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The Causality between Oil price, Financial Market Uncertainty and Economic Policy Uncertainty in the United States

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ABSTRACT

This study investigates the causal relationships between uncertainty measures and oil price dynamics, using monthly data over the period from February 1990 to September 2024. The autoregressive distributed lag model (ARDL) bound test is applied to examine the existence of a long-run relationship between the variables, while the granger causality test in a vector autoregressive (VAR) framework is conducted to examine the direction of the short-run causality. To investigate the long-run causal relationships between uncertainty and oil prices, the Toda and Yamamoto test in an augmented VAR (AVAR) is performed. The empirical results reveal no long-run cointegration among the variables. In the short run, there is a unidirectional causality from oil prices to economic policy uncertainty, while financial market uncertainty directly causes oil price movements. Additionally, both uncertainty measures indirectly cause oil prices through oil demand. The long-run causality results indicate a bidirectional causality between oil prices and economic policy uncertainty, while a unidirectional causality runs from financial market to oil prices. In addition, oil supply and financial market uncertainty indirectly cause oil prices through economic policy uncertainty. Unlike the short-run findings, the long-run results suggest that uncertainty does not cause oil prices through the demand channel.

Keywords: Economic Policy Uncertainty, Financial Market Uncertainty, Oil Prices, Vector Autoregressive
JEL Classifications: C32, Q43, E44

1. INTRODUCTION

Oil is an important driver of global economic activity, while its price fluctuations affect both macroeconomic stability and financial market behaviour (Wei et al., 2017; Ma et al., 2024; Zhang et al., 2025). Previous studies have shown that increases in oil prices frequently precede economic downturns, highlighting the importance of examining both the underlying causes of oil price shocks and the mechanisms through which they influence economic activity (Hamilton, 2003). These shocks, arising from supply and demand-side factors and their interaction, can result in asymmetric effects across economies and markets (Kilian, 2008; Le and Chang, 2015).

Therefore, it is important to study oil price shocks for the following reasons: First, oil is used an input in production across various industries, and oil price affects input costs, inflation and overall economic growth (Arce-Alfaro, 2025; Ma et al., 2024). Second, the heterogeneous nature of oil price shocks due to supply disruptions, aggregate demand changes, and shifts in precautionary demand requires an understanding of their separate economic effects (Kilian, 2008). For example, shocks related to precautionary demand, often driven by geopolitical events and uncertainty about future oil supply (Arce-Alfaro, 2025), can lead to immediate and sharp price increases, whereas shocks driven by changes in aggregate demand may have more gradual effects (Kilian, 2008). As a result, understanding oil price movements is important for policymakers developing macroeconomic stabilisation policies and for investors managing risk (Ma et al., 2024; Wei et al., 2017).

In parallel, uncertainty has emerged as a key determinant in the oil market, which affects oil prices by shaping market expectations and investor behavior (Aloui et al., 2016; Bloom, 2014; Che et al., 2024). In particular, recent studies have confirmed that uncertainty, whether economic policy uncertainty or financial market uncertainty, may not merely respond to oil shocks but can also act as a causal factor driving oil price volatility (Kilian, 2008; Zhang et al., 2025; Ma et al., 2024; Che et al., 2024; Le et al., 2023).

To quantify economic policy uncertainty and financial market uncertainty several indices have been developed, helping in understanding the unpredictability associated with policy actions and financial market volatility (Baker et al., 2016). The volatility seen in crude oil markets, often increased by rising uncertainty, has important implications for policymakers' decisions and investors' financial strategies (Wei et al., 2017; Yang, 2019; Zhang et al., 2025). Therefore, it is important to understand the direction of causality between oil prices, economic policy uncertainty, and financial market uncertainty.

This study examines the direct and indirect causality among oil prices, economic policy uncertainty, and financial market uncertainty to help policymakers and investors understand how different types of uncertainty affect the oil market.

2. LITERATURE REVIEW

2.1. Economic Policy Uncertainty and Oil Prices

Several studies have examined the relationship between EPU and oil prices, using different econometric techniques, time periods and regions. For instance, Sun et al. (2020), using wavelet coherence method and scale by scale linear Granger causality test on monthly data of G7 and emerging economies from January 1997 to August 2017, found that the interaction between EPU and oil prices strengthens from the short to the long term. Their analysis of west texas intermediate (WTI) crude oil prices and EPU indices indicates a negative interaction in the medium term and a positive interaction in the long term, suggesting that the temporal horizon significantly influences their relationship. The results show the dynamic nature of the EPU-oil price nexus, a relationship further explored by Hailemariam et al. (2019), who employed a nonparametric panel data model with time-varying coefficients on monthly data for G7 countries from January 1997 to June 2018. Their study indicates that the relationship between real WTI oil prices and EPU indices shifts from a negative in pre-great financial crisis (GFC) to a positive one post-GFC, noting the impact of major economic events on this relationship. Both studies emphasize the non-static nature of the EPU-oil price relationship, suggesting its sensitivity to economic conditions and the time frame of analysis.

In contrast, Antonakakis et al. (2014), using a structural vector autoregression (SVAR) model on monthly data from January 1997 to June 2013 for a sample of countries, including the US and Europe, presented a different perspective. Their analysis of real oil prices, world oil production, and EPU indices revealed a negative response between EPU and oil price changes. This finding suggests that increased EPU tends to exert downward pressure on oil prices, and vice versa, a result that contrasts with the longer-term positive relationship identified by Sun et al. (2020) for some time horizons. This result can arise from differences in the countries analysed, the examined time periods, or the different methodologies, highlighting the complexity of this relationship across various contexts.

