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Does M&A activity spin the cycle of energy prices?

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A B S T R A C T

This research investigates the predictive power of mergers and acquisitions (M&A) activity on returns and volatility in energy commodities from January 1997 to September 2023. Utilizing a novel time-varying robust Granger causality framework, we analyse the dynamic relationship between M&A activity and energy returns and volatility within the global oil and gas (O&G) industry. In addition, we examine the network structure of M&A activity and energy prices across different quantile regimes. We find that M&A activity exhibits significant time-varying forecasting ability for both energy returns and volatility. Specifically, M&A transactions led by oil acquirers, representing deals where both the acquirer and target are within the O&G industry, demonstrate stronger forecasting ability for energy returns than M&A transactions led by acquirers from non-O&G industries. Conversely, M&A activity by non-O&G acquirers shows greater predictive ability for energy volatility. Robustness checks support our main findings. First, our multi-horizon model reveals significant bi-directional causality between M&A activity and energy series for 3 and 6-month forecasting horizons, which affirms a lasting influence on energy returns and volatility. Second, the strength of connectedness at extreme quantiles surpasses that at the median, with its magnitude increasing over the forecasting horizon. Third, our baseline results remain stable across varying rolling window sizes. These findings have important implications for policymakers and investors, suggesting that M&A activity within the O&G industry should be considered when making decisions in the energy market, as it plays a crucial role in predicting the dynamic direction of energy prices.

1. Introduction

By 2019, the transition towards renewable energy sources grew in recognition due to the global warming threat highlighted by recent extreme weather events, the influence of Greta Thunberg, and the IPCC's 1.5 °C report. The importance of this transition was further underscored by the Green New Deal, particularly amidst the high energy market uncertainty triggered by the COVID-19 pandemic and the subsequent 2022 Russia–Ukraine military conflict. Many nations are shifting their economies from reliance on non-renewable energy sources to embracing renewable energy, aiming to reduce their economic and political dependence on fossil fuels (Erel et al., 2012; Ren et al., 2024). Despite this shift, fossil fuels such as crude oil, whether used as a raw resource in manufacturing or as a surface fuel in consumption, still play an indispensable role in numerous sectors and industries. These include manufacturing (Aye et al., 2014; Elder, 2021; Śmiech et al., 2021), agriculture (Sadorsky, 2014; Kang et al., 2017; Akyildirim et al., 2022b; Olkkonen et al., 2023), transportation (Serra and Zilberman, 2013; Yahya et al., 2022), health services (Scholtens and Yurtsever, 2012; Acemoglu et al., 2013), and tourism (Becken and Lennox, 2012; Chatziantoniou et al., 2013; Al-Mulali et al., 2020), among others. The transition from non-renewable to renewable energy sources will undoubtedly have a direct impact on firms within the oil and gas (O&G) industry, where fossil energy prices remain a major source of profit.

In response to the ongoing transformation of the global energy landscape, mergers and acquisitions (M&A) activity has become a significant factor in the energy sector. M&A activity serves as a strategic pathway for companies in the O&G industry to achieve sustainable growth under the stringent environmental regulations aimed at combating climate change and environmental degradation. Andriuškevičius and Štreimikienė (2022) highlight that M&A activity stimulates external growth by enhancing operational capabilities, expanding corporate and market presence, generating operational, financial, tax, and management synergies, reducing service redundancy,

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boosting shareholder value, and introducing new products and services. A notable example is Royal Dutch Shell's acquisition of its British competitor BG Group for $53 billion in 2016. This significant M&A deal enhanced Shell's global liquefied natural gas (LNG) market presence and deepwater exploration capabilities, thereby solidifying its leading position in the LNG sector. Thus, M&A between two O&G firms can be seen as a strategic value-adding move (Shen et al., 2021), leading to resource consolidation, enhanced operational performance, increased profitability, and cost reductions. Such actions can also increase market concentration, potentially influencing future energy prices. Therefore, investigating the relationship between M&A deals and energy price behavior is important.

Existing studies mostly concentrate on the relationship between M&A activity and the financial performance of firms. Nevertheless, there is less research on the interaction between M&A activity and core products like oil and natural gas, which drive profitability for energy companies. Ng and Donker (2013) find evidence that energy prices influence takeover activity in the Canadian O&G industry. Monge and Gil-Alana (2016) find that crude oil prices have an impact on M&A activity in the US. Similarly, Hsu et al. (2017) determine that oil prices are highly correlated with M&A activities in the US O&G industry. Monge et al. (2017) adopt a time-frequency approach and find that changes in oil prices significantly affect the number of M&A activities in the US O&G sector, though this relationship weakens over time. Bos et al. (2018) use a time-invariant quantile approach and discover that M&A activity in the US O&G sector significantly predicts oil returns and volatility across different quantiles. Park and Baek (2019) find that oil prices have asymmetric effects on M&A activity in the US and Canadian O&G industries. A recent study by Barrows et al. (2023) finds that oil price uncertainty is a main driver of M&A activity in the US O&G sector. Most past literature focuses on financial transactions that involve companies from the US and Canada, representing only 50% of the global M&A O&G market.[1] Little is known on a global scale. In this paper, we consider a broad set of M&A deals data from 202 countries, including Russia, which ranks among the top five globally in M&A activity. We empirically examine the effectiveness of M&A deals in predicting energy prices, considering the financial transaction vulnerabilities due to the COVID-19 pandemic and the subsequent 2022 Russia–Ukraine military conflict.

Our study investigates the interconnectedness and predictive power between M&A activity and energy markets. Using time-invariant Granger causality tests, we find modest evidence of causality between M&A deals and the returns and volatility of energy markets. Notably, M&A deals that involve O&G firms show a causal impact on natural gas returns and volatility. By contrast, the time-varying causality analysis provides strong evidence of bi-directional causality between M&A activity and energy series. Our scrutiny into the connectedness between M&A deals and natural gas uncovers significant impacts during specific periods. In-depth analysis reveals lasting impacts of M&A deals on energy markets, particularly during events like the US invasion of Iraq, the Global Financial Crisis (GFC), and the COVID-19 pandemic. Our study distinguishes between O&G and non-O&G acquirer and target deals, which provides insights into industry-specific connections. The results illustrate heightened interconnectedness during extreme events, which emphasizes the influence of market uncertainty on the relations between M&A activity and energy returns and volatility. Quantile directional spillover analysis indicates that M&A deals are more interconnected within the network than energy commodities, particularly during extreme market conditions. Net directional connectedness underscores the role of M&A deals as net transmitters of volatility, while energy commodities act as net receivers, with variations based on quantiles. The study underscores the importance of considering extreme events and quantiles for accurate assessments of spillover effects.

We conduct a series of robustness checks to further explore the link between M&A activity and energy prices and volatility. Firstly, we extend our examination over longer horizons. Using the TVP-GC framework, our multi-horizon model reveals significant bi-directional causality between M&A activity and energy series for 3 and 6-month forecasting horizons. This affirms a lasting influence on returns and volatility in energy markets. Secondly, we investigate the connectedness across various quantiles and extended forecasting horizons. The results reveal increased connectedness with growing forecasting horizons. Thirdly, we test the robustness of our main findings with different rolling window sizes. Stable Total Connectedness Index (TCI) values for returns at extreme quantiles underline a robust degree of connectedness during market turbulence, while the median results show a modest decline with increased window size. Overall, the rolling window size has a minimal impact on connectedness estimations. This aligns with our main findings for both returns and realized volatility series.

Our study contributes to the existing literature at least on five aspects. First, this paper contributes to the scarce but growing literature on energy risk management (see, e.g., Chkili et al., 2014; Kim and Choi, 2019; Hoque et al., 2023; Uddin et al., 2023), introducing a comprehensive framework that integrates the crude oil market, natural gas market, and M&A activity involving firms from the O&G industry. We systematically examine the spillover effects among these three determinants for the energy sector, offering a fresh perspective on cross-market spillovers. Although the direct relationship between energy prices and M&A activity is often overlooked, our results suggest a strong dependency between them. Second, the literature on spillovers in energy markets and M&A activity often neglects natural gas prices. Considering the importance of natural gas market, particularly after the COVID-19 pandemic and the 2022 Russia-Ukraine conflict, our study finds that the impact of natural gas on M&A activity in the O&G sector is as substantial as that of crude oil. Third, the existing literature on M&As has predominantly concentrated on M&A deals as a whole. To better comprehend the interactions between these deals and energy market pricing patterns, our paper undertakes a unique approach by disaggregating M&A deals into three categories based on the industry of the firms involved: i) M&A deals where both the acquirer and target firms belong to the O&G industry ($Deals_{stay}$), ii) M&A deals where the target firm is from the O&G industry, but the acquirer firm is from a non-O&G industry ($Deals_{enter}$), and iii) M&A deals where the acquirer firm is from the O&G industry, but the target firm is from a non-O&G industry ($Deals_{exit}$). To the best of our knowledge, we are the first to explore the impact of M&A activity on energy price trends, specifically considering deals that involve firms aiming to reduce their dependency on the O&G industry. Addressing this question is essential for understanding the implications of the 2030 Sustainable Development Goals on energy markets. Achieving a net-zero-carbon economy involves promoting investments in clean energy and imposing emission taxes, such as carbon taxes. Our study investigates how this transition influences pricing in energy markets. Fourth, our paper contributes to the literature on price volatility transmission in energy markets (see, e.g., Sadorsky, 1999) by exploring the interaction between the realized volatility of energy prices and M&A activity. Fifth, we extend the study of spillovers by examining the network response to different extreme market conditions, using a quantile spillover approach.

Beyond our analysis of the quantiles network structure of energy markets and M&A deals, we investigate the predictability of M&A deals for future energy prices and vice versa. We determine the exact periods of (dis)connectivity by employing a novel time-varying robust Granger causality framework. Notably, little is known about the dynamic lead-lag relationship between energy prices and M&A deals in the O&G industry, especially regarding whether the COVID-19 pandemic and the succeeding 2022 Russia–Ukraine military conflict have brought any disruptions or instabilities to those links. This study addresses this question.

The policy implications of this study underscore the necessity for a

[1] Authors' own calculations based on the data for M&A deals from SDC Platinum database of Thomson Reuters.

comprehensive approach to energy management, seamlessly integrated into a broader sustainable development strategy. Our findings highlight the crucial role of collaboration between the energy firms and local governments in supporting such an approach. Through the adoption of pertinent government policies, firms within the O&G sector can effectively address challenges related to energy reserves, prices, and their influence on takeover activity, value, and performance. This comprehensive approach seeks to strike a balance between economic growth with environmental sustainability, ensuring long-term energy security and reduced dependency on non-renewable resources. By aligning energy management practices with the 2030 Sustainable Development Goals, policymakers can actively promote a more resilient and sustainable energy sector.

The rest of this paper is organized as follows. Section 2 provides a survey of the existing literature. Section 3 introduces the major methodologies adopted. Section 4 provides a summary of the data, whereas Section 5 presents and discusses the empirical results. Section 6 conducts robustness checks, and finally, Section 7 concludes.

2. Literature review

According to the prospect synergy effect theory, companies are inclined to take greater risks in uncertain environments but adopt a more conservative approach when returns are predictable (Kahneman and Tversky, 1979). Given the high pace of restructuring in the energy sector, both in the United States and Europe, via the European Commission's Green Deal, the profitability and performance of energy companies may be significantly impacted. Consequently, many energy companies may be cautious about entering into M&A deals. The COVID-19 pandemic disrupted the global balance between energy supply and demand, causing pronounced fluctuations in oil prices (Sharif et al., 2020; Jiménez-Rodríguez, 2022). Industries with substantial energy consumption, relying on oil and natural gas as production inputs, experienced reduced costs, increased profits, and elevated share prices. Conversely, for energy suppliers, the decline in energy prices led to reduced profits, prompting many to exit the market (Foglia et al., 2022; González et al., 2022). Nonetheless, the post-pandemic economic recovery, along with the 2022 Russia–Ukraine military conflict, has driven energy prices to rebound, allowing many O&G companies to rebuild their profits. This indicates that profits in the O&G industry are highly uncertain and often linked to crude oil price fluctuations (Garfinkel and Hankins, 2011; Barrows et al., 2023). The uncertainty surrounding economic recovery and energy market volatility poses challenges for companies in the energy sector when assessing potential M&A targets.

Past literature has predominantly concentrated on the impact of M&A transactions on the performance of acquirers and targets (Oladunjoye, 2008; Furfine and Rosen, 2011; Goddard et al., 2012; Sabet et al., 2018; Renneboog and Vansteenkiste, 2019; Tanna and Yousef, 2019), and to a lesser extent on the stock market (Jensen and Ruback, 1983; Aktas et al., 2011; Gaur et al., 2013; McNichols and Stubben, 2015; Tao et al., 2017). M&A activity helps companies to achieve specific goals and develop strategies, while creating value for shareholders (Campa and Hernando, 2004). The M&A transactions result in redistribution of assets and potential synergy gains for companies (Tanna and Yousef, 2019). On one side, Chavaltanpipat et al. (1999) claim that M&A negatively impacts acquirers' shareholders while generating positive abnormal returns for the target firms' shareholders during the announcement period. Similarly, Rau and Vermaelen (1998) discover that acquiring corporations commonly underperform after M&A completion. On the other side, Jarrell et al. (1988) and Mulherin and Boone (2000) determine that M&A deals bring value to shareholders. Goddard et al. (2012) identify that M&A activity increases shareholder value for target firms, while acquirers' shareholders gain from purchasing underperforming targets. Mall and Gupta (2019) find that M&A announcements significantly influence the return and volatility of acquiring companies' stocks. Jensen and Ruback (1983) find that target firms' stock prices increase significantly post-merger. Delaney and Wamuziri (2004) investigate M&A effects on stock performance in UK construction companies and find that merger activity creates wealth for target firms' shareholders. Hackbarth and Morellec (2008) show that acquiring firms experience negative abnormal returns, whereas target firms see positive abnormal returns during M&A announcements. These findings indicate that M&A activity significantly impacts firms' value and performance.

