Do uncertainties affect biofuel prices?

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Do Uncertainties Affect Biofuel Prices?

Abstract

We investigate the impact of geopolitical risk, U.S. economic policy uncertainty, financial stress, and market volatility on prices of U.S. and Brazilian ethanol and Malaysian palm oil. We use quantile autoregressive and quantile causality methods and provide evidence of ethanol and palm oil prices being asymmetrically influenced in the downside and upside by each of the uncertainty measures considered. Malaysian palm oil prices are more attuned to increases in uncertainty measures. Increases rather than decreases in uncertainty more strongly impact ethanol and palm oil prices. Uncertainty causes large negative price fluctuations in the biofuel commodities, while moderate uncertainty changes only moderately influence prices. Large uncertainty increases cause large or extreme positive changes in ethanol and palm oil prices. Implications of the results are discussed.

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

1 Introduction

Biobased energy is becoming a central issue of consideration for actors in the global energy market, for example the energy sector and policy makers of developed and emerging economies. This is mainly due to rising energy demand, the emergence of new sources of renewable energy, and the increasing volatility in energy prices that followed the introduction of alternative energy markets. For instance, the rise of fossil fuel substitutes such as shale gas, ethanol fuel and palm oil (among others) have opened new possibilities and pose new challenges to government agents who play a role in determining a country's energy mix. Biofuels broaden the energy spectrum for diversification in economies that for decades have relied largely on traditional fossil fuel or on a small number of energy sources. Further, biofuels can be used to manage and mitigate the adverse effect the price volatility of crude oil has on energy and non-energy portfolios, and to make the issue of energy security less uncertain in countries not endowed with natural resources for energy generation. Lastly, fossil fuel substitutes, such as those considered in our study, and their price dynamics do provide greater flexibility in energy policy implementation and help counter energy market monopolization [1-9]. As biomass markets are less developed than traditional fossil fuel markets, being smaller and having lower market liquidity than the traditional crude oil market for instance, they can be more susceptible to downward trends in the traditional and long-established energy markets. And as a consequence, making them a less competitive and attractive alternative for new energy investment in an increasing global energy market [10].

The subject of price uncertainty in energy markets (biofuel: ethanol and palm oil markets in our study) is linked to the price of corn and palm tree stock, thus positively or negatively impacts producers and consumers (supply-demand) of those agricultural goods and the sector economies they create. These financial and economic issues are particularly important to countries and corresponding markets with the greatest output such as the U.S. and

Brazil, the world's ethanol production leaders, and Indonesia and Malaysia, the largest producers of palm oil in the world.

Insert Figure 1

Insert Figure 2

Fig. 1 and Fig. 2 depict the production levels of ethanol and biodiesel for the U.S., Brazilian and Malaysian markets. It is evident from these diagrams that there is a steady upward shift (trend) in production levels of those biofuel markets. Current estimates suggest that worldwide production of ethanol has shifted from 13,123 to 25,583 million gallons in the last decade. Such significant growth could be due to the concerns about increasing oil prices, energy security and climate change. The development has been considerable, specifically, as of 2016 the U.S. and Brazil controlled 58% and 27% of global ethanol production, respectively. The U.S. alone extracted 15,379 billion gallons of ethanol in 2016 [11] and by January 2020 it amounted to17.3 billion gallons per year [12]. 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 [13]. Earlier studies argue that biofuels as substitutes for fossil fuels have received considerable attention for reducing carbon emission volumes and to lessen the adverse impact of crude oil market volatility [2, 14].

Moreover, Fig. 1 and Fig. 2 demonstrate that the U.S. has emerged as the leading producer of biofuels. Approximately 40% of the U.S. corn is currently used for the production of biofuel. Doubtlessly promoting the use of biofuels limits the dependence on fossil fuel usage. Brazil, for instance, has already replaced 42% of its fuel (gasoline) with ethanol produced from sugarcane. This has led gasoline to be the alternative fuel in Brazil [14]. Moreover, a recent report, published by the U.S. department of Agriculture, indicates that corn ethanol relative to conventional gasoline currently decreases greenhouse emissions by as much as 43 percent, and would further reduce greenhouse gas emissions by 50 percent by 2022. It is foreseen that corn ethanol has the potential to reduce emissions by as much as 76 percent in the following decades [15-18]. These statistics suggest that the biofuel markets will witness a huge growth in coming years.

Hence, it is in the context of the aforementioned opportunities and challenges the ethanol and palm oil industries pose to corn and palm tree growers, biofuel producers, energy portfolio investors, and energy policy makers that an investigation of the impact uncertainties such as market volatility (VIX), U.S. economic policy uncertainty (EPU), global geopolitical risk (GPR), and financial stress (FSI) have on the price of ethanol and palm oil is worth undertaking. For this purpose, we implemented quantile autoregression and quantile causality methods on monthly observations of those uncertainty factors and of U.S. and Brazilian ethanol prices (US-EP and BR-EP), as well as Malaysian Palm Oil prices (MA-PP). While previous studies have mainly focused on the impact traditional crude oil, renewable and some biofuel markets have on the prices of ethanol and plam oil prices [19-23] little or no attention has been paid on the effect economic policy uncertainty, geopolitical risk and state fragility have on the price of biofuel commodities. Our study fills this gap.

Our results suggest that variables of political and global character such EPU, GPR and FSI should also be taken into consideration, and be monitored, by energy market participants, portfolio investors, ethanol and palm oil producers, corn and palm growers, and policy makers before and during the process of rebalancing portfolios, deciding production output, and developing appropriate policy guidelines related to subsidizing and energy sector investment. The asymmetric relationship between the measures of uncertainty and bioenergy prices implies that biofuels tend to display stronger positive price chocks when global geopolitical risk is high, when the economic outlook in the U.S. economy is ambiguous, and when the vulnerability in the most troubled countries around the world increases [10].

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature in the field and acknowledges the research gap that we fill. Section 3 describes and justifies the variables selected and provides the descriptive statistics of the sampled series of observations. Section 4 explains the choice of methodology and the motivation for implementing the selected methodology. Section 5 presents the empirical results. Section 6 concludes.

2 Literature Review

Previous studies have examined the relationship between energy market prices and those of financial and agricultural commodities. For instance, [24] used vector error correction (MVEC), multivariate generalized autoregressive conditional heteroskedasticity (MGARCH), and cointegration models to analyze interdependencies across prices of gasoline, ethanol and oil. Their results indicate a direct link between the prices of gasoline and those of ethanol and oil. Besides, their findings discard long-term price effects between the energy commodities considered. [25] used cointegration techniques to examine the short-run and long-run effects that biofuels such as ethanol, gasoline and crude oil have on agricultural commodities such as corn, soybeans, and sugar. Their results indicate the absence of long-term influence between the agricultural and energy commodities considered, however short-term effects do arise, with ethanol prices exerting the strongest influence.

[26] implemented autoregression methods to understand how crude oil prices affect U.S. ethanol, corn and gasoline. They identified a strong link between ethanol prices and those of corn and oil. Moreover, ethanol prices were found to positively correlate with corn and gasoline, with the latter having the strongest influence [27]. Trujillo-Barrera et al. [28] used Granger causality, vector error correction and the cointegration tests of Johansen [29] and found that spillovers of crude oil on corn and ethanol are similar in timing, however stronger on

ethanol markets. Oil was observed to cause ethanol and corn prices more strongly during the 2008 financial crisis. By fitting weekly and monthly minimal spanning and hierarchical trees on price series of biodiesel, ethanol and agricultural commodities Kristoufek et al. [30] identified weak short-term co-dependence between biodiesel and ethanol. However, biofuels in the medium term did become an influential factor on ethanol prices. Using the inference and cointegration methods of Johansen [32, 33], Natanelov et al. [31] acknowledge a strong influence of crude oil on corn and ethanol prices. They also documented that increasing corn market volatility resulting from increasing production of ethanol, and the U.S. government fuel policy is indicated to influence the relationship of corn and ethanol. Gardebroek and Hernandez [22] analyzed volatility transmission between oil, corn and ethanol prices in the U.S. using multivariate GARCH methods. Their results showed stronger volatility transmission between corn and ethanol markets post 2006. It is from this year on that ethanol becomes the only alternative to gasoline. They also found that crude oil volatility did not significantly impact corn and identified spillover volatility from corn to ethanol. Zafeiriou et al. [34] used monthly frequency data of ethanol, volume of gas emissions, gasoline and crude oil, along with Johansen cointegration techniques and showed that each pair of variables they model influences others. They also showed that increases in gas emissions and in gasoline prices are associated with increases in ethanol prices.

