Journal of Management, Accounting, General Finance and International Economic Issues
https://ojs.transpublika.com/index.php/MARGINAL
Online ISSN 2809-8013 | Print ISSN 2809-9222

https://doi.org/10.55047/marginal.v5i3.2326

Original Article

Volatility Spillover of World Oil Prices on the Rupiah Exchange Rate: Evidence from a Net Oil-Importing Emerging Economy

Aulia Keiko Hubbansyah[1*], Iha Haryani Hatta[2], Safitri Siswono[3], Arya Jati Kusuma Al-Ansori[4]

[1-4]Universitas Pancasila, Indonesia
Email: [1)] akhubbansyah@univpancasila.ac.id

Received : 24 June - 2026
Accepted : 28 July - 2026
Published online : 31 July - 2026

Abstract

Crude oil price volatility is a first-order source of macroeconomic risk for net oil-importing emerging economies, transmitting through the exchange rate to inflation, fiscal balances, and financial stability. Indonesia's transition since 2004 from a net oil exporter to a net oil importer has fundamentally altered this exposure, yet systematic empirical evidence quantifying the resulting transmission mechanism remains limited. This study examines volatility spillovers between world oil prices and the Indonesian rupiah exchange rate over 1990-2024, employing a two-stage framework combining ARCH-GARCH volatility extraction with a generalized VAR spillover-index approach incorporating generalized forecast error variance decomposition (FEVD) and rolling-window estimation. The results reveal a pronounced and asymmetric spillover structure: 26.79% of rupiah exchange rate forecast error variance is attributable to shocks originating in the global oil market, compared to only 5.85% in the reverse direction. The net spillover of +20.94 percentage points confirms that global oil markets operate as a dominant net transmitter of volatility, while the rupiah functions as a persistent net receiver; the Total Connectedness Index (TCI) of 32.6% indicates substantive interdependence between the two markets. Rolling-window analysis further reveals that spillover intensity is strongly state-dependent, amplifying during five major global shock episodes: the 1997-1998 Asian financial crisis, the 2004-2008 oil boom, the 2008-2009 global financial crisis, the 2014-2016 oil price collapse, and the 2020 COVID-19 pandemic. These findings carry concrete implications for Bank Indonesia's exchange rate surveillance, fiscal subsidy stress-testing, and energy diversification policy.

Keywords: Exchange Rate, Net Oil Importer, Oil Price Volatility, Rolling-Window, VAR Spillover Index.

1. Introduction

Crude oil occupies a structurally irreplaceable position in the global economy, functioning simultaneously as the world's most critical energy input and one of its most actively traded financial assets. Despite decades of renewable energy investment, petroleum continues to supply more than 30 percent of total global primary energy, a proportion that has proven remarkably resistant to displacement over three consecutive decades (BP, 2025). Its dual character, strategically essential for industrial production while simultaneously speculated upon in multi-trillion-dollar futures markets, endows oil price movements with macroeconomic propagation effects that extend far beyond the energy sector itself (Salem et al., 2024). Of all the macroeconomic variables through which oil price shocks transmit, the exchange rate is arguably the most immediate and consequential: it is the first-order price that governs the real cost of energy imports, the competitiveness of export sectors, and the credibility of monetary policy in open economies (Kilian, 2009).

The trade channel operates through the current account: rising oil prices increase energy import costs for oil-importing nations, deteriorate the trade balance, and generate excess demand for foreign currency that depreciates the nominal exchange rate (S.-S. Chen & Chen, 2007; Olstad et al., 2020). For oil exporters, the direction reverses: windfalls of oil revenue improve the current account and appreciate the domestic currency. The wealth channel operates through international portfolio rebalancing: oil exporters invest windfall revenues predominantly in dollar-denominated assets, creating additional demand for the U.S. dollar and appreciating it against trading partner currencies (Habib et al., 2016; Krugman, 1983). A third channel, increasingly prominent in the literature, is the expectation and risk channel: oil price uncertainty amplifies global financial risk aversion, triggers capital flight from emerging market assets toward safe-haven currencies, particularly the U.S. dollar and Japanese yen, and depresses emerging market exchange rates independently of any current account movement (Nekhili et al., 2024).

The intensity and even the direction of these transmission channels is fundamentally conditioned on whether a country is a net exporter or net importer of oil. This structural condition is not fixed, and when it shifts, as it did for Indonesia, it constitutes a first-order transformation of the country's macroeconomic risk architecture. Since 2004, Indonesia formally transitioned from a net oil exporter to a net oil importer, a structural reversal that fundamentally altered the country's exposure to global commodity price shocks. By 2023, Indonesia was importing 1.6 million barrels of crude oil per day, a dramatic inversion from its early 2000s position as a net exporter of 344,000 barrels per day (Damuri et al., 2024). The fiscal and monetary consequences of this transition are severe and quantifiable. Indonesia's energy subsidies peaked at IDR 886 trillion (approximately USD 59.7 billion) in 2022 before moderating to IDR 713.5 trillion (USD 45 billion) in 2024 (Suharsono et al., 2026). Critically, the Ministry of Finance (2022) estimates that each USD 1/barrel increase in oil prices adds IDR 5.8 trillion to the fiscal deficit, while each IDR 100/USD depreciation adds a further IDR 3.1 trillion, creating a mutually reinforcing cycle between external oil price shocks, exchange rate depreciation, and domestic fiscal pressure that makes Indonesia's macroeconomic stability acutely sensitive to developments in the global oil market.

This vulnerability is not merely theoretical. Wan et al. (2025) estimates that a USD 10/barrel oil price increase reduces the current account balances of Asian oil-importing nations significantly, with direct depreciatory implications for their exchange rates. IMF (2024) documented elevated rupiah volatility throughout 2023 and early 2024, attributing it partly to global commodity price uncertainty. Hoque et al. (2025), using time-frequency domain analysis across South and Southeast Asian markets, consistently identify Indonesia as a net recipient of global energy market shocks, a classification that has intensified since the transition to net importer status. Bui and Ngo (2025) confirm that all six Southeast Asian markets studied, including Indonesia, exhibit significant short- and long-run reactions to global energy market dynamics, with crisis periods generating disproportionate transmission intensity.

The empirical literature on oil price-exchange rate spillovers for Indonesia, however, remains thin relative to the economic magnitude of the phenomenon. Most extant studies examine either advanced economies or broad emerging market panels, without accounting for the structural break imposed by a country's transition between net exporter and net importer regimes. This constitutes a significant gap: the relevant transmission channels, their magnitudes, and their temporal dynamics are expected to differ systematically before and after such a transition. This study addresses this gap directly by applying the VAR Spillover Index framework of Diebold and Yilmaz (2008, 2012), enhanced by generalized forecast error variance decomposition and rolling-window estimation, across monthly data from 1990 to 2024. The 34-year sample is explicitly designed to straddle Indonesia's structural transition, enabling the first systematic empirical comparison of spillover dynamics across both regimes.