A scarce but growing body of literature focuses on the relationships between the M&A activity and energy market (Ng and Donker, 2013; Monge and Gil-Alana, 2016; Hsu et., 2017; Monge et al., 2017; Bos et al., 2018; Park and Baek, 2019; Barrows et al., 2023). Ng and Donker (2013) explore the links between purchasing reserves and the commodity market in the O&G industry in Canada. They find supportive evidence that energy reserves and prices cause and affect takeover activity, value, and performance. Monge and Gil-Alana (2016) find that increases in crude oil prices lead to significant increases in the M&A activity in the US. Hsu et al. (2017) determine that M&A activities are closely related to O&G output growth, with oil prices highly correlated with M&A activities in the US O&G industry. Monge et al. (2017) adopt time-frequency domain and wavelet analysis to investigate the relationship between M&A activity and crude oil prices in the US. They find that changes in oil price significantly affect the number of M&A activities, though this relationship weakens over time. Bos et al. (2018) use a time-invariant quantile approach to examine M&As' predictive ability on oil returns and volatility in the US O&G industry. The authors discover that M&A activity has significant predictive power across different quantiles. Park and Baek (2019) find that oil prices have asymmetric effects on M&A activities in the US and Canadian O&G industries. Barrows et al. (2023) investigate the impact of oil price uncertainty on M&A in the US O&G sector. They find that uncertainty is the main driver of M&A activity. Most academic work has focused on crude oil, while the interaction between the M&A deals and the natural gas market remains unclear. Our study is the first to investigate the dependence between the M&A activity and energy markets, including not only crude oil but also natural gas market, considering their tail structures and time-varying relations. This knowledge is essential for investors and policymakers to understand the interaction between pricing and financial transactions in energy markets beyond crude oil.

Moreover, past literature has predominantly focused on financial transactions that involve companies from the US and Canada, which collectively account for only 50% of the global M&A O&G market. However, there remains a significant gap in our understanding on a global scale. Our paper considers a broad set of M&A deals data to empirically examine the effectiveness of M&A deals in predicting energy prices, considering the financial transaction vulnerabilities due to the COVID-19 pandemic and the subsequent 2022 Russia–Ukraine military conflict.

3. Methodology

3.1. Time-varying robust granger causality approach

To investigate the impact of M&A activity on energy commodities such as crude oil and natural gas through changes in M&A volume, we employ the time-varying parameter robust Granger causality method (TVP-GC) introduced by Rossi and Wang (2019). This method offers advantages over conventional Granger causality tests by accounting for the presence of instabilities (Coronado et al., 2023). Given that our sample covers the COVID-19 pandemic and the 2022 Russia–Ukraine conflict, which have destabilized energy markets, the TVP-GC method allows us to examine time-varying causal relationships more robustly than standard tests. We specify a bivariate Vector Autoregressive (VAR) model with time-varying parameters as follows:

$$y_t = \psi_{1,t} y_{t-1} + \psi_{2,t} y_{t-2} + \ldots + \psi_{p,t} y_{t-p} + \epsilon_t \quad (1)$$

where $y_t = \left[y_{1,t}, y_{2,t} \ldots, y_{n,t}\right]'$ is a $n \times 1$ vector, $\psi_{j,t}$, where $j = 1, 2, \ldots p$, are functions of time-varying coefficient matrixes, p is the lag length, and ϵ_t are heteroscedastic and serially correlated idiosyncratic random disturbances. The null hypothesis tests whether Energy (M&A deals) does not Granger cause M&A deals (Energy), i.e., $H_0 : \Psi_t = 0$ for $\forall t = 1, 2, \ldots, T$, where $\Psi_t \subset (\psi_{1,t}, \psi_{2,t}, \ldots, \psi_{p,t})$, against its corresponding alternatives; where Energy represents either crude oil or natural gas, and M&A deals denotes the number/volume of M&A transactions. The test statistics, including Mean Wald (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) tests, based on Rossi (2005), are used to evaluate the null hypothesis. As rule of thumb, if at least two out of the three test statistics (fail to) reject the null hypothesis, we conclude the (non-)existence of causality. The lag length p of the VAR model is determined using the Bayesian Information Criterion (BIC). A standard trimming parameter of 0.10 is utilized in line with existing literature (see, Akyildirim et al., 2022b; Enilov and Mishra, 2023).

3.2. Quantile connectedness

To examine the dynamic spillovers between energy commodities and M&A deals across different quantiles, we employ the quantile-connectedness technique developed by Ando et al. (2022). This approach combines the connectedness methodology proposed by Diebold and Yilmaz (2012, 2014) with quantile regression techniques from Koenker and Xiao (2006). To model the quantile spillover, we use QVAR (τ, p) specifications. A stationary QVAR(τ, p) can be transformed into an infinite order vector moving average (MA) representation of a Quantile VAR model, QVAR (p), as follows:

$$y_t(\tau) = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) y_{t-j} + u_t(\tau) = \eta(\tau) + \sum_{i=0}^{\infty} \Omega_i(\tau) u_{t-i}(\tau) \tag{2}$$

where τ represents the desired quantile level, $\tau \in [0,1]$, t denotes the time, p denotes the autoregressive order, y_t is the n-dimensional vector of dependent variables, $\mu(\tau)$ ($\eta(\tau)$) is a vector of intercepts at quantile τ for the QVAR(τ, p) (QVMA(τ, ∞)) model. The function $\Phi_j(\tau)$ is a $n \times n$ matrix of lag coefficients, $u_t(\tau)$ is a $n \times 1$ vector of error disturbances, $\Omega_i(\tau)$ represents a $n \times n$ matrix of moving average lag coefficients.

To overcome the Cholesky-factor ordering issue, methods outlined by Koop et al. (1996) and Pesaran and Shin (1998) are employed. These methods are insensitive to the specific ordering of variables. This is crucial because shocks affecting each variable are not mutually orthogonal, leading to variations in their impacts on the forecast error variance decomposition. Consequently, the sum of their individual contributions is not necessarily equal to unity. To account for this, the scaled generalized forecast error variance decomposition (GFEVD), $\widetilde{\Theta}^g_{i\leftarrow j,\tau}(H)$normalizes the unscaled GFEVD, $\Theta^g_{i\leftarrow j,\tau}(H)$, in order that each row sums up to unity (see, Chatziantoniou et al., 2021; Ando et al., 2022; Rizvi et al., 2022; Aharon et al., 2023), such as:

$$\Theta^g_{i\leftarrow j,\tau}(H) = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \sum(\tau) \Omega_h(\tau)' e_i\right)} \tag{3}$$

$$\widetilde{\Theta}^g_{i\leftarrow j,\tau}(H) = \frac{\Theta^g_{i\leftarrow j,\tau}(H)}{\sum_{j=1}^{n} \Theta^g_{i\leftarrow j,\tau}(H)} \tag{4}$$

where $\sum_{j=1}^{n} \widetilde{\Theta}^g_{i\leftarrow j,\tau}(H) = 1$ and $\sum_{i,j=1}^{n} \widetilde{\Theta}^g_{i\leftarrow j,\tau}(H) = $ n. e_i is a zero vector with unity on the i-th position, H is the forecast horizon. $\widetilde{\Theta}^g_{i\leftarrow j}(H)$ is the pairwise directional connectedness from variable j to variable i, or the percentage share that variable j contributes to the scaled GFEVD of variable i.

Next, we compute total directional connectedness including "To", "From", and "Net" measures:

$$TO_{\blacksquare\leftarrow i,\tau}(H) = \sum_{j=1, i\neq j}^{n} \widetilde{\Theta}^g_{j\leftarrow i,\tau}(H) \tag{5}$$

$$FROM_{\blacksquare\rightarrow i,\tau}(H) = \sum_{j=1, i\neq j}^{n} \widetilde{\Theta}^g_{i\leftarrow j,\tau}(H) \tag{6}$$

$$NET_{\blacksquare\leftarrow i,\tau}(H) = TO_{\blacksquare\leftarrow i,\tau}(H) - FROM_{\blacksquare\rightarrow i,\tau}(H) \tag{7}$$

"TO" represents the total directional connectedness from variable i on all other variables j. Similarly, "FROM" represents the total directional connectedness from all other variables j to variable i. "NET" is the difference between the total directional connectedness TO others and the total directional connectedness FROM others. A negative (positive) *NET* value indicates the variable i is the net receiver (transmitter) of shocks. Lastly, we compute total connectedness, *TCI*, also known as system-wide connectedness:

$$TCI_\tau(H) = \frac{\sum_{i,j=1, i\neq j}^{n} \widetilde{\Theta}^g_{i\leftarrow j,\tau}(H)}{n-1} \tag{8}$$

The connectedness measures use a lag order of 2, as per BIC, and a forecast horizon of 1 month. To estimate the time variation, we adopt a rolling-window approach with a window size of 40 (see, Bouri et al., 2020; Farid et al., 2022, for details).

4. Data and preliminary statistics

This study uses monthly data on crude oil, natural gas, and M&A deals from January 1997 to September 2023. The start date is determined by the availability of natural gas data. We use West Texas Intermediate (WTI) crude oil prices (i.e., Crude Oil-WTI Spot Cushing U $/BBL) as a proxy for crude oil prices, and Henry Hub Natural Gas prices (i.e., Henry Hub Natural Gas Spot Price, Dollars per Million Btu) as a proxy for natural gas prices. The monthly price data for crude oil and natural gas are obtained from the Global Financial Data and the US Energy Information Administration (EIA) databases, respectively.[2] All of the above series are transformed into log returns, Y_t, where $Y_t = (ln(P_t) - ln(P_{t-1})) \times 100$, and P_t is the closing price (or M&A deals volume) at month t.

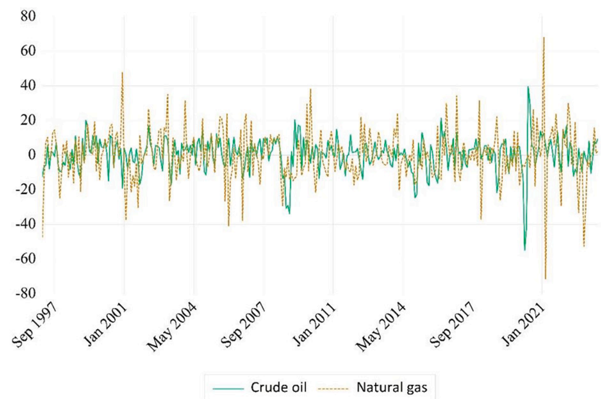
Energy markets often experience significant fluctuations during periods of economic uncertainty (Akyildirim et al., 2022a). High levels of uncertainty influence senior management teams' decisions on whether to engage in M&A activity (Lee, 2018). The impact of policy uncertainty on M&A activity is substantial enough to delay merger waves (Bonaime et al., 2018), particularly in the energy sector (Mohn and Misund, 2009; Henriques and Sadorsky, 2011; Phan et al., 2019; Barrows et al., 2023). Such delays can affect the volatility of energy prices through changes in the volume of M&A deals (Bos et al., 2018). Therefore, another contribution of our study is to investigate whether volatility of energy prices is

[2] We acknowledge that the WTI crude oil spot price data available in the EIA database is identical to and perfectly correlated with our data obtained from Global Financial Data. However, a potential limitation of utilizing data from different databases is the variation in accuracy, consistency, completeness, and timeliness across sources, which can complicate the process of achieving a unified data perspective (see Sampaio et al., 2015, for a discussion). Another possible limitation of using financial data from different sources is the potential mixture between futures and spot prices, which can affect the structure of the forward curve, leading to either contango and/or backwardation curves. Neglecting this data feature may distort the empirical outcomes of the models. Nonetheless, our study exclusively considers spot prices for the energy commodities, which are coherent within the EIS database.

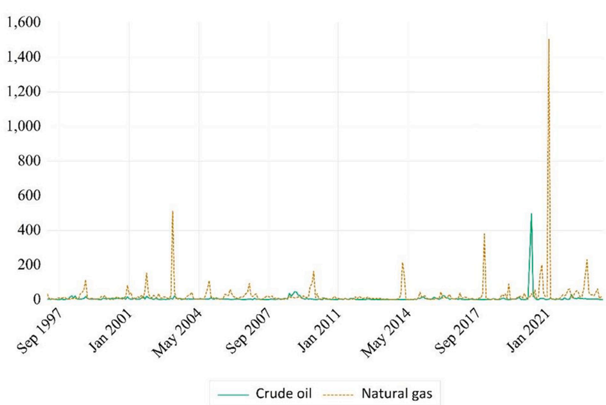
influenced by changes in the volume of M&A deals. Following existing literature, we use a model-free measure of volatility, namely realized volatility (RV) (Bos et al., 2018).[3] The RV is calculated as the sum of squared daily returns over a given month[4] such as:

$$RV_t = \sum_{d=1}^{D} r_{t,d}^2 \tag{9}$$

where $r_{t,d}^2$ denotes the squared daily returns on the d-th trading day of month t, and D represents the total number of trading days in each month t. In our study, we calculate realized volatility series for crude oil (Oil_{RV}) and natural gas (Gas_{RV}). To distinguish these from returns series of the respective energy prices, we denote the return series as crude oil returns ($Oil_{Returns}$) and natural gas returns ($Gas_{Returns}$). Fig. 1 shows the returns and realized volatility series in Panels A and B, respectively.



