The Role of Economic and Financial Uncertainties in Predicting Commodity Futures Returns and Volatility: Evidence from a Nonparametric Causality-in-Quantiles Test[#]

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Highlights

• The role of uncertainties in predicting commodity futures is analysed.
• Linear models are misspecified due to nonlinearity.
• A *k*-th order nonparametric causality-in-quantiles test is used.
• Uncertainties can predict returns and/or volatility of the commodities.

Abstract

We analyze the ability of economic and financial uncertainties in predicting movements in commodity futures markets. Using daily data over the period of 8th May, 1992 to 31st August, 2016 on 21 commodity futures covering agriculture, energy, metals and livestock, we find that: (a) Linear predictive tests provide virtually no evidence of predictability; (b) Linear models are misspecified due to nonlinearity and hence, results from the framework cannot be relied upon, and; (c) Using a *k*-th order nonparametric causality-in-quantiles test, which is robust to misspecification in the presence of nonlinearities, we find evidence that measures of uncertainty can predict returns and/or volatility of as many as 20 of the commodities considered at least at one point of their respective conditional distributions for returns and variance. In general, we highlight the importance of modeling nonlinearity, higher order moments, and quantiles of returns and volatility when carrying out predictability analysis involving commodity futures and uncertainty.

Keywords: Economic and Financial Uncertainty, Commodity Futures Markets, Returns, Volatility, Nonparametric Causality-in-Quantiles Test.
JEL Codes: C22, G13, Q02.

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1. Introduction

Commodity markets have been characterized by a high volatility in the past decades (Silvennoinen and Thorp, 2013). Commodity prices, measured by the Continuous Commodity Index (CCI), rose a remarkable 275% from 2001 to 2011 (with only a 25% increase in overall inflation), while individual commodities experienced even greater price increases (i.e. crude oil, gold and corn prices rose a 1050%, a 528% and a 348%, respectively). After reaching its maximum level in April 2011, CCI fell to its lowest record in February 2016. At the same time, commodity price have shown a higher correlation with each other as well as with stock prices (Tang and Xion, 2012; Silvennoinen and Thorp, 2013). These figures have raised different debates or questions in the economic literature. For example, the simultaneous increase of both agricultural prices and oil prices has raised the widespread debate on the pass-through from oil prices to food prices (Mensi et al., 2014). Furthermore, the concurrence of a rapid growth of commodity index investment with the increasing trend in commodity prices raised the question of whether the commodity prices are driven by supply and demand factors or by speculation due to the so-called "financialization" of the commodities markets (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013; Basak and Pavlova, 2016). In addition, the higher correlation of commodity prices with stock prices could reduce the attractiveness of investments in commodities as a diversification and a hedging tool (Erb and Harvey, 2006). Moreover, since commodities represent a significant proportion of developing economies' exports (World Economic Outlook, 2015) commodity price dynamics also constitute an economic growth and development factor in many developing countries, so that commodity price stability may constitute a policy objective to reduce poverty. The relevance of all these questions justifies the interest of any analysis on the driving factors of commodity future prices.

Furthermore, and in the wake of the 2008-09 financial crisis, economic policy uncertainty has raised a lot of interest due to its potential negative effects on many macroeconomic variables

(Bloom et al., 2007; Bloom, 2009; Pastor and Veronesi, 2012, 2013; Baker et al., 2015; Brogaard and Detzel, 2015; Balli et al., 2017), as well as on stock prices (Pastor and Veronesi, 2012; Bekiros and Uddin, 2016). Among the different measures of policy uncertainty, the Economic Policy Uncertainty (EPU) index based on newspaper coverage frequency proposed by Baker et al. (2015), the CBOE Volatility Index (VIX) and the news-based Equity Market Uncertainty (EMU) have become the most common measures of economic uncertainty.[1]

In this context, we, for the first time in the literature on predicting futures market movements, use a novel nonparametric causality-in-quantiles test of Balcilar *et al.* (2016a) to examine the impact of economic and financial market uncertainties on returns and volatility of 21 commodity futures covering agriculture, energy, metals and livestock. Specifically we look at the futures data on Cocoa, Coffee, Corn, Cotton, Orange Juice, Soybeans, Soybean Meal, Soybean Oil, Sugar, Wheat, Kansas wheat, Crude Oil, Heating Oil, Natural Gasoline, Gold, Silver, Copper, Palladium, Platinum, Live Cattle, and Lean Hogs. As far as economic uncertainty is concerned, it is captured by the news-based measure of US Economic Policy Uncertainty (EPU) of Baker *et al.*, (2016), and for financial market uncertainty, we use two measures: the CBOE Volatility Index ((VIX)), and a news-based measure of US Equity Market Uncertainty (EMU), again developed by Baker *et al.*, (2016). For our econometric analysis, we use daily data spanning the period of 8th May, 1992 to 31st August, 2016 for these variables.

The nonparametric causality-in-quantiles test combines elements of the test for nonlinear causality of *k*-th order developed by Nishiyama *et al.* (2011) with the causality-in-quantiles test developed by Jeong *et al.* (2012) and, hence, can be considered to be a generalization of the former. The causality-in-quantile approach has the following three novelties: Firstly, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series, which could prove to be particularly important as it is well known that

[1] See Strobel (2015) for a review of alternative approaches to measure uncertainty.

high frequency futures market returns display nonlinear dynamics (see Andreasson *et al.* (2016) for a detailed discussion in this regard). Secondly, via this methodology, we are able to test not only for causality-in-mean (1^{st} moment), but also for causality that may exist in the tails of the joint distribution of the variables, which in turn, is important if the dependent variable has fat-tails – something we show below to hold for futures returns. Finally, we are also able to investigate causality-in-variance and, thus, effect on volatility. Such an investigation is important because, during some periods, causality in the conditional-mean may not exist while, at the same time, higher-order interdependencies may turn out to be significant.

The rest of the paper is organized as follows: Section 2 describes the literature on this topic, Section 3 presents the methodology, and Section 4 discusses the data and the results. Finally, Section 5 concludes.

2. Literature Review

Commodities have been widely used for hedging and speculative purposes, and therefore, their prices and volatility can be affected by economic uncertainty through different channels, such as its impact on the economy (Bloom *et al.*, 2007), on stock prices (Pastor and Veronesi, 2012) and on expected market returns (Brogaard and Detzel, 2015). However, despite the vast literature on the drivers of commodity prices (Bekiros and Diks, 2008; Büyüksahin and Robe, 2014; Berger and Uddin, 2016; Reboredo and Uddin, 2016), there are only a few papers that empirically analyse the impact of economic policy uncertainty on commodity prices[2] and volatility. While most of the studies find a negative impact of economic uncertainty on stock prices, international economic uncertainty could also positively affect other country's stock markets by leading to an improvement in stock prices through the diversification channel of investor portfolios (Mensi *et al.*, 2014; Bekiros *et al.,* 2016; Balcilar *et al.*, forthcoming). Jöets *et al.* (2017) estimate a threshold

[2] Although the relationship between oil prices and economic policy uncertainty has been widely analysed (see Kang and Ratti, 2013), the impact of uncertainty on a sample of diverse commodity prices has not been so extensively studied.

vector autoregressive model on a sample of 19 commodity markets and find that most of the commodity prices (but not their volatility), mainly agriculture commodities, are affected by economic uncertainty. Furthermore, their results suggest that the effect is more important for commodities that are strongly related to the global business cycle, such as oil and agricultural and industrial commodities, while precious metals can still be used as hedge tools. Andreasson *et al.* (2016) examine the interactions between commodity futures returns and different driving facts, including economic policy uncertainty, and find evidence of a unidirectional nonlinear relationship from uncertainty to commodity futures. The relationship between commodity prices and economic policy uncertainty is also analysed in Wang *et al.* (2015), who find significant predictability of economic policy uncertainty using 23 commodity price changes, suggesting that commodity price changes can be taken as a leading indicator of EPU. Berger and Uddin (2016) also study the dependence between equity markets, commodity futures and uncertainty indexes and find that the dependence between these variables is significantly stronger in turmoil market periods.

Our paper can be considered to be an extension of the work by Andreasson *et al.*, (2016). These authors do provide some evidence, albeit weak, of the impact of the EPU and VIX indices in predicting three and seven commodity futures returns respectively, especially when nonlinear causality tests are employed.[3] However, these results are obtained from the conditional-mean based test of Diks and Panchenko (2006), and hence, are less informative, given that the test does not look at the entire conditional distribution of returns, and could possibly miss more instances of predictability with returns having heavy tails. Further using the Diks and Panchenko (2006), we are unable to say anything regarding possible asymmetric effect of uncertainty contingent on whether the markets are in bear (lower quantiles), normal (median) or bull (upper quantiles) phases, as we can do with our test. More importantly, the higher-order causality-in-

[3] Besides uncertainty, Andreasson *et al.* (2016) also looked at the role of financial speculation, exchange rate and stock market in predicting commodity futures returns.

quantiles test employed by us also allows us to study the impact of uncertainty on the entire conditional distribution of volatility of the commodity futures – something not analyzed by Andreasson *et al.* (2016). Note commodity futures prices are believed to help in predicting the spot prices (Reeve and Vigfusson, 2011; Chinn and Coibion, 2014), and hence, determining the drivers of the former is of tremendous importance in determining the future path of the spot market of commodities. Also, predicting volatility of the commodity futures returns is important since volatility is considered to be the barometer for the vulnerability of financial markets and the economy and central to asset pricing, derivative valuation, portfolio allocation, and risk management (Poon and Granger, 2003; Rapach *et al.*, 2008). Prediction of volatility is also important for traditional hedgers who use commodities in production, besides other types of investors such as commodity index funds who increasingly include commodity futures in their portfolios given the financialization of commodity markets (Tang and Xiong, 2012; Büyüksahin and Robe, 2014).

3. Methodology

By building on the framework of Nishiyama *et al.*, (2011) and Jeong *et al.*, (2012), we use a novel methodology as advanced by Balcilar *et al.*, (2016a), which in turn, is a method that is useful in detecting nonlinear causality across quantiles through a hybrid approach. The returns on futures is designated as y_t while the predictors, i.e., EPU, VIX and EMU are designated as x_t in turn. Formally, let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},...,x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the q-th quantile hypotheses to be tested can be specified as:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_q(Y_{t-1}) \mid Z_{t-1}\} = q\} = 1, \tag{1}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|\,Z_{t-1}\} = \theta\} < 1. \tag{2}$$

Jeong *et al.* (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t \,|\, Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \leq Q_\theta(Y_{t-1}) \,|\, Z_{t-1}\}] = \theta$ or, equivalently, $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong *et al.* (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s. \tag{3}$$

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \,|\, Y_{t-1}), \tag{5}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \,|\, Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \,|\, Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\big((Y_{t-1} - Y_{s-1})/h\big) 1(y_s \leq y_t)}{\sum_{s=p+1, s\neq t}^{T} L\big((Y_{t-1} - Y_{s-1})/h\big)}, \tag{6}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

In an extension of Jeong *et al.* (2012)'s framework, Balcilar *et al.,* (2016) develop a test for the *second* moment. In particular, we want to test the causality running from the various measures of uncertainty to volatility of the commodity futures. Adopting the approach in Nishiyama *et al.* (2011), higher order quantile causality can be specified as:

$$H_0: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})\,|\,Z_{t-1}\} = \theta\} = 1 \qquad \text{for } k = 1, 2, \ldots, K \tag{7}$$

$$H_1: \quad P\{F_{y_t^k|Z_{t-1}}\{Q_q(Y_{t-1})|Z_{t-1}\} = q\} < 1 \qquad \text{for } k = 1,2,\ldots,K \tag{8}$$

Integrating the entire framework, we define that x_t *Granger causes* y_t *in quantile* θ *up to the* k^{th} *moment* using Eq. (7) to construct the test statistic of Eq. (3) for each k. The causality-in-variance test is then calculated by replacing y_t in Eqs. (3) and (4) with y_t^2. However, it can be shown that it is not easy to combine the different statistics for each $k = 1,2,\ldots,K$ into one statistic for the joint null, because the statistics are mutually correlated (Nishiyama *et al.*, 2011).To efficiently address this issue, we include a sequential-testing method as described by Nishiyama *et al.* (2011). First, we test for the nonparametric Granger causality in the *first* moment $(i.e.\, k = 1)$. Nevertheless, failure to reject the null for $k = 1$ does not automatically lead to no-causality in the *second* moment. Thus, we can still construct the tests for $k = 2$.

