5 UNCERTAINTY AND SUSTAINABILITY: TIME-VARYING QUANTILE GRANGER CAUSALITY BETWEEN U.S. TRADE POLICY AND SUSTAINABLE FARMING

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Abstract

This study employs a rolling-window quantile Granger causality test to analyse the dynamic link between U.S. trade policy uncertainty (TPU) and the sustainable farming index, using the indices of Caldara et al. (2020) and Baker et al. (2016). The results show a nonlinear and time-varying bidirectional relationship: Caldara's TPU strongly influences stock fluctuations before 2022, especially at higher quantiles, while reverse effects appear mainly in the upper tails. Baker's TPU exhibits similar forward causality but limited feedback. These findings offer useful policy insights.

Keywords: *U.S. trade policy uncertainty; Sustainable farming; Granger causality test, Quantiles, Rolling-window technique*

JEL Classification: F51; E44; C32; H77

1. Introduction

Trade policy uncertainty (TPU) can significantly affect investment performance, especially in sectors closely connected to international markets. Changes in U.S. trade policies, including tariffs and trade negotiations, create uncertainty for firms and investors. Sustainable agriculture, which emphasizes efficiency, reduced resource use, and environmental impact, is particularly sensitive to such risks. The S&P Kensho Global Sustainable Farming Index (KGSF), covering companies

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in agricultural technology, precision farming, machinery, and biotechnology, provides a useful measure of investment performance in this sector. Despite its importance, the effect of U.S. TPU on sustainable agriculture investments has received limited attention. This study uses daily data to examine how TPU influences KGSF volatility, offering insights for both investors and policymakers.

Although research on TPU and sustainable farming is limited, TPU's effects on other asset classes are well documented. For example, He et al. (2021) show that U.S. TPU positively affects U.S. stocks but negatively impacts Chinese markets. Yi et al. (2025) find asymmetric and nonlinear interactions between TPU and cryptocurrency returns, with significant effects during extreme market conditions. Suwanprasert (2022) report that the removal of U.S. TPU after China's WTO accession increased exports for some trading partners while reducing exports for others.

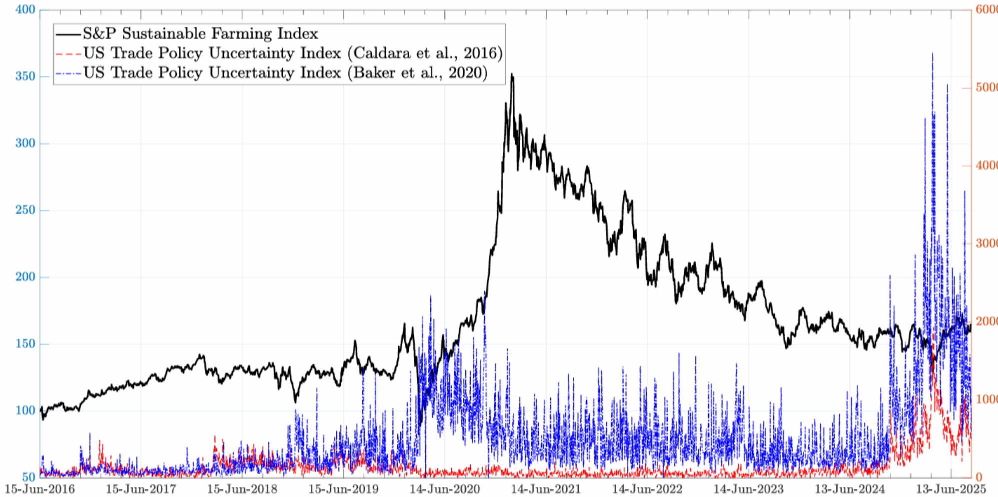
The main findings are as follows. Applying the rolling-window quantile Granger causality test reveals that this relationship is time-varying and quantile-dependent. Using Caldara et al.'s TPU index, trade policy uncertainty significantly Granger-causes sustain- able farming index fluctuations before 2022, especially at higher quantiles ($\tau = 0.6$–0.9), while effects near the median and lower quantiles are weaker or mixed. Conversely, sustainable farming index fluctuations consistently Granger-cause Caldara's TPU across most quantiles, particularly in the upper tails. Using Baker et al.'s TPU index, forward causality toward the farming index is also observed, but evidence for reverse causality is mostly insignificant, suggesting that Caldara's index captures precise trade policy shocks, whereas Baker's reflects broader media-driven uncertainty.

