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HOW DOES UNCERTAINTY IMPACT BIOFUEL PRICES?

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ABSTRACT

In this study we investigate the impact of Geopolitical Risk (GPR), US Economic Policy Uncertainty (EPU), St. Louis Fed Financial Stress Index (STLFSI), and market volatility (VIX) on the prices of US and Brazilian ethanol and Malaysian palm oil. By applying quantile autoregressive and quantile causality methods we can illustrate the dynamic relation between uncertainty and biofuel prices. Our results show that all measures of uncertainty influence ethanol and palm oil prices in both the lower and upper tails of the distribution. Furthermore, uncertainty seems to impact both U.S. and Brazilian ethanol prices price in a similar fashion, even if there are clear differences in the impact pattern. In the case of U.S. ethanol price, the results imply a slightly symmetrical impact pattern, with weak indications that uncertainty is triggering changes in price returns in the lower, towards the extreme, tails of the distribution. There are also clear indications that uncertainty impacts ethanol returns in the upper tails of the distribution, with a slight shift towards the middle quantiles. The results suggest that U.S. ethanol prices are more affected by uncertainty when the market conditions are positive rather than negative. In the case of Brazilian ethanol prices, the analysis also displays a symmetrical uncertainty impact pattern in both the lower and the upper tails of the distribution. However, unlike the other biofuel prices, there are indications that uncertainty also affects prices in the middle quantiles. Uncertainty has a stronger impact on Malaysian palm oil prices both near the middle quantiles as well as in the upper and extreme tails of the distribution. These results may indicate a sensitivity to uncertainty near normal market conditions and to large and extreme positive returns. Our results provide valuable insights into the price dynamics of biofuels. This knowledge is important for the transition to a sustainable energy system, especially in sectors not easily electrified such as aviation, shipping and certain types of industrial processes. Furthermore, our results also have implications for the financial sector and for risk management strategies.

Keywords: Biofuels; Uncertainty; Quantile Causality; Geopolitical Risk; Economic Policy Uncertainty.

NONMENCLATURE

Abbreviations

US-EP	U.S. Ethanol Price
BR-EP	Brazilian Ethanol Price
MA-PP	Malaysian Palm Oil price
VIX	S&P500 Implied volatility Index
EPU	Economic Policy Uncertainty Index
GPR	Geopolitical Risk Index
STLFSI	St. Louis Fed Financial Stress Index

1. INTRODUCTION

Currently, total primary energy demand is said to comprise about 80 % percent fossil fuels [1]. And in the process of depleting the fossil fuel sources, humans are continually contributing to increasing greenhouse gas emissions. Among the alternatives, biofuels are amongst the most environmental friendly sources [2], but despite the major growth in biofuels in recent years, shown in figure 1 and 2, additional capacity is needed. To reach the goal of a sustainable energy system, biofuels will play an increasingly important role as substitutes for fossil fuels, cubing carbon emission in sectors that are hard to electrify, such as aviation, shipping and to various industrial processes [3, 4].

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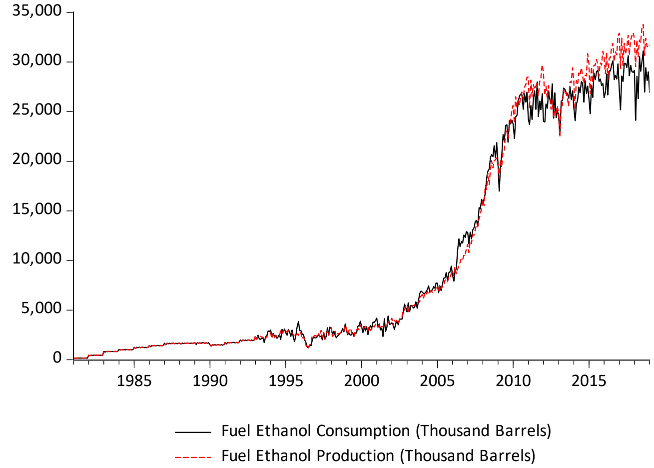

Fig 1 Global ethanol fuel, U.S. Energy Information Agency

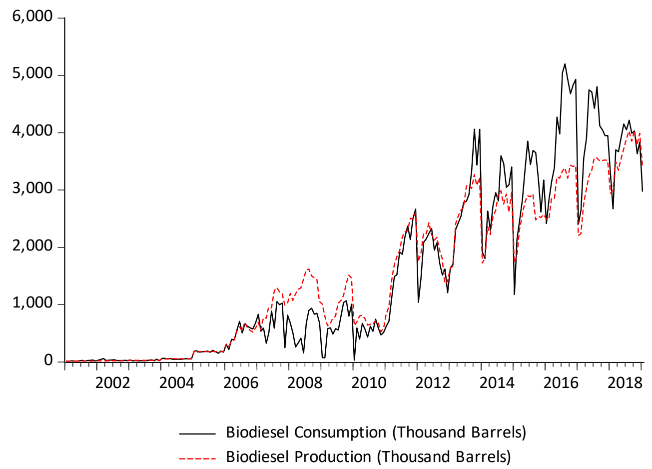

Fig 2 Global biodiesel and other renewable fuels, U.S. Energy Information Agency

For example, in the aviation industry, fuel is one of the major operating costs and almost 10 % of the crude oil is used to produce aviation jet fuel [5]. Thus, operation costs linked to fuel expenditure in the aviation industry is highly susceptible to crude oil prices and price volatility. Theoretically, sustainable aviation fuels could substitute 100% of conventional air fuel, requiring substantial investments in new biorefineries [6].

To reach the sustainable development scenario in the World Energy Outlook 2018 report [4], biofuel consumption will have to increase from 1.8 million barrels of oil equivalence per day (mboe/d) in 2017, corresponding to a 3 % share of total transport demand, to 7.3 mboe/d in 2040 which corresponds to a projected 15 % share of total transport demand.

In order to support the rising demand of biofuels, there is a need for substantial investments. In 2017 global average investments in transport biofuel amounted to \$2 billion, while the projected investments in the sustainable development scenario, amounts to \$25 - \$47 billion annually between 2018 to 2040 [4], this make biofuel capacity investment an increasing important issue for portfolio investors, sector investors [6-9] and policy makers [10, 11]. The financial aspect also concerns the increasing volatility in energy prices [12], a volatility likely to be boosted by the fluctuating attributes of renewable energy generation, i.e. intermittent periods of sun and wind, that leads to variable and intermittent power generation.

Among the biofuel producing countries, the U.S. has emerged as the leading producer of biofuels [13] and in 2016, the U.S. alone extracted 15,379 million gallons of ethanol [14]. Brazil, another major producer of biofuels, has already replaced 42 percent of its gasoline needs with sugarcane ethanol, making gasoline the alternative fuel in Brazil [15].Towards the end of 2017, Indonesia and Malaysia largely dominated the palm oil industry, accounting for 54% and 32% of global palm oil production, respectively [16].