Given that we are analyzing the predictability of uncertainty, which is often associated with volatility, we also check for the robustness of our results by recovering two alternative measures of conditional volatility from GARCH(1,1) and GJR-GARCH(1,1) models, besides squared-returns. The basics of GARCH(1,1) model is as follows:

$$y_t = \mu + \varepsilon_t \tag{9}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{10}$$

While, the GJR-GARCH(1,1) model of Glosten, Jagannathan and Runkle (1993) aimed at capturing the asymmetric effects of positive and negative shocks is given by:

$$y_t = \mu + \varepsilon_t \tag{11}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1} + \beta h_{t-1} \tag{12}$$

y_t represents the commodity futures return series and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (ω), the lagged error (ε_{t-1}^2) and the lagged conditional variance (h_{t-1}). The asymmetric effect in the GJR-GARCH (1,1) is captured by the $\varepsilon_{t-1}^2 d_{t-1}$ term, where $d_t = 1$

if $\varepsilon_t^2 < 0$; and $d_t = 0$ otherwise. The shocks have asymmetric impact on conditional variance if γ is statistically significant.

The empirical application of causality testing through quantiles require identifying three crucial choices: the lag order p, the bandwidth h, and the kernel type for $K(\cdot)$and $L(\cdot)$ in equations (3) and (6), respectively. In this study, we make use of lag order based on the Schwarz Information Criterion (SIC), since, when it comes to choosing lags, the SIC is considered being parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of overparametrization usually arising with nonparametric frameworks.[4] The bandwidth value is chosen by employing the least squares cross-validation techniques.[5] Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

3. Data and Empirical Findings

3.1. Data

Our data consists of three measures of uncertainty, with two being news-based: EPU and EMU and the other being the VIX used in forecasting returns and volatility of 21 commodity futures covering agriculture, energy, metals and livestock. Specifically we look at the futures data on Cocoa, Coffee, Corn, Cotton, Orange Juice, Soybeans, Soybean Meal, Soybean Oil, Sugar no. 11, Wheat, Kansas wheat, Light sweet Crude Oil, Heating Oil, Natural Gas, Gold, Silver, Copper, Palladium, Platinum, Live Cattle, and Lean Hogs. The commodity futures data is sourced from Datastream, with returns being computed as the daily percentage change of commodity futures settlement prices multiplied by 100 to convert the returns into percentages. Driven by liquidity considerations and to obtain representative futures returns series, we collect data on nearest and second nearest contracts. We suppose that the trader hold futures contract to the last day of a

[4] Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterized model, while the SIC is asymptotically consistent.

[5] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

specific month, which is one month prior to expiration of the contract. At that date, the trader rolls his or her position to the second nearest contract and hold it to the last day of the month prior to the delivery month. The procedure is then rolled forward to the next set of nearest and second nearest contracts.

As far as economic uncertainty is concerned, it is captured by the news-based measure of US Economic Policy Uncertainty (EPU) of Baker *et al.*, (2016), and for financial market uncertainty, we use two measures: the CBOE Volatility Index ((VIX)), and another news-based measure of US Equity Market Uncertainty (EMU), again developed by Baker *et al.*, (2016). VIX is a popular measure of the implied volatility of S&P 500 index options as calculated by the Chicago Board Options Exchange (CBOE). VIX is often referred to as the fear index or the fear gauge, and represents one measure of the market's expectation of stock market volatility over the next 30-day period. The data is sourced from the FRED databased of the Federal reserve Bank of St. Louis. The daily news-based EPU index developed by Baker *et al.*, (2016) is based on newspaper archives from Access World New's NewsBank service. The primary measure for this index is the number of articles that contain at least one term from each of sets of terms related to economic or economy, uncertain or uncertainty, and legislation or deficit or regulation or congress or federal reserve or white house. The data is available for download from: http://www.policyuncertainty.com/us_daily.html. The EMU index is constructed similarly using the same data source by Baker *et al.*, (2016), with the first two sets of terms being the same as in case of the EPU, but the third set of terms involve equity market, equity price, stock market, or stock price. The data is available at: http://www.policyuncertainty.com/equity_uncert.html. The EMU can be considered as a broader measure of financial market uncertainty relative to the VIX.[6]

[6] The correlation between the VIX and EMU was found to be 0.35.

