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Dynamic interlinkages between oil price shocks and stock markets: a quantile-on-quantile connectedness analysis in emerging economies

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ABSTRACT

This study examines the dynamic interplay between oil price fluctuations and stock markets across 11 emerging economies, encompassing both oil-exporting and oil-importing states. Leveraging quantile-on-quantile (QQ) connectedness and regression frameworks, we focus on the asymmetric spillover effects of oil price shocks on stock returns from 16 February 2006, to 14 June 2024, revealing nuanced insights into risk transmission across varying market conditions. Our findings demonstrate that oil-exporting countries, such as Saudi Arabia and Russia, display heightened sensitivity to oil price changes, while more diversified economies like China show comparatively subdued reactions. We further explore the implications of significant global events – such as the COVID-19 pandemic and geopolitical tensions related to the Russia-Ukraine conflict – on the interconnectedness of oil prices and stock markets. The results underscore the importance of strategic investment diversification for emerging markets to buffer against the adverse effects of oil price volatility. This research contributes to the existing literature on financial interconnectedness, providing valuable implications for policymakers and investors seeking to navigate the complexities of global oil market dynamics and enhance market resilience in the face of external shocks.

KEYWORDS
QQ connectedness; QQ regression model; oil price shocks; stock markets

JEL CLASSIFICATION
C32; G10; G12; Q54; C22

I. Introduction

Crude oil is a critical global energy source and an economic stability indicator due to its widespread use (Hanif, Hadhri, and El Khoury 2024). Price shocks in oil significantly affect both the real economy and financial markets, with fluctuations creating economic variability that can simultaneously impact economies worldwide (Asadi, Roubaud, and Tiwari 2022). Stock markets, as economic performance indicators, respond to oil price shifts, influencing household income, consumer spending, and capital flows (Alamgir and Amin 2021). Over the past decade, increased capital flow into oil futures – a phenomenon called 'financialization' – has intensified oil's role in financial markets, amplifying spillover effects across equities, bonds, and foreign exchange. This growing financialization has transformed oil into not only a commodity but also a financial asset subject to speculation, attracting diverse types of investors, including hedge funds, institutional investors, and retail traders. The heightened integration of oil futures into broader asset markets has amplified the spillover effects of oil price shocks, which reverberate across equities, bonds, and foreign exchange markets. This interconnectedness induces changes in oil prices can exerts considerable influence on the real economy, influencing inflation rates, investment decisions, and overall economic stability (Baumeister and Peersman 2013; Hamilton 2009; Tang and Xiong 2012).

The connection between oil price fluctuations and financial markets is further complicated by their effects on multiple economic sectors. Rising oil prices increase production costs, especially for energy-intensive industries, which can lead to profit margin squeezes and ultimately reduce stock market valuations (Kilian 2008). Additionally, for oil-exporting countries, high oil prices contribute positively to fiscal revenues and foreign exchange reserves, potentially boosting investor confidence in these economies' financial assets. Conversely, for oil-importing countries, elevated prices can lead to higher inflation, which may

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prompt central banks to tighten monetary policy, dampening economic growth and affecting financial markets (Basher and Sadorsky 2006; Degiannakis, Filis, and Arora 2018).

In recent decades, increased global economic integration has strengthened interdependencies among stocks worldwide. Financial markets have grown more volatile due to crises such as financial, political, war, and health-related events (Mensi et al. 2023). The COVID-19 pandemic, for instance, led to a historic drop in oil prices as quarantines reduced demand; prices began to recover as vaccines were rolled out (BP Energy (2021); Hanif, Hadhri, and El Khoury 2024). Russia's invasion of Ukraine further disrupted oil production, driving up prices due to anticipated sanctions and geopolitical tensions. By 7 March 2022, oil prices reached a 14-year high, influenced by both the conflict and OPEC's production announcements (Bagchi and Paul 2023; Q. Zhang et al. 2023). Many of these unexpected developments, often referred to as black swan events, have disrupted global financial markets and heightened financial instability. During periods of heightened uncertainty, these events have significantly widened the dispersion of risk across markets (Naeem and Arfaoui 2023). Moreover, these events have also strengthened the relationship between oil prices and stock markets (Hung and Vo 2021; Mensi et al. 2022). Since markets are closely linked via trade and investment channels, unpredictability in developed economies has a high potential to spread globally. Understanding the relationships between financial market uncertainties and stock market performance during turbulent periods is essential for improving financial risk management, making well-informed investment decisions, and promoting market stability.

Oil price fluctuations impact stock markets through both direct and indirect channels. Directly, they affect production costs, while indirectly, they influence investor confidence and capital flows. This connection suggests that oil price changes significantly impact stock markets by affecting cash flows or the interest rates used for discounting them (Salisu and Oloko 2015). Higher oil prices can hinder stock markets by slowing growth, raising costs, reducing profitability, and increasing general price levels, which collectively raise risk premiums and further pressure stock prices (Alamgir and Amin 2021).

Oil price changes affect oil-importing and oil-exporting countries differently. In oil-importing nations, rising oil prices increase production costs and reduce profitability, negatively impacting stock markets (Jammazi et al. 2017). In contrast, oil-exporting countries benefit from higher oil prices through increased revenues, boosting economic and stock market performance (Jimenez-Rodriguez and Sanchez 2005). This study examines 11 emerging markets, both oil-importing and oil-exporting, to capture these differentiated effects, including Türkiye, Argentina, Saudi Arabia, and China, which play key roles in the global economy and are sensitive to global shocks (Hanif, Hadhri, and El Khoury 2024; Quin et al. 2024). Saudi Arabia, for example, is central in global oil supply, making its market behaviour especially influential (Abdou et al. 2024). Covering data from 2006 to 2024, this study spans key events affecting oil Our research fills gaps in the existing literature by exploring the impact of oil shocks on stock returns in economies with different oil market structures. Our study concentrates on 11 emerging market economies, including Türkiye, Argentina, South Korea, Mexico, Saudi Arabia, Brazil, Russia, China, India, and South Africa, which are recognized for their dual roles as significant oil producers and consumers. Firstly, these economies have emerged as some of the most dynamic players in the global market, with an increasing reliance on oil for daily activities and production processes. Additionally, these nations serve as pivotal economic hubs, significantly contributing to global population, trade, and GDP (Quin et al., 2024). Secondly, these emerging economies are highly integrated into the global economic system through trade and capital flows, making their stock markets especially sensitive to global shocks (Hanif, Hadhri, and El Khoury 2024). Meanwhile, Saudi Arabia, the largest economy within the Arab world and the Gulf Cooperation Council (GCC), holds a central position in the global oil industry, acts as a major supplier to global oil markets. Thus, understanding the behaviour of the Saudi stock market, especially in relation to oil supply shocks, is essential for grasping its wider influence on global financial markets (Abdou et al. 2024). Finally, our dataset covers the period from 2006 to 2024, encompassing key global events that triggered significant oil price fluctuations. These cover the 2008 Global Financial Crisis, the 2011–2012 European Debt Crisis, the 2014–2016 Oil Price Collapse, the 2020 COVID-19 pandemic, and the 2022 Russia-Ukraine War. Each of these events caused substantial volatility in oil markets and had lasting impacts on global financial markets.