In the biofuel price area, there have been some studies addressing price uncertainty, but mostly they address the production processes and employ simulation tools [17-20]. Furthermore, studies often focus on: crop and feedstock issues [2, 14, 21-23]; the energy-food nexus [24-30].

Regarding economic effects originating from energy, there is ample research on how changes in oil and fuel prices affect economic activities, (symmetrically as well as asymmetrically), in both global and national circumstances [7, 31-33]. For example, it's has previously been shown that there exists a link between changes in fuel price and changes in airline stock returns and the evidence found supports the idea of market inertia [34].

However, It has also been shown that biofuel production also can aid in limiting the adverse economic impacts originating from crude oil market volatility [14, 35].

In the research regarding uncertainty and biofuels, there are findings that indicate that price variability can negatively impact profitability and potentially hinder investments and development of biofuel technology [36].

Other types of research, related to biofuels and uncertainties, involve climate uncertainties in energy system transition [37]. Another study, examining key sources of uncertainty in biofuel production, finds that a blending of primary and secondary feedstock may limit feedstock price uncertainty [38]. Additionally, some studies have focused on economic feasibility, comparing decarbonized conventional fossil fuels prices with biodiesel prices [39].

While previous biofuel studies have mainly focused on feedstock, production costs, little or no attention has been paid on what effect economic policy uncertainty, geopolitical risk and financial stress have on the price of biofuel commodities in different market conditions. Our study fills this gap in the relevant literature, by providing a detailed view of the dynamic relationship between uncertainty and biofuel commodity prices in different market conditions.

In our analysis, we focus on the effects on biofuel commodity prices, originating from uncertainty. And by including a set of uncertainty indices we can capture the effect differences or similarities between different types of uncertainties. To our knowledge, no other study has presented a model capable of capturing the uncertainty dynamics in a clear and comprehensive fashion.

According to our model, uncertainty causes large negative price changes in the biofuel commodities considered, while moderate uncertainty changes only moderately impact prices. And finally, uncertainty also causes large or extreme positive changes in the prices of ethanol and palm oil.

The implications of the results suggest that variables of political and global character such EPU, GPR and STLFSI should also be taken into consideration in the transition to a sustainable energy system. Uncertainty measures enable ethanol and palm oil actors (on the supply and demand side), corn and palm growers, and policy makers the possibility to monitor the price dynamics of biofuels in a straightforward manner when deciding production output and developing appropriate policy guidelines related to subsidizing and energy sector investment. From a financial perspective, our model gives portfolio investors the opportunity for improved risk management and a way to effectively rebalance portfolios.

2. DATA AND DESCRIPTIVE STATISTICS

2.1 Uncertainty measures and biofuel prices

This paper analyses the causal relationship between uncertainty measures and ethanol and palm oil returns. The uncertainty indicators used in the study are the CBOE Market Volatility Index (VIX), Global Economic Policy Uncertainty Index (EPU), Geopolitical Risk Index (GPR) and the St. Louis Fed Financial Stress Index (STLFSI).

The ethanol and biofuel series considered are the U.S. ethanol prices (U.S.-EP), the Brazilian ethanol prices (BR-EP) and the Malaysian Palm Oil prices (MA-PP).

U.S.-EP and MA-PP series consist of 139 monthly observations and have been collected from DataStream International. The data on Brazilian hydrous ethanol prices (BR-EP) are retrieved from the Centre for Advanced Studies on Applied Economics.

The selected VIX index is based on the implied volatilities of the S&P500 options index and accounts for market expectations of a 30-day time horizon, with no seasonal adjustment [40].

The global economic policy uncertainty index is a GDP-weighted average of national EPU indices for 20 countries. Each of the national indices reflects the relative frequency of domestic newspaper articles that include three terms related to economic (E), policy (P) and uncertainty (U). Each monthly national index represents a proportional share of the own-country newspaper articles in the native language [41, 42].

The GPR index is based on counting of the number of times words related to geopolitical tensions appear in international newspapers. This index would therefore be

Table 1 Descriptive statistics

	US-EP		BR-EP		MA-PP		VIX		EPU		GPR		STLFSI
Mean	2.13	0.73	0.55	-0.62	812.41	6.67	19.50	2.89	126.43	4.77	87.42	4.39	-0.44
Median	2.13	0.76	0.56	-0.58	797.50	6.68	16.91	2.83	121.42	4.80	73.50	4.30	-0.79
Maximum	5.00	1.61	0.87	-0.14	1277.50	7.15	62.64	4.14	283.36	5.65	246.24	5.51	4.62
Minimum	1.36	0.31	0.31	-1.17	430.00	6.06	10.13	2.32	50.07	3.91	41.01	3.71	-1.57
Std. Dev.	0.54	0.24	0.13	0.24	197.16	0.24	9.25	0.38	46.93	0.37	39.59	0.40	1.17
Skewness	1.43	0.44	0.20	-0.29	0.42	-0.09	2.29	0.96	0.95	-0.14	1.55	0.57	2.07
Kurtosis	7.80	3.10	2.54	2.41	2.51	2.48	9.47	3.88	4.21	2.93	5.60	2.79	7.68
Jarque-Bera	180.51***	4.61*	2.12	3.94	5.41*	1.77	364.16***	25.99***	29.63***	0.47	94.46***	7.68***	225.79***
Observations	139	139	139	139.00	139	139	139	139	139	139	139	139	139

Note: The first column of each variable is in level and the second column is in log level. The null hypothesis of the Jarque-Bera test is a joint hypothesis of the skewness being zero and the excess kurtosis being zero. The notations *. ** and *** indicate rejections of the null-hypothesis at 10%. 5% and 1% significance level.

expected to increase in value during times of regional and global political tension [43].

The St. Louis Fed Financial Stress Index measures the degree of financial stress in markets and consists of 18 weekly data series constructed by principal component analysis. The indices included are: seven interest rate series, six yield spreads and five other financial series [44]. The index is designed to measure developments as they occur and when tested, the index accurately captures key events amongst other the Russian debt moratorium in August 1998 and the financial crisis in 2008 and subsequent turmoil and financial stress [45].