Kang and Ratti (2014) using a SVAR model on monthly data from January 1995 to December 2011 for China, examine the relationship between oil price shocks, Chinese EPU, and stock market returns. Their findings indicated a significant relationship, with positive EPU shocks in China negatively impacting global oil prices over a longer horizon. This indicates the potential for policy uncertainty in large economies to have a substantial effect on the global oil market, a notion supported by Liu et al. (2016). Liu et al. (2016), using a SVAR framework with sign restrictions on daily WTI crude oil data from January 2000 to December 2014, identified oil demand, particularly from China, as a crucial driver of oil price changes. The implication is that EPU in countries with significant oil consumption can act as a key factor influencing global oil price dynamics. In addition, some studies have examined the relationship between specific types of oil price shocks and EPU. In particular, Antonakakis et al. (2014), distinguishing between supply-side, aggregate demand, and oil-specific shocks, found that EPU responds negatively to aggregate demand shocks, while EPU shocks negatively influence all types of oil price shocks. Similarly, Kang and Ratti (2013a), using a SVAR model on monthly US data from January 1985 to December 2011, demonstrated that precautionary demand shocks tend to increase US EPU, while aggregate demand shocks have the opposite effect. Therefore, these studies suggest that the origin of oil price fluctuations plays a critical role in shaping the subsequent response of EPU, with demand-related shocks exhibiting a particularly strong link to EPU.

Other studies have examined the predictive power of EPU for oil market behaviour. For example, Balcilar et al. (2017), using a bivariate quantile causality test on daily US data from 1986 to 2014, and Bonaccolto et al. (2018), using a modified quantile causality approach on similar data up to 2015, both concluded that EPU's ability to predict oil returns is most significant during periods of market extremes or distress. This suggests an asymmetric relationship where uncertainty becomes a more influential factor when the oil market experiences significant deviations from its normal state. This is in contrast with the findings of Ma et al. (2019), who, found a positive and significant short-lived impact of EPU on oil volatility, with US EPU showing long-term forecasting power, using the generalized autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS) model on daily oil returns and monthly EPU indices in from 1998 to 2018 (US, China, Europe, Russia, Canada and Mexico). Similarly, Wei et al. (2017), using GARCH-MIDAS models on daily WTI prices and monthly global and national EPU indices from 1997 to 2016, highlighted EPU indices as more informative predictors of oil volatility than traditional oil market fundamentals. Therefore, these studies noted the role of EPU in forecasting oil market volatility, although its predictive power for returns may be more conditional on market stability. Che et al. (2024), using a unified SVAR framework on monthly data from 1997 to 2022, offered a comparative perspective on oil price uncertainty (OPU) and global EPU (GEPU). Their finding that global economic activity is more sensitive to OPU shocks than GEPU shocks suggests that uncertainty specifically related to the oil market may have a more direct and substantial impact on the global economy compared to broader policy uncertainty. While some studies highlight the time-varying nature of the relationship and the impact of economic events, others emphasise a more consistent negative relationship. The influence of major economies like China and the US, the type of oil price shock, and the role of EPU in predicting oil market volatility and returns are also key points of discussion.

2.2. Financial Markets Uncertainty and Oil Prices

Other studies have examined the impact of financial markets uncertainty on oil prices, using various proxies to capture this relationship. For example, Aloui et al. (2016), used copula functions on daily data from January 2000 to May 2014, analysing WTI crude oil index and two US uncertainty measures: The equity markets uncertainty (EMU) index and the EPU index. Aloui et al. (2016) indicate that higher uncertainty (both EMU and EPU) could increase oil returns during specific periods, particularly before financial crises. Their analysis of daily oil returns and these news-based uncertainty indices revealed, however, an overall negative dependence across the entire sample. A key contribution of their work is highlighting the shift in dependence during extreme market conditions, where oil returns became more strongly linked to EMU than with EPU, suggesting a potential dominance of financial market volatility during crises. This context-dependent relationship between news-based uncertainty indices and oil prices is further examined by Balcilar et al. (2017) and Bonaccolto et al. (2018). Both studies suggest that the predictive power of equity market uncertainty for oil returns, similar to EPU, is conditional on the market regime, with greater predictive power during strong upward or downward market trends. However, Aloui et al.'s observation from their 2016 study of a potential positive short-term impact before crises showing the complexity of this relationship.

Shifting the focus to oil price volatility, Le et al. (2023) utilized the Chicago board options exchange (CBOE) volatility index (VIX), a volatility-based proxy of financial market uncertainty, along with other variables, in their time-varying parameter vector autoregression (TVP-VAR) analysis of weekly data from January 2008 to October 2021. Their analysis indicate that VIX is the most statistically significant factor positively influencing oil price volatility, while its impact is amplified during major economic crises. Ma et al. (2024) further broadened the scope by examining a Global Financial Uncertainty (GFU) index's ability to forecast monthly WTI crude oil price returns. Their analysis, comparing GFU with 15 economic indicators and 8 alternative uncertainty measures from July 1992 to May 2020, revealed a strong negative relationship, indicating that higher global financial uncertainty precedes lower oil returns. Specifically, GFU's predictive ability was more significant during high-risk periods. This global perspective complements the US-centric findings of the EMU and EPU-focused studies, suggesting that while domestic news-based uncertainties play a role, broader global financial instability can have a more significant impact on oil returns.

