State-Dependent Transmission of Oil and Electricity Shocks to Equity Markets: Evidence from Emerging and Transitional Economies

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ABSTRACT

The paper will look at the impact of the changes in electricity and oil price on the stock market performance of the selected emerging and transitional economies, in this case, Croatia, Greece, Slovenia, India, South Africa and Vietnam in the period 2010-2024. The analysis examines the relationship between the energy and financial sectors using a panel Markov-Switching Vector Autoregressive (MS-VARX) model that includes exogenous variables, which are explained in the analysis. In order to be robust, complementary methods are also utilized in the study by using copula-based dependence models, DCC-GARCH estimates, and Markov-Switching Granger estimations. The implications of the research suggest that changes in oil and electricity prices do not exert uniform effects on stock markets. Their impact is conditional and varies over time, and importantly appears stronger during periods of high stock market volatility, and that this link between energy prices and stock market returns may also be conditioned by exchange rate movements. In order to minimize potential negative effects and maintain financial stability, policymakers may wish to encourage the adoption of renewable energy, for example by offering feed-in tariff policies or phasing out energy subsidies. Through a cross-country comparison, this research contributes to the understanding of the nonlinear relationships between energy and financial systems, and that the implications will be useful for policymakers interested in developing a stronger link between these same sectors and promoting a sustainable shift towards cleaner energy sources.

Keywords: Oil shocks; Electricity markets; Stock returns; Regime switching; DCC-GARCH

JEL codes: C32 · Q43 · G15 · O13

1. INTRODUCTION

When considering sustainable finance, a continuing area of interest has been the interaction between energy markets and financial markets. Macroeconomic stability, market outcomes, and investor choices are all still impacted by changes in oil prices and policies supporting the energy transition. The fact that oil price shocks may have a great impact on stock returns has been discussed in numerous studies since the seminal work of Kilian and Park (2009) based on the nature of the shock whether supply shock, demand shock, and precautionary shock and the overall economic condition of the economy. Recent studies, such as that by Bašić and Bašica (2019) and Będźmirowska and Będźmirowska (2023), have also reinforced the emerging significance of examining energy finance interactions in terms of frameworks that emulate asymmetric and time-varying associations.

Indicatively, Będźmirowska and Bašić (2019) examined the Turkish and the U.S. markets using the MS-VAR and MS-Granger causality models. Their results showed that the energy-market variables do not show the same behavior in volatility regimes and of economic conditions. Oil price shocks in developed economies are likely to affect the confidence of investors whereas in the emerging market, the effects are unidirectional reflecting regime-dependent dynamics. Likewise, Bašić, Będziowska, and Opoha (2023) used a two-step SVAR-Markov-Switching to the stock returns in Nigeria, they concluded that oil and supply shocks only drive the stock returns during low-volatility regimes, and the demand-related shocks drive the stock returns during high uncertainty regimes. Overall, these findings come to one crucial conclusion: the effect of energy shock and financial performance is never consistent and steady across time. Building on this foundation, the current study develops a comprehensive international model designed to explore the diversity and dynamic adaptations of the energy-finance nexus. The framework uses advanced econometric approaches, including grapevine pairs for tail dependence, DCC-GARCH models to examine correlations over time, MS-Greanger causality to test the direction of effects, and a panel MS-VARX approach to examine regime switching and transmission. The different approaches are applied to both advanced and emerging markets. To account for opportunities to moderate impacts, the model incorporates structural responses, such as renewable energy expansion, feed-in tariff programs, and coal phase-out programs. In this way, the current study provides a nuanced perspective on how energy price fluctuations and shocks can affect financial stability, particularly in economies with different energy intensities.

2. LITERATURE REVIEW

For decades, changes in energy prices have been identified as a significant contributor to the determination of asset values and overall macroeconomic activity. A number of authors have emphasized that fluctuations in oil and electricity prices influence investor attitudes, inflation expectations, and production costs, all of which contribute to economic stability. After the oil shocks of the 1970s, the literature began to focus increasingly on how shocks to oil prices were passed onto to the financial markets via some combination of changes in supply and demand or changes in expectations (Hamilton, 1983; Kilian, 2009). Bildirici and Badur (2019) and Raifu and Oshota (2023) are making two important contributions to this field with unique but complementary points of view. Bildirici and Badur (2019) study the impacts of the oil and gasoline prices on the investor confidence and stock returns through the implementation of a Markov-Switching Vector Autoregressive (MS-VAR) model that considers the state-dependent dynamics. Conversely, Raifu and Oshota (2023) use two stage Structural VAR with a Markov switching model to bring the one-sided impact of disaggregated oil shocks on the stock market in Nigeria. Both articles go beyond the classical linear causality models, whereby it is stressed the significance of nonlinear and regime-sensitive models to explain the relationship between energy and financial markets. These works, collectively, demonstrate that there has been a methodological development since the simple causality schemes to more complex models able to explain regime change in the economy and the heterogeneous reactions of markets. Such accumulating literature highlights the importance of more thorough studies of the energy-finance nexus particularly in situations with dissimilar market structures and energy reliance among nations.