The contribution of this study is threefold. First, it provides the most comprehensive quantification to date of oil price volatility spillovers to the rupiah exchange rate, using a methodology that explicitly identifies transmission direction and magnitude. Second, by covering both the net exporter and net importer eras, it documents how a structural shift in commodity trade status alters the macroeconomic risk profile of an emerging economy. Third, through rolling-window estimation, it maps the temporal evolution of spillover intensity across five major global shock episodes, demonstrating the state-dependent, nonlinear character of transmission that has critical implications for risk management frameworks. The remainder of this paper is organized as follows: Section 2 reviews the theoretical and empirical literature; Section 3 details the data, research period, and methods of analysis; Section 4 presents and interprets the empirical results; and Section 5 derives conclusions and policy implications.

2. Literature Review

2.1. Theoretical Channels: From Oil Markets to Exchange Rates

The theoretical framework connecting oil price movements to exchange rate dynamics draws on multiple traditions in international macroeconomics, each illuminating a distinct transmission pathway. Understanding the interplay of these channels is essential for interpreting the empirical spillover results generated by this study.

The trade channel is the most direct and most extensively modeled mechanism. In the standard Mundell-Fleming framework extended to accommodate commodity prices, rising real oil prices increase production costs and the consumer price level in oil-importing nations, simultaneously deteriorating the merchandise trade balance through higher import values and exerting downward pressure on the nominal exchange rate through excess demand for foreign currency in spot markets (S.-S. Chen & Chen, 2007). The real exchange rate is also affected in the long run through purchasing power parity dynamics: higher domestic inflation relative to trading partners erodes the real exchange rate even if the nominal rate initially holds. Chen and Chen (2007), using panel data for G7 countries, demonstrated that real oil prices are powerful long-run predictors of real exchange rates, a finding replicated across diverse samples in subsequent literature. The direction of this effect is directly conditioned by a country's net oil trade position: for net importers, higher oil prices are definitively depreciatory, while for net exporters they are appreciatory.

Kilian (2009) introduced a fundamental refinement to this framework by demonstrating that the macroeconomic and exchange rate effects of oil price shocks depend critically on their source, not merely their magnitude. He decomposed oil price shocks into three structurally distinct types: supply-side disruptions (crude oil supply shocks), demand-side expansions driven by global economic growth (aggregate demand shocks), and precautionary demand shocks arising from speculative uncertainty about future oil availability. Crucially, these three shock types have different, and sometimes opposite, effects on exchange rates, inflation, and output. An oil supply disruption causes a terms-of-trade deterioration for importers that is unambiguously depreciatory; a global demand boom may simultaneously increase oil prices and the demand for emerging market exports, partially offsetting the depreciatory pressure; and a precautionary demand shock generates financial uncertainty that can trigger safe-haven flows irrespective of any fundamental trade balance movement.

The wealth channel operates through international asset portfolio rebalancing. Oil-exporting nations that accumulate foreign exchange reserves and sovereign wealth funds invest these windfalls predominantly in dollar-denominated instruments, U.S. Treasuries, money market funds, and corporate bonds. This systematic demand for dollar assets creates persistent upward pressure on the U.S. dollar against other currencies (Krugman, 1983). Habib et al. (2016), using panel data spanning 1980-2014, confirmed that oil price shocks significantly affect real exchange rates of both exporters and importers with opposite signs, consistent with the wealth channel prediction. Habib and Kalamova (2007) further showed that among major oil exporters, oil price movements explain a substantial share of real exchange rate variation, validating the concept of 'petro-currencies' whose valuations co-move with global oil prices.

The expectation and risk channel has gained prominence in the literature following the globalization of financial markets. Oil price volatility generates macroeconomic uncertainty that elevates investor risk aversion, measured inter alia by the VIX (CBOE Volatility Index). Heightened global risk aversion triggers capital reallocation from emerging market assets, including equities, bonds, and currencies, toward safe-haven assets, predominantly the U.S. dollar, Japanese yen, and Swiss franc. This dynamic can depress emerging market exchange rates even when the current account impact of oil price changes is theoretically beneficial, as documented by S. Chen et al. (2024) in their TVP-VAR analysis of oil-exporting versus oil-importing country exchange rates. Nekhili et al. (2024), using higher-order moment analysis, further demonstrate that the risk channel intensifies non-linearly during tail-risk events, generating disproportionate spillover magnitudes in crisis periods.

A fourth mechanism increasingly recognized in the literature is the monetary policy channel. Oil price shocks affect central bank behavior by simultaneously threatening inflation (via energy and food price pass-through) and growth (via demand compression), creating a policy trilemma for inflation-targeting central banks in open economies. Garcia et al. (2011) showed that the optimal degree of exchange rate smoothing in response to oil price shocks depends on the relative magnitudes of the inflation and output effects, parameters that shift systematically with a country's net oil trade status. For a net oil importer like Indonesia, rising oil prices impose both inflationary and recessionary pressure simultaneously, creating the most difficult configuration for monetary policy management.

2.2. Empirical Evidence: Oil Price Shocks and Exchange Rates

The empirical literature on oil price-exchange rate dynamics has grown considerably over the past two decades, with evidence accumulating across diverse methodological frameworks and country contexts. The findings are broadly consistent with the theoretical predictions of the trade and wealth channels, but reveal important heterogeneities related to country structure, crisis periods, and the asymmetry of oil price movements.

For net oil-importing countries, the predominant empirical finding is that rising oil prices cause exchange rate depreciation through the trade channel. Huang et al. (2021), applying pooled mean group (PMG) estimation to panel data from 1997 to 2015, documented a significantly negative relationship between oil prices and the exchange rates of net oil-importing nations, with the effect strengthening during periods of elevated oil price volatility. Salisu et al. (2019) extended this analysis to BRICS economies and confirmed that oil price increases consistently depreciate currencies of oil-importing members while appreciating those of oil-exporting members, providing clean empirical identification of the trade channel direction.

A critical strand of the literature emphasizes the asymmetric nature of oil price transmission, that price increases and decreases of equal magnitude have different effects on exchange rates. Kathuria and Sabat (2020), using GARCH and EGARCH models with 20 years of daily data for India, documented significant asymmetric effects: oil price increases generated larger and more persistent exchange rate depreciation than price decreases of equivalent size generated appreciation. Sharma et al. (2025), in the most recent study of this type using daily data from July 2009 to January 2024 for the Indian rupee, confirmed this asymmetric transmission and demonstrated that the asymmetry intensified in post-COVID data, reinforcing the importance of employing nonlinear or asymmetric specifications when modeling oil price-exchange rate dynamics.

The role of crisis periods in amplifying oil price-exchange rate transmission is well-documented. Bhatia (2021) found persistent long-run volatility transmission from oil prices to exchange rates across all five BRICS economies from 1999 to 2020, with COVID-19 significantly accelerating and amplifying the transmission mechanism. Chowdhury and Garg (2022) studied China, India, Japan, and South Korea during 2017-2020 using VAR and bivariate GARCH models and found that the pandemic substantially strengthened the dynamic linkage between oil price volatility and exchange rate volatility, a pattern inconsistent with the prediction that lower oil demand should reduce the trade channel impact, pointing instead to the dominance of the expectation and risk channel during extreme episodes. Ben Salem et al. (2024) provide the most methodologically comprehensive recent analysis, applying DCC-GARCH-connectedness to ten major exchange rates and demonstrating that the COVID-19 pandemic and the Russia-Ukraine conflict generated the highest oil-forex connectedness values in the sample, confirming the state-dependent, crisis-amplifying character of transmission.