The rest of the paper is organized as follows. Section 2 presents stylized facts and theoretical perspective. Section 3 describes the dataset. Section 4 introduces the time- varying quantile Granger causality test method. Section 5 presents the empirical results. Section 6 concludes and discusses policy implications.

2. Dataset

The S&P Kensho Sustainable Farming Index is constructed to capture the performance of companies engaged in developing agricultural innovations that aim to reduce resource intensity, enhance crop yields, and minimize agricultural waste.

Figure 1 Data Plot



Two indices are commonly used to capture U.S. trade policy uncertainty, namely those developed by Baker et al. (2016) and Caldara et al. (2020). The index by Baker et al. (2016) is constructed from the frequency of articles in major US newspapers that discuss policy related economic uncertainty and include references to trade policy. In contrast, Caldara et al. (2020) measure the frequency of joint occurrences of trade policy and uncertainty terms across leading newspapers. In this study, we employ daily data to investigate the causal relationships among the variables. The sample period spans from 15 June 2016 to 25 August 2025. To ensure stationarity and mitigate the risk of spurious regression, we transform the series by taking the logarithmic differences of the original data. We plot the datasets in Figure 1.

3. Quantile Granger Causality Test with Rolling-Window Technique

Following Troster (2018), the null hypothesis of no Granger causality from z_{2t} to z_{1t} is expressed as,

$$F_{Z_1}\left(z_1 \middle| I_t^{Z_1}, I_t^{Z_2}\right) = F_{Z_1}\left(z_1 \middle| I_t^{Z_1}\right)$$

where $I_t^{Z_1}$ and $I_t^{Z_2}$ denote historical information sets. Extending this to conditional quantiles gives,

$$Q_\tau^{Z_1,Z_2}\left(z_{1t} \middle| I_t^{Z_1}, I_t^{Z_2}\right) = Q_\tau^{Z_1}\left(z_{1t} \middle| I_t^{Z_1}\right)$$

for $\tau \in G \subseteq [0,1]$. The conditional quantiles satisfy,

$$\Pr\left\{z_{1t} \leq Q_\tau^{Z_1}\left(z_1 \middle| I_t^{Z_1}\right) \middle| I_t^{Z_1}\right\} = \tau$$

$$\Pr\left\{z_{1t} \leq Q_\tau^{Z_1,Z_2}\left(z_1 \middle| I_t^{Z_1}, I_t^{Z_2}\right) \middle| I_t^{Z_1}, I_t^{Z_2}\right\} = \tau$$

The test statistic is given by,

$$S_T = \frac{1}{Tn} \sum_{j=1}^{n} |\, \varphi'_{.j} w \varphi_{.j} |$$

where $w_{t,s} = \exp[-0.5(I_t - I_s)^2]$ and $\varphi_{ij} = \psi_{\tau_j}\left(z_{1i} - m\left(I_t^{Z_1}, \theta_T(\tau_j)\right)\right)$. Critical values are computed following Troster (2018).

The Quantile Autoregressive (QAR) model is specified as,

$$m^1\left(I_t^{y_1}, \theta(\tau)\right) = \mu_1(\tau) + \mu_2(\tau)y_{1,t-1} + \sigma_t \emptyset_\mu^{-1}(\tau)$$

where $\theta(\tau) = (\mu_1(\tau), \mu_2(\tau), \sigma_t)'$. Parameters are estimated via maximum likelihood, and $\emptyset_\mu^{-1}(\tau)$ denotes the inverse cumulative distribution function of the standard normal distribution.

To account for time-varying dynamics, we adopt the rolling-window approach proposed by Diebold and Yilmaz (2009, 2012), Balcilar et al. (2010), and Barunık and Krehlık (2018). In line with Barunık and Krehlık (2018), the rolling window size is set to 300 observations to ensure an adequate number of data points within each quantile.

