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Abstract

In this paper we investigate the dynamic relations between crude oil price returns and a set of energy price returns, namely diesel, gasoline, heating, and the natural gas. This is performed by means of Granger non-causality tests for US spot closing prices over the period from January 1997 to December 2017. In previous studies this has been done by testing for the added predictive value of including lagged values of one energy price return in predicting the conditional expectation of another. In this paper, we instead focus on different ranges of the full conditional distribution within the framework of a dynamic quantile regression model, and identify the quantile ranges from which causality arises. The results constitute a richer set of findings than what is possible by just considering a single moment of the conditional distribution, which can be useful for implementing better substitution investment strategies and effective policy interventions. We find several interesting one-directional dynamic relations between the employed energy prices, especially in the tail quantiles, but also a bi-directional causal relation between energy prices for which the classical Granger non-causality test suggests otherwise. Our results are robust to alternative measures of the price of oil and different data frequencies.

Key words: Energy price returns, Granger non-causality, Quantile regression, Tail quantiles

JEL classes: C22, G14, Q41

1 Introduction

In this paper we study the dynamic relations between crude oil price returns and a set of energy price returns, namely diesel, gasoline, heating, and the natural gas, in the spirit of Granger causality. As Bauwens *et al.* (2006, p. 306) put it, "the time-series notion of Granger (-Sims) causality is based on the idea that cause must precede effect, and that a factor cannot cause another variable if it doesn't contribute to the conditional distribution (or expectation) of that variable given the past. This concept has become very influential in time series and macroeconometric modelling." In the present paper we analyze the causal relationships, not only in the expectations, but also in the conditional quantiles of the employed energy price returns, by estimating quantile regressions [see Koenker and Bassett (1978) and Basset and Koenker (1982)] and testing the null hypothesis of Granger non-causality in quantiles using the sup-Wald test, as suggested by Koenker and Machado (1999).

Several advantages apply to the quantile Granger non-causality test compared to the classical Granger non-causality test in mean. First, the quantile causality test considers different scales and locations of the conditional distribution, and therefore provides a more complete description of the true dynamic causal relationship than the classical Granger non-causality test which only investigates average relationships (in the center of the conditional distribution). Presence of heterogeneity, which is a common characteristic in financial time series, can thereby lead to significant information loss about the true relationship, unless various quantile levels are investigated. Second, the quantile causality approach can help us capture asymmetric causal effects, since parameters may depend on the location of the dependent energy price return within its conditional distribution. This advantage is important for our study, since crude oil price return, for instance, can affect different parts of the future distribution of another energy price return to different degrees. Among the possible sources of this asymmetry are production and inventory adjustment lags while in economic terms asymmetry is interpreted as a different dynamic relationship under various market conditions or states of the economy. Third, by employing the quantile causality approach, no assumptions need to be specified regarding the asymmetric causal relationships whilst we overcome the need for an additional (threshold) parameter in the model. Last, we forgo the sample splitting procedure that is usually required when studying different market states, maintaining the time dependence structure in the original data and taking advantage of the complete sample size.

The relationship between crude oil and energy prices has been extensively investigated in numerous research papers. Serletis and Herbert (1999), in an influential study, explore the existence of common trends across Henry Hub and Transco Zone 6 natural gas prices, the fuel oil price for New York Harbor, and the PJM power market for electricity prices. They find shared trends among the prices, and thus evidence of effective arbitraging mechanisms for these prices across these markets, as well as causality and a feedback relationship between any two price pairs. Other empirical studies, such as for instance, Yücel and Guo (1994), employ rigorous econometric techniques to investigate fuel price comovement for energy tax policy purposes. They find evidence of a long-run relationship between coal, natural gas, and oil prices, and therefore conclude that a single-fuel tax in these markets would not be effective as a single tax policy. Villar and Joutz (2006) confirm the stable long-run cointegrating relationship between crude oil and natural gas prices, but also suggest that oil price is exogenous to natural gas price. Finally, Brown and Yücel (2008), similar to Asche *et al.* (2006), discuss substitutability and competition between natural gas and crude oil in electric power generation and provide evidence of cointegration between these fuel prices. In addition, they find that movements in natural gas prices are well explained by crude oil prices and that natural gas price Granger causes crude oil price, but only to a marginal extent.