For net oil-exporting countries, the relationship reverses direction but exhibits similar nonlinearities. Chen et al. (2024), applying TVP-VAR extended joint connectedness to a comparison of oil-exporting and oil-importing countries, found that oil-exporting currencies appreciate with oil price increases while oil-importing currencies depreciate, but that the magnitude of transmission is asymmetric and time-varying, intensifying substantially during global crises regardless of net trade position. This suggests that the expectation and risk channel, which operates symmetrically across exporters and importers, becomes dominant during crisis episodes.

For Nigeria, an economy that shares Indonesia’s structural ambiguity as both a major oil producer and a large domestic consumer, Adeniyi et al. (2011) found that oil price increases actually appreciate the exchange rate, reflecting the dominance of the wealth channel through oil export revenues. This finding sharply contrasts with purely oil-importing economies and underscores the analytical importance of correctly classifying a country’s net oil trade position before formulating hypotheses about transmission direction. It also makes Indonesia’s transition from net exporter to net importer particularly analytically significant: it effectively inverted the operative channel from wealth channel (appreciatory) to trade channel (depreciatory).

2.3. Indonesia and the Southeast Asian Context

Research specifically examining the volatility relationship between global oil prices and the Indonesian rupiah exchange rate remains comparatively limited, particularly when benchmarked against the economic magnitude of Indonesia’s oil import dependency. The majority of existing Indonesia-specific research has focused on equity market impacts rather than exchange rate dynamics.

In the equity market domain, Arifin et al. (2025) analyzed sectoral stock index returns on the Indonesia Stock Exchange from 2012 to 2024 and documented significant interactions between global oil prices, the rupiah-dollar exchange rate, and sector-specific returns, with energy-oriented sectors exhibiting the highest sensitivity to oil price movements. Their findings confirm that the rupiah functions as an important transmission vector between global commodity price shocks and domestic financial market conditions. Marpaung and Pangestuti (2024) similarly found for a longer Indonesian data sample that external factors including oil price movements and the global financial crisis significantly affected the rupiah-dollar exchange rate, which in turn transmitted shocks to the domestic capital market.

In the regional comparative context, Bui and Ngo (2025) examined six Southeast Asian stock markets, including Indonesia, using data from 2007 to 2023 and confirmed significant short- and long-run reactions to global energy market dynamics across the entire region, with crisis periods generating disproportionately strong reactions. Their results establish that Indonesia's financial markets are not insulated from global commodity price dynamics, but rather are systematically exposed to them across both time horizons. Hoque et al. (2024) corroborate this with time-frequency domain analysis showing that Indonesia is consistently identified as a net recipient of global energy shocks, a classification that strengthened materially after 2004.

The closest regional analog to Indonesia is Thailand, another mid-sized Southeast Asian economy that transitioned from moderate oil production to near-complete oil import dependency. Research by Pechdin et al. (2024) using Johansen cointegration and VECM on Thai data from 2000 to 2019 found a significant long-run negative relationship between oil prices and Thailand's real effective exchange rate (REER), estimating that a 1% increase in Dubai crude oil prices reduces Thai REER by 0.31%. This finding is directly relevant as a benchmark: both Indonesia and Thailand are net oil importers integrated into global commodity markets, making the Thai estimate a useful reference point for the expected order of magnitude of oil-to-exchange-rate transmission.

At the macroeconomic institutional level, the oil price-exchange rate-fiscal subsidy nexus in Indonesia has been documented by several major international bodies. Ihsan et al. (2024) and the Ministry of Finance (2022) quantify the dual fiscal transmission channel through which oil prices and the exchange rate jointly determine the subsidy burden, as already detailed in the Introduction. IMF (2024) further noted that while Indonesia's foreign exchange reserves provide an adequate liquidity buffer, the recurrent episodes of high rupiah volatility in 2023-2024 reflect the continued sensitivity of the exchange rate to external commodity price developments. MUFG Research (2025) specifically modeled the impact of oil price shocks on Asian oil-importing exchange rates, estimating that a USD 10/barrel oil price increase can materially compress Indonesia's current account position, generating direct depreciation pressure on the rupiah.

The collective body of this literature establishes a strong prior that the transition to net oil importer status has fundamentally altered Indonesia's macroeconomic exposure to global oil market volatility. However, no prior study has explicitly quantified this structural change through a systematic spillover index methodology applied across a sample that spans both regimes. This study fills that gap.

3. Methods

3.1. Data and Research Period

This study employs monthly time series data spanning January 1990 through December 2024, a 34-year sample deliberately designed to encompass two structurally distinct regimes in Indonesia's position in global oil markets: the net exporter era (1990-2000) and the net importer era (2004-2024). The transition period 2001-2003, during which Indonesia's net trade position shifted, is retained in the full-sample estimation but excluded from the comparative sub-period analysis to ensure clean structural contrast. The two primary variables are: (1) world oil price volatility, proxied from the spot prices of Brent crude oil (in USD per barrel) obtained from the U.S. Energy Information Administration (EIA) and Bloomberg; and (2) rupiah exchange rate volatility (USD/IDR), obtained from Bank Indonesia and the IMF International Financial Statistics. Both series are constructed as true monthly average prices, rather than end-of-month spot values, to avoid introducing spurious volatility from within-month timing noise. Volatility for each series is measured as the conditional standard deviation extracted from ARCH-GARCH models estimated in the first stage of the empirical procedure.

3.2. Volatility Extraction: ARCH-GARCH Models

The first stage of the empirical framework extracts conditional volatility series from the oil price and exchange rate return series using the Autoregressive Conditional Heteroscedasticity (ARCH) model of Engle (1982) and its generalization, the GARCH model of Bollerslev (1986). These models are the methodological standard for financial time series volatility measurement because they explicitly model two pervasive empirical regularities: volatility clustering, the tendency for large (small) shocks to be followed by large (small) shocks, and leptokurtosis, the prevalence of fat-tailed return distributions that violate the normality assumption of OLS-based approaches.

The mean equation for each series is specified as an ARMA(p,q) process to ensure white noise residuals, and the conditional variance equation follows a GARCH(r,m) specification:

$$h_t = \kappa + \alpha_1\varepsilon^2_{t-1} + \alpha_2\varepsilon^2_{t-2} + \cdots + \alpha_m\varepsilon^2_{t-m} + \delta_1 h_{t-1} + \delta_2 h_{t-2} + \cdots + \delta_r h_{t-r} \quad (1)$$

where h_t is the conditional variance at time t; $\kappa > 0$ is the long-run variance constant; α_n (n = 1,...,m) are the ARCH coefficients capturing the impact of past squared residuals (past shocks) on current conditional variance; and δ_n (n = 1,...,r) are the GARCH coefficients capturing the persistence of past conditional variance. The stationarity condition requires that $\Sigma\alpha_n + \Sigma\delta_n < 1$, which ensures that the conditional variance reverts to its long-run unconditional mean. The volatility series used in the second-stage spillover estimation is the conditional standard deviation $\sigma_t = \sqrt{h_t}$. Optimal lag orders (p, q, r, m) are selected by minimizing the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). The presence of ARCH effects is verified prior to estimation using the ARCH-LM (Lagrange Multiplier) test of Engle (1982). Post-estimation diagnostics include Ljung-Box Q-statistics on standardized residuals and squared residuals to confirm the absence of remaining serial correlation.