Figure 1a. Plot of Commodity Futures Returns

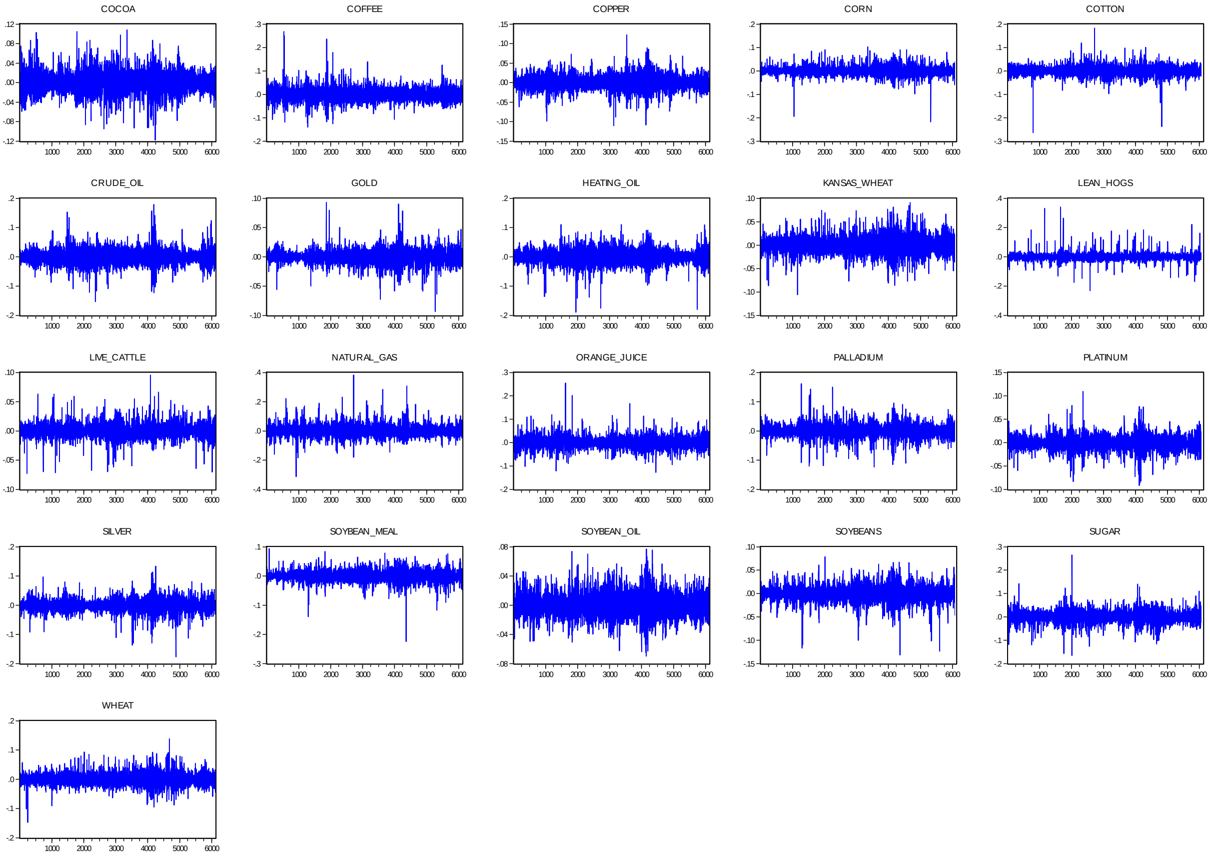

Figure 1b. Plot of Uncertainty Indices

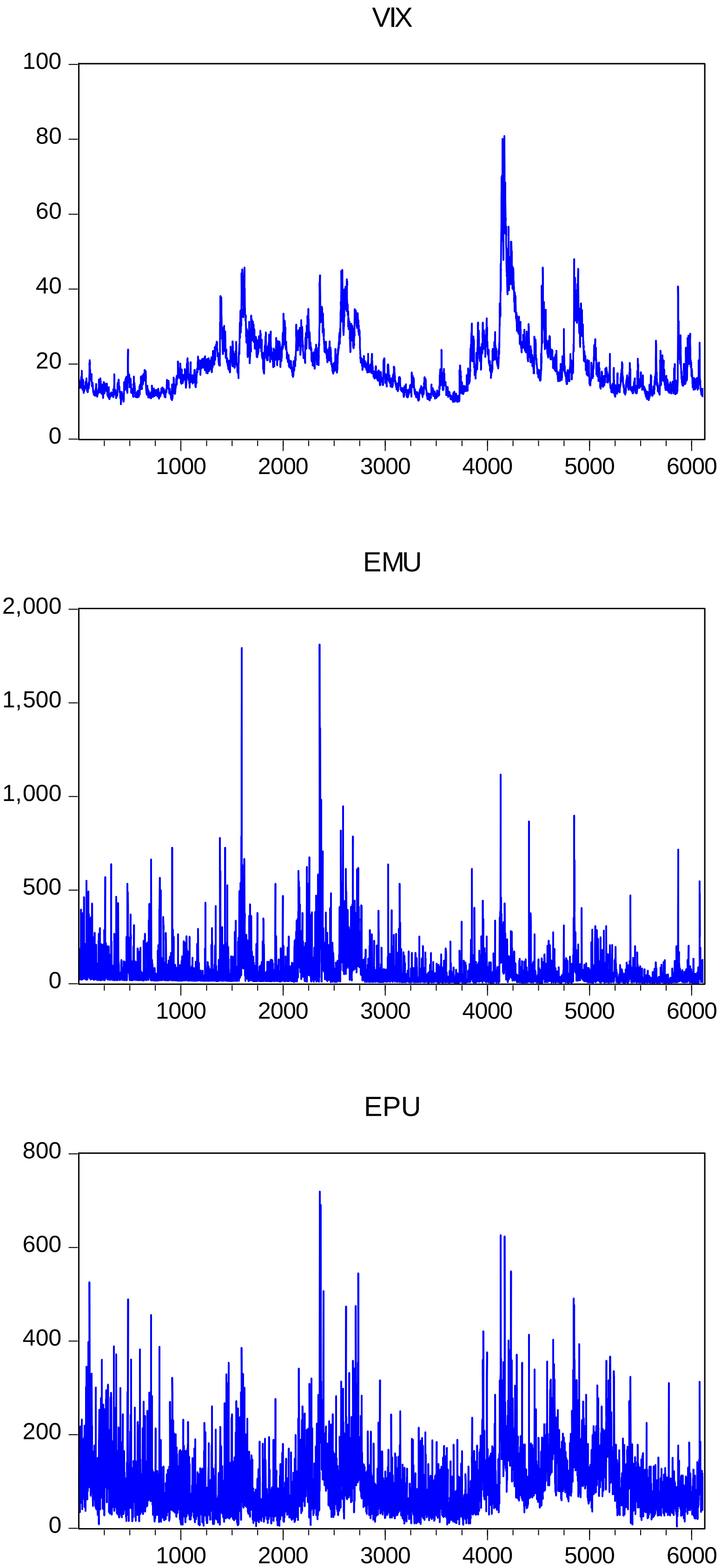

Table 1: Summary Statistics

	Variable	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	*p*-value
Agricultural	**Cocoa**	0,0401	0,0185	0,1223	3,149	2546,34	0
	Coffee	0,0429	0,0242	0,6742	8,566	19875,20	0
	Corn	0,0164	0,0169	-0,2896	10,251	26901,23	0
	Cotton	0,0187	0,0179	-0,6191	16,789	72319,09	0
	Orange Juice	0,0266	0,0207	0,6568	9,062	22163,46	0
	Soybeans	0,0183	0,0146	-0,6225	5,961	9463,79	0
	Soybean Meal	0,0307	0,0166	-0,6949	9,191	22047,01	0
	Soybean Oil	0,0174	0,0143	0,2357	2,476	1678,77	0
	Sugar	0,0343	0,0214	0,1192	7,961	16768,25	0
	Wheat	0,0159	0,0185	0,2431	3,653	3465,87	0
	Kansas wheat	0,0135	0,0166	0,1283	2,626	1840,82	0
Energy	**Crude Oil**	0,0388	0,0225	0,1812	4,911	6188,12	0
	Heating Oil	0,0411	0,0214	-0,3443	5,280	7234,80	0
	Natural Gas	0,0784	0,0345	0,6969	8,392	18465,44	0
Metal	**Gold**	0,0242	0,0102	0,0092	7,938	16078,99	0
	Silver	0,0368	0,0182	-0,5406	7,138	13297,57	0
	Copper	0,0220	0,0163	-0,0606	4,056	4201,33	0
	Palladium	0,0435	0,0199	-0,0676	5,452	7588,34	0
	Platinum	0,0186	0,0133	-0,2744	4,870	6128,60	0
Livestock	**Live Cattle**	0,0109	0,0102	-0,0252	7,138	13470,17	0
	Lean Hogs	0,0253	0,0209	2,3296	42,903	492294,26	0
Uncertainty indices	**VIX**	19,698	8,112	2,0958	7,398	18448,19	0
	EMU	69,693	103,477	4,9993	45,492	553592,68	0
	EPU	95,676	67,778	2,0912	7,733	19720,55	0

Note: *p*-value corresponds to the Jarque-Bera statistic with the null of normality.

While returns are commodity futures returns are stationary by design, natural logarithms of EPU, EMU and VIX also ensures stationarity in log-levels, which in turn satisfies our econometric requirement of having both dependent and independent variables as mean-reverting.[7] Our sample covers the daily period of 8th May, 1992 to 31st August, 2016 for these variables, i.e., a total of 6124 observations. Table 1 presents the summary statistics for commodity future returns and that of EPU, EMU and VIX. As can be seen, all variables (returns and uncertainties) are non-normal as indicated by the rejection of the null of normality under the Jarque-Bera test, thus providing us with initial motivation to consider a quantile-based approach to model the heavy mass in the tails. The data on the returns and three uncertainty indices have been plotted in Figures 1a and 1b respectively.

3.1. Empirical Findings

Although our objective is to analyze the causality-in-quantiles running from the various uncertainty indices to the returns and volatility of the commodity futures, for the sake of completeness, we also conduct the standard linear test for Granger non-causality. As indicated by the *F*-test statistics in Table 2, barring the cases of crude oil, heating oil and palladium being caused by EMU, and copper being predicted by VIX , there is no evidence of causality in any of the remaining 17 other commodities emanating from the three uncertainty indices at the conventional 5 percent level of significance. In other words, evidence of predictability due to uncertainty indices is at virtually non-existent for commodity futures returns.

Next, in order to motivate the use of the nonparametric quantile-in-causality test, we statistically investigate the possibility of nonlinearity in the relationship between the commodity futures returns and the VIX, EMU and EPU. To this end, we apply the Brock *et al.,* (1996, BDS) test on the residuals of the regression of the various commodity futures returns on its own p lags and p

[7] Complete details of unit root tests are available upon request from the authors.

Table 2: Linear Granger Causality Results

Commodities			*F*-statistic	*p*-value
Agricultural	**Cocoa**	***VIX***	0.008	0.931
		EMU	1.484	0.223
		EPU	0.032	0.857
	Coffee	***VIX***	0.545	0.461
		EMU	0.357	0.550
		EPU	0.000	0.983
	Corn	***VIX***	0.008	0.927
		EMU	2.524	0.112
		EPU	0.074	0.785
	Cotton	***VIX***	0.039	0.844
		EMU	0.365	0.546
		EPU	2.142	0.143
	Orange Juice	***VIX***	0.171	0.679
		EMU	0.501	0.479
		EPU	0.164	0.686
	Soybeans	***VIX***	0.194	0.660
		EMU	2.541	0.111
		EPU	0.504	0.478
	Soybean Meal	***VIX***	0.001	0.971
		EMU	3.075	0.080
		EPU	1.398	0.237
	Soybean oil	***VIX***	1.099	0.295
		EMU	0.304	0.582
		EPU	0.888	0.346
	Sugar	***VIX***	0.974	0.324
		EMU	0.706	0.401

		EPU	0.066	0.797
		VIX	0.077	0.781
	Wheat	***EMU***	0.106	0.745
		EPU	0.139	0.710
		VIX	0.185	0.667
	Kansas Wheat	***EMU***	0.002	0.969
		EPU	0.032	0.859
Energy		***VIX***	1.557	0.212
	Crude Oil	***EMU***	9.316	0.002
		EPU	2.896	0.089
		VIX	2.553	0.110
	Heating Oil	***EMU***	5.048	0.025
		EPU	2.599	0.107
		VIX	0.334	0.563
	Natural Gas	***EMU***	0.958	0.328
		EPU	0.083	0.773
Metal		***VIX***	0.309	0.578
	Gold	***EMU***	0.133	0.716
		EPU	0.234	0.628
		VIX	0.966	0.326
	Silver	***EMU***	0.585	0.445
		EPU	0.100	0.752
		VIX	5.120	0.024
	Copper	***EMU***	3.636	0.057
		EPU	0.431	0.511
		VIX	1.957	0.162
	Palladium	***EMU***	10.819	0.001*
		EPU	0.078	0.780

	Platinum	***VIX***	0.751	0.386
		EMU	0.298	0.585
		EPU	0.022	0.883
Livestock	**Live Cattle**	***VIX***	0.052	0.819
		EMU	1.028	0.311
		EPU	0.125	0.723
	Lean Hogs	***VIX***	0.120	0.729
		EMU	0.904	0.342
		EPU	0.024	0.878

Note: *p*-value corresponds to the null of no Granger causality from VIX, EMU or EPU to commodity returns.

Table 3: BDS Test

	Commodities		*m*=2	*m*=3	*m*=4	*m*=5	m=6
Agricultural	Cocoa	***VIX***	5.443***	7.595***	9.422***	11.044***	12.477***
		EMU	5.456***	7.58***	9.415***	11.047***	12.465***
		EPU	5.408***	7.559***	9.4***	11.027***	12.449***
	Coffee	***VIX***	9.402***	10.608***	11.461***	12.071***	12.943***
		EMU	9.466***	10.698***	11.557***	12.2***	13.076***
		EPU	9.445***	10.655***	11.492***	12.089***	12.939***
	Corn	***VIX***	13.933***	18.078***	20.486***	23.183***	25.942***
		EMU	13.915***	18.022***	20.417***	23.113***	25.864***
		EPU	13.919***	18.025***	20.429***	23.125***	25.872***
	Cotton	***VIX***	14.312***	15.85***	17.328***	18.805***	20.3***
		EMU	14.335***	15.873***	17.346***	18.813***	20.304***
		EPU	14.354***	15.923***	17.387***	18.848***	20.331***
	Orange Juice	***VIX***	10.359***	11.563***	12.175***	12.722***	13.273***
		EMU	10.307***	11.485***	12.094***	12.636***	13.195***
		EPU	10.351***	11.534***	12.131***	12.681***	13.261***
	Soybeans	***VIX***	10.287***	14.009***	15.79***	17.734***	19.592***
		EMU	10.245***	13.924***	15.667***	17.589***	19.438***
		EPU	10.294***	13.995***	15.728***	17.629***	19.479***
	Soybean Meal	***VIX***	10.15***	13.251***	15.769***	17.672***	19.362***
		EMU	10.05***	13.126***	15.628***	17.518***	19.205***
		EPU	10.175***	13.231***	15.725***	17.629***	19.317***
	Soybean oil	***VIX***	8.025***	10.742***	12.178***	13.504***	14.548***
		EMU	8.004***	10.716***	12.15***	13.489***	14.537***
		EPU	8.063***	10.823***	12.277***	13.617***	14.664***
	Sugar	***VIX***	9.113***	11.144***	12.702***	14.529***	15.989***
		EMU	9.055***	11.083***	12.636***	14.446***	15.899***
		EPU	9.129***	11.155***	12.712***	14.536***	15.992***

	Wheat	***VIX***	8.76***	11.612***	13.101***	14.653***	16.206***
		EMU	8.781***	11.605***	13.087***	14.646***	16.209***
		EPU	8.778***	11.604***	13.081***	14.643***	16.206***
	Kansas Wheat	***VIX***	11.343***	14.644***	16.715***	18.408***	20.142***
		EMU	11.375***	14.663***	16.721***	18.412***	20.143***
		EPU	11.353***	14.65***	16.716***	18.412***	20.151***
Energy	**Crude Oil**	***VIX***	11.691***	15.595***	18.371***	20.703***	23.292***
		EMU	11.888***	15.842***	18.619***	20.947***	23.502***
		EPU	12.084***	15.89***	18.644***	20.961***	23.527***
	Heating Oil	***VIX***	9.819***	13.933***	16.325***	18.773***	21.577***
		EMU	9.785***	13.948***	16.382***	18.861***	21.659***
		EPU	9.838***	13.966***	16.403***	18.866***	21.662***
	Natural Gas	***VIX***	10.465***	13.896***	15.985***	17.504***	19.408***
		EMU	10.492***	13.915***	15.999***	17.518***	19.425***
		EPU	10.472***	13.89***	15.966***	17.481***	19.388***
Metal	**Gold**	***VIX***	10.939***	14.715***	17.475***	20.06***	22.532***
		EMU	10.863***	14.699***	17.486***	20.05***	22.553***
		EPU	10.926***	14.715***	17.48***	20.057***	22.527***
	Silver	***VIX***	12.034***	14.911***	16.826***	18.591***	20.099***
		EMU	12.06***	14.923***	16.833***	18.584***	20.095***
		EPU	12.048***	14.914***	16.828***	18.581***	20.093***
	Copper	***VIX***	10.401***	13.049***	14.556***	15.718***	17.056***
		EMU	10.475***	13.258***	14.797***	15.906***	17.224***
		EPU	10.515***	13.284***	14.836***	15.97***	17.301***
	Palladium	***VIX***	18.665***	23.266***	25.986***	28.627***	31.102***
		EMU	18.529***	23.107***	25.863***	28.499***	30.981***
		EPU	18.653***	23.256***	25.989***	28.606***	31.086***
	Platinum	***VIX***	15.059***	19.174***	22.505***	24.757***	26.953***
		EMU	15.283***	19.363***	22.634***	24.853***	27.04***