Panel A: Returns



Panel B: Realized volatility

Fig. 1. Time-series graphs of returns and realized volatility series for energy commodities.

4.1. Relative proxies for mergers and acquisitions activity

Our dataset on M&A deals is compiled through a rigorous procedure. First, we measure M&A activity by the number of deals in each period, following the existing literature (see, Bos et al., 2018, for a discussion). Second, we collect data on 1,237,676 M&A deals from SDC Platinum database of Thomson Reuters. The allocation of M&A deals is based on the period when they were officially announced. Third, we exclude incomplete M&A deals to prevent any withdrawn M&A deals at a future date. Fourth, we render our sample to M&A deals where either acquirer, target, or both firms are involved in the O&G industry. This results in a sample of 57,080 M&A deals. Fifth, we categorize M&A deals into three groups: $Deals_{exit}$, $Deals_{enter}$, and $Deals_{stay}$. Precisely, $Deals_{stay}$ denotes M&A deals where both the acquirer and target firms belong to the O&G industry; $Deals_{enter}$ refers to M&A deals where the target firm is from the O&G industry, but the acquirer firm is from a non-O&G industry; and $Deals_{exit}$ refers to M&A deals where the acquirer firm is from the O&G industry, but the target firm is from a non-O&G industry. Consistent with energy series, all M&A deals series are calculated as log returns.

Fig. 2 shows the M&A deals series over the period spanning January 1997–September 2023. It is evident that most companies involved in O&G M&A deals aimed to expand their assets within the same sector ($Deals_{stay}$), particularly before the GFC. However, this pattern has shifted post-GFC. After the GFC, the number of non-O&G acquirers ($Deals_{enter}$) surpassed those within the O&G industry looking to either reinvest ($Deals_{stay}$) or exit ($Deals_{exit}$). One explanation for the decline in M&A deals among firms already in the O&G sector could be the stringent credit conditions post-GFC, which has led many exploration and production companies to face elevated interest rates when seeking capital. These factors may have also influenced energy prices. Interestingly, the graph shows that following the introduction of the European Green Deal, as well as during the periods of the COVID-19 pandemic and the 2022 Russia-Ukraine conflict, more O&G companies diversified their assets by investing in non-fossil industries rather than reinvesting in their own sector. A similar trend was observed in the late 1990s, during a period of high global economic uncertainty, such as the 1997 Asian financial crisis and the subsequent US invasion of Iraq. Our study encompasses all these periods to examine the potential impact of M&A deals on energy prices, including crude oil and natural gas.

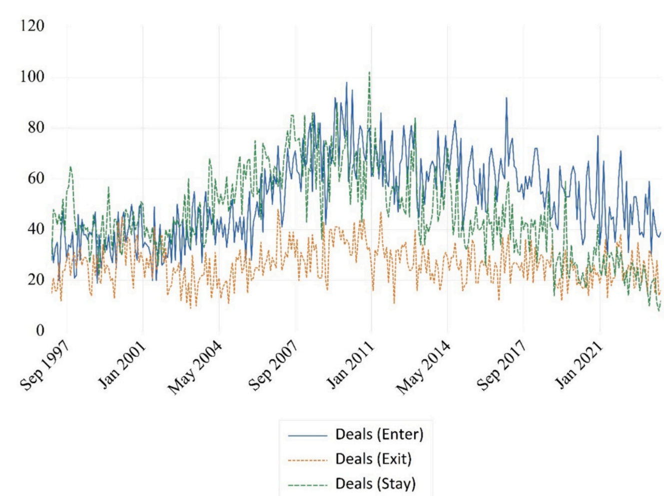


Fig. 2. M&A activities from January 1997 to September 2023.
Note: the plot represents the actual number of M&A deals.

[3] It is noted that the CBOE Crude Oil Volatility Index, which estimates the expected 30-day volatility of crude oil, is a relevant choice for our study, however, it is not selected for the following reasons. First, the data for the index is available only since 2007 and, therefore, we cannot capture the full cycle of the Global Financial Crisis (GFC). Also, this can shorten our analysed period by almost than a third. Second, the volatility index is available only for the crude oil market, but not the natural gas one.

[4] The daily data for the crude oil and natural gas is obtained from the from Global Financial Data and US Energy Information Administration (EIA) databases, respectively.

4.2. Preliminary analysis

Table 1 presents the summary statistics of monthly M&A deals, returns, and volatility of energy commodities. It indicates that deals between O&G companies exhibit a negative mean return of -0.265, while the other two types of deals have positive mean returns, with non-O&G acquirers achieving the highest mean return of 0.025. This shows that O&G companies, which expand within their own industry, are strongly affected by global economic uncertainty. Additionally, the results suggest that deals that involve non-O&G target companies ($Deals_{exit}$) exhibit the highest volatility, with a standard deviation of 38.528, compared to 28.035 for $Deals_{stay}$ and 28.638 for $Deals_{enter}$. The skewness and kurtosis results indicate that the distribution of M&A deals series is close to normal. For energy commodities, natural gas shows a negative mean return of -0.084, whereas crude oil has a positive mean return of 0.397. Natural gas also displays higher volatility among both energy commodities, with a standard deviation of 14.803, compared to a standard deviation of only 9.749 for crude oil. The realized volatility series suggest that crude oil is more stable than natural gas. Therefore, this study aims to investigate whether M&A deals in the O&G sector influence energy pricing and volatility. Lastly, all series satisfy the stationarity condition based on the Augmented Dickey and Fuller (ADF) (Dickey and Fuller, 1979) and Fourier ADF (Enders and Lee, 2012) unit root tests. The latter test is particularly suitable for handling structural breaks, as it allows for an unknown number of level breaks.

To assess whether M&A activity impacts energy prices through changes in M&A volume, we perform several tests. The first test is based on a time-invariant regression analysis and is used to determine the presence and sign direction of M&A activity on energy prices. The full sample regression model is defined as follows:

$$EP_t = \beta_1 + \beta_2 MA_t + \varepsilon_t \tag{10}$$

where EP_t denotes the energy series at time t, i.e., $EP = \{Returns_{oil}, Returns_{gas}, RV_{oil}, RV_{gas}\}$, MA_t corresponds to the M&A activity at time t, i.e., $MA = \{Deals_{stay}, Deals_{enter}, Deals_{exit}\}$, and ε_t denotes the error term.[5]

Table 2 presents the results from Eq. (10). It can be noted that different types of M&A deals have a heterogeneous impact on energy prices. Specifically, M&A deals that involve companies within the O&G sector negatively impact crude oil returns but positively impact natural gas returns. Conversely, M&A deals by non-O&G acquirers show the opposite effect on energy returns. Additionally, M&A deals that involve non-O&G target companies positively impact both crude oil and natural gas returns. Furthermore, $Deals_{stay}$ have a negative impact on the realized volatility of natural gas, but a positive impact on crude oil. M&A deals that include non-O&G companies positively impact the volatility of natural gas and negatively impact the volatility of crude oil. This finding suggests that M&A deals in the O&G sector have an asymmetric impact on energy returns compared to their volatility counterparts. Finally, the effects of M&A activity on energy prices remain insignificant in all the cases at the 10% significance level, except for$Deals_{enter}$ in the context of natural gas returns. This result implies that M&A activity by non-O&G acquirers is significant for natural gas returns but not for its volatility.

Overall, M&A activity may contribute to increased market concentration (Calipha et al., 2010), as merged entities can leverage their enhanced power to influence energy prices. This aligns with monopolistic theory, which posits that increased market concentration can lead to less competitive pricing and higher prices (Stigler, 1950). Our results reveal an interesting outcome: M&A activity between two O&G firms negatively impacts crude oil prices but positively affects natural gas prices. This suggests that monopolistic theory applies for certain commodities, like natural gas, but not to others, such as crude oil. This assertion is further supported by results from deals involving non-O&G companies. For example, new entrants into the O&G sector create market fragmentation and reduce natural gas prices, consistent with monopolistic theory. However, such deals positively impact crude oil prices, which aligns with herding behavior theory (Graham, 1999). This is because these deals generate positive incentives and optimism among market participants regarding future growth in energy prices (see, Youssef and Mokni, 2023).

The model presented in Eq. (10) does not account for possibility that the impact of M&A activity on energy series may vary over time. Previous studies have indicated that M&A deals may have a causal impact on crude oil in some periods but not in others (see, Bos et al., 2018). To address this, we extend Eq. (10) to a time-varying model by estimating the following rolling-window regression:

$$EP_{t,t+m} = \beta_{1,t+m} + \beta_{2,t+m} MA_{t,t+m} + \varepsilon_{t,t+m} \tag{11}$$

where $EP_{t,t+m} = EP_t, EP_{t+1}, \ldots, EP_{t+m}$ and $MA_{t,t+m} = MA_t, MA_{t+1}, \ldots, MA_{t+m}$, and m is the size of the rolling window. Following the existing literature, the size of the rolling window is set to 40 (see, Liu and Song, 2018; Enilov et al., 2023).

Table 3 reports the percentage frequency of significant β_2 coefficients from Eq. (11) at the 5% and 10% significance levels. The percentage frequency is calculated as the total number of significant β_2 coefficients divided by the total number of rolling window tests. This approach allows us to determine whether M&A deals have a time-varying impact on energy prices, and how frequently this impact occurs. Our findings indicate that M&A activity has a more pronounced impact on energy returns than on their volatility, regardless of the significance level. The only exception is M&A deals that involve a new entrant into the O&G sector, where the impact of M&A activity is found to be larger on the volatility of natural gas prices than on their returns. Additionally, deals that involve O&G companies on both sides generally have the least impact on energy prices. In contrast, deals where either the acquirer or the target company is not from the O&G industry in most cases have a more pronounced impact on energy market pricing and volatility. This observation is consistent with rational herding models, suggesting that investors, aware of their information disadvantage, may strategically follow the trades of more informed investors (Banerjee, 1992). Regarding crude oil, $Deals_{enter}$ generally have a larger impact on both returns and volatility, regardless of the significance level, compared to other type of deals. This aligns with the theoretical motives of overconfidence (Bernardo and Welch, 2001). Overall, our results demonstrate that M&A deals have a temporal impact on both returns and volatility in energy markets.

5. Empirical results

Before scrutinizing the empirical results, we provide a brief overview of the forthcoming discussion. We start with a causality analysis to discern the relationship between energy commodities and M&A activity. This begins with a standard (time-invariant) Granger causality test, followed by an expanded analysis utilizing a time-varying parameter Granger causality test to account for potential instabilities. Next, we conduct a quantile directional spillover analysis. This involves exploring time variability in connectedness measures by examining dynamic total connectedness. We also investigate the influence of net directional connectedness at both the M&A deals and energy markets to ascertain whether a market acts as a recipient or transmitter of shocks. This approach facilitates a more accurate understanding of the spillover dynamics between M&A activity and energy markets.

As a robustness check, we assess the lead-lag relationship between M&A deals and energy series by extending our time-varying causality

[5] We use Newey and West's (1987) kernel-based HAC covariance estimator with Newey and West's (1994) automatic bandwidth selection to handle possible heteroskedasticity and autocorrelation in the error term.

Table 1
Descriptive statistics

	$Deals_{stay}$	$Deals_{enter}$	$Deals_{exit}$	$Gas_{Returns}$	$Oil_{Returns}$	Gas_{RV}	Oil_{RV}
Mean	−0.265	0.025	0.020	−0.084	0.397	27.808	8.371
Std. Dev.	28.035	28.638	38.528	14.803	9.749	94.815	31.262
Skewness	−0.179	−0.169	−0.038	−0.188	−0.955	12.587	13.446
Kurtosis	3.360	3.438	2.986	6.425	7.816	188.615	198.706
ADF	−14.270***	−15.014***	−16.596***	−18.458***	−13.333***	−17.052***	−11.442***
Fourier ADF	−14.340***	−15.028***	−12.281***	−18.433***	−13.342***	−17.202***	−11.549***
№ obs.	320	320	320	320	320	320	320

Note: The table presents the descriptive statistics of our data. It reports the mean returns (Mean), standard deviation of the returns (Std. Dev.), skewness (Skewness), kurtosis (Kurtosis) and the number of observations (№ obs.). The table reports the test statistics from ADF and Fourier ADF tests. The ADF test has the null hypothesis of a unit root, against its corresponding alternative. The Fourier ADF test has the null hypothesis of a unit root series with unknown number of level breaks, while the alternative hypothesis is of the stationary process with unknown number of level breaks. The lag length is selected by using BIC. *** denotes statistical significance at the 1% level.