Let the time series be denoted by $\{x_t\}_{t=1}^T$ and $\{y_t\}_{t=1}^T$. For the *i*-th rolling window, the corresponding sub-samples are given by,

$$\{x_i, x_{i+1}, \dots, x_{i+w-1}\} \text{ and } \{y_i, y_{i+1}, \dots, y_{i+w-1}\}$$

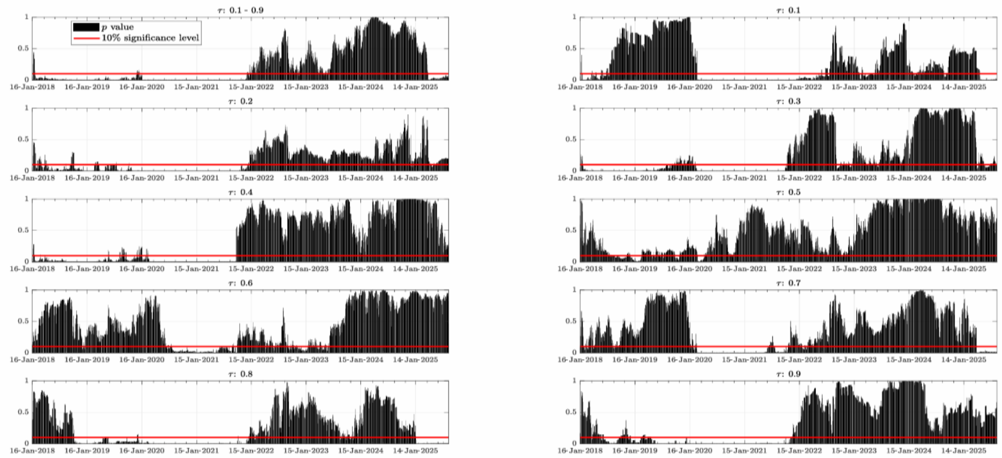
where w denotes the window length. Thus, the interval of window I spans from time point i to $i + w - 1$, with $i = 1,2, \dots, T - w + 1$. Applying this procedure, we compute a sequence of test statistics $\{S_t\}_{t=i}^{i+w+1}$ for each sub-sample, iterating over $i = 1,2, \dots, T - w + 1$.

4. Empirical Results

As discussed above, the existing literature uses two indices to describe U.S. trade policy uncertainty, such as one proposed by Caldara et al. (2020), and the other constructed by Baker et al. (2016). Thus, we consider these two indices separately in the following analyses. To implement the quantile Granger causality test with rolling window technique, the window size W is decided as 300 which is in line with Barunik and Krehlık (2018).

TPU index proposed by Caldara et al. (2020). The results are shown in Figure 2. The quantiles from 0.1 to 0.9, there are clear evidence that the null hypothesis that Δtpu_t^C does not Granger cause Δsf_t is rejected before 2022. However, no causal impacts are found after 2022. The results confirm the time-varying property in the causal impacts from Δtpu_t^C on Δsf_t. For the time-varying causality at specific quantiles, the results show that the causal effect of Δtpu_t^C on Δsf_t depends on the quantile. For higher quantiles (τ = 0.6–0.9), the null hypothesis is often rejected, especially from 2022 onward, indicating a stronger influence on the upper tail of Δsf_t. For lower quantiles (τ = 0.1–0.3), the effect is weaker and only occasionally significant. In the middle quantiles (τ = 0.4–0.5), the results are mixed, with causality sometimes significant and sometimes not, suggesting that the relationship is less consistent near the median.