		EPU	15.177***	19.267***	22.555***	24.777***	26.972***
Livestock	**Live Cattle**	***VIX***	5.652***	7.729***	8.98***	10.568***	11.593***
		EMU	5.766***	7.836***	9.061***	10.648***	11.666***
		EPU	5.616***	7.674***	8.94***	10.558***	11.594***
	Lean Hogs	***VIX***	6.079***	6.862***	7.489***	7.898***	8.344***
		EMU	6.084***	6.859***	7.479***	7.881***	8.318***
		EPU	6.076***	6.829***	7.45***	7.855***	8.298***

Note: *m* stands for the number of (embedded) dimension which embed the time series into *m*-dimensional vectors, by taking each *m* successive points in the series. Value in cell represents BDS *z*-statistic; *** indicates rejection of i.i.d. residuals at 1 percent level of significance.

lags of the three uncertainty indices in turn, with p being chosen by the SIC. As can be seen by inspecting the results summarized in Table 3, the null of *i.i.d.* residuals at various embedding dimensions (m) is rejected strongly at the highest level of significance. These results provide strong evidence of nonlinearity in the relationship between commodity futures returns and the uncertainty indices. In other words, the results of the linear test for Granger non-causality cannot be deemed robust and reliable.

As can be seen from Table 4, barring the cases of soybeans, gold, copper and palladium, we observe evidence of predictability from at least one measure of uncertainty for at least one quantile. Strong causality in the sense of coverage of the conditional distribution is observed for coffee, soybean meal, sugar, crude oil, natural gas, silver and platinum. At this stage, it is important to compare our results with those obtained by Andreasson *et al.*, (2016) under the EPU and the VIX based on the nonlinear causality test of Diks and Panchenko (2006). We concentrate on comparing the nonlinear test results rather than those obtained under the standard Granger causality, given that we do show that the linear model is misspecified. Under EPU, Andreasson *et al.* (2016) detected predictability for gold, silver and Kansas Wheat, while VIX was found to cause crude and heating oils, natural gas, platinum, gold, CBOT wheat and KBOT wheat. Even if we rule out EMU, since there are more cases of VIX predicting returns for the commodity futures in our case, we present much stronger evidence of predictability, and in the process, highlight the importance of using a nonparametric quantile causality procedure rather than a conditional-mean based nonlinear approach. Besides this, our test has the added advantage in allowing us to look for predictability in volatility of the commodity futures as measured by squared returns - which we discuss next.

As can be seen from Table 5, the evidence of predictability is weaker compared to that of the returns, with us observing causal impact of uncertainty on volatility in 9 (corn, cotton, soybean meal, sugar, crude oil, gold, silver, copper and palladium) out of the 21 commodities considered,

Table 4: Predictability of Uncertainties for Commodity Futures Returns

	Commodities		τ=0.1	τ=0.15	τ=0.2	τ=0.25	τ=0.3	τ=0.35	τ=0.4	τ=0.45	τ=0.5	τ=0.55	τ=0.6	τ=0.65	τ=0.7	τ=0.75	τ=0.8	τ=0.85	τ=0.9
Agricultural	Cocoa	*VIX*	**3.55**	**3.68**	**4.04**	**2.93**	**2.16**	1.58	1.28	1.26	0.86	1.28	1.51	**2.04**	**2.59**	**2.94**	**2.88**	**2.52**	1.44
		EMU	0.93	0.97	0.78	0.69	0.90	0.78	0.73	1.19	0.66	1.26	1.20	1.48	1.42	1.30	1.29	1.49	1.20
		EPU	1.53	**1.96**	1.67	1.27	1.14	1.04	1.03	1.42	1.13	1.91	1.90	**2.12**	1.78	1.28	1.27	1.64	1.39
	Coffee	*VIX*	**4.99**	**5.74**	**6.86**	**7.46**	**7.56**	**8.49**	**8.66**	**8.65**	**8.56**	**8.31**	**7.97**	**8.18**	**7.88**	**7.47**	**6.86**	**5.95**	**5.06**
		EMU	**3.34**	**3.68**	**4.64**	**4.66**	**5.02**	**5.37**	**5.55**	**5.67**	**5.67**	**5.86**	**6.01**	**5.94**	**5.83**	**5.47**	**4.66**	**4.35**	**3.61**
		EPU	**5.28**	**6.18**	**7.04**	**7.65**	**7.95**	**8.65**	**8.99**	**9.00**	**8.60**	**8.75**	**8.76**	**8.60**	**8.47**	**7.69**	**6.84**	**5.86**	**4.90**
	Corn	*VIX*	**4.11**	**2.80**	**2.98**	**3.19**	**2.67**	**2.24**	1.43	1.19	**8.26**	0.73	1.17	1.92	**2.53**	**3.09**	**3.15**	**4.39**	**4.25**
		EMU	**1.99**	1.48	1.70	1.76	1.45	1.17	0.71	0.76	**7.09**	1.01	1.16	1.77	**2.20**	**2.54**	**2.47**	**2.47**	**2.38**
		EPU	**2.41**	1.55	1.65	1.39	1.49	1.20	1.08	0.93	**9.17**	0.96	1.29	1.90	**2.29**	**2.63**	**2.64**	**2.68**	**2.33**
	Cotton	*VIX*	0.80	0.74	0.72	0.44	0.45	0.18	0.10	0.07	**4.75**	0.04	0.08	0.21	0.36	0.42	0.51	0.69	0.64
		EMU	0.46	0.40	0.32	0.22	0.23	0.09	0.09	0.10	**4.21**	0.06	0.06	0.15	0.28	0.38	0.41	0.63	0.51
		EPU	0.62	0.66	0.52	0.37	0.26	0.13	0.13	0.15	**5.07**	0.35	0.41	0.53	0.68	0.54	0.66	1.01	0.96
	Orange Juice	*VIX*	0.04	0.04	0.03	0.03	0.02	0.01	0.02	0.02	**7.55**	0.02	0.02	0.03	0.03	0.02	0.03	0.02	0.02
		EMU	0.03	0.03	0.03	0.03	0.02	0.01	<0.01	<0.01	**7.54**	0.02	0.03	0.03	0.04	0.03	0.03	0.02	0.02
		EPU	0.05	0.05	0.03	0.04	0.03	0.02	0.01	0.01	**7.46**	0.01	0.03	0.02	0.02	0.01	0.04	0.03	0.03
	Soybeans	*VIX*	0.21	0.20	0.24	0.23	0.15	0.06	0.02	0.01	0.00	<0.01	<0.01	0.02	0.04	0.07	0.15	0.13	0.16
		EMU	0.02	0.02	0.04	0.03	0.03	0.03	0.02	0.01	0.01	0.03	0.03	0.02	0.01	0.03	0.03	0.05	0.05
		EPU	0.03	0.02	0.04	0.03	0.03	0.04	0.04	0.02	0.01	0.01	0.02	<0.01	<0.01	0.02	0.02	0.02	0.02
	Soybean Meal	*VIX*	**4.28**	**5.98**	**7.15**	**7.41**	**7.23**	**6.70**	**6.47**	**6.92**	**7.23**	**6.64**	**6.94**	**7.41**	**7.39**	**6.94**	**6.75**	**5.54**	**4.04**
		EMU	**2.50**	**3.15**	**3.97**	**4.06**	**4.69**	**4.63**	**4.79**	**4.88**	**4.63**	**4.12**	**3.68**	**3.96**	**4.21**	**4.40**	**3.96**	**3.53**	**2.76**
		EPU	**3.47**	**4.38**	**5.13**	**5.39**	**5.41**	**5.66**	**6.07**	**6.62**	**6.38**	**5.78**	**5.87**	**5.60**	**5.18**	**5.54**	**5.17**	**4.51**	**3.82**
	Soybean Oil	*VIX*	1.67	1.63	1.55	1.84	1.85	1.86	**2.22**	1.90	**6.27**	1.69	1.69	1.71	1.94	1.71	1.89	1.86	**2.41**
		EMU	0.93	1.22	0.90	0.97	0.74	0.84	1.35	1.57	**5.80**	1.14	0.91	0.88	1.37	1.26	1.13	1.17	1.70
		EPU	1.19	1.83	1.72	1.66	1.95	**2.15**	**2.57**	**2.16**	**7.84**	**2.23**	**2.26**	1.73	1.95	1.57	1.24	1.40	1.62
	Sugar	*VIX*	**3.41**	**3.88**	**3.40**	**3.36**	**3.15**	**3.02**	**2.77**	**2.88**	**4.01**	**3.68**	**4.44**	**4.34**	**4.15**	**4.57**	**5.26**	**5.25**	**4.11**
		EMU	**3.32**	**3.48**	**3.49**	**3.43**	**2.57**	**2.28**	**2.20**	**2.77**	**4.33**	**2.99**	**3.33**	**3.06**	**3.19**	**2.88**	**3.24**	**2.38**	**2.37**
		EPU	**4.03**	**4.87**	**4.62**	**5.02**	**4.82**	**4.81**	**3.93**	**4.04**	**5.36**	**4.41**	**4.55**	**4.06**	**3.85**	**3.84**	**4.34**	**3.55**	**3.20**
	Wheat	*VIX*	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	**13.03**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	**13.03**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	**13.03**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Kansas wheat	*VIX*	0.647	0.799	0.725	0.569	0.427	0.210	0.146	0.191	**10.510**	0.191	0.192	0.331	0.526	0.530	0.852	1.064	1.382
		EMU	0.300	0.393	0.483	0.492	0.258	0.137	0.083	0.068	**9.683**	0.113	0.109	0.208	0.327	0.354	0.411	0.561	0.409
		EPU	0.576	0.468	0.465	0.342	0.186	0.119	0.097	0.082	**11.235**	0.422	0.381	0.332	0.265	0.290	0.611	0.671	0.702
ne rg	Crude Oil	*VIX*	**6.92**	**8.03**	**9.13**	**9.47**	**9.62**	**9.85**	**9.79**	**10.03**	**10.64**	**10.66**	**10.56**	**10.85**	**11.09**	**10.76**	**10.23**	**9.01**	**7.28**

