Spillover effects between commodities and currencies commodities

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Abstract. The paper identifies the volatility spillover effects between commodities and commodity currencies. These findings give better information about the transmissions of shocks between commodities and commodity currencies. The research is provided on a time-varying approach regarding the method of Diebold and Yilmaz (2009, 2012) and Ando et al. (2018). We identify commodities that transmit volatility to the commodity currencies but also currencies that receive volatility from commodities. Further, we bring evidence that commodity currencies react faster on shocks than commodities but in the longer term obtain volatility from these commodities during periods of economic turbulence. The study gives concrete investment recommendations for investors having their assets denominated in currencies and commodities.

Keywords: connectedness, commodities, exchange rates.

1. Introduction

The importance of the effects of volatility transmissions was highlighted by the Great financial crisis as the risk was spread over the countries. These effects rapidly increase during crises (3,4). The more global economic-policy shock is, the more the markets are interconnected, and the more asset classes are affected (5). However, shocks could be also connected to some local factors or specific assets. There are several studies about the negative effect of oil price drops on the currencies of countries that export oil (6,7). Currencies of the emerging countries are more connected to political shocks because of the vulnerable political situation in these regions.

In order to better watch the effects of transmission with the direct origins of these shocks, Diebold and Yilmaz (2009) created a method (DYCI). They started measuring volatility transmitted from one asset to other on a dynamic sample using a time-varying approach. The method is aimed at forecast error decomposition using vector autoregressions. It is able to identify the origins of the transmitted risk on the market and how it variated over time.

Among others, the time-varying connectedness has been identified in the forex markets (8,9). The risk is spilled over the currencies as investors rebalance their portfolios (10). Investors tend to rebalance their portfolios in domestic currencies mainly when economic-policy shocks occur in order to avoid currency risk (11). Several studies also identified connectedness between commodities (12–14). When volatility increases in oil, this volatility tends to transmit into a gas (15). Volatility from gold also tends to be transmitted to silver (14). There have been also some papers studying the relationship between increased volatility in the commodity markets and currencies finding that these volatility shocks on commodities play important role in managing currency risks (16). The connectedness has been identified mainly for the "commodity currencies"[1].

The commodity currencies are affected by commodity cycles besides other factors. But to the best of our knowledge, there are no studies dealing with the issue of volatility spillovers between currencies commodities and commodities in the context of commodity cycles (6,17). More detailed identification of what commodities transmitted volatility to commodity currencies and during what periods would improve the knowledge about the

[1] These currencies export selected commodities and therefore they are narrowly connected with

impact of commodity shocks on the volatility of commodity currencies. A better understanding of this issue helps the investors have their assets denominated in currencies commodities to manage the currency risk. Currency spillovers affect diversification strategies (18) as well as options strategies (19).

In this paper, we make several contributions. First, we identify the volatility transmission between commodity currencies and commodities most exported globally. Second, we cover the COVID-19 period including the biggest oil-price drop ever. Third, and mainly, we offer concrete recommendations for investors and portfolio managers having their investments denominated in commodity currencies.

The structure of this paper is as follows. Section 2 provides a review of studies connected with the issue of volatility spillovers. Methods and data are described in Section 3. Section 4 comments on the achieved results, and Section 5 concludes.

2. Literature Review

The currencies of the countries that export commodities are affected by the changes in the prices of commodities. When the price of the exported commodity rises it arises the export prices followingly. As the exporters want to change the profits from exports into domestic currencies there is pressure on the currency to appreciate (20). However, this causality could have also the opposite direction. Commodity currencies are more liquid and traded five days a week for the whole day. Because of this, the commodity currencies react to news faster and as the commodities are priced in these currencies, they tend to react to changes in exchange rates as well (17).

Among other currencies, the Australian dollar is affected by commodity prices also (6,7). The Australian economy is exporting many commodities and therefore there is increased demand for Australian dollars when exporters want to exchange their profits (20). However, the traditional transmission channels might be affected during periods of increased uncertainty (5). When some economic-policy shocks occur, traditional variables play a less important role in the valuation of the currencies. The volatility increases because of the increasing risk aversion of the subjects in the economy (11). As a result, the interpreting power of models based on traditional economic variables decreases (21). This is caused by the change in the behavior of the subjects (22). The subjects tend to sell assets that are considered to be riskier (11) but also the assets that are denominated in other currencies (10). During the economic turbulence, economic activity also decreases and that has a negative impact on oil prices. On the other side, gold is considered a safe haven asset during economic-policy shocks (7).