Table 2 BDS independence test

	m	First-difference detrending			AR(1)			GARCH (0,1)		
		ε = .5	ε = .7	ε = .9	ε = .5	ε = .7	ε = .9	ε = .5	ε = .7	ε = .9
US-EP	2	0.01191	0.026624***	0.018964***	0.013947*	0.026775***	0.018465***	0.01191	0.026624***	0.018964***
	3	0.017838*	0.052331***	0.050734***	0.018546*	0.052525***	0.050443***	0.017838*	0.052331***	0.050734***
	4	0.015356*	0.065012***	0.080285***	0.015852*	0.065734***	0.079555***	0.015356*	0.065012***	0.080285***
BR-EP	2	0.012988	0.007795	-0.001414	0.009767	0.00193	-0.003669	0.012988	0.007795	-0.001414
	3	0.019083*	0.01504	-0.002886	0.015845	0.001213	-0.00648	0.019083*	0.01504	-0.002886
	4	0.018641*	0.020316	-0.006239	0.015277*	0.005699	-0.011103	0.018641*	0.020316	-0.006239
MA-PP	2	0.013831*	0.017320*	0.006979	0.018341**	0.018238**	0.001765	0.013831*	0.017320**	0.006979
	3	0.014908*	0.029911**	0.018732*	0.019077**	0.032711**	0.008153	0.014908*	0.029911**	0.018732*
	4	0.014089*	0.034855**	0.027682*	0.013531*	0.037298**	0.014068	0.014089*	0.034855**	0.027682*
VIX	2	0.011162	0.008183	0.002256	0.012020*	0.009016	0.002409	0.011162	0.008183	0.002256
	3	0.019907**	0.018622	0.005877	0.020724**	0.019815	0.00635	0.019907**	0.018622	0.005877
	4	0.024186***	0.030337*	0.007014	0.024355***	0.030908*	0.008098	0.024186***	0.030337*	0.007014
EPU	2	0.011055*	0.005478	-0.002554	0.009017	0.005522	-0.002442	0.011055*	0.005478	-0.002554
	3	0.010768	0.013703	0.00175	0.008407	0.013075	0.002319	0.010768	0.013703	0.00175
	4	0.009721	0.019524	0.010013	0.005542	0.017356	0.010752	0.009721	0.019524	0.010013
GPR	2	0.008477	0.014882*	0.004167	0.011808**	0.013163*	0.00568	0.008477	0.014882**	0.004167
	3	0.013154*	0.027452**	0.013503	0.014568**	0.023346**	0.012774	0.013154*	0.027452**	0.013503
	4	0.011485*	0.032259**	0.023384*	0.012147*	0.027532**	0.020205*	0.011485*	0.032259**	0.023384*
STLFSI	2	0.058822***	0.062066***	0.018915**	0.046573***	0.047961***	0.024216***	0.058822***	0.062066***	0.018915**
	3	0.093407***	0.138751**	0.040639***	0.077613***	0.120123***	0.058842***	0.093407***	0.138751***	0.040639***
	4	0.092118***	0.187167***	0.073702***	0.076716***	0.167638***	0.096932***	0.092118***	0.187167***	0.073702***

Notes: All series are in log except STLFSI which is first-difference only. The term ε is the distance for testing proximity of the data points and is calculated as a fraction of pairs with three values 0.5, 0.7 and 0.9. The term *m* is the number of consecutive data points to include in the set. The P-values are bootstrapped with 5000 iterations. The notations *, ** and *** indicate rejections of the null-hypothesis at 10%, 5% and 1% significance levels.

2.2 Descriptive statistics and tests

Table 1 displays the time series descriptive statistics in log level, except for STLFSI which is in level due to negative values in the original form. The Jarque-Bera test shows that the VIX, GPR and STLFSI are not normally distributed at the 1 % and 5% significance level. Worth noticing is that all the uncertainty measures exhibit a clear pattern of non-normality according to the Jarque-Bera test, while the only biofuel series expressing non-normality is the U.S. ethanol prices. This is a strong first indication of non-normality in our data, making linear models suboptimal for the analysis. In order to further test for non-linearity in all of the variables, we performed a test for independence based on correlation, the so called BDS test [46] and the test results are presented in table 2. The BDS test seeks for evidence of non-linear aspects in our model i.e. independent and identically distributed variables (iid).

Table 3 Correlation matrix

	US-EP	**BR-EP**	**MA-PP**	**VIX**	**EPU**	**GPR**	**STLFSI**
US-EP	1						
BR-EP	0.369	1					
MA-PP	0.474	0.597	1				
VIX	0.020	-0.152	0.052	1			
EPU	-0.302	0.345	0.099	0.156	1		
GPR	-0.339	-0.071	-0.393	-0.509	0.059	1	
STLFSI	-0.039	-0.458	-0.152	0.823	-0.095	-0.382	1

Notes: Note: All log level except STLFSI which is in level.

The test procedure includes an initial detrending of the series and we use three different methods, first-difference detrending, AR(1) and GARCH (0,1). The results show a strong indication of non-normality at the 1 % level of significance for the US-EP and STLFSI time series. There is also a strong indication at the 5 % significance level that the MA-PP and GPR series have non-normality characteristics. The results indicate non-normality in all series except Brazilian ethanol prices (BR-EP) and economic policy uncertainty (EPU) even though there are indications of non-normality at the 10 % level of significance. From the performed tests, the results not only justify the use of non-linear methods as much as it requires it. Thus, nonlinear analysis is crucial for investigating the relationship between biofuel and uncertainty indicators.

Table 3 presents the correlation between the time series modelled. It is observed that the biofuels have a positive correlation amongst each other, and that the US-EP has a negative correlation with all variables except VIX. The BR-EP also has a negative correlation with all variables except the EPU. The MA-PP has a negative correlation with GPR and STLFSI.

In Table 4 we show the results from two unit root stationarity tests fitted to verify the integration order of the series modelled. It can be observed that the U.S.-EP, BR-EP, MA-PP, VIX and STLFSI series are integrated of order I(1), while the EPU and GPR are integrated for order I(0). For the analysis, all series will be differentiated in order for the quantile autoregression tests to be valid.

Figure 3 illustrates the graphs of level and log level for the biofuel and uncertainty time series. Several brakes characterize the biofuel series with notable negative large shifts around the financial crisis in 2008 and around 2014. These are time periods in which crude oil prices underwent sharp trends of decline. Among the uncertainty indicators, VIX, EPU and STLFSI have the most distinctive shifts in increasing uncertainty levels around the financial crisis of 2008.

