# Causal relationships between inflation uncertainty, geopolitical risks, and inflation: New insights from Granger causality-in-quantiles tests

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***Abstract***

This study investigates the direction and magnitude of linear and nonlinear Granger causality-in-quantiles between inflation and inflation uncertainty, as well as from global geopolitical risks to inflation in Saudi Arabia over the period January 2008–December 2025. While no causality is detected in the mean, the results reveal significant quantile-dependent relationships. Linear Granger causality-in-quantiles indicates significant bidirectional causality between inflation and inflation uncertainty, with a predominantly positive and significant causal effect running from inflation to its uncertainty across most quantiles, thereby supporting the Friedman (1977) hypothesis. In contrast, nonlinear Granger causality-in-quantiles uncovers state-dependent effects, with inflation uncertainty exerting a significant negative influence on inflation at lower and middle quantiles, thereby supporting the Friedman-Ball hypothesis. Meanwhile, both linear and nonlinear Granger causality-in-quantiles reveal significant causal effects from global geopolitical risk measures to inflation across most quantiles; however, the sign analysis indicates that these effects are unstable and largely insignificant, providing no consistent or robust sign pattern linking external risk factors to inflation dynamics in Saudi Arabia. Robustness checks using the world uncertainty index confirm that global uncertainty has a limited and non-systematic influence on inflation dynamics. Overall, the findings emphasize strong state-dependent and asymmetric effects, with domestic uncertainty playing a central role, while external risk factors contribute marginally to inflation dynamics in Saudi Arabia.

| ***Keywords*** | ***DOI*** | ***JEL code*** |
|---|---|---|
| *Inflation, inflation uncertainty, geopolitical risk, Granger causality-in-quantiles.* | *https://doi.org/10.54694/stat.2025.57* | *C11, C22, C52, D80, E31, H56* |

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## INTRODUCTION

Geopolitical uncertainty and persistent inflation continue to weigh heavily on the global economy, weakening growth prospects and leading to downward revisions to global economic forecasts. Geopolitical risk, broadly defined as the likelihood of conflicts, terrorist attacks, or other disruptions to international relations that undermine stability, has intensified in recent years due to rising international tensions. Key risks include Russia-NATO frictions, the ongoing Russia-Ukraine conflict, cyberattacks, U.S.-China strategic competition, climate-related risks, energy security challenges, and the lingering effects of the COVID-19 pandemic. These developments have heightened market volatility and amplified uncertainty around inflation dynamics (Yang et al., 2023; Bouri et al., 2023; Lee et al., 2023; Adeosun et al., 2023).

The complex interplay between geopolitical shocks and inflation has therefore attracted increasing attention from academics, policymakers, and market participants (Lee et al., 2023; Yang et al., 2023; Caldara and Iacoviello, 2025). Geopolitical disruptions can directly transmit into the macroeconomy, creating inflationary pressures. For example, heightened uncertainty often induces consumer caution and delays in consumption, while businesses suspend investments and accumulate precautionary savings (Yang et al., 2023). Such dynamics exacerbate cyclical downturns by reducing the perceived value of future income streams and investment opportunities. Moreover, the magnitude of these effects varies according to the nature, scale, and duration of the geopolitical events (Noguera-Santaella, 2016).

Energy-dependent economies such as Saudi Arabia are particularly exposed to these risks, as fluctuations in energy markets are closely tied to geopolitical developments (Aliedan, 2022). Although the practice of anticipating geopolitical behavior has been part of international relations for centuries, its systematic integration into economic and political analysis has become especially pronounced since the early 20th century (Aliedan, 2022). This underscores the importance of viewing geopolitics not merely as a background condition, but as a central driver of both economic volatility and inflationary dynamics in the contemporary global landscape.

Understanding the impact of geopolitical risk on inflation is increasingly important, particularly in Saudi Arabia, given current global political tensions and economic challenges. Major events, such as the COVID-19 pandemic and the Russia-Ukraine conflict, have driven sharp increases in commodity and food prices, fueling inflation worldwide. While central banks have responded with interest rate hikes, tighter fiscal conditions have contributed to a slowdown in global growth. Although recent inflationary pressures are largely short-term, they may pose long-term economic challenges, necessitating both immediate and strategic policy responses.

This study addresses the following research question: Do adverse global geopolitical shocks increase or decrease inflation in Saudi Arabia? Theoretically, Caldara and Iacoviello (2025) argued that the effect of geopolitical tensions on inflation is ambiguous, as such shocks influence both supply and demand. On the supply side, conflicts can destroy capital, redirect resources inefficiently, disrupt trade and capital flows, and impair supply chains. On the demand side, uncertainty can reduce economic activity, delay investment and hiring, erode consumer confidence, and tighten financial conditions.

In addition to geopolitical risk, inflation uncertainty may be considered as an alternative determinant of inflation in Saudi Arabia. Historically, inflation has remained moderate, averaging 3.44% in 2020, 3.06% in 2021, 2.47% in 2022, and 2.33% in 2023, although the Consumer Price Index has shown a steady upward trend since 2010. This study further tries to answer the following second research question: Does inflation uncertainty raise or lower inflation in Saudi Arabia? Inflation uncertainty, that is, the unpredictable volatility in inflation, poses significant challenges for monetary policymakers (Barnett et al., 2020). It can arise from differences in international monetary regimes or political instability, both of which affect inflation expectations (Cukierman and Meltzer, 1986). Economic agents continuously update their expectations in response to new information, making inflation uncertainty dynamic and complex. Four main hypotheses describe the interplay between inflation and its uncertainty: positive and negative causal effects of inflation on uncertainty (Friedman, 1977; Ball, 1992; Pourgerami and Maskus, 1987; Ungar and Zilberfarb, 1993) and positive and negative effects of uncertainty on inflation (Cukierman and Meltzer, 1986; Holland, 1995).

This study aims to complement existing research on the causal effects of inflation uncertainty and geopolitical risk on inflation in Saudi Arabia and to inform policy recommendations for managing the economy during periods of crisis. Understanding how these factors influence the general price level is essential for monetary authorities seeking to contain inflation. The significance of this work lies in its contribution to the literature, addressing a gap in previous studies that have not explored the potential effects of these factors on Saudi Arabia's inflation dynamics.

The current study makes two main contributions. First, it examines the causal relationship between inflation and inflation uncertainty, as well as the causal impacts of global geopolitical risks on inflation in Saudi Arabia, within a quantile-based framework that captures distributional dynamics beyond conventional mean-based approaches. Investigating this relationship across quantiles is particularly important as it may identify the state-dependent effects that may differ between low- and high-inflation regimes, especially over the period spanning from January 2008 to December 2025, which encompasses major global and regional shocks. Moreover, evaluating the quantile-specific causal effects of global geopolitical risk, geopolitical threats, and geopolitical risk acts on inflation is crucial in the Saudi context, given its strong exposure to external shocks and oil market fluctuations. This approach provides deeper insights into how different dimensions of global geopolitical risk transmit to domestic inflation across varying economic conditions. Second, our study incorporates the sign of both linear and nonlinear Granger causality-in-quantiles, allowing for a more comprehensive understanding of not only whether causal relationships exist but also their direction and economic interpretation across different states of the distribution. This is particularly important because the sign of causality enables a direct assessment of competing theoretical hypotheses on the inflation-uncertainty relationship. To the best of our knowledge, this study is the first to examine the sign of nonlinear Granger causality-in-quantiles, thereby introducing a novel dimension to the empirical literature. By combining direction, magnitude, and sign within a distributional framework, the analysis uncovers hidden asymmetries and state-dependent dynamics that conventional approaches cannot detect.

The remainder of the paper is structured as follows. Section 1 presents the literature review regarding the nexus between geopolitical risks, inflation uncertainty, and inflation. Section 2 describes the data and methodology used in this study. Section 3 presents and discusses the main empirical results. Section 4 outlines the conclusion, policy implications, and limitations of the study.

## 1 LITERATURE REVIEW

### 1.1 Geopolitical risks and inflation

The empirical literature on the relationship between geopolitical risks and inflation remains relatively scarce, with only a handful of studies addressing this nexus. Caldara et al. (2025) identified two channels linking geopolitical risks to inflation: supply-side disruptions (disruptions to resources and trade, inefficient reallocation, and supply chain problems) and demand-side effects (decreased investment, employment, and consumer confidence due to uncertainty), with the net inflationary effect depending on the dominant channel. In a related study, Caldara and Iacoviello (2025) argued that geopolitical risks drive commodity price inflation through supply and demand effects in commodity markets. Kyriazis et al. (2023) also found that currency values directly affect inflation and indirectly affect exports and geopolitical risks, revealing a geopolitical risk-driven inflation channel, most evident in the U.S., Brazil, and South Korea (and less so in France and Germany). In Russia, inflation, exchange rates, and exports were found to constitute geopolitical risks, particularly during the Russo-Ukrainian War.