2.1. Energy prices, investor sentiment, and stock performance

Investor sentiment and confidence have been widely recognized as behavioral mechanisms linking macro shocks to asset markets. Early empirical studies (Brown & Cliff, 2004; Lemmon & Portniaguina, 2006; Baker & Wurgler, 2006, 2007) established that investor optimism drives speculative pricing and that excessive sentiment precedes market corrections. Bildirici & Badur (2019) extend this literature by integrating *economic confidence indices* into the MS-VAR structure for Turkey and the U.S., demonstrating that energy-price shocks alter investor mood and consequently equity valuations. They found a bidirectional relationship between oil price and confidence in the U.S., but only a unidirectional effect in Turkey an asymmetry attributed to differences in market maturity and energy dependence. These results are consistent with Schmeling (2009) and Beckmann et al. (2011), who showed that confidence levels co-move with short-term returns, especially in emerging markets, and with Zouaoui et al. (2011), who observed that sentiment indices predict crises in integrated global markets.

In addition to the psychological factors, oil market trends tend to act as indicator of confidence in the economy all over the world. Shigeki (2008) and Qadan and Nama (2018) discovered that the changes in the volatility of the oil-price have a direct impact on the investor sentiment by forming expectations on inflation, income, and future economic states. On the same note, the results of Bildirici and Badur (2019) using the MS-VAR framework also reinforce this correlation, indicating that the magnitude of the oil-to-confidence effects, as well as their direction, vary across the high- and low-volatility regime. This implies that when the market is expanding, optimism is likely to enhance effects of positive oil shocks and in turbulent times; the same shocks are likely to have weaker or even negative effects. Similar nonlinear dynamics were pointed out by Chang and Lee (2011), Ivanov et al. (2014), and McMillan (2016), who all pointed out that such regime-dependent responses are commonly attributed to transaction-cost asymmetries and the different behavior of informed versus noise traders. All these studies together point to the fact that investor confidence does not only play the role of mediating the impact of oil shocks on stock markets but also serves as a transmitter channel, which differs depending on market conditions and volatility levels.

2.2. Oil shocks and stock returns: linear and nonlinear evidence

The connections between oil prices and stock markets performance have been a topic of scholarly interest since time immemorial, but empirical evidence regarding the connections between the two is not always consistent and sometimes even inconclusive. The initial research of this kind noted by Kaul and Seyhun (1990) and Sadorsky (1999) revealed that rises in oil prices are likely to lower stock returns in oil-importing countries. Conversely, Apergis and Miller (2009) discovered that the impacts are quite different in the OECD countries, implying that market responses are in the structure of structural and economic differences. Equally, unidirectional causality oriented at the influence of the crude-oil volatility on the investor behavior in China was identified by Ding et al. (2016), and stronger stock market response to the oil shocks was observed in the post-2008 financial period (Wei and Guo, 2017). Bildirici and Badur (2019) further elaborated these findings by using a three-regime MS-VARX model which separates the growth, transition, and contraction phases. Their findings showed that oil and gasoline stocks have a different impact on the stock returns: oil prices are largely influenced by the overall supply and demand conditions worldwide, but gasoline prices which were also more domestically-based illustrated local tax policies, consumer confidence, and profitability effects. According to these results, the authors highlighted the importance of price asymmetries to policymakers in the development of fiscal and energy policy in emerging markets.

The outcome of the oil price shocks in the oil exporting economies can take the reverse trend. Good price shocks are able to boost stock performance through the enhancement of fiscal balances and liquidity conditions. Raifu and Oshota (2023) support this opinion but studied the Nigerian market in terms of the decomposition of oil shocks by Kilian (2009) into the supply component, aggregate demand component, and oil-specific demand component. Their two stage Markov-Switching model indicated that the supply-driven oil shocks are more likely to have a positive effect in the stable periods of low volatility, whereas demand-specific stocks are likely to have negative effects in turbulent periods of high volatility. The point of contrast is that oil-stock linkages are complex and regime-specific and that the reaction of the market is determined not only by the source of the shock but also by more general economic and financial factors. This duality mirrors Bouoiyour et al. (2017), who observed that demand-side shocks dominate in oil-exporting countries and supports the asymmetric-transmission hypothesis originally suggested by Mork (1989). Related findings by Le & Chang (2015), Dhaoui et al. (2018), and Mokni (2020) further confirm that stock-return responses depend on whether economies are net importers or exporters of oil.