Table 2
Full sample estimates and relevant statistics

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	β_2	p-value	β_2	p-value	β_2	p-value
Panel A: Returns						
Crude oil	−0.005	0.752	0.020	0.355	0.012	0.331
Natural gas	0.027	0.396	−0.042*	0.055	0.010	0.634
Panel B: Realized volatility						
Crude oil	0.043	0.490	−0.072	0.270	−0.015	0.311
Natural gas	−0.065	0.634	0.077	0.533	0.020	0.848

Note: This table presents the time-invariant (full sample) impacts of different types of M&A deals on energy returns (Panel A) and realized volatility (Panel B). We consider two energy commodities: crude oil and natural gas. The estimated coefficient β_2 and p-value are summarized for $Deals_{stay}$, $Deals_{enter}$ and $Deals_{exit}$. *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 3
Time-varying estimates and relevant statistics

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	5%	10%	5%	10%	5%	10%
Panel A: Returns						
Crude oil	0.036	0.060	0.203	0.242	0.149	0.196
Natural gas	0.085	0.167	0.100	0.135	0.132	0.235
Panel B: Realized volatility						
Crude oil	0	0.028	0.011	0.128	0.068	0.093
Natural gas	0.053	0.075	0.057	0.146	0.011	0.068

Note: The table reports the percentage frequency of significant β_2 coefficients based on 5% and 10% level of significance. We consider two energy commodities: crude oil and natural gas. The percentage frequency is provided for both returns and realized volatility series, respectively, in Panels A and B, for different types of M&A deals, i.e., $Deals_{stay}$, $Deals_{enter}$ and $Deals_{exit}$.

model to perform multi-horizon forecasts. Specifically, we examine whether M&A deals remain persistent predictors of energy returns and volatility over time or if their effects diminish. Additionally, we evaluate the strength of connectedness among energy markets and M&A activity over longer periods and across different rolling window sizes.

5.1. Granger causality test results

This section presents the results of our Granger causality tests. We first employ a standard time-invariant Granger causality test, followed by the time-varying robust Granger causality test proposed by Rossi and Wang (2019) to account for parameter instability. Both tests examine the null hypothesis of non-causality against the alternative hypothesis of causality, with the optimal lag length determined by BIC.

Table 4 displays the results of the time-invariant Granger causality tests, organized into two panels: returns (Panel A) and realized volatility (Panel B). Our findings provide modest evidence of causality in either direction. Specifically, M&A deals that involve firms from the O&G sector show no significant impact on energy returns or volatility. The only instances of causality from M&A activity to energy markets are observed in $Deals_{enter}$ and $Deals_{exit}$, affecting natural gas volatility and returns, respectively. Interestingly, our results indicate that both returns and volatility in the crude oil market remain unaffected by M&A activity. Conversely, crude oil demonstrates a causal impact on non-O&G acquirer deals, for both returns and volatility. However, this evidence is absent for non-O&G target deals. This suggests that the predictive power of energy prices varies depending on the industry of the acquiring company. Regarding the volatility of natural gas prices, there is a significant impact observed only in $Deals_{exit}$, at the 10% level, with no significant effects found in other types of financial transactions.

Table 5 displays the results from the time-varying robust Granger causality method proposed by Rossi and Wang (2019). The table is organized into four sections, focusing on crude oil and natural gas, along with their respective returns and realized volatility measures. To ensure the robustness of our findings, we employ three distinct test statistics: MeanW, Nyblom, SupLR. As a rule of thumb, if at least two out of the three statistics are significant at the 10% significance level, we infer the existence of causality. Conversely, if fewer than two statistics are

Table 4
Results from standard time-invariant Granger causality test

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals
Panel A: Returns						
Crude oil	2.603	6.735*	0.118	19.562***	2.061	1.384
Natural gas	0.392	3.607	1.356	1.838	7.218**	1.528
Panel B: Realized volatility						
Crude oil	3.399	6.45*	3.887	13.588***	0.050	1.335
Natural gas	1.530	2.018	8.805**	4.228	1.122	5.151*

Note: The table summarizes the time-invariant Granger causality test between M&A deals and energy series, returns (Panel A) and realized volatility (Panel B). The test statistic follows a Chi-Square statistic, χ^2. The lag length is selected by BIC. “Deals” represents any of the following M&A activity: $Deals_{enter}$, $Deals_{exit}$, $Deals_{stay}$. “Energy” denotes any of the following energy series: $Oil_{Returns}$, $Gas_{Returns}$, Oil_{RV}, Gas_{RV}. H_0 : Deals⇏Energy (⇏ means “does not Granger-cause”). *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 5
Results from time-varying parameter Granger causality tests

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals	H_0: Deals ⇏ Energy	H_0: Energy ⇏ Deals
Panel A: $Oil_{Returns}$						
MeanW	131.471***	443.579***	98.491***	634.974***	121.589***	66.561***
Nyblom	3.988*	5.743**	4.535**	4.789**	1.878	1.795
SupLR	867.619***	1306.622***	241.255***	1904.254***	320.516***	422.356***
Panel B: $Gas_{Returns}$						
MeanW	103.853***	309.601***	91.904***	58.354***	166.648***	61.596***
Nyblom	5.041**	4.922**	2.946*	1.238	2.780	2.508
SupLR	369.797***	2754.141***	148.681***	292.027***	1040.156***	142.249***
Panel C: Oil_{RV}						
MeanW	159.898***	7745.188***	173.93***	3813.234***	34.408***	926.364***
Nyblom	2.645	5.568**	2.777	10.334***	1.289	3.166*
SupLR	308.861***	28,406.871***	419.138***	7526.442***	312.429***	2304.764***
Panel D: Gas_{RV}						
MeanW	210.795***	688.833***	128.786***	358.834***	152.173***	581.345***
Nyblom	58.336***	5.476**	75.211***	14.657***	9.732***	17.749***
SupLR	423.658***	5832.038***	499.701***	953.73***	391.81***	2434.919***

Note: Entries correspond to the mean Wald (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) test statistics from the time-varying robust Granger causality test of Rossi and Wang (2019). The lag length is based on BIC. "Deals" represents any of the following M&A activity: $Deals_{enter}$, $Deals_{exit}$, $Deals_{stay}$. "Energy" denotes any of the following energy series: $Oil_{Returns}$, $Gas_{Returns}$, Oil_{RV}, Gas_{RV}. H_0 : Deals⇏Energy (⇏ means "does not Granger-cause"). *, **,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

significant, we conclude that no causal link exists. The results in Table 5 unveil a bi-directional causality between M&A activity and energy series. This conclusion is supported by the MeanW, Nyblom, and SupLR statistics at the 10% significance level for both returns and volatility series. Thus, we can assert that M&A activity exerts a time-varying impact on both returns and volatility in energy markets. This finding adds to the existing literature, such as Monge et al. (2017) and Bos et al. (2018), which established a link between M&A activity and crude oil. Our study extends this by demonstrating a similar relationship with other energy commodities like natural gas. Furthermore, our findings reveal that M&A deals influence not only price fluctuations in the crude oil market but also those in the natural gas market. The latter has experienced heightened volatility due to the COVID-19 pandemic and the subsequent 2022 Russia-Ukraine military conflict. This research represents one of the initial attempts to explore the impact of M&A deals on energy markets during these critical periods, which highlights the dynamic and significant role M&A activity plays in influencing energy markets.

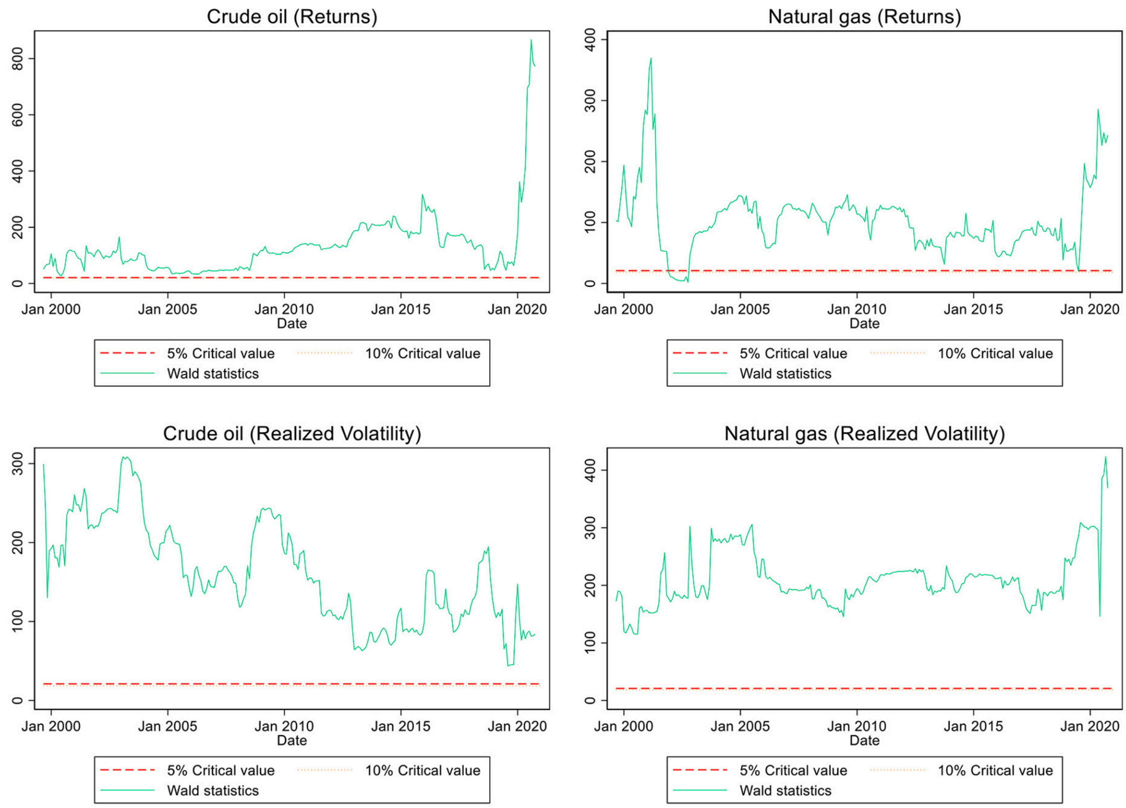
5.2. Time-varying causal graphical inferences

In this section, we explore the specific time periods during which a causal relationship exists between M&A deals and energy markets. This investigation holds significant importance for investors and policymakers. From an investor's perspective, our results assist in identifying whether M&A deals in the O&G industry impact energy prices and, thereby enabling investors to tailor their investment portfolios accordingly. For policymakers, our findings provide insights into whether M&A deals can predict energy price volatility, especially during significant events such as the US invasion of Iraq, the GFC, the COVID-19 pandemic, and the 2022 Russia–Ukraine conflict. If M&A deals can predict energy market behavior, policymakers might consider better regulation on financial transactions during certain periods to cushion their impact on energy price volatility.

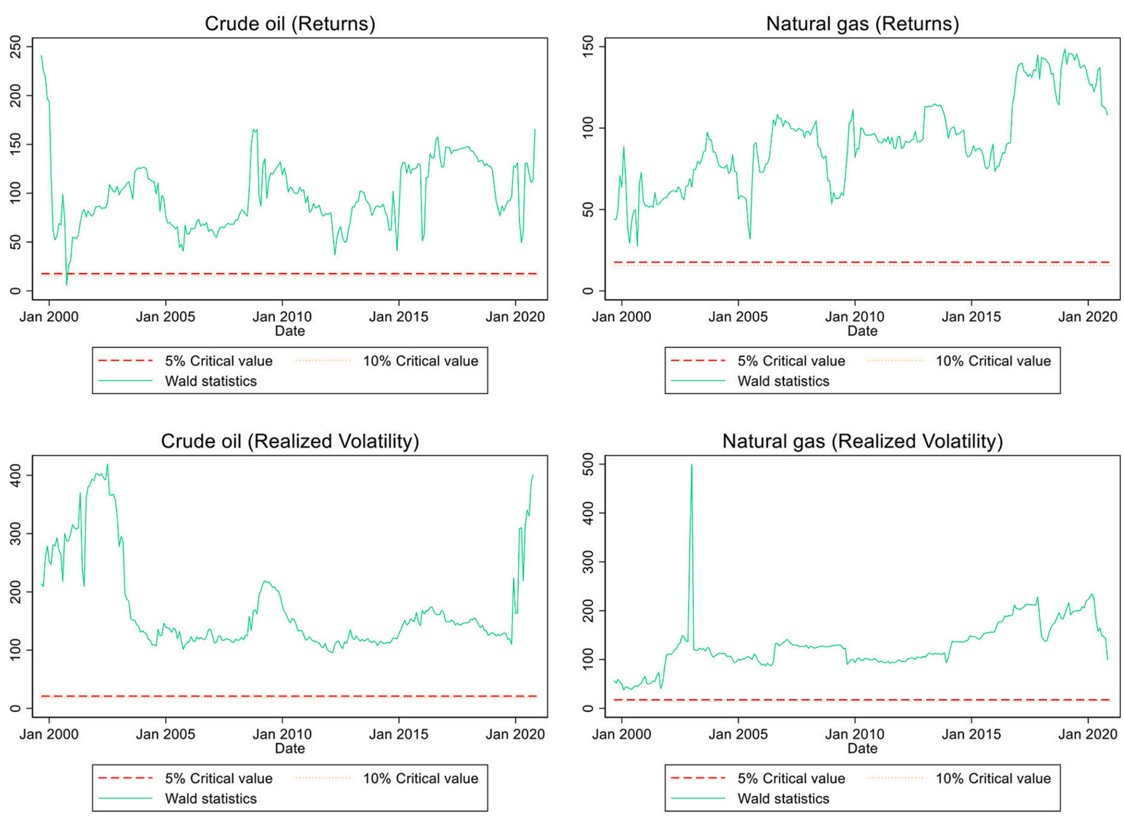
Notably, to the best of our knowledge, we are the first to investigate the linkages between M&A activity and natural gas. Previous literature has primarily focused on crude oil, overlooking the role of natural gas. However, the presence of a causal link between M&A deals and natural gas has important implications for social policy design, given that natural gas expenses constitute a substantial portion of consumers' budgets, especially during winter, and remain a significant cost factor for numerous industries year-round (Xiang and Lawley, 2019). To pinpoint the exact periods when M&A deals predict energy prices, we rely on the outcomes derived from the TVP-GC tests by Rossi and Wang (2019).