		EMU	**4.43**	**4.98**	**6.20**	**6.48**	**7.05**	**6.80**	**6.72**	**6.67**	**7.24**	**6.85**	**6.93**	**6.72**	**6.60**	**5.74**	**5.14**	**4.84**	**3.77**
		EPU	**6.51**	**7.52**	**8.86**	**9.60**	**10.11**	**10.54**	**10.66**	**10.76**	**10.51**	**10.10**	**9.95**	**9.63**	**9.64**	**8.83**	**8.44**	**7.35**	**6.18**
	Heating Oil	***VIX***	**2.29**	**2.69**	**2.25**	**2.34**	1.57	0.82	0.66	0.58	0.30	0.22	0.38	0.75	1.50	1.63	**2.22**	**2.70**	1.87
		EMU	0.79	1.07	0.89	0.89	0.64	0.39	0.52	0.46	0.24	0.12	0.18	0.25	0.38	0.58	0.60	0.77	0.50
		EPU	0.62	0.81	0.87	0.93	0.66	0.48	0.70	0.54	0.27	0.09	0.11	0.19	0.38	0.54	0.45	0.58	0.55
	Natural Gas	***VIX***	**4.37**	**4.23**	**4.44**	**4.48**	**3.66**	**3.21**	**2.88**	**2.95**	**3.91**	**3.18**	**3.09**	**2.80**	**3.33**	**3.31**	**3.39**	**3.71**	**2.63**
		EMU	**2.24**	**2.20**	1.87	1.82	1.94	1.60	1.46	1.70	**3.02**	**2.04**	**2.12**	**2.00**	**2.18**	**2.50**	**2.39**	**2.08**	1.72
		EPU	**3.12**	**3.50**	**2.91**	**3.32**	**3.60**	**3.43**	**3.57**	**3.79**	**4.53**	**3.97**	**4.16**	**4.30**	**3.82**	**3.64**	**3.71**	**2.97**	**2.31**
Metal	**Gold**	***VIX***	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Silver	***VIX***	**3.72**	**4.63**	**5.28**	**5.65**	**6.36**	**6.65**	**6.89**	**6.90**	**6.89**	**6.96**	**6.65**	**5.70**	**5.26**	**5.08**	**4.78**	**4.59**	**3.63**
		EMU	**2.41**	**3.53**	**3.11**	**3.71**	**4.45**	**5.57**	**5.98**	**6.00**	**5.62**	**5.35**	**4.86**	**4.59**	**4.29**	**3.90**	**3.92**	**3.53**	**2.95**
		EPU	**4.38**	**5.45**	**5.30**	**5.64**	**5.84**	**6.69**	**7.06**	**7.57**	**7.36**	**7.54**	**7.01**	**7.00**	**6.78**	**6.04**	**5.46**	**5.07**	**3.84**
	Copper	***VIX***	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Palladium	***VIX***	0.44	0.50	0.51	0.56	0.46	0.31	0.21	0.08	0.02	0.01	0.02	0.06	0.16	0.27	0.26	0.30	0.33
		EMU	0.18	0.24	0.23	0.20	0.12	0.07	0.05	0.04	0.02	0.01	0.02	0.06	0.05	0.07	0.07	0.07	0.05
		EPU	0.15	0.18	0.19	0.19	0.11	0.10	0.07	0.04	0.02	0.03	0.05	0.09	0.10	0.10	0.10	0.13	0.09
	Platinum	***VIX***	**4.48**	**4.79**	**5.28**	**5.67**	**5.51**	**4.78**	**4.84**	**4.95**	**4.84**	**4.53**	**5.28**	**5.63**	**5.73**	**6.77**	**6.84**	**6.41**	**5.61**
		EMU	**2.96**	**2.64**	**3.00**	**2.42**	**2.14**	1.71	1.78	**2.04**	**2.61**	**3.13**	**2.93**	**2.90**	**3.10**	**4.24**	**5.02**	**4.29**	**3.92**
		EPU	**4.02**	**4.06**	**4.60**	**4.33**	**4.83**	**4.55**	**4.83**	**4.69**	**4.78**	**4.92**	**4.88**	**4.84**	**4.78**	**4.78**	**5.30**	**4.23**	**4.22**
Livestock	**Live Cattle**	***VIX***	1.45	1.69	1.74	**2.34**	**2.80**	**2.91**	**2.98**	**2.85**	**4.75**	**2.75**	**3.02**	**2.83**	**2.90**	**3.06**	**3.56**	**3.15**	**2.53**
		EMU	1.17	1.24	1.42	1.54	1.63	**2.05**	**2.27**	**2.39**	**4.78**	**2.93**	**3.34**	**2.84**	**2.53**	**2.63**	**2.35**	1.70	1.39
		EPU	0.99	1.57	1.73	**2.09**	**2.03**	**2.61**	**3.01**	**3.25**	**5.47**	**3.38**	**4.09**	**3.80**	**3.36**	**3.04**	**2.67**	**2.33**	1.66
	Lean Hogs	***VIX***	**3.01**	**3.22**	**2.12**	1.47	1.52	1.35	1.00	0.75	0.80	0.86	0.97	1.39	1.15	1.14	1.69	**2.02**	**3.28**
		EMU	1.09	1.29	1.17	1.19	0.82	0.78	0.64	0.70	1.14	0.99	1.11	1.44	1.16	0.82	0.70	0.47	0.37
		EPU	0.93	1.39	0.99	0.68	0.74	0.74	0.84	0.75	1.01	0.81	1.14	1.26	0.96	0.66	0.79	1.08	0.71

Note: τ indicates a specific quantile; Significant values at the 5 percent level or better is denoted in bold; <0.01 for values with test statistic lower than 0.01.

Table 5: Predictability of Uncertainties for Commodity Futures Volatility (Squared Returns)

	Commodities		τ=0.1	τ=0.15	τ=0.2	τ=0.25	τ=0.3	τ=0.35	τ=0.4	τ=0.45	τ=0.5	τ=0.55	τ=0.6	τ=0.65	τ=0.7	τ=0.75	τ=0.8	τ=0.85	τ=0.9
Agricultural	Cocoa	***VIX***	0.04	0.04	0.05	0.09	0.11	0.15	0.15	0.19	0.21	0.26	0.25	0.22	0.24	0.23	0.19	0.17	0.16
		EMU	<0.01	<0.01	0.01	0.01	0.03	0.03	0.06	0.05	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.02
		EPU	0.02	0.04	0.03	0.04	0.07	0.07	0.08	0.08	0.08	0.10	0.10	0.09	0.12	0.12	0.09	0.07	0.03
	Coffee	***VIX***	1.37	1.55	1.53	1.37	1.07	1.60	1.48	1.49	1.26	1.34	1.10	1.19	0.87	1.29	1.03	0.99	0.79
		EMU	0.91	1.23	0.87	0.72	0.72	0.95	0.98	1.02	0.93	0.85	0.89	0.74	0.99	0.57	0.86	0.60	0.64
		EPU	0.94	1.60	1.57	1.46	1.31	1.66	1.49	1.44	1.64	1.51	1.32	1.24	1.18	1.34	1.44	1.26	0.93
	Corn	***VIX***	**10.02**	**12.12**	**13.84**	**15.04**	**16.17**	**16.89**	**18.01**	**18.23**	**18.33**	**18.46**	**18.20**	**17.47**	**16.68**	**16.02**	**14.34**	**12.40**	**9.73**
		EMU	**7.18**	**9.25**	**10.91**	**12.00**	**12.94**	**13.28**	**13.29**	**13.51**	**14.12**	**13.78**	**13.43**	**12.77**	**12.42**	**10.95**	**9.90**	**8.53**	**6.85**
		EPU	**10.65**	**13.16**	**14.83**	**16.27**	**17.36**	**17.83**	**18.14**	**18.27**	**18.34**	**18.38**	**18.28**	**17.52**	**16.88**	**15.43**	**14.06**	**12.54**	**10.15**
	Cotton	***VIX***	0.15	0.27	0.42	0.73	1.11	1.42	1.59	1.45	1.13	1.26	1.42	1.17	1.25	1.01	1.11	1.46	1.65
		EMU	0.27	0.32	0.41	0.57	0.64	0.88	0.90	0.75	0.69	0.79	0.72	0.64	0.54	0.57	0.65	0.65	0.34
		EPU	0.41	0.40	0.69	0.78	1.09	1.62	1.55	1.72	1.53	**2.13**	**2.21**	1.63	**2.01**	**2.18**	**2.18**	**2.63**	**2.18**
	Orange Juice	***VIX***	<0.01	<0.01	<0.01	<0.01	<0.01	0.02	0.01	0.01	0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	0.02	0.01	<0.01	<0.01	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.01	<0.01	<0.01	<0.01
		EPU	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.03	0.03	0.03	0.02	<0.01	<0.01
	Soybeans	***VIX***	0.06	0.04	0.09	0.22	0.34	0.55	0.88	0.88	0.84	0.93	1.19	1.00	1.14	0.72	0.71	0.49	0.48
		EMU	0.07	0.10	0.13	0.10	0.11	0.18	0.12	0.18	0.22	0.26	0.24	0.26	0.23	0.26	0.17	0.06	0.04
		EPU	0.03	0.10	0.14	0.08	0.08	0.19	0.07	0.13	0.13	0.15	0.14	0.16	0.17	0.10	0.07	0.07	0.12
	Soybean Meal	***VIX***	**5.53**	**7.17**	**7.98**	**8.69**	**8.95**	**10.36**	**11.28**	**11.88**	**12.26**	**12.29**	**12.35**	**11.49**	**11.16**	**10.12**	**8.79**	**7.62**	**5.74**
		EMU	**4.49**	**5.64**	**6.26**	**6.79**	**7.16**	**8.13**	**8.32**	**8.21**	**8.47**	**8.34**	**7.69**	**7.33**	**6.45**	**5.78**	**5.53**	**5.37**	**4.39**
		EPU	**6.03**	**7.35**	**8.16**	**8.87**	**9.47**	**10.07**	**10.54**	**10.83**	**11.24**	**10.66**	**10.55**	**10.12**	**9.56**	**8.56**	**7.95**	**6.66**	**5.79**
	Soybean Oil	***VIX***	0.03	0.01	0.04	0.02	0.03	0.03	0.04	0.07	0.13	0.20	0.22	0.25	0.20	0.36	0.44	0.61	0.53
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	0.01	0.01	<0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.01	<0.01	<0.01
		EPU	0.02	<0.01	0.02	0.02	0.04	0.05	0.02	0.02	<0.01	0.02	0.02	0.02	0.02	<0.01	0.01	<0.01	0.01
	Sugar	***VIX***	1.11	1.19	1.65	**2.75**	**2.73**	**2.99**	**3.11**	**4.73**	**5.12**	**5.77**	**6.84**	**8.60**	**7.36**	**7.71**	**6.37**	**5.95**	**4.00**
		EMU	0.66	0.99	0.74	1.47	1.21	1.20	**2.13**	**2.89**	**3.73**	**2.78**	**3.19**	**3.60**	**2.11**	0.98	0.85	0.71	0.93
		EPU	1.30	1.54	1.55	**2.26**	**2.33**	**3.22**	**3.11**	**3.76**	**3.57**	**3.34**	**3.28**	**4.47**	**3.26**	**2.42**	**2.94**	**2.60**	1.51
	Wheat	***VIX***	0.02	0.06	0.09	0.21	0.54	0.71	0.84	1.19	1.13	1.11	1.30	1.53	1.36	1.23	0.98	0.79	0.73
		EMU	0.11	0.14	0.12	0.10	0.05	0.08	0.04	0.05	0.08	0.05	0.05	0.07	0.04	0.02	0.05	0.04	0.01
		EPU	0.03	0.05	0.10	0.07	0.09	0.07	0.16	0.20	0.16	0.28	0.39	0.52	0.56	0.52	0.41	0.53	0.37
	Kansas wheat	***VIX***	0.02	0.07	0.11	0.09	0.10	0.19	0.28	0.27	0.32	0.34	0.54	0.52	0.85	0.97	1.00	1.10	0.82
		EMU	0.05	0.16	0.07	0.09	0.15	0.24	0.30	0.55	0.49	0.52	0.32	0.38	0.37	0.26	0.16	0.04	0.02
		EPU	0.37	0.28	0.15	0.09	0.09	0.07	0.06	0.04	0.04	0.08	0.12	0.18	0.28	0.46	0.43	0.76	0.31
ne rg	Crude Oil	***VIX***	1.48	**2.84**	**5.59**	**7.35**	**7.83**	**10.27**	**11.30**	**12.26**	**13.65**	**12.72**	**15.79**	**18.80**	**17.12**	**16.73**	**12.52**	**9.71**	**7.46**