Table 4 Unit root stationarity test

	ADF (ϕ)	Lags	ADF(ψ)	Lags	PP level (ϕ)	BW	PP (ψ)	BW
LUS-EP	-2.36	4	-6.92***	3	-4.74***	7	-12.82***	0
LBR-EP	-2.97	1	-9.18***	1	-2.79	2	-10.56***	4
LMA-PP	-2.96	1	-5.90***	5	-3.10	5	-9.14***	4
LVIX	-3.28*	1	-9.84***	1	-3.08	2	-12.05***	9
LEPU	-4.34***	0	-9.59***	2	-4.22***	2	-16.73***	17
LGPR	-6.00***	0	-9.36***	3	-5.82***	2	-52.74***	136
STLFSI †	-2.63	1	-9.82***	0	-2.51	4	-9.83***	1

Notes: Methods used in this test is Augmented Dickey-Fuller test (ADF) and the Philips-Perron test (PP). ϕ indicates test with intercept and trend in level. Ψ test with intercept and trend in first difference. †Only first difference. The notations *. ** and *** indicate the rejection of the null-hypothesis at 10%. 5% and 1% significance level. For ADF and PP the null-hypothesis is unit root process. ADF: Max lag 20 and AIC. PP: Bandwidth: (Newey-West automatic) using Bartlett kernel

The Figure 4 indicates the first difference of the time series corresponding to the uncertainty indicators VIX, EPU and GPR. It can be seen that the Brazilian ethanol prices are the most volatile between the 2006-2010 period.

The US ethanol prices are impacted the least during the 2008 global financial crisis, while the Malaysian palm oil prices are the most strongly affected. The largest

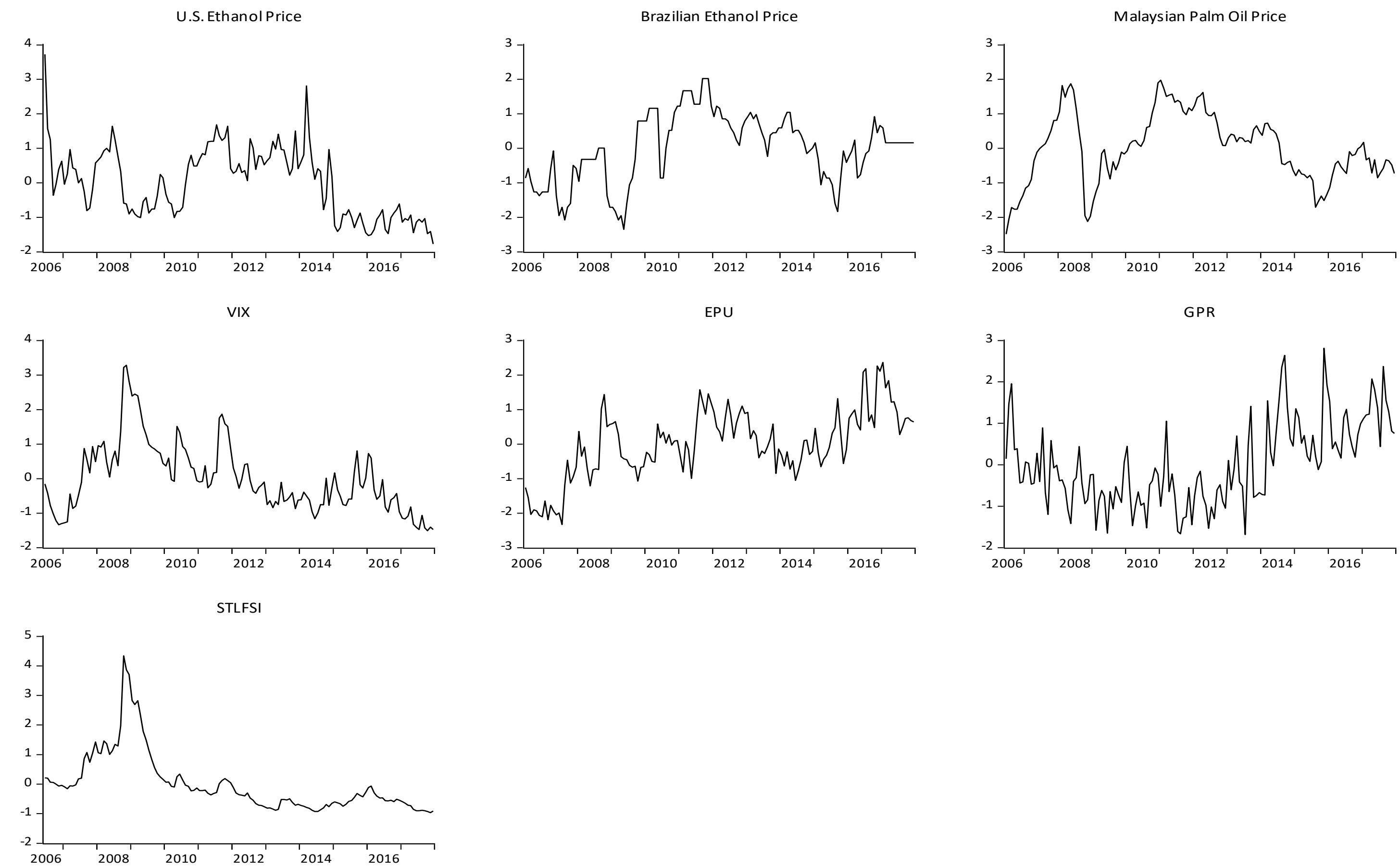

Fig 3 Time series in level.

Notes: Graphs of biofuels and uncertainty indicators normalized and in level and log level and at a first visual inspection indicate that some of the series are stationary in level.

