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by Diyah Sukanti Cahyaningsih

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The response of exchange rate to coal price, palm oil price, and inflation in Indonesia: Tail dependence analysis

Grahita Chandrarin [a], Kazi Sohag [b,*], Diyah Sukanti Cahyaningsih [a], Dani Yuniawan [a], Heyvon Herdhayinta [c]

[a] University of Merdeka Malang, Indonesia
[b] Graduate School of Economics and Management, Ural Federal University, Russia
[c] Universitas Gadjah Mada, Indonesia

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ABSTRACT

Given the significant concerns of currency devaluation and level of inflation in Indonesia, we measure their dynamic connectedness and cross-quantile dependence with prominent export items such as crude palm oil price and coal price. To this end, we apply the frequency connectedness approach and Cross-Quantilogram approach to measure volatility spillover utilising daily data from 2002 to 2021. The frequency connectivity analysis coincides with our proposition that exchange rate and inflation substantially respond to coal and crude palm oil prices. Next, we apply the cross-quantilogram framework to examine the cross-quantile dependence between exchange rate and other variables to capture the spillovers between these markets considering a wide range of market conditions. Our empirical analysis demonstrates that exchange and inflation are connected during extreme market volatility when they boom together. The exchange rate responds to palm oil price at the extreme quantile of the exchange rate in long-term horizons. The degree of connectedness between exchange rate and coal price is profound at the higher quantile in the long run horizon while it dissipates in the short run. Our findings provide important policy implications to the energy and monetary authority of Indonesia.

1. Introduction

The Indonesian economy is the largest in Southeast Asia (World Bank, 2021) and the 16th largest economy by nominal GDP (IMF, 2017). The economy is anticipated to be the fifth-largest one by 2030, with an expected GDP of USD 5.42 trillion (PricewaterhouseCoopers, 2017). As one of the fastest-growing economies, Indonesia has experienced rapid economic growth and a considerable VUCA (volatility, uncertainty, complexity & ambiguity). Further, dramatic changes of VUCA in the overall economy led to specific attention on currency devaluation and inflation rise in Indonesia. The economy encounters a constant exchange rate growth and inflation along with considerable fluctuations over time. Indonesia is a prominent exporter of coal briquette and crude palm oil; hence, the exchange rate is apparently highly anchored with them, which motivates us to conduct this study to explore the frequency and cross-quantile dependence among exchange rate, inflation, coal price and palm oil price in Indonesia.

The motivation of this study lies in the multi-folds. *First*, several empirical studies explored the response of exchange rate to the prices of significant import or export commodities in the respective countries. For instance, Sohag et al. (2021) and Bouoiyour et al. (2015) document that the Russian exchange rate is highly anchored with the international oil price. Similarly, some recent studies observed a significant co-movement between exchange rate and international oil price, e.g., Wen et al. (2020) for oil-exporting and oil-importing countries; Balcilar and Usman (2021) for BRICS; and Yildirim and Arifli (2021) for small oil-exporting economies. Most prior studies found consistent findings in demonstrating that an increase in international oil prices results in the appreciation of the local currency in oil-exporting countries and devaluation of local currency in oil-importing countries (e.g., Aloui et al., 2018; Bénassy-Quéré et al., 2007; Habib & Kalamova, 2007; Jiang et al., 2016; Khraief et al., 2020; Krugman, 1980; Lin & Su, 2020; Taghizadeh-Hesary et al., 2019; Taghizadeh-Hesary et al., 2016; Shahbaz et al., 2015). A considerable number of studies stresses measuring the co-movements among oil price, precious metals, and stock markets volatility Raza et al. (2016); Bouoiyour et al. (2017); Husain et al.

* Corresponding author.
E-mail addresses: grahitac@unmer.ac.id (G. Chandrarin), sohagkaziewu@gmail.com (K. Sohag), diyahsukanti@unmer.ac.id (D.S. Cahyaningsih), dani.yuniawan@unmer.ac.id (D. Yuniawan), heyvonh@ugm.ac.id (H. Herdhayinta).

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Table 1
Description of variables.

Variable	Description	Unit	Source
Exchange Rate (EXR)	Value of Indonesian Rupiah measured in IDR per USD.	IDR per US Dollar	Central Bank of Indonesia https://www.bi.go.id/en/statistik/ekonomi-keuangan/seki/Default.
Consumer Prices Index (CPI)	CPI is as a proxy of inflation.	Index	Central Bank of Indonesia https://www.bi.go.id/en/statistik/ekonomi-keuangan/seki/Default.aspx
Crude Palm Oil Price (POP)	Spot crude palm oil price.	USDper Metric tonne	Palm Oil Analytics. https://palmoilanalytics.com/price/crude-palm-oil-fob-indonesia/
Coal Price (CP.)	Spot coal price.	USDper Metric tonne	International Energy Agency (IEA) https://www.iea.org/countries/indonesia

Note: We take logarithmic transformation.

Table 2
Statistic Descriptive of exchange rate, consumer prices index, crude palm oil price and coal price.

Description	CP	CPI	EXR	POP
Mean	4.3440	0.0504	9.3446	6.5633
Median	4.3502	0.0444	9.3735	6.5435
Maximum	5.3528	0.1216	9.7306	7.1403
Minimum	3.6493	0.0130	9.0480	6.0392
Std. Dev.	0.3086	0.0238	0.1929	0.2541
Skewness	0.2360	0.8629	−0.0457	0.2471
Kurtosis	2.7995	3.4796	1.3474	2.3243
Jarque-Bera	41.6890	508.5018	434.0820	111.0414
Probability	0.0000	0.0000	0.0000	0.00000
Sum	16520.31	191.8036	35537.66	24960.27
Sum Sq. Dev.	362.1325	2.159256	141.5158	245.5124
Observations	3803	3803	3803	3803

Note: CP = Coal Price, CPI= Consumer Price Index as a proxy of Inflation, EXR = Exchange Rate, POP= Crude Palm Oil Price.

Table 3
Volatility Spillover among selected markets.

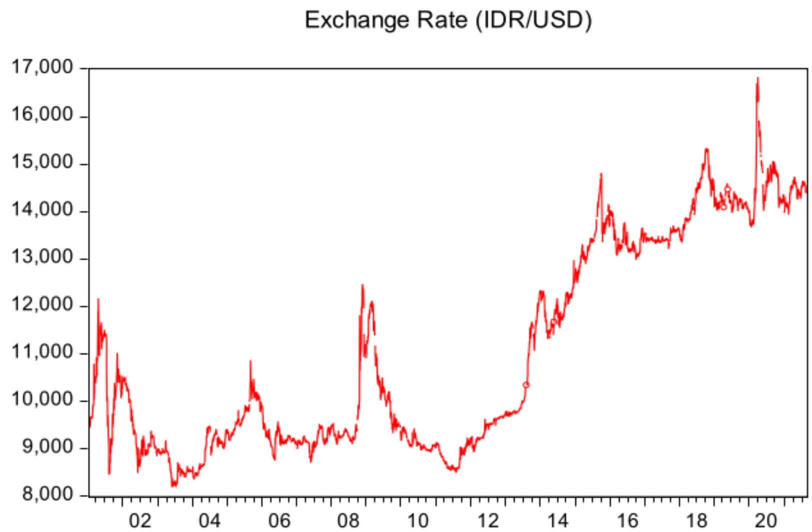
Description	CPI	EXR	POP	CP	FROM others
CPI	75.51	8.33	10.54	5.62	24.49
EXR	6.54	75.37	10.75	7.34	24.63
POP	8.36	7.30	76.20	8.13	23.80
CP	2.42	4.42	4.50	88.66	11.34
TO others	17.33	20.05	25.79	21.09	84.26
Inc. own	92.84	5.42	101.99	109.75	TCI
NET	−7.16	−4.58	1.99	9.75	21.06
NPDC	3.00	2.00	1.00	0.00	

