**Cyclicality of Commodity Markets with Respect to US Economic Policy Uncertainty Based on Granger Causality in Quantiles**

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*Given the importance of U.S. in global commodity markets, the goal is to explore whether US economic policy uncertainty impacts the price performance of certain commodities. The analysis uses the Granger causality in quantiles method that allows us to test whether there are different effects under different market conditions. The results document that economic uncertainty impacts the returns on the commodities considered, with the effects clustering around the tail of their conditional distribution. Robust evidence was obtained under alternative definitions of uncertainty.*

*Keywords*: US economic policy uncertainty; commodities; Granger causality; quantiles

*JEL codes*: G18; G11

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**Data availability**: The data that support the findings of this study are available from Datastream. However, certain restrictions apply to their availability, associated with license permissions by the university.

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**1. Introduction**

Investment commodities have been a substantial part of investors’ portfolio, thus, analysing the role of drivers of their prices is a significant research objective. The literature has emphasized both supply-side and demand side factors in determining their prices (Kilian, 2009; Kim and Vera, 2018; among others). There has been a specific strand in the literature (mostly for oil and gold) that provide solid evidence that these commodities are significantly influenced by certain non-fundamentals, such as Economic Policy Uncertainty (EPU) and investors’ attention (Aloui et al., 2016; Wang and Sun, 2017; Uddin et al., 2018). The findings document that these prices are positively associated with EPU. Aloui et al. (2016) use a copula approach and find that higher economic uncertainty significantly increases oil returns and only during certain periods, while Uddin et al. (2018) use an entropy-type of wavelet approach and reach similar results. Finally, Li and Lucey (2017) document that economic policy uncertainty positively affects gold returns, with Raza et al. (2018) providing similar findings. In terms of causality, Kang and Ratti (2013) and Balcilar et al. (2017) find the presence of causality is running from US EPU to oil and gold returns.

Pereira et al. (2017) also touch a very crucial characteristic of certain commodity markets, especially those under investigation in this paper, associated with the cyclicality the commodity markets display across regimes. More specifically, the authors explore the cyclical behaviour of commodities prices through the employment of regime-switching models. Such modelling efforts act as a filtering process that explicitly considers the cyclical behaviour of volatility, while they can accommodate nonlinearities and mean reversion processes, which is very important given the potential heterogeneous behaviour of many commodity assets across different regimes. Their findings confirm that commodity assets are distributed across certain clusters, a feature that identifies them as heterogeneous assets, which display substantial differences across different (volatility) regimes. Their results carry important implications in terms of significant potential diversification profits arising from adding commodity assets in international portfolios. At the same time, the literature has clearly identified that economic policy uncertainty has a clear tendency to display a cyclical pattern around major economic, financial and political periods/regimes, probably because policymakers have the tendency to experiment with new policies across more or less stressful times (Pastor and Veronesi, 2013). The literature provides solid support to the cyclicality pattern of the economic policy uncertainty indexes; this type of uncertainty dramatically changes across the economic business cycle phases (Jurado et al., 2015), while Bloom et al. (2018) document the cyclical behaviour of economic policy uncertainty, supporting that uncertainty shocks are likely to significantly differ across business cycles.

A point raised by a referee is the introduction section of the paper to explicitly discuss the fact that certain commodity markets under investigation by the paper are considered as safe heaven environment for international market participants. This could pose a potential threat to the way the economic policy uncertainty could impact the course of those commodity markets. Baur and Lucey (2010) highlight that certain commodity markets, such as precious metals, are not fully proved to act as safe heaven assets across the whole spectrum of competitive assets or business cycles. They do act so only in very stressful times, while the safe haven property is very short-lived. Overall, precious metals, such as gold, can act as a safe haven only in certain regimes, which also justifies the cyclicality and non-linear function of commodity markets and the necessity of further research as indicated below in this paper. Other similar papers also provide supportive evidence to the above arguments (Baur and Lucey, 2010, 2016; Ciner et al., 2013).