Economic turbulence and portfolio rebalancing increase the volatility of assets (23) which is spilled over the countries (24). Because of this the connectedness between assets and countries increases. This was confirmed by Chang et al. (2021) as they identified that volatility spillovers of nine major currencies from 2008 to 2015 were increasing mainly in connection with some economic and political shocks. The spillover effects are higher during negative shocks (Segal et al. 2015). This is confirmed by Baruník et al. (2017) in their study as well. They identify that volatility spillovers between six major currencies from 2007 to 2015 were higher during negative shocks. As they state, the negative spillovers are mainly tied to fiscal factors and the positive are more affected by monetary factors. Bartsch (2019) states that the asymmetric volatility phenomenon is driven mainly by fear. The study used the GARCH model including economic policy uncertainty indices of the UK and US on monthly data and analyzes the impact on exchange rate volatility.

Connectedness between assets has been the subject of several studies (1,2,9,16). Uluceviz and Yilmaz (2020) studied real financial connectedness between variables in the Swiss economy including the exchange rate, real activity index, and KOF-barometer but also stocks and bonds. They found that EUR-CHF played an important role mainly during the Great financial crisis and in 2015. Diebold and Yilmaz (2009) identified volatility transmissions between bonds, stocks, and currencies for nineteen countries from 1992 to 2007. Rajhans & Jain (2015) brought some evidence regarding the Australian dollar. They found that AUD-USD obtains volatility from global shocks.

Several studies have been made for the volatility connectedness between commodity markets. According to Nazlioglu et al. (2013), oil volatility affects the volatility of agronomical commodities mostly during periods after crises. Xiarchos and Burnett (2018) studied the relationship between the volatilities of Crude oil, Corn, and Ethanol from 1997 until 2014. They found that crude oil impacted the futures prices of Corn, but it was connected with seasonality as well. Křehlík and Baruník (2017) identified important volatility spillovers between oil and gasoline with a response shorter than one week.

Less studies have been made on the relationship between the volatility of commodities and currencies. Ghosh (2012) confirmed that the oil transmitted volatility to the currency of India for the period from 2003 to 2012. A closer study of these effects is very important for investors as currency volatility increases the risk of a portfolio denominated in that currency. This way the hedging strategies are affected (19) but the diversification of portfolios also (28).

3. Method

The set of data is built on an assumption that AUD-USD, CAD-USD, NOK-USD, and NZD-USD as "commodity currencies" (Bork et al., 2022) are affected by the volatility shocks of commodity markets. The data are downloaded from November 2010 until the end of February 2023. The period starts with the end of the Great financial crisis until the latest available date. The data are daily and transformed by logarithmic differences. The commodities downloaded are iron (TIO1), natural gas (NG1), gold (XAUUSD), coal (XW1), crude oil (WTI), wheat (ZW), copper (HG1), and silver (XAGUSD). The exchange rate and prices of commodities are downloaded from Bloomberg.

To calculate the volatility contributed by one variable to others we compute indices. These indices define both causalities separately – spillovers FROM and TO some currency. The volatility spillovers are identified by employing the DYCI method (1). It is variance decomposition demonstrating the quantity of information, that each variable adds to the other in regression and it demonstrates how much of the forecast error variance of each variable can be explained by exogenous shocks from the different variables.

The used method is based on quantile connectedness (2,29,30), a modification of DYCI, which connects the variance decomposition matrix connected to the vector autoregression of N-variables. The index value is calculated by the share of the forecast errors out of the diagonal components of the variance-covariance matrix on the sum of all components of the matrix. The authors (31) use variance decompositions that they can divide into forecast error parts, and these can be allocated to systemic shocks.

The study of the spreading of shocks by studying increased volatility needs to identify causality. This could be done by employing and modifying the generalized VAR approach (32) where the variance decompositions are independent of the order of variables. Because of this, the shocks are not orthogonalized which means that the sum of the contributions to forecasting error is not necessarily equal to one. This approach allows us to define shares on the variance as parts of H-step forecast errors x_i against shocks x_i and the shares of variances between variables defines as interconnectedness. That connectedness is understood as parts of H-stepped forecast errors in the forecasts x_i against shocks of the x_j variable ($i,j=1,2,\ldots, N$, while $i \neq j$). When the error component ε_t has a normal distribution, the generalized impulse response function is defined as follows:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \sum e_j\,, \qquad h = 0, 1, 2, \ldots \tag{1}$$