Bentivoglio et al. [35] in the context of Brazilian markets, and through the use of vector error correction and forecast error variance decomposition, indicate that the prices of fuel and sugar influence those of ethanol. Chiu et al.'s [2] study of interdependence between the prices of corn, ethanol and crude oil found evidence of mutual effects between those commodities. Accordingly, the price of corn drives that of ethanol, and crude oil displays a unidirectional relationship of causality with ethanol prices. Kristoufek et al. [36] employed a wavelet coherence methodology to analyze the comovements between the returns of Brazilian and U.S. ethanol and its feedstock, namely, corn and sugar, across frequencies and time scales. They found ethanol prices to positively correlate with those of corn and sugar in the long-term only. Moreover, the feedstock prices are said to lead those of ethanol. Dutta's [14] examination of nonlinear asymmetric and symmetric interdependence between the prices of Brazilian corn, ethanol and crude oil indicate that the international price of oil and sugar are important factors in determining the price of ethanol in the long run. The study also identified a short-term unidirectional relationship from sugar to the ethanol market. In the same year Dutta et al. [11] using a GARCH-jump model identified a positive and asymmetric response of U.S. ethanol to corn market volatility shocks. They observed that the asymmetric effect becomes more evident during extreme tail market downturns and upturns.

When it comes to the use of nonlinear analysis using the Granger noncausality in quantiles approach there is a study by Jiang, Zhou and Liu [37] where they investigated how uncertainty (GPU) affects carbon emissions. In their analysis, they found no statistically significant result at the median. Instead, they found a clear outstanding pattern in the lower and higher tails of the distribution, where the uncertainty effects were concentrated in the lower tails of the distribution. Another study by Wadström, Wittberg, Uddin and Jayasekera [38] analysed the asymmetric pattern of renewable energy in relation to Canadian industrial output using the GCQ approach. In their paper, they use GCQ in combination with quantile regression and the findings indicated clear tail patterns and weak median significance.

Our study employs measures of economic policy uncertainty, geopolitical risk, and financial stress which have not been studied before in a modeling framework that we use to understand their impact on ethanol and palm oil prices. Furthermore, the nonlinear aspects of the distribution in the data calls for a nonlinear analysis that can provide a deeper understanding of uncertainty and price mechanisms. Our study takes a novel approach and diverts considerably from traditional correlation studies in order to describe biofuel market dynamics.

3 Data and descriptive statistics

This paper analyzes the causal relationship between uncertainty and ethanol and palm oil returns. The uncertainty indicators used are Market Volatility Index (VIX), U.S. Economic Policy Uncertainty Index (EPU), Geopolitical Risk Index (GPR) and the St. Louis Fed Financial Stress Index (FSI). The ethanol and biofuel series considered are the U.S. ethanol prices (US-EP), the Brazilian ethanol prices (BR-EP) and the Malaysian Palm Oil prices (MA-PP). Our time series consist of 139 monthly observations, ranging from January 2006 to December 2017. BR-EP have been retrieved from the Centre for Advanced Studies on Applied Economics, and the US-EP and MA-PP data have been collected from DataStream International. The selected VIX is based on the implied volatilities of the S&P500 index options and accounts for market expectations of a 30-day time horizon. The EPU is based on three components. The first component measures newspaper coverage of uncertainty in U.S. economic policy. The second component refers to the quantity of future tax code provisions that are to expire. The third component examines and measures economic forecast disagreements. 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 expected to increase in value during times of regional and global political tension [39]. The FSI measures the degree of financial stress in markets and consists of 18 weekly data series constructed by principal component analysis[1] The indices included in the FSI are seven interest rate series, six yield spreads and five other financial series [40].

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[1] St. Louis Fed Financial Stress Index (STLFSI) is now discontinued and has been replaced with STLFSI2.

Table 1 displays the time series descriptive statistics in log level, except for FSI which is in level due to negative values in original form. The Jarque-Bera test shows that the VIX and FSI are not normally distributed at the 1 percent level of significance, and GPR at the 5 percent significance level. This fact could be an indication of non-linearity in our data, making linear models unsuitable. In order to further test for non-linearity in the data, we fitted a BDS independence test [41]. The BDS test evaluates non-linear aspects in our data by seeking evidence for a normal distribution i.e., independent and identically distributed variables (iid). Table 4 displays the results, which indicate strong nonlinearity in our data, making nonlinear analysis relevant for investigating the relationship between biofuel and uncertainty indicators.

Insert Table 1

Insert Table 2

Table 2 presents the correlation between the time series. 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 with VIX. The BR-EP also has a negative correlation with all variables except with EPU. The MA-PP has a negative correlation with GPR and FSI.

Insert Table 3

In Table 3 we show the results from the unit root tests fitted to verify the integration order of the series modeled. It can be observed that the US-EP, BR-EP, MA-PP, VIX and FS 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 FSI have the most distinctive shifts in increasing uncertainty levels around the financial crisis of 2008. 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 2006 and 2010. The U.S. 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 and most constant positive returns occur on the U.S. and Brazilian returns. The FSI 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.

Insert Figure 3

Insert Figure 4

Table 4 displays the results corresponding to the implemented BDS independence test. This test seeks for evidence of non-linear aspects in our model. Before testing, the linear structure in the time series is removed by detrending according to first-difference AR(1) and GARCH (0,1). The results show a strong indication of non-normality at the 1 percent level of significance for the US-EP and FSI time series. There is also a strong indication at the 5 percent significance level that the MA-PP and GPR time series are non-linearly behaved. The results justify the use of non-linear methods for investigating the relationship between biofuel and uncertainty indicators.

Insert Table 4

4 Quantile autoregressive and quantile causality models

As the most established application of Granger-causality is defined in relation to the conditional distribution (using the conditional mean), these models cannot evaluate or assess causal relations in the extremes of the distribution or in nonlinear circumstances. Troster [42, 43] shows that while a mean-causality relationship must impact at least a significant number of quantiles in order to indicate causality; a tail (extreme event) causal relation does not necessarily imply a causality in the mean. Given the absence of normal (Gaussian) distribution in the time series under examination, nonlinear models such as quantile autoregression and quantile causality are preferable to adequately account for the asymmetric impact of uncertainty on the ethanol and palm oil markets studied [44]. And so, rather than only testing for the basic necessary conditions for Granger-causality, we analyze the full continuous space of conditional quantile functions in the distribution. In this way this study provides a much more detailed and richer analysis of the entire conditional distribution, compared to the conditional mean. We will show that uncertainty (VIX, EPU, GPR, FSI) in fact are nonlinearly related with the different ethanol and palm oil prices. And we will also see that only studying the conditional mean will fail to capture the whole picture, gravely neglecting important information. Our nonlinear model is able to capture large or extreme changes in uncertainty that represent significant real-world events in the real-economy, finance and in energy markets that can be particularly important. A weakness with the quantile Granger-causality test lies in its inability to inform about the magnitude of the strength of association.