Fig. 3 presents the TVP-GC results for the impact of M&A deals on energy series, including returns and volatility. The results are organized in three panels based on the nature of M&A deals: $Deals_{stay}$, $Deals_{enter}$, $Deals_{exit}$. Our findings indicate that both crude oil and natural gas markets are significantly influenced by M&A activity. This extends past research, which has predominantly focused on how energy prices and volatility affect M&A deals, often neglecting the reverse relationship (see, Hsu et al., 2017; Park and Baek, 2019; Barrows et al., 2023). Specifically, nine out of the twelve cases reveal a persistent impact of M&A deals on energy prices without any disruptions. Only three cases show interruptions in the connectivity between M&A deals and energy prices. Notably, the impact of M&A deals between two O&G companies on natural gas returns was slightly disrupted in the early 2000s, particularly after the US invasion of Iraq and around the announcement of the European Green Deal. Similarly, the impact of non-O&G acquirer M&A deals on crude oil returns was briefly interrupted in the early 2000s but remained continuous afterwards. This finding aligns with the study of Monge et al. (2017), which suggests that the relationship between M&A activity and energy prices has experienced periods of upswings and downswings, fluctuating over time. The only scenario when M&A deals do not have a continuous impact on volatility is in the case of crude oil volatility and $Deals_{exit}$. Interestingly, $Deals_{exit}$ primarily impact volatility in the crude oil market during periods of financial turmoil. The degree of connectedness between M&A activity and energy markets appears to be most distinct during four main periods: the US invasion of Iraq, the GFC, the COVID-19 pandemic, and the 2022 Russia-Ukraine conflict. Overall, our study contributes to the existing literature by demonstrating that O&G companies, which expand their assets into non-O&G industries during times of high economic uncertainty, can significantly drive volatility in the crude oil market. Additionally, our results highlight that the type of M&A deals is crucial when considering their impact on energy market returns and volatility.

Fig. 4 presents the TVP-GC analysis results, which examine the influence of energy market dynamics on M&A transactions. The results are organized into three panels that represent different categories of M&A deals: $Deals_{stay}$, $Deals_{enter}$, $Deals_{exit}$. The analysis shows that all types of M&A transactions are persistently driven by crude oil movements, both in returns and volatility. This finding suggests that crude oil market

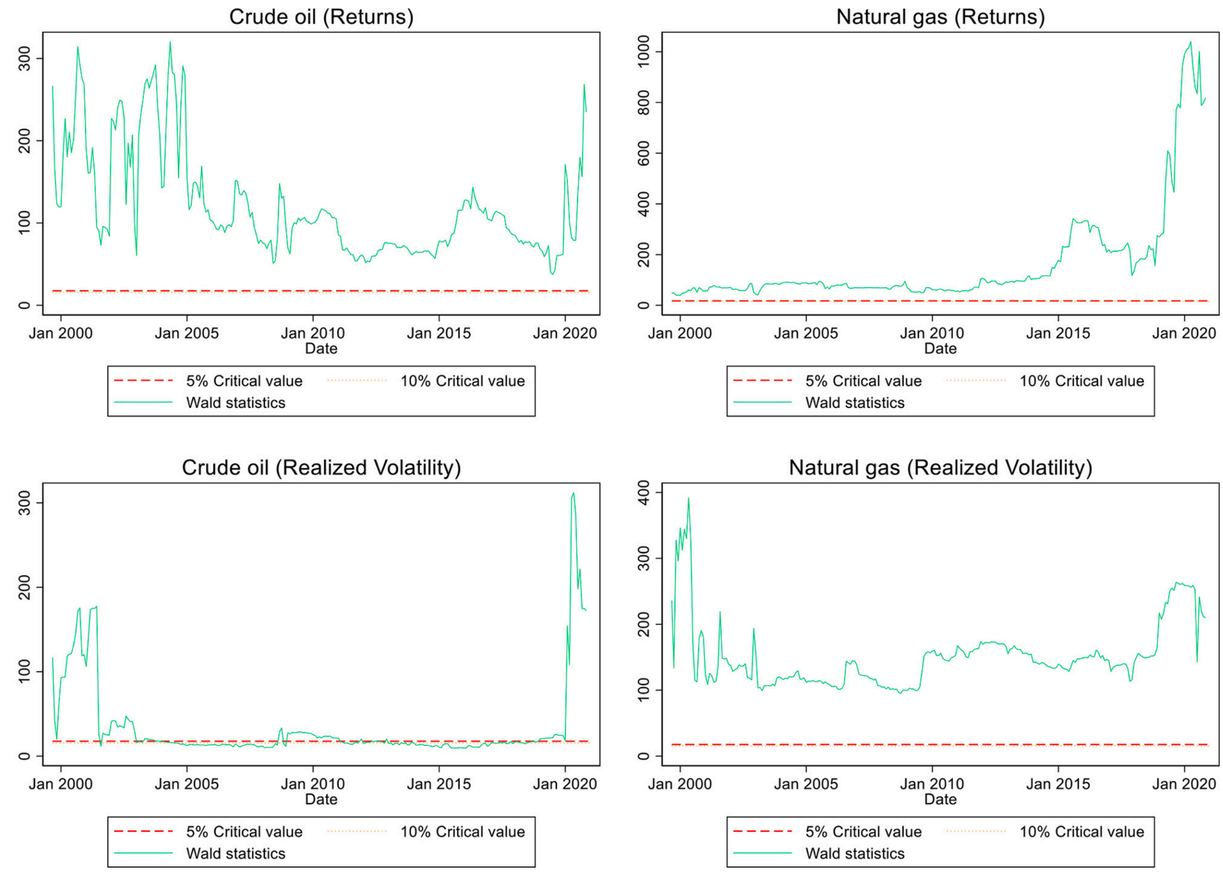


Panel A: $Deals_{stay}$



Panel B: $Deals_{enter}$

Fig. 3. Time-varying Wald test statistics: H_0 : $Deals \nRightarrow Energy$.



Panel C: $Deals_{exit}$

Fig. 3. (*continued*).

dynamics plays a significant role in shaping M&A decisions, which echoes the observations of Ng and Donker (2013). Additionally, the natural gas market plays a crucial role in influencing M&A deals. Notably, there are no discernible periods of discontinuity in the impact of natural gas volatility on M&A transactions, regardless of the deal type. This underscores the causal relationship between fluctuations in energy markets and M&A activity. As a result, portfolio managers stand to gain from closely monitoring energy market movements to forecast future M&A transactions. Past research demonstrates that M&A announcements can have an immediate effect on stock returns (Hackbarth and Morellec, 2008), thereby impacting investor gains (Barbopoulos et al., 2020). The analysis reveals that the impact of energy prices on M&A deals varies over time, particularly with respect to natural gas returns. Panel B in Fig. 4 highlights the causal impact of natural gas returns on non-O&G acquirers, which shows a tendency to diminish following the onset of the GFC but resurges after the oil market downturn in 2014. Similarly, natural gas returns exhibit a time-varying causal relationship with non-O&G target deals in the 2000s (Panel C), which is interrupted during the GFC. This suggests that the GFC significantly alters the relationship between M&A activity and natural gas markets. While M&A deals that involve new entrants to the O&G industry exhibit reduced sensitivity to energy prices post-GFC, transactions aimed at diversifying portfolios by investing in non-O&G firms demonstrate a sustained dependence on natural gas prices after the GFC. Importantly, neither the COVID-19 pandemic nor the subsequent Russia-Ukraine military conflict appears to sever the link between energy market dynamics and M&A transactions, as evidenced by Fig. 4. These findings underscore the lasting influence of energy prices on M&A activity, which highlights the importance of considering energy market dynamics in M&A decision processes.

Overall, our results can be explained by several theoretical frameworks suggesting that M&A deals interact with energy prices through a variety of mechanisms. Resource consolidation via M&A activity enhances companies' operational performance and profitability, subsequently impacting energy prices. This aligns with the operational synergies motive of M&A (Goold and Campbell, 1998), where improvements in efficiency and cost savings attained through synergies lead to more competitive pricing strategies in the energy market. Furthermore, technological innovations play an important role in shaping the relationship between M&A deals and energy prices. Firms may engage in M&As to acquire renewable energy innovations, which can enhance energy production efficiency and reduce costs, thereby influencing energy prices.

5.3. Dynamic total spillover connectedness

Fig. 5 illustrates the TCI across different quantiles. Panel A (returns) and Panel B (realized volatility) present the findings for returns and realized volatility, respectively. The results indicate that extreme events amplify the connectedness between M&A deals and energy markets. Specifically, at the 5th (95th) percentiles in Panel A and Panel B, the TCI stands at 50.70% (51.16%) and 39.15% (47.65%) respectively. A subtle symmetrical pattern is discernible in the TCI fluctuations between the extreme left and right tails, particularly for realized volatility. After the Great Oil Bust of 2014, a modest divergence between TCI returns at extreme quantiles emerges, which indicates intensified uncertainty in global energy markets. For median quantiles, the TCI averages 14.12% for returns and 11.00% for realized volatility. This suggests a degree of consistency in connectedness but also unveils asymmetric behavior in commodity market responses to shocks in the network.

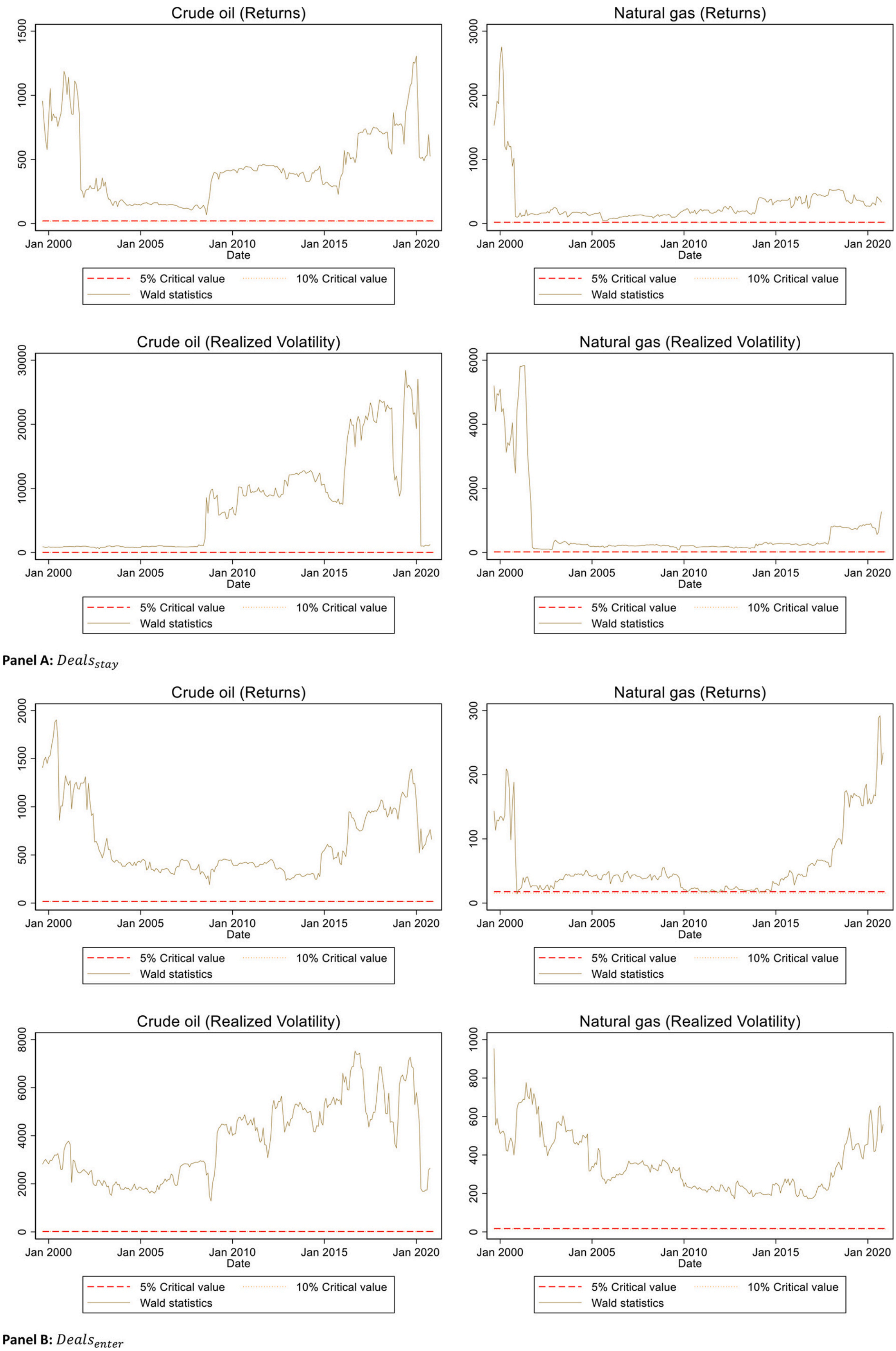
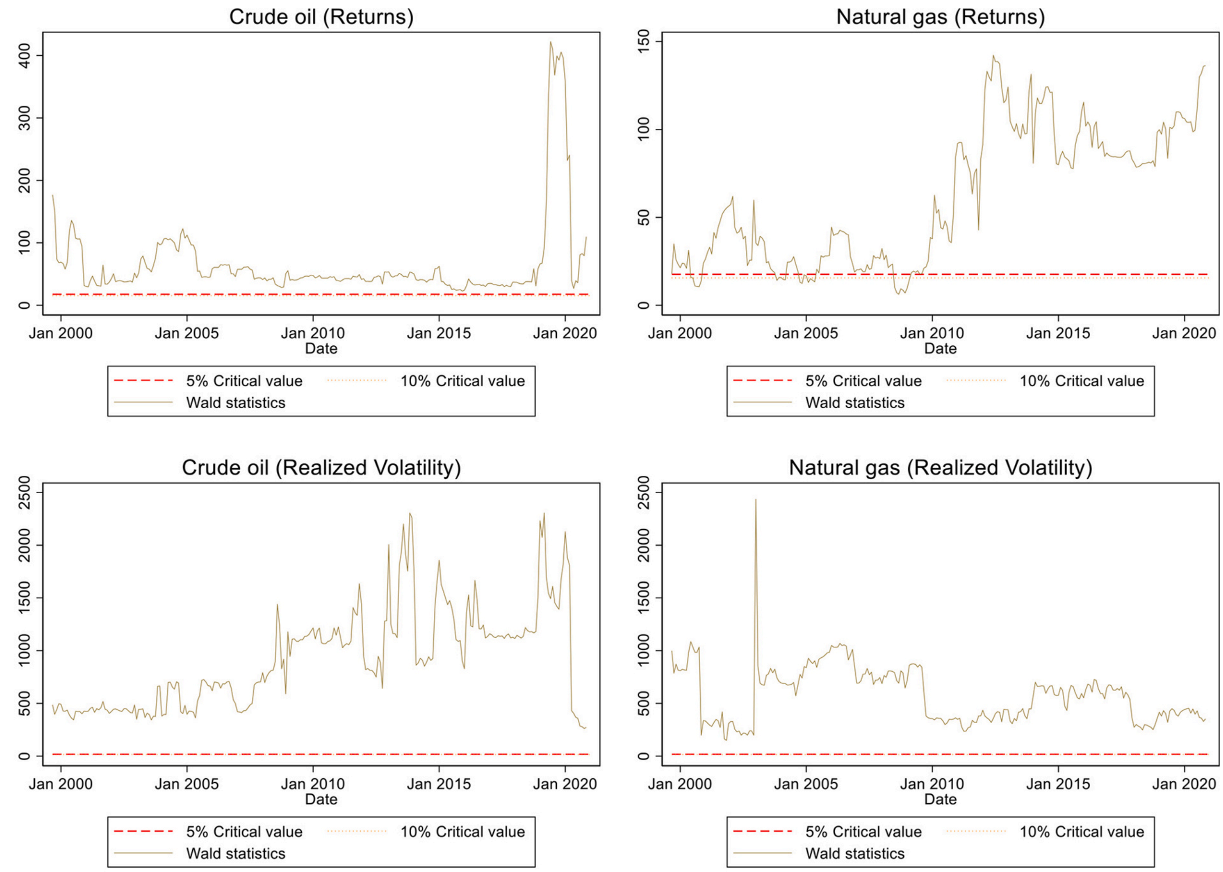