(2019); Nasir et al. (2019); Lahiani et al. (2017); Mensi et al. (2021). A recent study observed that the degree of connectivity between oil and gold prices reduced significantly (Mensi et al., 2020 Salisu et al., 2021). The economy is a significant exporter and coal; the prices of this commodity determine the exchange rate and vice-versa. Due to the evaluation of the local currency, the export industries enjoy a higher flow of revenues, while import industries encounter a loss. Thus, a flat exchange rate is paramount to stabilising the economy. The importance of hydrocarbon prices became more profound after adopting oil and gas law in 2001 in terms of removing fuel subsidy toward gaining fiscal efficiency, transparency, and environmental sustainability. However, we believe the Indonesian exchange rate is more exposed to palm oil and coal rather than oil price. Because, coal briquette is Indonesia's main export item, with an export value of USD13 billion (World Bank, 2021). Coal reserves in Indonesia accounts for 2.2% of the total world's reserves (BP - British petroleum, 2018). Despite the discouragement to the use coal, Indonesia keeps exporting thermal coal to China, Japan, Vietnam and India. Besides, Indonesia coal demand thrived since building 11.7 GW of coal-fired power capacity, and China's coal import ban from Australia. Hence, coal price is expected to play a pivotal role in stabilising and destabilising the exchange rate.

Second, Indonesia exports approximately 97% of crude palm oil with a value of USD11 billion. The economy enjoys higher foreign revenue by exporting palm oil. The literature argues that demand for palm oil and associated item prices experience a sharp rise because of cheap biofuel and edible use (Carter et al., 2007). The production of crude palm oil has increased sixfold in the last two decades. Interestingly, Corley (2009) argues that the demand for palm oil would be 240 Mt in 2050 approximately; hence, it is expected that the price of palm be like to increase, which has a considerable implication for Indonesia economy. Theoretically, a high price of palm enables Indonesia to enjoy a higher inflow of foreign currency, which eventually should appreciate the local currency. Thus, import industries would be benefited from the terms of trade. While the exchange rate is unpredictable due to its high volatility, the main determinants of its dynamics consist of the position of net foreign assets as well as commodity prices such as palm oil price and coal price (Dauvin, 2014; Gagnon, 1996; Clark & MacDonald, 1999; Lane & Milesi-Ferreti, 2001). According to Dauvin (2014), there is a certain threshold at which the real effective exchange rate of both energy and commodity exporters reacts to oil price through the term of trade. When the oil price variation is low, the exchange rate is not determined by the total but by other ordinary fundamentals. However, when the oil market is highly volatile, currencies follow the "oil currency" regime to become an essential driver of the actual exchange rate. On the other hand, Indonesia may encounter a low inflow of foreign currency due to low crude palm oil prices. Hence, analysing the linkage of crude palm oil price and coal price with the exchange rate in Indonesia is a plausible research question.

Third, hydrocarbon prices are also connected to inflation through various macroeconomic channels. For instance, Husaini and Lean (2021) argue that the impact of hydrocarbon price on price level differs depending on net exporter and importer and the size volume of trade. A humpy amount of hydrocarbon revenue may appreciate the local currency; hence, it eventually reduces inflation (Fisher and Huh, 2002). On the contrary, a higher amount of hydro revenue enables the economy to adopt expansionary fiscal and monetary policy; therefore, it can augment the price index (Kim and Roubini, 2008). As per the macroeconomic theory, domestic inflation and local currency value are inversely connected (Uzoma et al., 2012). However, prior literature shows mixed evidence on the correlation between inflation and exchange rate depreciation (Kara and Nelson 2003). When the export volume of Indonesia from crude palm oil increases due to higher demand, it influences increasing coal and crude palm oil prices. Pertaining to those motivations, we aim to we measure the response of exchange rate to those two items' prices along with inflation rate.

Finally, we apply the cross-quantilogram approach in modelling the dependence structure among exchange rate, inflation, bank rate and crude oil price, given the mounting importance of those variables on the national economy. Cross-quantilogram, recently developed by Han et al. (2016), is a model-free approach to analyse correlation across quantile between bivariate time series variables (Uddin et al., 2019). The technique follows quantile hits instead of moment conditions. Eventually, this method allows for analysing the direction, duration, and magnitude of the co-movement variables and time series analysis with heavy tails (Pham, 2021). Cross-quantilogram offers the benefit of providing a comprehensive bivariate analysis of return spillovers and directional predictability at different quantiles, rather than just at the median (Jiang et al., 2016). The cross-quantilogram analysis on the linkage between inflation and exchange rate is vital due to its significant contribution to methodology development to capture the abnormal volatility of series



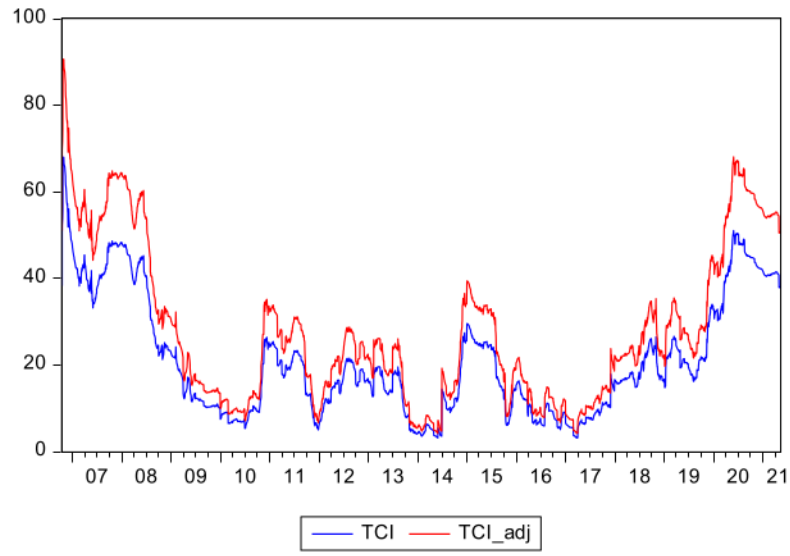


Fig. 1. Total Connectivity Index among four Variables Note: TCI is Total Connectivity Index.

(Sohag et al., 2022a,b).