Meanwhile, Yang et al. (2023) showed that the links between geopolitical risks and oil price shocks and inflation in China, the U.S. and 27 European countries are time-varying, with post-COVID-19 inflation driven by shrinking oil reserves, higher oil prices and supply and demand imbalances, which are exacerbated by geopolitical risks. Similarly, Lee et al. (2023) found that geopolitical risks related to crude oil significantly affect the average and variance of core inflation in the United States and China, with the effect increasing during major geopolitical events and varying by country and type of causality. Alternatively, Adeosun et al. (2023) investigated the interplay among economic policy uncertainty, geopolitical risks, and inflation in the U.S., Canada, the UK, Japan, and China. They found that geopolitical risks in the U.S. and Canada display strong short- and medium-term coherence with inflation. In contrast, the UK and China exhibit strong short-term but weaker medium-term coherence, while Japan shows strong coherence only in the short term. Finally, Bouri et al. (2023) showed that the transmission of geopolitical risk and inflation across European and North American economies rose sharply during the Russian-Ukrainian war, exceeding even the levels of the 1970s energy crisis, and found that the global geopolitical risk (GPR) index positively predicts future inflation transmission, whereas the GPR Acts index only affects large transition changes.

### 1.2 Inflation uncertainty and inflation

The relationship between inflation and inflation uncertainty has been investigated in two main directions, each grounded in different economic perspectives. One strand focuses on the causal link running from inflation to inflation uncertainty. Within this strand, the literature is further divided according to the expected sign of the relationship. Friedman (1977) posited that inflation positively impacts uncertainty, since inconsistent monetary policy makes predicting future policy difficult—a view formally supported by Ball (1992). In contrast, Pourgerami and Maskus (1987) and Ungar and Zilberfarb (1993) argued for an inverse relationship, reasoning that higher inflation encourages greater effort in forecasting, thus reducing uncertainty. The second economic context addresses the opposite direction of causation, where uncertainty about inflation affects inflation itself. In this context, studies offer two opposing explanations, depending on the direction of the relationship. Cukierman and Meltzer (1986) argued for a positive causal effect, suggesting that increased uncertainty about inflation motivates policymakers to create a sudden inflationary surge, leading to higher inflation. In contrast, Holland (1995) proposed a negative causal effect, asserting that increased uncertainty prompts independent central banks to reduce inflation to minimize the real costs associated with that uncertainty.

The causal relationship between inflation and its uncertainty remains unclear and controversial (Barnett et al., 2020). Most empirical evidence supports Friedman's (1977) hypothesis (e.g., Berument and Dincer, 2005; Fountas et al., 2006, among others), although other studies have found evidence of a bidirectional causal relationship (e.g., Conrad and Karanasos, 2005; Albulescu et al., 2019, among others).

## 2 MATERIALS AND METHODS

### 2.1 Data and preliminary analysis

In this paper, we use monthly, seasonally adjusted Consumer Price Index (CPI) data from the International Monetary Fund (IMF) database to calculate the inflation rate (INFR).[2] We also collect monthly data on the global Geopolitical Risk (GPR) index, obtained from PolicyUncertainty.com. The GPR index, developed by Caldara and Iacoviello (2022), is calculated by counting the number of news articles related to adverse geopolitical events each month, relative to the total number of articles. This index provides a quantitative measure of geopolitical tensions and associated risks, with data tracing back to 1900. According to Caldara

[2] $INFR_t = 100 \times ((CPI_t - CPI_{t-12})/CPI_{t-12})$

and Iacoviello (2022), higher GPR values signal lower investment, stock prices, and employment, as well as an increased likelihood of economic crises and downside risks to the global economy. We supplement the baseline global GPR index with three alternative indicators. In particular, we employ the geopolitical risk threats (GPRT) index, which captures risks associated with rising tensions and the anticipation of conflict, and the geopolitical risk acts (GPRA) index, which reflects realized geopolitical events. Our dataset covers the period from January 2008 to December 2025, constrained by the availability of WUI data. All unadjusted series were seasonally adjusted using the X-13-ARIMA-SEATS program.

We further construct a new measure of inflation uncertainty (INFRU) based on the best-performing time-varying volatility model among several alternatives. Following Chan and Grant (2016), we estimate and compare variants of GARCH and SV models using Bayesian model comparison via Bayes factors to identify the most suitable proxy for inflation uncertainty.[3]

**Table 1** Summary statistics

| | INFR | INFRU | GPR | GPRT | GPRA | WUI |
|---|---|---|---|---|---|---|
| Minimum | –2.202 | 0.197 | 4.068 | 3.973 | 3.348 | 9.111 |
| Median | 2.469 | 1.082 | 4.522 | 4.578 | 4.453 | 9.943 |
| Mean | 2.975 | 1.880 | 4.580 | 4.639 | 4.465 | 10.024 |
| Maximum | 11.080 | 8.479 | 5.765 | 6.001 | 5.525 | 11.715 |
| Std. Dev. | 2.640 | 1.863 | 0.263 | 0.320 | 0.366 | 0.470 |
| Skewness test | 0.858*** | 1.579*** | 1.012*** | 0.866*** | 0.093 | 1.174*** |
| Kurtosis test | 4.063** | 5.478*** | 4.570*** | 4.335*** | 3.433 | 4.768*** |
| Jarque-Bera test | 36.690*** | 144.998*** | 59.037*** | 43.053*** | 2.002 | 77.791*** |
| ARCH-LM(10) | 184.293*** | 188.703*** | 111.687*** | 113.308*** | 122.929*** | 140.606*** |
| Q(10) | 1034.105*** | 903.566*** | 452.152*** | 527.077*** | 626.826*** | 477.168*** |
| $Q^2(10)$ | 999.530*** | 851.018*** | 436.654*** | 505.655*** | 591.237*** | 489.263*** |
| Observation | 216 | 216 | 216 | 216 | 216 | 216 |

**Notes:** The ARCH-LM test is performed for 10 lags. The superscripts ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.
**Source:** Author's compilation

To evaluate the robustness of our results, we further incorporate the World Uncertainty Index (WUI) as a broader proxy for global uncertainty derived from country-level reports. The consistency of our results across this alternative proxy would reinforce the robustness and credibility of our empirical conclusions.

Table 1 presents preliminary summary statistics for the data series. Except for INFR and INFRU, all uncertainty indicators were converted to their logarithmic form. All series have positive mean and median values that are broadly similar. The WUI series exhibits the highest average, while INFR is the most volatile. Except for GPRA, all remaining series exhibit asymmetric distributions and positive

[3] The GARCH-class models include the GARCH (1,1), GARCH (2,1), GARCH-J, GARCH-M, GARCH-MA, and GARCH-*t* models as well as the GJR-GARCH model. For the SV-class models, we consider the standard SV, SV-2, SV-J, SV-M, SV-MA, SV with *t* innovations (SV-*t*), and SV-L models. For more details about these models as well as the estimation and comparison procedures, see Chan and Grant (2016).

kurtosis, indicating fat-tail behaviour. These characteristics violate the normality assumption, as confirmed by Skewness, Kurtosis, and Jarque-Bera tests, suggesting that all series, except GPRA, may respond differently to positive and negative shocks.

**Table 2** Linearity test results

| Variables | Harvey et al. (2008)'s test | | | Harvey et al. (2007)'s test | | | |
|---|---|---|---|---|---|---|---|
| | statistic $W_\lambda$ | Decision | | statistic $W^*_{10\%}$ | statistic $W^*_{5\%}$ | statistic $W^*_{1\%}$ | Decision |
| INFR | 2.62 | Linear | | 3.24 | 3.76 | 3.97 | Linear |
| INFRU | 5.26* | Nonlinear | | 7.24 | 7.65 | 7.71 | Linear |
| GPR | 6.85** | Nonlinear | | 7.89* | 8.95 | 9.66 | Nonlinear |
| GPRT | 6.87** | Nonlinear | | 7.97* | 8.39 | 9.35 | Nonlinear |
| GPRA | 6.89** | Nonlinear | | 8.25* | 8.49 | 9.79 | Nonlinear |
| WUI | 5.74* | Nonlinear | | 8.67* | 8.43 | 8.56 | Nonlinear |
| Critical Values | | | | | | | |
| 1% | 9.21 | | | | | 13.27 | |
| 5% | 5.99 | | | | 9.48 | | |
| 10% | 4.60 | | | 7.77 | | | |

**Notes:** ***, **, and * denote rejection of the null hypothesis of linearity at the 1%, 5%, and 10% levels, respectively. The $W_\lambda$ statistic follows the chi-square distribution, and the relevant critical values are 9.21 (1%), 5.99 (5%), and 4.60 (10%). The critical values for $W^*$ statistic are 13.27 (1%), 9.48 (5%), and 7.77 (10%).
**Source:** Author's compilation

All series also exhibit significant ARCH effects, suggesting that ARCH and GARCH-type models are suitable for capturing excess kurtosis and asymmetry. Additionally, Ljung-Box Q statistics for the levels and squared series indicate the presence of both linear and non-linear serial correlation. Given these characteristics, it is necessary to employ asymmetric modelling approaches.

