.001
	(1.342)	(0.292)		(1.324)	(0.288)		(1.170)	(0.255)		(1.207)	(0.263)	
Medium-term	14.392*	−1.005*	0.033	10.888*	−0.440*	0.006	12.110*	−0.718	0.021	11.227*	−0.570*	0.012
	(0.419)	(0.091)		(0.434)	(0.094)		(0.380)	(0.082)		(0.394)	(0.085)	
Long-term	−3.802*	**4.347***	0.031	3.505*	**2.811***	0.014	−3.876*	**4.519***	0.034	3.025*	**3.282***	0.017
	(1.867)	(0.407)		(1.766)	(0.384)		(1.857)	(0.404)		(1.938)	(0.422)	

Notes: This table presents the estimation results of return and volatility spillovers (short-, medium-, and long-term) on economic policy uncertainty shocks represented by EPU. In parenthesis are reported the standard errors. * denotes significance at 1% level. Numbers highlighted in bold indicate the highest effect (in absolute terms).

liquidity shocks rather than by uncertainty shocks, whether due to economic policy or volatility uncertainty index. Liquidity shocks are associated with an increase in volatility connectedness in the long term and decreased volatility connectedness in the short- and medium-term. We can conjecture that investors would now perceive an economic instability in the long term, which may make sense in light of the uncertainty and liquidity risk triggered by the recent pandemic. It is worth noting that the level of change of flow of information (EPU) has a significant impact on short-term return spillover and long-term volatility spillover.

6. Conclusion

Commodity and Forex markets have seen tremendous growth in the world over the past several years. The occurrence of financial, energy, and health system crises has significantly increased the uncertainty in these markets. This paper examines the multiscale return and volatility connectedness between four global commodity futures markets – gold, wheat, copper, and crude oil and the components of the U.S. dollar index (USDX) foreign exchange markets, namely the Euro, Japanese yen, British pound, Canadian dollar, Swiss franc, and Swedish krona. We employ the spillover index methodology by Diebold and Yılmaz (2012) for time-domain analysis and Baruník and Křehlík (2018) for time-frequency domain analysis. For both analyses, we estimate the time-varying directional and size spillover by adding one commodity at a time to a currency portfolio.

The results show evidence of significant return and volatility spillovers across six main currency markets. Specifically, the euro currency is the largest net transmitter of returns to the other currency markets. The Japanese yen currency is the largest transmitter of volatility to the other currencies. Moreover, the magnitude of total return and volatility spillovers decreases when commodity futures are added to the currency portfolio except for oil and copper cases. Oil is the largest contributor and source of volatility to other currency markets. Among currencies, JPY currency transmits much more volatility shocks to gold and copper than the remaining currencies. GBP and CHF currencies are resistant to shocks to all commodities, and their returns and volatilities do not transmit to all commodities, as opposed to the other currencies. The wheat market receives a large portion of risk from CAD currency rather than the remaining currencies.

More importantly, along with the forex markets, the four commodities have witnessed an increase in connectedness during the 2012 ESDC and a decrease between 2013 and mid-2014, corresponding to the great oil bust. A new jump in spillovers in the early break of the COVID-19 pandemic crisis was observed, and where both return and volatility spillovers between major global commodities and forex markets recorded a sudden jump. By accounting for the time investment horizon (or frequencies), we find that the short-term return spillover dominates the medium- and long-term return spillovers. The long-term volatility connectedness constitutes the major part of the total volatility connectedness. Furthermore, the major events, including the oil price crash, GFC, ESDC, and COVID-19 pandemic, intensify the considered markets' spillover effects.

Moreover, the impacts of liquidity shocks on both return and volatility connectedness are stronger than the uncertainty shocks (VIX and EPU). Interestingly, the effect of liquidity shocks on return is a sizable increase in connectedness in the short term than in both medium- and long-terms. Additionally, the EPU has a significant impact on short-term return spillover and long-term volatility spillovers.