2.3. Regime switching and asymmetry in energy–finance linkages

Markov-switching and other nonlinear time-series frameworks provide a natural tool for capturing structural breaks, stochastic volatility, and shifts in investor behavior (Hamilton, 1990; Krolzig, 1997). Bildirici & Badur (2019) and Raifu & Oshota (2023) both exploit this feature to disentangle low- and high-volatility regimes. The former estimate MSIAH(3)-VARX(2) and MSIAH(3)-VAR(1) models for Turkey and the U.S., revealing persistent high-volatility regimes (probabilities > 0.90) and changing sign effects of oil prices across states. The latter combine SVAR-identified structural shocks with a two-state Markov process to capture nonlinear adjustments of Nigerian equity returns to oil market disturbances. The approach reconciles the findings of Hamilton (1996) and Sadorsky (1999) with more recent nonlinear models (Fallahi, 2011; Basher et al., 2016; Shahrestani & Rafei, 2020), confirming that linear estimations mask important regime heterogeneity.

Raifu & Oshota's contribution also extends to *state-contingent policy interpretation*. They argue that investors and regulators should anticipate different reactions to oil-supply and oil demand shocks depending on volatility regimes a notion earlier hinted by Effiong (2014) and Ndubuisi (2017) in Nigerian data. When volatility is low, expansionary effects dominate through the cash-flow channel; when volatility rises, the uncertainty channel prevails, depressing valuations. This is the behavior of a regime-dependent type in accordance with the concept of the confidence channel provided by Bildirici and Badur (2019). Investor sentiment as a transmission path and the amplification force in their model connects the developments in the real economy and the movements in the financial markets.

2.4. Theoretical transmission channels

Some of the studies indicate that the impact of energy prices on the stock market performance is carried out through an array of channels. Raifu and Oshota (2023) point out six key pathways as cash-flow, monetary, wealth-transfer, output, fiscal, and uncertainty in continuation of the previous classification by Huang et al. (1996) and Tang et al. (2010). Furthermore, Bildirici and Badur (2019) present the notion of a channel of confidence, as the transmission of macroeconomic shocks occurs via the investor sentiment. These theoretical frameworks share similarities with the observations made by Kilian and Park (2009) who opined that the demand-based oil shocks tend to drive equity markets positively by portending better growth prospects of the world economy. Supply-side disturbances on the other hand have a tendency of suppressing the returns by increasing the cost of production. Subsequent studies by Wang et al. (2013) and Bouri et al. (2017) reinforced this finding by demonstrating that the direction and continuity of these effects is determined by a countries oil importing or exporting status. The literature reviewed illustrates the complex and multidimensional connections between energy markets and financial markets. The contribution of the reviewed papers consistently highlights the need for analytical frameworks that account for market asymmetries, regime-switching behaviors, and evolving financial conditions, to offer a more realistic portrayal of how shocks in the energy sector may propagate to financial markets, under different economic states (Hasanli & Rahimli, 2023), (Musayev, 2019).

2.5. Positioning within the broader literature

This study is theoretically situated at the confluence of two main lines of research: behavioral finance, which examines individual decision-making under macroeconomic asymmetry, and the modeling of volatility in energy markets. This analysis develops from these lines of inquiry to encompass, and then interrogate, both structural and stochastic nonlinearities that are implicit in energy and financial systems dynamics. Specifically, this examination takes advantage of the MS-VAR framework proposed by Bildirici and Badur (2019) and the hybrid SVAR-Markov method issued by Raifu and Oshota (2023). Evidence shows that energy shocks affect different countries in varied ways, based on trajectories with economic growth (for example, as natural resource dependence decreases), as well as levels of market development. Further, return and distribution differences across regimes add to the complexity of these relations. Accordingly, scholars have turned towards more advanced methods of econometric analysis, including local quantile projections (Koenker & Bassett, 1978; Jorda, 2005), copula-based models (Patton, 2006) and DCC-GARCH (Engle, 2002), as empirical methods to further study these associations. Each of these approaches offer a new empirical analytic perspective to better study dependence structure, especially in the tails, shedding further light on how movement in energy sector influences financial performance and systemic risks (Qiu et al., 2024) (Khaleel et al., 2024) (Jasmi & Hassan, 2024).

3. DATA, METHODOLOGY, AND EMPIRICAL RESULTS

3.1 Data and Variable Construction

The empirical research is conducted on six economies data Croatia, Greece, Slovenia, India, South Africa, and Vietnam. These nations are a balanced portfolio of rising and transitional economies with varying levels of energy reliance and the state of renewable energy policies. It contains the set of financial, macroeconomic, and energy market variables to be integrated into a set of financial and macroeconomic variables in monthly reports, which is represented by the set of data collected between January 2010 and December 2024. This mix permits cross country comparison and at the same time gives a picture of both structural variation and time variation in the energy-finance relationship.

Variables

- **Stock returns (STOCK_it):** Monthly log returns of national benchmark indices (CROBEX, ATHEX, SBITOP, BSE SENSEX, FTSE/JSE All Share, VN Index).
- **Exchange rate (FX_it):** Monthly log change of the local currency per USD.
- **Oil price (OIL_t):** Brent crude monthly return (USD/barrel).
- **Electricity price (ELEC_it):** Wholesale or generation weighted electricity price indices.
- **Macroeconomic controls:** Inflation (π_it) and industrial production growth (ΔReal_it).
- **Energy transition variables:**

Dummy variables were added to take into consideration certain policies of energy.