The interpretation of the quantile causality test resembles that of the ordinary linear causality test and as such provides information about the predictive power of a certain variable on others at a specific quantile (τ). Compared to correlation studies, the causality method applied in this paper focuses on the predictive power, and not the comovements, of an explanatory variable on a dependent variable. As defined by Troster (2018) let $\{Y_t, Z_t\} t \epsilon \mathbb{Z}$ be a strictly stationary and ergodic time series where $Y_t \epsilon \mathbb{R}$ is the dependent variable and there is an explanatory variable $I_t \equiv (I_t^{Y\prime}, I_t^{Z\prime}) \in \mathbb{R}^d, d = s + q$, where $I_t^Y := (Y_{t-1}, \ldots Y_{t-s})' \in \mathbb{R}^s$ and $I_t^Z := (Z_{t-1}, \ldots Z_{t-s})') \in \mathbb{R}^q$ for A' denoting the transpose matrix of A. Then let $Fy(y|I_t^Y, I_t^Z)$ and $Fy(y|I_t^Y)$ be the conditional distribution functions of Y_t given (I_t^Y, I_t^Z) and I_t^Y. Then a series of Z_t does not Granger-cause another series Y_t if previous Z_t does not increase the predictive value of Y_t given previous Y_t. The theoretical null-hypothesis is thus:

$$H_0^{Z\nrightarrow Y}: \mathrm{Fy}\ (\mathrm{y}|I_t^Y, I_t^Z) = \ Fy\ (y|I_t^Y), \text{ for all } y \in \mathbb{R}. \text{ (eq1)}$$

Equation 1 is denoted as Granger-causality in distribution. However, the null-hypothesis in equation 1 indicates non-causality in mean and Z_t does not Granger-cause Y_t in mean if:

$$E(Y_t|I_t^Y, I_t^Z) = E(Y_t|I_t^Y) \text{ a.s., (eq2)}$$

Where $E(Y_t|I_t^Y, I_t^Z)$ and $E(Y_t|I_t^Y)$ denote the mean of $Fy(\cdot\ |I_t^Y, I_t^Z)$ and $Fy(\cdot\ |I_t^Y)$ respectively. In this regard, Granger-noncausality can be extended to higher orders even if this form of Granger-causality in mean overlooks conditional tail dependencies in the distribution. Thus, we continue with the proposed testing of Granger-noncausality in conditional quantiles of the distribution. Which allows for determining the causality pattern and fulfills the conditions for testing for causality in distribution. And so, let $Q_\tau^{Y,Z}(\cdot\ |I_t^Y, I_t^Z)$ and $Q_\tau^{Y,Z}(\cdot\ |I_t^Y)$ denote the $\tau-$quantiles of $Fy(\cdot\ |I_t^Y, I_t^Z)$ and $Fy(\cdot\ |I_t^Y)$. Then we reformulate equation 1 as:

$$H_0^{QC:Z\nrightarrow Y}: Q_\tau^{Y,Z}\ (\mathrm{Y}|I_t^Y, I_t^Z) = \ Q_\tau^Y\ (Y|I_t^Y), a.s. for\ all\ \tau \in \mathcal{T}, (eq\ 3)$$

where $\mathcal{T}$ is a compact set in such way that $\mathcal{T} \subset\ [0,1]$ and where the conditional $\tau-$quantiles satisfies the restrictions given in the works of Troster [42][2]. From these definitions we can fit our model for analyzing biofuel prices and uncertainty as defined in equation 4. The Granger noncausality in quantiles test also includes lags of the dependent variable to control

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[2] For more details see eq 4 and 5 in the method development in Troster (2018)

for spurious relationships. In testing granger causality for quantiles, we perform the following tests:[3]

$$H_0^{\Delta \mathrm{Ui} \nrightarrow \Delta RE}: E\left\{1\left[\Delta\ \mathrm{Bio}_t\ \leq m\left(I_t^{\Delta \mathrm{Bio}}, \theta_0(\tau)\right)\right] I_t^{\Delta \mathrm{Bio}}, I_t^{\Delta \mathrm{Ui}}\right\} = \tau\,, a.s. for\ all\ \tau \in \mathcal{T}\ \text{(eq 4)}$$

versus:

$$H_A^{\Delta \mathrm{Ui} \nrightarrow \Delta \mathrm{Bio}}: E\left\{1\left[\Delta\ \mathrm{Bio}_t\ \leq m\left(I_t^{\Delta \mathrm{Bio}}, \theta_0(\tau)\right)\right] I_t^{\Delta \mathrm{Bio}}, I_t^{\Delta \mathrm{Ui}}\right\} \neq \tau\,, a.s. for\ \text{some}\ \tau \in \mathcal{T}\ \text{(eq 5)}$$

where $m\left(I_t^{\Delta \mathrm{Ui}}, \theta_0(\tau)\right)$ specifies the conditional $Q_\tau^Y(\cdot \mid I_t^Y)$, for all $\tau \in \mathcal{T}$. The linear Granger causality null-hypothesis is tested against the nonlinear Granger causality alternative hypothesis. The innovative application of this test is applied in energy economics (Troster et al., 2018). In accordance with the model specification introduced by Troster et al. (2018), we will apply the following test statistics:

$$S_T := \int_\tau \int_w |v_t(\boldsymbol{\omega}, \tau)|^2 dF_\omega(\omega) dF_\tau(\tau)\ \text{(eq 6)}$$

Where $F_\omega(\cdot)$ stands for a conditional distribution function of a *d*-variate standard normal vector, $F_\tau(\cdot)$ is ruled by a uniform discrete distribution over a grid of $\mathcal{T}$ for *n* equally spaced points,

$\mathrm{T}_n = \{\tau_j\}_{j=1}^n$, and the weight vector $\boldsymbol{\omega} \in \mathbb{R}^d$ which follows a standard normal distribution. The statistic for the test of *Equation 6* is calculated according its sample analog. Let ψ be a T x n matrix that consists of 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 $\Psi_{\tau j}(\varepsilon) := 1(\varepsilon \leq 0) - \tau_j$. Then the following test statistic is applied:

$$S_T = \frac{1}{Tn} \sum_{j=1}^n \left|\psi \cdot {}_J \hat{\boldsymbol{W}} \psi \cdot {}_J\right|\ \text{(eq 7)}$$

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

Where **W** is defined as a T x T matrix that has components $\boldsymbol{w}_{t,s} = \exp[-0{,}5(I_t - I_s)^2$, and $\psi \cdot j$ designates a j-th column of ψ parameters. 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.

The limitations of the applied methodology, besides not providing a parametric magnitude of the causality, lies in its explanatory properties. Apart from displaying the predictive power, no other information is provided by the model. This is why we include several uncertainty measurements as explanatory variables. The selected uncertainty measures are composed of individual components, enabling a more detailed investigation of uncertainty impacts. Furthermore, in order to handle any spurious causality relations, we will mainly consider results at the 1 % significance level in our analysis, however, results at the 5% significance level will also be noted. It is also noteworthy that we have not corrected for the presence of structural breaks in the time series. Given that structural breaks are usually detected in commodity markets, affecting statistical inference, traditional approaches can sometimes lead to unreliable results. However, the Granger noncausality in quantiles methodology is not as sensitive to this problem as other statistical or econometric methods. In fact, uncertainty can be one of the causes of structural shifts, and thus, making our approach suitable.

The practical work of applying Granger noncausality in quantiles was performed in MATLAB Simulink programing software, where the equations were translated into coded scripts (see Appendix A).