Based on the above discussion, it is obvious that the link between economic policy uncertainty (EPU) shocks and commodity markets has certain critical implication for policymakers’ future choices of economic policy, as well as for investors’ portfolio diversification strategies. In the case of high levels of uncertainty, firms and market participants follow a ‘wait-and-see’ approach and thus delay their spending and investment plans (Bloom, 2009; Jens, 2017). As a result, the demand for commodities as raw materials for the production process is expected to fall, while there is downward pressure on commodity prices (Liu et al., 2018). In addition, commodities can be used as a hedge or safe-haven assets in portfolio decisions to reduce downside risk, especially during periods of high uncertainty in economic policy (Cheng et al., 2015), leading to portfolio rebalancing. However, the literature has not explored the potential non-linear impact of economic policy uncertainty on commodity prices and returns. Instead, the literature has examined such asymmetric effects only for other classes of assets, such as stock-bond correlations in the U.S. (Bekiros et al., 2016). At the same time, the majority of financial variables’ (including those of commodities) distributions are non-normal and exhibit fat tails with leptokurtosis, skewness, and volatility clustering, it is necessary for empirical purposes to use non-linear econometric methods lying in the domain of quantile models, since this approach can depict the entire conditional distribution of the dependent variable, can capture vital information on the tails of the distribution, and be robust to the cases of nonnormality. More importantly, and this is the crucial factor that really motivated this work, the economic environment is characterized as highly unstable (especially after the global financial crisis in 2008), which apparently changes consistently the link between commodity markets and economic risk factors, thus, recommending the presence of a nonlinear relationship between them. This motivates research to explore the above link in regime shift environments, which can definitely offer a clear response to critical questions in asset pricing and portfolio management, presenting a comprehensive picture on risk factors' influence on the performance of commodity markets.

 Therefore, the goal of the paper is to use a parametric Granger causality test in quantiles, proposed by Troster (2018), to study for the first time whether the US EPU index can predict the returns of certain commodities. The novelties of the paper are related to the fact that instead of focusing on specific episodes of market periods for the examination of the predictive effect of US EPU on commodity returns, the analysis employs a parametric quantile causality approach. This method is capable of considering all market conditions jointly (i.e., bearish, bullish), which allows us to explore under what conditions the US EPU could predict commodity returns. In addition, the recommended method has two novel characteristics: first, it takes into consideration different locations and scales of the conditional distribution, which provides richer information on causality than the traditional mean causality approach. Moreover, it can address the problem of structural breaks and sample segmentation, given that many studies have illustrated that oil and gold prices have nonlinear and structural mutation characteristics (Chen et al., 2014; Gil-Alana et al., 2015). However, segmentation tends to lose important sample information (Pershin et al., 2016). The findings clearly indicate that while there is no evidence supporting a causal link between the US EPU and commodity returns at the median of the conditional distribution, this link clusters around the tails of this distribution. US EPU has a strong predictive power on the majority of commodity returns when the markets are in a bearish state (with the exception of the precious metal markets); in the bullish state, this link disappears. In the case of the precious metal markets, the findings document that only when these markets are in a bullish state, causality running from US EPU to commodity returns does exist.

**2. Methodology**

The empirical analysis makes use of the Granger causality test in quantiles proposed by Troster (2018) to explore how the U.S. economic policy uncertainty can predict the returns of certain commodities across different conditional quantiles. Assume that the U.S. economic policy uncertainty is Zt and the returns of the commodities under study are FY(y|IZt).

According to Granger causality, a series Zt does not Granger-cause another series Yt if the past Zt does not help to predict future Yt, given past Yt. Let us assume the explanatory vector It = (ItY, ItZ) €Rd , d = s + q, where ItY: (Yt-1, …, Yt-s)’ € Rs, and ItZ: (Zt-1, …, Zt-q)’ € Rq. The null hypothesis of non-causality from Zt to Yt goes as follows: H0: FY(y|IZt) = FY(y|IYt), for all y € R (1)

where FY(y|IZt) and FY(y|IYt) are the conditional distribution functions of Yt given FY(y|IZt) and ItY, respectively. Test Granger non-causality in mean, which is only a necessary condition for (1). In this case, Zt does not Granger cause Yt in mean if:

E(y|IZt) = E(y|IYt) (2)

Where E(y|IZt) and E(y|IYt) are the means of FY(y|IZt) and FY(y|IYt), respectively. Granger non-causality in mean can be easily extended to higher-order moments. However, causality in mean overlooks the dependence that may appear in the conditional tails of the distribution. Therefore, a Granger non-causality in conditional quantiles test is proposed. Let QτY,Z (.|IZt, IYt) be the τ-quantiles of E(y|IZt, IYt); then we rewrite Equation (1) as follows:

H0: QτY,Z (Y|IZt, IYt) = QτY (Y|IYt) for all τ € T (3)

where the conditional τ-quantiles of Yt satisfy the following restrictions:

Pr{Yt ≤QτY (Yt | ItY)|ItY} for all τ € T

Pr{Yt ≤QτY,Z (Yt | ItY, ItZ)|ItY,ItZ} for all τ € T (4)

Given an explanatory vector It, the analysis has:

Pr{Yt ≤Qτ (Yt | It)|It} = E{I|Yt ≤Qτ (Yt | It)|It}

where I(Yt≤y) is an indicator function of the event that is less or equal than y. Thus, expressions (4) yield:

{1|Yt ≤QτY,Z (Yt | ItY, ItZ)|ItY,ItZ} = E{I{Yt ≤QτY (Yt | ItY)|ItY,ItZ} for all τ € T (5)

where the left-hand side of (5) is equal to the τ-quantile of FY(. | ItY, ItZ) by definition. Following Troster (2018), the analysis postulates a parametric model to estimate the τ-th quantile of FY(.|ItY), where we assume that Qτ(.|It) is correctly specified by a parametric model m(.,θ(τ)) belonging to a family of functions М={m(.,θ(τ))|θ(⋅)τ→€ Θ⊂RP, τ€Τ⊂[0, 1]}. Let В⊂М be a family of uniformly bounded functions τ→θ(τ), such that θ(τ) € Θ⊂RP. Then, under the null hypothesis in (3), the τ-conditional quantile QτY(⋅|ItY) is correctly specified by a parametric model m(ItY, θ0(τ)), for some θ0€В, using only the restricted information set ItY, and we redefine the testing problem in (3) as:

H0: E[I(Yt≤m(ItY, θ0(τ))|ItY, ItZ] = τ for all τ € T (6)

against:

H1: E[I(Yt≤m(ItY, θ0(τ))|ItY, ItZ] ≠ τ for some τ € T (7)

where m(ItY, θ0(τ) correctly specifies the true conditional quantile QτY(.|ItY), for all τ € T. We rewrite (6) as:

H0: E[I(Yt - m(ItY, θ0(τ))≤0) – τ||ItY, ItZ] = 0

Then, we can characterize the null hypothesis (6) by a sequence of unconditional moment restrictions:

H0: E{[I(Yt - m(ItY, θ0(τ))≤0) – τ]|exp(iωIt)} = 0 (8)

where exp(iϖIt) = exp[i(ϖ1 (Yt-1, Zt-1)’ + … ϖr (Yt-r, Zt-r)’)] is a weighting function, for all ϖ € Rd with r≤d, and i =√-1 is the imaginary root. The test statistic is a sampled analogue of E{[І(Υt – m(ItY, θ0(τ))≤0) – τ]exp(iωIt)}:

 T

vT(ϖ, τ) = 1/√T Σ[І(Υt-m( ItY, θ0(τ))≤0) -τ] exp(iϖ’It) (9)

 i=1

where θT is √T-consistent estimator of θ0(τ), for all τ€T. Then, we apply the test statistic:

 ST = ∫∫| vT (ϖ, τ)|2 dFϖ(ϖ)dFτ(τ) (10)

where Fϖ(⋅) is the conditional distribution function of the ad-variate standard normal random vector, Fτ(⋅) as a uniform discrete distribution over a grid of Τ in n equidistributed points, Τn = {τj}n,j=1. The vector of weights ϖ € Rd is drawn from a standard normal distribution. The test statistic in (10) can be estimated using its sample counterpart. Let Ψ be the T x n matrix Ψ with elements ψi,j = Ψτj (Yi – m(IiY, θT(τj))). Then, the test statistic ST has the form:

 n

ST = 1/Tn Σ|ψ’j Wψj| (11)

 j=1

where W is the T x T matrix with elements wt,s = exp[-0:5(It -IS)2], and ψj denotes the jth column of Ψ. It rejects the null hypothesis whenever it observes ‘large’ values of ST. Next, the analysis uses the subsampling procedure of Troster (2018) to calculate critical values for ST in (11). Given our series {Xt = (Yt, Zt)} of sample size T, we generate B = T – b + 1 subsamples of size b (taken without replacement from the original data) of the form {Xi, …, Xi+b-1}. Then, the test statistic ST in (11) is calculated for each subsample; we obtain p-values by averaging the subsample test statistics over the B subsamples. Following Troster (2018), we choose a subsample of size b = [kT2/5], where [⋅] is the integer part of a number, and k is a constant parameter. To apply the ST test in (11), we specify three different quantile auto regressive (QAR) models m(⋅), for all τ€Γ⊂[0, 1], under the null hypothesis of non-Granger-causality in (9) as follows:

QAR(1) : m1(ItY, θ(τ)) = μ1(τ) + μ2(τ)Yt-1 + σtΦu-1 (τ)

QAR(2) : m2 (ItY, θ(τ)) = μ1(τ) + μ2(τ)Yt-1 + μ3(τ)Yt-2 + σtΦu-1 (τ)

QAR(3) : m3 (ItY, θ(τ)) = μ1(τ) + μ2(τ)Yt-1 + μ3(τ)Yt-2 + μ4(τ)Yt-3 + σtΦu-1 (τ) (12)

where the parameters θ(τ) = (μ1(τ), μ2(τ), μ3(τ), μ4(τ), σt )’ are estimated by maximum likelihood in an equally spaced grid of quantiles and Φu-1 (⋅) are the inverse of a standard normal distribution function. To verify the signature of the causal relationship between the variables, we estimate the quantile autoregressive models in (12), including lagged variables of another variable. The empirical analysis presents the results using only a QAR (3) model with the lagged values of the other variable as follows:

QτY,Z (Yt|ItY, ItZ) = μ1(τ) + μ2(τ)Yt-1 + μ3(τ)Yt-2 + μ4(τ)Yt-3 + β(τ) Zt-1 + σiΦu-1(τ) (13)

**3. Data**

The empirical analysis considers monthly price data from certain commodity markets (i.e., oil, natural gas, gold, silver, platinum, copper, nickel, and aluminium). Related price series start in January 1990 and end at December 2018. All commodity prices are transformed into first-logarithmic differences (i.e., returns). In terms of economic policy uncertainty, the analysis uses the US economic policy uncertainty index recommended by Baker et al. (2016) and which is constructed as a weighting average including three components, capturing the news associated with policy-related uncertainty, the number of federal tax code provisions set to expire in the future, and disagreement among economic forecasters. Data on commodity prices are obtained from Datastream, while those on the Global Economic index are obtained from [www.policyuncertainty.com](http://www.policyuncertainty.com) and on the KOF Swiss Economic Institute indicator available from https://kof.ethz.ch/en/forecasts-andindicators/indicators/kof-globalbaro.html; the EPU index data are obtained from Baker’s site. The Global Uncertainty Index is available from 1997, while the KOF Leading Indicator index is available from 1991. Table 1 provides certain summary statistics, while Figures 1 and 2 depict the correlation between the EPU index and oil and natural gas prices.

**[Insert Table 1 about here]**

**[Insert Figures 1 and 2 about here]**

**4. Empirical Analysis**

This part analyzes the importance of the US economic policy uncertainty index in predicting the returns of our commodities considering the quantiles conditional distribution through the method recommended by Troster (2018). This non-linearity method has been shown and supported by Lacheheb and Sirag (2019), where they show that positive and negative oil price changes have different effects on inflation. In particular, their findings document the presence of a significant relation between oil price increases and the inflation rate, whereas, a significant relation between oil price reduction and inflation was absent. Table 2 reports the p-values for the test of the quantile-causality running from the economic policy uncertainty index to commodity returns. The table also reports the results from the entire distribution. The findings clearly indicate that in terms of the entire distribution, causality is detected only in the cases of oil and gold returns and at the 10% significance level, indicating that this uncertainty index does not have a strong ability in predicting the returns of an extended set of commodity returns. By contrast, when it comes down to quntiles, causality is strongly found in the tails of the distribution across all commodity returns.

