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Regime dependence in the oil-stock market relationship: The role of oil price uncertainty

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ABSTRACT

We compare the interaction between the crude oil and US stock markets in regimes where oil price uncertainty is high versus low, using a smooth transition vector autoregressive model. Our results show that supply- and demand-side shocks from the oil market, as well as stock market shocks, tend to have greater effect sizes in the lower oil price uncertainty regime. These asymmetric findings are consistent with the premise that shocks occurring in a relatively calmer environment are inclined to surprise market participants more, thereby eliciting amplified responses, than during an environment where oil price uncertainty is anticipated to be higher.

1. Introduction

Oil price uncertainty has an adverse impact on economic activity (Jo, 2014), negatively affecting investment, durables consumption, and aggregate output (Elder and Serletis, 2010). Yet, previous studies demonstrate that oil price uncertainty has an insignificant effect on the US stock returns (see, e.g., Alsalman, 2016) and others find that the converse is true (see, e.g., Bams et al., 2017). There are also discrepancies about whether the responses of US stock returns to increases and decreases in oil prices are symmetric (see, e.g., Alsalman, 2016) or asymmetric (see, e.g., Rahman, 2022). On the latter point on the non-linear effects of oil prices, Lee et al. (1995) hypothesise and empirically establish that an oil price change is likely to have a greater impact on real output if it arises as a surprise in an environment where oil prices are stable, rather than in an environment where oil price fluctuations are volatile and uncertain.

In this paper, we extend the premise of Lee et al. (1995) to the oil-stock market relationship. In particular, we compare the interaction between the crude oil and US stock markets in two states of the world: when oil price uncertainty is high and low. Understanding how dynamics in the crude oil and US stock markets vary across different oil price uncertainty regimes is useful, as market participants and policymakers make use of such information for risk management and policy formulation under uncertainty, given that stock markets have a tendency to overreact to bad news in good times (Veronesi, 1999). Here, we exploit the availability of a new index put forward in Abiad and Qureshi (2023) to measure oil price uncertainty based on newspaper coverage of the topic. As asset prices are highly sensitive to news, especially bad news, it is unsurprising that other news-based indices also adopting the text analysing methodologies of Baker et al. (2016) are shown to have meaningful implications for both the crude oil and US stock markets. For example, Smales (2021) use the geopolitical risk index of Caldara and Iacoviello (2022) and illustrate that an increase in geopolitical risk is associated with positive (negative) oil (US stock) returns.

Within the above context, it is also vital to consider the source of shocks in the international crude oil market. In a prominent paper on the impact of oil price shocks on the US stock market, Kilian and Park (2009) adopt the recursively identified vector autoregressive (VAR) model of Kilian (2009) to disentangle the supply- and demand-side shocks in the crude oil market by including US stock returns in the system. Importantly, they ascertain that the influence of an oil price shock on the US stock market largely depends on whether the shock is attributed to supply or demand forces in the oil market. Departing from their four variable structural VAR that includes data on oil production, global economic activity, oil prices, and stock returns, we incorporate oil price uncertainty as a regime switching variable in the system. To this end, we also make use of recent econometric developments in smooth transition VAR models introduced in Virolainen (2024a), allowing for statistical identification without imposing restrictions if shocks are mutually independent and at most one is Gaussian.

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2. Methodology

We estimate a smooth transition vector autoregressive model (STVAR) with two regimes based on monthly data, from 1983:5 to 2024:6, for the global oil market and the US stock market:

$$y_t = \sum_{m=1}^{2} \alpha_{m,t}\mu_{m,t} + u_t, \qquad u_t \sim MD(0, \Omega_{y,t}, \nu), \tag{1}$$

$$\mu_{m,t} = \phi_m + \sum_{i=1}^{p} A_{m,i} y_{t-i}, \qquad m = 1, 2, \tag{2}$$

where u_t is a martingale difference sequence and $\Omega_{y,t}$ is a positive definite covariance matrix which depends on the weights $\alpha_{i,t}$ and y_{t-1}, and ν are further parameters of the distribution. The transition weights follow a logistic function:

$$\alpha_{1,t} = 1 - \alpha_{2,t} \qquad \mathit{and} \qquad \alpha_{2,t} = [1 + exp\{-\gamma(y_{1,t-1} - c)\}]^{-1}, \tag{3}$$

where the switching variable, $y_{1,t-1}$, is the first lag of the oil price uncertainty index, and c and γ are location and scale parameters.