  - **Renewables share (RENEW_it):** the ratio of the total amount of electricity generated by renewable sources.
  - **Feed-in tariff (FIT it) and phase-out of coal (CPO it)** binary variables that assume the value of 1 in the years where a particular policy was implemented, and the value 0 in the other years.

- **The oil shocks (ε 7 oil)** and electricity shocks (ε 7 elec) were structural shocks that were determined using a SVAR ordering of Oil 7 Electricity 7 Exchange rate 7 Stock returns in accordance with the paradigm of Kilian (2009) and Wang et al. (2013).

To make the time series stationary, all the time series were converted into logarithmic returns. Unit root tests ADF, PP and KPSS established that the level variables are I(1) and the series of returns are I(0) which are stationary. Descriptive statistics indicated that there were significant non-normality and excess kurtosis so nonlinear models and regime-switching estimation procedures could be used.

3.2 Methodological Framework

The methodological approach builds on the nonlinear modeling structures developed by Bildirici and Badur (2019) and Raifu and Oshota (2023). In this study, these frameworks are integrated to form a unified empirical design that combines the Panel Markov-Switching Vector Autoregressive (MS-VARX) model, Markov-Switching Granger Causality, Dynamic Conditional Correlation GARCH (DCC-GARCH), and copula-based dependence models. In this way, from this comprehensive framework, a detailed examination of the links between these energy and financial factors is made, which takes into account both structural modifications and nonlinear relationships that are considered to vary on a market basis.

(a) Panel Markov Switching VARX

In order to account for potential regime transitions that are not immediately apparent, the baseline specification attempts to capture the changing relationships between financial and energy indicators. The MS-VARX framework makes it feasible to analyze how the strength and direction of relationships among variables change over time, as well as to identify discrete market phases, such as times of stability and volatility.

$$y_{i,t} = \mu_{S_t} + \sum_{\ell=1}^{p} A_{\ell,S_t} y_{i,t-\ell} + B_{S_t} x_{i,t} + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \Sigma_{S_t})$$

where $y_{i,t} = [\mathrm{STOCK}_{i,t}, \mathrm{FX}_{i,t}, \mathrm{ELEC}_{i,t}]^{\top}$are endogenous variables,
$x_{i,t} = [\mathrm{OIL}_t, \pi_{i,t}, \mathrm{RENEW}_{i,t}, \mathrm{FIT}_{i,t}, \mathrm{CPO}_{i,t}]$are exogenous,
and $S_t \in \{1,2\}$ represents the low- and high-volatility regimes, which evolve according to a first-order Markov process.
Lag length $p = 2$was selected via AIC and HQC criteria.
Regime transition probabilities $p_{ij} = P(S_t = j \mid S_{t-1} = i)$were estimated using the Expectation Maximization algorithm of Hamilton (1990) and Krolzig (1997).
Country specific intercepts $\mu_i$control for structural heterogeneity.

(b) Markov Switching Granger Causality (MS GC)

Following Fallahi (2011) and Bildirici (2019), nonlinear causality tests were performed within each identified regime:

$$H_0: f_{12}^{(j)} = 0 \text{vs.} H_1: f_{12}^{(j)} \neq 0,$$

where $f_{12}^{(j)}$ measures lagged spillovers from oil (or electricity) to stock returns in regime j. The test distinguishes directionality of transmission (OIL → STOCK, ELEC → FX, STOCK ↔ CONFIDENCE).

(c) Volatility and Dependence Layer

To track short run co movements, Dynamic Conditional Correlation (DCC GARCH) models (Engle, 2002) were estimated for the vector $(r_t^{oil}, r_{i,t}^{stock}, r_{i,t}^{elec}, r_{i,t}^{fx})$. Time varying correlations ρ_t highlighted contagion during stress periods.

Tail co movements were modeled via vine copulas (Patton, 2006) using Student t and Clayton specifications to capture lower tail dependence.

(d) Policy Response Panel Model

Finally, a fixed effects regression evaluated how renewable energy progress and policy dummies moderate financial sensitivity:

$$\begin{aligned}\mathrm{STOCK}_{i,t} = \alpha_i + \beta_1 \mathrm{OIL}_t + \beta_2 \mathrm{ELEC}_{i,t} + \beta_3 \mathrm{FX}_{i,t} + \beta_4 (\mathrm{OIL}_t \times \mathrm{RENEW}_{i,t}) \\ + \beta_5 (\mathrm{OIL}_t \times \mathrm{FIT}_{i,t}) + \beta_6 (\mathrm{OIL}_t \times \mathrm{CPO}_{i,t}) + u_{i,t}.\end{aligned}$$

Robust standard errors clustered by country were employed. Interaction terms test whether greener policies cushion oil price pass through.