In particular, the test results provide strong evidence that in the cases of oil, natural gas, copper, nickel and aluminium causality significantly exists in the lower quantiles, i.e. around 0.1, 0.2, 0.3 and 0.4 quantiles, while this is not the case in higher quantiles. This finding, however, is not valid for the cases of gold, silver and platinum. These results imply that the explanatory power of the economic policy uncertainty for commodity returns seems to be heterogeneous across different market conditions. For instance, when the markets are in a bearish state (commodity returns at the lower quantiles), policy uncertainty has a significant impact on returns; by contrast, under a bullish state (commodity returns at the higher quantiles), the impact is highly limited (insignificant). Thus, for this group of commodities such results document that economic uncertainty causes panic conditions in relevance to the uncertainty of future policy, leading to lower demand. These bear market conditions, in turn, imply low commodity prices (and returns) comparatively to bullish market conditions. These results are in conflict with those by Balcilar et al. (2017) for oil returns about the strong role of the US economic policy uncertainty and in terms of the entire distribution.

By contrast, in terms of gold, silver and platinum returns, the findings document that economic policy uncertainty has a major role to play only in the higher quantiles of their conditional distribution. In other words, policy uncertainty matters only when these two markets are in a bullish scenario. In that case, investors choose gold to avoid potential future risks and in order to secure high profits in the bull markets. These findings are in conflict with those provided by Jones and Sackley (2016) and Li and Lucey (2017) for gold returns.

**[Insert Table 2 about here]**

Although the importance of the US economic policy uncertainty for a variety of asset prices, including has been documented in the literature (Albulescu et al., 2019), this part of the analysis checks the robustness of the previous results by repeating the estimation after replacing the US EPU index with an alternative index. In particular, Davis (2016) recommends a Global Economic Policy Uncertainty (GEPU) index constructed by considering a GDP-weighted average of national EPU indices for 20 countries that account for two-thirds of global output (Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, and the UK). The national EPU indices are constructed following Baker et al.’s (2016) newspaper-based approach. The new results are reported in Table 3 and provide robust support to those in Table 2, albeit with stronger algebraic estimates in the cases of statistical significance.

 Moreover, this part of the analysis provides further robustness evidence by considering the leading indicator of economic activity as it is measured through the KOF Economic Barometer as it is released by the KOF Swiss Economic Institute (this point also raised by a referee). The analysis makes use of the latest version of the indicator based on a multisectoral design (Graff, 2010). The new results are reported in Table 3a. Given that the KOF index is much less volatile, and truly forward looking, the findings provide even stronger support to the baseline results, given that economic policy uncertainty affects a smaller set of the commodities under investigation. In particular, non-linear causality is identified at the high uncertainty quantiles of the indicator with respect to the commodities of oil, natural gas, gold, and copper.

 **[Insert Tables 3 and 3a about here]**

Finally, this part considers a multivariate framework to re-estimate the causality modelling. In particular, for oil and natural gas commodities, the additional variables are those of global aggregate demand and the US dollar effective exchange rare (Kilian and Zhou, 2019). The proxy for the former comes from the OECD Monthly Economic Indicators (MEI) and it is aggregated industrial production across OECD countries (Ciccarelli and Mojon, 2010). For the precious metal commodities, the new framework considers the variables of global demand, a global inflation index obtained from Ciccarelli and Mojon (2010) and the stock market indexes of Dow Jones, FTSE100, Nikkei225 and DAX30. Finally, for the cases of copper, nickel and aluminium the additional drivers include the global demand index, the US effective dollar rate and their opposite competitive prices. All data come from Datastream. The new results (with the VIX index) are presented in Table 4. They clearly lend support to the previous findings, with the exception of copper, nickel and aluminum prices, where the results are statistically insignificant across all quantiles.