3.3. The Diebold-Yilmaz VAR Spillover Index Framework

The core of the empirical methodology is the VAR Spillover Index framework introduced by Diebold and Yilmaz (2008) and extended in their landmark 2012 paper. This framework measures volatility spillovers using the forecast error variance decomposition (FEVD) of a Vector Autoregression (VAR) model, enabling the explicit quantification of cross-market transmission magnitudes and directions. The framework has three key components: the VAR specification, the generalized FEVD, and the construction of spillover indices.

Let $y_t = (y_{1t}, y_{2t}, \ldots, y^{\circ}_t)^T$ be a K-dimensional vector of covariance-stationary endogenous variables. In this study, K = 2, with y_{1t} denoting oil price conditional volatility and y_{2t} denoting rupiah exchange rate conditional volatility. The VAR(P) model is:

$$y_t = \Theta_1 y_{t-1} + \Theta_2 y_{t-2} + \cdots + \Theta^p y_{t-p} + \varepsilon_t \quad (2)$$

where Θ_i ($i = 1, 2, \ldots, P$) are $K \times K$ matrices of autoregressive coefficients, and $\varepsilon_t \sim iid(0, \Sigma)$ is a K-dimensional vector of reduced-form disturbances with covariance matrix Σ. The VAR has an equivalent moving-average (MA) representation:

$$y_t = \Psi(L)\varepsilon_t = \Sigma_{k=0}\infty\ \Psi_k\varepsilon_{t-k} \qquad (3)$$

where Ψ_k are $K \times K$ moving-average coefficient matrices satisfying the recursion $\Psi_k = \Sigma^{j}{}_{=1}{}^{P}\ \Psi_{k-}{}^{j}\Theta^{j}$, with $\Psi 0 = I^{ɔ}$ and $\Psi_k = 0$ for $k < 0$. The MA representation is the foundation for computing the FEVD. Stationarity of the VAR is confirmed by the Augmented Dickey-Fuller (ADF) unit root test applied to each element of y_t prior to estimation. Optimal lag length P is determined by the AIC, yielding $P = 6$ in this application consistent with the presence of substantial low-frequency dynamics in monthly financial data.

The critical methodological challenge in FEVD-based spillover measurement is that the standard Cholesky-factor decomposition produces variance decompositions that depend on the ordering of variables in the VAR, an arbitrary choice that can materially affect results. Diebold and Yilmaz (2012) resolve this by adopting the generalized FEVD (GFEVD) of Koop et al. (1996) as well as Pesaran and Shin (1998), which produces variable-ordering-invariant decompositions by using the actual historical distribution of shocks rather than an artificially orthogonalized shock. The H-step-ahead generalized forecast error variance decomposition, the share of variable i's forecast error variance at horizon H attributable to shocks in variable j is:

$$\phi_{ir}(H) = \sigma_{rr}{}^{-1} \times \Sigma^{h}{}_{=0}{}^{H-1}(e_i{}^{T}\ \Psi^{h}\ \Sigma\ e_r)^2 \,/\, \Sigma^{h}{}_{=0}{}^{H-1}(e_i{}^{T}\ \Psi^{h}\ \Sigma\ \Psi^{hT}\ e_i) \qquad (4)$$

where $\sigma_{rr} = (\Sigma)_{rr}$ is the (j,j) element of the residual covariance matrix Σ (the variance of the j-th equation's disturbance); Ψ^{h} is the $K \times K$ moving-average coefficient matrix at horizon h; e_i is a $K \times 1$ selection vector with one in the i-th position and zeros elsewhere; and H is the forecast horizon (set to $H = 10$ months in this study, consistent with the convention in the literature). Because the generalized decompositions use the actual covariance structure of shocks rather than orthogonalized shocks, their rows do not necessarily sum to unity. Each entry is therefore normalized by the row sum:

$$\phi\square_{ir}(H) = \phi_{ir}(H) \,/\, \Sigma^{ɔ}{}_{i=1}\ \phi_{ir}(H) \qquad (5)$$

such that $\Sigma^{ɔ}{}_{r=1}\ \phi\square_{ir}(H) = 1$ and $\Sigma^{ɔ}{}_{ir=1}\ \phi\square_{ir}(H) = K$ by construction. The normalized GFEVD entry $\phi\square_{ir}(H)$ has a direct economic interpretation: it is the fraction of variable i's H-step-ahead forecast error variance that can be attributed to innovations (shocks) in variable j, holding the dynamic structure of the entire system constant.

From the normalized GFEVD matrix $[\phi\square_{ir}(H)]_{ir=1}{}^{ɔ}$, Diebold and Yilmaz (2012) construct four key spillover measures that collectively characterize the connectedness architecture of the system.

The Total Connectedness Index (TCI) measures the average share of forecast error variance in the system attributable to cross-variable shocks (i.e., off-diagonal elements of the GFEVD matrix):

$$TCI(H) = \Sigma^{ɔ}{}_{i,r=1,\ i\neq r}\ \phi\square_{ir}(H) \,/\, \Sigma^{ɔ}{}_{i,r=1}\ \phi\square_{ir}(H) \times 100 \qquad (6)$$

A TCI of zero indicates a completely isolated system where each variable's forecast error variance is entirely driven by its own shocks; a TCI of 100 indicates perfect connectedness where all variance originates from cross-market spillovers.

The Directional Spillover FROM variable i (the amount of variance received by variable i from all other variables $j \neq i$) is:

$S_{i\cdot}(H) = \Sigma^{ɔ}_{r=1,\, r\neq i}\, \phi\square_{ir}(H) \,/\, \Sigma^{ɔ}_{i,r=1}\, \phi\square_{ir}(H) \times 100$ .... (7)

The Directional Spillover TO variable i (the amount of variance transmitted by variable i to all other variables $j \neq i$) is:

$S_{\cdot i}(H) = \Sigma^{ɔ}_{r=1,\, r\neq i}\, \phi\square_{ri}(H) \,/\, \Sigma^{ɔ}_{i,r=1}\, \phi\square_{ri}(H) \times 100$ .... (8)

The Net Spillover for variable i is the difference between what it transmits and what it receives:

$S^{net}_{i}(H) = S_{\cdot i}(H) - S_{i\cdot}(H)$ .... (9)

A positive net spillover identifies variable i as a net transmitter of volatility, it exports more variance to the system than it imports. A negative net spillover identifies variable i as a net receiver, it imports more variance than it exports. Table 1 below provides a conceptual representation of the full GFEVD connectedness matrix for the bivariate system in this study.