Before conducting the empirical analysis, we perform a second set of preliminary tests to examine the linear properties of each series, using the tests of Harvey et al. (2007, 2008) with the null hypothesis of linearity against the alternative of non-linearity. Table 2 shows mixed results: the $W_\lambda$ test (Harvey et al., 2008), which generally has better size and power than the W* test (Harvey et al., 2007), rejects the null of linearity for four cases at the 5% and 10% significance levels. However, linearity is not rejected for INFR, indicating that only uncertainty indices and INFRU exhibit non-linear patterns.

**Table 3** Conventional unit root test results without structural breaks

| Variables | ADF test | | | | PP test | | |
|---|---|---|---|---|---|---|---|
| | Level | FD | I(d) | | Level | FD | I(d) |
| INFR | −2.350 | −7.783*** | I(1) | | −2.919 | −13.723*** | I(1) |
| INFRU | −4.166*** | −8.042*** | I(0) | | −3.629** | −12.239*** | I(0) |
| GPR | −5.510*** | −13.424*** | I(0) | | −7.259*** | −21.660*** | I(0) |
| GPRT | −6.260*** | −13.408*** | I(0) | | −8.523*** | −22.772*** | I(0) |
| GPRA | −4.214*** | −13.662*** | I(0) | | −5.210*** | −21.421*** | I(0) |
| WUI | −2.981 | −14.137*** | I(1) | | −5.019*** | −20.471*** | I(0) |

**Notes:** ***, and ** denote rejection of the null hypothesis at the 1% and 5% significance levels, respectively.
**Source:** Author's compilation

We further test the stationarity of the variables using the Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests, focusing on the null hypothesis with intercept and trend. Results in Table 3 show that INFR and WUI are generally I(1), while GPR, GPRT, and GPRA are mostly I(0). In addition, none of the series is I(2). In the presence of nonlinear structures and structural breaks, the conventional unit root tests may lose their explanatory power to reject the null of a unit root and thus provide misleading or biased results. These conventional tests may deceptively prove the variables to be I(1) or I(2) when there are one or more structural breaks in the series. To overcome these issues, we further apply the Zivot-Andrews (ZA) unit root test with a single unknown structural break, and the Lee-Strazicich (LS) unit root test with two unknown structural breaks. These tests have the advantage of accounting for one and two endogenous structural breaks in the intercept and both the intercept and trend terms, respectively. Using these tests allows us to determine evidence of structural break(s) in the data series and to prove the exclusion of I(2) variables.

**Table 4** Unit root test results with structural breaks

| Variables | ZA test | | | LS test | | |
|---|---|---|---|---|---|---|
| | ADF-stat | TB | | LM-stat | TB1 | TB2 |
| *Level series* | | | | | | |
| INFR | –3.973 | Feb–09 | | –5.560* | May–20 | Aug–21 |
| INFRU | –4.763** | Mar–09 | | –5.353* | Dec–11 | Jun–19 |
| GPR | –5.670*** | Oct–20 | | –6.619*** | Sep–15 | Jul–21 |
| GPRT | –6.003*** | Jul–20 | | –5.942** | Nov–21 | Dec–22 |
| GPRA | –4.820** | Aug–20 | | –6.227** | Dec–14 | Jul–21 |
| WUI | –4.857** | Jul–24 | | –6.213** | Jul–20 | Mar–23 |
| *First-Difference series* | | | | | | |
| ΔINFR | –8.754*** | Jun–20 | | –8.745*** | Nov–17 | Jun–20 |
| ΔINFRU | –7.541*** | Jan–17 | | –7.872*** | Jan–19 | Apr–20 |
| ΔGPR | –11.790*** | Apr–25 | | –10.292*** | Nov–19 | Sep–23 |
| ΔGPRT | –11.624*** | May–25 | | –10.313*** | Nov–19 | Jul–21 |
| ΔGPRA | –11.704*** | Sep–23 | | –10.665*** | Mar–17 | Jun–17 |
| ΔWUI | –11.590*** | Aug–23 | | –10.405*** | Jan–20 | Jul–22 |

**Notes:** *** denotes rejection of the null hypothesis at the 1% significance level.
**Source:** Author's compilation

The results of ZA and LS tests were summarized in Table 4. They indicate that most variables, including INFR and WUI, are I(0) once structural breaks are accounted for. The findings also confirm the presence of time breaks in the data series and show that none of the variables in the model is I(2). The identified break dates can be attributed to global economic and financial crises, socio-economic turbulence, and several political and institutional factors in Saudi Arabia and worldwide.

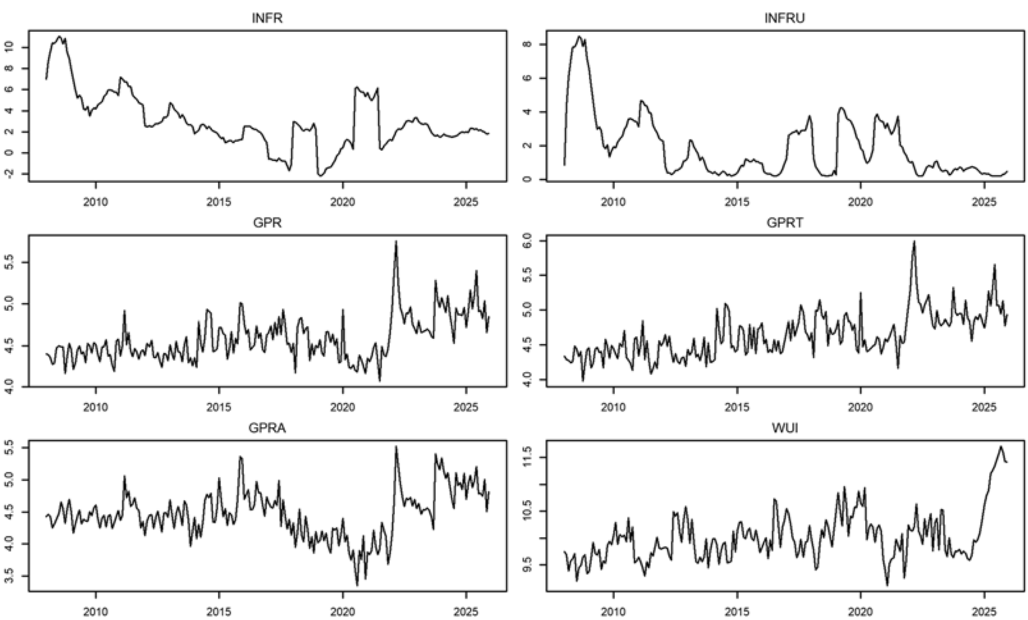
**Table 5** LML of GARCH and SV models for INFR

| GARCH | GARCH–2 | GARCH–J | GARCH–M | GARCH–MA | GARCH–t | GARCH–GJR |
|---|---|---|---|---|---|---|
| –433.438 (0.094) | –409.498 (0.139) | –370.239 (0.185) | –402.978 (0.020) | –403.658 (0.062) | –407.325 (0.081) | –409.345 (0.194) |
| SV | SV–2 | SV–J | SV–M | SV–MA | SV–t | SV–L |
| –417.419 (0.020) | –418.060 (0.062) | –419.655 (0.049) | –407.034 (0.032) | –408.547 (0.056) | –418.773 (0.028) | –419.045 (0.025) |

**Notes:** The numbers between parentheses denote the numerical standard errors.
**Source:** Author's compilation

Given that unit root tests allowing for structural breaks indicate level stationarity for all variables, we proceed with level data for our subsequent empirical analyses. Interestingly, we model the inflation volatility and hence construct the INFRU series using fourteen time-varying volatility models, including seven GARCH models and their SV counterparts. Then, we compare model performance using Bayesian techniques (Chan and Grant, 2016; Barnett et al., 2020). Comparisons are conducted pairwise between GARCH and SV models, and between flexible and standard variants within each class. Model selection is based on log marginal likelihoods (LML) computed via the improved cross-entropy method (Chan and Eisenstat, 2015), with the model exhibiting the highest LML considered the best fit. Results, displayed in Table 5, indicate that GARCH-J is identified as the most suitable model for estimating INFRU.[4]

**Figure 1** Dynamics of inflation, inflation uncertainty, and external risk measures




**Source:** Author's compilation

[4] Due to space considerations, we do not report the estimation results of the GARCH and SV models. These findings are available upon request from the corresponding author.

The summary statistics for the INFRU measure were reported in Table 1. INFRU is highly variable and right-skewed, indicating occasional large upward movements and a fat-tailed, non-normal distribution. Diagnostic tests show strong persistence and volatility clustering. Besides, the results in Tables 3–4 validate the stationarity assumption of the INFRU series at the level.

The plot of the INFRU series is shown in Figure 1. A comparison of INFR and INFRU plots across major crises shows a close but potentially nonlinear and positive relationship. INFR adjusts more gradually during events such as the global financial crisis, oil price shocks, the COVID-19 disruption, and subsequent geopolitical disturbances. At the same time, INFRU reacts with sharp, short-lived spikes that often precede or exceed inflation movements.