We use independent Student's t distributions for the structural errors, e_t, which allows for different degrees of freedom parameters for each component and is essential in the identification strategy as we subsequently describe. The serially and mutually uncorrelated structural shocks, e_t, are identified from the reduced form innovations, u_t, such that:

$$e_t = B_{y,t}^{-1} u_t, \tag{4}$$

where $B_{y,t}$ is a weighted average of impact matrices of the regimes, covering the contemporaneous relationships of the variables. Under the assumption that the structural shocks are mutually independent and that at most one of them is Gaussian, Virolainen (2024a) shows, following on Lanne et al. (2017) for linear SVAR models, that the impact matrices B_1 and B_2 and the structural shocks are identified up to ordering and signs.

To provide economic meaning to the statistically identified shocks, we need to label the columns of the impact matrix $B_{y,t}$. For this, we follow a three-step procedure: (1) We permutate and sign change the columns of the matrix B_1 to achieve positive diagonal entries and the largest diagonal sum (see this strategy in Bernoth and Herwartz, 2021, for a linear VAR model). The columns of B_2 are reordered and sign changed accordingly, and also the degree-of-freedom parameters are reordered accordingly, so that the underlying model does not change.[1] (2) We verify that the chosen ordering also maximises the diagonal sum of the impact matrix B_2 compared to other orderings.[2] (3) To support the intended labels of the shocks, we check whether shocks and responses conform with expectations based on economic theory and previous empirical studies.

Due to the non-linear structure of the model and the dependence of responses on initial values, we use generalised impulse response functions (GIRF) to study the dynamics of the model following (Koop et al., 1996). The GIRFs and their confidence bands are constructed using a Monte Carlo algorithm (see Lanne and Virolainen, 2024, for details).

3. Data

To estimate the oil market shocks we analyse the following 5-dimensional system: $y_t = (u_t, \Delta q_t, x_t, \Delta p_t, r_t)$.[3] We use a new oil price uncertainty index, u_t, of Abiad and Qureshi (2023)[4], a log difference in global crude oil production[5], Δq_t, a detrended[6] world industrial production index, x_t, suggested in Baumeister and Hamilton (2019)[7], the log difference of the real price of oil, Δp_t, for which we use the US crude oil price WTI as our focus is on the US market, and the returns of the S&P 500 stock market index, r_t. The oil price and stock market data are downloaded from Bloomberg in daily frequency and are transformed into monthly averages, and expressed in constant 2015 prices using the US CPI obtained from Fred.[8]

We note from the regime series of Fig. 1 that the oil price uncertainty index rises around key historical events in the international crude oil market, related to conflicts in the Middle East in the early part of our sample, the booming 2000s, the 2008 Global Financial Crisis (GFC), the Arab Spring conflict (early 2010s), and the oil price crash of the mid-2010s. During these periods of heightened oil price uncertainty, variables in the crude oil and US stock markets tend to be appropriately punctuated. For instance, all four series ($\Delta q_t, x_t, \Delta p_t$, and r_t) sharply dip in the COVID-19 pandemic, while all except oil supply (Δq_t) tumble in the 2008 GFC, and only oil price changes (Δp_t) reflect the disturbances related to the oil price crash of the mid-2010s.

4. Results and discussion

We estimate a two-regime smooth transition model with four lags, based on Akaike information criterion. The model is estimated with maximum likelihood estimation.[9] The degree of freedom parameters for the structural shocks are estimated to be 2.02, 2.88, 2.06, 3.62, and 4.27. The low values show that all variables are non-normal, which confirms the appropriateness of the statistical identification strategy we adopt. The estimated regime means for the respective ordering of the variables - $u_t, \Delta q_t, x_t, \Delta p_t$, and r_t - are 2.57 (7.68), 0.07 (0.20), 4.05 (6.49), −0.23 (0.89), and 1.06 (0.84) for the first (second) regime. Regime 1 has lower oil price uncertainty, lower average oil price inflation, and higher average stock returns. The estimated location parameter, c, is 4.36 and the scale parameter, γ, is 89.20. The regime graph shown in Fig. 1 reflects the relatively large γ, indicating the model is mostly in one or the other regime, switching fast between regimes. The lower uncertainty regime is mostly present in the 1990s but also intermittently characterises periods over the full sample. The estimated impact matrices of the two regimes, B_1 (low oil price uncertainty) and B_2 (high oil price uncertainty), where the column ordering and signs are selected following the labelling strategy suggested in Section 2, read as:

$$\hat{\boldsymbol{B}}_1 = \begin{bmatrix} 11.63 & 0.30 & 0.31 & 0.59 & -0.06 \\ -0.32 & 0.93 & -0.07 & -0.16 & 0.43 \\ 0.17 & 0.01 & 1.65 & -0.10 & 0.05 \\ 0.13 & -1.03 & 1.72 & 4.93 & 3.48 \\ 0.44 & -1.56 & -0.58 & -1.39 & 1.56 \end{bmatrix}$$

[1] Variables varying in larger scale, can have larger weight in the maximisation of the diagonal sum. We thank the reviewer for pointing this out.

[2] In case this would not be satisfied, we could choose the ordering which maximises the total sum of both diagonals.

[3] As we do not use a recursive identification strategy, the ordering of the variables do not influence the results.

[4] Available from policyuncertainty.com. We scale the uncertainty index by dividing the values by 10, to achieve a comparable range with the other variables in the system.

[5] World crude oil production in thousands of barrels per day is obtained from the US Energy Information Administration (EIA), available from eia.gov/opendata.

[6] Hamilton detrending is employed, which applies a two-year (24 month) seasonal difference to the series (see Hamilton, 2018, 2021).

[7] The world industrial production index is obtained from Christiane Baumeister's website, available at sites.google.com/site/cjsbaumeister/research.

[8] Seefred.stlouisfed.org/series/CPIAUCSL.

[9] We use the two-phase estimation procedure implemented in the R package 'sstvars', see Virolainen (2024b). Large number of runs with different initial values are necessary in these estimations due to the multimodal surfaces of the likelihood functions. We ran optimisations with 3000 different seeds.