where $\sum$ is the forecast error variance matrix of the vector ε and σ_{jj} is the standard deviation of the error part of the variable j and e_i is a vector with the value 1 of i-th component and zeros as other values. The contribution of the j component against forecast of the error part of the I component j is defined as follows:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)}, \tag{2}$$

while the sum of the components of decomposed variances of each row is not necessarily equal to 1, $\sum_{j=1}^{N} \theta_{ij}^g(H) \neq 1$ (33). To normalize the information of the formula, Diebold and Yilmaz (2012) normalize each entry by the sum of the rows:

$$C_{i \leftarrow j}^H = \frac{\theta_{i,j}^g(H)}{\sum_{j=1}^{N} \theta_{i,j}^g(H)}. \tag{3}$$

The formula is further explained: $\sum_{j=1}^{N} C_{i \leftarrow j}^H = 1$ a $\sum_{i,j=1}^{N} C_{i \leftarrow j}^H = N$. By using normalized entries of generalized decompositions of variances Diebold and Yilmaz (2009) created the Total spillover index:

$$C^H = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} C_{i \leftarrow j}^H}{\sum_{i,j=1}^{N} C_{i \leftarrow j}^H} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} C_{i \leftarrow j}^H}{N} \tag{4}$$

It measures the contribution of volatility of one pair to the volatility of other pairs by measuring the share of one pair's volatility on the forecast error of the other one.

To quantify volatility spillover directional applied the Index From all other assets ($FROM$), Index To all other assets (TO) and the Net spillover index (NET). To measure the repercussions received by asset i from all other assets j the Index from all other assets ($FROM$) was applied. These are the spillovers received by the range of assets i of the range of all other assets $j = 1, \ldots, N, j \neq i$, relative to the total Forecast Error Variance (FEV) in the system, as given by:

$$FROM_i^H = \frac{\sum_{j=1, j \neq i}^{N} \theta_{i \leftarrow j}^g(H)}{N} . 100 \tag{5}$$

To measure the repercussions of volatility transmitted by asset i to all other assets j, TO was used – these are the spillovers transmitted by the range from asset i to all other assets $j = 1, \ldots, N, j \neq i$, relative to Total FEV in the system, which is given by:

$$TO_i^H = \frac{\sum_{j=1, j \neq i}^{N} \theta_{i \rightarrow j}^g(H)}{N} . 100 \tag{6}$$

The side effects of the net volatility of the asset i for all other assets j, NET was estimated – which are the spillovers transmitted from asset i's range to everyone's range the other assets $j = 1, \ldots, N, j \neq i$, minus spillovers received from the range of all other assets $j = 1, \ldots, N, j \neq i$, in relation to the total FEV in the system

$$NET_i^H = TO_i^H - FROM_i^H \tag{7}$$

Finally, the repercussions of volatility between assets i and j, through Net pairwise spillover index

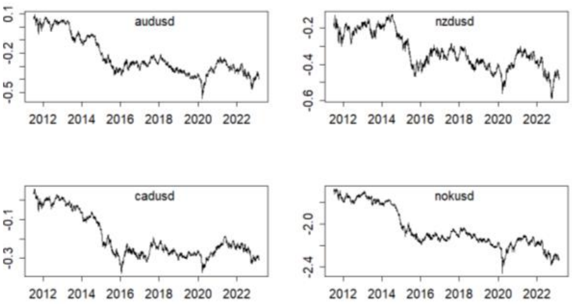
($PAIR$) – what are the spillovers transmitted from the range of asset i to the range of one specific asset $j, j \neq i$, minus repercussions received of the interval of this asset j, in relation to the total FEV, defined by:

$$PAIR_{ij}^{H} = \frac{\theta_{i\leftarrow j}^{g}(H)-\theta_{i\rightarrow j}^{g}(H)}{N}.100 \quad (8)$$

4. Results

In Figure 1 we present the logarithmized values of the commodity currencies AUDUSD, NZDUSD, CADUSD, and NOKUSD. We can observe that commodity currencies and financial market indices exhibit an abnormal decline at the beginning of the covid-19 pandemic (March 2020).

Figure 1. Plots of exchange rates, logaritmized values.