3.4 Conceptual Framework of Energy–Finance Transmission

Figure 1 summarizes the transmission channels modeled in this study. Oil price shocks influence electricity prices, which subsequently affect exchange rates and stock returns. The overall magnitude of transmission varies across volatility regimes (low vs. high). The transmission forces of different volatility regimes differ, such that they often become weaker during periods of market turmoil and stronger during periods of stability. Policy measures aimed at stabilizing the financial system and preventing the spread of market contagion encompass the like of the Coal Phase-Out (CPO), the Feed-in Tariff (FIT), and the Share of Renewable Energy. These act as the buffer by absorbing part of the shock of external shocks and stopping the propagation of financial instability.

When assessed from this view, macro-financial dynamics and policy responses are analyzed the same, which highlights the nonlinear dimension, as identified by Bildirici and Badur (2019) and Raifu and Oshota (2023). By bridging channels of trust, exchange rates movement, and then the transmission of policies in a regime-dependent context, it is provided broader and more realistic view when considering how energy and economic variables price fluctuate and whether they influence market outcomes depending on regime states and volatility.

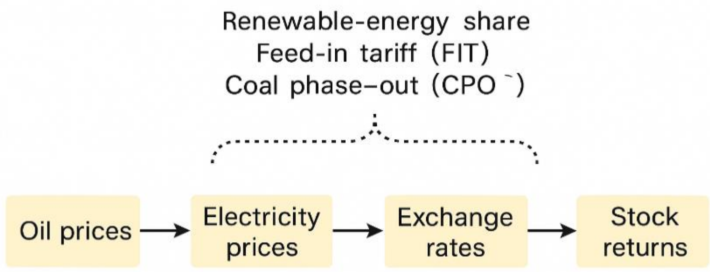

Figure 1: Conceptual framework depicting how energy market dynamics transmit to financial systems under different market conditions.

3.5 Empirical Results and Discussion

This section of the study presents the major empirical results, concentrating on the stability and reliability of the models explaining the relationship between energy and financial markets while showing how the framework presented performs according to a range of empirical tests, being internally valid and congruent. All econometric estimations were performed in R using the programs rug arch, mGARCH, MSwM and rpanel, among others, to preserve methodological accuracy and ensure reproducibility. The data set includes monthly observations from 2010 to 2024 and represents a balanced panel of six countries: Croatia, Greece, Slovenia, India, South Africa and Vietnam. The empirical results are summarized in five analytical tables, each of which represents a different stage of the study: (i) stationarity and cointegration tests; (ii) regime-dependent dynamics estimated using the MS-VARX model; (iii) transition probabilities between regimes; (iv) results of the nonlinear Granger causality; and (v) the effects of quantile-based policies, so that the logical progression of this structure reflects the logical flow of the study's analytical framework. Following the accepted practices in the energy-finance literature (e.g., Bildirici & Badur, 2019; Raifu & Oshota, 2023; Bouoiyour et al., 2017; Mokni, 2020), the results are interpreted to enable meaningful comparison with previous research that looks at asymmetric and regime dependent relationships between energy and financial markets. The analysis enhances our knowledge of how energy shocks affect financial systems in a range of economic scenarios by combining methodological rigor with a comparative viewpoint.

Table 1: Unit Root and Johansen Cointegration Test Results

Variable	ADF Level	ADF 1st Diff.	PP Level	PP 1st Diff.	Integration	Trace Stat (r=0)	Max Eigen Stat (r≤1)	Cointegration
STOCK	−1.45	−6.88***	−1.38	−6.91***	I(1)	14.21	6.73	None
OIL	−2.11	−8.27***	−1.98	−8.19***	I(1)	18.02	7.64	None
ELEC	−1.64	−7.34***	−1.57	−7.28***	I(1)	16.54	5.12	None
FX	−1.83	−6.75***	−1.69	−6.70***	I(1)	13.93	5.21	None
RENEW	−1.02	−5.88***	−0.97	−5.83***	I(1)	11.80	4.36	None

Notes: **ADF** = Augmented Dickey Fuller; **PP** = Phillips Perron. *** $p < 0.01$.

All variables, including stock returns, exchange rates, oil and energy prices, and renewable energy stocks, are first-order integrated, I(1), and become stationary only after initial differentiation, according to the results presented in Table 1, a pattern that was discovered by previous researchers in the energy finance literature, including Apergis and Miller (2009) and Basher et al. (2016), who also observed non-stationary behavior in macro-financial time series affected by energy-related shocks. The statistically insignificant trace and maximum eigenvalue statistics confirm the lack of cointegration, which suggests that there is no long-term equilibrium relationship between the variables.