Furthermore, there is an extended literature exploring the existence of asymmetry in the relationship between crude oil and other energy prices. Bacon (1991), in a seminal study for the crude oil and gasoline markets in the United Kingdom, describes the asymmetric mechanism as 'rockets and feathers,' thus referring to the fact that gasoline prices rise rapidly like rockets in response to crude oil price increases, but fall slowly like feathers in response to crude oil price declines. Balke *et al.* (1998) investigate the asymmetric relationship between crude oil and gasoline prices in the United States and provide mixed evidence of asymmetry. In doing so, they consider two identical model specifications, which differ only in the specification of asymmetry, and find evidence for rare and small, but also large and pervasive asymmetry. Borenstein et al. (1997) support the view of asymmetric responses in the U.S. gasoline markets which they explain through inventory adjustment lags and temporary market power among retail gasoline sellers. More recently, Chang and Serletis (2016) investigate the relationship between crude oil and gasoline prices for the United States and confirm the asymmetric effects, while providing evidence in support of the 'rockets and feathers' behaviour.

Motivated by growing environmental concerns as well as costly fossil fuels, Reboredo *et al.* (2017) use continuous and discrete wavelet methods, and linear and non-linear Granger causality tests, to study co-movement and causality between oil price variation and renewable energy stock returns. Their findings indicate weak, but in the long run gradually strengthened, dependence between oil price and renewable energy stock returns. They also find evidence of non-linear causality propagating from renewable energy indices to oil prices at different time horizons, as well as mixed evidence of Granger causality running from crude oil to renewable energy prices. Employing similar renewable energy stock indices, Kyritsis and Serletis (2019) investigate the effects of oil price shocks on the financial performance of the renewable energy and technology sectors, and find evidence of symmetric price transmission, which they explain through the insignificant effect of uncertainty about oil prices on the renewable energy stock returns. From a different point of view, Atil *et al.* (2014) use the nonlinear autoregressive distributed lags model to examine the pass-though of crude oil prices into gasoline and natural gas prices, and conclude that oil prices affect gasoline prices and natural gas prices in an asymmetric and non-linear transmission way, with the negative oil price shocks inducing greater effects than positive shocks. The authors attribute the larger asymmetric impact of the oil price decreases to downward price expectation spirals that affect gasoline and natural gas prices during downward economic conditions, and show that energy price dynamics are more complex than a simple and stable relationship.

A new strand of literature has emerged in recent years trying to explain the complex energy price dynamics through the financialization of energy markets, rather than merely by changes in economic variables. Indeed, since the early 2000s the financialization of commodity markets, and more particularly the crude oil market, started taking place with financial investors and portfolio managers using energy assets as a means to diversify their portfolios and hedge their exposure against uncertainty risk. See, for instance, Ta and Xiong (2012), Hamilton and Wu (2014), Kyritsis and Serletis (2018). In fact, it is estimated that the total value of assets allocated to commodity index trading strategies increased from \$15 billion at the end of 2003 to \$260 in mid-2008 (Commodity Futures Trading Commission, 2011). Daskalaki and Skiadopoulos (2011) attribute the financialization of energy markets to different return behavior and low correlation with stock returns, while new stylised facts, such as increased price volatility, as well as prices above fundamental values have emerged in energy prices during the last decades. Signals given by economic policy interventions, however, can significantly affect energy prices through supply and demand fundamentals and thus counteract the impact of financial investors in energy markets. Adjusting economic policy with respect to market conditions is therefore of great importance, especially considering the varying price transmission mechanisms.