Our study contributes to the existing literature in several ways. First, best of our knowledge, this study is the first attempt to scrutinize the time-frequency connectedness among several local and global macro-economic indicators including exchange rate, inflation, coal price and palm oil price. We also measure the bi-directional response of exchange rate to respective variables considering different economic circumstances. Second, given the high frequency daily data with substantial fluctuations, we apply two sophisticated time-series approaches to attain our research objectives. Our first method that is Time-Varying Parameter Vector Autoregressive (TVP-VAR) based dynamic connectedness framework to measure volatility Spillovers. Eventually, we apply Cross-Quantilogram method with bootstrapping standard error considering short, medium and long memories in the presence of bidirectional fat-tailed relationship. Third, our empirical analysis retrieves several new insights for Indonesian economy. For instance, we find strong co-movements (84%) among exchange rate, crude palm oil price, coal price and inflation in Indonesian economy. Coal price and crude palm oil price appear as net volatility contributor, whereas inflation and exchange rate prevail as net volatility receivers. Besides, our cross-quantilogram analysis demonstrations that exchange rate responds negatively towards international coal price at medium to higher quantile of coal price and lower to medium quantile of exchange rate considering long memory. The negative response of exchange rate to coal price implies that Indonesia currency appreciates against US dollar. Our empirical findings provide several policy implications to central bank authority in controlling inflation level and exchange rate. Besides, our analysis is further conducive to devise policy to optimize benefit of coal and palm oil rents through the channel of exchange rate regimes.

The rest of this paper is organised as follows. Section 2 discusses the research methods, data, and analysis. Section 3 presents results and discussion. Section 4 is the conclusion of the paper and our recommendation.

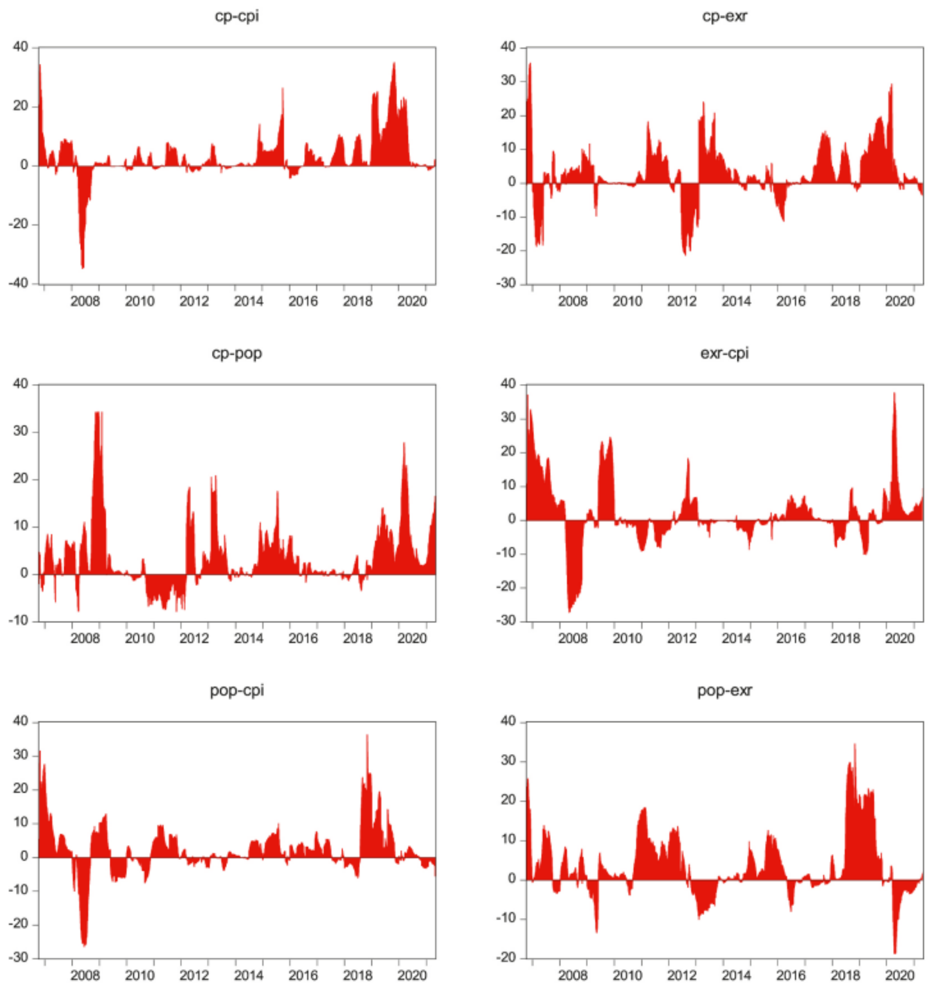


Fig. 2. Bivariate spillover effects over time.

2. Method and data

2.1. Time-varying parameter vector autoregression

In order to estimate the volatility transmission among exchange rate, coal price, palm oil price and CPI, we apply dynamic connectedness under time-varying parameter vector autoregression (TVP-VAR) approach developed by Antonakakis & Gabauer (2017). The main advantage of this approach is that it allows variance to be different by employing stochastic volatility Kalman Filter estimation and forgetting factors by Koop and Korobilis (2014). Hence, the framework allows overcoming inconsistent parameters, which can occur because of random selection of rolling-window-size. Moreover, Dynamic Connectedness under TVP-VAR framework is applicable for less frequency data as well as for the short period of time series.

TVP-VAR method is defined as follows:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \quad \varepsilon_t|F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu_t \quad \nu_t|F_{t-1} \sim N(0, R_t) \tag{2}$$

where Y_t denotes a $N \times 1$ conditional volatility vector, Y_{t-1} indicates the lagged conditional vector of Y_t with $N_p \times 1$ dimension. β_t represents the time-varying coefficient matrix following the $N \times N_p$ order. ε_t denotes the vector of error having $N \times 1$ order along with $N \times N$ time-varying covariance matrix S_t. The vector of the coefficient matrix β_t relies on their respective values β_{t-1} following $N \times N_p$ dimensional residual matrix along with an $N_p \times N_p$ variance-covariance matrix. This approach subsequently measures the generalised connectedness following Diebold and Yılmaz (2014) considering of time-varying parameters and error covariances. This framework eventually allows to estimate volatility spillover by utilising generalised impulse response functions (GIRF), and generalised forecast error variance decompositions (GFEVD) suggested by Koop et al. (1996) and Pesaran and Shin (1998) respectively. Thus, by transforming the VAR to the vector moving average (VMA) we obtain representation for GIRF and GFEVD estimation following the Wold theorem which is defined as:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t \tag{3}$$