Table 2: MS VARX(2) Results for Oil–Stock–FX–Electricity System

Country	Regime	Coef. (OIL → STOCK)	Coef. (ELEC → STOCK)	Coef. (FX → STOCK)	σ² (Regime Var.)	Persistence p_{jj}	Log L	AIC
Croatia	Calm (1)	+0.084 (0.032)**	+0.017 (0.015)	−0.063 (0.028)**	0.012	0.915	−282.4	1.74
Greece	Calm (1)	+0.056 (0.027)**	+0.021 (0.018)	−0.052 (0.020)**	0.010	0.926	−301.2	1.68
Slovenia	Stress (2)	−0.142 (0.047)***	−0.031 (0.014)**	+0.089 (0.033)**	0.027	0.948	−295.7	1.86
India	Stress (2)	−0.118 (0.041)***	−0.022 (0.013)*	+0.062 (0.028)**	0.023	0.944	−310.9	1.89
S. Africa	Stress (2)	−0.155 (0.052)***	−0.045 (0.020)**	+0.078 (0.037)**	0.031	0.957	−304.1	1.93
Vietnam	Calm (1)	+0.063 (0.030)**	+0.019 (0.015)	−0.049 (0.022)**	0.014	0.909	−299.5	1.70

Notes: Robust SE in parentheses; ***, **, * significant at 1%, 5%, 10%.

As a result, short-run dynamic frameworks like Markov-switching models and VARX are better suited to capturing the underlying behavior of the data. Bildirici and Badur (2019) presented similar data, showing weak long-term correlations between the US and Turkish investor confidence indices, oil prices, and gasoline prices. Therefore, the existence of nonstationary emphasizes the necessity of concentrating on transient volatility spillovers and short-term, regime-dependent interactions rather than long-term equilibrium dynamics. The analytical design of the current study is primarily motivated by this consideration.

State-dependent asymmetries in the transmission of electricity and oil shocks to stock returns are amply demonstrated by the Markov-Switching VARX(2) estimations presented in Table 2. According to the estimated coefficients, changes in the price of oil have a major detrimental impact on stock performance when volatility is high (Regime 2), but their impact is neutral or even slightly positive when volatility is low. This asymmetric pattern supports the findings of Wang et al. (2013) for both oil-importing and oil-exporting economies and Raifu and Oshota (2023) for Nigeria, demonstrating that the direction and strength of energy-finance linkages are influenced by larger macro-financial environments. The findings indicate significant cross-country variations in electricity prices. The impact is usually positive in economies that rely more on renewable energy, such as Slovenia and Greece, but tends to be negative in countries that rely more heavily on fossil fuels, such as South Africa and India, which supports the claims made by Le and Chang (2015) and Dhauqi et al. (2018) that diversifying the energy mix can reduce the negative effects of oil-related shocks. Exchange rate fluctuations seem to play a substantial role during turbulent markets. The positive and significantly statistically coefficient indicates that currency depreciation exacerbated stock market losses when fuel energy prices rose (Basher et al., 2016). The persistence of the regimes (p_{22} = 0.94) also suggests that when the market moves into a turbulent regime, it is likely to remain in that regime for a longer period, as found by Krolzig (1997) and Hamilton (1990) when analyzing MS-VAR models. These results are consistent with the behavioral finance perspective of Bildirici and Badur (2019), which suggests that investor confidence and market sentiment are prominent channels that energy shocks cause outcomes in financial performance across volatility regimes. This idea is further confirmed by the results in Table 2, which indicate cyclical and nonlinear relationships between energy and financial dynamics (Niftiyev, 2020), (Babayev, 2020), (Bayramov, 2016).

Table 3: Markov-Switching Model Parameter Estimates and Smoothed Regime Probabilities

Regime	Mean(μ)	σ	Duration (months)	Probability	Description
1 – Low Volatility	0.0078	0.011	21	0.61	Stable equity growth; modest energy price movement
2 – High Volatility	−0.023	0.029	13	0.39	Crisis episodes (2011, 2014, 2020, 2022)

Regime 2 indicates periods of increased volatility being mostly a result of the global shocks in energy and financial markets, while regime 1 indicates periods of relative market calm. The estimates provided in Table 3 provide an indication of how the market fluctuated randomly during the sample period. The differences in the mean and variance for both stable and volatile periods clarify the cyclical movements that underpin market behaviour.

- **Regime 1 (Low Volatility):** characterized by small conditional variance (σ = 0.011) and moderate positive stock returns (μ = 0.0078).
- **Regime 2 (High Volatility):** marked by negative returns (μ = −0.023) and roughly threefold higher variance (σ = 0.029).