Table 1. Generalized FEVD Connectedness Matrix: Conceptual Structure for the Bivariate System

	x1 (Oil Vol)	x2 (FX Vol)	FROM$_{i\cdot}$(Received)	Net$_i$
x1 (Oil Vol)	$\phi\square_{11}(H)$	$\phi\square_{12}(H)$	$S_{1\cdot}(H)=\phi\square_{12}$	$S1^{net}$
x2 (FX Vol)	$\phi\square_{21}(H)$	$\phi\square_{22}(H)$	$S_{2\cdot}(H)=\phi\square_{21}$	$S2^{net}$
TO$_{\cdot i}$(Transmitted)	$S_{\cdot 1}(H)=\phi\square_{21}$	$S_{\cdot 2}(H)=\phi\square_{12}$	TCI(H)	

Note: $\phi\square_{ir}(H)$ denotes the normalized H-step-ahead GFEVD entry; diagonal entries (shaded) represent own-variable variance contributions; off-diagonal entries represent cross-market spillovers. TCI is computed from normalized off-diagonal entries only.

Source: Adapted from Diebold and Yilmaz (2012)

3.4. Rolling Window Estimation

A key methodological contribution of this study is the application of rolling-window estimation to generate a time-varying version of the spillover indices. The rolling-window approach involves fixing a window of W consecutive observations, estimating the full VAR and computing all spillover indices for that window, then advancing the window by one period and repeating. The output is a time series of spillover indices $\{TCI(t), S_{i\cdot}(t), S_{\cdot i}(t), S^{net}_{i}(t)\}$ indexed by t, where each observation reflects the spillover dynamics prevailing in the W-period window ending at t.

The primary advantage of rolling-window estimation over static full-sample estimation is that it does not require the researcher to pre-specify structural break points, a choice that is necessarily arbitrary and has been shown to materially influence conclusions in the extant literature (Baur, 2012). By contrast, the rolling-window approach allows the data to endogenously reveal periods of intensified or diminished transmission, providing a model-free characterization of temporal dynamics in spillover relationships. The window length W represents a bias-variance tradeoff: longer windows yield more stable, precise estimates but are slower to detect structural changes; shorter windows are more responsive to regime shifts but noisier. Window length selection follows the convention in the Diebold-Yilmaz literature, balancing these considerations for monthly data at the sample frequency used in this study.

4. Results and Discussion

4.1. Descriptive Statistics

Table 2 presents descriptive statistics for oil price and exchange rate conditional volatility across three observation periods: the full sample (1990-2024), the net exporter sub-period (1990-2000), and the net importer sub-period (2004-2024). This tripartite structure is designed to quantify the structural change in volatility patterns that corresponds to Indonesia's fundamental transition in global oil trade status.

Table 2. Descriptive Statistics of Oil Price and Exchange Rate Conditional Volatility

Variable	Mean	Std. Dev.	CV (%)	Min	Max	Skewness
Panel A: Full Sample (1990-2024)						
Oil Price Volatility	4.65	3.21	69.03	0.86	18.36	1.84
Exchange Rate Volatility	348.49	484.50	139.02	3.21	3338.23	3.72
Panel B: Net Exporter Period (1990-2000)						
Oil Price Volatility	1.82	1.05	57.69	0.86	6.47	1.43
Exchange Rate Volatility	398.24	787.10	197.64	3.21	3338.23	3.16
Panel C: Net Importer Period (2004-2024)						
Oil Price Volatility	6.39	2.98	46.63	1.85	18.37	1.12
Exchange Rate Volatility	299.44	208.71	69.77	35.27	1245.88	2.18

Volatility series are conditional standard deviations extracted from ARCH-GARCH models. CV = Coefficient of Variation (Std. Dev./Mean × 100).

Source: Authors' estimation (2026)

The descriptive statistics reveal a structurally significant reversal in the relative volatility profiles of the two series across sub-periods. In the net exporter era (Panel B), oil price volatility was comparatively modest (mean = 1.82; CV = 57.69%) while exchange rate volatility was extreme (mean = 398.24; CV = 197.64%). The maximum exchange rate volatility of 3,338.23 reflects the 1997-1998 Asian financial crisis, during which the rupiah collapsed from approximately IDR 2,500 to nearly IDR 17,000 per dollar, one of the most severe currency depreciations in modern economic history. The extreme skewness of 3.16 in the net exporter exchange rate series confirms a distribution dominated by this single catastrophic outlier event rather than systematic exposure to oil market dynamics.

In the net importer era (Panel C), the pattern fundamentally inverts. Oil price volatility more than tripled in absolute terms (mean = 6.39 vs. 1.82), driven by the superposition of the 2004-2008 oil boom, the 2008-2009 crash, the 2014-2016 collapse, and the 2020 COVID-19 shock. Exchange rate volatility, conversely, declined dramatically across all measures: the mean fell from 398.24 to 299.44, the standard deviation collapsed from 787.10 to 208.71, and most tellingly, the CV fell from 197.64% to 69.77%, a nearly two-thirds reduction in relative volatility. This improvement reflects the strengthening of Bank Indonesia's monetary policy framework, reserve accumulation to USD 146 billion by end-2023 (IMF, 2024), and improved fiscal-monetary coordination. Collectively, these statistics indicate a fundamental shift in the primary source of Indonesia's macroeconomic instability: from domestic crisis risk (the dominant factor in the net exporter era) to external oil market exposure (the dominant factor in the net importer era).

4.2. The VAR Spillover Index

Prior to VAR estimation, ADF unit root tests confirmed stationarity of both series at level I(0), permitting VAR estimation in levels. The optimal lag length determined by AIC is P = 6, indicating that volatility dynamics in this system exhibit substantial memory, consistent with the persistence of oil price and exchange rate volatility documented in the GARCH literature. The full-sample Diebold-Yilmaz VAR Spillover Index results are presented in Table 3.

Table 3. Volatility Spillover Index

	Oil Price Volatility (%)	Exchange Rate Volatility (%)	FROM Others Received (%)
Oil Price Volatility	94.15	5.85	5.9
Exchange Rate Volatility	26.79	73.21	26.8
TO Others - Transmitted (%)	26.79	5.85	
Contribution Including Own	120.90	79.10	
Net Spillover	+20.94 (Net Transmitter)	−20.94 (Net Receiver)	TCI = 32.6%

H = 10-month forecast horizon. Entries are normalized GFEVD percentages. TCI = Total Connectedness Index. Net spillover = TO − FROM; positive values = net transmitter; negative values = net receiver.
Source: Authors' estimation (2026)

The spillover table 3 reveals a clear and quantitatively substantial asymmetry in the transmission architecture between global oil markets and the Indonesian rupiah exchange rate. The diagonal entries, 94.15% for oil price volatility and 73.21% for exchange rate volatility, represent the proportion of H-step-ahead forecast error variance explained by each variable's own past shocks. The near-complete self-determination of oil price volatility (94.15%) is consistent with the price-taker assumption underlying small open economy models: Indonesia, as a small emerging market, exerts negligible influence on the formation of global crude oil prices, which are instead determined by OPEC+ production decisions, U.S. shale supply dynamics, global demand from China and other major consumers, and geopolitical developments in producing regions.