While extensive research has examined the relationship between oil price shocks and stock markets, our study advances the literature in several critical ways. First, we employ the QQ connectedness approach, which allows us to capture non-linear, asymmetric, and time-varying spillover effects – insights that traditional methods often overlook. This methodological refinement enables us to distinguish periods where stock market movements influence oil prices, shedding light on the transmission mechanisms between emerging economies and global energy markets. Second, by examining a diverse set of both oil-exporting and oil-importing emerging economies, our study offers a comparative perspective on how these markets respond differently to oil price fluctuations. This dual focus is crucial, as it pinpoints the heterogeneous transmission channels of oil shocks in economies with varying dependencies on crude oil.

Moreover, our dataset spans 2006 to 2024, covering multiple global financial and geopolitical crises – including the 2008 Global Financial Crisis, the 2011–2012 European Debt Crisis, the 2014–2016 Oil Price Collapse, the COVID-19 pandemic, and the 2022 Russia-Ukraine War – providing a long-term perspective on how major external shocks reshape oil-stock dynamics. By integrating these crisis episodes, our study offers policy-relevant insights into how oil price volatility interacts with broader financial stability concerns. Finally, as a robustness check, we complement our main analysis with quantile regression techniques, further reinforcing the heterogeneous effects of oil price shocks across different stock return distributions. These contributions not only expand our understanding of the evolving interplay between oil prices and stock markets but also provide practical implications for policymakers, investors, and financial regulators in emerging economies, emphasizing the need for diversified investment strategies and macroeconomic policies to mitigate risks associated with oil price fluctuations.

This study is structured as follows: Section II reviews the relevant literature, and Section III summarizes the data. Section IV describes the main methodology, while Section V presents the results. Finally, Section VI draws the main findings of the study and concludes.

II. Literature review

Economies heavily reliant on oil are keen to mitigate risks associated with price and supply fluctuations (Mensi et al. 2021). Therefore, the evolving linkage between oil prices and stock markets – encompassing aspects of volatility, causality, spillover, and contagion – has garnered considerable attention in the literature. Kling (1985) was among the earliest researchers to examine the link between oil prices and stock markets through the application of a Granger causality test. The study has revealed that stock markets generally react negatively to shocks in crude oil prices, detailing the direction and impact of the interaction between these two variables. In the following periods, studies examining the interdependence of the oil market and stock market rapidly increased and formed a comprehensive literature. In this vein, studies have yielded notable findings. Filis, Degiannakis, and Floros (2011) used a time-varying dynamic correlation method to examine the relationship between stock prices and oil prices, contrasting oil-importing with oil-exporting countries. Chang, McAleer, and Tansuchat (2013) applied volatility models to measure the dynamic conditional correlations between oil and stock markets, revealing asymmetric effects of similarly sized positive and negative shocks on the conditional variances of crude oil returns and stock index returns. Lu et al. (2021) analysed U.S. stock market volatility in response to oil price shocks with the use of the MS-Lasso model, which captures shifts in volatility dynamics under varying economic conditions. Their findings indicate that the link between those variables has strengthened considerably in the period following the financial crisis. Transmission effects related to oil and stock markets are vital for informing diversification strategies and risk management (Dai et al. 2022). A precursor study in this research line was unveiled by Diebold and Yilmaz (2009, 2012, 2014), known as the DY method, that employed forecast error variance decomposition from the VAR model with a rolling window to determine connectedness. Wang and Li (2021) analysed the asymmetric volatility relationship between the oil market and China's financial markets by combining the DCC-MIDAS model with the DY spread index model to capture these asymmetries. Their findings indicated that China's financial markets experienced asymmetric volatility spillover effects from the crude oil market, with adverse spillover effects occurring during both short-term and long-term financial crises. Bouri et al. (2021) examined time-varying spillover interactions between U.S. stock markets, crude oil, and gold. Their findings revealed that spillovers in realized volatility among these markets are substantial, while those in realized skewness and kurtosis are also significant. Notably, the stock index mainly acted as a net transmitter of realized volatility, while oil emerged as the primary net transmitter. Arouri, Jouini, and Nguyen (2012) analysed volatility spillovers between oil and stock markets using the VAR – GARCH methodology. Their findings indicated significant volatility spillovers between oil prices and European market performance. Ji et al. (2020) investigated the evolving interdependence and risk transmissions between stock returns and different categories of oil shocks in the BRICS region. By applying a Structural VAR model and a CoVaR methodology, their results indicated that this dependence fluctuates over time, with significant transmission of risks driven by oil-specific demand shocks affecting the market returns of the BRICS countries. Additionally, a pronounced asymmetry in risk spillovers was observed in Brazil, Russia, and India.

The DY method by Diebold and Yilmaz (2009, 2012, 2014) advanced the analysis of connectedness by measuring forecast variance in oil-stock linkages. Further studies, like Wang and Li (2021), showed asymmetric volatility spillovers between the oil and Chinese markets, while Bouri et al. (2021) found that U.S. stocks and oil transmit significant realized volatility to each other. Research by Arouri, Jouini, and Nguyen (2012) and Ji et al. (2020) demonstrated substantial volatility spillovers, especially in BRICS countries, with notable asymmetries in Brazil, Russia, and India.

Recent studies have examined the interplay between oil prices and stock market returns, particularly through spillover effects and advanced quantitative methods. Olayungbo et al. (2024) analysed these effects during the COVID-19 pandemic and Russia-Ukraine conflict using a Markov Switching model, finding significant volatility spillovers between oil and stock markets in various nations, including bi-directional spillovers in the U.S. and Europe. Quantile-based methodologies, such as those by Ando, Greenwood-Nimmo, and Shin (2018), have enabled detailed examination of risk spillovers across quantiles, capturing contagion mechanisms during extreme shocks. Mensi et al. (2024) used this approach to study crude oil and gold, finding intensified spillovers during market extremes. Similarly, Hanif, Hadhri, and El Khoury (2024) showed that oil demand shocks impact major oil-producing nations, while risk shocks primarily affect the U.S., China, and India.

A strand of studies has utilized quantile-based approaches to examine how oil price fluctuations impact stock markets, consistently finding that these relationships shift significantly across different market conditions, particularly during periods of heightened volatility or crisis. Sim and Zhou (2015) examined the relationship between oil prices and U.S. stock returns, employing both quantile regression and quantile-on-quantile regression techniques to analyse this relationship across different quantiles. Their findings indicate that market dependence varies considerably, especially during extreme market conditions – such as periods of very low or high volatility – where asymmetric risks become more pronounced. Their findings offered valuable insights for both investors and policymakers, helping them better understand how oil price variations impact stock markets across different risk categories. Naeem et al. (2020) examined the relationship between the stock markets of BRICS countries and gold and oil prices across different return levels and time-frequency dimensions, both before and after the Global Financial Crisis (GFC). Utilizing quantile-on-quantile (QQ) regression and quantile coherency (QC) approaches, they found that the positive dependence between gold and BRICS stock markets at lower return levels intensified after the GFC. Likewise, the previously neutral relationship between oil and BRICS stock returns at low return levels shifted to a positive correlation post-GFC. The QC analysis further indicated that, prior to the GFC, there was no short-term relationship between gold, oil, and BRICS stock markets; however, a moderately positive association emerged at all return levels in the post-crisis period. Over the long term, the already positive relationship observed before the GFC became even stronger after the crisis. Hamdi et al. (2019) analysed the volatility relationship between oil prices and sector-based stock indices in GCC countries using quantile regression. Although all sectors show dependence on oil prices, the banking and insurance sectors exhibit insensitivity to oil price volatility in the 10th, 25th, and 75th quantiles. The frequency domain causality analysis revealed substantial interdependence and contagion effects connecting oil prices with sector-specific stock returns. Qin et al. (2024) examined the role of interest rates in the oil-stock market relationship by employing TVP-VAR model based on quantile regression. They found that in high-interest-rate environments, oil price volatility exerts a stronger influence on stock markets in emerging economies. This interconnectedness and sensitivity are especially heightened in high-risk conditions, such as during crises. Naeem et al. (2022) explored the asymmetric impacts of extreme oil price shocks on BRIC stock markets using an extreme quantile approach. Their results indicated that oil price shocks elicit asymmetric responses in BRIC markets, with these effects being especially pronounced under extreme market conditions.