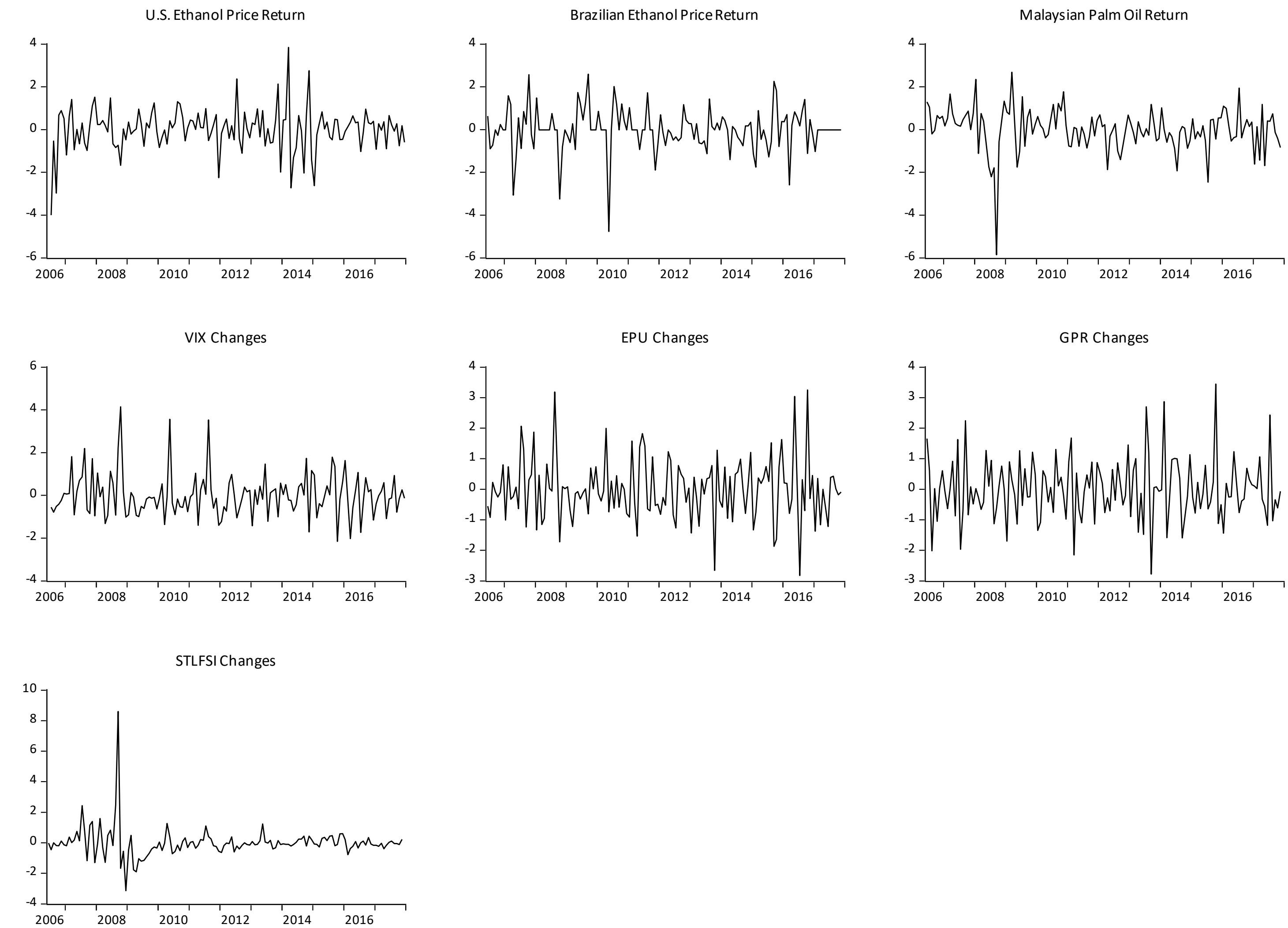

Fig 4 Time series in first difference (return series)

Notes: Graphs of biofuels and uncertainty indicators normalized and in first-difference indicates that some of the series are stationary in level.

and most constant positive returns occur on the US and Brazilian returns. the St. Louis Fed Financial Stress Index records its highest values throughout 2009, while remaining constant and close to zero throughout the sample period. The market volatility and economic policy uncertainty indices also record some of their highest values during the global financial crisis.

2.3 Autoregressive and quantile causality model

Given the absence of Independent and identically distributed variables (iid) in the examined time series, nonlinear models such as quantile autoregression and quantile causality are preferable to adequately account for the impact of uncertainty on the biofuel commodity prices and returns considered [47].

As we will show in our study, uncertainty measures represented by VIX, EPU, GPR, STLFSI are nonlinearly related with ethanol and palm oil prices. The interpretation of the quantile causality test resembles that of the ordinary linear causality test and thus provides information about the predictive power of an independent variable on the dependant variable in a given quantile (τ). The test also includes lags of the dependent variable to control for autoregressive dynamics. A weakness of the quantile Granger-causality test lies in its inability to inform about the magnitude of the strength of association. To test for granger causality in quantiles we will perform the following tests:[1]

$$H_0^{\triangle Ui \nrightarrow \triangle BioF}: E\left\{1\left[\triangle BioF_t \le m\left(I_t^{\triangle BioF}, \theta_0(\tau)\right)\right] I_t^{\triangle BioF}, I_t^{\triangle Ui}\right\} = \tau, a.s.\ for\ all\ \tau \in T \quad (1)$$

versus:

$$H_A^{\triangle Ui \nrightarrow \triangle BioF}: E\left\{1\left[\triangle BioF_t \le m\left(I_t^{\triangle BioF}, \theta_0(\tau)\right)\right] I_t^{\triangle BioF}, I_t^{\triangle Ui}\right\} \neq \tau, a.s.\ for\ some\ \tau \in T \quad (2)$$

Where $m\left(I_t^{\triangle \mathrm{Ui}}, \theta_0(\tau)\right)$ correctly specifies the true conditional $Q_\tau^Y(\cdot \mid I_t^Y)$, for all $\tau \in \mathrm{T}$. The null-hypothesis of linear Granger causality is tested against the alternative hypothesis of nonlinear Granger causality. In accordance with the model specification introduced by Troster [48], we will apply the following test statistics:

$$S_T := \int_\tau \int_w |v_t(\boldsymbol{\omega}, \tau)|^2 dF_\omega(\omega) dF_\tau(\tau), \quad (3)$$

Where $F_\omega(\cdot)$ is the conditional distribution function of a *d*-variate standard normal vector, $F_\tau(\cdot)$ follows a uniform discrete distribution over a grid of T in *n* equally spaced points, $\mathrm{T}_n = \{\tau_j\}_{j=1}^n$, and the vector of weights of $\boldsymbol{\omega} \in \mathbb{R}^d$ is drawn from a standard normal distribution. The test statistic in *Equation 3* can be estimated using its sample analog. Let ψ be a T x n matrix with elements $\psi_{i,j} = \Psi_{\tau j}(Y_i - m\left(I_i^Y, \theta_T(\tau_j)\right))$ and $\Psi_{\tau j}(\cdot)$ is the function $\Psi_{\tau j}(\varepsilon) := 1(\varepsilon \le 0) - \tau_j$. Then the following test statistic is applied:

$$S_T = \frac{1}{Tn}\sum_{j=1}^{n} \left|\psi_{\cdot j} \hat{\boldsymbol{W}} \psi_{\cdot j}\right| \quad (4)$$

Where **W** is the *T* x *T* matrix with elements $\boldsymbol{w}_{t,s} = \exp[-0{,}5(I_t - I_s)^2$, and $\psi \cdot j$ denotes the j-th column of ψ. This methodology is adequate to account for nonlinearities and extreme quantile observations, an aspect that is of our concern in trying to identify those uncertainty factors that most strongly influence ethanol and palm oil prices as uncertainty increases or decreases.

3. RESULTS

3.1 U.S. ethanol

Table 5 displays the p-values of the Granger-causality in quantiles test for U.S. ethanol price returns and the uncertainty indices.