2.3. Transmission Mechanisms of Uncertainty in the Oil Market

The interaction between uncertainty and the oil market is characterised by transmission channels, where various forms of uncertainty influence oil prices and market dynamics, and conversely, oil market shocks can reshape uncertainty. One such medium involves the impact of EPU on aggregate demand and, consequently, oil prices. Antonakakis et al. (2014), in their SVAR analysis noted that EPU shocks cause a reduction in aggregate demand, which subsequently drives oil prices lower. This highlights a clear channel where concerns arising from policy uncertainty directly translate into diminished economic activity and thus reduced oil consumption. Che et al. (2024) reinforces this by finding that positive GEPU shocks strongly reflect negative aggregate demand shocks, resulting in simultaneous declines in global economic activity (WIP), oil production, and oil price. This provides strong evidence for GEPU's role in transmitting demand-side contractionary effects to the oil market.

Beyond aggregate demand, precautionary demand for crude oil acts as another significant transmission channel. Kang and Ratti (2013b), using a structural VAR model and monthly data for US over the period January 1985-December 2011, demonstrated that positive oil price shocks arising from increased precautionary demand are associated with significant increases in US EPU. While this points to oil market dynamics influencing uncertainty, it frames precautionary demand as a specific mechanism. This implies that when market participants, driven by perceived uncertainty about future oil availability, increase their demand for oil as a hedge, their actions can further increase policy uncertainty. Conversely, Antonakakis et al. (2014) also noted that increased policy uncertainty is conducive to lower demand for oil, and thus lower uncertainty about its future availability, suggesting a complex interplay where initial uncertainty feeds into demand, and subsequent demand adjustments influence uncertainty levels.

Antonakakis et al. (2014) notes that the supply side also serves as a transmission channel for uncertainty as unanticipated positive EPU shocks cause a decrease in oil production. This mechanism suggests that policy uncertainty can deter investment in exploration and production, leading to constrained supply. Kang et al. (2017), in their SVAR model on monthly US and non-US oil production data from January 1985 to December 2015, found that US EPU shocks cause a statistically significant positive effect on US oil production immediately. This might suggest an initial domestic supply response to policy changes, perhaps reflecting altered regulatory environments or incentives within the US. They further emphasised that oil supply shocks (from both US and non-US origins) significantly explain variations in EPU, establishing a reverse transmission where actual supply disruptions can increase policy uncertainty.

Understanding the time-varying nature of these transmissions and the net directional flow of shocks is crucial for understanding how these mechanisms operate. For instance, Yang (2019), employing multivariate time series analysis on monthly data for G7 countries from 1998 to 2017, found that crude oil prices act mostly as net receivers of information from EPU, regardless of time scale. This suggests a consistent directional flow where policy uncertainty is more of a "sender" of shocks to oil prices. However, Antonakakis et al. (2014) provided a more in-depth perspective on the net spillovers, finding that EPU is the main transmitter of shocks up until the end of the global financial crisis (2007-2009), after which changes in oil prices assume this role. When disaggregating oil price shocks, they observed that all variables could be either net transmitters or recipients depending on the time period and type of oil price shock, challenging static assumptions about the transmission.

Furthermore, the interconnectedness of different types of uncertainty forms a crucial transmission channel. Ajmi et al. (2015), analysing daily US EPU and equity market uncertainty (EMU) from 1985 to 2013, found time-varying bidirectional causality, with EMU more consistently increasing EPU. This means financial market uncertainty can amplify EPU, and transmit it to the oil market through various channels. Zhang and Yan (2020), using a dynamic conditional correlation - generalized autoregressive conditional heteroskedasticity (DCC-GARCH) and network connectedness models on monthly US EPU indices and WTI returns from February 1985 to May 2019, identified significant spillover effects between various EPU components and WTI returns, particularly heightened during major international events, once again substantiating the results from Aloui et al. (2016), Balcilar et al. (2017), and Bonaccolto et al. (2018). Their findings indicate that while most US EPU indices are "transmitters" of spillover to WTI returns, some, like trade policy uncertainty, tend to be "receivers," highlighting differentiated transmission roles based on the specific policy areas.

Despite the growing body of research examining oil price dynamics and uncertainty, few attempt to map how uncertainty measures interact with market fundamentals such as oil supply, demand, and inventories across both short- and long-run horizons. What remains missing is a more holistic causal investigation that separates the direct and indirect channels through which these uncertainties shape oil price behaviour over time. This paper fills that gap by examining the causal relationship between oil prices, uncertainty measures (economic and financial), and fundamental variables, helping in designing future policies.

3. METHODOLOGY

3.1. Theoretical Framework

This study investigates the causal relationships between uncertainty measures and oil price dynamics by incorporating Financial Market Uncertainty and Economic Policy Uncertainty and traditional oil market determinants. The model captures both the individual and combined effects of these variables on oil prices, examining direct and indirect causality. This allows us to examine how financial volatility and policy uncertainty, together with supply-demand dynamics, influence oil prices. Following the study by Le et al. (2023), the model is as follows:

$$OILP_{t=}[OILS_t, OILD_t, USD_t, OILONV_t, EPU_t, FMU_t] \quad (1)$$

Where $OILP_t$ denotes the oil price, $OILS_t$ is the US domestic supply of crude, $OILD_t$ is the oil demand and USD_t is the US dollar rate. $OILINV_t$ is the petroleum inventories (oil supply-demand balance), while FMU_t and EPU_t represent the financial market uncertainty and US Economic Policy Uncertainty respectively (description of model variables in Appendix, Table A1).