The present paper contributes to the above literature by providing empirical evidence regarding causal relations and dynamic interactions between crude oil and a set of energy price returns. To the best of our knowledge, no study has previously investigated Granger causality on different ranges of the full conditional distribution between these wholesale energy markets. Our paper contributes to the existing literature by filling this void and provides insights on information dynamics that are of high importance for optimal hedging strategies and portfolio risk management, as well as for policy-makers who must have a clear understanding of these complex price relations before implementing specific policy interventions, such as single-fuel taxes, explicit carbon prices, and import tariffs. To this end, we employ the quantile approach that enables us to test for non-causality between the energy price returns in different quantiles of each variable, and therefore identify the quantile ranges from which causality arises. On the contrary, the classical Granger non-causality test can be a poor reflection of the true energy price relations if the latter solely occur over some locations of the conditional distribution, and in particular outside the interquartile range. The same methodological approach has previously been followed by Chuang *et al.* (2009) and Ding *et al.* (2014), who investigate causal relationships between stock return and volume and stock and real estate markets, respectively. Our results indicate significant dynamic interactions between the employed energy price returns, and especially in the lower- and upper-level quantiles. We also find the existence of bi-directional causal relations, for instance between heating and crude oil price returns, for which the classical Granger non-causality test suggests otherwise. Finally, it is to be noted that we interpret causality in terms of predictability, and not as implying underlying structural economic relations.

The remainder of this paper is structured as follows. In Section 2 we introduce the classical Granger non-causality test and the sup-Wald test of non-causality in quantiles by

Koenker and Machado (1999) and Chuang *et al.* (2009). In Section 3 we describe the employed energy price return series and present the empirical evidence while robustness of our results is examined with respect to alternative measures of the price of oil and different data frequencies. Section 4 concludes the paper with a brief discussion of our findings and implications for economic reforms and policy interventions.

2 Econometric methodology

2.1 Classical Granger causality test

When a variable x does not Granger-cause another variable y, it suggests that

$$F_{y_t}(z|(y,x)_{t-1}) = F_{y_t}(z|y_{t-1}), \quad \forall z \in \mathbb{R}, \tag{1}$$

holds where $F_{y_t}(\cdot|\Omega)$ is the conditional distribution of y_t with Ω denoting the information set available at time $t-1$, and $(y,x)_{t-1}$ denotes the information set generated by y_t and x_t up to time $t-1$ (Granger, 1969). On the contrary, when Equation (1) fails to hold, the variable x is said to Granger-cause y. A necessary condition for Equation (1) is that

$$\mathbb{E}(y_t|(y,x)_{t-1}) = \mathbb{E}(y_t|y_{t-1}) \tag{2}$$

where $\mathbb{E}(y_t|(y,x)_{t-1})$ is the conditional mean of the variable y_t. Usually Equation (2) is used as the starting point for tests of Granger causality. There could be, at least, two reasons for this. Firstly, the test is sometimes used to investigate if a variable is worthwhile using in forecasting another. Modelling the conditional mean rather than the entire conditional distribution is then a natural starting point. Secondly, estimating the full conditional distributions is more cumbersome than implementing the classical Granger causality test, which can be done by means of a vector autoregressive (VAR) model. The estimation can even be done by ordinary least squares regression. As an example, if crude oil is denoted y_t and gasoline prices x_t, the classical test could be performed within the framework of the bivariate VAR-model

$$\mathbb{E}(y_t|y_{t-i}, x_{t-j}) = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \epsilon_{y,t} \tag{3}$$

$$\mathbb{E}(x_t|x_{t-i}, y_{t-j}) = \gamma_0 + \sum_{i=1}^{p} \gamma_i x_{t-i} + \sum_{j=1}^{q} \delta_j y_{t-j} + \epsilon_{x,t}, \tag{4}$$

where $\epsilon_t = (\epsilon_{y,t}, \epsilon_{x,t})'$ is a vector of i.i.d random disturbances. The null hypothesis of Granger non-causality in mean from x_t to y_t is rejected if the coefficients of $x_{t-1}, x_{t-2}, ..., x_{t-q}$ in Equation (3) are jointly significantly different from zero. In the same vein, if the coefficients of lagged y_t $(\delta_1, \delta_2, ..., \delta_q)$ in Equation (4) are not significantly different from zero, then we conclude that y_t does not Granger-cause x_t in mean. Note, however, that this notion of non-causality is not sufficient for Granger non-causality in distribution. Therefore, although a failure to reject the null hypothesis means that x does not Granger-cause y in the mean, it does not preclude causality in other moments or distribution characteristics.