$$Y_t = A_t \varepsilon_t \tag{4}$$

$$A_{0,t} = I \tag{5}$$

$$A_{i,t} = \beta_{1,t} A_{i-1,t} + \ldots + \beta_{p,t} A_{i-p,t} \tag{6}$$

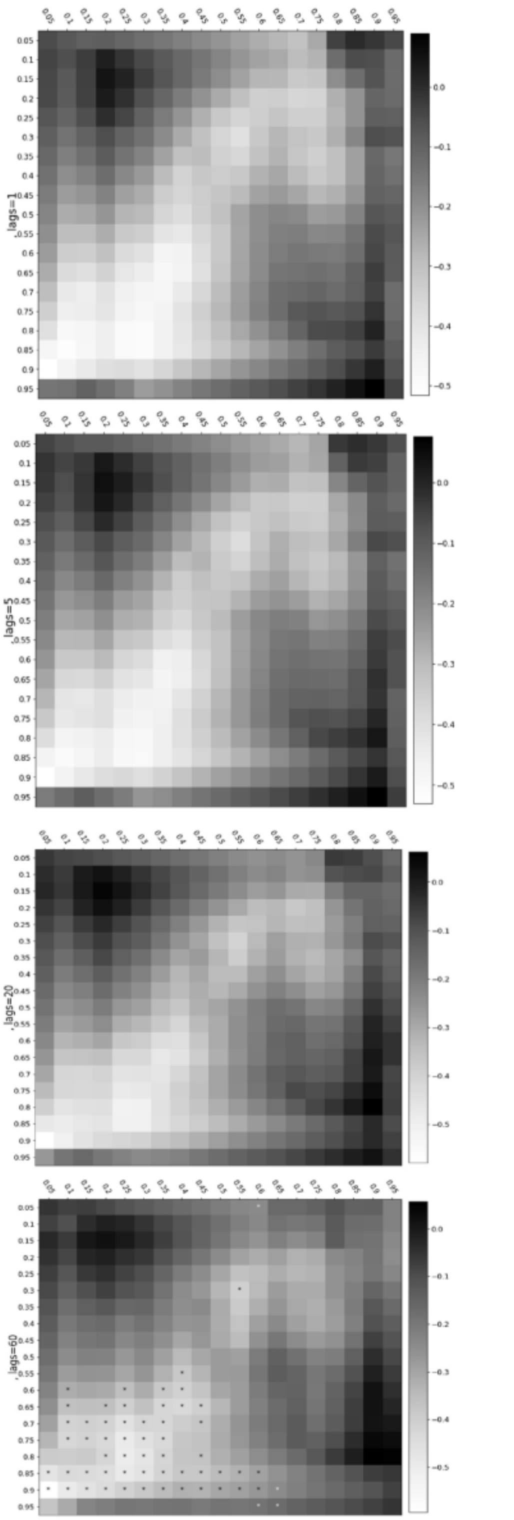


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Fig. 3a. CP to EXR **Note:** Fig. 3a: the vertical axis shows the quantile of inflation level while the horizontal axis shows the quantile of the exchange rate. Fig. 3b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of coal price. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

where $\beta_t = [\beta_{1,t}, \beta_{2,t}, \ldots, \beta_{p,t}]'$ and $A_t = [A_{1,t}, A_{2,t}, \ldots, A_{p,t}]'$, consequently $\beta_{i,t}$ *and* $A_{i,t}$ are dimensional parameter matrices following an order *NxN*.

The GIRFs demonstrate how all respective variables respond to a shock in variable *i*.

We test the differences between a $J - step - ahead\ forecast$ both when variable *i* shocked and not shocked since the model we employ does not follow a structural modelling.

Eq. (7) shows how we estimate the difference to the shock in variable *i*.

$$GIR_t(J, \delta_{j,t}, F_{t-1}) = E(\varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(F_{t-1}) \tag{7}$$

$$\psi^g_{j,t}(J) = \frac{A_{J,t}S_t\varepsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \delta_{j,t} = \sqrt{S_{jj,t}} \tag{8}$$

$$\psi^g_{j,t}(J) = S_{jj,t}^{-\frac{1}{2}} A_{J,t}S_t\varepsilon_{j,t} \tag{9}$$

In our study oil price is taken as variable *i*, and foreign liabilities, foreign assets and net assets represent variable *j*, which is also reflecting the forecasting period, $\delta_{j,t}$ is the selection vector, and F_{t-1} represents the information set until $t-1$. Thereafter, the GFEVD is examined which is the ratio of variance share of one variable to other variables. We normalise the examined variances merging rows into one row, representing that the forecast error variance of variable *i* is described by all variables. Eq. (10) demonstrates the described estimation:

$$\tilde{\phi}^g_{ij,t}(J) = \frac{\Sigma_{t=1}^{J-1}\Psi^{2,g}_{ij,t}}{\Sigma_{j=1}^{N}\Sigma_{t=1}^{J-1}\Psi^{2,g}_{ij,t}} \tag{10}$$

With $\sum_{j=1}^{N}\tilde{\phi}^N_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N}\tilde{\phi}^N_{ij,t}(J) = N$. By employing GFEVD, we examine the total connectedness index by the following equations:

$$C^g_t(J) = \frac{\sum_{i,j=1, i\neq j}^{N}\tilde{\phi}^g_{ij,t}(J)}{\sum_{i,j=1}^{N}\tilde{\phi}^g_{ij,t}(J)}*100 \tag{11}$$

$$= \frac{\sum_{i,j=1, i\neq j}^{N}\tilde{\phi}^g_{ij,t}(J)}{N}*100 \tag{12}$$

The first step of TVP-VAR is to assess how shock in a variable spillover affects other variables. The process when shock variable *i* influences other variables *j*, is described as eq. (13)

$$C^g_{i\to j,t}(J) = \frac{\Sigma_{j=1, i\neq j}^{N}\tilde{\phi}^g_{ji,t}(J)}{\Sigma_{j=1}^{N}\tilde{\phi}^g_{ji,t}(J)}*100 \tag{13}$$

The second step is to compute total directional connectedness from others, which shoes what spillover effect *i* receives it from variables j. The calculation is represented above:

$$C^g_{i\leftarrow j,t}(J) = \frac{\Sigma_{j=1, i\neq j}^{N}\tilde{\phi}^g_{ij,t}(J)}{\Sigma_{i=1}^{N}\tilde{\phi}^g_{ij,t}(J)}*100 \tag{14}$$

Eventually, total directional connectedness to others is subtracted from total directional connectedness from others. In doing so, we get the