This pattern suggests that large shocks generate disproportionately strong uncertainty responses, indicating state-dependent and asymmetric dynamics in which uncertainty rises rapidly during stress periods and eases as conditions stabilize. Figure 1 also shows that geopolitical measures remain relatively stable over time but exhibit episodic surges, especially around 2022, reflecting heightened global tensions and their persistence at elevated levels thereafter. Meanwhile, WUI shows a more pronounced structural shift, remaining broadly stable before 2020 but increasing markedly in the post-COVID-19 pandemic period, indicating a transition toward a more uncertain global environment. Collectively, these patterns suggest that while inflationary pressures have become more contained over time, geopolitical developments and broader uncertainty have emerged as increasingly salient sources of macroeconomic risk.

## 2.2 Methods

### *2.2.1 Granger causality-in-mean tests*

Let $Y_t$ and $X_t$ be two stationary time series. Let $\mathcal{F}_{t-1}^{Y} \equiv \left(Y_{t-1},\ldots,Y_{t-s}\right)' \in \mathbb{R}^s$ and $\mathcal{F}_{t-1}^{X} \equiv \left(X_{t-1},\ldots,X_{t-q}\right)' \in \mathbb{R}^q$ denote the past information sets of $Y_t$ and $X_t$, respectively. The null hypothesis of Granger causality-in-distribution (Granger, 1969) from $X_t$ to $Y_t$ is given by:

$$F_Y\left(y \mid \mathcal{F}_{t-1}^{Y}, \mathcal{F}_{t-1}^{X}\right) = F_Y\left(y \mid \mathcal{F}_{t-1}^{Y}\right); \quad \forall y \in \mathbb{R} \tag{1}$$

where $F_Y(.)$ is the conditional distribution function operator.

In practice, the linear Granger causality-in-mean test is commonly used, with the null hypothesis given by:

$$\mathbb{E}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}, \mathcal{F}_{t-1}^{X}\right) = \mathbb{E}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}\right) \tag{2}$$

where $\mathbb{E}(.)$ is the conditional mean operator.

The null hypothesis given by Formula (2) is tested using the following VAR(p) model:

$$Y_t = \sum_{j=1}^{p} \alpha_j Y_{t-j} + \sum_{j=1}^{p} \beta_j X_{t-j} + \varepsilon_t \tag{3}$$

where $p$ is selected using BIC.

We test for nonlinearity in VAR residuals using BDS and parameter stability tests (SupF, AveF, and ExpF) proposed by Andrews (1993), Andrews and Ploberger (1994), and Hansen (1997). If nonlinearity is detected, we apply nonlinear Granger causality-in-mean tests (Hiemstra and Jones, 1994; Diks and Panchenko, 2006 on the standardized VAR residuals.

### *2.2.2 Granger causality-in-quantiles tests*

The Granger causality-in-mean tests overlook dependence in the tails of the conditional distribution. Therefore, we employ the Granger causality-in-quantiles test of Troster (2018), which allows detecting the possibly nonlinear or asymmetrical relationship between and across the conditional distribution[5]. This test is described by the following null hypothesis:

$$Q_\tau^{Y,X}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}, \mathcal{F}_{t-1}^{X}\right) = Q_\tau^{Y}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}\right); \quad \forall\, \tau \in (0,1) \tag{4}$$

where $Q_\tau^{Y,X}\left(. \mid \mathcal{F}_{t-1}^{Y}, \mathcal{F}_{t-1}^{X}\right)$ and $Q_\tau^{Y}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}\right)$ denote the $\tau$-quantiles of $F_Y\left(. \mid I_t^Y, I_t^X\right)$ and $F_Y\left(. \mid I_t^Y\right)$, respectively.

Under the null hypothesis, Troster (2018) proposed the following test statistic[6]

$$S_T = \frac{1}{Tn}\sum_{j=1}^{n}\left|\psi'_{.j}\boldsymbol{W}\psi_{.j}\right| \tag{5}$$

where $\boldsymbol{W}$ is a weighting matrix, $\psi'_{.j}$ is the jth column of the ψ matrix, with elements $\psi_{i,j} = \Psi_{\tau j}\left(Y_i - m\left(\mathcal{F}_i^Y, \theta_T\left(\tau_j\right)\right)\right)$. Here, the function $\Psi_{\tau j}(.)$ is defined as $\Psi_{\tau j}(\varepsilon) \equiv 1(\varepsilon \le 0) - \tau_j$ for all $\tau \in (0,1)$, and $m\left(\mathcal{F}_i^Y, \theta_T\left(\tau_j\right)\right)$ is a parametric quantile autoregressive (QAR) model for the conditional $\tau$-quantile of $Y_i$.

We implement the $S_T$ statistic defined in Formula (5) by specifying the following three linear parametric QAR models to model the conditional quantiles of $Y_t$ for all $\tau \in (0,1)$:

$$QAR(1): m^1\left(\mathcal{F}_{t-1}^{Y}, \theta_T(\tau)\right) = \mu_0(\tau) + \mu_1(\tau)Y_{t-1} + \sigma_t\Phi_\varepsilon^{-1}(\tau) \tag{6}$$

$$QAR(2): m^2\left(\mathcal{F}_{t-1}^{Y}, \theta_T(\tau)\right) = \mu_0(\tau) + \mu_1(\tau)Y_{t-1} + \mu_2(\tau)Y_{t-2} + \sigma_t\Phi_\varepsilon^{-1}(\tau) \tag{7}$$

$$QAR(3): m^3\left(\mathcal{F}_{t-1}^{Y}, \theta_T(\tau)\right) = \mu_0(\tau) + \mu_1(\tau)Y_{t-1} + \mu_2(\tau)Y_{t-2} + \mu_3(\tau)Y_{t-3} + \sigma_t\Phi_\varepsilon^{-1}(\tau) \tag{8}$$

where the parameters $\theta(\tau) = \left(\mu_0(\tau), \mu_1(\tau), \mu_2(\tau), \mu_3(\tau), \sigma_t\right)'$ are estimated using the maximum likelihood method for all $\tau \in (0,1)$, and $\Phi_\varepsilon^{-1}(\tau)$ denotes the inverse of the standard normal distribution function.

To check the sign of the causal relationship between the series, we estimate the QAR models in Formula (6)- Formula (8) including lagged variables of another variable. We provide the results using the following extended QAR models:

$$QAR(1): Q_\tau^{Y}\left(Y_t \mid \mathcal{F}_{t-1}^{Y}, \mathcal{F}_{t-1}^{Z}\right) = \mu_1(\tau) + \mu_2(\tau)Y_{t-1} + \beta(\tau)Z_{t-1} + \sigma_t\Phi_\varepsilon^{-1}(\tau) \tag{9}$$

[5] For more details, see Troster et al. (2018), Troster et al. (2019), Ahmed et al. (2022), Mighri et al. (2022), Mighri and Sarkodie (2024), and Mighri et al. (2026), among others.

[6] The critical values for $S_T$ are obtained via subsampling.

$$QAR(2): Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y, \mathcal{F}_{t-1}^Z\right) = \mu_1(\tau) + \mu_2(\tau) Y_{t-1} + \mu_3(\tau) Y_{t-2} + \beta(\tau) Z_{t-1} + \sigma_t \Phi_\varepsilon^{-1}(\tau) \quad (10)$$

$$QAR(3): Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y, \mathcal{F}_{t-1}^Z\right) = \mu_1(\tau) + \mu_2(\tau) Y_{t-1} + \mu_3(\tau) Y_{t-2} + \mu_4(\tau) Y_{t-3} + \beta(\tau) Z_{t-1} + \sigma_t \Phi_\varepsilon^{-1}(\tau) \quad (11)$$

where the parameters $\mu_i(\tau)$ for $i = 1,2,3$, $\beta(\tau)$, and $\sigma_t$ are estimated by maximum likelihood for all $\tau \in (0,1)$.

In Formula (9)–Formula (11), we focus on the sign of the estimated parameter $\beta(\tau)$. If $\beta(\tau) > 0$, then increases (decreases) in $Z$ will lead to increases (decreases) in $Y$. On the contrary, if $\beta(\tau) < 0$, then increases (decreases) in $Z$ will result in decreases (increases) in $Y$.

The modeling framework advanced by Troster (2018) allows for any $\sqrt{T}$-consistent estimator of $\theta_T(\tau)$ such as the CAViaR estimator by Engle and Manganelli (2004). Troster et al., 2019 introduced nonlinear QAR models using CAViaR specifications, which specify an AR process of conditional quantiles. Interestingly, we employ two specifications of the nonlinear CAViaR models, namely the symmetric absolute value (SAV) and the asymmetric slope (AS). Formally, both SAV and AS are specified as follows:

$$SAV: Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y\right) = \alpha(\tau) + \beta(\tau) Q_\tau^Y\left(Y_{t-1} \setminus \mathcal{F}_{t-2}^Y\right) + \gamma(\tau)\left|Y_{t-1}\right| \quad (12)$$

$$AS: Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y\right) = \alpha(\tau) + \beta(\tau) Q_\tau^Y\left(Y_{t-1} \setminus \mathcal{F}_{t-2}^Y\right) + \gamma(\tau)\left(Y_{t-1}\right)^+ + \delta(\tau)\left(Y_{t-1}\right)^- \quad (13)$$

where $(Y_{t-1})^+ = \max(Y_{t-1}, 0)$ and $(Y_{t-1})^- = -\min(Y_{t-1}, 0)$.