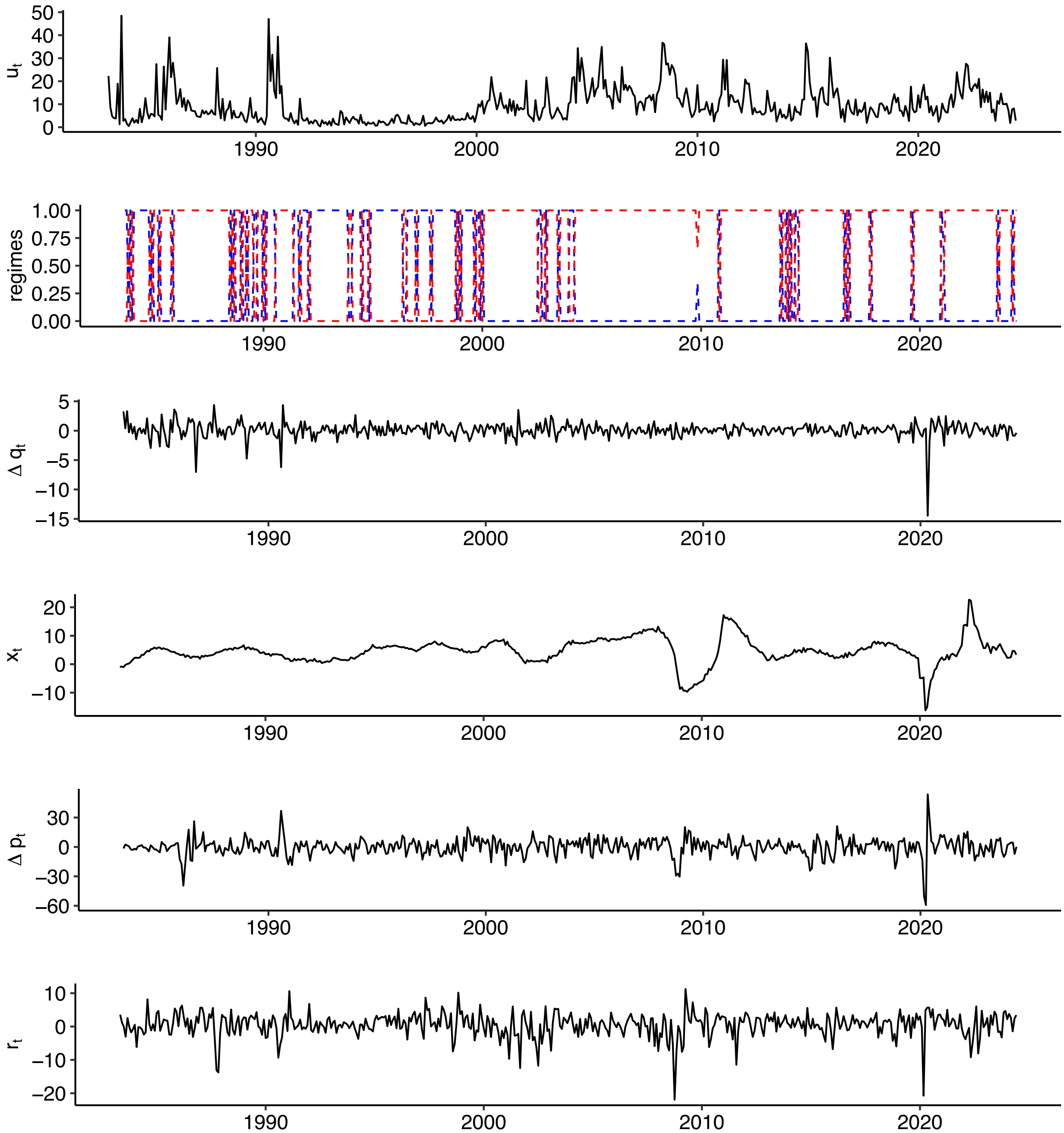

Fig. 1. Time series plots and the two estimated regimes from the smooth transition VAR. For explanations of the variables $u_t, \Delta q_t, x_t, \Delta p_t$, and r_t, refer to Section 3. In the second graph depicting transition weights of the two regimes, Regime 1 in blue (Regime 2 in red) is the low (high) oil price uncertainty environment.

$$\hat{\boldsymbol{B}}_2 = \begin{bmatrix} 32.58 & 0.27 & 0.50 & -1.64 & 0.23 \\ -1.04 & 1.24 & -0.03 & -0.07 & -0.06 \\ -0.37 & -0.02 & 3.14 & 0.02 & 0.02 \\ 11.60 & 0.82 & 1.09 & 8.53 & 2.26 \\ -4.53 & -0.13 & -0.10 & -0.68 & 3.40 \end{bmatrix}$$

where the ordering of the variables is $y_t = u_t, \Delta q_t, x_t, \Delta p_t, r_t$. The labelling of the oil price uncertainty shock, determined by the impact responses of variables in the estimates of B_1 and B_2, are in line with expectations based on external information from economic theory and previous empirical studies. For instance, the impact effect of the oil price uncertainty shock on the oil price uncertainty index is expected to be positive and large under both regimes. Additionally, the impact effect of the oil price uncertainty shock on the supply of oil is expected to be negative in both regimes and more substantial in the higher uncertainty environment, as investment is more cautious at higher levels of uncertainty (see, e.g., Bloom et al., 2007). Indeed, if rising uncertainty reduces investment, it follows that rising oil price uncertainty reduces oil investments. Furthermore, the impact effect of the oil price uncertainty shock on global economic activity should be adverse (negative) in the higher uncertainty regime. This is consistent with the findings of Jo (2014), who show that a doubling of oil price uncertainty leads to a cumulative decline in world industrial production of 0.3%. While oil price uncertainty constrains oil production, as seen from its impact effect on oil supply, economic theory implies that the fall in supply should increase the price of oil, which is expected to be more pronounced in the high oil price uncertainty regime. Moreover, average oil price returns are higher (lower) in the high (low) oil price uncertainty regime. In addition, the impact effect of the oil price uncertainty shock on the US stock market returns is negative in the high uncertainty regime, relative to the muted effect in the low