The empirical analysis uses monthly data over the period February 1990-September 2024 obtained from the energy information administration (EIA), the federal reserve economic database (FRED), the Chicago board options exchange (CBOE) and investing.com (2025). In particular, West Texas intermediate futures price is used as proxy for the oil price ($OILP_t$), as it serves as the benchmark for U.S. crude and is directly influenced by domestic production, inventory levels, and macroeconomic factors, unlike Brent, which proxies international oil prices (Yang, 2019; Kang and Ratti, 2014). In addition, the futures price is preferred over the spot price due to its ability to capture market expectations and forward-looking sentiment (Bekiros et al., 2015; Liu et al., 2016; Zhang and Yan, 2020; Sun et al., 2020; Bonaccolto et al., 2018; Balcilar et al., 2017; Aloui et al., 2016). The US field production of crude oil is used as a proxy for domestic oil supply ($OILS_t$), capturing the supply-side disruptions from OPEC policy or shale production changes (Le et al., 2023; Luo et al., 2024).

In addition, the industrial production is used as proxy for oil demand ($OILD_t$), as the U.S. remains a net importer and major oil consumer, making industrial production a key indicator of economic activity and demand (Liu et al., 2016; Luo et al., 2024). The U.S. Dollar Index is used as a proxy for USD_t, capturing the dollar's strength and its role in the global oil market. As oil is dollar-denominated, USD fluctuations affect oil affordability for importers and production costs for dollar-pegged exporters (Le et al., 2023; Luo et al., 2024). US petroleum inventories, including the strategic petroleum reserve (SPR), is used to capture the supply-demand balance ($OILINV_t$), as inventories influence spot market supply and WTI pricing, as anticipated shortages increase inventory demand, reducing current supply and raising prices. This reflects the convenience yield, which decreases as inventory levels rise, stabilising prices (Le et al., 2023; Baumeister and Kilian, 2016; Luo et al., 2024).

The CBOE volatility index, derived from implied volatilities of S and P 500 options, serves as a forward-looking proxy of financial market uncertainty (FMU_t), as increased volatility typically leads to risk aversion, affecting asset prices, including oil (Le et al., 2023; Luo et al., 2024). In addition, US economic policy uncertainty, developed by Baker et al. (2016), is used as a proxy for economic policy uncertainty (EPU_t), reflecting broader policy-related uncertainty involving news-based policy uncertainty, expiring federal tax provisions, and forecast dispersion (Ajmi et al., 2015; Wei et al., 2017; Zhang and Yan, 2020).

3.2. Econometric Methods

The analysis starts by examining the stationary properties of the time series, applying the tests of Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and augmented Dickey-Fuller (ADF). However, since these tests may produce biased results when structural breaks are present, the modified

Augmented Dickey-Fuller test with a structural break (ADFBP) is also performed (Perron, 1989; Vogelsang and Perron, 1998).

To examine the existence of a long-run relationship between the variables, this study applies the autoregressive distributed lag (ARDL) bounds test for cointegration (Pesaran et al., 2001). To ensure that the ARDL models are well-specified and stable, diagnostic tests are conducted to ensure that the errors are homoscedastic, uncorrelated, and normally distributed. In addition, the ARDL model parameters are assessed using the cumulative sum of recursive residuals (CUSUM) test (Brown et al., 1975).

To investigate the causality among oil price, financial market uncertainty and economic policy uncertainty, the Granger causality test (Granger, 1969) is performed in a vector autoregressive model (VAR) framework (Sims, 1980).

If the variables are cointegrated, a restricted vector autoregressive model (VAR) (vector error correction model) is estimated:

$$\begin{bmatrix} \Delta LOILP_t \\ \Delta LOILS_t \\ \Delta OILD_t \\ \Delta LOILINV_t \\ \Delta USD_t \\ FMU_t \\ EPU_t \end{bmatrix} = \sum_{(j=1)}^{p} \beta_{ij} \begin{bmatrix} \Delta LOILP_{t-j} \\ \Delta LOILS_{t-j} \\ \Delta OILD_{t-j} \\ \Delta LOILINV_{t-j} \\ \Delta USD_{t-j} \\ FMU_{t-j} \\ EPU_{t-j} \end{bmatrix} + \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \\ \lambda_5 \\ \lambda_6 \\ \lambda_7 \end{bmatrix} ECT_{t-1} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \quad (2)$$

where $\sum_{j=1}^{p=d\max} \beta_{ij}$ are the model parameters, while λ_{1-7} are the coefficients of the error correction terms.

If the variables are not cointegrated, a VAR Model in first difference (VARD) is estimated:

$$\begin{bmatrix} \Delta LOILP_t \\ \Delta LOILS_t \\ \Delta OILD_t \\ \Delta LOILINV_t \\ \Delta USD_t \\ FMU_t \\ EPU_t \end{bmatrix} = \sum_{(j=1)}^{p} \beta_{ij} \begin{bmatrix} \Delta LOILP_{t-j} \\ \Delta LOILS_{t-j} \\ \Delta OILD_{t-j} \\ \Delta LOILINV_{t-j} \\ \Delta USD_{t-j} \\ FMU_{t-j} \\ EPU_{t-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \quad (3)$$

where Δ is the difference operator; $\sum_{j=1}^{p} \beta_{ij}$ are the model parameters, while p is the optimal lag order chosen based on the Schwarz information criterion (SIC).

In addition, diagnostic tests are conducted to ensure that the model is well-specified, while the CUSUM tests is performed to confirm the parameter stability of the estimated equations of $OILP_t$, FMU_t and EPU_t.