To evaluate the sign of nonlinear Granger causality-in-quantiles, we extend the nonlinear CAViaR models by including lagged values of $Z_t$, i.e.,

$$SAV: Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y\right) = \alpha(\tau) + \beta(\tau) Q_\tau^Y\left(Y_{t-1} \setminus \mathcal{F}_{t-2}^Y\right) + \gamma(\tau)\left|Y_{t-1}\right| + \theta(\tau) Z_{t-1} \quad (14)$$

$$AS: Q_\tau^Y\left(Y_t \setminus \mathcal{F}_{t-1}^Y\right) = \alpha(\tau) + \beta(\tau) Q_\tau^Y\left(Y_{t-1} \setminus \mathcal{F}_{t-2}^Y\right) + \gamma(\tau)\left(Y_{t-1}\right)^+ + \delta(\tau)\left(Y_{t-1}\right)^- + \theta(\tau) Z_{t-1} \quad (15)$$

The sign of nonlinear Granger causality-in-quantiles is determined by the estimated coefficient $\theta(\tau)$. Specifically, if $\theta(\tau) > 0$, this indicates positive nonlinear causality, implying that increases (decreases) in $Z_{t-1}$ lead to increases (decreases) in the conditional quantile of $Y_t$. Conversely, if $\theta(\tau) < 0$, this indicates negative nonlinear causality, implying that increases (decreases) in $Z_{t-1}$ lead to decreases (increases) in the conditional quantile of $Y_t$.

## 3 RESULTS AND DISCUSSION

### 3.1 Preliminary test results

We begin the causality analysis with the conventional linear Granger causality test based on VAR(p) models. Consistent with the unit root test results, we use the variables in levels rather than their first differences. The findings, reported in Table 6, indicate no strong evidence of linear Granger causality between uncertainty indicators and inflation. The only weak result is a marginal effect from INFR to GPRT at the 10% significance level. This lack of significance may reflect nonlinearity or non-normality in the data. Additionally, the BG (Breusch, 1978; Godfrey, 1978) and ES (Edgerton and Shukur, 1999) tests indicate no serial correlation in the VAR residuals, confirming that the models are well specified.

Overall, linear relationships between inflation and uncertainty measures are absent, suggesting that standard linear Granger causality tests in the mean may be misspecified.

**Table 6** Tests for linear Granger causality in mean and serial correlation in VAR residuals

| | p-value (F-test) | *p* | P-Value (BG-test) | p-value (ES-test) |
|---|---|---|---|---|
| INFRU to INFR | 0.417 | 2 | 0.300 | 0.317 |
| GPR to INFR | 0.784 | 1 | 0.219 | 0.238 |
| GPRT to INFR | 0.327 | 2 | 0.727 | 0.765 |
| GPRA to INFR | 0.997 | 2 | 0.216 | 0.241 |
| WUI to INFR | 0.147 | 1 | 0.185 | 0.199 |
| INFR to INFRU | 0.623 | 2 | 0.300 | 0.317 |

**Note:** The optimal lag length p of VAR model is selected based on BIC, with a maximum lag length set to 12, such that VAR residuals are serially uncorrelated under the null hypothesis. To address potential heteroskedasticity in the residuals, we employ a robust heteroskedasticity-consistent covariance matrix estimator for VAR residuals (MacKinnon and White, 1985). The superscript ** indicates statistical significance at the 5% level.
**Source:** Authors' compilation

We further examine potential nonlinearity in the causal relationships between inflation and uncertainty measures using the BDS test for nonlinearity in VAR residuals (see Table 7). Significant results appear only for GPRT → INFR, showing strong evidence of nonlinearity. However, most remaining pairs of variables show insignificant nonlinearity. Overall, there is evidence of nonlinear dynamics, particularly involving geopolitical risk threats and inflation, suggesting that linear models may be insufficient and thus supporting the use of nonlinear models.

**Table 7** Tests for nonlinearity in VAR residuals, parameter constancy, and parameter stability

| | BDS (m=2) | BDS (m=3) | BDS (m=4) | SupF | AveF | ExpF |
|---|---|---|---|---|---|---|
| INFR, INFRU | 0.617 | 0.542 | 0.464 | 0.000*** | 0.056* | 0.000*** |
| INFR, GPR | 0.119 | 0.212 | 0.348 | 0.000*** | 0.050* | 0.000*** |
| INFR, GPRT | 0.007*** | 0.011** | 0.007*** | 0.001*** | 0.123 | 0.002*** |
| INFR, GPRA | 0.778 | 0.673 | 0.569 | 0.001*** | 0.108 | 0.001*** |
| INFR, WUI | 0.116 | 0.210 | 0.344 | 0.000*** | 0.047** | 0.001*** |
| INFRU, INFR | 0.986 | 0.895 | 0.866 | 0.000*** | 0.000*** | 0.000*** |

**Note:** The superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
**Source:** Authors' compilation

In addition, we assess parameter constancy and stability using the SupF, AveF, and ExpF tests. The results in Table 7 indicate that all SupF and ExpF statistics are statistically significant, implying parameter instability and structural changes in the relationships between inflation and uncertainty variables. Only limited evidence of stability appears in some AveF results. Overall, the results suggest that model parameters are generally not constant over time, supporting the presence of structural changes and reinforcing the need for nonlinear or time-varying modelling approaches.

Based on the BDS test results, we apply nonlinear Granger causality tests in the mean. Table 8 reports test results for nonlinear Granger causality in the mean using the HJ (Hiemstra and Jones, 1994) and DP (Diks and Panchenko, 2006) tests. The findings indicate no evidence of nonlinear causality from uncertainty indicators to inflation. There is only evidence of a nonlinear causality from inflation to its uncertainty using the DP test. Overall, nonlinear effects mainly run from inflation to inflation uncertainty, while the remaining uncertainty indicators do not significantly predict inflation in a nonlinear framework.

**Table 8** Tests for nonlinear Granger causality-in-mean

| | ***L*** | **P-value (HJ)** | **P-value (DP)** |
|---|---|---|---|
| INFRU to INFR | 2 | 0.734 | 0.640 |
| GPR to INFR | 1 | 0.899 | 0.912 |
| GPRT to INFR | 2 | 0.633 | 0.316 |
| GPRA to INFR | 2 | 0.609 | 0.337 |
| WUI to INFR | 1 | 0.945 | 0.931 |
| INFR to INFRU | 2 | 0.978 | 0.041** |

**Note:** The optimal lag length ***L*** of bivariate VAR models is selected based on BIC such that VAR residuals are serially uncorrelated under the null hypothesis. The superscript ** indicates statistical significance at the 5% level.
**Source:** Authors' compilation

### 3.2 Linear Granger causality-in-quantiles results

To apply the linear Granger causality-in-quantiles test, we use a grid of 9 quantiles, i.e., $T_n = \{\tau_j\}_{j=1}^{n} =$ .[0.10,0.90].[7] We classify the distribution into lower ([0.10, 0.30]), middle ([0.40, 0.60]), and upper ([0.70, 0.90]) quantile intervals. Interestingly, we examine the Granger causality at each quantile $\tau$ using the $S_T$ test statistic, while considering only stationary variables. The $S_T$ statistic is calculated using a subsample size of $b = \left[ kT^{2/5} \right] \approx 43$, with $k = 5$ and T = 216.[8]

The results in Table 9 suggest that inflation uncertainty and geopolitical risk play an important role in shaping inflation dynamics in Saudi Arabia, particularly during extreme inflation conditions. The significant causality from inflation uncertainty and geopolitical risk measures to inflation at the lower and upper quantiles indicates that external uncertainty and global risk shocks affect Saudi inflation mainly during periods of unusually low or high inflation, rather than during normal conditions. This reflects Saudi Arabia's strong integration with global markets, especially through oil prices, trade and financial channels, making domestic inflation sensitive to global uncertainty shocks in stressed environments.

Meanwhile, the strong causal effect from inflation to inflation uncertainty across most quantiles implies that higher or more volatile inflation increases uncertainty about future price developments, highlighting feedback effects in domestic price dynamics. Besides, the findings are highly consistent across the two- and three-lag specifications of the QAR model, suggesting that the detected causal relationships are robust and not sensitive to lag length. Overall, the results indicate that Saudi inflation is driven by both internal uncertainty and global geopolitical risk conditions, with effects that are asymmetric and state-dependent.

[7] To conserve space, we do not report the results for a grid of 19 quantiles as they do not alter our conclusion. These results are available from the corresponding author upon request.
[8] Our results remain similar for other values of the constant parameter *k*.