In

Figure **2**, we present time series in logarithms of the commodities COAL, WHEAT, COPPER, NATGAS, SILVER, WTI, and IRON. We notice a similar trend for COAL and COPPER. We can also see similarities in the behavior of WHEAT and IRON, as they were not impacted by the Covid-19 shock in March 2020. On the other hand, the commodity most affected by the Covid-19 shock was WTI.

Figure 2. Plots of commodities, values in logarithms.

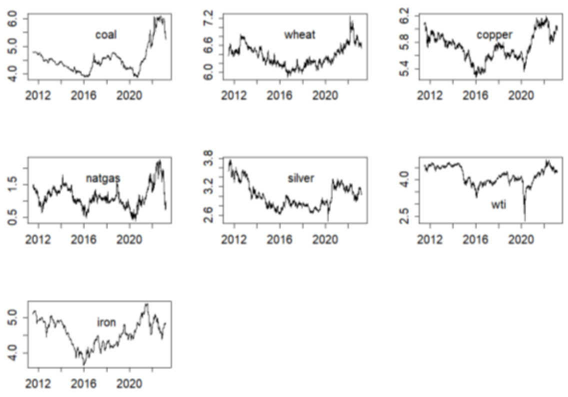


Table 1 presents the descriptive statistical analysis of the exchange rates (AUDUSD, NZDUSD, CADUSD, and NOKUSD), and the commodities COAL, WHEAT, NATGAS, SILVER, WTI, and IRON. Across 2934 observations, coin returns are on average negative between -0.02 and -0.01. NOKUSD has the highest asymmetry and kurtosis. The Elliott, Rothenberg, and Stock (ERS) unit root test is significant in all currencies, demonstrating that there is no serial correlation of the error term, that is, the series is stationary. Among commodities, the asset with the highest return is COAL (value of 0.02) and NATGAS is the asset with the highest volatility (value of 3.49). Unconditional correlations to Quantile Q(20) are shown to be significant in NOKUSD currency and all commodities. In Quantile Q2(20) they are presented as significant in all currencies and commodities.

Pearson's correlation is significant between almost all variables, with the exception between COAL and NZDUSD and between WHEAT, COPPER, and SILVER commodities, all in relation to COAL.

Table 2 presents the total connectedness table estimated by a quantile VAR (extreme upper quantile tau=0.95) model with a 200-day window and lag length of order 6 (AIC) and a 10-step-ahead forecast.

Table 1. Summary of descriptive statistics and unit root tests, autocorrelation and correlation of log-returns (Period from 04/12/2012 to 02/28/2023).

	Exchange rates				Commodities						
	AUDUSD	NZDUSD	CADUSD	NOKUSD	COAL	WHEAT	COPPER	NATGAS	SILVER	WTI	IRON
nobs	2934	2934	2934	2934	2934	2934	2934	2934	2934	2934	2934
Mean	-0.02	-0.01	-0.01	-0.02	0.02	0.01	0.00	-0.01	-0.02	-0.01	-0.01
Stdev	0,67	0,70	0,48	0,75	2,05	1,93	1,40	3,49	1,79	2,95	1,82
Skewness	-0.13***	-0.11***	-0.07	-0.79***	-3.06***	0.46***	-0.07	0.16***	-0.72***	-2.81***	-2.46***
Ex.Kurtos.	2.15***	1.87***	1.87***	9.07***	126.37***	5.38***	2.19***	9.22***	7.60***	77.08***	33.09***
ERS	-9.85***	-23.74***	-15.53***	-18.33***	-21.04***	-4.01***	-11.18***	-18.66***	-4.81***	-11.07***	-4.68***
Q(20)	12.63	13.71	4.09	17.26**	34.92***	14.96	14.20	40.92***	14.43	107.03***	52.63***
Q2(20)	376.74***	212.16***	286.50***	509.90***	75.63***	1053.80***	319.32***	580.54***	227.83***	627.97***	5.47
Pearson Correlation											
AUDUSD	1.00***	0.82***	0.68***	0.64***	0.04**	0.11***	0.46***	0.05***	0.44***	0.24***	0.08***
NZDUSD	0.82***	1.00***	0.62***	0.60***	0.03	0.10***	0.39***	0.04**	0.42***	0.19***	0.05**
CADUSD	0.68***	0.62***	1.00***	0.60***	0.04**	0.13***	0.43***	0.05***	0.39***	0.36***	0.07***
NOKUSD	0.64***	0.60***	0.60***	1.00***	0.05***	0.10***	0.40***	0.06***	0.40***	0.35***	0.04**
COAL	0.04**	0.03	0.04**	0.05***	1.00***	0.03	0.02	0.05***	0.02	0.10***	0.09***
WHEAT	0.11***	0.10***	0.13***	0.10***	0.03	1.00***	0.12***	0.05***	0.12***	0.12***	0.02
COPPER	0.46***	0.39***	0.43***	0.40***	0.02	0.12***	1.00***	0.05***	0.42***	0.32***	0.14***
NATGAS	0.05***	0.04**	0.05***	0.06***	0.05***	0.05***	0.05***	1.00***	0.02	0.09***	0.02
SILVER	0.44***	0.42***	0.39***	0.40***	0.02	0.12***	0.42***	0.02	1.00***	0.19***	0.05***
WTI	0.24***	0.19***	0.36***	0.35***	0.10***	0.12***	0.32***	0.09***	0.19***	1.00***	0.06***
IRON	0.08***	0.05**	0.07***	0.04**	0.09***	0.02	0.14***	0.02	0.05***	0.06***	1.00***