The critical off-diagonal entries reveal the spillover architecture. Oil price volatility contributes 26.79% to the forecast error variance of rupiah exchange rate volatility, meaning that nearly one-third of the short-run unpredictability of the rupiah exchange rate originates from disturbances in global oil markets. The reverse transmission is substantially weaker: rupiah exchange rate volatility contributes only 5.85% to the forecast error variance of oil price volatility. This four-to-one asymmetry in transmission magnitudes (26.79% vs. 5.85%) provides rigorous econometric confirmation that the dominant causal direction in this system runs from the oil market to the exchange rate, not the reverse, consistent with Indonesia's status as a price-taking net oil importer.

In Diebold and Yilmaz (2012) terminology, global oil markets operate as net transmitters with a net spillover of +20.94 percentage points, while the rupiah exchange rate functions as a net receiver at -20.94. The Total Connectedness Index (TCI) of 32.6% indicates that approximately one-third of all forecast error variance in the bivariate system originates from cross-market spillovers rather than own-variable shocks, a level of interdependence that is economically meaningful and statistically robust. This finding is consistent with Ben Salem et al. (2024), who document that global energy markets are dominant net transmitters of volatility to forex markets across a ten-currency sample, and with Nekhili et al. (2024), who confirm crude oil's net transmitter status across multiple currency pairs using TVP-VAR connectedness.

4.3. Rolling Window Spillover Analysis

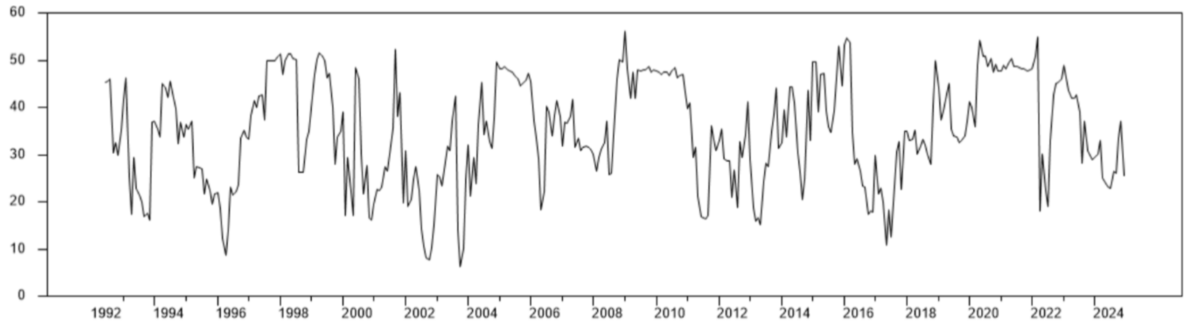

Figure 1. Total Volatility Spillovers between World Oil Prices and the Rupiah Exchange Rate

The rolling-window total spillover series (Figure 1) provides a temporal dimension that fundamentally enriches the static full-sample results. The time-varying TCI reveals a strongly state-dependent pattern: cross-market transmission intensifies dramatically during global shock episodes and subsides during periods of relative macroeconomic stability. Five historically distinct episodes of elevated spillover are identifiable across the 34-year sample.

The first episode coincides with the 1997-1998 Asian financial crisis. Although Indonesia remained a net oil exporter during this period, the catastrophic financial contagion across regional markets created conditions in which shocks from multiple sources including commodity markets were amplified and transmitted disproportionately. The rupiah's extreme depreciation from IDR 2,500 to nearly IDR 17,000 was primarily driven by domestic financial vulnerabilities and regional contagion rather than oil market dynamics, but even in this context the oil market contributed to the instability of the macroeconomic environment.

The second and most structurally significant episode spans 2004-2008, coinciding precisely with Indonesia's transition to net oil importer status and the global oil boom that drove Brent crude from approximately USD 40/barrel in early 2004 to a historical peak above USD 147/barrel in July 2008. The sharp and sustained increase in rolling-window spillover during this period marks the structural break in the oil-rupiah relationship: for the first time, rising oil prices ceased to benefit Indonesia's trade balance and instead exacerbated current account deterioration and inflated the energy subsidy burden borne by the national budget.

The third episode, the 2008-2009 global financial crisis, demonstrated that spillover transmission is symmetric with respect to the direction of oil price movement, the precipitous collapse of oil prices from USD 147 to below USD 40/barrel generated comparable transmission intensity to the preceding price surge. This symmetry is consistent with the dominance of the expectation and risk channel during crisis periods: it is the volatility and uncertainty of oil prices, rather than their level or direction, that drives exchange rate spillovers in extreme episodes.

The fourth episode in 2014-2016 reflects the dramatic collapse of global oil prices triggered by the convergence of U.S. shale production expansion, Saudi Arabia's decision to defend market share rather than price, and slowing Chinese demand growth. Despite the theoretical prediction that lower oil prices should benefit Indonesia's trade balance, rolling-window spillover increased during this period, a paradox explained by the risk channel: the prolonged uncertainty about the depth and duration of the oil price collapse elevated global risk aversion and weakened capital flows to emerging markets including Indonesia, consistent with the risk-channel dominance documented during periods of prolonged oil-price uncertainty by Chowdhury and Garg (2022) and Nekhili et al. (2024).

The fifth and most acute episode occurred in 2020, when the COVID-19 pandemic collapsed global oil demand so severely that WTI crude oil spot prices turned negative in April 2020, an unprecedented event in commodity market history. Rupiah exchange rate volatility spiked simultaneously, generating the highest directional spillover from oil to the exchange rate in the sample period. The post-pandemic recovery episode in 2022-2023, driven by the energy supply crisis following Russia's invasion of Ukraine, sustained elevated transmission intensity, confirming that the structural intensification of oil-to-rupiah spillovers is a persistent feature of the net importer era rather than an artifact of any single crisis.

4.4. Directional Spillover Dynamics

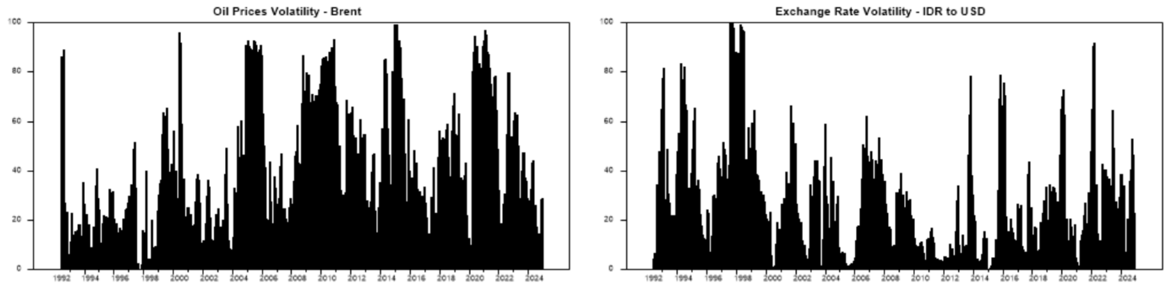

Figure 2. Directional Volatility Spillovers TO: Oil Price Volatility (Brent) and Exchange Rate Volatility IDR/USD (1992-2024)

The rolling-window directional spillover series, quantifying specifically how much of rupiah exchange rate forecast error variance at each point in time is attributable to oil market shocks, corroborates and sharpens the full-sample results. During the 1990s, directional spillover from oil to the rupiah was persistently low, reflecting the wealth channel dominance of Indonesia's net exporter status: oil price increases generated export revenue gains that partially insulated the exchange rate (figure 2). The 1997-1998 Asian crisis generated a transient spike attributable to global financial contagion rather than the oil market per se.