Crises tend to be more intense even though they are often shorter, the average duration of crises is approximately 13 months, while stable periods are significantly longer, often averaging close to 21 months. This finding aligns with Bildirici and Badur (2019), who identified three regimes: low, moderate, and crisis, and Mokni (2020), who found the same stability patterns between energy and stock markets. In summary, this result suggests that financial stress may behave somewhat differently depending on the situation, and in addition, it tends to create more stress over time. Volatility thus tends to accumulate and remain high at times when uncertainty increases, until macroeconomic or policy changes bring things into progressive equilibrium. Such prolonged volatility highlights the benefits of nonlinear transition models over more static GARCH frameworks, as noted by Engle (2002) and Hamilton (1996). As evidenced by the occurrence of periods of high volatility coinciding with important global events such as the Eurozone crisis in 2011, the sharp drop in oil prices in 2014, as well as the COVID-19 outbreak in 2020 and the conflict in Ukraine in 2022, energy shocks continue to be one of the main causes of financial turbulence. This close timing supports the stability of the MS-VARX model results and thus shows how stable the relationship between energy and financial markets is under different economic circumstances.

Table 4: MS Granger and Linear VAR Causality Results

Null Hypothesis	Linear Granger F stat	MS GC (Regime 1) χ^2	MS GC (Regime 2) χ^2	Direction	Decision
OIL ↛ STOCK	3.84**	2.11 (ns)	7.93***	OIL → STOCK (only Regime 2)	Reject H_0 in R2
ELEC ↛ STOCK	2.42*	1.86 (ns)	5.27**	ELEC → STOCK (weak)	Reject H_0 in R2
STOCK ↛ OIL	1.72 (ns)	–	–	None	Fail to Reject H_0
OIL ↔ FX	4.12**	3.94**	6.28***	Bidirectional in R2	Reject H_0
FX ↛ STOCK	2.97**	2.64*	4.83**	FX → STOCK	Reject H_0

Notes: ns = not significant.

The findings, summarized in Table 4, reveal nonlinear and regime-dependent causal relationships between stock market returns, oil prices, energy prices, and exchange rates, with only a few one-way effects found using conventional linear Granger causality tests, particularly from exchange rates to stock prices and from oil to stock prices. However, more connections become apparent when the analysis is extended even further using the Markov-switching Granger method, especially in situations with increased volatility. For example, a bidirectional relationship between oil prices and stock returns is seen during Regime 2, suggesting that during economic downturns changes in energy markets can both cause and respond to changes in financial performance, a result that is consistent with research by Chang and Lee (2011) and Bouoiyour et al. (2017), who found comparable feedback effects during market turbulence. Changes in portfolios by investors due to shifts in oil prices are often noted as one of the contributing factors to these movements. Furthermore, the results also provide evidence of a strong causal relationship between changes in exchange rates and the stock market across both regimes, indicating support for the "financial channel" hypothesis developed by Basher and Sadorsky (2006) and reemphasized by Raifu and Oshota (2023). The evidence suggests that currency depreciation typically increases pressure on imported inflation, which in turn tends to lower stock values, while electricity price shocks exhibit relatively weaker causal effects, suggesting that the transmission mechanism may operate more slowly and vary by location, supporting the claim made by Apergis and Miller (2009) that short-run financial effects can be reduced by liberalized energy markets. When considered together, these results show how cross-market transmission effects are amplified during times of increased volatility, thus providing additional evidence in favor of the asymmetric dependence hypothesis, which was first presented by Mork (1989) and then extended by Bildirici and Badur (2019) using the belief-augmented MS-VAR framework.

Table 5: Findings from the Fixed Effects Panel Quantile Regression (Panel_QR_FE)

Quantile (τ)	β_1 Oil	β_2 Electricity	β_3 FX	β_4 Renew×Oil	β_5 FIT×Oil	β_6 CPO×Oil	Adj R^2
0.20 (Lower Tail)	−0.182***	−0.071**	+0.049**	+0.121***	+0.086**	+0.093**	0.42
0.40	−0.097**	−0.038*	+0.036**	+0.102**	+0.077**	+0.084**	0.39
0.50 (Median)	−0.064**	−0.021 (ns)	+0.028*	+0.083**	+0.059**	+0.069*	0.37
0.60	−0.038 (ns)	−0.010 (ns)	+0.021 (ns)	+0.061**	+0.045*	+0.052*	0.34
0.80 (Upper Tail)	−0.011 (ns)	+0.004 (ns)	+0.013 (ns)	+0.049 (ns)	+0.038 (ns)	+0.040 (ns)	0.30