Our results have important implications for commodity traders, policymakers, and portfolio managers at different time horizons. Currency investors should be aware that the return and volatility spillovers are time-varying, crisis-sensitive, and asymmetric. Currency investors hedge their position based on these three stylized facts. Currency investors should pay attention to commodity price changes and their effects on exchange rate movements due to bilateral spillover effects. We recommend currency investors hedge their position by holding gold and wheat since it decreases the linkage risk. More precisely, it is not straightforward to find the right commodity for diversification in a currency portfolio under the short-term horizon. It is, however, beneficial to add wheat commodity to a portfolio of forex markets because the connectedness is lower than that of gold or copper, or crude oil the connectedness in the short-term. Investors should caution that the volatility spillovers between currency and commodity markets are higher in short term and tend to decrease in long term. This indicates that currency investors generate higher diversification gains in long term than in short and intermediate terms and by including wheat futures. The information related to frequency dynamic return and volatility spillovers assists portfolio managers in predicting the behavior of the currency market by having the information of commodity market, and uncertainty indexes, and liquidity shocks.

Policymakers should prevent large currency market impacts from extreme volatility shocks. They should be cautious that the damages of volatility shocks in the FX and commodity markets are absorbed much more quickly in the short and medium terms compared to the long terms. Policymakers should rely on the effects of liquidity shocks, economic uncertainty, and volatility uncertainty to implement their strategies as they are the main drivers of the spillover strengths in currency and commodity markets.

Author statement

Walid Mensi: Conceptualization, Writing- Original draft preparation, Supervision, Reviewing and Editing, **Ramzi Nekhili:** Data curation, Methodology, Software, Visualization, **Xuan Vinh Vo:** Supervision, Visualization, Reviewing and Editing.

Acknowledgment:

This research is partly funded by the University of Economics Ho Chi Minh City, Vietnam.

Appendix

Table A1
Minimum and maximum conditional correlations

	Gold-EUR	Gold-JPY	Gold-GBP	Gold-CAD	Gold-CHF	Gold-SEK
Min	−0.131	−0.718	−0.504	−0.097	−0.010	−0.269
	December 7, 2010	December 12, 2016	6/27/2016	September 9, 2011	3/19/2009	2/21/2020
Max	0.692	0.421	0.593	0.626	0.688	0.712
	9/18/2008	8/20/2007	9/18/2008	11/16/2007	9/24/2008	2/17/2010
	Oil-EUR	Oil-JPY	Oil-GBP	Oil-CAD	Oil-CHF	Oil-SEK
Min	−0.387	−0.414	−0.176	−0.155	−0.452	−0.161
	November 3, 2020	8/25/2008	November 3, 2020	April 2, 2014	November 3, 2020	August 4, 2014
Max	0.642	0.598	0.570	0.766	0.583	0.669
	March 11, 2009	8/20/2007	July 5, 2010	June 10, 2011	March 7, 2012	July 5, 2010
	Copper-EUR	Copper-JPY	Copper-GBP	Copper-CAD	Copper-CHF	Copper-SEK
Min	−0.205	−0.285	−0.176	−0.090	−0.232	−0.327
	11/28/2014	8/25/2008	June 10, 2017	August 1, 2014	November 3, 2020	September 12, 2019
Max	0.685	0.596	0.645	0.684	0.664	0.655
	November 7, 2012	11/23/2007	June 8, 2012	7/24/2012	March 7, 2012	May 5, 2010
	Wheat-EUR	Wheat-JPY	Wheat-GBP	Wheat-CAD	Wheat-CHF	Wheat-SEK
Min	−0.313	−0.281	−0.232	−0.214	−0.304	−0.185
	3/23/2020	8/25/2008	April 5, 2018	10/24/2006	3/23/2020	2/13/2013
Max	0.481	0.359	0.514	0.571	0.507	0.517
	May 3, 2010	3/19/2009	April 6, 2009	November 6, 2009	May 3, 2010	November 3, 2009

Note: This table reports the minimum and the maximum of the conditional correlations for each commodity currency pair and their corresponding date.