The average dynamic volatility connectedness (absolute return) for each market is generated by the FEV/VAR model. The corrected Total Connectedness Index (cTCI) and Total Connectedness Index (TCI) suggest the longer the forecast horizon, the greater the amount of information transmitted by the system, thus the TCI value for a forecast horizon of 10 days in a window of 200 trading days is 95.76% and 87.06%, respectively. This suggests that after the appearance of a price shock in one market, information flows quickly and affects the prices of other commodity markets or commodity currencies.

Dynamic connectedness has a bidirectional characteristic. The results show that the volatility of the commodity currency NZDUSD contributes to the forecast error variance of all other markets transmitting levels of (88.25%), followed by CADUSD (87.38%), NOKUSD (85.41%), and AUDUSD (84.71%). Among commodities, COAL is the biggest contributor to the error variance of all other markets (93.67%), followed by NATGAS (89.55%), WTI (86.85%), SILVER (86.25%), WHEAT (85.93%), IRON (85.35%), and COPPER (84.28%). Commodity currency NZDUSD and commodity IRON are also the biggest receivers of volatility (87.71% and 87.73%, respectively). The largest Contribution Including

Own (Inc. Own) is of the NZDUSD, for commodities currents, add your own volatility (9.76%) with the volatility transmitted to the system (88.25%) and you get total transmission (101.16%). For the commodities is the COAL (107,08%).

NET suggests that AUDUSD is a net volatility variation receiver (-2.93%), as well as NOKUSD (-2.30%) and CADUSD (-0.06%), which are impacted by the volatility dynamics of the other markets. Among commodities, the net receivers of volatility are COPPER (-3.08%), IRON (-2.38%), SILVER (-1.24%), WHEAT (-0.72%), and WTI (-0 .25%).

The only currency transmitting a net volatility shock is NZDUSD (1.16%) and the two commodities transmitting net volatility shock are COAL (7.08%) and NATGAS (4.73%). Now, the corrected Total Connectedness Index (cTCI) and Total Connectedness Index (TCI), take on the values of 48.41% and 44.01%, respectively.

Table 2. Volatility connectedness based the quantile VAR (extreme upper quantile tau=0.95, 0.50, and 0.1).