5 Results

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, $\tau = (0.05 - 0.95)$, there is causality running from uncertainty indicators to the U.S. ethanol return in 8 out of 10 model specifications at the 1% level of significance. This information implies that uncertainty impacts U.S. ethanol prices in both market downturns (lower quantiles) and market upturns (larger quantiles). It can also be observed that the impact of uncertainty is asymmetric in both tails positive and negative, as the strength of association between uncertainty measures and ethanol logarithmic differences that is significant is more evident in the lower and larger quantiles. The significance of the influence uncertainty has is more predominant in the highest quantiles, meaning causing higher prices when economic policy is more ambiguous, and when geopolitical risk and financial stress increase. Looking at the lower quantiles (0.05-0.35) there is causality running from VIX, EPU, GPR and FSI to ethanol price return at τ = (0,15) at the 1% and 5% significance levels in model specifications 1 to 3. For FSI 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 impacts lead to large negative price returns for U.S. ethanol, possibly as a consequence of diminishing demand. Considering substitution effects, decreases in U.S. ethanol that in turn could affect gasoline prices negatively [45].

Insert Table 5

Considering the middle quantiles (0.40-0.60) there is causality running from VIX, EPU, GPR and FSI to ethanol price return at τ = (0,45) for 10% and 5% significance levels, however the causality is not constant across all three model specifications. Note that causality at the mean is located in the middle section of the quantile distribution. And as there is little or no indication of causality in the middle quantiles in Table 5, only performing a mean causality test would have missed the causality pattern in the tails. And therefore, we cannot really conclude with full certainty the presence of causality in the middle quantiles. This indicates that uncertainty does not Granger-cause moderate changes in U.S. ethanol return. A possible explanation for this is that the U.S. ethanol market is a relatively stable market compared to the Brazilian.

Considering the upper quantiles (0.65-0.95) there is causality at τ = (0.70) at the 1% significance level for EPU in all model specifications. There is also causality at quantiles τ = (0.75 – 0,85) for all uncertainty indicators, but the significance levels vary between 1% and 10% in the three model specifications. Indicating that some uncertainty events lead to large positive changes in U.S. ethanol price return. Overall, uncertainty impacts U.S. ethanol prices in the lower extreme tail of the distribution (meaning the most adverse price events) and also the upper parts of the distribution, however not the most extreme tail events. The implications of asymmetric impact of uncertainty on U.S. ethanol prices shows that uncertainty can potentially lead to higher demand for oil-based fuels at moderate positive price changes and lower demand in the extreme negative price changes. The shocks to energy prices may in turn cause price shocks in the agricultural and commodity markets.

Insert Table 6

Table 6 displays the p-values of the Granger-causality in quantiles test for Brazilian ethanol 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. In the lower and upper quantiles, there is similarities between the Brazil ethanol market and the U.S. ethanol market, although not entirely displaying the same pattern. A striking feature is the significance of the impact in the middle quantiles for Brazilian ethanol, that is more dominant something also found in other research [46]. A broad comparison between the Granger-causality for U.S. ethanol prices and Brazilian ethanol prices indicates that the uncertainty measures VIX, EPU, GPR and FSI more noticeable influences the U.S. ethanol prices in the higher quantiles, making the U.S. ethanol market more responsive to increases in U.S. economic policy uncertainty and geopolitical risk, for instance.

Looking at the lower quantiles of the distribution for Brazilian ethanol prices, 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 lead to large negative changes in Brazilian ethanol prices, with a potential increase of demand that in turn has spillover effects on related Brazilian agricultural, commodity and energy markets [47].

Considering the middle quantiles in table 6, there is causality at τ = (0.45) at the 1% level of significance and τ = (0.60) at the 1% and 10% level of significance for all indices. While there are some indications that uncertainty causes moderate changes in ethanol prices in some quantiles, the overall assessment is that uncertainty at least has some impact on the middle quantiles.

In the upper quantiles in table 6, there is causality at τ = (0.65 – 0,70) at the 1% level of significance for all uncertainty indicators and model specifications, indicating that some uncertain situations lead to large positive changes in Brazilian ethanol prices. The overall assessment of our results is that uncertainty have a broader impact on the Brazilian ethanol prices, making the Brazilian ethanol market less stable compared to the U.S. market. However, as in the case of U.S. ethanol prices, uncertainty can be transmitted through the market and potentially leading to increasing demand for fuel types other than biofuel with positive impact on short run fuel prices.

Insert Table 7

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. This feature is also found in the Brazilian ethanol returns and may indicate an uncertainty or price linkage between ethanol and palm oil prices [48]. A comparison of the 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 (0.75-0.95), making Malaysian palm oil prices the most responsive to market volatility, U.S. economic policy uncertainty, geopolitical risk and financial stress. In the lower distribution quantiles causality is observed at $\tau = (0.20)$ at the 1% level of significance and the results are also robust for model specification 1 to 3. There is also causality at $\tau = (0.35 - 0.40)$ at the 1% and 5% level of significance for all uncertainty indicators. This indicates that uncertainty leads to large negative or extreme negative changes in Malaysian palm oil returns. Hence, decreasing 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].

Considering the middle quantiles there is causality at $\tau = (0.40)$ at the 1% and 5% significance levels and at $\tau = (0.50)$ at the 1% and 10% significance levels for all indices. Results from U.S. and Brazil indicate that uncertainty might lead to moderate changes in ethanol prices. However, the overall assessment is that uncertainty has a limited effect in the middle quantiles for Malaysian palm oil returns (prices).

In the upper quantiles there is causality at $\tau = (0.80 - 0{,}90)$ and at the 1% significance level for all uncertainty indicators and model specifications. There is also causality at $\tau = (0.75)$ at 1% and 5% significance level for all indicators and at $\tau = (0{,}95)$ at 1% and 10% significance levels, indicating that large or extreme increases in uncertainty lead 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 U.S. economic policy uncertainty, geopolitical risk and state fragility impact palm oil prices asymmetrically. This implies that large or extreme price increases (decreases) in uncertainty would impact palm oil prices more severely affecting palm oil production, the price of substitute biofuels, and energy policy making in Malaysia [49].

6 Discussion and Conclusion

Overall, our results suggest that the global biofuel markets are sensitive to shocks stemming from different financial and economic uncertainty indicators, namely, EPU, VIX, FSI and GPR. More importantly, we find an asymmetric linkage between uncertainty indexes and biofuel markets, and a similar association is observed for Malaysian palm oil prices. The presence of asymmetric relationship among the variables under study has significant implications. For example, the existence of a symmetric linkage would enable the biofuel producers to properly measure the influence of global economic shocks, while dealing with such a risk could be challenging when the impact of economic or financial shocks are asymmetric. As increases and decreases in economic indicators might cause cyclical fluctuations in investments, exploring the asymmetric connection between the uncertainty indexes and biofuel markets is of paramount importance to investors and policymakers.

The reason behind these results could be recognized from the relationship between traditional fossil-based energy carriers and renewable energy carriers [50]. Increasing economic, financial and geopolitical risk and uncertainty can severely impact and deteriorate the business environment and in turn diminish their demands for oil [51-53]. In line with this reasoning, an increase in global or regional uncertainty in crude oil producing countries would limit oil supply as well. Hence, economic or financial shocks could influence oil price volatility via the supply and demand channels [54, 55]. Accordingly, when international crude oil markets become highly volatile as a consequence of rising uncertainties, there could be a shift towards alternative energy markets, thereby influencing the prices of renewable energy carriers. Furthermore, markets actors anticipations of market behavior can impact trust in biofuel markets, and further influence their investment decisions [50]. Hence, variations in uncertainty exert significant influence of clean energy prices through market participants and investor sentiment.

Moreover, geopolitical risk has an important role to play in determining biofuel prices. Given that some of the major oil-exporting countries often experience substantial geopolitical conflicts, a diversified energy consumption structure may moderate the supply risks of oil importers [56]. In addition to this, the increase in geopolitical risk concerning climate change, the oil-exporting countries may also seek to diversify energy exports [57]. Therefore, geopolitical risk would encourage policy makers to promote the progress of energy transition, which may have a positive impact on the price levels of renewable fuels.