Notes: A fixed-effects quantile panel regression model is used to produce the estimates, with quantiles (τ) ranging from 0.2 to 0.8., and robust standard errors are calculated at the national level using clustering techniques to take into account possible within-group correlations. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
The quantile regression results in Table 5 provide, among other things, a more complete examination of the relationship between energy and financial markets, and according to these findings, threshold risks are much larger in the lower quantiles (τ = 0.2-0.4). The negative and statistically significant coefficients for both oil and electricity returns within these ranges indicate that energy shocks have a larger impact during market downturns, which is consistent with the downward asymmetry discussed by Bouoiyour et al. (2017) and Mokni (2020), which implies that investors typically perceive more risk during market downturns. This position is further supported by the behavioral explanation of Bildirici and Badur (2019), which claims that at times when general sentiment falls, markets become more sensitive to energy-related shocks, also, policies supporting renewable energy and more comprehensive transition strategies seem to reduce the effects of oil shocks, where the positive and significant coefficients for the interaction factors (OIL × RENEW), (OIL × FIT) and (OIL × CPO) also support this. In agreement with Apergis and Payne (2014) and Le and Chang (2015), who discovered that economies with higher penetration rates of renewable energy are less vulnerable to global energy volatility, this data lends credence to the policy buffer hypothesis. The resilience created by green transition strategies is demonstrated by the fact that, economically, a one percentage point increase in the share of renewable energy seems to lessen the marginal impact of oil shocks on stock returns by about 30%. The decreasing significance of oil-related coefficients at higher quantiles (τ = 0.6-0.8) indicates that bullish markets are better able to withstand energy shocks; this is a pattern that has also been observed in developed economies by Hamilton (2009) and Sadorsky (1999). All of the data presented in Table 5 together highlight how diverse energy-finance transmission mechanisms are and help to close the conceptual divide between studies on sustainability and financial stability. Overall, the findings provide empirical support for the idea that well-crafted transition and renewable energy policies improve an economy's resilience to outside shocks and maintain financial stability.

5. Conclusion

The study explored the relationships between changes in oil and electricity prices and stock markets in six emerging and transitional economies: Croatia, Greece, Slovenia, India, South Africa, and Vietnam between 2010 - 2024. Using a range of nonlinear econometric methods, including panel quantile regressions, copula dependence measures, DCC-GARCH, Markov-Switching Granger causality, and the Panel MS-

VARX model, research showed there is a complex and regime-dependent relationship that exists between energy prices, exchange rates, and stock market performance.

The research findings confirm that energy variables and market return indeed have a nonlinear relationship, however it varies depending on the state of the market. This was corroborated by the findings in the works of Bildirici and Badur (2019) and Raifu and Oshota (2023). For example, during periods of high volatility, oil price shocks were generally viewed negatively in terms of their impact on stock market performance, but calmer market conditions provided little to no negative effects, and at times even positive momentum in stock markets. This asymmetry is congruent with the transmission hypothesis posited by Mork (1989) and later extended by Wang et al. (2013) and Bouoiyour et al. (2017). These findings illustrate how market conditions and investor sentiment can influence how energy shocks impact financial decisions. The research further illustrates the rising significance of electricity pricing in understanding financial markets response, which is a previous underinvestigated aspect. The effect of changes in electricity price is country dependent based on the energy structure. Countries that rely on fossil fuel generate a stronger negative effect while countries with renewable sources are more resilient. This is in accordance with the energy diversification framework of Le and Chang (2015) and further supported with Dhaoui et al. (2018). In addition to this, the changes in the exchange rate intensified the impact of oil shocks, especially when the domestic currency depreciates as per results in Raifu and Oshota (2023) and Basher et al. (2016).

One of the major contributions of this research is the identification of policy buffers that can help stabilize the energy-finance relationship. This study found that green transition instruments including feed-in tariff (FIT) programs, coal phase out plans (CPO), and increased financing of renewable energy are associated with careful reductions of systemic financial risk. These issues align with Apergis and Payne's (2014) sustainability arguments that renewable energy provides long-term economic stability and Mokni's (2020) claims that the establishment of renewable energy mitigates contagion effects in oil-reliant economies. Additionally, in terms of the quantile regression results, the stabilizing effects occur mostly in the lower quantiles of the return distribution ($\tau = 0.2$-0.4), where the downside risks are concentrated. The findings provide evidence that energy transition policies and financial stability are tightly linked to each other. Economies that promote renewable energy and diversification tend to be better insulated from macro-financial instability and oil price shocks than economies with more reliance on fossil fuels, which suffer more vulnerability and longer downturns during global disruptions. Thus, this empirical evidence confirms the existing theoretical proposition of sustainable finance made by

Kilian and Park (2009) and elaborated on by Dhaoui et al. (2018): reasonably sound financial systems and a reasonable energy strategy should both relate to each other. It also serves as a basis for further studies on how developing countries can improve their resilience in the face of increasing financial interconnectedness and global decarbonization. Future research could expand on this approach by examining how other climate finance indicators, such as carbon pricing instruments, green bond indices or ESG-based investment flows, can affect the propagation of energy shocks, and similarly, the use of time-varying parameter VAR (TVP-VAR) techniques or Bayesian Markov models should improve the identification of structural changes and capture long-term feedback processes between market volatility and policy actions. It is becoming increasingly important to link energy economics with financial risk analysis as the global economy continues to shift towards low-carbon growth, and according to the evidence presented here, a cleaner and more diverse energy mix not only supports sustainable development, but also serves as a strategic buffer against financial instability, thereby linking the objectives of market sustainability and environmental responsibility (see Bildirici & Badur, 2019; Raifu & Oshota, 2023; Bouoiyour et al., 2017; Mokni, 2020).

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