To examine the short-run causality between oil price, financial market and economic policy uncertainty, the Granger causality test in VAR framework is performed using the Chi-square statistic. In particular, the direct and indirect short-run causal relationships are examined by testing the null hypotheses H_0: $\sum_{j=1}^{p} \beta_{ij} = 0$. To examine the long-run causality between oil price, financial market uncertainty and economic policy uncertainty the study performs the Toda and Yamamoto test (Toda and Yamamoto, 1995) in the following augmented VAR model:

$$\begin{bmatrix} LOILP_t \\ LOILS_t \\ OILD_t \\ LOILINV_t \\ USD_t \\ FMU_t \\ EPU_t \end{bmatrix} = \begin{bmatrix} \alpha_{1t} \\ \alpha_{2t} \\ \alpha_{3t} \\ \alpha_{4t} \\ \alpha_{5t} \\ \alpha_{6t} \\ \alpha_{7t} \end{bmatrix} + \sum_{(j=1)}^{(p+dmax)} \beta_{ij} \begin{bmatrix} LOILP_{t\_j} \\ LOILS_{t\_j} \\ OILD_{t\_j} \\ LOILINV_{t\_j} \\ USD_{t\_j} \\ FMU_{t\_j} \\ EPU_{t\_j} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \quad (4)$$

p is the optimal lag length and dmax is the maximum order of integration of the model variables. To examine the long-run causality, the Chi-square test is applied to the first p VAR coefficients and the direct and indirect causal relationships are examined by testing the null hypotheses H_0: $\sum_{j=1}^{p=d\max} \beta_{ij} = 0$.

4. EMPIRICAL ANALYSIS

Tables 1 and 2 present the unit root test results at level and 1st difference. The PP, ADF and ADFBP test results show that the null hypothesis of non-stationarity cannot be rejected, except for EPU_t and FMU_t, at conventional significance levels. In particular, the null hypothesis of non-stationarity is rejected for EPU_t and FMU_t at 1% significance level. The KPSS results indicate that the null hypothesis of stationarity is rejected for $LOILP_t$, $LOILS_t$, $OILD_t$ *and* $LOILINV_t$ at 1% significance level. As for the variables USD_t, EPU_t *and* FMU_t, they are found to be stationary at conventional levels. Therefore, all variables are found to be non-stationary, except from EPU_t and FMU_t. As for the first differenced variables, the PP, ADF and ADFBP tests confirm that all previously non-stationary variables become stationary at 1% significance level. The KPSS results confirm the stationary of the variables, except for $\Delta OILINV_t$, which is found to be non-stationary at 10% significance level.

As the integration order of the variables is I(0) and I(1), the ARDL cointegration test is used. Table 3 reports the ARDL results. In particular, the F-statistic (1.93) is less that the critical value of lower bounds at both 5% and 1% level, indicating the absence of a long-run relationship between the model variables. To confirm the stability of the ARDL model parameters, the CUSUM test is applied. As shown in Figure 1 the test statistic remains within the 5% significance lines, confirming the constancy of the parameters.

As there is no cointegration between the variables, a VARD is estimated, and the Granger causality test results are reported in

Table 1: Unit root test results at level

Variables	PP	KPSS	ADF	ADFBP	Break
$LOILP_t$	−2.60$^{(a)}${13}	0.33$^{(a)}${16}***	−3.10$^{(a)}$[1]	−1.99$^{(a)}$[1]	June 01, 2014
$LOILS_t$	−1.29$^{(a)}$ {8}	0.66$^{(a)}${16}***	−1.26$^{(a)}$[2]	−3.28$^{(b)}$[2]	September 01, 2011
$OILD_t$	−1.95$^{(b)}${5}	0.46$^{(a)}${16}***	−1.99$^{(b)}$[2]	−3.06$^{(b)}$[2]	April 01, 2020
USD_t	−2.19$^{(b)}${4}	0.24$^{(b)}${16}	−2.01$^{(c)}$[0]	−2.52$^{(b)}$[0]	January 01, 2002
LOILINVt	−0.43$^{(c)}${3}	0.24$^{(a)}${16}***	−0.52$^{(c)}$[2]	−3.36$^{(b)}$[12]	January 01, 2003
EPU_t	−6.00$^{(b)}${6}***	0.09$^{(a)}${14}	−6.14$^{(b)}$[0]***	−7.93$^{(b)}$[0]***	April 01, 2020
FMU_t	−6.31$^{(b)}${5}***	0.10$^{(b)}${15}	−6.59$^{(b)}$[0]***	−7.49$^{(b)}$[0]***	October 01, 2008

***Denote the rejection of the null hypothesis at 1% significance level. The optimal lags for the ADF and ADFBP tests are selected based on SIC and are shown in [ ]. Bandwidths, displayed in { }, are calculated using the Bartlett kernel estimation method. The PP, ADF, and ADFBP tests are conducted using models with: $^{(a)}$ constant and trend, $^{(b)}$ constant only, and $^{(c)}$ neither constant nor trend. For the KPSS test, the models $^{(a)}$ and $^{(b)}$ are used. The dates refer to the structural breaks (selected by maximizing the Dickey-Fuller t-statistic)