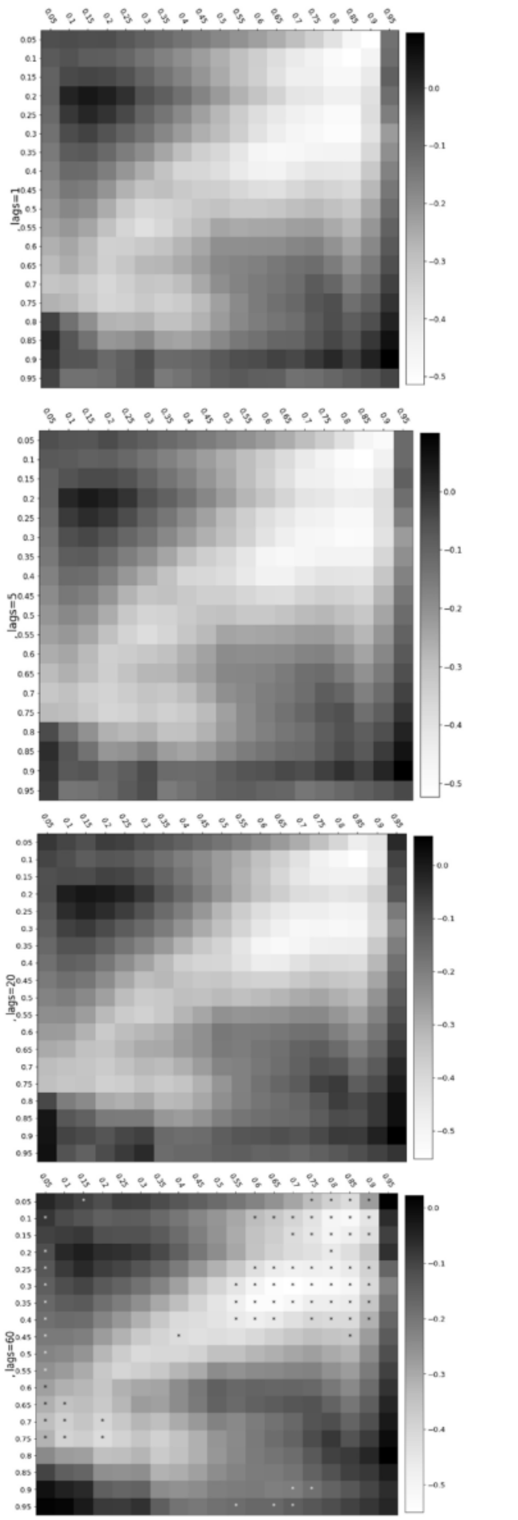

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Fig. 3b. EXR to CP **Note:** Fig. 3a: the vertical axis shows the quantile of inflation level, while the horizontal axis shows the quantile of the exchange rate. Fig. 3b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of coal price. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

net total directional connectedness, which measures the magnitude of variable i's impact on the network of variables. The calculation of the net total directional connectedness is shown in eq. (15)

$$C^g_{i,t}(J) = C^g_{i\to j,t}(J) - C^g_{i\leftarrow j,t}(J) \tag{15}$$

In case when $C^g_{i,t}(J)$ is positive, the strength of variable i's impact is more profound than the influence of other variable on variable i, indicating that all other variables are influenced by variable i. In contrary, when $C^g_{i,t}(J)$ is negative, the influence of variable of other variable on variable i is more profound than the influence of variable i on all other variables.

2.2. Cross-quantilogram

In order to estimate the volatility transmission among exchange rate, coal price, palm oil price and CPI, we apply a cross-quantilogram (CQ) approach developed by Han et al. (2016) due to several reasons. First of all, the method is applicable for different parts of data distribution including extreme observations and the central part of the distribution. Second, by using this method we can calculate the magnitude stock price volatilities on the dependent variables. Third, CQ technique relaxes the assumption moment conditions. Hence, the method is suitable for the fat-tailed distribution. Finally, the method allows taking long lags in assessing strength of the oil price effect, its duration and direction at the same time.

equation (16) represents cross-quantilogram between two events $\{y_{1t} \le q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$, where k signifies the lag length $(k = \pm 1, \pm 2)$ for a pair of τ_1 and τ_2:

$$\rho_\tau(k) = \frac{E[\psi_{\tau_1}(y_{1t} \le q_{1t}(\tau_1))\psi_{\tau_2}(y_{2t-k} \le q_{2t-k}(\tau_2))]}{\sqrt{E\left[\psi^2_{\tau_1}(y_{1t} \le q_{1t}(\tau_1))\right]}\sqrt{E\left[\psi^2_{\tau_2}(y_{2t-k} \le q_{2t-k}(\tau_2))\right]}} \tag{16}$$

where y_{it} represents stationary time series, i is equal to 1, 2 or 3 and indicates medicine care cost or medicine cost, and t is time (t = 1,2, ...T). $F_i(\cdot)$ and $f_i(\cdot)$ report the distribution and density functions of y_{it}, i = 1,2. $q_{it}(\tau_i) = \inf\{v : F_i(v) \ge \tau_i\}$ is the corresponding quantile function for $\tau_i \in (0,1)$ and $\psi_a(u) = 1[u < 0] - a$ is the quantile-hit process.

The CQ approach allows catching the serial dependence between variables at various quantiles and monotonic transformation in both series. When considering two events $\{y_{1t} \le q_{1t}(\tau_1)\}$ and $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$, $\rho_\tau(k) = 0$ means no cross-sectional dependence from event $\{y_{2t-k} \le q_{2t-k}(\tau_2)\}$ to event $\{y_{1t} \le q_{1t}(\tau_1)\}$. When assessing how $\rho_\tau(k)$ vary with the lag length k, we are able to identify how the cross-quantile dependence between foreign liabilities, assets and net assets vary across different time horizons, thereby quantifying magnitude and duration of dependence. We consider k = ... in our study.

Afterwards, we test the statistical significance of $\rho_\tau(k)$ by employing a Ljung-Box type test, where the test statistic is calculated as follows (17):

$$Q^*_\tau(p) = T(T+2)\sum_{k=1}^{p}\widehat{\rho}^2_\tau(k) \Big/ (T-k) \tag{17}$$

where $\widehat{\rho}_\tau(k)$ represents cross-quantilogram calculated as follows:

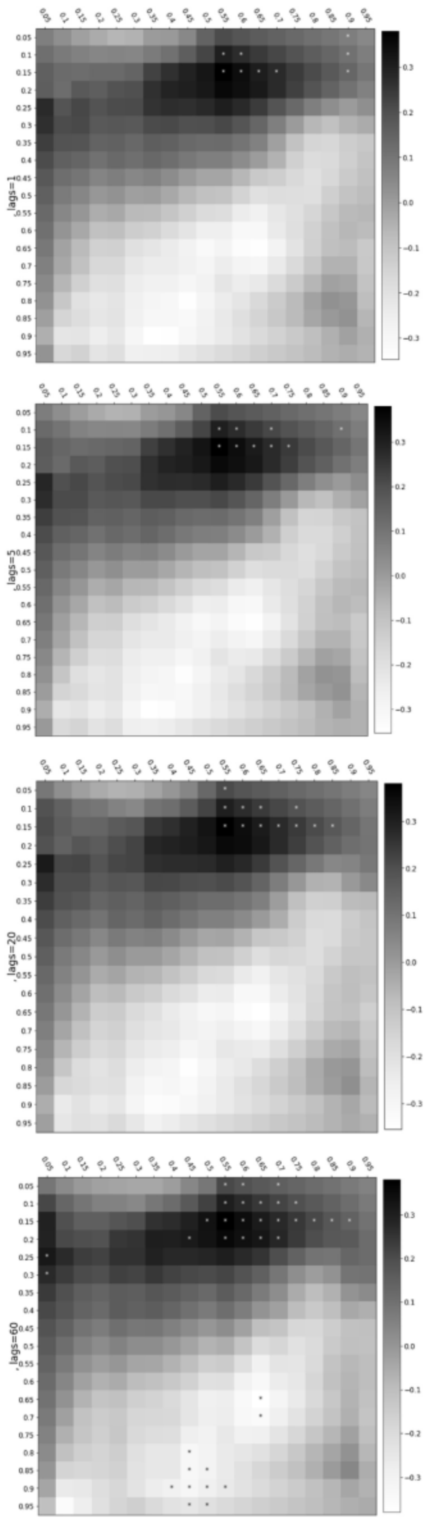

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Fig. 4a. Palm Oil Price to EXR **Note:** Fig. 4a: the vertical axis shows the quantile of inflation level, while the horizontal axis shows the quantile of the exchange rate. Fig. 4b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of Palm Oil Price. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

$$\widehat{\rho}_\tau\left(K\right) = \frac{\sum_{t=k+1}^{T}\psi_{\tau_1}(y_{1t} - \widehat{q}_{1t}(\tau_1))\psi_{\tau_2}(y_{2t-k} - \widehat{q}_{2t-k}(\tau_2))}{\sqrt{\sum_{t=k+1}^{T}\psi^2_{\tau_1}\left(y_{1t} - \widehat{q}_{1t}(\tau_1)\right)}\sqrt{\sum_{t=k+1}^{T}\psi^2_{\tau_2}\left(y_{2t-k} - \widehat{q}_{2t-k}(\tau_2)\right)}} \tag{18}$$

where $\widehat{q}_{it}(\tau_i)$ $(i = 1, 2)$ indicates the estimated quantile function.