Recent studies have expanded on these analyses by incorporating novel methodological frameworks to examine financial market interactions. For instance, Olasehinde-Williams, Özkan, and Akadiri (2023) employed a DCC-GARCH approach to examine the risk connectedness between crude oil prices and sustainable investments in the United States, demonstrating that risk spillovers intensify during periods of economic and geopolitical uncertainty. Their findings highlight that crude oil primarily serves as a risk transmitter, while sustainable investments act as risk receivers, reinforcing the importance of understanding volatility transmission mechanisms in oil-stock market interactions.

While numerous studies have examined the relationship between oil price shocks and stock markets (see Broadstock, Wang, and Zhang 2012; Hamilton 2003; Kilian and Park 2009; Kocaarslan and Soytas 2019), many rely on linear methodologies that fail to capture the nonlinear, asymmetric, and time-varying nature of this relationship. Furthermore, most prior research primarily focuses on developed markets or individual emerging economies (e.g. Filis, Degiannakis, and Floros 2011; D. Zhang and Broadstock 2020), lacking a comparative perspective that distinguishes between oil-exporting and oil-importing emerging markets. Additionally, the evolving dynamics between oil prices and stock markets in the wake of recent economic and geopolitical shocks, such as the COVID-19 pandemic and the Russia-Ukraine war, remain underexplored (Narayan 2020, Sharif, Aloui, and Yarovaya 2020).

To bridge these gaps, our study employs a QQ connectedness approach, which provides a more granular and flexible analysis of the oil-stock nexus by accounting for nonlinear and asymmetric spillovers across different market conditions. Unlike previous studies that examine either oil-exporting or oil-importing economies in isolation, our research offers a comparative analysis of 11 emerging economies to assess how their stock markets respond differently to oil price fluctuations. Furthermore, by incorporating recent global crises, we provide timely and policy-relevant insights into how external shocks reshape financial interconnectedness. Finally, we complement our analysis with quantile regression techniques, ensuring a robust examination of the heterogeneous effects of oil price fluctuations on stock returns.

III. Data

We employed log daily returns for Brent oil and stock markets from South Africa, Türkiye, Indonesia, Argentina, Brazil, South Korea, Mexico, India, Saudi Arabia, Russia, and China.[1,2] These countries were chosen to represent a diverse mix of emerging and established markets with sig-

[1]Turkiye: BIST100, Indonesia: JCI, South Africa: FTSEJSE, Argentina: MERV, Brazil: BOVESPA, South Korea: KOSPI, Mexico: IPC, India: BSE SENSEX, Saudi Arabia: Tadawul All Share Index-TASI, Russia: RTS Index-RTSI, and China: Shenzhen Stock Exchange-SZSE.

[2]Türkiye, Argentina, South Korea, Mexico, Saudi Arabia, Brazil, Russia, China, India, and South Africa – are predominantly classified as emerging markets based on MSCI, IMF, and World Bank classifications. However, South Korea is sometimes categorized as a developed market by MSCI, while China is considered an emerging market but has aspects of a transitioning economy due to its significant global financial influence.

nificant exposure to oil price fluctuations, both as net importers and exporters. The data was sourced from the Refinitiv database, covering the sample period from 16 February 2006, to 14 June 2024, based on the longest available data alignment.

An overview of the statistics for the return series is presented in Table 1, while Figure 1 illustrates their respective trends.

As shown in Table 1, all return series, except for TASI, show positive average returns, with MERV having the highest mean, followed by BIST100 and SZSE, while TASI and RTSI have the lowest. MERV also exhibits the highest volatility, consistent with the risk-return trade-off principle. All return series display leptokurtic distributions and are left-skewed, except for IPC and BSE. The JB test confirms significant deviations from normality across the distributions. Furthermore, the series exhibit strong autocorrelations and significant ARCH/GARCH effects. The returns are also positively correlated, highlighting their economic significance.

Upon examining return trends presented in Figure 1, we observe that the returns exhibited substantial fluctuations corresponding to financial/geopolitical turbulences such as the 2007–2008 global financial crisis, the May 2010 flash, and August 2011 stock market crashes, the 2015–2016 stock market sell-off in August 2015, the 2020 stock market downturn in February 2020, and the 2022 Russian Ukrainian conflict.

The Brent oil series exhibits significant volatility and sharp drops, particularly around 2014 and early 2020, corresponding to the oil price collapse due to increased U.S. shale production and the COVID-19 pandemic, respectively. These oil price shocks likely influenced oil-dependent economies, such as Saudi Arabia (TASI) and Russia (RTSI), more intensively.

The pandemic led to sharp, synchronized declines across all indices in early 2020, reflecting the global economic slowdown. Brent oil also experienced a historic drop in prices, including negative prices for the crude oil, due to drastically reduced demand and storage constraints.

Emerging markets like Argentina (MERV) and Türkiye (BIST100) generally exhibit higher volatility compared to more developed markets, aligning with the higher risk-return profile typically associated with emerging economies. Argentina (MERV) and Russia (RTSI) display particularly high volatility, consistent with higher perceived risks in these economies, while indices like South Korea's KOSPI and India's BSE Sensex demonstrate relatively more stable returns.

Fluctuations in Brent oil returns likely have varying degrees of impact on each country depending on their oil dependency. Net oil exporters, such as Saudi Arabia (TASI) and Russia (RTSI), may show more sensitivity to Brent oil volatility, while net importers may experience inflationary pressures due to rising oil prices.

IV. Methodology

Quantile-on-quantile connectedness methodology

We implement the quantile-on-quantile (QQ) connectedness methodology, as proposed by Gabauer and Stenfors (2024). A detailed explanation is provided in Appendix A1.

Quantile-on-quantile regression

We employ the QQ regression technique developed by Sim and Zhou (2015). Further details are in Appendix A2.

V. Empirical results

Examining directly- and reversely-related dynamic total connectedness results outlined in Figure 2, we observe that reverse-connected quantiles, where the influence flows from Brent oil back to stock indices ($[\tau_1 = 5\%, \tau_2 = 95\%]$ to $[\tau_1 = 95\%, \tau_2 = 5\%]$), are notably stronger than direct-connected quantiles ($[\tau_1 = 5\%, \tau_2 = 5\%]$ to $[\tau_1 = 95\%, \tau_2 = 95\%]$), indicating that Brent oil exerts substantial feedback effects on stock markets in emerging economies. The presence of lengthy episodes during which reverse TCI significantly overshoots direct TCI suggests that shocks originating in oil prices have a pronounced impact on these stock markets, particularly during periods of market distress. This reverse influence could reflect the fact that global oil demand and supply expectations can influence economic conditions in these countries – often energy producers or

Table 1. Descriptive statistics.