	Exchange rates				Commodities							
	AUDUSD	NZDUSD	CADUSD	NOKUSD	COAL	WHEAT	COPPER	NATGAS	SILVER	WTI	IRON	FROM
						tau=0.95						
AUDUSD	12.35	9.76	9.21	8.78	8.97	8.34	8.33	8.53	8.79	8.53	8.39	87.65
NZDUSD	9.49	12.91	8.83	8.88	9.02	8.66	8.26	8.46	8.39	8.54	8.56	87.09
CADUSD	8.81	9.20	12.56	8.72	9.24	8.50	8.48	8.77	8.32	8.78	8.62	87.44
NOKUSD	9.08	9.37	9.08	12.29	9.08	8.53	8.49	8.38	8.72	8.65	8.31	87.71
COAL	7.98	8.67	8.68	8.34	13.40	9.05	8.48	9.02	8.64	9.00	8.74	86.60
WHEAT	7.95	8.45	8.55	8.18	9.77	13.35	8.45	9.20	8.73	8.74	8.62	86.65
COPPER	8.55	8.67	8.47	8.42	9.49	8.63	12.64	8.81	8.79	8.54	8.99	87.36
NATGAS	7.91	8.35	8.64	8.53	9.07	8.55	8.29	15.19	8.53	8.69	8.26	84.81
SILVER	8.45	8.95	8.83	8.67	9.46	8.37	8.50	9.04	12.51	8.78	8.44	87.49
WTI	8.27	8.26	8.50	8.41	9.69	8.46	8.47	9.90	8.73	12.90	8.43	87.10
IRON	8.22	8.59	8.58	8.47	9.88	8.84	8.53	9.42	8.60	8.59	12.27	87.73
TO	84.71	88.25	87.38	85.41	93.67	85.93	84.28	89.55	86.25	86.85	85.35	957.62
Inc. Own	97.07	101.16	99.94	97.70	107.08	99.28	96.92	104.73	98.76	99.75	97.62	cTCI/TCI
NET	-2.93	1.16	-0.06	-2.30	7.08	-0.72	-3.08	4.73	-1.24	-0.25	-2.38	95.76/ 87.06
						tau=0.50						
AUDUSD	42.13	13.74	8.54	7.66	3.58	3.55	4.75	3.09	5.21	4.00	3.76	57.87
NZDUSD	14.34	43.11	7.55	8.13	3.19	3.08	4.34	3.16	5.22	4.18	3.70	56.89
CADUSD	9.05	7.94	46.38	8.13	3.24	3.30	4.54	3.32	4.88	5.20	4.03	53.62
NOKUSD	8.80	8.13	7.95	47.38	3.27	3.03	4.55	3.07	5.00	4.80	4.03	52.62
COAL	2.03	1.63	1.58	1.66	76.36	2.16	1.69	2.45	1.67	2.62	6.15	23.64
WHEAT	3.46	4.01	4.13	4.09	4.92	59.72	3.92	3.77	3.83	4.47	3.67	40.28
COPPER	5.88	4.57	5.38	5.41	3.99	3.65	51.07	4.10	5.98	5.38	4.58	48.93
NATGAS	3.86	3.36	3.65	3.65	4.12	3.83	3.70	61.45	3.79	4.49	4.10	38.55
SILVER	6.28	6.00	4.87	5.69	3.71	3.10	5.30	3.32	53.86	4.12	3.74	46.14
WTI	4.53	4.21	5.15	5.49	4.64	3.87	5.63	4.26	4.33	53.99	3.92	46.01
IRON	1.64	1.34	1.49	1.20	6.05	1.38	1.42	1.76	1.89	1.42	80.40	19.60
TO	59.86	54.91	50.30	51.11	40.72	30.94	39.85	32.30	41.79	40.68	41.69	484.15
Inc. Own	101.99	98.03	96.68	98.49	117.08	90.66	90.92	93.75	95.65	94.67	122.09	cTCI/TCI
NET	1.99	-1.97	-3.32	-1.51	17.08	-9.34	-9.08	-6.25	-4.35	-5.33	22.09	48.41/ 44.01
						tau=0.05						
AUDUSD	25.58	13.59	10.60	9.60	3.84	5.78	7.87	5.40	7.88	6.36	3.49	74.42
NZDUSD	13.74	25.89	9.73	9.72	3.80	5.78	7.39	5.92	7.94	6.70	3.40	74.11
CADUSD	10.99	10.01	26.80	9.85	3.62	6.26	7.85	5.55	7.78	7.70	3.59	73.20
NOKUSD	10.60	10.09	9.85	27.21	3.46	6.43	7.73	5.90	8.14	7.34	3.26	72.79
COAL	4.93	4.79	4.59	4.08	48.71	5.86	4.54	5.60	5.01	5.54	6.37	51.29
WHEAT	6.94	7.07	7.69	7.49	5.40	33.13	7.18	6.84	7.11	6.95	4.19	66.87
COPPER	8.98	7.97	8.53	7.92	4.01	6.53	29.05	6.36	8.49	8.24	3.94	70.95
NATGAS	6.78	7.15	6.98	6.93	5.07	7.19	7.10	34.80	6.81	7.18	4.00	65.20
SILVER	8.83	8.90	8.13	8.50	3.89	6.21	8.35	5.74	30.49	7.15	3.82	69.51
WTI	7.30	7.32	8.47	8.34	4.98	6.54	8.65	6.44	7.28	30.84	3.84	69.16
IRON	4.72	4.15	4.58	3.64	6.70	4.94	4.61	4.29	4.97	4.53	52.88	47.12
TO	83.79	81.03	79.15	76.08	44.76	61.50	71.27	58.03	71.42	67.69	39.90	734.61
Inc. Own	109.37	106.92	105.95	103.29	93.47	94.63	100.32	92.84	101.91	98.52	92.77	cTCI/TCI
NET	9.37	6.92	5.95	3.29	-6.53	-5.37	0.32	-7.16	1.91	-1.48	-7.23	73.46/ 66.78

Notes. Total connectedness table is estimated by a quantile VAR model with 200-day window and lag length of order 6 (AIC) and a 10-step-ahead forecast.