Thus, the role of biofuels, such as ethanol and palm oil, in a country's energy mix are important from the perspectives of energy diversification, energy security, carbon emissions, and energy policy making. Price fluctuations in those biofuel assets in specific serve for the determination of investment and subsidies in the sector and in related energy sectors. They also help growers of the feedstock (corn and palm trees) used for the production of those biofuels to determine quantities on the supply side and to assess more accurately medium- and long-term accounting liabilities. The present study examined the characteristics of interdependence between U.S. and Brazilian ethanol, Malaysian palm oil, and measures of global uncertainty such market volatility, U.S. economic policy uncertainty, geopolitical risk and financial stress. The main research questions of our study were: i) Does any of the measures of uncertainty considered significantly impact the price of ethanol and palm oil? ii) Does any of the uncertainty measures impact the price of ethanol and palm oil asymmetrically?

The empirical results obtained through the implemented quantile autoregression and quantile causality methods indicate that all U.S., Brazil and Malaysia ethanol and palm oil prices are subject to and influenced by changes (increases and decreases) in market volatility, U.S. economic policy uncertainty, global geopolitical risk, and by changes in the degree of financial stress. The influence of the uncertainty measures on ethanol and palm oil prices is observed to be asymmetric in the downside and upside, with uncertainty increases most strongly impacting biofuel prices. Malaysian palm oil prices are the most responsive to increases in VIX, GRP, EPU and FSI. Comparing the causality impacts in the U.S.. and Brazilian ethanol markets, we find both differences and similarities. For example, we observe that, uncertainty triggers either moderate to large positive changes in U.S. ethanol prices or extreme negative price changes. Moreover, the impact pattern displays a clear skew towards moderate positive price changes. This indicate a market volatility mechanism caused by uncertainty, that in turn have the potential to impact market demand and the utilization of energy [53].

The Individual downside and upside price change asymmetric characteristics are identified in all three biofuel markets, where changes in uncertainty levels (i.e., changes in VIX, EPU, GPR, FSI) influences more strongly positive prices changes rather than negative price changes. This means that uncertainty mainly moderately increases the price of biofuels, following previous research in uncertainty and energy prices [52, 58], and in contrast with, for example stock prices that reacts negatively to uncertainty changes [59, 60]. The pattern of increasing energy prices is also in line with previous research [51, 61, 62], and will have to be considered as price changes will impact different actors in different ways [54]. However, our results also indicate that uncertainty cause severe or extreme negative price shocks in biofuel markets.

The implications of the results suggest that variables of political and global character such EPU, GPR and FSI should also be taken into consideration, and be monitored, by energy market participants, investors, ethanol and palm oil producers, corn and palm growers, and policy makers before and during the process of rebalancing portfolios, deciding production output, and developing appropriate policy guidelines related to subsidizing and energy market actors.

The asymmetric relationship between the measures of uncertainty and the U.S., Brazilian and Malaysian ethanol and palm oil markets implies that the prices of those biofuels tend to display stronger negative trends when global geopolitical risk is higher; when the outlook of U.S. economic policy uncertainty is ambiguous, and when the vulnerability in the most troubled countries around the world increases. Given that fluctuations in uncertainty lead to changes in the ethanol and palm oil prices, policymakers should adopt effective measures to manage the price volatility on these markets. One such strategy could be the improvement of market monitoring systems by upgrading the futures market for biofuels and edible oils. A developed and improved futures market could then reduce the influence of different uncertainty measures on the global ethanol and palm oil markets efficiently, which in turn make these industries more secure. Additionally, governments should also adopt appropriate measure with a view to stabilizing the feedstock prices. For instance, lifting the levels of biodiesel feedstock reserves could result in lower edible oil prices amid the periods of high uncertainty. Otherwise, future volatilities of feedstock prices could be affected by supply shortages because of the growing demand for alternative fuels [63]. Subsidies granted from public institutions should be considered as well, because subsidies could minimize the feedstock price volatility (and hence the biofuel price uncertainty) if the increased demand cannot be met by the supply [63, 64]. Thus, to deal with such risks, the importance of optimal storage along with the long-term feedstock supply contracts will likely increase for alternative energy sectors. Overall, it is important for policymakers and developers to react effectively to global uncertainty shocks and moderate the price volatility of biofuel and its allied markets.

The results have implications for biofuel researchers as well. For instance, the existence of asymmetric linkages between the uncertainty measures and biofuel markets should shift the investigators from applying linear models to the application of nonlinear approaches while analyzing the market dependencies. Besides, the nature of the relationship between variables studied may differ depending on the market conditions. In particular, the association among uncertainty indices and renewable fuels could behave differently during periods of high market stress and extreme market conditions, suggesting the need for exploring the connection between the examined variables via the use of advanced modeling techniques such as for example copulas.

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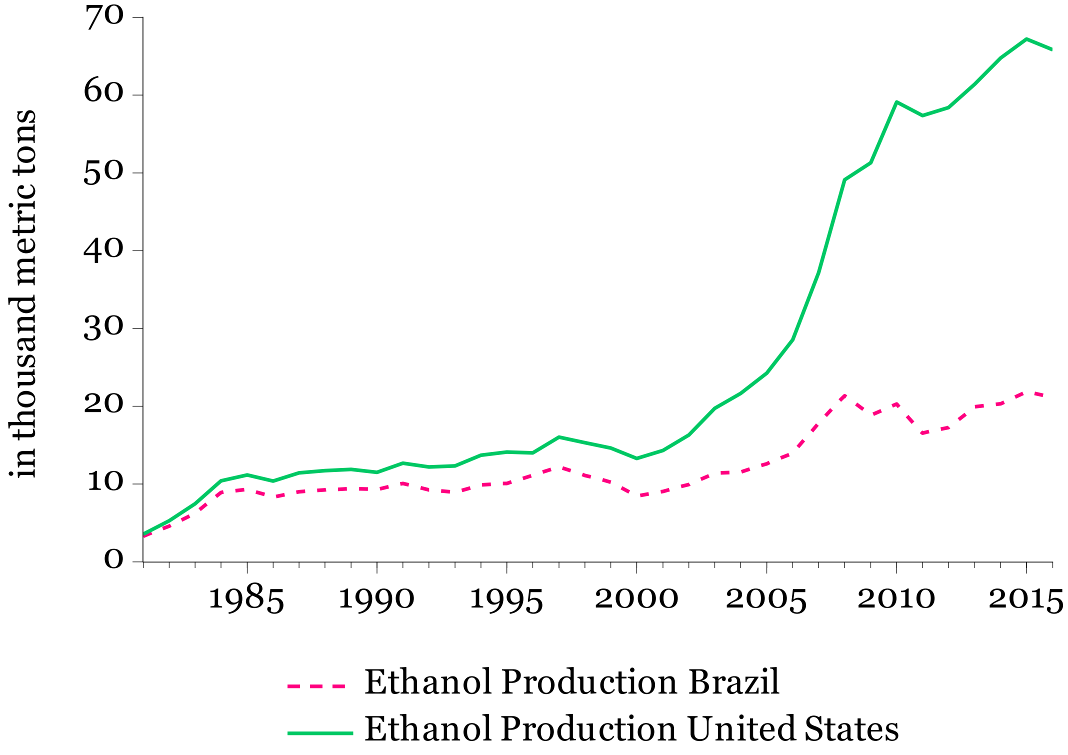
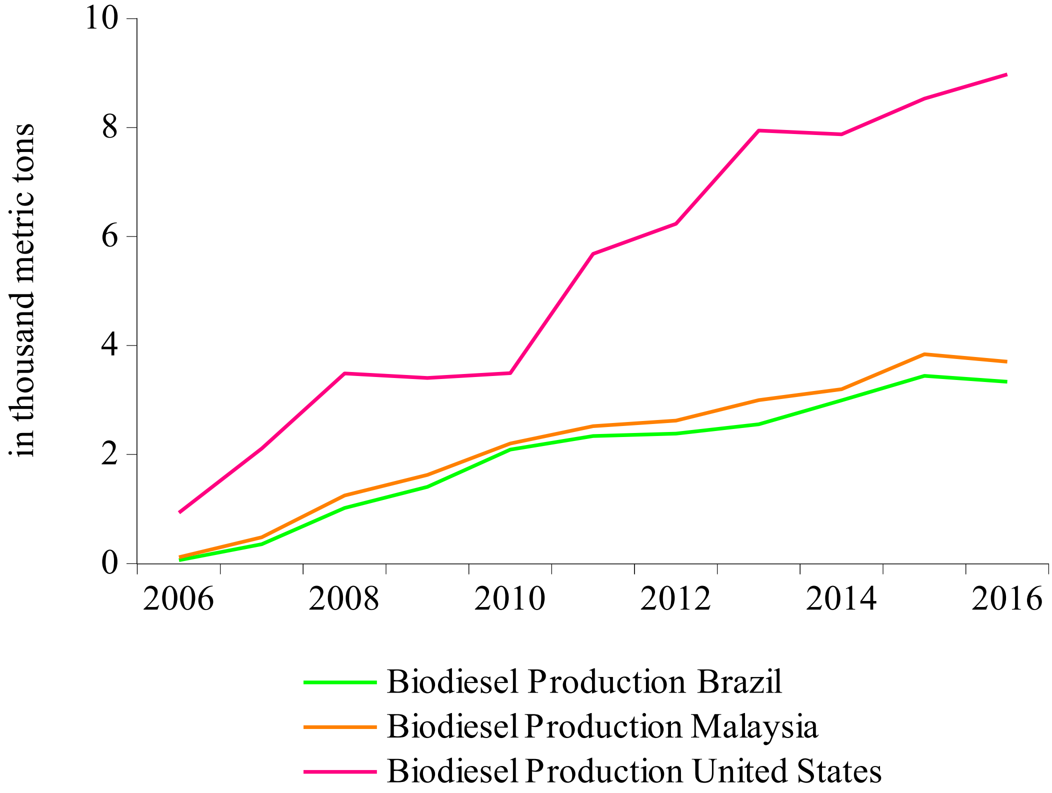
Figure 1 Ethanol Production