	BIST100	JCI	FTSEJSE	MERV	BOVESPA	KOSPI	IPC	BSE	TASI	RTSI	SZSE	Brent
Mean	0.079***	0.043**	0.038**	0.170***	0.037	0.023	0.029*	0.051***	−0.001	0.019	0.054**	0.031
Variance	2.723	1.427	1.670	5.269	2.718	1.412	1.364	1.769	1.985	4.584	2.945	4.832
Skewness	−0.278***	−0.384***	−0.105***	−0.973***	−0.130***	−0.272***	0.114***	0.05	−0.425***	−0.993***	−0.615***	−0.293***
Excess Kurtosis	4.429***	9.447***	4.818***	20.577***	9.830***	9.510***	7.195***	13.694***	15.860***	35.167***	3.648***	8.035***
JB	3970.135***	17895.625***	4633.392***	85103.914***	19263.061***	18076.434***	10322.987***	37358.593***	50252.369***	247155.524***	2952.791***	12930.277***
ERS	−10.616	−24.958	−3.948	−30.712	−27.131	−10.747	−32.231	−10.865	−7.825	−8.006	−26.355	−13.576
$Q(20)$	22.355***	59.714***	41.033***	14.879	38.236***	20.659**	50.345***	65.179***	81.711***	33.152***	34.401***	11.509
$Q^2(20)$	551.771***	1566.939***	3334.830***	192.428***	4116.720***	2977.020***	2148.765***	1276.176***	1869.478***	747.066***	1265.894***	1174.882***
Kendall												
BIST100	1.000***	0.151***	0.244***	0.138***	0.170***	0.156***	0.191***	0.201***	0.094***	0.243***	0.045***	0.085***
JCI	0.151***	1.000***	0.195***	0.072***	0.100***	0.280***	0.132***	0.251***	0.119***	0.171***	0.109***	0.074***
FTSEJSE	0.244***	0.195***	1.000***	0.180***	0.219***	0.246***	0.273***	0.258***	0.135***	0.315***	0.131***	0.170***
MERV	0.138***	0.072***	0.180***	1.000***	0.328***	0.089***	0.258***	0.108***	0.081***	0.200***	0.044***	0.193***
BOVESPA	0.170***	0.100***	0.219***	0.328***	1.000***	0.121***	0.365***	0.141***	0.085***	0.214***	0.056***	0.199***
KOSPI	0.156***	0.280***	0.246***	0.089***	0.121***	1.000***	0.156***	0.263***	0.130***	0.195***	0.168***	0.084***
IPC	0.191***	0.132***	0.273***	0.258***	0.365***	0.156***	1.000***	0.177***	0.097***	0.226***	0.063***	0.153***
BSE	0.201***	0.251***	0.258***	0.108***	0.141***	0.263***	0.177***	1.000***	0.123***	0.219***	0.107***	0.103***
TASI	0.094***	0.119***	0.135***	0.081***	0.085***	0.130***	0.097***	0.123***	1.000***	0.141***	0.062***	0.097***
RTSI	0.243***	0.171***	0.315***	0.200***	0.214***	0.195***	0.226***	0.219***	0.141***	1.000***	0.083***	0.213***
SZSE	0.045***	0.109***	0.131***	0.044***	0.056***	0.168***	0.063***	0.107***	0.062***	0.083***	1.000***	0.056***
Brent	0.085***	0.074***	0.170***	0.193***	0.199***	0.084***	0.153***	0.103***	0.097***	0.213***	0.056***	1.000***

***, **, * represent 1%, 5% and 10% significance levels. Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott, Rothenberg, and Stock (1996) unit-root test;$Q(20)$ and $Q^2(20)$:Fisher and Gallagher (2012) weighted Portmanteau test statistics.

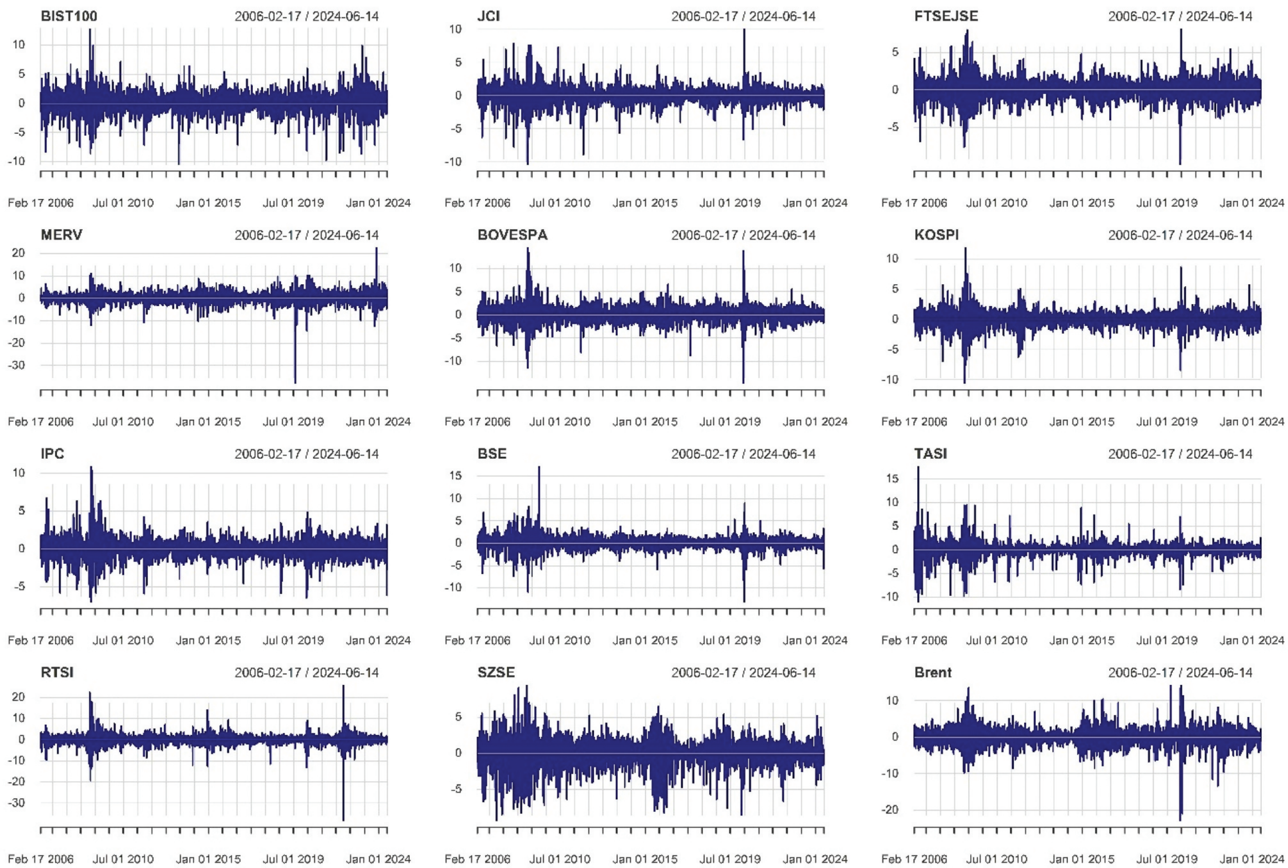

Figure 1. Trends in returns.

large consumers of oil – can create pressures on, thus affecting stock prices.