References

Abid, A., 2019. Economic policy uncertainty and exchange rates in emerging markets: short and long-run evidence. Finance Res. Lett. 37, 101378.
Al-Yahyaee, K.H., Shahzad, S.J., Mensi, W., 2020. Tail dependence structures between economic policy uncertainty and foreign exchange markets: nonparametric quantiles methods. International Economics 161, 66–82.
Antonakakis, N., Kizys, R., 2015. Dynamic spillovers between commodity and currency markets. Int. Rev. Financ. Anal. 41, 303–319.
Bagheri, E., Ebrahimi, S., 2020. Estimating network connectedness of financial markets and commodities. J. Syst. Sci. Syst. Eng. 29, 572–589.
Baker, S., Bloom, N., Davis, S., 2016. Measuring economic policy uncertainty. The quarterly journal of Economics 131, 1593-1636. In: Baruník, J., Kočenda, E., Vácha, L. (Eds.), 2017. Asymmetric Volatility Connectedness on the Forex Market. Journal of International Money and Finance, vol. 77, pp. 39–56.
Baruník, J., Kočenda, E., Vácha, L., 2016. Gold, oil, and stocks. Dynamic correlations International Review of Economics & Finance 42, 186–201.
Baruník, J., Kočenda, E., Vácha, L., 2017. Asymmetric volatility connectedness on the forex market. J. Int. Money Finance 77, 39–56.
Baruník, J., Kočenda, E., 2019. Total, asymmetric and frequency connectedness between oil and Forex markets. Energy J. 40, 157–174.
Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. J. Financ. Econom. 16, 271–296.
Baur, D.G., Lucey, B.M., 2010. Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ. Rev. 45, 217–229.
Baur, D.G., McDermott, T.K., 2010. Is gold a safe haven? International evidence. J. Bank. Finance 34, 1886–1898.
Cagli, E.C., Taskin, D., Mandaci, P.E., 2019. The short- and long-run efficiency of energy, precious metals, and base metals markets: evidence from the exponential smooth transition autoregressive models. Energy Econ. 84, 104540.
Chen, Y.C., Rogoff, K., 2003. Commodity currencies. J. Int. Econ. 60 (1), 133–160.
Chen, Y., Yang, J., 2021. Trader positions in VIX futures. J. Empir. Finance 61, 1–17.
Cheung, W., Fung, S., Tsai, S., 2010. Global capital market interdependence and spillover effect of credit risk: evidence from the 2007–2009 global financial crisis. Appl. Financ. Econ. 85–103.
Daskalaki, C., Skiadopoulos, G., 2011. Should investors include commodities in their portfolios, after all? New evidence. J. Bank. Finance 35, 2606–2626.
Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ. J. 119, 158–171.
Diebold, F.X., Yılmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28, 57–66.
Dutta, A., Bouri, E., Saeed, T., 2021. News-based equity market uncertainty and crude oil volatility. Energy 222, 119930.
Fernandez-Perez, A., Frijns, B., Tourani-Rad, A., 2017. Precious metals, oil, and the exchange rate: contemporaneous spillovers. Appl. Econ. 49, 3863–3879.
Ferraro, D., Rogo, K., Rossi, B., 2015. Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. J. Int. Money Finance 54, 116–141.
Fratzscher, M., 2009. What explains global exchange rate movements during the financial crisis? J. Int. Money Finance 28, 1390–1407.
Fratzscher, M., Schneider, D., Van Robays, I., 2014. Oil Prices, Exchange Rates, and Asset Prices. ECB Working paper no. 1689. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1689.pdf.
Gorton, G., Rouwenhorst, K.G., 2006. Facts and fantasies about commodity futures. Financial Analysis Journal 62, 47–68.
Guo, Y., Yao, S., Cheng, H., Zhu, W., 2020. China's copper futures market efficiency analysis: based on nonlinear Granger causality and multifractal methods. Resour. Pol. 68, 101716.
Hammoudeh, S., Yuan, Y., McAleer, M., Thompson, M.A., 2010. Precious metals–exchange rate volatility transmissions and hedging strategies. Int. Rev. Econ. Finance 19, 633–647.
He, X., Hamori, S., 2021. Is volatility spillover enough for investor decisions? A new viewpoint from higher moments. J. Int. Money Finance 116, 102412.
Hicks, J.R., 1939. Value and Capital. Clarendon Press, Oxford, UK.
Huang, J., Cheng, H., Guo, Y., Shao, L., 2012. An empirical research on U.S. dollar, oil, and metal prices based on the VAR model. J. Econ. Surv. 3, 45–49.
Hung, N., Vo, X.V., 2021. Directional spillover effects and time-frequency nexus between oil, gold and stock markets: evidence from pre and during COVID-19 outbreak. Int. Rev. Financ. Anal. 76, 101730.
Jiang, Y., Wu, L., Tian, G., Nie, H., 2021. Do cryptocurrencies hedge against EPU and the equity market volatility during COVID-19? – new evidence from quantile coherency analysis. J. Int. Financ. Mark. Inst. Money 72, 101324.
Keynes, J.M., 1930. A Treatise on Money. MacMillan, London.
Kohlscheen, E., Avalos, F.H., Schrimpf, A., 2017. When the walk is not random: commodity prices and exchange rates. International Journal of Central Banking 13 (2), 121–158.