Considering all the quantiles, τ = {0.05 – 0.95}, there is causality running from uncertainty measures to the U.S. ethanol price returns in 8 out of 12 model specifications at the 1 % level of significance.

Table 5 Quantile causality U.S. ethanol price

	ΔVIX to ΔUS-EP			ΔEPU to ΔUS-EP			ΔGPR to ΔUS-EP			Δ STLFSI to ΔUS-EP		
τ	$I^{\Delta US\text{-}Ep} = 1$	$I^{\Delta US\text{-}Ep} = 2$	$I^{\Delta US\text{-}Ep} = 3$	$I^{\Delta US\text{-}Ep} = 1$	$I^{\Delta US\text{-}Ep} = 2$	$I^{\Delta US\text{-}Ep} = 3$	$I^{\Delta US\text{-}Ep} = 1$	$I^{\Delta US\text{-}Ep} = 2$	$I^{\Delta US\text{-}Ep} = 3$	$I^{\Delta US\text{-}Ep} = 1$	$I^{\Delta US\text{-}Ep} = 2$	$I^{\Delta US\text{-}Ep} = 3$
0.05	0.88	0.96	0.89	0.84	0.90	0.90	0.68	0.84	0.83	0.63	0.89	0.92
0.10	0.01***	0.01***	0.11	0.01***	0.01***	0.07*	0.01***	0.01***	0.10*	0.01***	0.01***	0.02**
0.15	0.04**	0.05**	0.01***	0.04**	0.05**	0.01***	0.04**	0.05**	0.01***	0.04**	0.05**	0.01***
0.20	0.06*	0.27	0.19	0.04**	0.19	0.16	0.06*	0.26	0.16	0.09*	0.28	0.18
0.25	0.14	0.55	0.01***	0.07*	0.55	0.01***	0.02**	0.47	0.01***	0.14	0.56	0.01***
0.30	0.57	0.05**	0.12	0.57	0.04**	0.12	0.51	0.04**	0.14	0.66	0.08*	0.12
0.35	0.13	0.35	0.79	0.10*	0.27	0.59	0.15	0.25	0.62	0.18	0.25	0.51
0.40	0.11	0.68	0.80	0.11	0.68	0.71	0.12	0.52	0.74	0.11	0.36	0.66
0.45	0.07*	0.03**	0.40	0.08	0.03**	0.32	0.09*	0.03**	0.30	0.03**	0.03**	0.26
0.50	0.03**	0.14	0.81	0.03**	0.14	0.86	0.10*	0.17	0.83	0.03**	0.14	0.59
0.55	0.45	0.53	0.74	0.48	0.54	0.75	0.53	0.60	0.80	0.51	0.52	0.51
0.60	0.67	0.62	0.39	0.70	0.60	0.38	0.79	0.71	0.52	0.76	0.61	0.42
0.65	0.03**	0.27	0.01***	0.03**	0.27	0.01***	0.07*	0.46	0.01***	0.09*	0.41	0.01***
0.70	0.01***	0.02**	0.01***	0.01***	0.01***	0.01***	0.04**	0.08*	0.01***	0.12	0.01***	0.01***
0.75	0.01***	0.06*	0.01***	0.01***	0.04**	0.01***	0.01***	0.06*	0.01***	0.01***	0.06*	0.01***
0.80	0.05**	0.04**	0.01***	0.05**	0.04**	0.01***	0.05**	0.04**	0.01***	0.05**	0.04**	0.01***
0.85	0.01***	0.08*	0.05**	0.01***	0.08*	0.05**	0.01***	0.08*	0.05**	0.01***	0.08*	0.05**
0.90	0.11	0.09*	0.11	0.11	0.09*	0.11	0.11	0.07*	0.11	0.11	0.09*	0.11
0.95	0.40	0.35	0.52	0.40	0.35	0.56	0.40	0.35	0.23	0.40	0.35	0.60
[All τ]	0.01***	0.08*	0.01***	0.01***	0.07*	0.01***	0.01***	0.09*	0.01***	0.01***	0.08*	0.01***

Notes: This table presents the subsampling p-values of the ST - test in eq 4. The term $I^{\Delta US\text{-}Ep}$ = 1,2,3 represents the number of lags of the dependant variable under the null-hypothesis: No Granger causality in eq 2. The subsample size is b=36 for our sample of T=138 observations. The notations *, ** and *** indicate rejections of the null-hypothesis at 10%, 5% and 1% significance levels. The US-EP, VIX, EPU and GPR series is in log and first difference. The STLFSI is in first difference only due to negative values in level.

[1] The notation (Ui) represents all uncertainty indicators VIX, EPU, GPR and STLFSI and BioF represents all biofuels U.S. ethanol, Brazilian ethanol and Malaysian palm oil.

More importantly, the results indicate an asymmetric impact in both market downturns (lower quantiles) and market upturns (upper quantiles).

However, the uncertainty impact is significantly stronger in the upper quantiles, where the majority of the quantiles ranging from τ = {0,70 to 0,85} are at 1% significance level. In the lower quantiles τ = {0,10 to 0,25} there is causality running from VIX, EPU, GPR and STLFSI to ethanol price return at τ = {0,15} at the 1 % and 5 % significance levels in model specifications 1 to 3.

For STLFSI there is also causality at τ = {0,10} at the 1% and 5 % significance levels in model specifications 1 to 3. These results indicate that uncertainty has an impact on medium, τ = {0,65 to 70}, to large increases, τ = {0,70 to 85}, in prices and returns (i.e. normal and good market conditions), as well as in large to extreme negative, τ = {0,10 to 0,15}, price (returns) for U.S. ethanol.

Worth noticing is that all uncertainty measures, with some differences, seem to affect the U.S. ethanol price in the same manner, indicating an uncertainty mechanism specific to U.S. ethanol price.

In summary, the results imply a slightly symmetrical impact pattern, with weak indications that uncertainty triggers changes in returns in the lower, towards the extreme, tails of the distribution. And also, a clear and much stronger indication that uncertainty impacts price (returns) in the upper tails of the distribution, with a slight shift towards the middle quantiles. These results suggest that U.S. ethanol prices are more affected by uncertainty when the market conditions are positive rather than negative. Also, uncertainty appears to interact with the biofuel prices in closer to normal market condition on the positive return side.

3.2 Brazilian ethanol

Table 6 displays the p-values of the Granger-causality in quantiles test for Brazilian ethanol price (returns). Considering all the quantiles, τ = {0.05 – 0.95}, there is causality in the direction running from all uncertainty indicators to Brazilian ethanol price at the 1 % significance level in all autoregressive model specifications.

Alas, we cannot dismiss the situation that uncertainty is affecting the whole distribution. In the lower quantiles of the distribution there is causality at τ = {0.10} and at τ = {0.25} at the 1 % significance level for all uncertainty indicators and the results are robust for model specifications 1 to 3 of the auto-regressive model.