Fig. 4. Time-varying Wald test statistics: H_0 : *Energy*$\nRightarrow$*Deals*



Panel C: $Deals_{exit}$

Fig. 4. (*continued*).

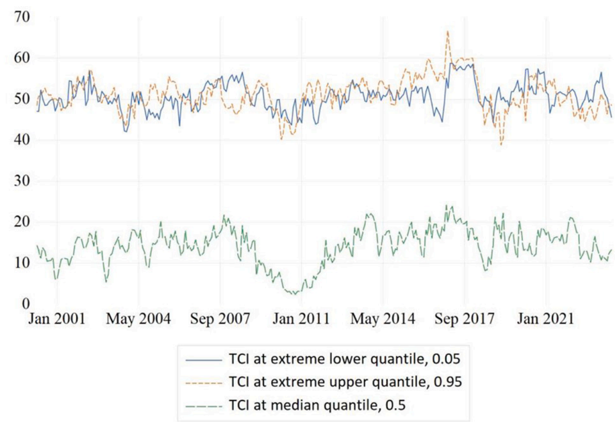
While the return TCIs at extreme quantiles follow each other closely, volatility TCIs behave differently. Until the onset of the GFC, there is evidence of increasing disparity between volatility TCIs, with similar dynamic spillover patterns at extreme upper and lower quantiles during the GFC. This indicates that the connectedness between energy markets and M&A deals in the O&G sector is equally impacted by high and low volatility movements during the GFC, responding similarly to both positive and negative news during periods of financial instability. The volatility TCIs at the extreme quantiles show a growing discrepancy from the mid-2010s, coinciding with the oil price plummet of 2014–2016, which heightened uncertainty in energy markets. Notably, the peak disparity between the TCIs for realized volatility at extreme quantiles occurs following the onset of the 2022 Russia-Ukraine conflict. Our findings align with the previous literature, which suggests that the Russia-Ukraine conflict has significantly impacted energy firms (see, Nerlinger and Utz, 2022; Balsalobre-Lorente et al., 2023; Roy et al., 2023).

In summary, dynamic total spillover peaks during periods of high energy market uncertainty, such as the US invasion in Iraq, the oil price plunge of 2014–2016, and the 2022 Russia–Ukraine military conflict. The spillover effects between energy markets and M&A activity are generally higher in the upper quantiles than in the lower ones. Additionally, the results in both panels of Fig. 5 reveal that volatility evolves asymmetrically when comparing extreme quantiles with the median quantile. This suggests that focusing on median quantile estimations may underestimate the average spillover effects between energy markets and M&A activity in the O&G sector by nearly four times. Furthermore, geopolitical instabilities significantly drive M&A activity and influence energy markets. For example, the US invasion of Iraq, and the ongoing 2022 Russia-Ukraine conflict greatly impact the dynamics of supply and demand for energy, facilitating M&A activity within the O&G industry (Shen et al., 2021). Companies tend to engage in M&A deals to consolidate their market positions and mitigate geopolitical risks, where non-O&G acquirers take advantage of market opportunities to secure energy resources, which enables them to hedge against the energy price volatility.

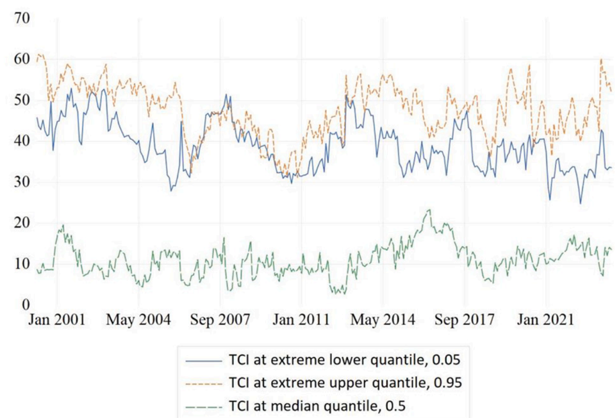
5.4. *Quantile directional spillover effects and connectedness*

Tables 6 and 7 present the results from the quantile directional spillover analysis for returns and realized volatility series. Each table is divided into three panels: Panel A shows the quantile spillovers at lower quantiles ($\tau = 0.05$), Panel B at median quantiles ($\tau = 0.5$), and Panel C at upper quantiles ($\tau = 0.95$). This method enables us to identify asymmetries in spillovers and examine the connectedness between energy markets and M&A activity at the tails of the distribution.

Table 6 presents the outcomes from the returns series. The estimates on the main diagonal capture idiosyncratic shocks (own-variable shocks), while off-diagonal elements signify the connectedness among different markets. Specifically, we observe that energy commodities exhibit a forecast error variance attributed to within-market shocks that is, on average, higher than their M&A counterparts. Consequently, energy commodities are less exposed to external shocks than M&A deals in the O&G sector, maintaining a lower level of connection to the energy industry. Nonetheless, the within-market variance values are relatively close among the main diagonals for each panel, resulting only in marginal differences. Our analysis reveals that M&A deals are the most impacted within the network. For extreme quantiles, 52.47% (51.71%) of $Deals_{enter}$ variance and 51.62% (52.21%) of $Deals_{stay}$ variance is driven by interactions within the energy market network at the 5th and 95th



Panel A: Returns



Panel B: Realized volatility

Fig. 5. Total Connectedness Index (TCI) across different quantiles

percentiles, respectively. Considering the median quantile, $Deals_{enter}$ are still the most interconnected, with 15.76% of their variance attributed to the network, followed by $Deals_{exit}$, while $Deals_{stay}$ become the least interconnected with just 12.73% of their variance attributed to it. Conversely, energy commodities show the lowest level of connectedness within the network at both the lower and upper extreme quantiles, particularly noteworthy are natural gas (48.93%, 5th percentile) and crude oil (50.42%, 95th percentile). This suggests that energy pricing has a slightly larger impact on M&A activity in the O&G industry than the reverse effect. Nevertheless, the minor differences in variance FROM other variables make it challenging to draw definitive conclusions on this matter. The TCI for the upper (lower) quantile of Table 6, is 51.16% (50.70%) compared to only 14.12% for the median quantile, which implies that interdependence within this network of variables is much stronger during extreme events. This implies a high degree of connectedness between energy prices and M&A activity in the O&G sector, especially during periods of market turmoil.

When examining the net directional connectedness values, particularly under stressful market conditions ($\tau = 0.05$ & $\tau = 0.95$), it is observed that, energy prices are net receivers of spillovers in the system. Specifically, natural gas emerges as the primary receiver of shocks in the system at the lower quantile, with a value of -1.92, while crude oil ranks first among all variables at the upper quantile, with a value of -0.84. For the median quantile, crude oil remains a net receiver of spillovers, while natural gas becomes a net transmitter. This suggests

Table 6
Quantile directional spillovers, returns

	Crude oil	Natural gas	$Deals_{stay}$	$Deals_{enter}$	$Deals_{exit}$	FROM
Panel A: Spillover at extreme lower quantile ($\tau = 0.05$)						
Crude oil	50.09	13.25	13.10	12.96	10.61	49.91
Natural gas	13.46	51.07	13.32	12.09	10.06	48.93
$Deals_{stay}$	12.60	12.77	48.38	12.75	13.49	51.62
$Deals_{enter}$	12.55	11.33	12.49	47.53	16.11	52.47
$Deals_{exit}$	10.40	9.66	13.69	16.81	49.44	50.56
TO	49.01	47.01	52.59	54.62	50.27	253.5
NET	−0.90	−1.92	0.97	2.14	−0.29	TCI = 50.70
Panel B: Spillover at median quantile ($\tau = 0.5$)						
Crude oil	85.94	4.70	1.96	5.42	1.98	14.06
Natural gas	4.65	86.18	3.68	2.77	2.72	13.82
$Deals_{stay}$	1.94	3.79	87.27	2.76	4.24	12.73
$Deals_{enter}$	5.20	2.67	2.63	84.24	5.26	15.76
$Deals_{exit}$	1.97	2.73	4.14	5.38	85.78	14.22
TO	13.76	13.88	12.41	16.34	14.19	70.58
NET	−0.30	0.06	−0.32	0.58	−0.02	TCI = 14.12
Panel C: Spillover at extreme upper quantile ($\tau = 0.95$)						
Crude oil	49.58	14.87	12.27	12.49	10.79	50.42
Natural gas	14.73	49.19	14.26	11.72	10.11	50.81
$Deals_{stay}$	11.85	13.92	47.79	12.48	13.96	52.21
$Deals_{enter}$	12.25	11.65	12.61	48.29	15.2	51.71
$Deals_{exit}$	10.76	10.01	14.37	15.52	49.34	50.66
TO	49.58	50.45	53.51	52.2	50.07	255.82
NET	−0.84	−0.36	1.30	0.50	−0.60	TCI = 51.16

Note: This table presents the estimates from the quantile directional spillover analysis of the returns series for different quantiles (τ). TCI is Total Connectedness Index.

that the connectedness behavior of natural gas depends largely on market conditions. Similarly, $Deals_{exit}$ remain a net receiver of spillovers, whereas $Deals_{enter}$ act as transmitters regardless of the quantile. This finding has interesting implications for policymakers who may adapt different policies depending on whether the M&A financial transaction targets O&G firms or non-O&G firms. $Deals_{stay}$ are net transmitters of spillovers during extreme market events, but in normal market conditions, they act as net receivers. Overall, we can conclude that the net connectedness is quite similar in directionality between crude oil and M&A deals where the target company is not from the O&G sector. In this context, M&A activity within the energy sector may lead to the financialization of commodity markets, influenced by such transactions. This phenomenon has significant implications for the pricing of energy commodities (see Basak and Pavlova, 2016, for further discussion). Specifically, for O&G acquirers, M&A transactions often attract financial interests, which results in higher levels of speculative trading and market volatility, thereby rendering energy prices more sensitive to financial capital inflows. For non-O&G firms, engaging in M&A activity can introduce new financial instruments such as derivates and hedging, which may further influence energy prices. Consequently, non-O&G firms may view participation in O&G M&A deals as an opportunity to enhance revenue generation and pursue diversification strategies, leveraging commodities' role as safe havens (see, Ciner et al., 2013; Antonakakis and Kizys, 2015; Özgür and Wirl, 2020; Naeem et al., 2022; Enilov et al., 2023).