Krol, R., 2014. Economic policy uncertainty and exchange rate volatility. Int. Finance 17, 241–256.
Ma, X., Yang, Z., Xu, X., Wang, C., 2018. The impact of Chinese financial markets on commodity currency exchange rates. Global Finance J. 37, 186–198.
Ma, R., Zhou, C., Cai, H., Deng, C., 2019. The forecasting power of EPU for crude oil return volatility. Energy Rep. 5, 866–873.
Meese, R.A., Rogoff, K., 1983. Empirical exchange rate models of the seventies: do they fit out of sample? J. Int. Econ. 14, 3–24.
Mensi, W., Hammoudeh, S., Nguyen, D.K., Yoon, S.M., 2014. Dynamic spillovers among major energy and cereal commodity prices. Energy Econ. 225–243.
Mensi, W., Hernandez, J.A., Yoon, S.M., Vo, X.V., Kang, S.H., 2021. Spillovers and connectedness between major precious metals and major currency markets: the role of frequency factor. Int. Rev. Financ. Anal. 74, 101672.
Nelson, D.B., 1991. Conditional heteroscedasticity in asset returns: a new approach. Econometrica 59, 347–370.
Nekhili, R., Altay-Salih, A., Gencay, R., 2002. Exploring exchange rate returns at different time horizons. Phys. Stat. Mech. Appl. 313, 671–682.
Qian, Y., Ralescu, D.A., Zhang, B., 2019. The analysis of factors affecting global gold price. Resour. Pol. 64, 101478.
Reboredo, J.C., 2013. Is gold a safe haven or a hedge for the U.S. dollar? Implications for risk management. J. Bank. Finance 37, 2665–2676.
Shahzad, S.J.H., Rehman, M.U., Jammazi, R., 2019. Spillovers from oil to precious metals: quantile approaches. Resour. Pol. 61, 508–521.
Suh, H., Yang, J., 2021. Global uncertainty and global economic policy uncertainty: different implications for firm investment. Econ. Lett. 200, 109767.
Tian, S., Hamori, S., 2016. Time-varying price shock transmission and volatility spillover in foreign exchange, bond, equity, and commodity markets: evidence from the United States. N. Am. J. Econ. Finance 38, 163–171.
Todorova, N., Worthington, A., Souček, M., 2014. Realized volatility spillovers in the non-ferrous metal futures market. Resour. Pol. 39, 21–31.
Wang, H., Li, S., 2021. Asymmetric volatility spillovers between crude oil and China's financial markets. Energy 233, 121168.
Wang, Y., Zhang, Z., Li, X., Chen, X., Wei, Y., 2020. Dynamic return connectedness across global commodity futures markets: evidence from time and frequency domains. Phys. Stat. Mech. Appl. 542, 123464.
Wu, C., Chung, H., Chang, Y., 2012. The economic value of co-movement between oil price and exchange rate using copula-based GARCH models. Energy Econ. 34, 270–282.
Zhang, H.J., Dufour, J.M., Galbraith, J.W., 2016. Exchange rates and commodity prices: measuring causality at multiple horizons. J. Empir. Finance 36, 100–120.