For VIX, EPU and GPR there is also causality at τ = {0.15} at 1 % and 5 % significance level. This indicates that uncertainty impact the large negative changes in Brazilian ethanol prices.

Considering the middle quantiles, there is causality at τ = {0.45} at the 1 % levels of significance and τ = {0.60} at the 1% and 10 % level of significance for all indices,

Table 6 Quantile causality Brazilian ethanol price

	ΔVIX to ΔBR-EP			ΔEPU to ΔBR-EP			ΔGPR to ΔBR-EP			Δ STLFSI to ΔBR-EP		
τ	$l^{\Delta BR\text{-}EP} = 1$	$l^{\Delta BR\text{-}EP} = 2$	$l^{\Delta BR\text{-}EP} = 3$	$l^{\Delta BR\text{-}EP} = 1$	$l^{\Delta BR\text{-}EP} = 2$	$l^{\Delta BR\text{-}EP} = 3$	$l^{\Delta BR\text{-}EP} = 1$	$l^{\Delta BR\text{-}EP} = 2$	$l^{\Delta BR\text{-}EP} = 3$	$l^{\Delta BR\text{-}EP} = 1$	$l^{\Delta BR\text{-}EP} = 2$	$l^{\Delta BR\text{-}EP} = 3$
0.05	0.37	0.17	0.21	0.62	0.02**	0.06*	0.56	0.07*	0.11	0.28	0.02**	0.02**
0.10	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.15	0.02**	0.01***	0.01***	0.02**	0.01***	0.01***	0.02**	0.01***	0.01***	0.01***	0.17	0.17
0.20	0.23	0.08*	0.01***	0.23	0.08*	0.01***	0.23	0.08*	0.01***	0.23	0.02**	0.01***
0.25	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.30	0.06*	0.30	0.25	0.06*	0.30	0.25	0.06*	0.30	0.25	0.06*	0.30	0.25
0.35	0.07*	0.34	0.20	0.07*	0.34	0.19	0.07*	0.33	0.19	0.09*	0.33	0.21
0.40	0.01***	0.14	0.14	0.01***	0.14	0.13	0.01***	0.14	0.13	0.04*’	0.17	0.13
0.45	0.01***	0.03**	0.01***	0.01***	0.03**	0.01***	0.01***	0.03**	0.01***	0.01***	0.04**	0.01***
0.50	0.03**	0.53	0.61	0.03**	0.51	0.59	0.04**	0.57	0.66	0.04**	0.55	0.65
0.55	0.04**	0.29	0.30	0.02**	0.26	0.27	0.04**	0.32	0.30	0.04**	0.35	0.36
0.60	0.02**	0.06*	0.01***	0.02**	0.06*	0.01***	0.02**	0.06*	0.04**	0.02**	0.04**	0.01***
0.65	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.70	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.75	0.01***	0.11	0.07*	0.01***	0.01***	0.01***	0.01***	0.11	0.01***	0.01***	0.11	0.03**
0.80	0.14	0.09*	0.03**	0.14	0.09*	0.03**	0.14	0.09*	0.03**	0.14	0.09*	0.03**
0.85	0.01***	0.01***	0.28	0.01***	0.01***	0.28	0.01***	0.01***	0.30	0.01***	0.01***	0.28
0.90	0.14	0.45	0.43	0.16	0.39	0.37	0.14	0.60	0.55	0.12	0.42	0.38
0.95	0.49	0.27	0.27	0.50	0.24	0.27	0.74	0.25	0.28	0.49	0.24	0.27
[All τ]	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***

Notes: This table presents the subsampling p-values of the ST - test in eq 4. The term $l^{\Delta US\text{-}Ep}$ = 1,2,3 represents the number of lags of the dependant variable under the null-hypothesis: No Granger causality in eq 2. The subsample size is b=36 for our sample of T=138 observations. The notations *, ** and *** indicate rejections of the null-hypothesis at 10%, 5% and 1% significance levels. The BR-EP, VIX, EPU and GPR series is in log and first difference. The STLFSI is in first difference only due to negative values in standard form.

showing that uncertainty has some effects in normal market conditions.

While there are some indications that uncertainty causes moderate changes in ethanol prices in some quantiles, the overall assessment is that uncertainty has limited effects on the middle quantiles.

In the upper quantiles there is causality at τ = {0.65 – 0,70} at the 1 % level of significance for all uncertainty indicators and model specifications, indicating that uncertainty leads to large positive changes in Brazilian ethanol prices.

As in the U.S. ethanol case, uncertainty can potentially lead to increasing demand for fuel types other than biofuel with positive impact on short run fuel prices.

In the case of Brazilian ethanol prices, the analysis also displays a symmetrical uncertainty impact pattern in both the lower and the upper tails of the distribution. But unlike the U.S. ethanol and Malaysian palm oil, there is distinct indications that uncertainty also affects prices in the middle quantiles.

3.3 Malaysian palm oil

Table 7 presents the p-values of the Granger-causality in quantiles test for the Malaysian palm oil returns. Considering all the quantiles, τ = {0.05 – 0.95}, there is causality in the direction running from all uncertainty indicators to Malaysian palm oil prices and returns at the 1 % level of significance in all models of the autoregressive models.

A comparison between Granger-causality for U.S. and Brazilian ethanol and Malaysian palm oil prices indicates that the causality for the latter is more pronounced and consistent in the highest quantiles τ = {0.75-0.95}, making Malaysian palm oil prices the most responsive to increases in market volatility, US economic policy uncertainty, geopolitical risk and state vulnerability.

In the lower distribution quantiles causality is observed at τ = {0.20} at the 1% level of significance and the results are also robust for model specification 1 to 3. There is also causality at τ = {0.35 – 0.40} at the 1% and 5% levels of significance for all uncertainty measures.

This indicates that uncertainty impact large negative or extreme negative changes in Malaysian palm oil returns.

Considering the middle quantiles there is causality at τ = {0.40} at the 1% and 5% significance levels and at τ = {0.50} at the 1% and 10% significance levels for all indices. While there are some indications that uncertainty can cause moderate changes in ethanol prices in some quantiles, the overall assessment is that uncertainty has a limited effect on the middle quantiles for Malaysian palm oil returns (prices).