The structural break after 2004 is unambiguous: directional spillover from oil to the rupiah increased to a persistently higher level that has not reverted to pre-2004 magnitudes in any subsequent period. This is the empirical manifestation of the channel shift from wealth channel to trade channel as the operative mechanism: every increase in global oil price volatility now translates directly into import cost uncertainty, current account pressure, and exchange rate instability for Indonesia. The progressive intensification of directional spillover across successive crisis episodes (2004-2008 < 2014-2016 < 2020) reflects the deepening of Indonesia's oil import dependency over time, as domestic oil production continued to decline while consumption grew with the economy.

These findings are fully consistent with the theoretical predictions of Kilian (2009) and the empirical results of Chen et al. (2024): the direction and magnitude of oil price transmission to exchange rates is systematically conditioned by a country's net oil trade position, and this conditioning is not static but intensifies as the net importer position deepens. The downside bias documented by Sharma et al. (2025) that oil price increases generate larger exchange rate effects than equivalent price decreases is also consistent with the asymmetric fiscal consequences documented for Indonesia: oil price increases simultaneously worsen the current account and expand the subsidy burden, while price decreases provide only partial offsetting benefits due to price floor policies in the domestic fuel market.

5. Conclusion

This study produces three principal empirical findings that collectively characterize how Indonesia's structural transition in global oil markets has transformed its macroeconomic risk profile and the mechanism of external volatility transmission to the domestic exchange rate.

The first finding concerns the structural reversal of volatility profiles across regimes. Comparative descriptive statistics document a dramatic contrast: in the net exporter era (1990-2000), rupiah exchange rate volatility was extremely high (CV = 197.64%) and dominated by a single domestic crisis event (the 1997-1998 Asian financial crisis), while oil price volatility was modest (CV = 57.69%). In the net importer era (2004-2024), this pattern inverted, exchange rate volatility declined substantially across all measures (CV falling to 69.77%), while oil price volatility more than tripled in absolute terms. The primary source of Indonesia's macroeconomic instability shifted from domestically-driven exchange rate risk to externally-sourced oil market risk.

The second finding quantifies the asymmetric spillover transmission. The full-sample VAR Spillover Index documents that 26.79% of rupiah exchange rate forecast error variance is attributable to global oil market shocks, compared to only 5.85% in the reverse direction. The resulting net spillover of +20.94 percentage points from oil to the rupiah, and the Total Connectedness Index of 32.6%, confirm that global oil markets function as the dominant net transmitter of volatility in this bivariate system, consistent with Indonesia's price-taking net importer status.

The third finding is temporal: rolling-window analysis reveals that spillover intensity is strongly state-dependent and has progressively intensified across the net importer era. Five major global shock episodes generated identifiable spillover peaks, with crisis-period transmission substantially exceeding tranquil-period baselines. The post-2004 structural increase in directional spillover from oil to the rupiah has not reversed, confirming that the channel shift from wealth to trade channel is a permanent feature of Indonesia's macroeconomic landscape, not a transient cyclical phenomenon.

The findings carry four concrete and urgent policy implications. First, Bank Indonesia should integrate real-time global oil market surveillance explicitly into its exchange rate monitoring and intervention framework. Given that 26.79% of rupiah volatility variance originates in oil market shocks, oil price developments, including futures positioning, global inventory levels, OPEC+ policy signals, and geopolitical risk indicators, should be embedded in the bank's early warning system alongside traditional balance-of-payments and capital flow indicators. The foreign exchange reserve buffer of USD 146 billion (10.7% of GDP; IMF, 2024) must be maintained at levels adequate to absorb the intervention requirements of crisis-period spillover amplification, which rolling-window results indicate can be several times the tranquil-period baseline.

Second, fiscal planning must incorporate oil price stress scenarios consistent with the historical volatility documented in this study. The Ministry of Finance's sensitivity estimates, IDR 5.8 trillion per USD 1/barrel oil price increase and IDR 3.1 trillion per IDR 100/USD depreciation (Ministry of Finance, 2022), combined with the TCI of 32.6% and the crisis-period amplification patterns identified in rolling-window analysis, suggest that the worst-case fiscal impact of a combined oil price surge and rupiah depreciation episode substantially exceeds central scenario projections. Structural energy subsidy reform, particularly targeted subsidy schemes that decouple fiscal exposure from global oil price volatility, is necessary to break the transmission chain from oil market shocks to fiscal instability.

Third, the most durable solution to Indonesia's structural vulnerability is energy diversification: as long as Indonesia imports 1.6 million barrels per day, the rupiah will remain systematically exposed to global oil market volatility. Acceleration of renewable energy deployment, electrification of the transportation sector, and improvement of national energy efficiency are not merely environmental policies, they are fundamental macroeconomic stabilization instruments that directly reduce the coefficient of oil price transmission to the exchange rate. Each barrel of domestic oil production that substitutes for imports, and each electric vehicle that displaces a gasoline-powered one, represents a structural reduction in the TCI that no monetary policy intervention can achieve.

Fourth, the development of deeper and more liquid rupiah hedging instruments, including longer-tenor forward contracts, exchange-traded rupiah futures, and commodity-linked currency derivatives, would enable energy importers, exporters, and financial institutions to manage oil-exchange rate co-movement risk more efficiently. The current shallow hedging market amplifies the pass-through of oil price volatility to the real economy by limiting the ability of economic agents to pre-insure against adverse price combinations.

These findings should be interpreted in light of several limitations. The empirical framework is a bivariate system that excludes other macroeconomic variables, such as interest rate differentials, capital flows, and domestic inflation, that may also condition the oil-exchange rate relationship; incorporating these into a multivariate spillover framework could refine the attribution of transmission magnitudes reported here. Second, the dating of the transition period (2001-2003) between Indonesia's net exporter and net importer regimes involves an element of judgment, and alternative break-date specifications could be examined in future work. Third, as with any two-variable VAR spillover exercise, the possibility of omitted-variable bias affecting the estimated spillover magnitudes cannot be fully ruled out. Future research could extend this framework to a multivariate connectedness system, or apply it comparatively to other economies that have undergone a similar transition from net oil exporter to net oil importer status, such as Thailand, to assess the generality of the findings reported here.