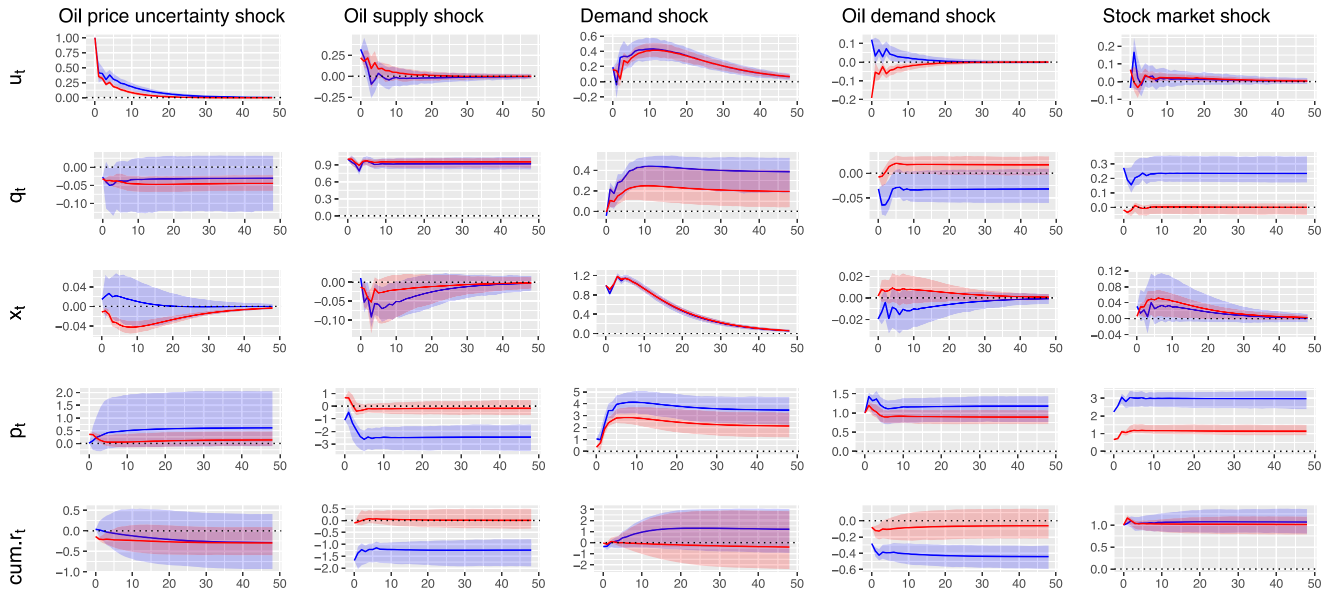

Fig. 2. Regime comparison of generalised impulse response functions (GIRFs) using scaled shocks. The high (low) oil price uncertainty Regime 2 (Regime 1) is displayed in red (blue) colour. Shaded areas represent the 95% confidence bands accompanying the responses to reflect uncertainty about the initial values within the regime, which are computed using Monte Carlo simulations with 1000 repetitions. Impulse responses to the five statistically identified shocks in the two regimes are projected over a 4-year forecast horizon (h = 0, 1, …, 48 months ahead), using one-standard-error shocks based on 1000 draws of initial values. Every row can be read as the GIRFs for a given variable (u_t, Δq_t, x_t, Δp_t, and r_t) to each of the five identified shocks. Alternatively, every column can be read as the impact of a given shock on each of the five variables in the system. For all other details, refer to the main text.

uncertainty regime, in line with related literature (see, e.g., Bams et al., 2017). Thus, consolidating external information with the estimates of the impact matrices, we appropriately label the first shock as the oil price uncertainty shock.

The labelling of other shocks in the system also appear broadly reasonable based on external information. For example, the impact effect of the oil production shock on oil prices in the relatively certain regime is consistent with the *ceteris paribus* assumption of an oil supply shock reducing prices in the crude oil market. Following on this, the impact effect of world industrial production positively stimulates oil prices in both regimes, permitting us to view this as an aggregate demand shock. Also, the impact effect of the oil price shock on stock market returns is negative, in line with evidence from the theoretically identified VAR model (Kilian and Park, 2009) based on delay restrictions, allowing us to interpret this shock as an oil demand shock. Finally, as the impact effect of the stock returns shock is stimulating to both world industrial production and oil prices, we are able to label this as a stock market shock.