Table 7 presents the results from the realized volatility series. We observe that natural gas exhibits the largest variance share attributed to within-market shocks, followed by crude oil. Consequently, the realized volatility of energy prices is less exposed to external shocks compared to M&A deals in the O&G sector during extreme market conditions. Regarding the interconnectedness, natural gas is consistently the most

Table 7
Quantile directional spillovers, realized volatility

	Crude oil	Natural gas	$Deals_{stay}$	$Deals_{enter}$	$Deals_{exit}$	FROM
Panel A: Spillover at extreme lower quantile ($\tau = 0.05$)						
Crude oil	67.10	4.13	8.80	8.36	11.61	32.90
Natural gas	4.50	77.75	5.54	6.13	6.07	22.25
$Deals_{stay}$	7.66	4.15	54.44	16.74	17.01	45.56
$Deals_{enter}$	7.30	4.64	16.29	53.36	18.42	46.64
$Deals_{exit}$	9.72	4.38	16.24	18.04	51.63	48.37
TO	29.18	17.29	46.86	49.28	53.12	195.73
NET	−3.72	−4.95	1.30	2.63	4.74	TCI = 39.15
Panel B: Spillover at median quantile ($\tau = 0.5$)						
Crude oil	89.48	2.18	1.43	4.79	2.12	10.52
Natural gas	2.11	92.12	2.22	1.33	2.22	7.88
$Deals_{stay}$	1.45	2.15	90.23	2.48	3.69	9.77
$Deals_{enter}$	4.56	1.35	2.41	86.41	5.27	13.59
$Deals_{exit}$	2.05	2.16	3.63	5.38	86.78	13.22
TO	10.17	7.84	9.70	13.98	13.31	54.99
NET	−0.36	−0.04	−0.08	0.39	0.09	TCI = 11.00
Panel C: Spillover at extreme upper quantile ($\tau = 0.95$)						
Crude oil	56.03	9.96	11.16	11.80	11.05	43.97
Natural gas	10.10	56.68	11.51	10.32	11.39	43.32
$Deals_{stay}$	10.46	10.64	49.76	13.70	15.44	50.24
$Deals_{enter}$	11.23	9.61	13.67	50.27	15.21	49.73
$Deals_{exit}$	10.28	10.42	15.25	15.03	49.02	50.98
TO	42.08	40.62	51.59	50.85	53.09	238.23
NET	−1.88	−2.70	1.35	1.12	2.11	TCI = 47.65

Note: This table presents the estimates from the quantile directional spillover analysis of the realized volatility series for different quantiles (τ). TCI is Total Connectedness Index.

disconnected variable, regardless of the quantile. In comparison, crude oil generally demonstrates a higher dependency on financial transactions in the O&G industry than natural gas. Our findings in Table 7 show that M&A deals are the most interconnected with other variables in the network. Specifically, $Deals_{exit}$ are the most interconnected at both upper and lower quantiles, while $Deals_{enter}$ take the lead at the median quantile. The TCI results are qualitatively similar between the returns and realized volatility series. The TCI at the upper quantile of Table 7 is 47.65% and at the lower quantile is 39.15%, compared to only 11.00% at the median quantile, implying that interdependence within this network of variables is much stronger during extreme events. Moreover, the interdependence in favorable market conditions is stronger than during market turmoil, regardless of whether the return or realized volatility series are considered.

Focusing on the net directional connectedness outcomes from Table 7, we find results similar to those obtained from the returns series, with a few exceptions. Both crude oil and natural gas consistently act as receivers of spillovers across all quantiles, while $Deals_{enter}$ remain a net transmitter of spillovers. Similarly, $Deals_{stay}$ act as a transmitter of spillovers at extreme market regimes but shift to a net receiver in normal market conditions. The largest divergence between our returns and realized volatility findings concerns $Deals_{exit}$. $Deals_{exit}$ act as a net transmitter of spillovers across all the quantiles for energy price volatilities but revert to being a net receiver of spillovers for energy returns, as shown in Tables 7 and 6, respectively. This suggests that returns and realized volatility have an asymmetric impact on variables in the network, a critical consideration for institutional investors when constructing their portfolios. Overall, our results from Table 7 imply qualitatively similar behavior in terms of directional transmission for our variables across different quantiles, with the exception for $Deals_{stay}$ at the median quantile. However, the magnitude of net spillovers varies significantly across different quantiles.

Fig. 6 graphically represents the net directional connectedness for the returns and realized volatility in Panels A and B, respectively. Our results reveal that natural gas receives sizable spillovers from the network at the extreme lower quantile, followed by crude oil. This finding holds across both panels. Meanwhile, M&A activity generally remains a transmitter of spillovers at the lower quantile in both panels, except for $Deals_{exit}$ in the returns series. The transmission patterns for the upper quantile are similar to those of the lower quantile, with energy commodities being net receivers of spillovers and M&A deals acting as transmitters. Again, the only exception is $Deals_{exit}$ in the returns series. Notably, there is no directional spillover between natural gas and crude oil markets at the extreme quantiles in Panel B, however, they are connected in Panel A. At the upper quantile in Panel A, natural gas returns spill over to crude oil returns, but this direction reverses at the lower quantile. This indicates asymmetric behavior in returns transmission across different market regimes. At the median quantile, crude oil and natural gas are disconnected in Panel A but connected in Panel B, where natural gas acts as a transmitter of spillovers to crude oil. The only series that remain consistently connected across both panels and all quantiles are crude oil and $Deals_{enter}$. This indicates that non-O&G companies that enter the energy market impact crude oil prices regardless of market conditions.

6. Robustness checks

In this robustness exercise, we explore the connectedness and forecasting between M&A activity and energy prices and volatility. Section 6.1 extends our analysis over longer horizons, with a special emphasis on the lasting impact of M&A deals. Section 6.2 further scrutinizes quantile connectedness. Specifically, this exercise examines the connectedness across different quantiles and extended forecast horizons. Section 6.3 tests robustness by considering different rolling window sizes. By applying variations of 100, 150, 200, and 250 months, stable TCI values for returns at extreme quantiles underline a robust connection during market turbulence.

6.1. Time-varying granger causality over extended horizons

To assess the long-term impact of M&A activity on forecasting energy prices and volatility, we conduct an in-depth analysis over an extended timeframe. Prior research has highlighted the variability in forecasting accuracy across different periods and time horizons (Quaedvlieg, 2021; Müller et al., 2022), noting a rapid decay in volatility predictive accuracy as the horizon increases (Christoffersen and Diebold, 2000). It is imperative to investigate the persistency of M&A deals in forecasting energy prices and volatility over longer time horizons. Our study pioneers in evaluating the long-term forecasting properties of M&A deals in energy markets, specifically concerning natural gas. To do so, we extend the TVP-GC framework into a multi-horizon TVP-GC forecasting model with time-varying parameters. This allows us to explore the out-of-sample forecasting performance of M&A deals on returns and volatility in energy markets. We consider the following multi-horizon TVP-GC forecasting model:

$$y_{t+h} = \psi_{1,t}y_{t-1} + \psi_{2,t}y_{t-2} + \ldots + \psi_{p,t}y_{t-p} + \epsilon_{t+h} \tag{12}$$

The forecasting horizons, denoted by 'h,' in our analysis, encompass periods of 3 and 6 months.[6]

Tables 8 and 9 provide the results derived from the time-varying robust Granger causality method developed by Rossi and Wang (2019)

[6] As part of our robustness exercise, we also examine horizons of 9 and 12 months. We find qualitatively similar results, although they are not reported here. However, these additional findings can be made available from the authors upon request.

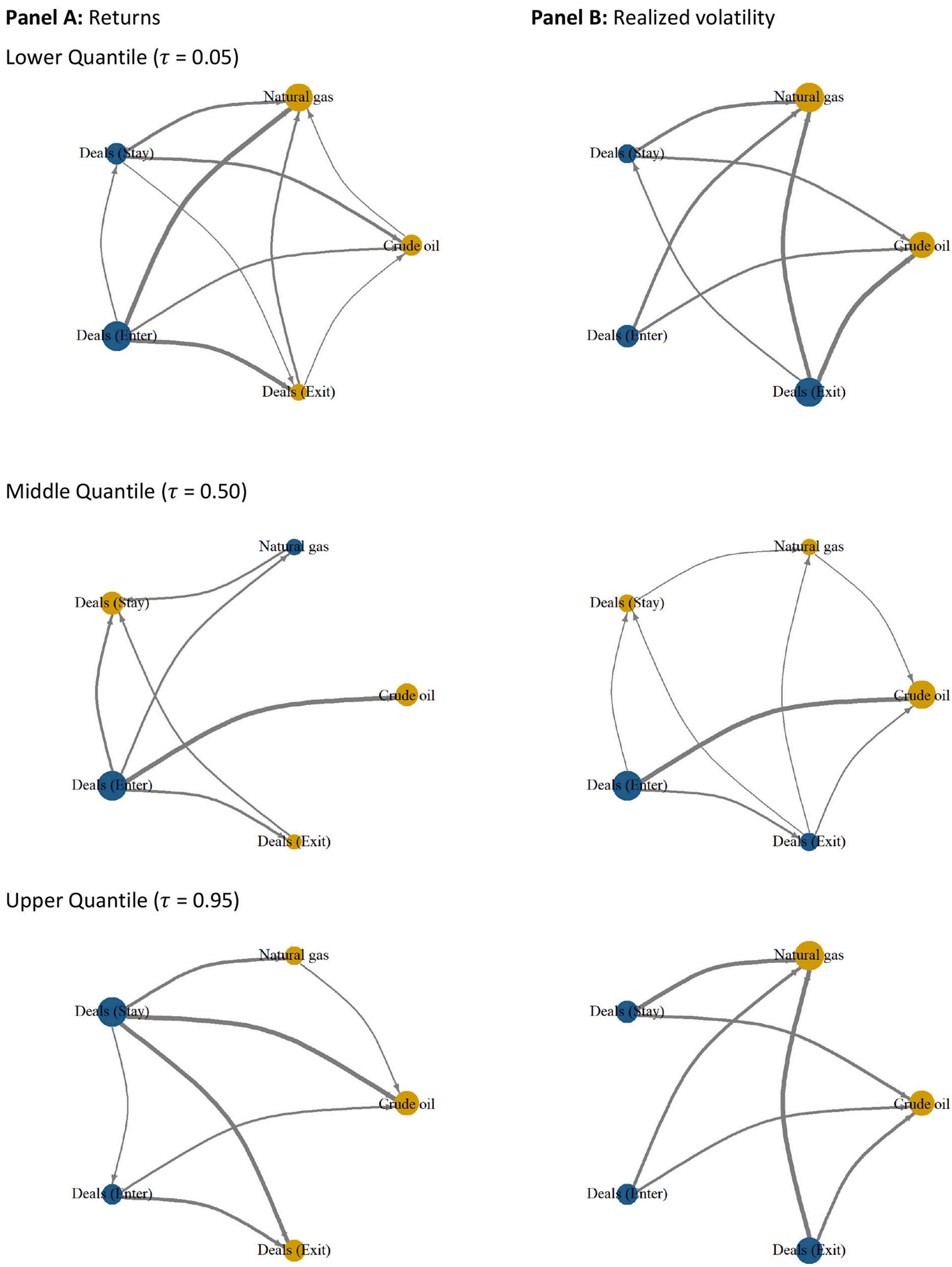


Fig. 6. Spillover Network.

for the two aforementioned horizons. The results are organized into four panels, distinguishing between energy commodities – specifically, crude oil and natural gas – and their associated returns and realized volatility measures. Consistent with our main analysis, we infer causality if at least two out of the three statistics are significant at the 10% level. The findings consistently indicate bi-directional causality between M&A activity and energy series for both 3 and 6-month forecasting horizons. This conclusion is based on the statistical significance of all three statistics at the 10% level for both returns and volatility series. In summary, our results show that M&A activity exerts a longer-term, time-varying

Table 8
Results from time-varying parameter Granger causality tests, 3-month forecasting horizon

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals
Panel A: $Oil_{Returns}$						
MeanW	244.163***	169.565***	70.228***	300.259***	59.478***	87.427***
Nyblom	2.701	3.128	4.323**	7.51***	2.537	3.072*
SupLR	967.703***	897.247***	630.026***	1180.923***	367.718***	438.294***
Panel B: $Gas_{Returns}$						
MeanW	67.449***	199.943***	38.657***	81.66***	165.707***	192.58***
Nyblom	4.249*	6.914***	2.846	3.68**	2.376	2.214
SupLR	397.29***	447.227***	264.07***	533.838***	385.338***	2117.341***
Panel C: Oil_{RV}						
MeanW	204.553***	1225.524***	197.612***	993.517***	70.781***	317.331***
Nyblom	7.838***	18.087***	188.803***	5.455**	3.112*	2.691
SupLR	992.614***	10,017.536***	1028.991***	1889.787***	379.077***	3455.197***
Panel D: Gas_{RV}						
MeanW	123.072***	388.585***	90.654***	677.164***	103.293***	5071.688***
Nyblom	11.675***	11.389***	5.412***	1.611	1.363	6.446***
SupLR	1253.74***	964.834***	344.062***	1805.782***	379.257***	14,938.403***