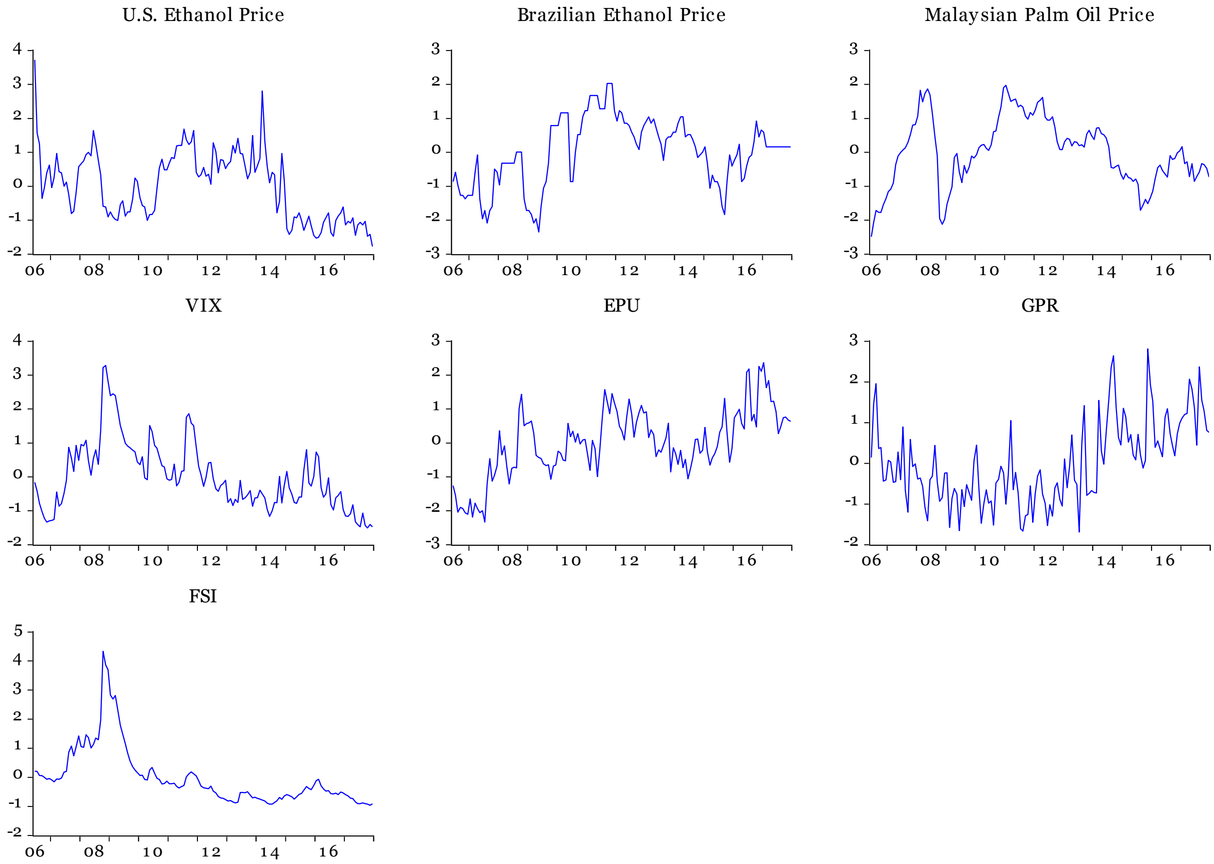
Notes: International Energy Statistics–EIA. Thousands of metric tons of produced ethanol fuel in Brazil and the U.S.

Figure 2 Biodiesel Production



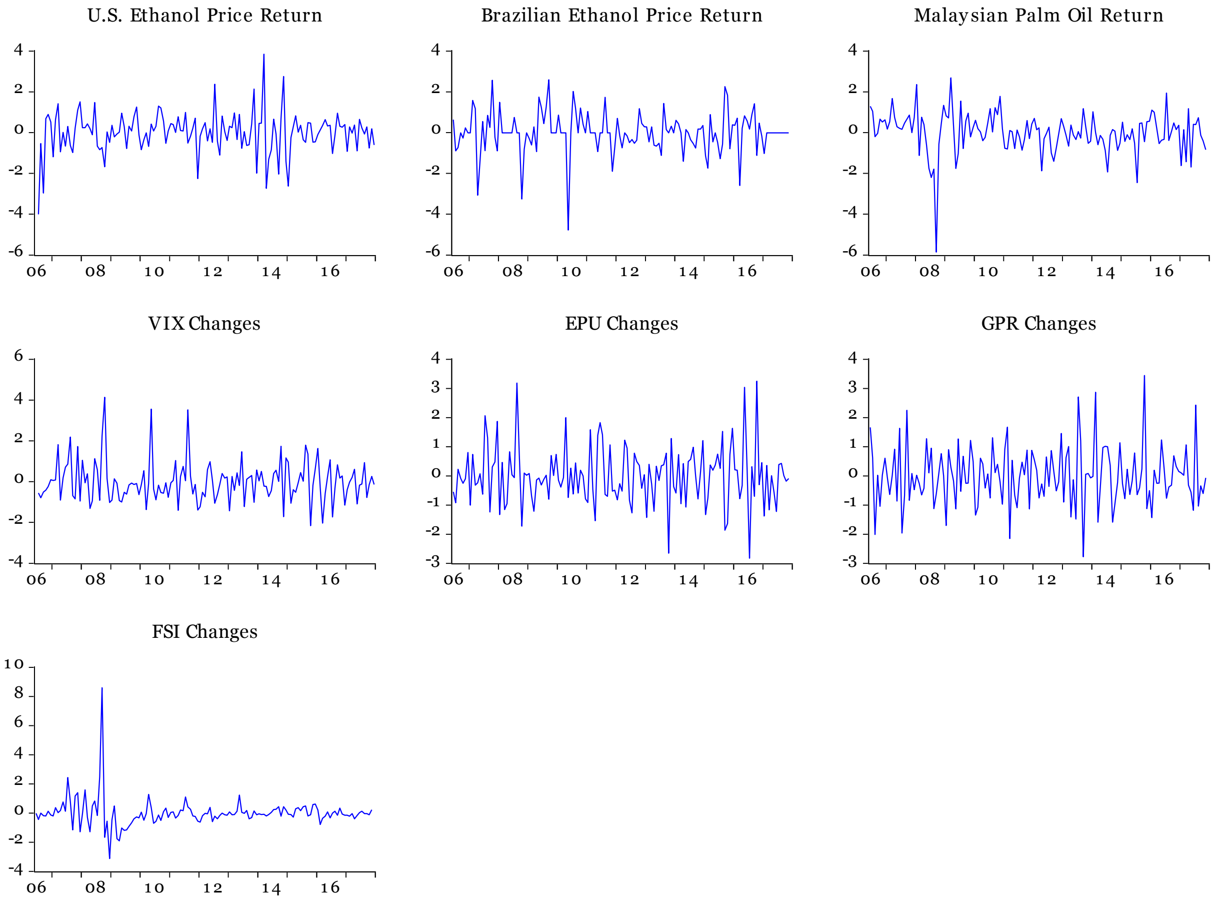
Notes: International Energy Statistics–EIA. Thousands of metric tons of produced ethanol fuel in Brazil, Malaysia and the U.S.