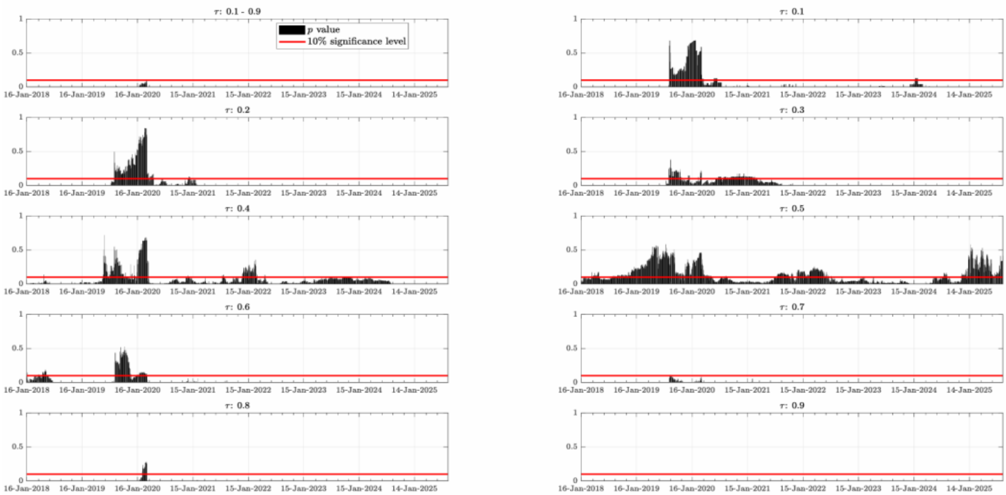
Figure 2: Granger causality at Quantiles from Δtpu_t^C to Δsf_t



Note: The black bars represent the p-values calculated for each sub-sample, while the red line indicates the 10% significance level.

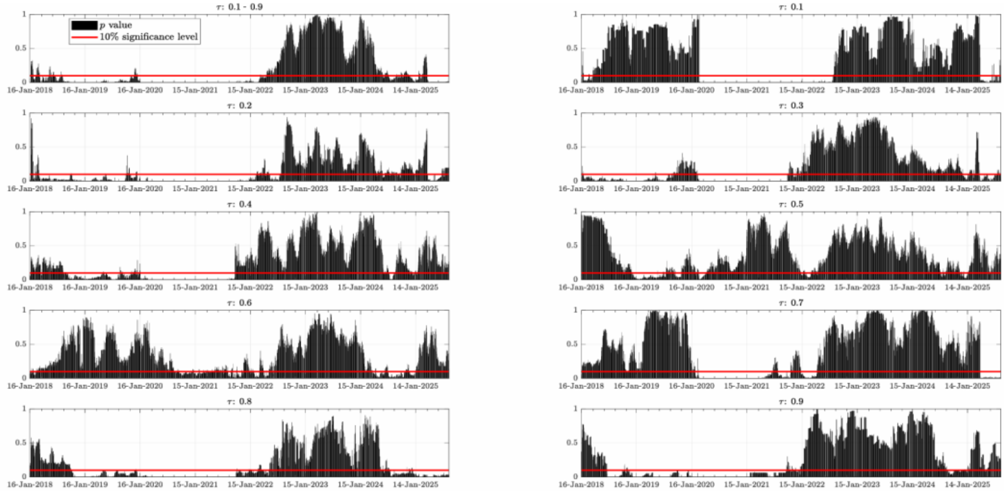
We further investigate the causal relationship from Δsf_t to Δtpu_t^C using the quantile Granger causality test with a rolling window approach. The results are shown in Figure 3. Across the overall quantile range (0.1–0.9), the null hypothesis of non-causality is consistently rejected throughout the sample period. At the lower quantiles (τ = 0.1 and 0.2), non-causality is rejected during the period from June 2019 to March 2020. At the upper quantiles (0.7–0.9), the null hypothesis is rejected across the entire sample period, indicating a robust causal effect in the higher tails of the distribution. By contrast, the results at the middle quantiles (0.3–0.5) are less conclusive, showing mixed evidence of causality.

Figure 3: Granger causality at Quantiles from Δsf_t to Δtpu_t^C



Note: The black bars represent the p-values calculated for each sub-sample, while the red line indicates the 10% significance level.

Figure 4: Granger causality at Quantiles from Δtpu_t^B to Δsf_t



Note: The black bars represent the p-values calculated for each sub-sample, while the red line indicates the 10% significance level.