**Table 9** Linear Granger causality-in-quantiles test results

| $\tau$ | INFRU to INFR | | | INFR to INFRU | | | GPR to INFR | | |
|---|---|---|---|---|---|---|---|---|---|
| | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** |
| 0.10 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.20 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.30 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.40 | 0.006*** | 0.017** | 0.006*** | 0.128 | 0.070* | 0.093* | 0.006*** | 0.006*** | 0.006*** |
| 0.50 | 0.576 | 0.500 | 0.517 | 0.105 | 0.006*** | 0.006*** | 0.523 | 0.488 | 0.500 |
| 0.60 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.70 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.80 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.90 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| $\forall\tau$ | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| $\tau$ | **GPRT to INFR** | | | **GPRA to INFR** | | | **WUI to INFR** | | |
| | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** | ***L*** **= 1** | ***L*** **= 2** | ***L*** **= 3** |
| 0.10 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.20 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.30 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.40 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.50 | 0.529 | 0.488 | 0.494 | 0.523 | 0.488 | 0.500 | 0.576 | 0.547 | 0.523 |
| 0.60 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.70 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.80 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| 0.90 | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| $\forall\tau$ | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |

**Note:** This table reports the subsampling p-values for the $S_T$ statistic. $L$ is the lag order of the QAR model. The superscripts ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.
**Source:** Authors' compilation

The linear Granger causality-in-quantiles analysis reveals the lead-lag relationships between uncertainty measures and inflation. However, understanding these relationships requires not only establishing causality but also determining the direction and sign of the causal effects. To address this, we employ quantile regression (QR) estimates, which complement Granger causality-in-quantiles by allowing interpretation of the sign of causal relationships. More importantly, we assess the sign of linear Granger causality-in-quantiles by estimating three QAR models as described in Formula (9)–Formula (11).

Table 10 reports the sign and magnitude of the linear Granger causality-in-quantiles effects using QAR models, showing whether the causal impact is positive or negative across quantiles. The results indicate that global geopolitical risk and inflation uncertainty generally exert positive effects on Saudi inflation, although their impacts are not consistently significant across all quantiles. In contrast, inflation strongly and positively influences inflation uncertainty across most quantiles, indicating a reinforcing feedback effect in domestic price dynamics and hence supporting the Friedman-Ball hypothesis. The findings also show that geopolitical threats generally exert a positive but weak effect on Saudi inflation, with significance mainly at lower quantiles, while geopolitical acts have no systematic impact on inflation.

**Table 10** Sign of linear Granger causality-in-quantiles

| $\tau$ | INFRU to INFR | | | | INFR to INFRU | | | | GPR to INFR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | QAR(1) | QAR(2) | QAR(3) | | QAR(1) | QAR(2) | QAR(3) | | QAR(1) | QAR(2) | QAR(3) |
| 0.10 | 0.130 | 0.121 | 0.136 | | 0.263*** | 0.286*** | 0.289*** | | 0.246 | 0.342 | 0.212 |
| 0.20 | 0.033 | 0.046 | 0.052 | | 0.333*** | 0.333*** | 0.331*** | | 0.325 | 0.224 | 0.164 |
| 0.30 | 0.055 | 0.015 | 0.023 | | 0.322*** | 0.322*** | 0.323*** | | −0.003 | −0.007 | −0.130 |
| 0.40 | 0.047 | −0.004 | −0.031 | | 0.310*** | 0.309*** | 0.312*** | | −0.002 | −0.063 | −0.047 |
| 0.50 | 0.029 | −0.025 | −0.030 | | 0.312*** | 0.314*** | 0.309*** | | 0.041 | 0.039 | 0.048 |
| 0.60 | 0.080 | −0.041 | −0.046 | | 0.321*** | 0.322*** | 0.322*** | | 0.022 | −0.034 | 0.001 |
| 0.70 | 0.108 | −0.024 | −0.047 | | 0.332*** | 0.328*** | 0.324*** | | 0.053 | 0.047 | 0.047 |
| 0.80 | 0.107 | 0.090 | −0.050 | | 0.347*** | 0.332*** | 0.284*** | | 0.309 | 0.340 | 0.172 |
| 0.90 | 0.092 | 0.143 | 0.101 | | 0.246*** | 0.250*** | 0.253*** | | 0.146 | 0.199 | 0.207 |
| $\tau$ | GPRT to INFR | | | | GPRA to INFR | | | | WUI to INFR | | |
| | QAR(1) | QAR(2) | QAR(3) | | QAR(1) | QAR(2) | QAR(3) | | QAR(1) | QAR(2) | QAR(3) |
| 0.10 | 0.400 | 0.445 | 0.211 | | 0.101 | 0.111 | 0.004 | | −0.048 | −0.046 | −0.053 |
| 0.20 | 0.310* | 0.328* | 0.328* | | 0.000 | −0.009 | −0.081 | | 0.093 | 0.077 | 0.092 |
| 0.30 | 0.004 | 0.018 | −0.001 | | −0.019 | −0.087 | −0.105 | | 0.123 | 0.119 | 0.130 |
| 0.40 | −0.002 | −0.051 | −0.041 | | 0.016 | 0.009 | 0.004 | | 0.041 | 0.047 | 0.049 |
| 0.50 | 0.006 | −0.004 | −0.010 | | 0.058 | 0.054 | 0.058 | | 0.021 | 0.032 | 0.030 |
| 0.60 | 0.010 | −0.036 | −0.042 | | 0.010 | 0.005 | 0.001 | | 0.007 | −0.001 | −0.003 |
| 0.70 | 0.047 | 0.045 | 0.046 | | 0.026 | 0.037 | 0.031 | | −0.048 | −0.055 | −0.040 |
| 0.80 | 0.251 | 0.275 | 0.261 | | 0.192 | 0.100 | 0.067 | | −0.077 | −0.102 | −0.103 |
| 0.90 | 0.145 | 0.159 | 0.183 | | −0.027 | −0.028 | −0.044 | | −0.057 | −0.081 | −0.093 |

**Note:** The superscripts ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.
**Source:** Authors' compilation

### 3.3 Nonlinear Granger causality-in-quantiles results

We now turn to the nonlinear Granger causality-in-quantiles test results using nonlinear CAViaR models (SAV and AS). To motivate this choice, we first compare quantile forecasts for INFR using linear and nonlinear QR models. Specifically, we compare the root mean squared error (RMSE) of 120 recursive monthly out-of-sample quantile forecasts of all selected quantiles of the distribution. The first forecast was performed on January 1, 2016. For each forecast, the in-sample period was expanded by one month to generate updated predictions.

**Table 11** RMSE of out-of-sample quantile forecasts

| $\tau$ | QAR(1) | QAR(2) | QAR(3) | SAV | AS |
|---|---|---|---|---|---|
| 0.10 | 1.0298 | **1.0072** | 1.0240 | 1.7306 | 1.0605 |
| 0.20 | 0.9721 | **0.9672** | 0.9708 | 1.4103 | 0.9902 |
| 0.30 | 0.9572 | **0.9534** | 0.9577 | 1.3497 | 0.9671 |
| 0.40 | 0.9538 | **0.9506** | 0.9516 | 1.3421 | 0.9608 |
| 0.50 | 0.9542 | 0.9552 | 0.9563 | 1.3486 | 0.9539 |
| 0.60 | 0.9570 | 0.9557 | 0.9574 | 1.3642 | 0.9541 |
| 0.70 | **0.9615** | 0.9635 | 0.9647 | 1.3714 | 0.9696 |
| 0.80 | 0.9908 | 0.9992 | 1.0027 | 1.3447 | 0.9809 |
| 0.90 | **1.0398** | 1.0494 | 1.0604 | 1.3657 | 1.1633 |

**Note:** The model with the lowest RMSE value is in bold.
**Source:** Authors' compilation

Table 11 compares the forecasting performance of linear QAR and nonlinear CAViaR models (SAV, AS) for predicting changes in inflation. The results indicate that forecasting performance varies across inflation regimes. Linear QAR models yield the lowest RMSE values, particularly at the lower and upper quantiles, thereby outperforming and offering better specification than their competing nonlinear CAViaR models. This finding suggests that inflation dynamics are relatively stable and linear during low- and high-inflation periods. However, nonlinear CAViaR models become more competitive or outperform at the middle and upper quantiles, indicating that inflation exhibits stronger nonlinear and asymmetric behaviour in normal and high-inflation regimes.