Figure 3: Time series in level



Notes: Graphs of biofuels and uncertainty indicators normalized and in level and log level (Log = ln(Pt) - ln(Pt-1)) may indicate that some of the series are stationary in level.

Figure 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 DLog = ln(Pt) - ln(Pt-1).

Table 1: Descriptive statistics

	S-EP	R-EP	A-PP	IX	PU	PR	SI
Mean	.73	0.62	.67	.89	.77	.39	0.44
Median	.76	0.58	.68	.83	.80	.30	0.79
Maximum	.61	0.14	.15	.14	.65	.51	.62
Minimum	.31	1.17	.06	.32	.91	.71	1.57
Std. Dev.	.24	.24	.24	.38	.37	.40	.17
Skewness	.44	0.29	0.09	.96	0.14	.57	.07
Kurtosis	.10	.41	.48	.88	.93	.79	.68
Jarque-Bera	.61	.94	.77	5.99	.47	.68	25.79
Probability	.10*	.14	.41	.00***	.79	.02**	.00***
Observations	39	39	39	39	39	39	39

Notes: All log level except FSI which is in level.

Table 2: Correlation matrix

	S-EP	R-EP	A-PP	IX	PU	PR	SI
S-EP							
R-EP	.369						
A-PP	.474	.597					
IX	.020	0.152	.052				
PU	0.302	.345	.099	.156			
PR	0.339	0.071	0.393	0.509	.059		
SI	0.039	0.458	0.152	.823	0.095	0.382	

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

Table 3: Stationarity test

	DF (φ)	ags	DF(ψ)	ags	P level (φ)	W	P (ψ)	W
US-EP	2.36		6.92***		4.74***		12.82***	
BR-EP	2.97		9.18***		2.79		10.56***	
MA-PP	2.96		5.90***		3.10		9.14***	

VIX	3.28*	9.84***	3.08	12.05***	
EPU	4.34***	9.59***	4.22***	16.73***	7
GPR	6.00***	9.36***	5.82***	52.74***	36
SI†	2.63	9.82***	2.51	9.83***	

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.

Table 4: BDS independence test

	Fist-difference detrending			AR(1)			GARCH-Process		
	= .5	= .7	= .9	= .5	= .7	= .9	= .5	= .7	= .9
	,01191	,026624***	,018964***	,013947*	,026775***	,018465***	,01191	,026624***	,018964***
S-EP	,017838*	,052331***	,050734***	,018546*	,052525***	,050443***	,017838*	,052331***	,050734***
	,015356*	,065012***	,080285***	,015852*	,065734***	,079555***	,015356*	,065012***	,080285***
	,012988	,007795	0,001414	,009767	,00193	0,003669	,012988	,007795	0,001414
R-EP	,019083*	,01504	0,002886	,015845	,001213	0,00648	,019083*	,01504	0,002886
	,018641*	,020316	0,006239	,015277*	,005699	0,011103	,018641*	,020316	0,006239
	,013831*	,017320*	,006979	,018341**	,018238**	,001765	,013831*	,017320**	,006979
A-PP	,014908*	,029911**	,018732*	,019077**	,032711**	,008153	,014908*	,029911**	,018732*
	,014089*	,034855**	,027682*	,013531*	,037298**	,014068	,014089*	,034855**	,027682*
	,011162	,008183	,002256	,012020*	,009016	,002409	,011162	,008183	,002256
IX	,019907**	,018622	,005877	,020724**	,019815	,00635	,019907**	,018622	,005877
	,024186***	,030337*	,007014	,024355***	,030908*	,008098	,024186***	,030337*	,007014
	,011055*	,005478	0,002554	,009017	,005522	0,002442	,011055*	,005478	0,002554
PU	,010768	,013703	,00175	,008407	,013075	,002319	,010768	,013703	,00175
	,009721	,019524	,010013	,005542	,017356	,010752	,009721	,019524	,010013
	,008477	,014882*	,004167	,011808**	,013163*	,00568	,008477	,014882**	,004167
PR	,013154*	,027452**	,013503	,014568**	,023346**	,012774	,013154*	,027452**	,013503
	,011485*	,032259**	,023384*	,012147*	,027532**	,020205*	,011485*	,032259**	,023384*
	,058822***	,062066***	,018915**	,046573***	,047961***	,024216***	,058822***	,062066***	,018915**
SI	,093407***	,138751**	,040639***	,077613***	,120123***	,058842***	,093407***	,138751***	,040639***
	,092118***	,187167***	,073702***	,076716***	,167638***	,096932***	,092118***	,187167***	,073702***

Notes: All series in log diff except FSI which is first-difference only. 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. *m* is the number of consecutive data points to include in the set. P-values are bootstrapped with 5000 iterations. Test includes detrending series using first-difference detrending, AR(1) and GARCH (0,1). Results show strong indication of non-normality at the 1 % level of significance for the US-EP and FSI. Also, a strong indication at the 5 % significance level that the MA-PP and GPR series have non-normality characteristics. The results show non-normality in all series except Brazilian ethanol prices (BR-EP) and economic policy uncertainty (EPU) and indications of non-normality at the 10 % significance level.