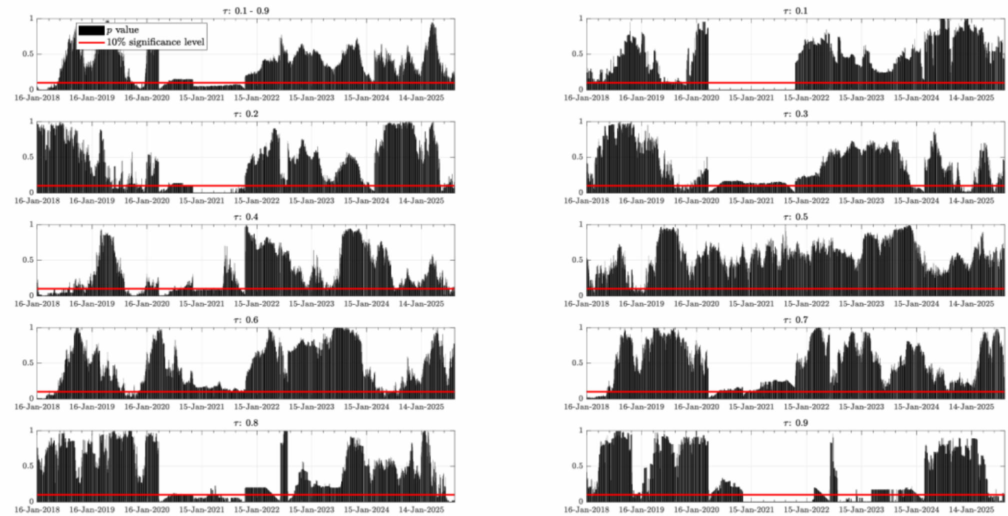
TPU index proposed by Baker et al. (2016). The index proposed by Baker et al. (2016) is constructed using keyword counts in newspaper articles, capturing broad media attention to trade policy uncertainty, though it may include some noise. In contrast, Caldara's TPU index builds on similar news-based data but applies machine learning and topic modelling to filter and focus specifically on U.S. trade policy events, such as tariffs, negotiations, and sanctions. Thus, while Baker et al.'s measure reflects general perceptions of trade-related uncertainty, Caldara et al.'s index provides a more precise indicator of actual U.S. trade policy shocks, making it especially useful in analysing episodes like the U.S.–China trade war. The baseline results are derived using the TPU index constructed by Caldara et al. (2020), while robustness checks are conducted with the alternative measure proposed by Baker et al. (2016).

Figure 4 illustrates the causal effects of Δtpu_t^B on Δsf_t. Across most quantiles (0.1 to 0.9), the null hypothesis of Granger non-causality is rejected in the periods prior to 2022, suggesting a significant causal relationship. At the individual quantile level, the results reveal time-varying patterns of causality that closely resemble the empirical findings reported in Figure 2. Figure 5 shows the causal effects of Δsf_t on Δtpu_t^B. The results indicate that no significant causality is detected across most sample periods and quantiles. This finding stands in clear contrast to the results in Figure 3, which provides evidence of causal impacts.

5. Concluding Remarks

This study combines quantile Granger causality with a rolling-window approach to examine the link between U.S. trade policy uncertainty (TPU) and sustainable farming stocks, using TPU measures by Baker et al. (2016) and Caldara et al. (2020). Results reveal a nonlinear, quantile-dependent, and bidirectional causal relationship, stronger at distributional extremes. Rolling-window tests show time-varying effects: Caldara's TPU significantly drives stock fluctuations before 2022, especially at higher quantiles, while stock movements also influence policy uncertainty in upper tails. Baker's TPU shows similar forward causality but weaker reverse effects, suggesting Caldara's index better captures trade shocks. Policy implications include the need for transparent trade policies to reduce uncertainty shocks, contingency measures to support agriculture during stress, and monitoring financial markets as early indicators of rising TPU. The results also highlight the importance of using precise TPU measures and promoting sustainable finance tools, such as green bonds, to enhance sector resilience.

Figure 5: Granger causality at Quantiles from Δsf_t to Δtpu_t^B



Note: The black bars represent the p-values calculated for each sub-sample, while the red line indicates the 10% significance level.

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