2.2 Quantile causality test

As discussed earlier, for many cases the conditional mean approach may not describe the complete causal relationship between two time series variables. Given the fact that a distribution is completely determined by its quantiles, Lee and Yang (2006) first considered Granger non-causality in terms of the conditional quantiles of the distribution. Hence, Equation (1) is equivalent to

$$Q_{y_t}(\tau|(y,x)_{t-1}) = Q_{y_t}(\tau|y_{t-1}), \quad \forall\tau \in (0,1), \tag{5}$$

where $Q_{y_t}(\tau|\Omega)$ denotes the $\tau - th$ quantile of $F_{y_t}(\cdot|\Omega)$. Thus, we say that x does not Granger-cause y in all quantiles if Equation (5) holds. Note, however, that in this case non-causality is tested only in a particular quantile level, and not quantile intervals.

Rather than testing non-causality in a moment (mean or variance) or in a fixed quantile level τ, in this study we are interested in investigating causal relations in different quantile intervals by testing Equation (1). In doing so, we follow Chuang *et al.* (2009) who, in an influential study, investigate the causal relations between stock return and volume and define Granger non-causality in the quantile range [a, b] $\subset$ (0,1) as

$$Q_{y_t}(\tau|(y,x)_{t-1}) = Q_{y_t}(\tau|y_{t-1}), \quad \forall\tau \in [a,b], \tag{6}$$

where $Q_{y_t}(\tau|\Omega)$ denotes the quantile of $F_{y_t}(\cdot|\Omega)$ for $\tau \in [a,b]$. The quantile causality test is performed considering several quantile ranges $[a,b] \subset (0,1)$ for $\tau \in [a,b]$, using the quantile regression method proposed by Koenker and Bassett (1978) and Basset and Koenker (1982), and the sup-Wald statistic test suggested by Koenker and Machado (1999); see also Koenker (2005) for a more comprehensive study of quantile regression. To test for Granger-non causality in quantiles, we consider the following conditional quantile versions of Equations (3) and (4)

$$Q_{y_t}(\tau|\Omega_{t-1}) = \phi_0(\tau) + \sum_{j=1}^{p}\phi_j(\tau)y_{t-j} + \sum_{h=1}^{q}\psi_h(\tau)x_{t-h} \tag{7}$$

$$Q_{x_t}(\tau|\Omega_{t-1}) = \omega_0(\tau) + \sum_{j=1}^{p}\omega_j(\tau)x_{t-j} + \sum_{h=1}^{q}\xi_h(\tau)y_{t-h}, \tag{8}$$

where Ω_{t-1} denotes the information set generated by past values of y_t and x_t. The null hypothesis of non-causality in quantiles is

$$H_0 : \psi(\tau) = 0, \quad \forall\tau \in [a,b], \tag{9}$$

for Equation (7). Hence, if the parameter vector $\psi(\tau) = [\psi_1(\tau), \psi_2(\tau), ..., \psi_q(\tau)]'$ is equal to zero, it implies that x_t does not Granger-cause y_t at the quantile interval $\tau \in [a,b]$. In a similar way, if $\xi(\tau) = [\xi_1(\tau), \xi_2(\tau), ..., \xi_q(\tau)]'$ is equal to zero, then we can say that y_t does not Granger-cause x_t at the quantile interval $\tau \in [a,b]$.

For a given τ, the parameter vector $\psi(\tau)$ is estimated by minimizing asymmetrically weighted absolute deviations:

$$\min_{\phi_0(\tau),\phi_j(\tau),\psi_h(\tau)} \sum_{t=1}^{T} \rho_\tau \Big(y_t - \phi_0(\tau) - \sum_{j=1}^{p} \phi_j(\tau) y_{t-j} - \sum_{h=1}^{q} \psi_h(\tau) x_{t-h} \Big) \tag{10}$$

where $\rho_\tau(u) = (\tau - \mathbf{1}(u < 0))u$, $\mathbf{1}(A)$ is the indicator function of the event A, and T is the sample size, following Koenker and Bassett (1978). For a specific quantile $\tau \in (0, 1)$ we can write the Wald statistic of $\psi(\tau) = 0$ as:

$$W_T(\tau) = T \frac{\hat{\psi}_T(\tau)' \hat{\Omega}(\tau)^{-1} \hat{\psi}_T(\tau)}{\tau(1-\tau)} \tag{11}$$

where $\hat{\Omega}(\tau)$ is a consistent estimator of $\Omega(\tau)$, which is the variance-covariance matrix of $\psi(\tau)$. Wald statistic process follows the following weak convergence:

$$W_T(\tau) \Rightarrow \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2 \tag{12}$$

where $\mathbf{B}_q(\tau) = [\tau(1-\tau)]^{-1/2} N(0, I_q)$ is a vector of q independent Brownian bridges and the weak limit is the sum of squares of q independent Bessel processes. For the null hypothesis of non-causality over a quantile interval, Koenker and Machado (1999) suggest a sup-Wald test which can be written as:

$$\sup_{\tau \in T} W_T(\tau) \to \sup_{\tau \in T} \left\| \frac{\mathbf{B}_q(\tau)}{\sqrt{\tau(1-\tau)}} \right\|^2 \tag{13}$$

In this empirical work we consider different quantile intervals $[a, b] \subset (0, 1)$. In order to do so, we generated a regular quantile sequence of length n from a to b ($a = \tau_1 < ... < \tau_n = b$) and applied a quantile regression for each τ_i and for different lag orders. The sup-Wald test for (9) is computed as:

$$\sup W_T(\tau) = \sup_{i=1,\dots,n} W_T(\tau_i) \tag{14}$$

The results of the sup-Wald test on various quantile ranges may be used to identify $[a, b]$ from which the causality arises. For instance, if the null hypothesis of Granger non-causality is rejected for some $\tau \in (0, 1)$ but not for some $\tau \in [a, b]$, we may infer that causality arises from the quantile intervals outside $[a, b]$.

In order to determine the significance level of the sup-Wald test, for each range and each lag order, we generate 100,000 independent simulations approximating the standard Brownian motion through the use of a Gaussian random walk with 3,000 i.i.d. $N(0, 1)$ innovations to identify the critical values at the 1%, 5%, and 10% significance levels.[1] Furthermore, since

[1] The table of critical values is available on request. Some critical values of the sup-Wald test have also been tabulated in De Long (1981) and Andrews (1993).

Table 1: Summary statistics

Series	Mean	Variance	Minimum	Maximum	Skewness	Kurtosis	Normality
Diesel	1.724	0.807	0.391	3.894	0.375**	-0.991***	16.218***
Gasoline	1.591	0.689	0.307	3.292	0.320**	-1.098***	16.955***
Heating	1.608	0.805	0.304	3.801	0.430***	-0.949***	17.212***
Natural gas	4.410	4.961	1.720	13.420	1.423***	2.375***	144.252***
RAC	53.968	957.025	9.810	129.030	0.476***	-0.995***	19.910***
WTI	55.598	884.283	11.350	133.880	0.415***	-0.929***	16.280***

Notes: Sample Period, monthly observations, 1997:01-2017:12. Asterisks indicate rejection of null hypothesis of skewness, excess kurtosis, and normality. The skewness and excess kurtosis statistics include a test of the null hypothesis that each is zero. The Jarque-Bera test is used to test for normality. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

we need to select the optimal lag for each quantile range in order to conduct the sup-Wald test, we use the sequential lag selection method to determine the optimal lag truncation order [see Chuang *et al.* (2009) and Ding *et al.* (2014)]. For instance, if the null hypothesis $\psi_q(\tau) = 0$ for [0.05, 0.5] is not rejected for the lag-q model but the null $\psi_{q-1}(\tau) = 0$ for [0.05, 0.5] is rejected for the lag-$(q-1)$ model, then we set the desired lag order as $q^* = q - 1$ for the quantile interval [0.05, 0.5]. If no test statistic, however, is significant over that interval, we select the lag length of order one. We calculate the sup-Wald test statistics to check the joint significance of all coefficients of lagged past values for each quantile interval. Hence, if the selected lag order is q^*, then the null hypothesis is $H_0 : \psi_1(\tau) = \psi_2(\tau) = \psi_q(\tau) = 0$ for [0.05, 0.5].[2] For simplicity, we do not assume different lag orders, hence $p = q$. Therefore, by employing the methodology of quantile Granger non-causality while considering various quantile ranges $[a, b]$, we capture the quantile intervals from which the true causal relations arise.