Table 5: Quantile causality U.S. ethanol price

	ΔVIX to ΔUS-EP			ΔEPU to ΔUS-EP			ΔGPR to ΔUS-EP			ΔFSI to ΔUS-EP		
	$^{\Delta US\text{-}Ep} = 1$	$^{\Delta US\text{-}Ep} = 2$	$^{\Delta US\text{-}Ep} = 3$	$^{\Delta US\text{-}Ep} = 1$	$^{\Delta US\text{-}Ep} = 2$	$^{\Delta US\text{-}Ep} = 3$	$^{\Delta US\text{-}Ep} = 1$	$^{\Delta US\text{-}Ep} = 2$	$^{\Delta US\text{-}Ep} = 3$	$^{\Delta US\text{-}Ep} = 1$	$^{\Delta US\text{-}Ep} = 2$	$^{\Delta US\text{-}Ep} = 3$
.05	.88	.96	.89	.84	.90	.90	.68	.84	.83	.63	.89	.92
.10	.01***	.01***	.11	.01***	.01***	.07*	.01***	.01***	.10*	.01***	.01***	.02**
.15	.04**	.05**	.01***	.04**	.05**	.01***	.04**	.05**	.01***	.04**	.05**	.01***
.20	.06*	.27	.19	.04**	.19	.16	.06*	.26	.16	.09*	.28	.18
.25	.14	.55	.01***	.07*	.55	.01***	.02**	.47	.01***	.14	.56	.01***
.30	.57	.05**	.12	.57	.04**	.12	.51	.04**	.14	.66	.08*	.12
.35	.13	.35	.79	.10*	.27	.59	.15	.25	.62	.18	.25	.51
.40	.11	.68	.80	.11	.68	.71	.12	.52	.74	.11	.36	.66
.45	.07*	.03**	.40	.08	.03**	.32	.09*	.03**	.30	.03**	.03**	.26
.50	.03**	.14	.81	.03**	.14	.86	.10*	.17	.83	.03**	.14	.59
.55	.45	.53	.74	.48	.54	.75	.53	.60	.80	.51	.52	.51
.60	.67	.62	.39	.70	.60	.38	.79	.71	.52	.76	.61	.42
.65	.03**	.27	.01***	.03**	.27	.01***	.07*	.46	.01***	.09*	.41	.01***
.70	.01***	.02**	.01***	.01***	.01***	.01***	.04**	.08*	.01***	.12	.01***	.01***
.75	.01***	.06*	.01***	.01***	.04**	.01***	.01***	.06*	.01***	.01***	.06*	.01***
.80	.05**	.04**	.01***	.05**	.04**	.01***	.05**	.04**	.01***	.05**	.04**	.01***
.85	.01***	.08*	.05**	.01***	.08*	.05**	.01***	.08*	.05**	.01***	.08*	.05**
.90	.11	.09*	.11	.11	.09*	.11	.11	.07*	.11	.11	.09*	.11
.95	.40	.35	.52	.40	.35	.56	.40	.35	.23	.40	.35	.60
All τ]	.01***	.08*	.01***	.01***	.07*	.01***	.01***	.09*	.01***	.01***	.08*	.01***

Notes: This table presents the subsampling p-values of the ST - test in eq XX. $I^{\Delta US\text{-}Ep} = 1,2,3$ represents the number of lags of the dependent variable under the null-hypothesis: No Granger causality in eq XX. 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 level. The US-EP, VIX, EPU and GPR series is in log and first difference. FSI is in first difference only due to negative values in standard form.

Table 6: Quantile causality Brazilian ethanol price

	ΔVIX to ΔBR-EP			ΔEPU to ΔBR-EP			ΔGPR to ΔBR-EP			ΔFSI to ΔBR-EP		
	$^{\Delta BR\text{-}EP} = 1$	$^{\Delta BR\text{-}EP} = 2$	$^{\Delta BR\text{-}EP} = 3$	$^{\Delta BR\text{-}EP} = 1$	$^{\Delta BR\text{-}EP} = 2$	$^{\Delta BR\text{-}EP} = 3$	$^{\Delta BR\text{-}EP} = 1$	$^{\Delta BR\text{-}EP} = 2$	$^{\Delta BR\text{-}EP} = 3$	$^{\Delta BR\text{-}EP} = 1$	$^{\Delta BR\text{-}EP} = 2$	$^{\Delta BR\text{-}EP} = 3$
.05	.37	.17	.21	.62	.02**	.06*	.56	.07*	.11	.28	.02**	.02**
.10	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***
.15	.02**	.01***	.01***	.02**	.01***	.01***	.02**	.01***	.01***	.01***	.17	.17
.20	.23	.08*	.01***	.23	.08*	.01***	.23	.08*	.01***	.23	.02**	.01***
.25	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***
.30	.06*	.30	.25	.06*	.30	.25	.06*	.30	.25	.06*	.30	.25
.35	.07*	.34	.20	.07*	.34	.19	.07*	.33	.19	.09*	.33	.21
.40	.01***	.14	.14	.01***	.14	.13	.01***	.14	.13	.04*’	.17	.13
.45	.01***	.03**	.01***	.01***	.03**	.01***	.01***	.03**	.01***	.01***	.04**	.01***
.50	.03**	.53	.61	.03**	.51	.59	.04**	.57	.66	.04**	.55	.65
.55	.04**	.29	.30	.02**	.26	.27	.04**	.32	.30	.04**	.35	.36
.60	.02**	.06*	.01***	.02**	.06*	.01***	.02**	.06*	.04**	.02**	.04**	.01***
.65	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***
.70	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***
.75	.01***	.11	.07*	.01***	.01***	.01***	.01***	.11	.01***	.01***	.11	.03**
.80	.14	.09*	.03**	.14	.09*	.03**	.14	.09*	.03**	.14	.09*	.03**
.85	.01***	.01***	.28	.01***	.01***	.28	.01***	.01***	.30	.01***	.01***	.28
.90	.14	.45	.43	.16	.39	.37	.14	.60	.55	.12	.42	.38
.95	.49	.27	.27	.50	.24	.27	.74	.25	.28	.49	.24	.27
All τ]	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***	.01***

Notes: This table presents the subsampling p-values of the ST - test in eq XX. $I^{\Delta US\text{-}Ep} = 1,2,3$ represents the number of lags of the dependent variable under the null-hypothesis: No Granger causality in eq XX. 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 level. The BR-EP, VIX, EPU and GPR series is in log and first difference. FSI is in first difference only due to negative values in standard form

Table 7: Quantile causality Malaysian palm oil price

	ΔVIX to ΔMA-PP			ΔEPU to ΔMA-PP			ΔGPR to ΔMA-PP			ΔFSI to ΔMA-PP		
	ΔMA-PP = 1	ΔMA-PP = 2	ΔMA-PP = 3	ΔMA-PP = 1	ΔMA-PP = 2	ΔMA-PP = 3	ΔMA-PP = 1	ΔMA-PP = 2	ΔMA-PP = 3	ΔMA-PP = 1	ΔMA-PP = 2	ΔMA-PP = 3
.05	.10*	,01***	,01***	,12	,01***	,01***	,10*	,01***	,01***	,35	,01***	,01***
.10	.36	,33	,32	,36	,33	,32	,36	,33	,32	,36	,33	,31
.15	.11	,18	,15	,11	,18	,15	,11	,18	,15	,11	,18	,15
.20	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***
.25	.01***	,06*	,01***	,01***	,06*	,01***	,01***	,06*	,04**	,01***	,06*	,03**
.30	.05**	,01***	,01***	,05**	,01***	,01***	,05**	,03**	,02**	,05**	,08*	,03**
.35	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,02**
.40	.03**	,01***	,05**	,03**	,01***	,05**	,03**	,01***	,05**	,03**	,01***	,05**
.45	.15	,15	,13	,15	,15	,13	,20	,24	,17	,11	,17	,12
.50	.01***	,08*	,08*	,01***	,08*	,03**	,05**	,10*	,09*	,01***	,08*	,03**
.55	.40	,55	,57	,35	,34	,44	,22	,56	,58	,38	,74	,71
.60	.96	,34	,36	,89	,26	,24	,66	,27	,24	,95	,41	,46
.65	.39	,85	,82	,40	,81	,90	,40	,90	,72	,12	,90	,82
.70	.77	,12	,13	,73	,12	,13	,37	,02**	,03**	,56	,11	,13
.75	.01***	,01***	,02**	,01***	,01***	,02**	,01***	,01***	,02**	,01***	,01***	,02**
.80	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***
.85	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***
.90	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***
.95	.01***	,02**	,07*	,01***	,02**	,07*	,03**	,02**	,07*	,01***	,02**	,07*
All τ]	.01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***	,01***

Notes: This table presents the subsampling p-values of the ST – test in eq XX. $I^{\Delta US\text{-}Ep}$ = 1,2,3 represents the number of lags of the dependent variable under the null-hypothesis: No Granger causality in eq XX. 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 level. The MA-PP, VIX, EPU and GPR series is in log and first difference. FSI is in first difference only due to negative values in standard form.