Table 7 Quantile causality Malaysian palm oil price

	ΔVIX to ΔMA-PP			ΔEPU to ΔMA-PP			ΔGPR to ΔMA-PP			ΔSTLFSI to ΔMA-PP		
τ	$I^{\Delta MA-PP} = 1$	$I^{\Delta MA-PP} = 2$	$I^{\Delta MA-PP} = 3$	$I^{\Delta MA-PP} = 1$	$I^{\Delta MA-PP} = 2$	$I^{\Delta MA-PP} = 3$	$I^{\Delta MA-PP} = 1$	$I^{\Delta MA-PP} = 2$	$I^{\Delta MA-PP} = 3$	$I^{\Delta MA-PP} = 1$	$I^{\Delta MA-PP} = 2$	$I^{\Delta MA-PP} = 3$
0.05	0.10*	0.01***	0.01***	0.12	0.01***	0.01***	0.10*	0.01***	0.01***	0.35	0.01***	0.01***
0.10	0.36	0.33	0.32	0.36	0.33	0.32	0.36	0.33	0.32	0.36	0.33	0.31
0.15	0.11	0.18	0.15	0.11	0.18	0.15	0.11	0.18	0.15	0.11	0.18	0.15
0.20	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.25	0.01***	0.06*	0.01***	0.01***	0.06*	0.01***	0.01***	0.06*	0.04**	0.01***	0.06*	0.03**
0.30	0.05**	0.01***	0.01***	0.05**	0.01***	0.01***	0.05**	0.03**	0.02**	0.05**	0.08*	0.03**
0.35	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.02**
0.40	0.03**	0.01***	0.05**	0.03**	0.01***	0.05**	0.03**	0.01***	0.05**	0.03**	0.01***	0.05**
0.45	0.15	0.15	0.13	0.15	0.15	0.13	0.20	0.24	0.17	0.11	0.17	0.12
0.50	0.01***	0.08*	0.08*	0.01***	0.08*	0.03**	0.05**	0.10*	0.09*	0.01***	0.08*	0.03**
0.55	0.40	0.55	0.57	0.35	0.34	0.44	0.22	0.56	0.58	0.38	0.74	0.71
0.60	0.96	0.34	0.36	0.89	0.26	0.24	0.66	0.27	0.24	0.95	0.41	0.46
0.65	0.39	0.85	0.82	0.40	0.81	0.90	0.40	0.90	0.72	0.12	0.90	0.82
0.70	0.77	0.12	0.13	0.73	0.12	0.13	0.37	0.02**	0.03**	0.56	0.11	0.13
0.75	0.01***	0.01***	0.02**	0.01***	0.01***	0.02**	0.01***	0.01***	0.02**	0.01***	0.01***	0.02**
0.80	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.85	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.90	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
0.95	0.01***	0.02**	0.07*	0.01***	0.02**	0.07*	0.03**	0.02**	0.07*	0.01***	0.02**	0.07*
[All τ]	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***

Notes: This table presents the subsampling p-values of the ST – test in eq 4. The term $I^{\Delta US-Ep}$ = 1,2,3 represents the number of lags of the dependant variable under the null-hypothesis: No Granger causality in eq 2. The subsample size is b=36 for our sample of T=138 observations. The notations *, ** and *** indicate rejections of the null-hypothesis at 10%, 5% and 1% significance levels. The MA-PP, VIX, EPU and GPR series is in log and first difference. The STLFSI is in first difference only due to negative values in standard form.

In the upper quantiles there is causality at τ = {0.80 – 0,90} and at the 1% significance level for all uncertainty indicators and model specifications.

There is also causality at τ = {0.75} at 1% and 5% significance level for all indicators and at τ = {0,95} at 1% and 10% significance levels, indicating that uncertainty can leads to large or extreme positive changes in Malaysian palm oil returns and prices. The higher Granger causality values on the lower and upper quantiles for Malaysian palm oil prices shows that US economic policy uncertainty, geopolitical risk and state fragility impact palm oil prices asymmetrically.

This implies that uncertainty would impact palm oil prices more severely, in turn perhaps affecting palm oil production, the price of substitute biofuels, and energy policy making in Malaysia [49].

In summary, uncertainty has a stronger impact on Malaysian palm oil prices both near the middle quantiles as well as in the upper and extreme tails of the distribution. These results may indicate a sensitivity to uncertainty near normal market conditions on the downside market and to large and extreme positive returns.

3.4 Discussion

The quantile causality model presents quite interesting results in terms of market dynamics. Where both U.S and Brazilian ethanol prices display similar, but not identical, patterns. If we consider tables 5 to 7 as a visualisation of the studied biofuel markets, we can see that uncertainty causes prise changes closer to normal market conditions, while palm oil is more visibly asymmetrically affected.

An interpretation of this pattern can be that the ethanol market is a more mature market and that actors react to uncertainty already at marginal price increases. And again, on the down market side, reacts to uncertainty at large negative price changes.

In the case of Malaysian palm oil, actors react to uncertainty first at high positive price changes, alternatively to smaller negative prise changes.

Hence, uncertainty can potentially increase demand for palm oil in biodiesel production, which in turn can cause an expansion of palm oil production and raise ethical issues concerning sustainability, deforestation and environmental damages [49].

3.5 Conclusions

The price dynamics of biofuel will become an even more important factor in the future, especially in sectors where (bio)fuel expenditure constitute a significant share of the operational cost, such as in aviation and shipping. From a financial perspective, our model gives portfolio investors the opportunity for improved risk management and a way to effectively rebalance portfolios, including hedging and risk management strategies.

The importance of biofuel price dynamics is even greater if we consider the perspectives of energy diversification, energy security, carbon emissions, and energy policy making. Price fluctuations in biofuel assets heavily influences the determination of investment and subsidies in the sector and in related energy sectors. In turn, affecting not only biofuel as an energy carrier, but also feedstock production and food supply.

The implications of the results suggest that variables of political and global character such EPU, GPR and STLFSI should also be taken into consideration in the transition to a sustainable energy system.

The obtained empirical results indicate that all US, Brazil and Malaysia ethanol and palm oil prices are all affected by changes in market volatility, US economic policy uncertainty, global geopolitical risk and financial stress. Both downside and upside asymmetric characteristics are identified in all three biofuel markets, in with uncertainty (i.e., VIX, EPU, GPR, STLFSI) impacts more strongly in good market conditions rather than bad market conditions. High Malaysian palm oil prices are more susceptible to uncertainty and generally uncertainty more strongly influence increases rather than decreases in ethanol and palm oil prices.

According to our model, uncertainty causes large negative price changes in the biofuel commodities, while moderate uncertainty changes only moderately impacts prices. And finally, uncertainty also causes large or extreme positive changes in the prices of ethanol and palm oil.

Uncertainty measures, and non-linear approaches like quantile causality, provides actors in the whole ethanol and palm oil value chain, like corn and palm growers, the possibility to monitor the price dynamics of biofuels in a straightforward manner when deciding production output and developing appropriate policy guidelines related to subsidizing and energy sector investment.

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