Table 2: Unit root test results at first difference

Variables	PP	KPSS	ADF	ADFBP	Break
$\Delta LOILP_t$	−17.40$^{(c)}${22}***	0.06$^{(b)}${18}	−17.35$^{(c)}$[0]***	−17.88$^{(b)}$[0]***	May 01, 2020
$\Delta LOILS_t$	−23.73$^{(a)}${4}***	0.05$^{(a)}${3}	−23.36$^{(a)}$[0]***	−24.18$^{(b)}$[0]***	May 01, 2021
$\Delta OILD_t$	−16.28$^{(c)}${2}***	0.22$^{(b)}${5}	−15.02$^{(b)}$[1]***	−15.20$^{(b)}$[1]***	June 01, 2000
ΔUSD_t	−18.60$^{(c)}${8}***	0.06$^{(b)}${6}	−18.66$^{(c)}$[0]***	−19.15$^{(b)}$[0]***	March 01, 1991
$\Delta LOILINV_t$	−11.55$^{(c)}${13}***	0.35$^{(b)}${3}*	−12.41$^{(c)}$[1]***	−13.56$^{(b)}$[1]***	April 01, 2020

*, ***denote the rejection of the null hypothesis at 10% and 1% significance level, respectively. The optimal lags for the ADF and ADFBP tests are selected based on SIC and are shown in [ ]. Bandwidths, displayed in { }, are calculated using the Bartlett kernel estimation method. The PP, ADF, and ADFBP tests are conducted using models with: $^{(a)}$ constant and trend, $^{(b)}$ constant only, and $^{(c)}$ neither constant nor trend. For the KPSS test, the models $^{(a)}$ and $^{(b)}$ are used. The dates refer to the structural breaks (selected by maximizing the Dickey-Fuller t-statistic)

Table 3: ARDL Bounds test results

H_0	Bounds test value F-statistic	Bounds critical value			
		5%		1%	
		I (0)	I (1)	I (0)	I (1)
r=0	1.93 (*k*=*6*)	2.27	3.28	2.88	3.99

The diagnostic tests for $LOILP_t$ ARDL (1,1,2,2,1,4,1) indicate that the model is well specified: (LM F[4,389]=0.06, H-het χ2{18}=0.25). In addition, the CUSUM test confirm the constancy of the parameters

Figure 1: CUSUM ARDL (1,1,2,2,1,4,1)

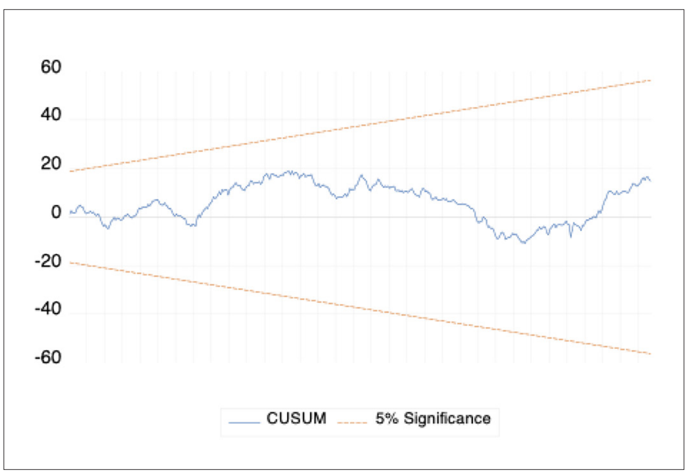


Table 4. The short-run Granger causality results show that the null hypothesis of non-causality from EPU_t to oil price cannot be rejected at conventional significance levels, indicating that the causality does not run from EPU_t to oil price. However, the null hypothesis of non-causality from oil price to EPU_t is rejected at the 10% level, providing evidence that a unidirectional causality runs from oil price to EPU_t. Also, an indirect causality runs from oil price to EPU_t, through oil demand. In contrast, a direct unidirectional causality runs from FMU_t to oil price, as the null hypothesis of non-causality is rejected at 5% significance level. This indicates that only FMU_t directly cause oil price in the short-run, while the converse is true in the case of EPU_t.

Moreover, the results show that EPU_t and FMU_t Granger cause oil demand (industrial production) both at the 1% level. Thus, given that oil demand cause oil price, EPU_t and FMU_t indirectly cause oil price thought oil demand. Finally, all the variables in the model jointly oil price at 5% significance level, while all variables jointly cause oil demand, oil inventories and EPU_t at 1% significance level.

Since the aim of this study focuses on the causality between oil price, financial market uncertainty and economic policy uncertainty, the parameters' constancy is assessed by performing the CUSUM test. As it can be seen from Figure 2, there is no movement outside the 5% critical lines, confirming the parameters' stability.

The results of the Toda and Yamamoto causality test, reported in Table 5, show that the null hypothesis of non-causality from EPU_t to oil price is rejected at the 10% level, as is the null hypothesis of non-causality from oil price to EPU_t. Therefore, a bi-directional causality exists between oil price and EPU_t. As for FMU_t, it Granger causes oil price at the 5% level, while there is no evidence to support the converse. Moreover, oil supply Granger causes oil price indirectly through EPU_t, while FMU_t also indirectly causes oil price through EPU_t.

In addition, all the variables in the model jointly cause oil price and USD_t at 10% and 5% significance level respectively, while all variables jointly cause oil demand and supply, oil inventories and EPU_t at 1% significance level. In contrast with the short-run causality results, in the long-run, EPU_t and FMU_t do not Granger cause oil price through oil demand. The results are reported in Table 5.