The analysis identifies several extended periods in which the reverse Total Connectedness Index (TCI) significantly exceeds the direct TCI, indicating that shocks in oil prices can reverberate into stock markets, particularly during periods of economic turbulence. This dynamic suggests that economic stress in countries highly dependent on oil – whether as producers or consumers – can influence global oil prices by altering expectations of demand or supply (Baumeister and Kilian 2016; Cashin et al. 2014; Hong et al. 2024), which, in turn, can impact stock markets.

The increased reverse connectedness indicates that stock markets in major emerging economies, such as Brazil (BOVESPA), Russia (RTSI), and Saudi Arabia (TASI), are particularly sensitive to signals from the oil market. During periods of heightened distress in the oil market, driven by supply or demand conditions, tend to reverberate back into stock prices. This reverse effect is less pronounced in more diversified economies, such as China (SZSE) and India (BSE), where the impact of oil prices is moderated by other sectors. Overall, this feedback loop underscores a complex interdependence, wherein stock markets not only react to changes in oil prices but also actively influence them, reflecting broader economic vulnerabilities and investor sentiment within each country.

In the QQ connectedness analysis, certain stock markets like Brazil (BOVESPA), Russia (RTSI), and Türkiye (BIST100) display notable periods, particularly around 2013–2014,[3] where the reverse TCI significantly surpasses the direct TCI. This implies that during these years, economic and

[3]The 2013–2014 period was challenging for emerging markets like Brazil's BOVESPA, Russia's RTSI, and Türkiye's BIST100, marked by both global economic shifts and domestic pressures. Brazil faced an economic slowdown, high inflation, and a major political scandal, shaking investor confidence. Russia dealt with international sanctions following the annexation of Crimea and a sharp drop in oil prices, leading to economic strain and currency depreciation. Meanwhile, Türkiye grappled with political unrest from the Gezi Park protests, currency volatility fuelled by U.S. monetary policy shifts, and geopolitical pressures from neighbouring conflicts. These factors collectively caused heightened market volatility, capital outflows, and reduced investor confidence in these markets.

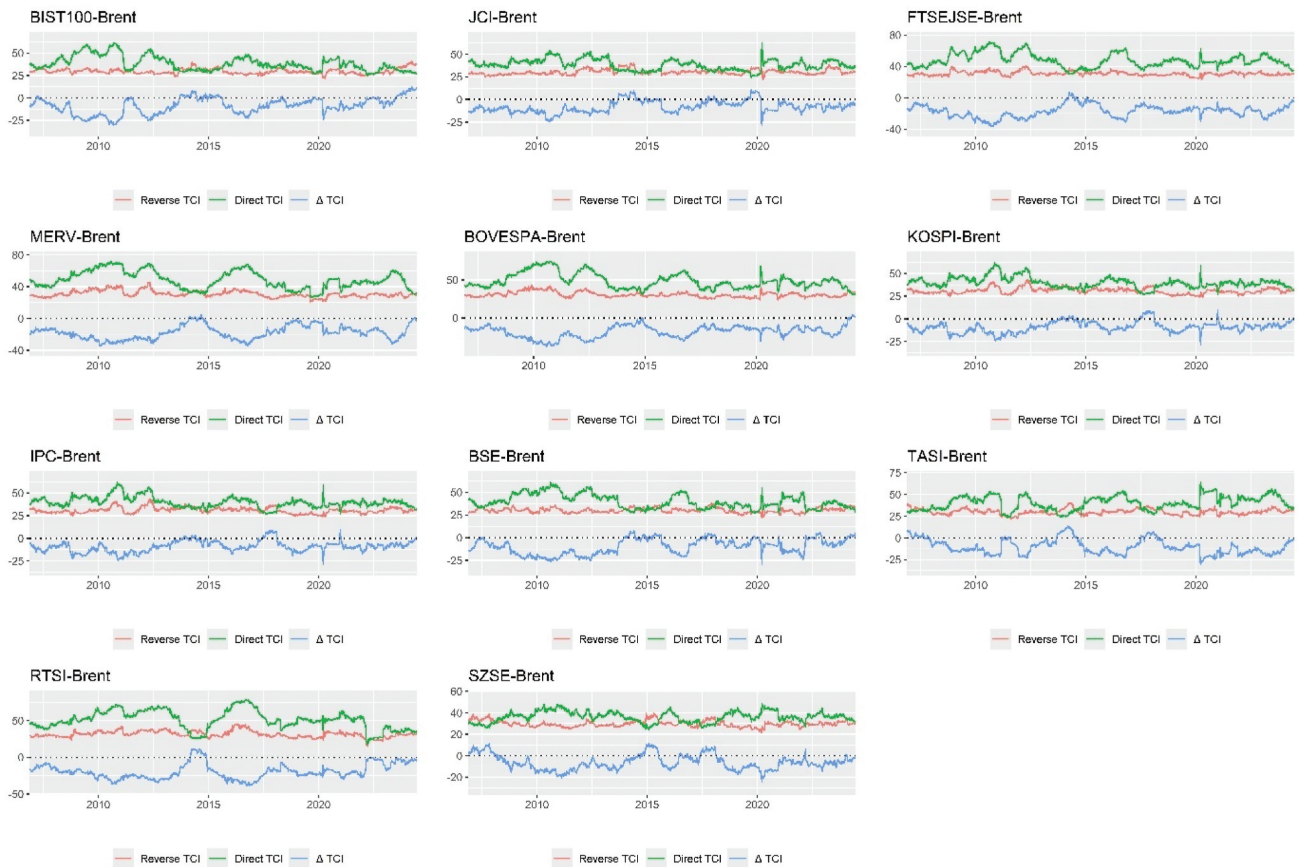

Figure 2. Dynamic directly- and reversely related quantiles overall connectedness. The results are obtained from a QVAR (τ_1, τ_2) model with a 200-day rolling window, employing a lag length of 1 as determined by the Bayesian Information Criterion (BIC) and producing a 20-step-ahead forecast.

financial shocks within these emerging markets had a strong feedback effect on Brent oil prices, overshadowing the direct influence of oil prices on these indices.

For example, in 2013–2014, Türkiye (BIST100) experienced increased volatility due to political instability and currency depreciation, which likely contributed to heightened reverse TCI, indicating that shocks within Turkey's market amplified concerns about broader economic stability and energy demand in the region.

In Russia (RTSI), the period of 2013–2014 was marked by geopolitical tensions, notably the annexation of Crimea in 2014, which led to sanctions from Western countries. This escalated investor fears and induced economic strain, as Russia is a significant oil producer. The pronounced reverse TCI during this period indicates that financial instability within Russia affected global oil prices, signalling risks of disrupted supply and decreased economic growth. Overall, the 2013–2014 period highlights how political and economic disturbances in emerging markets can create feedback loops that ripple through the global oil market, emphasizing the interconnectedness of regional financial and energy sectors.

The onset of COVID-19 in early 2020 experienced a significant rise in the direct Total Connectedness Index (TCI) between Brent oil and stock markets, reflecting a prevalent trend across the markets (Gil-Alana and Monge 2020). This period witnessed a drastic global economic downturn as countries went into lockdown, disrupting supply chains and severely impacting oil demand. The sharp drop in oil prices initially had a strong direct effect on these stock markets, reflecting concerns over economic stability and revenue losses in sectors tied to energy. However, as the pandemic's impact deepened, the reverse TCI also surged, indicating that the stress originated from global oil markets fed back into financial stress in these emerging economies. Investors anticipated prolonged demand reductions from these countries, creating a feedback loop where economic distress in major oil-importing markets exacerbated price volatility in the oil market, highlighting the global interdependencies exacerbated by the pandemic.