		EMU	0.34	0.28	0.40	0.42	0.63	0.58	1.01	0.74	0.71	0.42	0.31	0.27	0.51	0.69	0.35	0.39	0.48
		EPU	0.56	0.63	0.58	0.72	0.76	0.60	0.64	0.47	0.50	0.50	0.71	0.58	0.70	0.82	0.45	0.59	0.48
	Heating Oil	*VIX*	<0.01	0.01	0.06	0.16	0.25	0.45	0.58	0.75	0.74	0.83	0.76	0.93	1.01	1.00	0.82	0.82	0.67
		EMU	<0.01	0.01	0.01	0.01	0.02	0.05	0.05	0.07	0.04	0.04	0.06	0.07	0.10	0.11	0.07	0.08	0.10
		EPU	0.01	0.01	0.01	0.01	0.01	0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.01	0.02	0.04
	Natural Gas	*VIX*	0.09	0.19	0.32	0.37	0.63	0.67	0.65	0.94	0.98	0.91	0.89	0.86	0.87	0.93	0.68	0.59	0.39
		EMU	0.02	0.03	0.05	0.04	0.06	0.10	0.06	0.15	0.19	0.18	0.13	0.13	0.12	0.09	0.07	0.08	0.08
		EPU	0.05	0.07	0.15	0.07	0.10	0.07	0.07	0.13	0.19	0.13	0.11	0.16	0.17	0.12	0.05	0.05	0.03
Metal	Gold	*VIX*	**2.81**	**4.64**	**6.26**	**6.89**	**7.69**	**8.99**	**7.70**	**7.71**	**7.82**	**7.92**	**7.45**	**7.16**	**6.41**	**6.78**	**6.52**	**5.34**	**3.68**
		EMU	1.75	**2.54**	**3.59**	**5.11**	**6.20**	**5.92**	**6.06**	**6.01**	**6.33**	**6.00**	**5.89**	**5.78**	**6.22**	**6.40**	**5.54**	**3.87**	**2.96**
		EPU	**3.04**	**3.89**	**4.32**	**4.86**	**5.06**	**5.29**	**5.33**	**6.15**	**5.96**	**6.24**	**5.49**	**5.29**	**5.08**	**5.41**	**5.12**	**4.26**	**3.65**
	Silver	*VIX*	**2.60**	**2.73**	**2.93**	**2.87**	**2.88**	**2.76**	**3.06**	**3.41**	**3.78**	**3.80**	**4.07**	**4.24**	**4.10**	**3.79**	**3.22**	**2.50**	**2.04**
		EMU	1.49	1.91	**2.55**	**2.16**	**2.07**	**2.13**	**2.35**	**2.10**	**2.27**	**2.70**	**2.51**	**3.02**	**3.19**	**3.08**	**2.86**	**2.65**	**2.82**
		EPU	**2.60**	**2.51**	**2.79**	**3.28**	**3.35**	**3.63**	**3.74**	**4.12**	**4.55**	**3.93**	**3.99**	**4.08**	**4.37**	**4.09**	**3.64**	**2.94**	**2.25**
	Copper	*VIX*	1.05	1.04	1.32	1.81	**2.20**	**3.15**	**3.13**	**2.91**	**3.56**	**3.69**	**3.05**	**2.91**	**2.16**	**2.04**	**2.97**	**2.04**	**2.11**
		EMU	0.54	0.74	0.70	1.09	1.34	1.45	**2.36**	**2.54**	**2.50**	**2.61**	**2.04**	**2.24**	**2.19**	1.57	0.96	0.70	0.67
		EPU	0.64	0.86	1.12	1.19	1.25	1.41	1.69	1.79	1.87	1.96	1.71	1.81	1.79	1.71	1.69	1.47	1.38
	Palladium	*VIX*	**4.82**	**6.05**	**7.45**	**7.35**	**8.24**	**8.76**	**9.64**	**10.46**	**11.76**	**11.34**	**11.69**	**11.56**	**10.77**	**10.22**	**8.87**	**6.96**	**6.20**
		EMU	**2.85**	**3.64**	**4.53**	**4.65**	**5.44**	**5.54**	**5.70**	**5.65**	**5.78**	**5.83**	**5.88**	**6.02**	**5.82**	**5.46**	**4.63**	**3.90**	**3.65**
		EPU	**4.57**	**5.59**	**6.49**	**7.03**	**7.76**	**7.85**	**8.05**	**8.01**	**8.68**	**8.10**	**8.67**	**9.91**	**9.70**	**8.91**	**7.31**	**6.05**	**5.21**
	Platinum	*VIX*	0.16	0.45	0.71	1.03	1.10	1.31	1.71	**2.20**	**2.39**	**2.99**	**2.82**	**3.21**	**3.02**	**2.66**	**2.68**	1.81	1.55
		EMU	0.02	0.05	0.08	0.09	0.06	0.06	0.07	0.11	0.09	0.12	0.16	0.16	0.10	0.05	0.09	0.07	0.12
		EPU	0.09	0.09	0.14	0.21	0.28	0.27	0.26	0.30	0.39	0.60	0.76	0.73	0.61	0.54	0.54	0.25	0.17
Livestock	Live Cattle	*VIX*	0.04	0.17	0.26	0.35	0.37	0.55	0.66	0.75	0.83	0.65	0.76	0.88	1.00	0.88	0.57	0.33	0.19
		EMU	0.01	0.01	0.04	0.05	0.04	0.07	0.09	0.14	0.16	0.15	0.21	0.15	0.19	0.19	0.14	0.10	0.04
		EPU	0.02	0.02	0.04	0.05	0.06	0.07	0.10	0.14	0.14	0.18	0.26	0.19	0.23	0.21	0.16	0.17	0.08
	Lean Hogs	*VIX*	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Note: See Notes to Table 4.

with strong effects are observed for the agricultural (barring cotton) and metal futures. Note, comparing results in Table 4 and 5, uncertainty predicts both returns and volatility for corn, cotton, soybean meal, sugar and crude oil. In Tables 6 and 7, we look at the results when we use GARCH and GJR-GARCH models to create a measure of conditional volatility, as a matter of robustness check for results obtained under square returns. With volatility measured by a GARCH model, we observe only five significant cases associated with crude and heating oils, soybean meal, live cattle, and live hogs. The evidence is weakened further when we use the GJR-GARCH based measure of conditional volatility, with causality detected for only platinum, soybeans and orange juice. However, we believe that since squared returns as a measure of volatility follows directly from the *k*-th order test and is independent of a model-based estimate of volatility (which could vary depending on what model we choose), the use of squared returns is more appropriate in our context, and so is the reliability of the associated results (see Balcilar *et al.*, (2016b) for a detailed discussion in this regard).[8] Overall, our findings suggest that economic and financial market uncertainty does predict commodity futures returns and/or volatility for 20 of the 21 cases considered, with the exception being soybeans in terms of both returns and volatility. Note however, if we consider the GJR-GARCH results, uncertainty predicts volatility of soybeans as well.

Note that, in terms of greater impact of uncertainty on commodity futures market returns than volatilites, our results are actually in line with Joëts et al., (2017). These authors indicate that although in a general sense uncertainty is defined as the conditional volatility of an unforecastable disturbance, the empirical literature has usually relied on proxies (such as the EMU, EPU and VIX), which in turn can pick up fluctuations that are actually predictable and hence, can erroneously be attributable to uncertainty. Thus, it is important to distinguish between uncertainty in a series and its conditional volatility, i.e., properly measuring uncertainty

[8] Note that, the GARCH model has a deterministic volatility generation function and does not allow for volatility shocks, limiting its capacity to produce realistic uncertainty series for the commodity returns.

Table 6: Predictability of Uncertainties for Commodity Futures Volatility (GARCH(1,1))