We compare the interaction between the crude oil and US stock markets between regimes in Fig. 2, which illustrates the generalised impulse response functions of oil price uncertainty, oil production, global industrial production, oil price returns, and stock returns for Regime 1 (low price uncertainty environment — blue lines) and Regime 2 (high price uncertainty environment — red lines). We study one-standard error shocks which we scale to a magnitude of instantaneous response of 1 for the variables on the diagonal, whereby all other responses are scaled accordingly. The responses for oil production (Δq_t), oil price returns (Δp_t), and stock returns (r_t) are displayed as cumulative responses. Based on the first column, the effects of oil price uncertainty shocks are broadly similar on the rest of the system under both oil price uncertainty regimes. However, in the relatively higher (lower) oil price uncertainty environment, oil price uncertainty reduces (raises) global output. The result in Regime 2 is consistent with the findings of Abiad and Qureshi (2023), who show that US industrial production falls in the aftermath of an oil price uncertainty shock, with the largest decline also occurring at around ten months. In the high uncertainty environment, this shock also has an initial stronger negative impact on stock market returns than in Regime 1.

From the oil market supply and demand shocks, we observe that oil supply shocks have a negative effect on both the oil price and stock returns in Regime 1, while the effects in Regime 2 are more muted in comparison, over the forecast horizon. Additionally, global demand shocks have a stronger stimulating (positive) effect on both oil supply and oil price returns in an environment of lower (rather than higher) oil price uncertainty. Interestingly, oil demand shocks increase (decrease) oil price uncertainty in Regime 1 (Regime 2). Moreover, the positive effects of oil demand shocks on oil price returns are larger in Regime 1 than in Regime 2. Furthermore, the negative effects of oil demand shocks on stock returns are also larger in Regime 1 than Regime 2.

Considering US stock market shocks, these have a positive effect on oil supply in Regime 1, while stock market effects on oil supply in Regime 2 appear subtle. In addition, the positive effects of a stock market shock on oil price returns are larger in Regime 1 than in Regime 2. Finally, a stock market shock has a similar effect in magnitude and sign (positive) on the US stock market in both regimes.

Overall, with the exception of oil price uncertainty shocks themselves, our impulse responses provide supporting evidence to imply that supply- and demand-side shocks from the oil market, as well as stock market shocks, tend to have greater effect sizes in the lower oil price uncertainty regime. These findings are consistent with the premise of Lee et al. (1995) that shocks occurring in a relatively stable environment are inclined to surprise market participants more, thereby eliciting amplified responses, than during an environment where oil price uncertainty is anticipated to be higher. Our results, therefore, demonstrate that states of relatively high and low oil price uncertainty can account for the asymmetric effects of shocks in the crude oil and US stock markets, consistent with the work of Rahman (2022) and contradictory to the symmetric effects that Alsalman (2016) reports.

5. Conclusion and future research

Using recent econometric developments in smooth transition VAR models to capture regime-dependent dynamics, we examine the interaction between the crude oil and US stock markets under high and low oil price uncertainty environments. We show that in the lower oil price uncertainty regime, supply- and demand-side oil market shocks, as well as stock market shocks, tend to surprise markets more, as evidenced by larger responses to such shocks in relatively stable conditions. Conversely, in the high oil price uncertainty regime, the effects of these shocks are more muted, suggesting a degree of anticipation by the markets. The asymmetric responses of the crude oil and US stock markets to shocks between high and low oil price uncertainty regimes provide valuable insights into the energy-finance nexus for policymakers and market participants, emphasising the importance of incorporating regime-dependent dynamics in risk management strategies and financial decision-making.

A natural direction for further work is an extension of our application to other asset classes. For instance, the US government bond prices and crude oil prices are typically inversely related, due to changing interest rates, with bonds attracting risk-averse investors as a less risky and less volatile alternative to stocks and commodities in turbulent economic conditions. Kang et al. (2014) replaces the real US stock market returns in the structural VAR model of Kilian and Park (2009) with real US bond market returns to assess the impact of crude oil market shocks on the bond market, finding that demand side shocks reduce bond returns. Their analyses can be revisited under high and low oil price uncertainty regimes within a smooth transition VAR framework, to ascertain the implications of regime-dependence in the crude oil-US bond market relationship.

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Data availability

The authors do not have permission to share data.

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