Notes. Total connectedness table is estimated by a quantile VAR model with 200-day window and lag length of order 6 (AIC) and a 10-step-ahead forecast.

Dynamic connectedness has a bidirectional characteristic. The results show that the volatility of AUDUSD contributes to the forecast error variance of all other markets transmitting 59.86%, followed by NZDUSD (54.91%), NOKUSD (51.11%), and CADUSD (50.30%). Among commodities, SILVER is the biggest contributor to the error variance of all other markets (41.79%), followed by IRON (41.69%), COAL (40.72%), WTI (40.68%), COPPER (39.85%), NATGAS (32.30%), and WHEAT (30.94%). Commodity currency AUDUSD and commodity COPPER are also the biggest receivers of volatility (57.87% and 48.93%, respectively). The largest Contribution Including Own (Inc. Own) is of the AUDUSD, for commodities currents, add your own volatility (42.13%) with the volatility transmitted to the system (59.8%) and you get total transmission (101.99%). For the commodities is the IRON we obtained value of 122.09%.

NET now indicates that the receiving commodity currencies are: CADUSD (-3.32%), NZDUSD (-1.97%), and NOKUSD (-1.51%) which are impacted by the variation in the volatility of other markets. Among commodities, the net receivers of volatility are WHEAT (-9.34%), COPPER (-9.08%), NATGAS (-6.25%), WTI (-5.33%), and SILVER (-4.35%).

The only commodity currency transmitting net volatility shocks is AUDUSD (1.99%) and the two commodities transmitting net volatility shocks are IRON (22.09%) and COAL (17.08%).

By a quantile VAR (extreme upper quantile tau=0.05) we employ a model with a 200-day window and lag length of order 6 (AIC) and a 10-step-ahead forecast. Now, the corrected Total Connectedness Index (cTCI) and Total Connectedness Index (TCI), take on the values of 73.46% and 66.78%, respectively.

The results show that the volatility of the commodity currency AUDUSD contributes to the forecast error variance of all other markets transmitting levels of 83.79%, followed by NZDUSD (81.03%), CADUSD (79.15%), and NOKUSD (76.08%). Among commodities, SILVER is the biggest contributor to the error variance of all other markets (71.42%), followed by COPPER (71.27%), WTI (67.69%), WHEAT (61.50%), NATGAS (58.03%), COAL (44.76%), and IRON (39.90%). AUDUSD and commodity COPPER are again the biggest receivers of volatility (74.42% and 70.95%, respectively). The largest Contribution Including Own (Inc. Own) is of the AUDUSD, for commodities currents, the addition if your own volatility (25.58%) with the volatility transmitted to the system (83.79%), generate the total transmission (109.37%). For the commodities, SILVER achieved a value of 101.91%.

The NET now indicates that there are no commodity receiving currencies, indicating that they are not impacted by the variation in the volatility of the other markets in this quantile. Among commodities, net receivers of volatility are IRON (-7.23%), NATGAS (-7.16%), COAL (-6.53%), WHEAT (-5.37%) and WTI (-1 .48%).

All commodity currencies transmitting a volatility shock in net comparison have the following values: AUDUSD (9.37%), NZDUSD (6.92%), CADUSD (5.95%), and NOKUSD (3.29%), and the two commodities transmitting net volatility shock are SILVER (1.91%) and COPPER (0.32%).

Figure 3 shows the volatility connectedness network between commodity currencies and commodities for quantiles 0.9, 0.5, and 0.05. For quantile 0.9, the transmitters COAL, NATGAS, and NZDUSD are highlighted in blue, and in yellow are marked the receivers: NOKUSD, CADUSD, AUDUSD, IRON, WTI, SILVER, COPPER, and WHEAT. The network illustrates that the volatility of COAL generates strong volatility connectedness with the IRON and AUDUSD, as well as the commodity COPPER. NATGAS has strong volatility connectedness with WTI and IRON.