3 The data and empirical analysis

This study uses spot closing energy prices, namely crude oil, diesel, gasoline, heating, and natural gas prices for the United States. As a proxy for the price of crude oil we use the West Texas Intermediate (WTI) crude oil spot price, while for robustness purposes we also employ a second proxy, namely the U.S. refiner's acquisition cost (RAC) for a composite of domestic and imported crude oil.[3] Both crude oil prices are expressed in US dollars per barrel. We use the Los Angeles ultra-low sulfur No 2 diesel price in US dollars per gallon

[2]The results for lag order selection of the quantile causality tests are not reported here in order to preserve space, but they can be provided upon request.

[3]The U.S. refiner's acquisition cost (RAC) for composite crude oil is a weighted average of domestic and imported crude oil costs. It includes transportation and other fees paid by refiners, but does not include the cost of crude oil purchased for the Strategic Petroleum Reserve.

for the diesel price, the New York Harbour conventional gasoline price in US dollars per gallon for the price of gasoline, the New York Harbour No 2 heating oil price in US dollars per gallon for the price of heating, and the Henry Hub natural gas price in US dollars per MBTU for the price of natural gas. All prices are obtained from the U.S. Energy Information Administration (EIA) on a monthly basis, over the period from January 1997 to December 2017, and are in nominal terms. The development of energy price series alongside with their logarithmic returns, which are scaled up by a factor of 100, are illustrated in Figure 1.

We present the summary statistics of the energy price series in Table 1. The average monthly prices range from \$1.591 per gallon for gasoline to \$55.598 per barrel for crude oil. On a monthly basis, the energy prices reached their maximum values in June 2008 for diesel (\$3.894), gasoline (\$3.292), and heating (\$3.801), which is also shown in Figure 1. The highest peak in natural gas price (\$13.420) and crude oil price (\$133.880) was observed in October 2005 and July 2008, respectively. It is worth mentioning that during the first half of 2008 all energy prices increased from 41.05% for the case of gasoline to 58.82% for natural gas, with crude oil increasing by 47.22%, while during the second half of 2008 all of them experienced a remarkable drop of more than 47%, thus providing evidence for a strong price relationship. Table 1 also shows that all price series are positively skewed and deviate from normality, while natural gas price exhibits excess kurtosis, heavy tails, and in particular longer right tail than a normal distribution. The latter distribution characteristics are also depicted in the different plots in Figure 2 and provide further support for our decision to investigate Granger causality on different ranges of the full conditional distribution, rather than solely on the conditional mean. In fact, the histograms illustrate deviation from normality with the red line representing the theoretical normal distribution, while the corresponding quantile-quantile plots verify skewness and other distributional characteristics, such as heavy or long tails (see particularly the case of gasoline and natural gas).

An interesting feature of the data related to the contemporaneous correlations across the logarithmic energy price returns is provided in Table 2. In order to determine whether these correlations are statistically significant, we follow Pindyck and Rotemberg (1990) and perform a likelihood ratio test of the hypotheses that the correlation matrices are equal to the identity matrix. The test statistic is

$$-2ln(|R|^{N/2})$$

where $|R|$ is the determinant of the correlation matrix and N is the number of observations. The test statistic is distributed as χ^2 with $q(q-1)/2$ degrees of freedom, where q is the number of series. For the case of the West Texas Intermediate crude oil, the test statistic is equal to 920.364 with a p-value of 0.000, and we can therefore clearly reject the null hypothesis that these series are uncorrelated. The same conclusion holds for the case of the U.S. refiner's acquisition cost for composite crude oil, for which the test statistic is equal to 888.782 with a p-value of 0.000[4].

[4]The contemporaneous correlation dynamics for the case of the U.S. refiner's acquisition cost (RAC) are available on request.