6. References

Adeniyi, O., Oyinlola, A., & Omisakin, O. (2011). Oil price shocks and economic growth in Nigeria: are thresholds important? *OPEC Energy Review*, *35*(4), 308–333. https://doi.org/10.1111/j.1753-0237.2011.00192.x

Arifin, A. F., Ababil, M. I., W, R. P., Peri, L. R., & Pandin, M. Y. R. (2025). The Impact of Inflation, World Oil Prices, and the Rupiah Exchange Rate on Sectoral Stock Index Returns in the Indonesia Stock Exchange. *Journal of Macroeconomics and Social Development*, *3*(2), 6. https://doi.org/10.47134/jmsd.v3i2.1002

Baur, D. G. (2012). Financial contagion and the real economy. *Journal of Banking & Finance*, *36*(10), 2680–2692. https://doi.org/10.1016/j.jbankfin.2011.05.019

Bhatia, P. (2021). Sustainability Of Exchange Rates And Crude Oil Prices Connection With Covid-19: An Investigation For Brics. *Annals - Economy Series*, *5*, 19–29. https://ideas.repec.org/a/cbu/jrnlec/y2021v5p19-29.html

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Bui, Q. D. P., & Ngo, T. T. M. (2025). The Response of Southeast Asian Stock Markets to Energy Market Dynamics. *Energy RESEARCH LETTERS*, *7*(Early View). https://doi.org/10.46557/001c.144070

Chen, S.-S., & Chen, H.-C. (2007). Oil prices and real exchange rates. *Energy Economics*, *29*(3), 390–404. https://doi.org/10.1016/j.eneco.2006.08.003

Chen, S., Chang, B. H., Fu, H., & Xie, S. (2024). Dynamic analysis of the relationship between exchange rates and oil prices: a comparison between oil exporting and oil importing countries. *Humanities and Social Sciences Communications*, *11*(1), 801. https://doi.org/10.1057/s41599-024-03183-2

Chowdhury, K. B., & Garg, B. (2022). Has COVID-19 intensified the oil price–exchange rate nexus? *Economic Analysis and Policy*, *76*, 280–298. https://doi.org/10.1016/j.eap.2022.08.013

Damuri, Y. R., Friawan, D., Wardhana, A., Yazid, E. K., & Febiandita, S. (2024). *Energy Subsidy Reform Report*. Centre for Strategic and International Studies (CSIS). https://www.csis.or.id/publication/energy-subsidy-reform-report/

Diebold, F. X., & Yilmaz, K. (2008). Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal*, *119*(534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, *50*(4), 987. https://doi.org/10.2307/1912773

Garcia, C. J., Restrepo, J. E., & Roger, S. (2011). How much should inflation targeters care about the exchange rate? *Journal of International Money and Finance*, *30*(7), 1590–1617. https://doi.org/10.1016/j.jimonfin.2011.06.017

Habib, M. M., Bützer, S., & Stracca, L. (2016). Global Exchange Rate Configurations: Do Oil Shocks Matter? *IMF Economic Review*, *64*(3), 443–470. https://doi.org/10.1057/imfer.2016.9

Habib, M. M., & Kalamova, M. M. (2007). Are There Oil Currencies? The Real Exchange Rate of Oil Exporting Countries. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1032834

Hoque, M. E., Akhter, T., Bilgili, F., Uddin, M. A., & Tariq, S. B. (2025). Time-Varying Connectedness Among Oil Price Shocks, Global Conditions, and Financial Stress in South and Southeast Asian Markets. *Computational Economics*, *68*(2), 1337–1377. https://doi.org/10.1007/s10614-025-11068-y

Huang, B.-N., Lee, C.-C., Chang, Y.-F., & Lee, C.-C. (2021). Dynamic linkage between oil prices and exchange rates: new global evidence. *Empirical Economics*, *61*(2), 719–742. https://doi.org/10.1007/s00181-020-01874-8

Ihsan, A., Abriningrum, D. E., Suharnoko, B. S., Rahmawati, A., & Giannozzi, S. (2024). *Indonesia's Fuel Subsidies Reforms*. World Bank. https://doi.org/10.1596/41617

IMF. (2024). Indonesia: 2024 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for Indonesia. *IMF Staff Country Reports*, *2024*(270). https://doi.org/10.5089/9798400284588.002

Kathuria, V., & Sabat, J. (2020). Is Exchange Rate Volatility Symmetric to Oil Price Volatility? An Investigation for India. *Journal of Quantitative Economics*, *18*(3), 525–550. https://doi.org/10.1007/s40953-020-00212-0

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, *99*(3), 1053–1069. https://doi.org/10.1257/aer.99.3.1053

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, *74*(1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4

Krugman, P. (1983). Oil Shocks and Exchange Rate Dynamics. In *Exchange Rates and International Macroeconomics* (pp. 259–284). National Bureau of Economic Research, Inc. https://ideas.repec.org/h/nbr/nberch/11382.html

Marpaung, N. N., & Pangestuti, I. R. D. (2024). Macroeconomic Factors and Jakarta Stock Exchange: A Comparative Analysis Pre-and Until the COVID-19 Pandemic. *SAGE Open*, *14*(2), 21582440241247896. https://doi.org/10.1177/21582440241247894

Nekhili, R., Mensi, W., Vo, X. V., & Kang, S. H. (2024). Dynamic spillover and connectedness in higher moments of European stock sector markets. *Research in International Business and Finance*, *68*, 102164. https://doi.org/10.1016/j.ribaf.2023.102164

Olstad, A., Filis, G., & Degiannakis, S. (2020). Oil and currency volatilities: Co-movements and hedging opportunities. *International Journal of Finance & Economics*, *26*(2), 2351–2374. https://doi.org/10.1002/ijfe.1911

Pechdin, W., Bunditsakulchai, P., & Ho, T. D. N. (2024). A nexus of crude oil prices and real effective exchange rate movement in Thailand. *Journal of Infrastructure Policy and Development*, *8*(9), 5969. https://doi.org/10.24294/jipd.v8i9.5969

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*(1), 17–29. https://doi.org/10.1016/s0165-1765(97)00214-0

Salem, L. Ben, Zayati, M., Nouira, R., & Rault, C. (2024). Volatility spillover between oil prices and main exchange rates: Evidence from a DCC-GARCH-connectedness approach. *Resources Policy*, *91*, 104880. https://doi.org/10.1016/j.resourpol.2024.104880

Salisu, A. A., Adekunle, W., Alimi, W. A., & Emmanuel, Z. (2019). Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. *Resources Policy*, *62*, 33–56. https://doi.org/10.1016/j.resourpol.2019.03.006

Sharma, A., Rishad, A., Tyagi, V. K., & Singla, J. (2025). When the Oil Price Spillover: Examining the Volatility Spillover Effect between Crude Oil Price and Rupee-Dollar Exchange Rates. *Economic Research Guardian*, *15*(1), 27–46. https://ideas.repec.org/a/wei/journl/v15y2025i1p27-46.html

Suharsono, A., Bridle, R., Wahida, A., & Maulidia, M. (2026). *Indonesia's Energy Support Measures Government exposure to short-term energy price spikes and longer-term inflation*. International Institute for Sustainable Development (IISD). https://www.iisd.org/publications/digital-story/indonesia-energy-support-measures

Wan, M., Li, L., Chan, L., & Lee, K. S. (2025). *Asia: The impact of oil price shock on Asia FX - a scenario analysis*. MUFG. https://www.mufgresearch.com/fx/asia-the-impact-of-oil-price-shock-on-asia-fx-a-scenario-analysis-23-june-2025/