In early 2022, the Russian Ukrainian war significantly increased both direct and reverse TCI between Brent oil and various stock markets, particularly in regions highly dependent on Russian energy exports, such as Eastern Europe and Asia. This aligns with findings by Hanif, Hadhri, and El Khoury (2024), which observed heightened uncertainty in the oil market during this period. The volatility was driven by imbalances in oil supply and demand, resulting from prolonged production disruptions and exacerbated by the conflict's onset. The conflict led to a surge in oil prices due to fears of supply disruptions, directly affecting stock markets in energy-dependent economies like Türkiye (BIST100) and India (BSE SENSEX). The reverse TCI also displayed a marked increase, especially for countries in close economic connection with Russia. The financial instability resulting from sanctions on Russia, concerns over potential energy shortages, and the knock-on effects on global commodity prices created feedback pressures on global stock markets. This period illustrates how geopolitical events with energy implications can create a dual channel of influence between oil prices and stock markets, amplifying the transmission of shocks across financial and commodity markets worldwide.

To present compelling statistical evidence in this context, we will now examine the QQ regression results concerning the conditional quantiles of time-varying correlations between oil returns and the quantiles of stock returns. By analysing the results illustrated in Figures 3 and 4, we find that the sensitivity of stock returns to fluctuations in oil prices varies significantly across different markets. For instance, Brazil's BOVESPA and Russia's RTSI

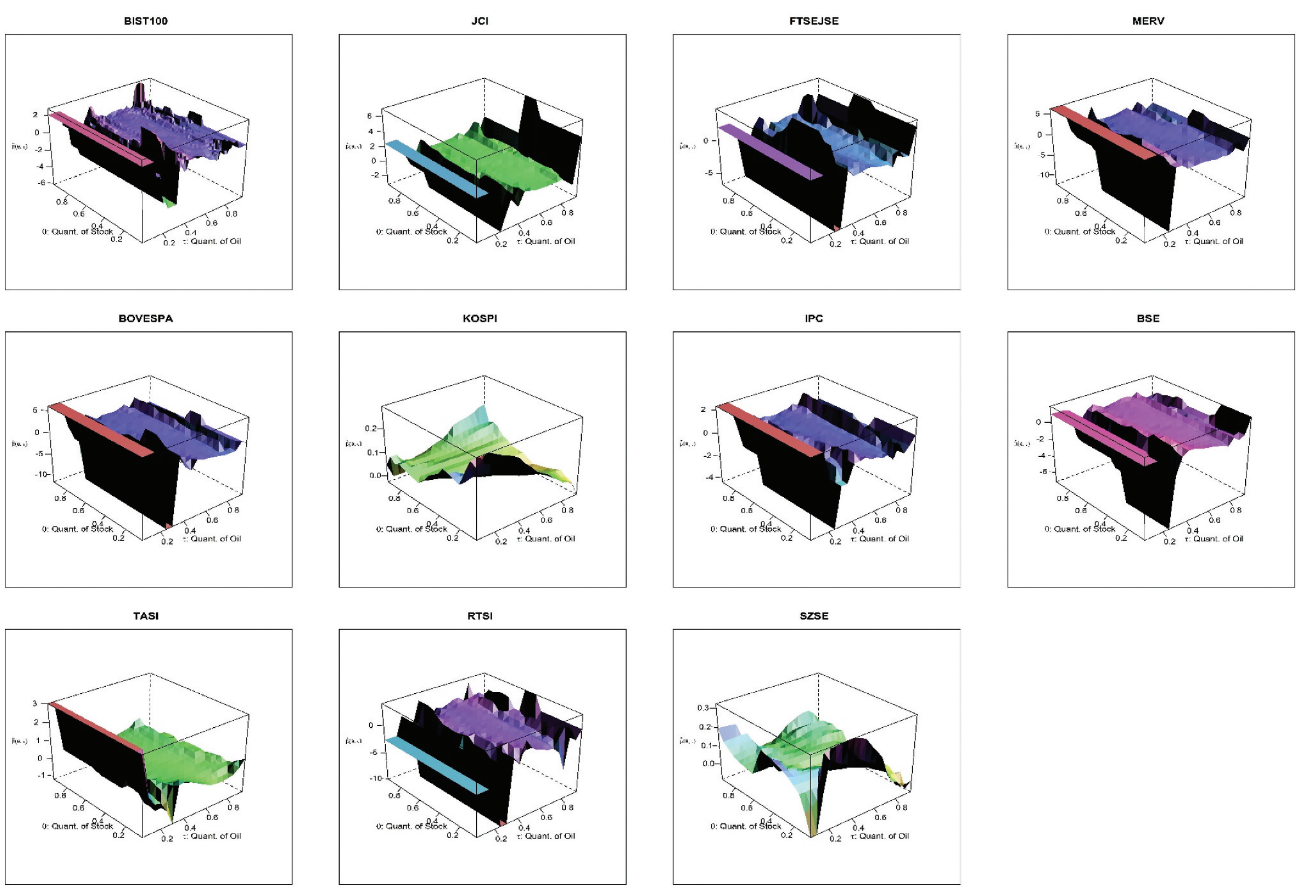

Figure 3. QQ regressions-based estimated impact of oil returns on stock returns. x-axis: quantiles of oil return, y-axis: quantiles of stock return, z-axis: slope.