**[Insert Table 4 about here]**

**5. Conclusion**

The analysis highlighted the predictable effect of economic policy uncertainty with respect to certain commodity returns only at the tails of their conditional distribution. Gold, silver and platinum displayed different responses to policy uncertainty against the markets of oil, natural gas, copper, nickel and aluminium. While the majority of commodities reacted to bearish environments, the three precious metals reacted to bullish conditions. The results survived certain robustness tests in terms of an alternative definition of uncertainty and a multivariate framework. These findings infer significant implications for investors. More specifically, they imply that investors should be aware that there exists predictive power of policy uncertainty for commodity returns (and prices) observed during extreme market conditions (low and high commodity price periods). Moreover, they inspire precious metals investors that more prudent investment strategies are needed when their markets are in a bullish state.

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Table 1: Descriptive Statistics

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Variable Mean SD Min Max

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Oil 47.42 29.67 11.35 133.88

Natural gas 4.76 2.73 1.72 13.05

Gold 717.49 460.54 252.90 1896.50

Silver 11.41 8.50 3.95 35.12

Platinum 856.84 459.82 360.02 1,719.03

Copper 4,241.1 2,487.2 1,341.3 9,970.0

Nickel 13,306.8 8,137.7 4,009.5 50,575.0

Aluminium 1,760.6 439.3 1,025.8 3,106.3

EPU 107.3 71.9 10.1 626.0

GEPU 108.3 44.9 49.4 271.3

KOF index 99.99 9.16 60.1 119.5

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SD = standard deviation. EPU = economic policy uncertainty, GEPU = global economic policy uncertainty. Commodity prices were obtained from Datastream. The Global Economic index was obtained from www.policyuncertainty.com (available from 1997) and the KOF Swiss Economic Institute indicator from <https://kof.ethz.ch/en/forecasts-andindicators/indicators/kof-globalbaro.html> (available from 1991); the EPU index was obtained from Baker’s site. All data are on a monthly basis, Time span: 1990-2018.

Table 2: Quantile Causality Results: (EPU and Commodity Returns)

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Commodity Lag Mean 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

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Oil 1 0.037\* 0.088\*\*\* 0.086\*\*\*  0.046\*\* 0.024 0.027 0.025 0.021 0.018 0.015

[0.08] [0.00] [0.00] [0.03] [0.18] [0.16] [0.19] [0.24] [0.29] [0.33]

Natural gas 1 0.019 0.094\*\*\* 0.091\*\*\*  0.063\*\*\* 0.029 0.028 0.022 0.020 0.019 0.011

[0.28] [0.00] [0.00] [0.01] [0.16] [0.16] [0.21] [0.23] [0.24] [0.32]

Gold 1 0.034\* 0.016 0.015 0.021 0.025 0.024 0.048\*\* 0.063\*\*\* 0.080\*\*\* 0.092\*\*\*

[0.10] [0.27] [0.28] [0.24] [0.21] [0.21] [0.03] [0.01] [0.00] [0.00]

Silver 2 0.012 0.013 0.011 0.019 0.022 0.024 0.042\*\* 0.056\*\* 0.072\*\*\* 0.088\*\*\*

[0.33] [0.32] [0.35] [0.30] [0.27] [0.25] [0.04] [0.02] [0.00] [0.00]

Platinum 1 0.009 0.012 0.014 0.018 0.024 0.025 0.053\*\* 0.070\*\*\* 0.088\*\*\* 0.102\*\*\*

[0.36] [0.33] [0.31] [0.28] [0.26] [0.25] [0.02] [0.00] [0.00] [0.00]

Copper 2 0.018 0.076\*\*\* 0.068\*\*\* 0.051\*\*\* 0.036\* 0.020 0.018 0.014 0.012 0.008

[0.25] [0.00] [0.00] [0.01] [0.08] [0.27] [0.29] [0.35] [0.37] [0.43]

Nickel 1 0.034\* 0.083\*\*\* 0.072\*\*\* 0.057\*\*\* 0.039\* 0.018 0.013 0.011 0.008 0.003