By applying stationary bootstrap, we approximate the null distribution of the cross-quantilogram (18) and the Q-statistic (17).

Further, we calculate partial-cross-quantilogram (PCQ) between OP and dependent variables (FA, FI and NA) in order to account for the effect of uncertainties. Let $z_t = [\psi_{\tau_3}(y_{3t} - q_{3t}(\tau_3)), \ldots, \psi_{\tau_l}(y_{lt} - q_{lt}(\tau_l))]$ be an $(l-2) \times 1$ vector for $l \geq 3$ of control variables. The correlation matrix of the quantile hit process and its inverse matrix are defined as:

$$R_{\underline{\tau}} = E\left[h_t\left(\underline{\tau}\right)h_t\left(\underline{\tau}\right)^T\right]; P_{\underline{\tau}} = R_{\underline{\tau}}^{-1} \tag{19}$$

where $h_t\left(\underline{\tau}\right) = \psi_{\tau_1}(y_{1t} - q_{1t}(\tau_1)), \ldots, \psi_{\tau_l}(y_{lt} - q_{lt}(\tau_l))$ be an $l \times 1$ vector of the quantile hit process. For $i, j \in [1, \ldots, l]$, let $r_{\underline{\tau}ij}$ and $p_{\underline{\tau}ij}$ be the il-th element of $R_{\underline{\tau}}$ and $P_{\underline{\tau}}$. Note that the cross-quantilogram is $r_{\underline{\tau}12}/\sqrt{r_{\underline{\tau}11}r_{\underline{\tau}22}}$. The partial cross-quantilogram is represented as follows:

$$\rho_{\underline{\tau}|z} = -\frac{p_{\underline{\tau}12}}{\sqrt{p_{\underline{\tau}11}p_{\underline{\tau}22}}}$$

$\rho_{\underline{\tau}|z}$ can be regarded as the cross-quantilogram between y_{1t} and y_{2t} conditional on the control variable z.

2.3. Data description

We analyse cross-quantile dependence among exchange rate, inflation, crude palm oil price and coal price with daily data from December 2, 2002, to July 30, 2021. The total sample analysed for approximately 19 years of the observation period is 3803 observations. Secondary data was obtained from the Central Bank of Indonesia (Bank Indonesia) database, published in the International Energy Agency (IEA) database. Table 1 shows the description of each variable.

3. Results and discussion

3.1. Descriptive statistics

We analyse the cross-quantile dependence among the exchange rate (EXR), Consumer Prices Index (CPI) as a proxy of inflation, crude palm oil price (POP) and coal price (CP). Table 2 reports the descriptive statistics of the exchange rate, consumer prices index as a proxy of inflation, crude palm oil price and coal price. We check the data abnormality by performing a Jarque-Bera normality test proposed by Jarque and Bera (1980). The results of the Jarque-Bera test state that the observed data are normally distributed. Due to the skewness and kurtosis in the data, we apply quantile approaches to address these problems. In econometric theory, when the observed data is large, there is a tendency for the data to have a normal distribution.

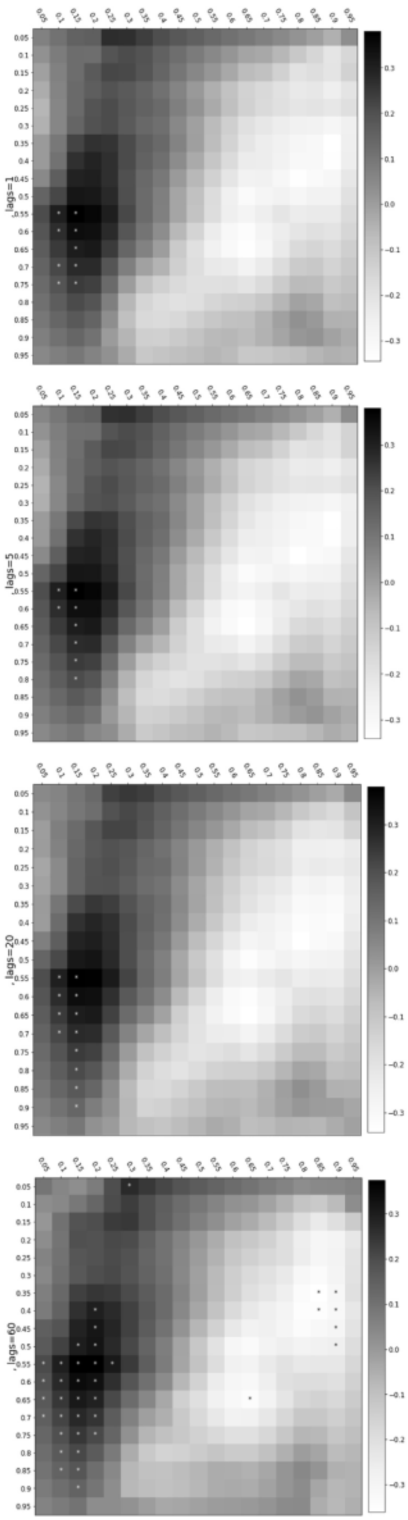

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Fig. 4b. EXR to Palm Oil Price **Note:** Fig. 4a: the vertical axis shows the quantile of inflation level, while the horizontal axis shows the quantile of the exchange rate. Fig. 4b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of Palm Oil Price. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

3.2. Volatility spillover among selected market

Table 3 reports the volatility spillover among the exchange rate markets, inflation, crude palm oil price, and coal price. Inflation volatility is influenced 24.49% by the other three markets, and its effect on the other three markets is 17.33%, so the net influence is −7.16%. Other markets influence inflation volatility, respectively 75.51% (from inflation itself), 8.33% (from exchange rate), 10.54% (from crude palm oil price) and 5.62% (from coal price). Other markets influence the exchange rate, respectively 6.54% (from inflation), 75.37% (from exchange rate itself), 10.75% (from crude palm oil price) and 7.34% (from coal price). Exchange rate volatility is influenced 24.63% by the other three markets, and its effect on other markets is 20.05%, so that the net influence is −4.58%. The results of net influence both of them are negative. A negative net directional volatility connectedness indicates that other variables of the network drive variable. It means that both inflation and exchange rate are less powerful influencers (just as receivers and not contributors).