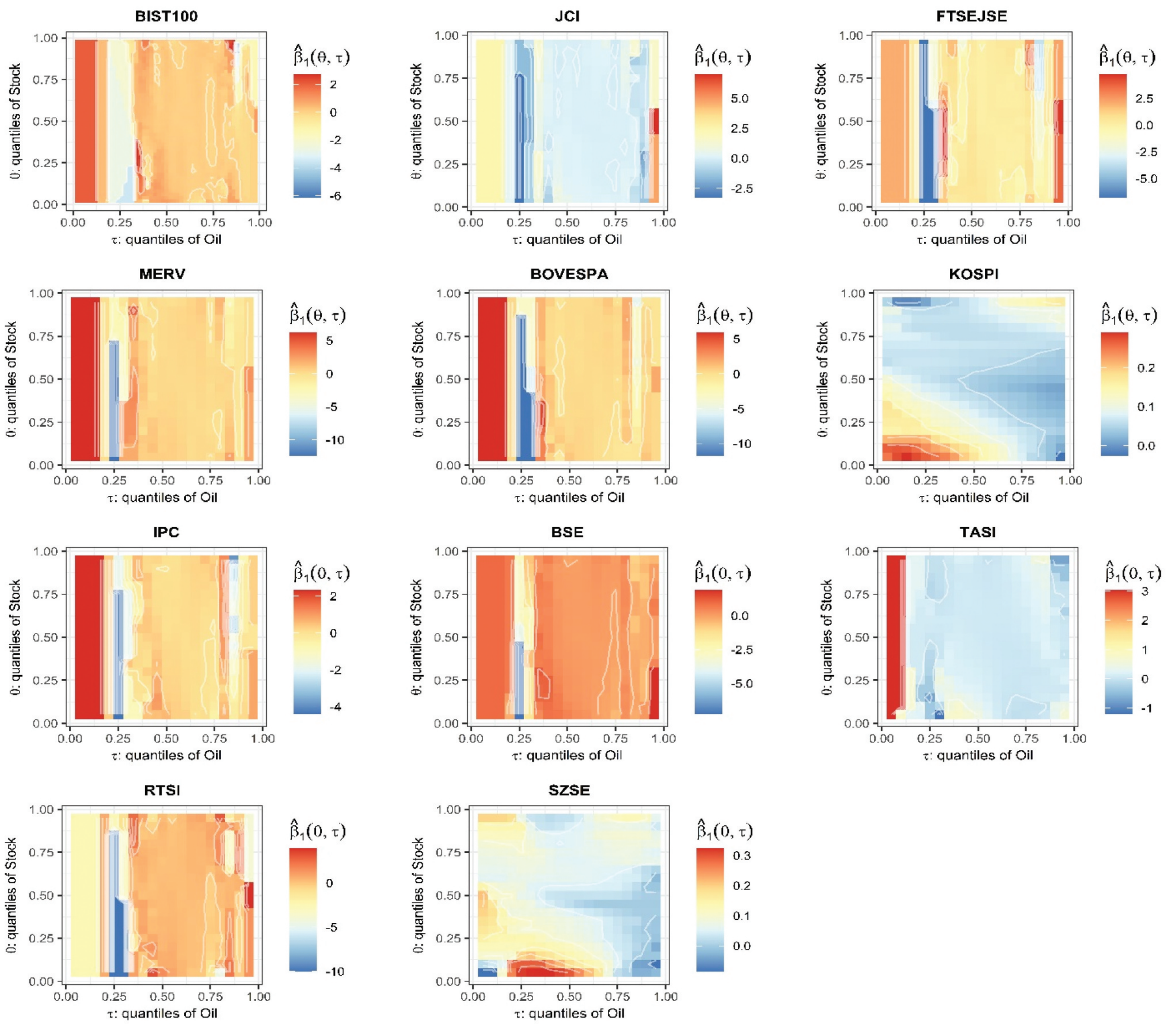

Figure 4. Heatmap plots of the QQ regressions-based estimated impact of oil returns on stock returns.

exhibit more intense colours, indicating a stronger response to changes in oil prices, while South Korea's KOSPI and China's SZSE show relatively muted responses, signalling a weaker interaction.

This variation reveals that some markets, particularly in oil-dependent or resource-rich economies, respond more asymmetrically across quantiles of oil prices. In Turkey's BIST100 and Russia's RTSI, for example, we observe strong responses at the extremes of oil price quantiles, indicating that these stock markets are highly sensitive to both sharp increases and decreases in oil prices. Such asymmetry suggests that extreme oil price fluctuations – whether high or low – have a pronounced effect on these economies, likely due to their reliance on oil imports or exports and their susceptibility to energy price volatility.

In contrast, stock markets in oil-importing countries like India's BSE, South Korea's KOSPI, and China's SZSE display heightened sensitivity primarily to higher oil quantiles. As oil prices rise, these economies experience increased energy costs, which tend to negatively impact stock returns. This pattern highlights the economic pressure that rising oil prices impose on energy-importing nations, reflecting how higher oil prices can lead to inflationary pressures and reduced corporate profitability, dampening investor sentiment in these markets.

On the other hand, oil-exporting regions, such as Saudi Arabia's TASI and Russia's RTSI, show a positive response in higher oil quantiles, aligning with expectations that increased oil revenues improve economic performance and boost stock market returns in these countries. The QQ regression method thus reveals that the relationship between oil prices and stock markets is quantile-dependent and often most pronounced during extreme oil market conditions. This suggests that shifts in oil prices can have varying economic impacts across regions, shaped by each market's energy dependency, structural characteristics, and sensitivity to global risk factors, particularly during periods of significant oil price volatility.

The results also highlight a clear pattern of asymmetric behaviour in the response of stock returns to Brent oil prices across different markets. This asymmetry is especially evident in Türkiye's BIST100 and Russia's RTSI, where stock returns are significantly impacted during extreme oil price conditions – both at very low and very high oil quantiles. Such asymmetric behaviour suggests that these markets react more strongly to shocks in oil prices, with both sharp increases and decreases exerting a substantial influence. For oil-importing countries like Türkiye, extreme increases in oil prices likely create economic strain due to rising energy costs, while sudden drops may bring temporary relief but signal global economic instability, which can also affect investor sentiment. Similarly, for oil-exporting nations like Russia, high oil prices tend to support positive economic and stock market outcomes, while low oil prices can negatively impact government revenues and market confidence. This asymmetry underscores how oil price volatility has varied implications depending on each market's economic structure and energy dependence, resulting in non-linear and sometimes opposite reactions at different oil price levels.

Overall, the QQ regression results provide a comprehensive view of market resilience and vulnerability across different countries. For policymakers, such insights can guide economic strategies to mitigate the impact of oil price shocks, particularly in markets where high quantiles indicate increased correlations during oil price surges. For example, diversification efforts may be valuable in oil-dependent economies to reduce exposure to oil-related volatility. Likewise, for investors, understanding these nuanced relationships can inform portfolio diversification decisions by identifying countries that may offer stability or heightened risk during oil price fluctuations.

VI. Conclusion

In this study, we examined the dynamic interplay between oil prices and stock market returns in a selection of emerging economies, utilizing data on daily log returns for Brent crude oil and stock markets from countries with varying degrees of exposure to oil price fluctuations. Using the QQ connectedness model, we analysed how shocks in oil prices propagate through different quantiles of stock market returns across these economies. This methodology allowed us to capture heterogeneous impacts of oil price shocks on stock returns, reflecting varying levels of dependence and market sensitivities under different economic conditions.

The findings reveal that countries with high oil dependency, such as Saudi Arabia and Russia, showed heightened sensitivity to oil price fluctuations, especially during periods of significant oil price movements, such as the 2014 shale production boom and the 2020 COVID-19 pandemic. These patterns highlight the importance of oil price shocks as a potential risk factor for economies that are closely tied to the oil market, with significant implications for both policy and investment strategies.

Our analysis further demonstrates that emerging markets like Argentina and Türkiye tend to exhibit higher volatility compared to more established economies, aligning with the higher risk-return profile typically associated with emerging markets. Additionally, the impact of oil price shocks varies across quantiles of stock returns, with evidence that extreme positive or negative shocks in oil prices can disproportionately affect stock returns in these economies. This underscores the value of the QQ connectedness approach in capturing nonlinear and asymmetric responses to oil price shocks, which may not be evident with traditional linear methods.

Our findings have significant implications for policymakers and financial regulators in emerging economies, particularly those heavily reliant on oil imports or exports. Policymakers should consider implementing strategies to mitigate the effects of oil price shocks, such as building fiscal buffers, diversifying export bases, or creating strategic oil reserves. Additionally, financial regulators might look to introduce policies aimed at stabilizing markets during periods of heightened volatility, such as circuit breakers or trading halts during extreme fluctuations. Given the observed interconnectedness between oil and stock markets, an emphasis on financial risk management tools, like hedging strategies, could help mitigate portfolio risks for investors in these countries. Finally, international collaboration among emerging markets to reduce volatility spillovers could be beneficial, as collective action might provide a cushion against global shocks that disproportionately impact individual economies.