[0.09] [0.00] [0.00] [0.01] [0.07] [0.29] [0.34] [0.36] [0.40] [0.45]

Aluminum 1 0.025 0.081\*\*\* 0.070\*\*\* 0.061\*\*\* 0.042\*\* 0.020 0.016 0.010 0.005 0.001

[0.14] [0.00] [0.00] [0.00] [0.05] [0.27] [0.31] [0.37] [0.43] [0.48]

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Figures in brackets denote p-values. The estimation applied a sub-sampling method to calculate the p-values, where the subsample size is 11. The analysis implemented tests for Granger-causality in quantiles by testing the null over a grid of nine quantiles, where the null hypothesis of Granger non-causality holds if it is not rejected. \*: p≤0.10; \*\*: p≤0.05; \*\*\*: p≤0.01.

Table 3: Quantile Causality Results: (GEPU and Commodity Returns)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Commodity Lag Mean 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

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Oil 1 0.043\*\* 0.096\*\*\* 0.093\*\*\*  0.061\*\* 0.021 0.023 0.020 0.015 0.012 0.010

[0.05] [0.00] [0.00] [0.02] [0.22] [0.19] [0.27] [0.31] [0.36] [0.39]

Natural gas 2 0.027 0.108\*\*\* 0.102\*\*\*  0.080\*\*\* 0.023 0.024 0.016 0.014 0.012 0.007

[0.15] [0.00] [0.00] [0.00] [0.20] [0.18] [0.29] [0.33] [0.36] [0.39]

Gold 2 0.025 0.013 0.012 0.017 0.023 0.022 0.060\*\* 0.079\*\*\* 0.094\*\*\* 0.103\*\*\*

[0.13] [0.31] [0.35] [0.27] [0.18] [0.19] [0.02] [0.00] [0.00] [0.00]

Silver 2 0.009 0.010 0.008 0.016 0.019 0.022 0.055\*\* 0.069\*\* 0.086\*\*\* 0.097\*\*\*

[0.37] [0.35] [0.39] [0.26] [0.29] [0.26] [0.02] [0.02] [0.00] [0.00]

Platinum 1 0.005 0.008 0.012 0.016 0.023 0.022 0.065\*\* 0.083\*\*\* 0.097\*\*\* 0.113\*\*\*

[0.39] [0.36] [0.33] [0.30] [0.28] [0.29] [0.02] [0.00] [0.00] [0.00]

Copper 1 0.024 0.088\*\*\* 0.075\*\*\* 0.058\*\*\* 0.043\* 0.024 0.013 0.010 0.006 0.005

[0.20] [0.00] [0.00] [0.00] [0.06] [0.23] [0.33] [0.38] [0.42] [0.44]

Nickel 1 0.046\* 0.090\*\*\* 0.078\*\*\* 0.065\*\*\* 0.044\* 0.014 0.010 0.006 0.004 0.000

[0.07] [0.00] [0.00] [0.00] [0.06] [0.34] [0.38] [0.42] [0.46] [0.58]

Aluminum 2 0.032 0.087\*\*\* 0.076\*\*\* 0.069\*\*\* 0.048\*\* 0.016 0.012 0.007 0.003 0.000

[0.11] [0.00] [0.00] [0.00] [0.04] [0.34] [0.39] [0.41] [0.49] [0.60]

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Similar to those in Table 2.

Table 3a: Quantile Causality Results: (the KOF Indicator and Commodity Returns)

\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_\_

Commodity Lag Mean 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

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Oil 1 0.034\* 0.076\*\*\* 0.072\*\*\*  0.040\*\* 0.019 0.023 0.022 0.016 0.012 0.010

[0.09] [0.01] [0.01] [0.05] [0.24] [0.20] [0.21] [0.30] [0.35] [0.39]

Natural gas 1 0.016 0.078\*\*\* 0.070\*\*\*  0.051\*\* 0.025 0.023 0.018 0.015 0.013 0.008

[0.32] [0.01] [0.01] [0.02] [0.21] [0.23] [0.27] [0.31] [0.34] [0.40]