We can also see that there is no connectedness between WHEAT and COPPER, between SILVER, WTI, and IRON, and between WTI, IRON, and AUDUSD.

For quantile 0.5, in blue are the transmitters: COAL, IRON, and AUDUSD, and in yellow are the receivers: NOKUSD, CADUSD, NZDUSD, WTI, SILVER, NATGAS, COPPER, and WHEAT. The network illustrates that the volatility of the commodity IRON generates strong volatility connectedness with the currency commodity NOKUSD and the commodity COPPER, as well as the currencies commodities CADUSD and NZDUSD. COAL is a strong volatility transmitter to WHEAT, COPPER, NATGAS, SILVER, and WTI.

It can be noticed that there is no connectedness between CADUSD and NZDUSD, and between WHEAT, COPPER, NATGAS, SILVER, and WTI.

For quantile 0.05, the results show that all currencies are transmitters of volatility, and two commodities, SILVER, and COPPER. The other commodities are receivers of volatility.

Figure 3. Net pairwise directional connectedness network for quantiles 0.95, 0.50, and 0.05.

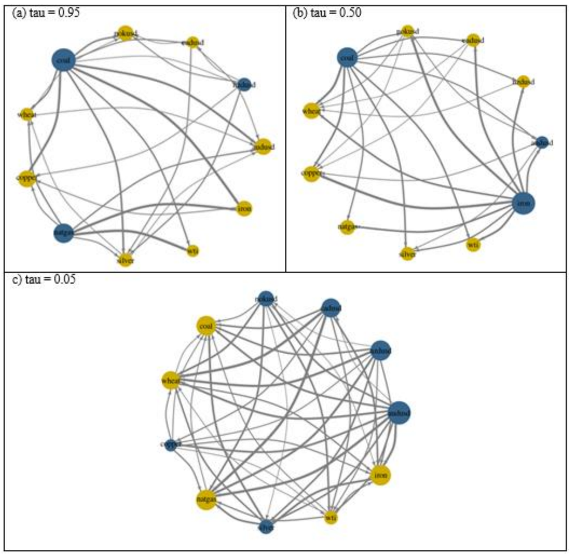
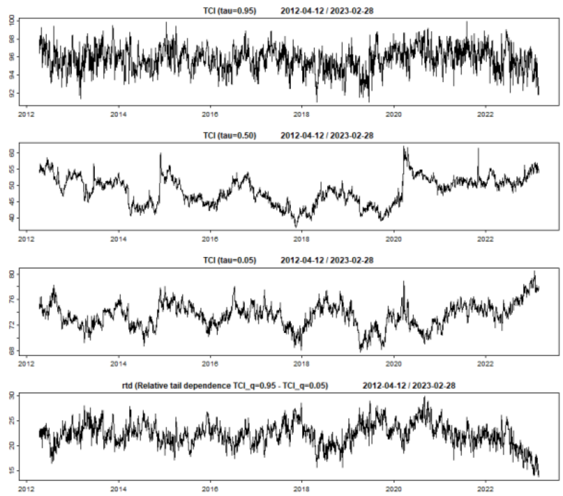


Figure 4 illustrates the computed time-varying TCI based on a 200-day rolling window and 10-step-ahead forecast horizon, for quantiles 0.95, 0.50, and 0.05, and the relative tail dependence (rtd) between TCI with quantiles 0.95 and 0.05.

TCI measures the average influence existing in commodity currencies and commodities. Note that the TCI with tau = 0.90 shows fluctuations ranging from 0% to 100% over the analyzed period, with tau = 0.50 showing fluctuations between 35% and 60%, and with tau = 0.05 between 62% and 82%, about.

The rtd oscillates between 15% and 30%. Interestingly, there is a significant change in the connection trend between commodity currencies and commodities. In March 2020, there was a peak of around 60% (tau = 0.50) during the first months of the coronavirus crisis.

Figure 4. Time-varying Total Connectedness Index (TCI) computed based on a rolling window 200 days and 10 step-ahead forecast horizon.



5. Discussion and Conclusion

The study identified the connectedness between commodity currencies and seven commodities. To the best of our knowledge, these volatility spillovers have not been identified yet. Following the results, we bring several important contributions. Currency commodity AUDUSD is a net volatility transmitter to commodities (1.99%), for quantile 0.50, and COAL is the biggest volatility transmitter to commodities and commodity currencies (17.08%). The relationship with other commodities is more neutral and variable in time.

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