In addition to these measures, central banks in oil-dependent economies should adopt countercyclical monetary policies to stabilize inflation and mitigate exchange rate fluctuations triggered by oil price shocks. Enhancing financial literacy and investor awareness on risk-mitigation strategies, such as commodity-linked investment products and portfolio diversification, could further strengthen market resilience. Lastly, integrating sustainable energy policies – including investments in renewable energy and reducing reliance on fossil fuel imports – can help mitigate long-term exposure to oil price fluctuations, fostering economic stability and resilience against future energy market disruptions.

Future research could incorporate longer time horizons or monthly/quarterly data to capture structural changes over time. Additionally, our reliance on quantile-on-quantile methods assumes that the model adequately represents the relationships across quantiles, though non-linear effects and structural breaks may still exist. Methods like machine learning or non-parametric approaches could be applied to detect such non-linearities and better model these relationships. Moreover, future studies could expand the dataset to include more diverse countries, particularly underrepresented emerging markets, to allow for a broader understanding of oil-stock linkages in a wider global context.

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Appendices

Appendix A1. Quantile-on-quantile connectedness

This study implements the quantile-on-quantile (QQ) connectedness model developed by Gabauer and Stenfors (2024), which extends the quantile connectedness framework originally introduced by Chatziantoniou, Gabauer, and Stenfors (2021).

Let's define a $QVAR(p)$ model as follows:

$$y_t = \mu(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + u_t(\tau) \tag{A.1}$$

y_t, and y_{t-i} are $N \times 1$ endogenous vectors across multiple dimensions, τ representing a vector of quantiles within the interval $[0,1]$. The parameter p refers to the lag length in the QVAR model. The conditional mean vector $\mu(\tau)$ has dimensions $N \times 1$, while the QVAR coefficient matrix $B_i(\tau)$ is of size $N \times N$. $u_t(\tau)$ represents $N \times 1$ dimensional error vector with a $N \times N$ dimensional variance-covariance matrix, $F(\tau)$. By employing the Wold representation theorem, the QVAR model is converted into its QVMA form:

$$y_t = \mu(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau) u_{t-i}(\tau) \tag{A.2}$$

The consequences of an external jolt in series i on series j over H steps is quantified by the forecast error variance decomposition, as shown below:

$$\emptyset^{g}_{j\leftarrow i}(H) = \frac{\sum_{h=0}^{H-1} \left(e_j^{'} A_h(\tau) F(\tau) e_j\right)^2}{F_{ii}\left(\sum_{h=0}^{H-1}\left(e_j^{'} A_h(\tau) F(\tau) A_h(\tau)^{'} e_j\right)\right)} gSOT_{j\leftarrow i,\tau}(H) = \frac{\emptyset^{g}_{j\leftarrow i}(H)}{\sum_{i=1}^{n} \emptyset^{g}_{j\leftarrow i}(H)} \tag{A.3}$$

in which e_j is a $N \times 1$ zero vector with j—th element set to one.

To compute the rescaled GFEVD, $gSOT_{j\leftarrow i,\tau}(H)$, we normalize $\emptyset^{gen}_{j\leftarrow i}(H)$by calculating its proportion relative to the row sum.

The TO measure illustrates the influence that series j exerts on the remaining series, while the FROM measure reflects the impact that all other series have on series j. These connectedness measures are calculated as follows:

$$S^{gen,to}_{j\to *,\tau}(H) = \sum_{n=1, j\neq i}^{N} gSOT_{j\leftarrow n,\tau} \tag{A.4}$$

$$S^{gen,from}_{j\leftarrow *,\tau}(H) = \sum_{n=1, j\neq i}^{N} gSOT_{n\leftarrow j,\tau} \tag{A.5}$$

The NET total directional connectedness for series i is derived by deducting the total directional connectedness received (FROM) from the total directional connectedness given (TO);

$$S^{gen,net}_{j,\tau}(H) = S^{gen,to}_{j\to *,\tau}(H) - S^{gen,from}_{j\leftarrow *,\tau}(H) \tag{A.6}$$

The revised total connectedness index (TCI) as introduced by Chatziantoniou, Gabauer, and Stenfors (2021) calculated as:

$$TCI^{H}_{\tau} = \frac{N}{N-1}\sum_{n=1}^{N} S^{gen,from}_{n\leftarrow *,\tau} \equiv \frac{N}{N-1}\sum_{n=1}^{N} S^{gen,to}_{n\to *,\tau} \tag{A.7}$$

Appendix A2. Quantile-on-quantile regression

Sim and Zhou (2015) advanced the QQ regression method, building upon the foundational quantile regression model developed by Koenker and Bassett (1978). This approach enables the examination of how specific quantiles of an explanatory variable impact the conditional quantiles of an outcome variable by integrating nonparametric estimation with quantile regression methods. In our study, we apply the QQ regression method to evaluate the impact of oil price returns (denoted as x) on the time-varying conditional correlations (denoted as y) of each stock return.

Here, the superscript θ denotes the quantile of the y and x, allowing us to model the for the θ-quantile of y as a function of the x:

$$y_t = \beta^{\theta} x_t + \varepsilon^{\theta}_t, \tag{A.8}$$

where ε^{θ}_t is a stochastic term that has a zero θ-quantile.

Due to our limited knowledge of the relationship between the variations in y and x, We recognize that the association is yet to be established $\beta^{\theta}(x_t)$. To analyse the connection between the θ-quantile of y and τ-quantile of x, represented as x^{τ}, we employ a first-order Taylor expansion to linearize the function $\beta^{\theta}(x_t)$ around x^{τ}:

$$\beta^{\theta}(x_t) \approx \beta^{\theta}(x^{\tau}) + \beta^{\theta'}(x^{\tau})(x_t - x^{\tau}) \tag{A.9}$$

Building upon the research of Sim and Zhou (2015), we redefine $\beta^{\theta}(x^{\tau})$ and $\beta^{\theta'}(x^{\tau})$, respectively, as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$. Following this, the Equation (9) can be re-formulated represented as:

$$\beta^{\theta}(x_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau}) \tag{A.10}$$

Finally, we insert Equation (10) into equation (8) to yield the following:

$$y_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau}) + \varepsilon_t^{\theta} \tag{A.11}$$

The notation: $\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(x_t - x^{\tau})$ represents the association between the θ-quantile of the y and τ-quantile of x, with $\beta_0$and β_1 are aligned with θ and τ.

To estimate (11), we solve for:

$$\min_{\beta_0 \beta_1} \sum_{i=1}^{n} \rho_{\theta}\left[y_t - \beta_0 - \beta_1(x_t - x\hat{\tau})\right] K\left(\frac{F_n(x_t) - \tau}{h}\right) \tag{A.12}$$

and derive the predictions $\hat{\beta}_0(\theta, \tau)$ and $\hat{\beta}_1(\theta, \tau)$. In this context, the function ρ_{θ} is the asymmetrical absolute value function that generates the θ-conditional quantile of y_t as the result. To consider the local effects by the τ-quantile of x, we apply a Gaussian kernel $K(.)$ to assign weights to the observations in the near x^{τ}, based on bandwidth h (= 0.05). The weights exhibit inverse relationship to the distance of x_t from x^{τ}, i.e. which is represented by the distance of the empirical distribution functions as follows:

$$F_n(x_t) = \frac{1}{n} \sum_{k=1}^{n} I(x_k < x_t) \tag{A.13}$$

from τ, where τ denote the value of the distribution function corresponding to x^{τ}.