Note: Entries correspond to the mean Wald (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) test statistics from the time-varying robust Granger causality test of Rossi and Wang (2019). The lag length is based on BIC. "Deals" represents any of the following M&A activity: $Deals_{enter}$, $Deals_{exit}$, $Deals_{stay}$. "Energy" denotes any of the following energy series: $Oil_{Returns}$, $Gas_{Returns}$, Oil_{RV}, Gas_{RV}. H_0 : Deals$\nRightarrow$Energy ($\nRightarrow$ means "does not Granger-cause"). *, **,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table 9
Results from time-varying parameter Granger causality tests, 6-month forecasting horizon

	$Deals_{stay}$		$Deals_{enter}$		$Deals_{exit}$	
	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals	H_0: Deals $\nRightarrow$ Energy	H_0: Energy $\nRightarrow$ Deals
Panel A: $Oil_{Returns}$						
MeanW	310.483***	137.933***	143.331***	55.083***	183.015***	27.113***
Nyblom	4.752**	3.269	1.97	3.37*	2.592	1.854
SupLR	1299.39***	549.774***	747.664***	168.366***	570.493***	89.242***
Panel B: $Gas_{Returns}$						
MeanW	246.357***	122.502***	174.299***	75.008***	137.715***	100.412***
Nyblom	3.988*	5.241**	2.457	4.684**	1.651	3.658**
SupLR	716.628***	321.678***	370.221***	283.987***	592.978***	927.008***
Panel C: Oil_{RV}						
MeanW	100.768***	1889.149***	180.206***	1762.519***	86.128***	134.009***
Nyblom	189.735***	16.976***	13.278***	23.18***	6.22***	3.956**
SupLR	322.016***	4069.837***	1192.734***	3890.918***	505.173***	2239.618***
Panel D: Gas_{RV}						
MeanW	57.645***	306.266***	77.08***	607.592***	55.422***	39.691***
Nyblom	44.243***	4.493**	16.743***	8.179***	3.378*	5.444***
SupLR	375.549***	1560.98***	230.907***	1034.26***	140.955***	141.434***

Note: Entries correspond to the mean Wald (MeanW), Nyblom (Nyblom), and Quandt Likelihood Ratio (SupLR) test statistics from the time-varying robust Granger causality test of Rossi and Wang (2019). The lag length is based on BIC. "Deals" represents any of the following M&A activity: $Deals_{enter}$, $Deals_{exit}$, $Deals_{stay}$. "Energy" denotes any of the following energy series: $Oil_{Returns}$, $Gas_{Returns}$, Oil_{RV}, Gas_{RV}. H_0 : Deals$\nRightarrow$Energy ($\nRightarrow$ means "does not Granger-cause"). *, **,*** denote statistical significance at the 10%, 5% and 1% level, respectively.

impact on both returns and volatility in energy markets; notably, this impact does not decay over the horizon.

6.2. Quantile connectedness over extended horizons

In this section, we dig deeper into the connectedness between M&A activity and energy series across different quantiles of the distribution, considering extended forecast horizons. Specifically, we consider forecasting horizons $h \in \{2, 3, \ldots, 12\}$ for robustness testing. The results in Table 10 show TCI values at different quantiles τ for the specified forecasting horizons h. Our findings suggest a strengthening of connectedness as the forecasting horizon increases. Notably, a substantial disparity emerges between our tail results and those at the median, which further reinforces our assertion regarding variability in connectedness under different market conditions. We observe that the connectedness at the quantiles is consistently stronger than at the median for both returns and realized volatility estimates. This reaffirms the suitability of our chosen econometric approach and validates the robustness of our main findings over extended forecasting horizons. Interestingly, our findings diverge from previous literature that suggests a decay in forecasting ability with an increase in the horizon (Christoffersen and Diebold, 2000). We find that connectedness is stronger at the lower tail of the distribution than at the upper tail for returns when $h > 2$, while the opposite holds for realized volatility. TCI values indicate similar connectedness across extreme quantiles for returns, while for realized volatility, the connectedness is stronger at the upper quantile than the lower quantile. The results in Table 10 strongly support the robustness of our main findings.

Table 10
Quantile connectedness (TCI) over extended forecasting horizons

	Returns			*Realized volatility*		
Horizon(h)	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
2	54.52	22.52	55.97	43.19	20.13	54.98
3	60.84	29.95	60.28	48.19	26.70	60.07
4	64.29	34.27	63.23	51.10	30.25	63.05
5	66.37	36.70	65.04	52.71	32.29	65.63
6	67.67	37.86	66.33	53.82	33.18	67.81
7	68.37	38.67	67.24	54.76	33.89	69.91
8	69.18	39.21	67.90	55.45	34.31	71.43
9	69.82	39.50	68.51	56.10	34.57	72.82
10	70.42	39.83	68.98	56.65	34.74	73.78
11	70.98	40.02	69.45	57.15	34.91	74.77
12	71.35	40.18	69.83	57.63	35.02	75.51

Note: The table represents the Total Connectedness Index (TCI) at different forecast horizons, h, for a desired quantile level, τ.

6.3. Quantile connectedness: Robustness across varying rolling window sizes

Recognizing the potential variability in our findings based on the chosen rolling window size, we conduct robustness testing with different rolling window sizes *rw* of 100, 150, 200, and 250 months, as suggested by prior research (Diebold and Yılmaz, 2014; Baruník et al., 2016; Greenwood-Nimmo et al., 2016, 2019; Demirer et al., 2018; Bouri et al., 2020; Ding et al., 2021). The results of the quantile connectedness are presented in Table 11, showing TCI values at various quantiles τ. Our results reveal that TCI values for returns at the extreme quantiles remain relatively stable across different window sizes. However, median results exhibit a modest decline with increasing rolling window size. On the one hand, this finding reaffirms the robust connection between M&A activity and energy returns during turbulent market episodes, regardless of the window size. On the other hand, it emphasizes the substantial underestimation of the connection by models that rely on median quantile estimations. Turning to realized volatility, the results align with our main findings: extreme quantiles exhibit substantially stronger connections, as measured by TCI values, compared to the median. Additionally, the network connections are stronger at the upper tail than at the lower tail. This underscores the importance for policymakers to carefully examine transmission patterns between M&A activity and volatility in energy markets during turbulent market conditions. Ultimately, our study concludes that the choice of window size has a limited impact on connectedness estimations, and these findings align qualitatively with our main findings across both returns and realized volatility series.

7. Conclusion

We study the dynamic relationship between mergers and acquisitions (M&As) in the oil and gas (O&G) industry and the volatility of energy markets. This study gains prominence in the context of the global transition towards renewable energy sources, growing environmental concerns, the Green New Deal, and geopolitical events such as the ongoing war between Russia and Ukraine.

Table 11
Quantile connectedness (TCI) across different rolling window sizes

	Returns			*Realized volatility*		
Rolling-window (rw)	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$	$\tau = 0.05$	$\tau = 0.5$	$\tau = 0.95$
100	63.99	8.61	63.66	44.00	7.06	51.31
150	65.46	7.47	64.96	44.03	6.52	49.28
200	66.48	6.90	65.74	43.81	6.06	47.68
250	66.74	6.17	66.08	41.62	5.29	44.84

Note: The table represents the Total Connectedness Index (TCI) across different rolling window sizes, *rw*, for a desired quantile level, τ.

We provide novel evidence on the relationship between energy prices and M&A activity within the O&G industry, a topic often overlooked in existing research. Unlike conventional studies that primarily focus on crude oil, our research underscores the pivotal role of natural gas prices, particularly in the post-COVID-19 and conflict-laden global landscape. Natural gas emerges as a significant driver of M&A activity within the O&G sector. Our novel approach categorizes M&As into three types based on the industries of the acquiring and target firms: i) both parties from the O&G industry, ii) a target firm from the O&G industry and an acquirer from a non-O&G industry, and iii) an acquirer from the O&G industry and a target from a non-O&G industry.

We explore both time-invariant and time-varying links between M&A activity and energy markets. In the time-invariant framework, we find limited evidence of causality between M&A deals and energy markets. Notably, crude oil returns and volatility appear to Granger cause M&A activity under specific conditions, with distinct patterns emerging in the natural gas market. Specifically, crude oil returns and volatility Granger cause M&A activity when both parties belong to the O&G industry or when the acquirer is from a non-O&G industry. In contrast, M&A activity Granger causes price changes in the natural gas market when the target firm is from a non-O&G industry and causes volatility when the acquirer is from a non-O&G industry. A limitation of the time-invariant framework is its assumption of a constant relationship over time.

In the time-varying framework, our results reveal a dynamic impact of M&A activity on both returns and volatility in energy markets. We find that M&A deals cause fluctuations in prices not only in the crude oil market, but also in the natural gas market, which has experienced large swings over the COVID-19 pandemic and the 2022 Russia-Ukraine military conflict. Overall, M&A deals provide information that is priced into energy markets. Notably, the causality also runs in the opposite direction: returns and volatility in energy markets influence M&A deals. The dynamic total spillovers demonstrate that extreme events amplify the connectedness between M&A deals and energy markets. Moreover, M&A deals, especially when the acquirer is from a non-O&G industry, act as transmitters of spillovers.

We conduct a battery of robustness checks. First, we examine the connectedness over longer horizons, with special emphasis on the lasting impact of M&A deals. Leveraging the TVP-GC framework, our multi-horizon model unveils significant bi-directional causality between M&A activity and energy series for 3 and 6-month forecasting horizons, which confirms the lasting influence on returns and volatility in energy markets. Second, we dig deeper into the connectedness across various quantiles and extended forecasting horizons. Results indicate that the degree of connectedness grows with increasing forecasting horizons. This underscores variability under distinct market conditions. The stronger connectedness at extreme quantiles compared to the median validates the robustness of our approach. Third, we test the robustness of our main findings to different rolling window sizes. Employing windows of 100, 150, 200, and 250 months, stable TCI values for returns at extreme quantiles underscore a robust connection during market turbulence. Conversely, median results exhibit a modest decline with an increases of the window size. This exposes the underestimation of connectedness by models relying on median quantile estimations. We conclude that window size minimally impacts connectedness estimations, which aligns qualitatively with our main findings for both returns and realized volatility series.

This research has significant practical implications. First, our results can inform investors who design portfolios around M&A transactions. Investors should consider sector-specific impacts of M&A activity on energy markets. For instance, M&A deals involving oil and gas (O&G) companies have significant effects on energy prices, especially in crude oil and natural gas markets. This suggests that portfolios heavily invested in energy commodities should be adjusted based on the type and timing of M&A activities within the sector. Understanding how different types of deals influence energy markets allows for more informed short-term investment strategies. Moreover, the study indicates that M&A deals, particularly those involving non-O&G firms acquiring O&G companies, have persistent predictive power over energy returns and volatility. Investors can use this information to anticipate future market movements, revise their short-term investment strategies, and even design long-term investment strategies. Second, the findings on total connectedness and spillover effects during extreme events provide insights for risk management. Investors can adjust their risk tolerance and investment decisions based on the increased interdependence between M&A deals and energy markets during turbulent periods. Given the observed bi-directional causality between M&A activity and energy market volatility, investors may need to adopt strategies that account for increased volatility during periods of significant M&A announcements. This may involve using derivatives or hedging strategies to mitigate risks associated with price fluctuations influenced by M&A activities. Additionally, regulators should enhance their capabilities to monitor systemic risks arising from M&A activities in the energy sector. This includes monitoring interconnectedness between M&A deals and energy markets to identify potential systemic vulnerabilities and take pre-emptive measures. Third, policymakers can assess M&A deals as predictors of energy price volatility. They can use this research to develop an early warning system for energy price volatility. If M&A deals are identified as predictors of energy market fluctuations, policymakers can implement measures to mitigate their impact during critical periods, such as geopolitical conflicts and financial crises. The study suggests that M&A deals can amplify energy price volatility during these times, necessitating policies that could stabilize markets or mitigate excessive speculative activities. More importantly, policymakers should consider that returns and volatility in the natural gas market have crucial implications for consumers and industries. For instance, most European economies still depend on natural gas supplies. Therefore, large swings in energy prices increase macroeconomic uncertainty, which limits economic growth. Policies aimed at enhancing energy security should take into account the impact of M&A activity on energy markets. Encouraging diversification in energy sources or promoting renewable energy investments may help mitigate the influence of M&A-driven volatility in fossil fuel markets. Fourth, regulatory bodies may benefit from enhanced surveillance of M&A activities within the energy sector. This can ensure fair market practices and prevent monopolistic behaviors that can distort energy prices. Hence, regulators may consider requiring greater transparency in M&A transactions within the energy sector, especially for deals involving significant market players. This transparency can help mitigate information asymmetries that may exacerbate market volatility. Likewise, antitrust regulations can be applied more rigorously to M&A activities within the energy sector to prevent consolidation leading to market manipulation or unfair pricing practices. This can potentially promote competition and potentially stabilize energy prices.

Future research may explore the role of firm-level M&A activity in the competitive structure and industrial organization of the O&G industry, as well as the shift of the economy and society towards sources of green energy and its impact on dirty energy prices.

Inclusion and diversity

The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

CRediT authorship contribution statement

Jianuo Wang: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Martin Enilov:** Writing – review & editing, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Renatas Kizys:** Writing – review & editing, Visualization, Validation, Supervision, Formal analysis, Conceptualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107781.

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