Table 4: Short-run granger causality test

	Dependent variable						
Source of causality	$\Delta LOILP_t$	$\Delta LOILS_t$	$\Delta OILD_t$	ΔUSD_t	$\Delta LOILINV_t$	EPU_t	FMU_t
$\Delta LOILP_t$	-	4.08	40.48***	6.52	12.75**	9.23*	7.60
$\Delta LOILS_t$	5.69	-	35.62***	3.32	8.64*	11.47**	4.40
$\Delta OILD_t$	9.05*	12.00**	-	2.24	8.26*	22.07***	2.67
ΔUSD_t	1.84	0.25	3.43	-	3.65	7.54	2.81
$\Delta LOILINV_t$	5.68	21.16	15.25***	7.81*	-	3.32	3.73
EPU_t	5.40	6.86	23.53***	2.77	1.45	-	3.54
FMU_t	12.81**	3.16	31.40***	0.86	6.78	41.38***	-
ALL	36.68**	62.78	202.22***	32.78	57.25***	96.66***	29.89

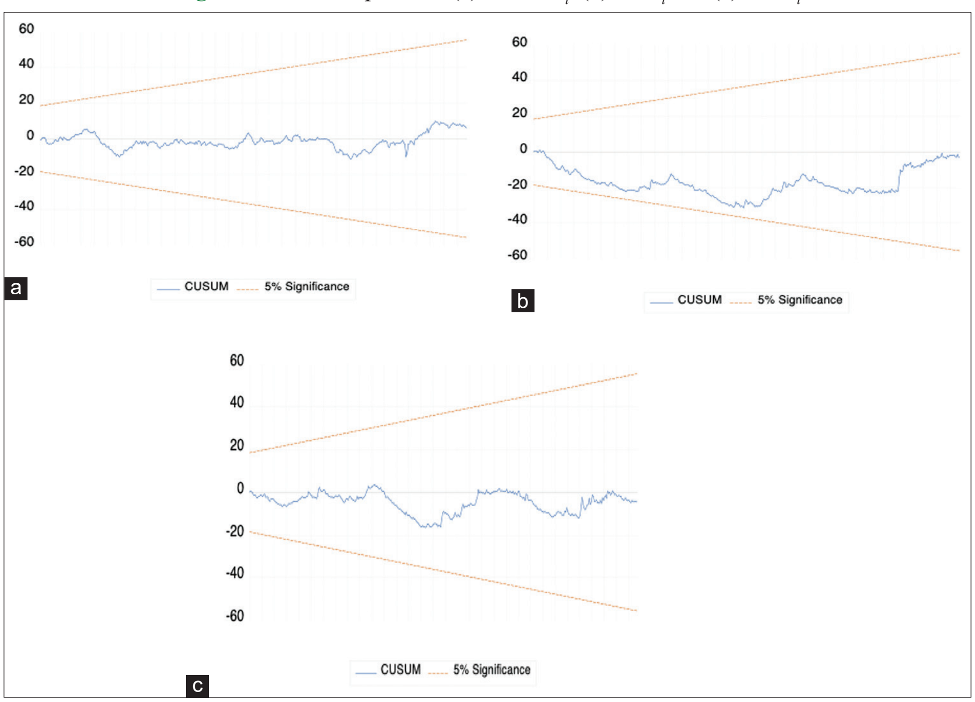
***, ** and *show significance at 1%, 5% and 10% respectively ((χ^2df (4) and χ^2df (24)). The lag order for the VARD is selected based on SIC. The diagnostic tests for the VARD indicate that the model is well specified, while the VARD stability is confirmed using the AR Roots test and CUSUM plots for each equation

Table 5: Toda Yamamoto test

	Dependent variable						
Source of causality	$LOILP_t$	$LOILS_t$	$OILD_t$	USD_t	$LOILINV_t$	EPU_t	FMU_t
$\boldsymbol{LOILP_t}$	-	3.82	37.56***	7.55	16.25***	8.62*	6.75
$LOILS_t$	5.53	-	28.63***	3.73	6.16	10.13**	5.23
$OILD_t$	7.75	12.21**	-	4.83	9.27*	18.53***	2.31
USD_t	1.57	0.28	3.50	-	3.08	6.23	2.77
$LOILINV_t$	1.95	13.60***	16.17***	6.97	-	4.92	3.02
EPU_t	7.83*	6.58	23.50***	5.84	2.38	-	3.32
FMU_t	12.86**	2.51	31.67***	1.82	8.72*	46.69***	-
ALL	33.23*	60.36***	190.95***	38.64**	63.75***	97.85***	29.06

***, ** and *show significance at 1%, 5% and 10% respectively ((χ^2df (2) and χ^2df (24)). The optimal lag order is selected based on the SIC. The diagnostic tests for the VAR(p) show that the model is well specified and stable

Figure 2: CUSUM plots for (a) $\Delta LOILP_t$, (b) EPU_t and (c) FMU_t



In the short run, the direct causal relationship from oil prices to EPU_t shows that the sudden fluctuation in oil prices poses immediate macroeconomic challenges such as higher inflation and reduced output (Antonakakis et al., 2014; Sun et al., 2020; Zhang and Yan, 2020), leading to heightened EPU_t. In contrast, the direct effect of FMU_t on oil prices reflects investor reactions and quick changes in market sentiment. This supports the statistically significant role of financial market uncertainty in driving oil price movements, as investors respond to perceived market instability (Liu et al., 2016; Ajmi et al., 2015; Le et al., 2023; Yang, 2019; Ma et al., 2024; Zhang et al., 2025). It should be noted that in the short run, EPU_t and FMU_t Granger causing oil demand establishes an indirect demand-side channel through which both uncertainties affect oil prices.

In contrast, in the long-run, there is a shift in the transmission channels where EPU_t and FMU_t do not Granger cause oil price indirectly through oil demand, suggesting that the indirect demand channel becomes less significant over longer horizons as the market adjusts to structural changes in the economy. In the long-run, the bidirectional causal relationship between oil prices and EPU is in line with Sun et al. (2020), Hailemariam et al. (2019), and Ma et al. (2019), noting that EPU can affect long-term investment, consumption, and energy policy decisions, which in turn affects the demand and supply of oil and its price. FMU_t on the other hand, retains its unidirectional influence on oil prices in the long run emphasising that persistent markets instability regardless of time horizon can rapidly affect oil prices (Ajmi et al., 2015).