	Commodities		τ=0.1	τ=0.15	τ=0.2	τ=0.25	τ=0.3	τ=0.35	τ=0.4	τ=0.45	τ=0.5	τ=0.55	τ=0.6	τ=0.65	τ=0.7	τ=0.75	τ=0.8	τ=0.85	τ=0.9
Agricultural	Cocoa	**VIX**	0.07	0.26	0.21	0.39	0.96	0.88	0.80	0.84	0.99	1.18	1.03	1.25	1.32	0.83	0.49	0.42	0.43
		EMU	0.15	0.09	0.09	0.06	0.05	0.08	0.11	0.07	0.15	0.16	0.10	0.13	0.13	0.10	0.07	0.09	0.18
		EPU	0.14	0.12	0.06	0.08	0.11	0.20	0.24	0.24	0.17	0.16	0.13	0.12	0.10	0.10	0.08	0.13	0.16
	Coffee	**VIX**	0.00	0.01	0.02	0.01	0.03	0.06	0.07	0.06	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00
		EMU	0.06	0.03	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.08	0.06	0.10	0.07	0.04	0.04	0.03	0.01
		EPU	0.01	0.01	0.01	0.01	0.03	0.03	0.02	0.02	0.03	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01
	Corn	**VIX**	0.08	0.12	0.13	0.14	0.19	0.28	0.25	0.30	0.20	0.20	0.10	0.11	0.17	0.12	0.05	0.05	0.07
		EMU	0.12	0.16	0.24	0.19	0.25	0.47	0.43	0.55	0.41	0.30	0.24	0.20	0.26	0.19	0.10	0.06	0.03
		EPU	0.07	0.30	0.38	0.39	0.49	0.52	0.43	0.42	0.27	0.36	0.37	0.25	0.27	0.21	0.09	0.06	0.04
	Cotton	**VIX**	0.06	0.11	0.11	0.07	0.16	0.42	0.52	0.41	0.44	0.31	0.39	0.31	0.38	0.41	0.39	0.35	0.58
		EMU	0.14	0.21	0.23	0.13	0.13	0.31	0.42	0.29	0.30	0.15	0.22	0.17	0.28	0.34	0.35	0.34	0.32
		EPU	0.08	0.11	0.06	0.03	0.07	0.22	0.34	0.20	0.28	0.25	0.34	0.29	0.43	0.54	0.48	0.45	0.38
	Orange Juice	**VIX**	0.21	0.37	0.58	0.64	1.02	1.00	0.79	1.15	1.94	1.81	1.59	1.50	1.56	1.93	1.57	1.39	0.54
		EMU	0.26	0.14	0.24	0.37	0.89	0.80	0.65	0.80	1.34	1.44	0.93	0.95	0.99	1.28	0.94	0.77	0.46
		EPU	0.24	0.38	0.56	0.85	1.13	1.25	1.13	1.36	1.75	1.43	0.87	0.89	1.04	1.23	1.13	1.08	0.63
	Soybeans	**VIX**	0.06	0.11	0.17	0.42	0.39	0.47	0.68	0.86	0.76	0.58	0.67	0.54	0.45	0.53	0.39	0.19	0.14
		EMU	0.45	0.63	0.78	0.79	0.43	0.42	0.66	0.84	0.89	1.00	0.70	0.53	0.28	0.35	0.19	0.19	0.13
		EPU	0.10	0.37	0.69	0.79	0.74	0.70	0.96	1.05	0.86	0.91	0.59	0.59	0.31	0.25	0.16	0.14	0.19
	Soybean Meal	**VIX**	0.51	1.37	1.82	**2.32**	**3.01**	**3.94**	**4.00**	**4.17**	**5.12**	**4.17**	**3.70**	**4.80**	**4.60**	**4.34**	**3.25**	1.64	1.08
		EMU	0.90	1.20	1.35	1.31	1.78	**2.21**	**2.55**	**3.30**	**3.03**	**2.50**	1.83	1.70	1.31	1.12	1.13	0.70	0.49
		EPU	0.57	1.40	1.57	1.58	**2.37**	**3.26**	**3.35**	**3.97**	**3.48**	**2.82**	1.62	1.60	1.31	1.02	1.00	0.74	0.67
	Soybean Oil	**VIX**	0.42	0.30	0.57	0.58	0.80	0.72	0.76	0.57	0.65	0.60	0.55	0.43	0.63	0.80	0.81	0.80	0.63
		EMU	0.70	0.57	0.82	0.55	0.75	0.72	0.81	0.68	0.66	0.64	0.47	0.23	0.38	0.41	0.59	0.38	0.25
		EPU	0.36	0.78	0.70	0.66	1.02	0.60	0.57	0.57	0.58	0.69	0.61	0.67	0.85	1.14	1.12	1.35	0.79
	Sugar	**VIX**	0.06	0.08	0.13	0.12	0.07	0.15	0.27	0.28	0.25	0.31	0.29	0.30	0.35	0.20	0.20	0.20	0.11
		EMU	0.03	0.02	0.03	0.05	0.08	0.09	0.19	0.22	0.28	0.32	0.29	0.23	0.20	0.12	0.15	0.10	0.05
		EPU	0.02	0.02	0.06	0.08	0.11	0.24	0.31	0.32	0.35	0.36	0.34	0.34	0.22	0.22	0.18	0.14	0.09
	Wheat	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Kansas wheat	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
ne rg	Crude Oil	**VIX**	**2.04**	**2.77**	**3.02**	**3.61**	**3.56**	**4.19**	**4.88**	**4.15**	**4.27**	**4.45**	**4.16**	**4.24**	**3.79**	**3.23**	**3.00**	**2.83**	**2.06**

		EMU	1.61	1.48	1.60	**2.26**	**2.08**	**2.61**	**2.80**	**2.69**	**3.00**	**3.24**	**2.63**	**2.26**	**2.24**	**1.97**	**1.97**	**2.16**	1.77
		EPU	1.62	**1.96**	1.89	**2.43**	**2.51**	**2.85**	**3.07**	**3.30**	**3.50**	**3.72**	**3.76**	**3.79**	**3.60**	**3.37**	**2.88**	**2.26**	1.77
		VIX	0.14	0.12	0.19	0.32	0.54	0.98	1.44	1.76	1.92	**2.93**	**2.64**	**3.13**	**3.18**	**2.65**	**2.80**	**2.31**	**1.97**
	Heating Oil	**EMU**	0.36	0.43	0.41	0.56	0.60	0.71	1.14	1.19	1.19	1.78	1.54	1.23	1.53	0.99	1.11	1.06	0.74
		EPU	0.54	0.57	0.74	0.90	0.72	1.03	1.44	1.51	1.45	1.42	1.56	0.94	1.75	1.04	1.21	1.04	0.57
		VIX	0.01	0.09	0.17	0.35	0.58	0.66	0.65	0.49	0.62	0.83	0.76	0.70	0.99	0.86	0.72	0.52	0.21
	Natural Gas	**EMU**	0.13	0.04	0.05	0.07	0.13	0.17	0.20	0.11	0.20	0.23	0.19	0.18	0.21	0.15	0.20	0.25	0.24
		EPU	0.06	0.04	0.06	0.08	0.13	0.24	0.19	0.06	0.17	0.14	0.16	0.09	0.18	0.13	0.11	0.19	0.12
		VIX	0.27	0.42	0.56	0.70	1.09	0.64	0.63	0.66	0.56	0.61	0.65	0.56	0.93	0.81	1.06	0.72	0.57
	Gold	**EMU**	0.32	0.62	0.71	0.60	0.83	0.45	0.55	0.57	0.45	0.49	0.43	0.16	0.24	0.22	0.27	0.25	0.21
		EPU	0.21	0.47	0.55	0.46	0.58	0.44	0.48	0.66	0.73	0.67	1.13	0.74	0.60	0.73	0.86	0.69	0.79
		VIX	0.02	0.07	0.11	0.08	0.18	0.26	0.34	0.40	0.53	0.44	0.56	0.66	0.55	0.55	0.50	0.26	0.04
	Silver	**EMU**	0.19	0.12	0.13	0.11	0.06	0.08	0.06	0.06	0.04	0.04	0.07	0.16	0.09	0.09	0.12	0.07	0.03
		EPU	0.03	0.11	0.09	0.03	0.06	0.09	0.19	0.32	0.22	0.46	0.34	0.41	0.51	0.42	0.31	0.16	0.09
		VIX	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Metal	**Copper**	**EMU**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		VIX	0.07	0.08	0.09	0.27	0.28	0.34	0.38	0.30	0.34	0.47	0.45	0.47	0.61	0.61	0.48	0.35	0.38
	Palladium	**EMU**	0.18	0.16	0.14	0.24	0.31	0.29	0.21	0.16	0.20	0.19	0.16	0.17	0.22	0.12	0.05	0.03	0.06
		EPU	0.02	0.05	0.08	0.14	0.20	0.17	0.13	0.09	0.20	0.26	0.23	0.24	0.18	0.12	0.07	0.06	0.09
		VIX	0.07	0.13	0.16	0.15	0.17	0.11	0.22	0.33	0.87	1.18	1.14	0.63	0.81	0.78	0.72	0.57	0.46
	Platinum	**EMU**	0.09	0.28	0.23	0.21	0.17	0.17	0.14	0.11	0.18	0.14	0.16	0.18	0.20	0.13	0.18	0.18	0.14
		EPU	0.04	0.08	0.09	0.05	0.08	0.07	0.04	0.05	0.26	0.17	0.21	0.12	0.04	0.06	0.10	0.13	0.07
		VIX	0.48	0.76	0.72	1.17	1.62	1.82	**2.61**	**3.01**	**3.21**	**3.04**	**3.11**	**3.30**	**3.18**	**2.39**	1.78	**2.02**	1.65
	Live Cattle	**EMU**	0.39	0.44	0.29	0.53	0.60	0.79	0.88	0.68	0.78	1.03	1.26	1.41	1.44	1.05	1.02	1.41	1.22
Livestock		**EPU**	0.30	0.55	0.66	1.05	1.03	1.02	1.15	1.05	1.12	1.44	1.51	1.49	1.32	1.12	1.13	1.92	1.57
		VIX	**4.38**	**5.84**	**6.89**	**8.08**	**6.56**	**5.75**	**4.72**	**4.12**	**3.42**	**3.47**	**2.51**	**2.00**	1.24	0.60	0.88	1.15	0.56
	Lean Hogs	**EMU**	**2.29**	**2.75**	**2.94**	**3.40**	**2.71**	**2.95**	**3.23**	**2.80**	**2.57**	**2.06**	1.30	1.11	0.67	0.46	0.49	0.52	0.69
		EPU	1.75	1.92	**2.11**	**2.10**	1.84	1.25	1.70	1.45	1.52	1.48	1.29	1.57	**2.01**	1.85	1.57	1.56	0.81

Note: See Notes to Table 4.

Table 7: Predictability of Uncertainties for Commodity Futures Volatility (GJR-GARCH)