Furthermore, the crude palm oil price is influenced 23.80% by the other three markets, and its effect on other markets is 25.79%. Hence, the net contribution of crude palm oil price to additional market volatility is 1.99%. Other markets influence the volatility of crude palm oil price, respectively 8.36% (from inflation), 7.30% (from exchange rate), 76.20% (from crude palm oil price) and 8.13% (from coal price). Then, the volatility of coal oil price is influenced by other markets, respectively 2.42% (from inflation), 4.42% (from exchange rate), 4.50% (from crude palm oil price) and 88.66% (from coal price). The coal price is influenced 11.34% by the other three markets, and its effect on other markets is 21.09%, so the net influence is 9.75%. Coal price has the most significant net influence compared to inflation, exchange rate and crude palm oil price. The results of net influence both crude palm oil price and coal price are positive. A positive net directional volatility connectedness indicates that a variable affects other variables more than it is affected by others. It means that both crude palm oil price and coal price are influential contributors to market volatility.

In addition, the average total connectivity index (TCI) among all four variables is 21.06%. Fig. 1 in the next section illustrates TCI generated from this analysis. The Net Pairwise Directional Connectedness (NPDC) are 3.00 for inflation, 2.00 for the exchange rate, 1.00 for crude palm oil price and 0.00 for coal price. NPDC refers to the numbers of variable act as a net transmitter among all pairwise directional connectedness (see Fig. 2).

3.3. Total connectivity index among four variables

Fig. 1 illustrates the total connectivity index (TCI) among exchange rate, inflation, crude palm oil price and coal price variables. TCI is generated from the volatility spillover among selected variables as explained in Table 3. This figure indicates that the behaviour of the exchange rate is not linear. It fluctuates until around 2010 then shows a constant rise over the last decade. Then, it increases gradually from 2017 until the end of the period. In general, there is a tendency for the price level to go up in Indonesia, indicating the problem of currency weakening. In addition, the pattern of the total connectivity index among the four markets shows repeated downturns during crises and turbulence.

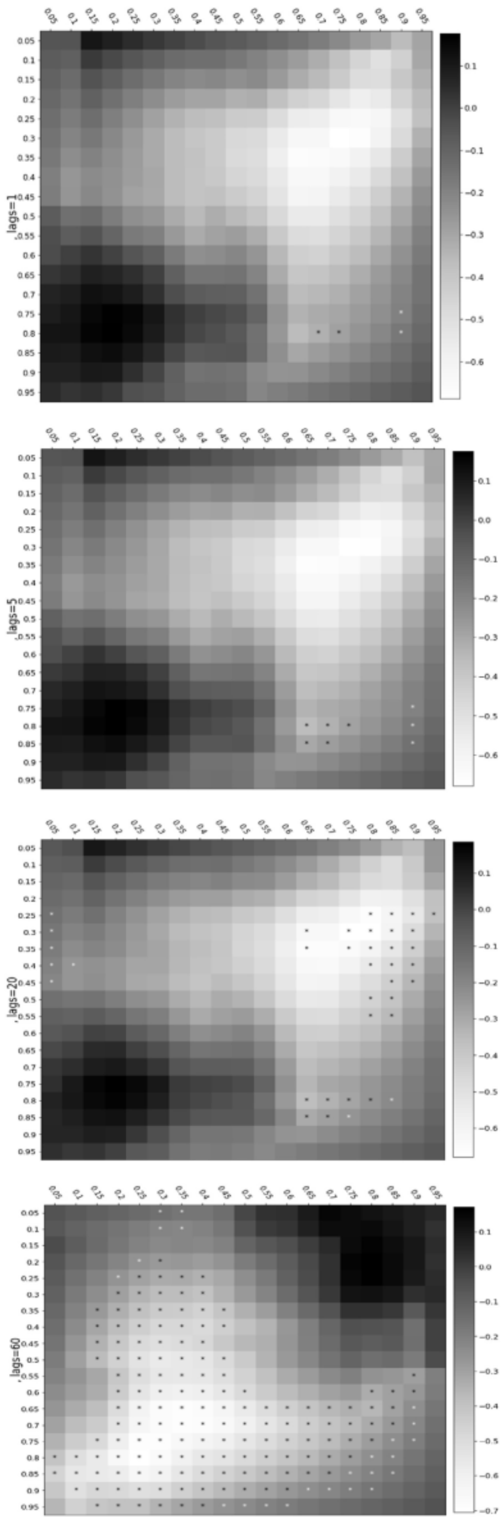

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Fig. 5a. Inflation to EXR **Note:** Fig. 5a: the vertical axis shows the quantile of inflation level, while the horizontal axis shows the quantile of the exchange rate. Fig. 5b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of inflation. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

3.4. *The cross-quantile dependence between exchange rate and other respective variables*

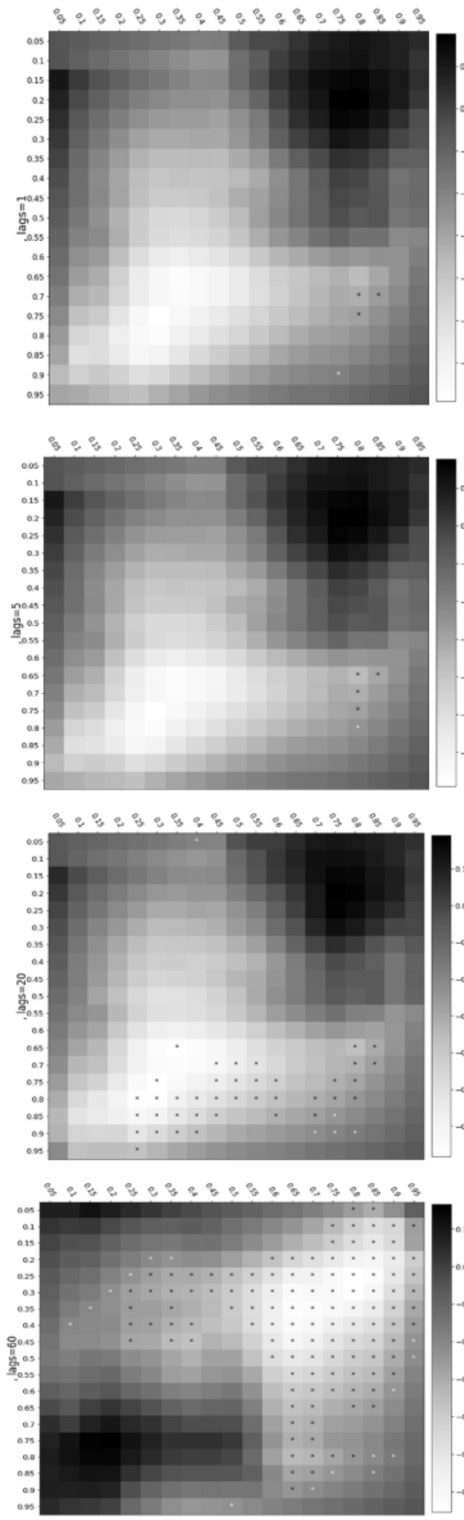
We apply the Cross-quantilogram approach to measure volatility spillover utilising daily data from 2002 to 2021. We use four different lag orders. Each lag shows spillover effects between variables considering daily (lag-1), weekly (lag-5), monthly (lag- 20) and quarterly (lag −60). Each diagram consists of 19x19 quantiles (q = 0.05–0.95) and captures all bivariate quantile combinations for each pair of markets at each lag length. Box-Ljung test is used to determine the statistical significance of each cross-quantilogram. A positive cross-quantilogram correlation is identified by black colour, while a negative cross-quantilogram correlation is identified by white colour. Any statistically significant correlation is identified as star(s).