**Table 12** Nonlinear Granger causality-in-quantiles test results

| $\tau$ | INFRU to INFR | | | INFR to INFRU | | | GPR to INFR | |
|---|---|---|---|---|---|---|---|---|
| | SAV | AS | | SAV | AS | | SAV | AS |
| ∀τ | 0.007*** | 0.355 | | 0.014** | 0.022** | | 0.007*** | 0.341 |
| 0.10 | 0.007*** | 0.551 | | 0.029** | 0.022** | | 0.007*** | 0.348 |
| 0.20 | 0.007*** | 0.464 | | 0.007*** | 0.007*** | | 0.007*** | 0.326 |
| 0.30 | 0.007*** | 0.486 | | 0.029** | 0.036** | | 0.007*** | 0.696 |
| 0.40 | 0.007*** | 0.203 | | 0.159 | 0.180 | | 0.080* | 0.572 |
| 0.50 | 0.268 | 0.558 | | 0.094* | 0.138 | | 0.290 | 0.638 |
| 0.60 | 0.377 | 0.377 | | 0.145 | 0.145 | | 0.399 | 0.239 |
| 0.70 | 0.449 | 0.384 | | 0.159 | 0.087* | | 0.391 | 0.188 |
| 0.80 | 0.333 | 0.181 | | 0.065* | 0.043** | | 0.225 | 0.167 |
| 0.90 | 0.493 | 0.058* | | 0.065* | 0.130 | | 0.384 | 0.036** |
| $\tau$ | GPRT to INFR | | | GPRA to INFR | | | WUI to INFR | |
| | SAV | AS | | SAV | AS | | SAV | AS |
| ∀τ | 0.007*** | 0.312 | | 0.007*** | 0.275 | | 0.007 | 0.268 |
| 0.10 | 0.007*** | 0.406 | | 0.007*** | 0.283 | | 0.007*** | 0.420 |
| 0.20 | 0.007*** | 0.261 | | 0.007*** | 0.500 | | 0.007*** | 0.275 |
| 0.30 | 0.007*** | 0.652 | | 0.007*** | 0.725 | | 0.007*** | 0.283 |
| 0.40 | 0.080* | 0.594 | | 0.087* | 0.601 | | 0.058* | 0.457 |
| 0.50 | 0.297 | 0.645 | | 0.297 | 0.630 | | 0.261 | 0.623 |
| 0.60 | 0.391 | 0.246 | | 0.399 | 0.210 | | 0.362 | 0.254 |
| 0.70 | 0.384 | 0.181 | | 0.362 | 0.167 | | 0.362 | 0.232 |
| 0.80 | 0.210 | 0.116 | | 0.210 | 0.087* | | 0.348 | 0.507 |
| 0.90 | 0.326 | 0.036** | | 0.341 | 0.036** | | 0.341 | 0.065* |

**Note:** This table reports the subsampling p-values for the $\boldsymbol{S_T}$ statistic. The superscripts ***, **, and * indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.
**Source:** Authors' compilation

Table 12 displays the nonlinear Granger causality-in-quantiles test results for INFR using nonlinear quantile specifications under $H_0$ in Formula (3). The results show evidence of nonlinear, quantile-dependent causality between inflation and uncertainty measures. This suggests that Saudi inflation responds asymmetrically to global uncertainty and domestic inflation dynamics, particularly during specific economic conditions. The SAV specification reveals strong nonlinear causal effects from inflation uncertainty and geopolitical risk indicators (GPR, GPRT, GPRA) to Saudi inflation, mainly at lower quantiles, indicating that uncertainty and external risk shocks influence domestic inflation primarily during low-inflation periods. This may reflect a stronger sensitivity of domestic prices to global developments when inflationary pressures are subdued, possibly through oil prices, import costs, and global market conditions. The strong nonlinear feedback from inflation to its uncertainty, particularly at lower and (extreme) upper quantiles, implies that inflation fluctuations increase uncertainty about future price movements, reinforcing instability in domestic price expectations. Overall, the findings highlight the dominant role of external uncertainty in shaping Saudi inflation and the presence of asymmetric state-dependent inflation dynamics.

Table 13 reports the sign of nonlinear Granger causality-in-quantiles, allowing us to identify not only whether causal relationships exist but also whether their effects are positive or negative across different quantiles of the distribution. The results indicate that the only robust nonlinear causal relationship is from inflation uncertainty to inflation, which is significantly negative at lower and middle quantiles, implying that higher uncertainty dampens inflation, particularly in low-inflation regimes. This effect gradually weakens and becomes insignificant toward the upper quantiles, highlighting strong state-dependent behaviour. In contrast, there is no evidence of a reverse causal effect (INFR to INFRU), and geopolitical risk measures exhibit sporadic and mostly insignificant effects, with only limited significance at specific quantiles. Overall, the direction of causality is predominantly negative and driven by domestic uncertainty, while external risk factors play a minor and inconsistent role across different market conditions.

**Table 13** Sign of nonlinear Granger causality-in-quantiles

| $\tau$ | INFRU to INFR | | | INFR to INFRU | | | GPR to INFR | |
|---|---|---|---|---|---|---|---|---|
| | SAV | AS | | SAV | AS | | SAV | AS |
| 0.10 | −0.773*** | −0.021 | | 0.006 | 0.002 | | −0.323 | −0.074 |
| 0.20 | −0.520*** | 0.014 | | 0.015 | −0.004 | | 0.618 | −0.054 |
| 0.30 | −0.422*** | 0.02 | | 0.01 | −0.004 | | 0.331 | 0.087 |
| 0.40 | −0.345*** | 0.026 | | 0.021 | 0.019 | | 0.22 | 0.042 |
| 0.50 | −0.198* | 0.006 | | 0.003 | 0.003 | | 0.128 | −0.092 |
| 0.60 | −0.082 | 0.047 | | 0.006 | 0.007 | | 0.046 | −0.076 |
| 0.70 | −0.05 | 0.057 | | −0.008 | −0.009 | | −0.001 | −0.08 |
| 0.80 | −0.026 | 0.077 | | 0.004 | 0.031 | | 0.037 | −0.09 |
| 0.90 | 0.012 | 0.065 | | −0.002 | −0.003 | | −0.028 | −0.068 |
| $\tau$ | GPRT to INFR | | | GPRA to INFR | | | WUI to INFR | |
| | SAV | AS | | SAV | AS | | SAV | AS |
| 0.10 | 1.183 | 0.188 | | 0.183 | −0.039 | | −0.094 | 0.009 |
| 0.20 | 0.45 | −0.06 | | 0.322 | 0.066 | | 0.122 | 0.008 |
| 0.30 | 0.269 | 0.081 | | 0.212 | −0.054 | | 0.038 | 0.008 |
| 0.40 | 0.193 | 0.072 | | 0.108 | 0.043 | | 0.062 | 0.001 |
| 0.50 | 0.152 | 0.021 | | 0.084 | −0.061 | | 0.081 | 0.001 |
| 0.60 | 0.064 | 0.035 | | −0.0003 | −0.072 | | 0.006 | 0.008 |
| 0.70 | 0.12 | −0.033 | | −0.02 | −0.076 | | 0.018 | 0.007 |
| 0.80 | 0.087 | −0.038 | | −0.123 | −0.158 | | 0.054 | 0.039 |
| 0.90 | 0.195 | −0.006 | | −0.157 | −0.151 | | −0.009 | 0.099 |

**Note:** The superscripts ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.
**Source:** Authors' compilation

### 3.4 Robustness checks

As a robustness check, the inclusion of WUI as an alternative global risk measure confirms the limited role of external uncertainty in driving inflation dynamics in Saudi Arabia. While the nonlinear Granger causality-in-quantiles results indicate some evidence of causality from WUI to inflation at specific quantiles, particularly in the lower and upper tails, these effects are neither consistent nor stable across the distribution. Moreover, the sign analysis reveals that the impact of WUI is weak, mixed, and statistically insignificant across most quantiles, with no clear directional pattern. Overall, these findings suggest that global uncertainty does not exert a robust or systematic influence on inflation, reinforcing the conclusion that domestic factors, rather than external risk measures, play a more dominant role in shaping inflationary dynamics in Saudi Arabia.

## 4 CONCLUSION, POLICY IMPLICATIONS, AND LIMITATIONS

The findings of this study underscore the importance of nonlinear and state-dependent dynamics in understanding inflation dynamics in Saudi Arabia. While linear Granger causality-in-quantiles confirms bidirectional linkages between inflation and inflation uncertainty, the sign analysis reveals that inflation tends to increase its uncertainty, whereas nonlinear results show that inflation uncertainty can reduce inflation in lower and middle regimes, supporting the Friedman and Friedman-Ball hypotheses, respectively. In contrast, although global geopolitical risk measures exhibit significant causal effects, their direction is unstable and lacks consistency, indicating a limited and non-systematic role in driving inflation.

These results carry several important policy implications. First, the Saudi central bank should strengthen policy credibility and communication strategies to anchor inflation expectations and reduce uncertainty, particularly given its measurable impact on inflation dynamics. Second, the negative effect of uncertainty on inflation in low-inflation regimes suggests that policymakers should avoid excessive tightening during such periods, as uncertainty itself may already dampen inflationary pressures. Third, given the weak and unstable influence of global geopolitical risks, monetary policy should remain primarily focused on domestic conditions, while external shocks should be managed through targeted fiscal and structural policies, especially those linked to oil revenue stabilization. Finally, the presence of quantile-dependent effects highlights the need for state-contingent policy frameworks, where policy responses are adapted to prevailing inflation regimes rather than relying on a uniform approach, thereby enhancing the effectiveness of macroeconomic stabilization in Saudi Arabia.