While short-term aggregate demand is sometimes associated with lower EPU as it signals booming economic conditions (Hailemariam et al., 2019; Antonakakis et al., 2014), can also strain production capacity or deplete inventories, setting the stage for longer-term supply-side volatility that transmits to oil prices via EPU. Our findings indicate that this channel through which oil supply influences oil prices indirectly through EPU, acts as a conduit of uncertainty rather than a direct shock transmitter. This relationship is further examined by Kang et al. (2017), who found that supply-side disruptions, both US and non-US, significantly explain variations in EPU, establishing a reverse channel via which physical market imbalances amplify policy uncertainty, shaping the oil price. This mechanism aligns with our empirical results which indicate that EPU operates as both a transmitter and recipient of causality, while oil prices, though largely acting as transmitters, also exhibit receiver behaviour in the long run (Yang, 2019; Antonakakis et al., 2014; Wei et al., 2017).

5. CONCLUSION

This paper provides evidence on the causal relationship between oil price, financial market uncertainty and economic policy uncertainty in the US from February 1990 to September 2024. The ARDL results confirm the absence of long-run relationship between the model variables and the Granger causality test in VARD framework was performed to assess the direction of the causality.

The short-run analysis reveals a unidirectional causality from oil prices to EPU_t, suggesting that oil market fluctuations exert macroeconomic pressures that elevate policy uncertainty. In contrast, FMU_t is found to directly cause oil prices, indicating that the investors' sentiment and market volatility shape short-term oil pricing. These findings are consistent with prior studies (Antonakakis et al., 2014; Zhang and Yan, 2020), which highlight the asymmetric and synchronous effects of oil price shocks on economic sentiment, as well as the predictive strength of financial uncertainty measures on oil (Ajmi et al., 2015; Le et al., 2023; Ma et al., 2024; Zhang et al., 2025). Additionally, both EPU_t and FMU_t indirectly cause oil prices through oil demand, supporting the view that uncertainty affects industrial activity and consumption (Bloom, 2014; Bernanke, 1983), with further effect on oil price. While EPU_t causes oil prices only indirectly in the short run, oil prices affect EPU_t both directly and indirectly, indicating a broader influence of oil market dynamics on policy uncertainty (Hailemariam et al., 2019; Bonaccolto et al., 2018).

In the long run, EPU_t and FMU_t no longer cause oil prices through oil demand. Instead, a direct bidirectional causal relationship exists between oil prices and EPU_t, while FMU_t continues to directly cause oil price. These results are in line with the studies by Yang (2019), Sun et al. (2020), Ma et al. (2024), and Zhang et al. (2025), which indicate that, over extended horizons, EPU becomes embedded in decision-making, affecting oil price through its influence on investment, regulation, and strategic planning. Moreover, oil supply shocks cause oil price indirectly through EPU_t, showing its role as a transmission conduit rather than a direct cause of oil price volatility. This supports findings by Kang et al. (2017), who demonstrate that unanticipated supply shocks can elevate policy uncertainty due to their inflationary and fiscal implications.

From a policy perspective, these results emphasize the need to reduce policy uncertainty during periods of oil market volatility. Transparent fiscal and regulatory frameworks can help reduce uncertainty that feeds back into commodity prices. Additionally, central banks and fiscal authorities may benefit from monitoring financial market uncertainty as an early-warning indicator for energy price shocks, given its predictive power across both short- and long-run horizons.

It should be noted that the use of monthly data may miss volatility clustering seen in daily observations. Additionally, the EPU and FMU (proxied by VIX) indices, while widely used, may not fully capture sectoral or geopolitical dimensions of uncertainty. Future research could incorporate sectoral/cross-country uncertainty measures and disaggregated oil price shocks within a regime-switching framework to capture nonlinear dynamics.

6. AUTHOR CONTRIBUTIONS

Saimanish Prabhakar wrote the introduction, literature review, and conclusion, contributed to the theoretical framework, and collected the data. Dr. Athanasia Stylianou Kalaitzi also contributed to the theoretical framework, and developed and wrote the methodology, conducted the econometric analysis, and interpreted the results

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APPENDIX

Table A1: Description of model variables

Variable	Variable description	Measurement
$LOILP_t$		
WTI crude oil futures	A benchmark crude oil used globally, reflecting price movements in the oil market	USD per barrel in logarithmic form
$LOILS_t$		
US field production of crude oil	Represents the total volume of crude oil produced domestically in the United States	Thousands of barrels per day (kb/d) in logarithmic form
$OILD_t$		
US industrial production	Measures the real output of the U.S. industrial sector, indicating economic demand for oil	Index (April 2017=100)
$LOILINV_t$		
US petroleum stocks (inventories)	Indicates the level of crude oil stockpiles in the U.S., signalling supply and demand balance	Thousands of barrels in logarithmic form
USD_t		
US dollar index	Tracks the value of the U.S. dollar against a basket of major foreign currencies.	Index (April 2017=100)
FMU_t		
CBOE volatility index	Measures market expectations of near-term volatility, reflecting investor sentiment	A percentage value that represents the expected volatility over the next 30 days
EPU_t		
Economic policy uncertainty index - US	Quantifies uncertainty in U.S. economic policy, influencing market expectations and behaviour.	Index (April 2017=100)