	Commodities		τ=0.1	τ=0.15	τ=0.2	τ=0.25	τ=0.3	τ=0.35	τ=0.4	τ=0.45	τ=0.5	τ=0.55	τ=0.6	τ=0.65	τ=0.7	τ=0.75	τ=0.8	τ=0.85	τ=0.9
Agricultural	Cocoa	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	0.15	0.07	0.08	0.06	0.05	0.09	0.09	0.09	0.12	0.21	0.07	0.17	0.13	0.10	0.09	0.05	0.14
		EPU	0.11	0.09	0.05	0.07	0.12	0.22	0.31	0.21	0.22	0.19	0.14	0.12	0.09	0.10	0.07	0.05	0.11
	Coffee	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.01	<0.01	0.02	0.02	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.02	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.02	0.02	0.02	<0.01	<0.01	<0.01	<0.01	<0.01
	Corn	**VIX**	0.09	0.11	0.12	0.13	0.16	0.19	0.26	0.21	0.13	0.19	0.16	0.10	0.14	0.10	0.12	0.09	0.12
		EMU	0.14	0.17	0.19	0.17	0.22	0.27	0.45	0.43	0.30	0.29	0.21	0.16	0.21	0.11	0.08	0.06	0.02
		EPU	0.10	0.25	0.31	0.34	0.33	0.36	0.40	0.40	0.26	0.31	0.28	0.25	0.21	0.14	0.10	0.07	0.03
	Cotton	**VIX**	0.07	0.08	0.12	0.08	0.20	0.47	0.51	0.42	0.46	0.35	0.38	0.44	0.44	0.46	0.47	0.53	0.43
		EMU	0.17	0.15	0.15	0.11	0.15	0.34	0.44	0.28	0.30	0.18	0.24	0.30	0.34	0.43	0.42	0.53	0.29
		EPU	0.08	0.06	0.03	0.04	0.10	0.25	0.32	0.20	0.26	0.33	0.33	0.39	0.46	0.59	0.38	0.59	0.35
	Orange Juice	**VIX**	0.37	0.57	0.81	0.84	1.79	1.85	**2.04**	**2.33**	**2.53**	**2.51**	1.74	1.74	**1.99**	**2.66**	1.62	1.53	0.69
		EMU	0.68	0.71	1.09	1.37	**2.23**	**2.14**	**2.28**	**2.14**	**2.23**	**2.13**	1.47	1.64	1.30	1.07	0.66	0.42	0.24
		EPU	0.62	1.22	1.86	1.94	**2.32**	**2.10**	**2.19**	**2.02**	1.79	1.71	1.38	1.33	1.15	0.94	0.79	0.69	0.44
	Soybeans	**VIX**	0.18	0.30	0.46	0.54	0.59	0.87	1.01	1.24	0.96	1.00	0.76	0.63	0.48	0.49	0.30	0.35	0.42
		EMU	0.62	1.08	1.39	1.10	0.84	1.05	0.76	1.01	1.10	0.98	0.88	0.87	0.86	0.44	0.36	0.46	0.39
		EPU	0.19	0.71	1.19	1.32	1.52	1.72	1.67	**2.17**	1.68	1.33	1.37	1.04	0.78	0.58	0.48	0.36	0.23
	Soybean Meal	**VIX**	0.02	0.07	0.20	0.33	0.32	0.38	0.29	0.32	0.34	0.28	0.47	0.66	0.52	0.43	0.36	0.22	0.04
		EMU	0.12	0.11	0.13	0.07	0.12	0.18	0.26	0.18	0.19	0.24	0.25	0.16	0.12	0.12	0.09	0.06	0.02
		EPU	0.04	0.07	0.12	0.05	0.06	0.17	0.27	0.31	0.21	0.14	0.18	0.13	0.10	0.12	0.09	0.04	0.02
	Soybean Oil	**VIX**	0.02	0.02	0.03	0.04	0.05	0.06	0.05	0.05	0.06	0.07	0.23	0.27	0.27	0.20	0.39	0.29	0.25
		EMU	0.09	0.07	0.09	0.08	0.09	0.10	0.13	0.14	0.08	0.05	0.05	0.04	0.10	0.07	0.10	0.04	0.03
		EPU	0.03	0.16	0.15	0.09	0.09	0.13	0.11	0.11	0.06	0.09	0.05	0.06	0.15	0.16	0.27	0.16	0.16
	Sugar	**VIX**	0.05	0.08	0.14	0.12	0.07	0.15	0.27	0.27	0.26	0.31	0.29	0.29	0.36	0.20	0.20	0.18	0.11
		EMU	0.03	0.02	0.04	0.05	0.08	0.08	0.19	0.22	0.28	0.32	0.29	0.22	0.21	0.12	0.14	0.09	0.05
		EPU	0.02	0.02	0.06	0.08	0.10	0.24	0.31	0.31	0.35	0.36	0.34	0.33	0.21	0.22	0.18	0.13	0.09
	Wheat	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Kansas wheat	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
ne rg	Crude Oil	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	**2.88**	**4.82**	**5.88**	**8.06**	**10.15**	**12.28**	**13.98**	**14.82**	**16.33**	**18.09**	**18.64**	**17.84**	**16.95**	**16.77**	**13.99**	**13.10**	**9.56**
	Heating Oil	**VIX**	0.14	0.10	0.12	0.19	0.47	0.85	1.30	1.18	1.90	**2.07**	**2.02**	**2.44**	**2.61**	**2.81**	**2.01**	**2.07**	1.83
		EMU	0.31	0.36	0.28	0.41	0.55	0.61	0.88	0.77	1.07	1.23	1.11	0.95	0.96	1.22	0.79	0.80	0.63
		EPU	0.41	0.41	0.34	0.70	0.65	0.76	1.36	1.40	1.36	1.16	1.02	0.85	0.90	1.04	0.85	0.79	0.40
	Natural Gaz	**VIX**	0.01	0.10	0.16	0.30	0.65	0.75	0.64	0.70	0.62	0.82	0.66	0.64	1.19	0.87	0.92	0.59	0.24
		EMU	0.13	0.05	0.05	0.08	0.13	0.17	0.17	0.16	0.18	0.26	0.17	0.17	0.27	0.15	0.30	0.28	0.24
		EPU	0.06	0.06	0.07	0.09	0.16	0.28	0.19	0.09	0.18	0.16	0.17	0.14	0.23	0.13	0.17	0.19	0.17
Metal	**Gold**	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Silver	**VIX**	0.25	0.27	0.31	0.33	0.49	0.65	1.19	0.94	0.48	0.86	0.76	1.14	0.99	0.61	0.61	0.23	0.05
		EMU	0.39	0.40	0.38	0.45	0.25	0.24	0.52	0.28	0.19	0.18	0.31	0.29	0.31	0.25	0.23	0.11	0.06
		EPU	0.10	0.24	0.16	0.20	0.22	0.33	0.73	0.59	0.55	0.60	0.64	0.65	0.40	0.48	0.52	0.37	0.08
	Copper	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	0.07	0.29	0.23	0.38	0.94	0.79	0.96	1.02	0.88	1.25	1.14	1.14	1.39	0.80	0.50	0.52	0.33
	Palladium	**VIX**	0.06	0.08	0.06	0.22	0.24	0.31	0.30	0.30	0.30	0.37	0.42	0.37	0.52	0.53	0.39	0.31	0.31
		EMU	0.17	0.13	0.10	0.18	0.26	0.30	0.19	0.16	0.17	0.15	0.15	0.13	0.17	0.11	0.04	0.02	0.04
		EPU	0.02	0.03	0.04	0.11	0.17	0.18	0.10	0.11	0.15	0.18	0.21	0.21	0.14	0.11	0.06	0.07	0.08
	Platinum	**VIX**	0.58	0.99	1.04	1.23	1.80	1.94	**1.97**	1.88	1.70	**2.27**	**2.18**	**2.08**	1.90	1.89	1.44	1.52	0.98
		EMU	0.63	1.03	1.64	1.20	1.79	1.95	1.70	1.64	1.22	1.22	1.13	0.73	1.05	0.95	0.73	0.81	0.58
		EPU	0.87	1.25	1.73	1.54	1.64	1.58	1.19	1.12	1.06	1.14	1.22	1.17	1.05	1.05	0.95	1.12	0.65
Livestock	**Live Cattle**	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
	Lean Hogs	**VIX**	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EMU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
		EPU	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Note: See Notes to Table 4.

would require one to remove the forecastable component of the considered series before computing the conditional volatility. In this sense, uncertainty in a series is not necessarily equivalent to the conditional volatility of the raw series. In addition, Joëts et al., (2017) indicate that ideally macroeconomic uncertainty is defined as the common variation in uncertainty across many series rather than any single series, as suggested by the uncertainty-based business cycle theories (which implicitly assume a common variation in uncertainty across a large number of series). Given this they suggest using a measure like the one proposed by Jurado et al., (2015), whereby uncertainty is defined as the conditional volatility of the purely unforecastable component of the future value of multiple series. But unfortunately, this index is only available at monthly and not daily frequency. Hence, at this stage, we have to rely on uncertainties measured by EPU, EMU and the VIX, and the weak evidence of volatility predictability could be put down to the fact that our measures of uncertainties are probably not necessarily capturing volatility per se to show up in the volatility of the commodity market futures, i.e., due to measurement issues.[9]

4. Conclusion

Commodity futures markets have recently emerged as a highly popular asset class for investors and fund managers. The rapidity in financialization of commodity markets has also caused the number of market participants to increase significantly. Besides being used for hedging and speculative purposes, commodity futures can also help to diversify away the risk of diversified stock/bond portfolios, particularly in times of financial crises and bearish equity markets. Thus, the knowledge of factors that drives commodity futures markets is likely to constitute valuable information for investors. Given this, for the first time in the literature on predicting futures market movements, we use a novel nonparametric causality-in-quantiles test to examine the impact of economic and financial market uncertainties on daily returns and volatility of 21

[9] Also, as indicated by Yin and Han (2014), what seems to matter for volatility of commodity returns is volatility of uncertainty and not necessarily uncertainty itself. This however poses a different challenge, whereby one would not only need a relevant measure of uncertainty, but also a model to estimate the volatility of the same.

commodity futures covering agriculture, energy, metals and livestock. Based on our analysis, we draw the following conclusions: (a) Standard linear Granger causality tests show virtually no evidence of predictability for commodity futures returns emanating from measures of uncertainty; (b) However, tests of nonlinearity show that the linear framework is misspecified, and hence, results from the standard Granger causality test cannot be relied upon; (c) Using the higher-order nonparametric causality-in-quantiles test. We find that measures of uncertainty can predict 17 of the 21 commodities considered for at least one of the quantiles of the conditional distribution of returns; (d) In terms of volatility, while the evidence is weaker relative to returns, with only 9 significant cases out of 21, combining the cases of predictability observed for returns and volatility, 20 out of the 21 commodities are found to be caused by measures of uncertainty, and; (e) Our results, in general, highlight the importance of modeling nonlinearity, analyzing not only returns but also volatility, i.e., higher order moments, and also considering the entire conditional distribution of returns and volatility when carrying out predictability analysis involving commodity futures and uncertainty. Since, unlike the previous literature which depicts weak evidence of predictability of uncertainty for commodity markets (based on conditional-mean based linear and non-linear tests), we are able to provide comprehensive proof of causality based on our k-th order nonparametric causality-in-quantiles test.

As part of future research, our study can be extended in several directions: (a) The objectives of our paper was to highlight the misspecifcation associated with linear models of predictability, and hence in turn, the importance of using a nonparametric approach that detects predictability over the entire conditional distribution of not only returns but also volatility. At this stage, we can say that portfolio managers should be using this nonlinear approach rather than a standard linear framework to make correct inferences in terms of predicting movements of commodities in their portfolios, since if a linear model is used, they would incorrectly conclude that commodity markets are in general unaffected by movements in uncertainty and are possible safe-havens. But, using the nonparametric causality-in-quantiles test, currently we cannot draw definitive conclusions regarding a portfolio allocation exercise given its bivariate nature, and also due to the fact that we are silent about the sign of the impact of uncertainties on returns and volatilities. Though one could speculate that returns are likely to go down and volatility heightened in the wake of increased uncertainties, we actually need to estimate the sign of the impact[10], ideally in a multivariate framework allowing for more than one commodity simultaneously, to decide whether commodities are acting as hedge or safe-havens in response to uncertain periods; (b) Given the weak impact of uncertainties on volatility, it might also be worthwhile to analyze the impact on alternative measures of volatility, like realized volatility, and also more discontinuous aspect of volatility volatility jumps (i.e., bad volatility) computed from high-frequency intraday data, and; (c) It would also be interesting to examine if these results continue to hold in an out-of-sample exercise, since in-sample predictability does not guarantee the same in a forecasting set-up (Rapach and Zhou, 2013; Bonaccolto *et al.,* 2015).

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[10] While, the causality-in-quantiles approach comes with its advantages, unlike a linear framework, obtaing a sign of the effect is not that straight-forward. To do so, one will need to employ the first-order partial derivative. Estimation of the partial derivatives for nonparametric models can experience complications because nonparametric methods exhibit slow convergence rates, which can depend on the dimensionality and smoothness of the underlying conditional expectation function. What one could however do is to look at a statistic that summarizes the overall effect or the global curvature (i.e., the global sign and magnitude), but not the entire derivative curve. In this regard, a natural measure of the global curvature is the average derivative (AD). One could use the conditional pivotal quantile, based on approximation or the coupling approach of Belloni et al., (2017), to estimate the partial ADs. The pivotal coupling approach additionally can approximate the distribution of AD using Monte Carlo simulation.

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