This study is not without limitations and offers avenues for future research. Future studies may extend the analysis by integrating time-frequency coherence and quantile causality frameworks, employing wavelet transforms to capture dynamic interactions and lead-lag relationships across different frequencies. Moreover, future research could expand the analysis to include all Gulf Cooperation Council countries, enabling a comparative assessment of inflation-uncertainty dynamics across oil-dependent economies. Finally, given the increasing political tensions between the U.S. and Iran, which have recently intensified and affected regional stability, energy infrastructure, and economic conditions in the Gulf, further investigation is warranted to better understand how such evolving geopolitical risks influence inflation dynamics in Saudi Arabia and the broader region.

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## *References*

ADEOSUN, O. A., TABASH, M. I., VO, X. V., ANAGREH, S. (2023). Uncertainty measures and inflation dynamics in selected global players: a wavelet approach. *Quality and Quantity* 57, 3389-3424. https://doi.org/10.1007/s11135-022-01513-7.

AHMED, A., GRANBERG, M., TROSTER, V., UDDIN, G. S. (2022). Asymmetric dynamics between uncertainty and unemployment flows in the United States. *Studies in Nonlinear Dynamics and Econometrics*, 26(1), 155–172. https://doi.org/10.1515/snde-2019-0058.

ALBULESCU, C. T., TIWARI, A. K., MILLER, S. M., GUPTA, R. (2019). Time–frequency relationship between US inflation and inflation uncertainty: evidence from historical data. *Scottish Journal of Political Economy*, 66(5), 673–702. https://doi.org/10.1111/sjpe.12207.

ALIEDAN, M. (2022). The Geopolitics of International Trade in Saudi Arabia: Saudi Vision 2030. *Cuadernos de Economia*, 45(127), 11–19. https://doi.org/10.32826/cude.v1i127.601.

ANDREWS, D. W. K. (1993). Tests for Parameter Instability and Structural Change With Unknown Change Point. *Econometrica*, 61(4), 821. https://doi.org/10.2307/2951764.

ANDREWS, D. W. K., PLOBERGER, W. (1994). Optimal Tests when a Nuisance Parameter is Present Only Under the Alternative. *Econometrica*, 62(6), 1383. https://doi.org/10.2307/2951753.

BALL, L. (1992). Why does high inflation raise inflation uncertainty? *Journal of Monetary Economics*, 29(3), 371–388. https://doi.org/10.1016/0304-3932(92)90032-W.

BARNETT, W. A., JAWADI, F., FTITI, Z. (2020). Causal relationships between inflation and inflation uncertainty. *Studies in Nonlinear Dynamics and Econometrics* 24(5). https://doi.org/10.1515/snde-2019-0094.

BERUMENT, H., DINCER, N. (2005). Inflation and inflation uncertainty in the G-7 countries. *Physica A: Statistical Mechanics and Its Applications*, 348, 371–379. https://doi.org/10.1016/j.physa.2004.09.003.

BOURI, E., GABAUER, D., GUPTA, R., KINATEDER, H. (2023). Global geopolitical risk and inflation spillovers across European and North American economies. *Research in International Business and Finance*, 66, 102048. https://doi.org/10.1016/j.ribaf.2023.102048.

BREUSCH, T. S. (1978). Testing for Autocorrelation in Dynamic Linear Models. *Australian Economic Papers*, 17(31), 334–355. https://doi.org/10.1111/j.1467-8454.1978.tb00635.x.

CALDARA, D., IACOVIELLO, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, 112(4), 1194-1225. https://doi.org/10.1257/aer.20191823.

CALDARA, D., CONLISK, S., IACOVIELLO, M., PENN, M. Do Geopolitical Risks Raise or Lower Inflation?. *Journal of International Economics*, 159, 104188. https://doi.org/10.1016/j.jinteco.2025.104188.

CHAN, J. C. C., EISENSTAT, E. (2015). Marginal Likelihood Estimation with the Cross-Entropy Method. *Econometric Reviews*, 34(3), 256–285. https://doi.org/10.1080/07474938.2014.944474.

CHAN, J. C. C., GRANT, A. L. (2016). Modeling energy price dynamics: GARCH versus stochastic volatility. *Energy Economics*, 54, 182–189. https://doi.org/10.1016/j.eneco.2015.12.003.

CONRAD, C., KARANASOS, M. (2005). On the inflation-uncertainty hypothesis in the USA, Japan and the UK: A dual long memory approach. *Japan and the World Economy*, 17(3), 327–343. https://doi.org/10.1016/j.japwor.2004.03.002.

CUKIERMAN, A., MELTZER, A. H. (1986). A Theory of Ambiguity, Credibility, and Inflation under Discretion and Asymmetric Information. *Econometrica*, 54(5), 1099. https://doi.org/10.2307/1912324.

DIKS, C., PANCHENKO, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. *Journal of Economic Dynamics and Control*, 30(9–10), 1647–1669. https://doi.org/10.1016/j.jedc.2005.08.008.

EDGERTON, D., SHUKUR, G. (1999). Testing autocorrelation in a system perspective testing autocorrelation. *Econometric Reviews*, 18(4), 343-386. https://doi.org/10.1080/07474939908800351.

ENGLE, R. F., MANGANELLI, S. (2004). CAViaR: Conditional autoregressive value at risk by regression quantiles. *Journal of Business and Economic Statistics*, 22(4), 367–381. https://doi.org/10.1198/073500104000000370.

FOUNTAS, S., KARANASOS, M., KIM, J. (2006). Inflation uncertainty, output growth uncertainty and macroeconomic performance. *Oxford Bulletin of Economics and Statistics*, 68(3), 319–343. https://doi.org/10.1111/j.1468-0084.2006.00164.x.

FRIEDMAN, M. (1977). Nobel Lecture: Inflation and Unemployment. *Journal of Political Economy*, 85(3), 451–472. https://doi.org/10.1086/260579.

GRANGER, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, 37(3), 424-438. https://doi.org/10.2307/1912791.

HARVEY, D. I., LEYBOURNE, S. J., TAYLOR, A. M. R. (2007). A simple, robust and powerful test of the trend hypothesis. Journal of Econometrics, 141(2), 1302–1330. https://doi.org/10.1016/j.jeconom.2007.02.005.

HARVEY, D. I., LEYBOURNE, S. J., XIAO, B. (2008). A powerful test for linearity when the order of integration is unknown. Studies in Nonlinear Dynamics & Econometrics 12(3), 1-24. https://doi.org/10.2202/1558-3708.1582.

HOLLAND, A. S. (1995). Inflation and Uncertainty: Tests for Temporal Ordering. Journal of *Money, Credit and Banking*, 27(3), 827-837. https://doi.org/10.2307/2077753.

LEE, C. C., OLASEHINDE-WILLIAMS, G., ÖZKAN, O. (2023). Geopolitical oil price uncertainty transmission into core inflation: Evidence from two of the biggest global players. *Energy Economics*, 126. https://doi.org/10.1016/j.eneco.2023.106983.

MIGHRI, Z., RAGOUBI, H., SARWAR, S., WANG, Y. (2022). Quantile Granger causality between US stock market indices and precious metal prices. *Resources Policy*, 76, 102595. https://doi.org/10.1016/j.resourpol.2022.102595.

MIGHRI, Z., SARKODIE, S. A. (2024). Interdependency and causality between green technology innovation and consumption-based carbon emissions in Saudi Arabia: fresh insights from quantile-on-quantile and causality-in-quantiles approaches. *Environmental Science and Pollution Research*, 31(6), 9288–9316. https://doi.org/10.1007/s11356-023-31571-9.

MIGHRI, Z., RAGOUBI, H., SARWAR, S. (2026). Do Stock Market Return and Volatility Respond to U.S. Partisan Conflict Uncertainty? *Scottish Journal of Political Economy*, e70075. https://doi.org/ 10.1111/sjpe.70075.
NOGUERA-SANTAELLA, J. (2016). Geopolitics and the oil price. *Economic Modelling*, 52(January 1973), 301–309. https://doi.org/10.1016/j.econmod.2015.08.018.
POURGERAMI, A., MASKUS, K. E. (1987). The effects of inflation on the predictability of price changes in Latin America: Some estimates and policy implications. *World Development*, 15(2), 287–290. https://doi.org/10.1016/0305-750X(87)90083-0.
TROSTER, V. (2018). Testing for Granger-causality in quantiles. *Econometric Reviews*, 37(8), 850–866. https://doi.org/10. 1080/07474938.2016.1172400.
TROSTER, V., BOURI, E., ROUBAUD, D. (2019). A quantile regression analysis of flights-to-safety with implied volatilities. *Resources Policy*, 62, 482–495. https://doi.org/10.1016/j.resourpol.2018.10.004.
TROSTER, V., SHAHBAZ, M., UDDIN, G. S. (2018). Renewable energy, oil prices, and economic activity: A Granger-causality in quantiles analysis. *Energy Economics*, 70, 440–452. https://doi.org/10.1016/j.eneco.2018.01.029.
YANG, T., DONG, Q., DU, M., DU, Q. (2023). Geopolitical risks , oil price shocks and inflation : Evidence from a TVP–SV–VAR approach. *Energy Economics*, 127(PB), 107099. https://doi.org/10.1016/j.eneco.202.