3.4.1. Spillovers effect from coal price to exchange rate

Fig. 3a and b shows the spillover effect from coal price to exchange rate and vice-versa considering short, medium and long memories under different economic circumstance. Our results show that bidirectional Spillovers from coal price to exchange rate and vice versa are statistically insignificant at bearish state considering short to medium memories. Interestingly, the response of exchange rate to coal price is profound at medium to higher quantile of coal price and lower to medium quantile of exchange rate. Moreover, the response of exchange rate to coal price negative and significant, implying that Indonesia currency appreciates against US dollar. Our findings are partially in harmony with Sohag et al. (2022) and Bouoiyour et al. (2015) Wen et al. (2020) Balcilar and Usman (2021) for BRICS; and Yildirim and Arifli (2021); Aloui et al. (2018); Bénassy-Quéré et al., (2007); Habib & Kalamova, (2007); Jiang et al. (2016); Lin & Su, (2020); Taghizadeh-Hesary et al. (2019); Taghizadeh-Hesary et al. (2016) and Shahbaz et al. (2015) those who observed a strong co-movement between hydrocarbon price shocks and local exchange rate. Fig. 3b shows that coal price also responds negatively to exchange rate at lower to medium quantile of coal price and higher quantile of exchange rate under long memory. Our empirical findings echo with view of Sohag et al. (2022) who argue that Russian economy responds to oil and gas price in long memory due a time lag of shipment and payment. Specifically, the results show a negative dependence when coal price and exchange rate are opposite quantiles. For example, coal price is in a lower quantile, and the exchange rate is higher and vice versa. Overall, these results indicate that coal price and exchange rate are not dependent in the short run. Several recent empirical studies coincide with our proposition. A recent study Khan et al. (2021) argue that coal prices encountered several bubbles due to oil price shocks, innovation, geopolitical turmoil and overproduction.

3.4.2. Spillovers effect from palm oil price to exchange rate

Indonesia is the prominent export of palm oil and a significant player in producing palm oil. We use international crude palm oil data and analyse its relationship with the exchange rate. Fig. 4a and b shows the spillover effect from crude palm oil price to exchange rate and vice versa. The significance level of the spillover effect from exchange rate to crude palm oil price are shown in the lower quantiles of exchange rates and median to higher quantiles of crude palm oil price. Specifically, we find positive and statistically significant directional spillovers from



(caption on next column)

Fig. 5b. EXR to Inflation **Note:** Fig. 5a: the vertical axis shows the quantile of inflation level, while the horizontal axis shows the quantile of the exchange rate. Fig. 5b: the vertical axis shows the quantile of the exchange rate, while the horizontal axis shows the quantile of inflation. Lag-1, 5, 20 and 60, respectively, is going to be daily, weekly, monthly and quarterly. Matrix scale from 0 to 1. This is a 19x19 matrix. Every metric, every element shows the relationship between inflation and ER. Star shows significance level. Negative or positive directions are presented based on the white and black colour. The white-grey box-plot shows negative relation (minus 5), while the dark (black) box area indicates positive relation between inflation and exchange rate.

crude palm oil price to exchange rate and vice versa. Finally, our cross-quantilograms suggest that directional spillovers from crude palm oil price to exchange rate and in the opposite direction are similar across all the four lags (1, 5, 20, 60). However, directional spillovers from crude palm oil price to exchange rate slightly dissipate at longer lag lengths. Meanwhile, directional spillovers from exchange rate to crude palm oil price slightly grow at longer lag lengths.

3.4.3. Spillovers effect from inflation to exchange rate

Based on the cross-quantilogram analysis, our results show that inflation is associated with the exchange rate. If the price level goes up, the exchange rate follows. These results strengthen the theory and the results of previous studies which have stated that the relationship between inflation and exchange rate should be statistically significant positive. Fig. 5a and b shows the spillover effect from inflation to exchange rate and vice versa. The significance level of the spillover effect from inflation to exchange rate and vice versa are different among quantiles (daily, weekly, monthly and quarterly). The degree of co-movement is profound in the more extended lags order, indicating exchange rate and inflation relation follow a long memory to respond to each other. Lag-1 shows that cross-quantile dependence between inflation and exchange rate is significant and vice versa only in the highly high quantiles. Then, the significant levels increase over the longer lag 5, 20, and 60. Such a result may indicate that the cross-quantile dependency between inflation and exchange rate is strengthening. In lag-60, directional spillovers of inflation and exchange rate are negatively significant in most of the quantiles. Our finding is consistent with many prior studies e.g. Kim and Roubini (2008); Uzoma et al. (2012); and Kara and Nelson (2003).

4. Conclusion and policy implications

Indonesia as a prominent exporter of crude palm oil and coal, we measure the response of exchange rate to those two items' prices, along with the inflation rate. Due to high volatility and non-normal properties of our variables, we apply the time-frequency connectedness approach at the first stage to comprehend the magnitude of total connectedness among our respective variables. Besides, we also identify which macroeconomic indicators are net volatility contributors and receivers, respectively. At the second stage, we apply cross-quantilogram approach to measure the response of exchange rate to inflation, crude palm oil price and coal price considering short, medium, and long memories.

Our empirical analysis demonstrates that the magnitude of total connectedness among exchange rate, crude palm oil price, coal price and inflation is about 84%. We also find that coal price is the highest volatility contributor. Crude palm oil appears to be a net volatility contributor, but marginally. Conversely, inflation and exchange rate are found to be net volatility receivers from coal price and crude palm oil price.

At the second stage, our cross-quantilogram analysis shows that the exchange rate responds negatively towards international coal price at medium to higher quantile of coal price and lower to medium quantile of exchange rate considering long memory. The negative response of the exchange rate to coal price implies that Indonesia's currency appreciates against US dollar. The response of exchange rate to coal price is profound at the higher quantile in the long run horizon while it dissipates in the short run. However, the response of the exchange rate to crude palm oil follows a distinct pattern than to coal price. Our findings confirm the Rupiah (IDR) depreciates at lower quantile of palm oil price and medium of higher quantile of exchange rate from short to medium memories. Interesting, at higher quantile of palm oil price, Rupiah (IDR) appreciates. Finally, we find a strong association between the exchange rate and inflation level in Indonesia. Our finding corroborates the purchasing power parity (PPP) theory under the floating exchange rate regime and price flexibility. The co-movement between inflation and exchange becomes more profound in the long memory as price adjustment takes time due to menu-cost.

Our empirical findings provide several policy implications to central bank authority in devising an effective policy in controlling inflationary pressure. Our finding is helpful for coal industry and palm oil exporters to optimize foreign earning through the channel of exchange rate.

Credit authorship contribution statement

Grahita Chandrarin: Supervision and Funding; **Kazi Sohag:** Conceptualization, Methodology and Data Analysis, Supervision, Validation and Review; **Diyah Sukanti Cahyaningsih:** Discussion, Review; and **Dani Yuniawan:** Discussion, Review; **Heyvon Herdhayinta:** 1st draft.

Data availability

Data will be made available on request.

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