Gold 1 0.029\* 0.013 0.012 0.017 0.023 0.020 0.041\*\* 0.050\*\* 0.072\*\*\* 0.079\*\*\*

[0.10] [0.30] [0.32] [0.28] [0.24] [0.26] [0.04] [0.03] [0.01] [0.00]

Silver 2 0.010 0.011 0.015 0.017 0.019 0.021 0.025 0.0290.035 0.038

[0.35] [0.33] [0.27] [0.24] [0.30] [0.28] [0.24] [0.23] [0.16] [0.14]

Platinum 1 0.004 0.009 0.012 0.016 0.021 0.023 0.038 0.042 0.039 0.041

[0.40] [0.36] [0.33] [0.30] [0.28] [0.31] [0.14] [0.12] [0.16] [0.12]

Copper 2 0.015 0.064\*\*\* 0.056\*\* 0.043\*\* 0.027 0.023 0.014 0.010 0.005 0.002

[0.27] [0.01] [0.02] [0.05] [0.13] [0.17] [0.35] [0.39] [0.46] [0.54]

Nickel 1 0.025 0.031 0.026 0.018 0.017 0.014 0.010 0.007 0.006 0.001

[0.14] [0.12] [0.14] [0.20] [0.22] [0.31] [0.38] [0.44] [0.47] [0.55]

Aluminum 1 0.019 0.044 0.037 0.032 0.027 0.018 0.014 0.008 0.002 0.000

[0.20] [0.11] [0.15] [0.21] [0.25] [0.33] [0.39] [0.47] [0.54] [0.58]

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Similar to those in Table 2.

Table 4: Quantile Causality Results: (VIX and Multivariate Model)

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Commodity Lag Mean 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9

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Oil 1 0.029\* 0.061\*\*\* 0.055\*\*\* 0.036\*\* 0.014 0.019 0.012 0.011 0.010 0.006

[0.10] [0.00] [0.00] [0.05] [0.28] [0.25] [0.31] [0.35] [0.39] [0.51]

Natural gas 1 0.010 0.074\*\*\* 0.067\*\*\* 0.043\*\*  0.020 0.015 0.010 0.009 0.004 0.002

[0.39] [0.00] [0.00] [0.03] [0.26] [0.31] [0.40] [0.47] [0.59] [0.68]

Gold 1 0.022 0.008 0.004 0.009 0.016 0.021 0.037\*\* 0.052\*\*\* 0.064\*\*\* 0.072\*\*\*

[0.14] [0.39] [0.46] [0.40] [0.34] [0.28] [0.05] [0.01] [0.00] [0.00]

Silver 1 0.004 0.006 0.010 0.019 0.015 0.018 0.031\*\* 0.045\*\* 0.057\*\*\* 0.070\*\*\*

[0.53] [0.39] [0.37] [0.28] [0.34] [0.33] [0.05] [0.03] [0.01] [0.00]

Platinum 1 0.003 0.006 0.010 0.017 0.018 0.021 0.043\*\* 0.053\*\*\* 0.070\*\*\* 0.078\*\*\*

[0.48] [0.41] [0.38] [0.30] [0.33] [0.27] [0.03] [0.01] [0.00] [0.00]

Copper 1 0.009 0.036 0.031 0.020 0.016 0.011 0.005 0.003 0.002 0.000

[0.36] [0.19] [0.26] [0.40] [0.49] [0.54] [0.60] [0.63] [0.69] [0.73]

Nickel 1 0.025 0.031 0.023 0.019 0.017 0.010 0.005 0.003 0.000 0.000

[0.13] [0.16] [0.22] [0.31] [0.35] [0.42] [0.55] [0.63] [0.75] [0.86]

Aluminum 2 0.016 0.032 0.025 0.018 0.013 0.010 0.006 0.002 0.000 0.000

[0.25] [0.16] [0.27] [0.39] [0.51] [0.58] [0.64] [0.72] [0.78] [0.86]

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As in Table 2.

**Figure 1**. EPU and Oil Prices: 1990-2018

**Figure 2**. EPU and Natural Gas Prices: 1990-2018