Figure 1: Time series of energy prices and their logarithmic returns

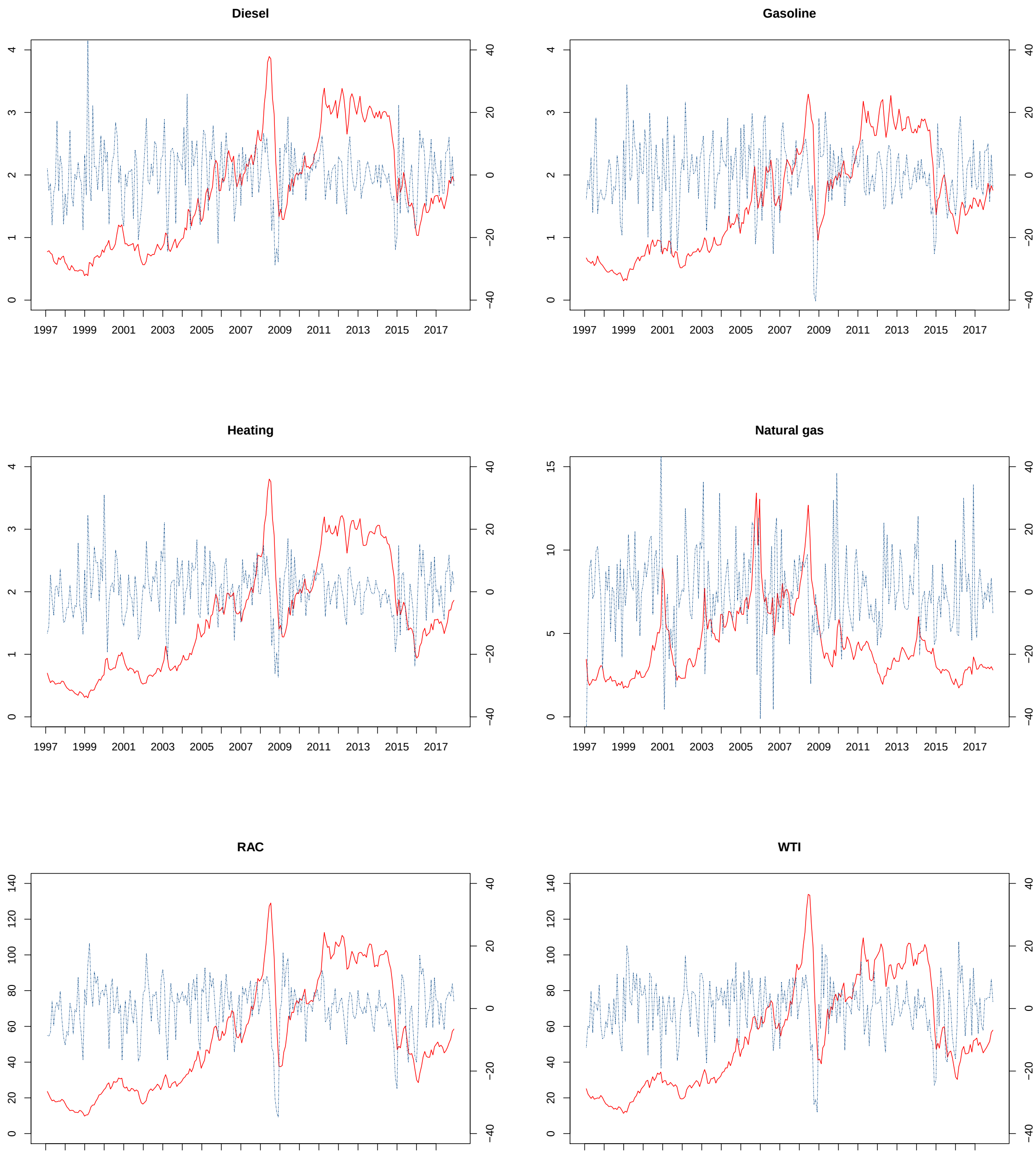

Figure 2: Histogram of energy prices with their respective quantile plots

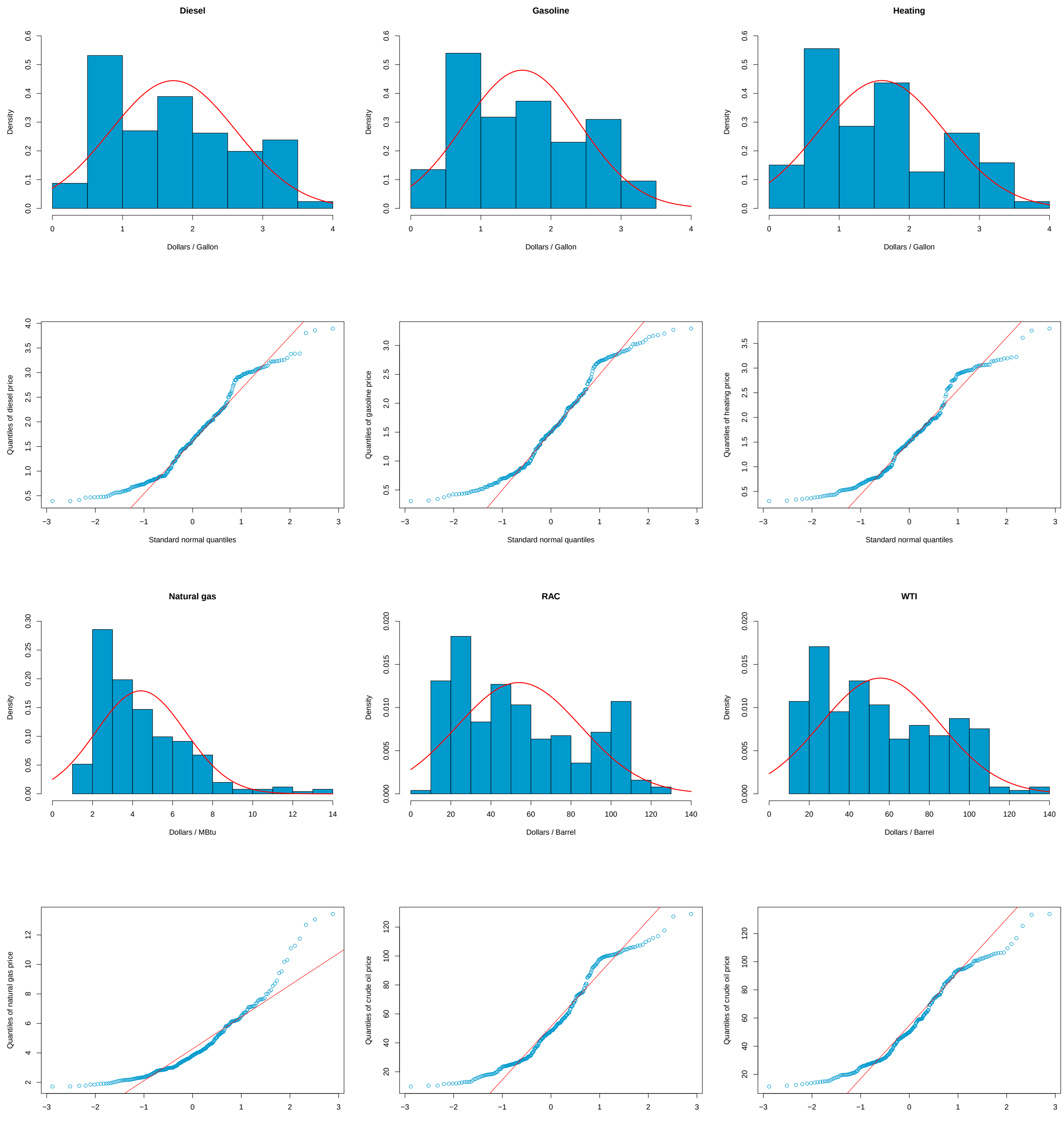

Table 2: Contemporaneous correlations

Series	Diesel	Gasoline	Heating	Natural gas	WTI
Diesel	1	0.716	0.809	0.207	0.759
Gasoline	0.716	1	0.728	0.208	0.818
Heating	0.809	0.728	1	0.346	0.838
Natural gas	0.207	0.208	0.346	1	0.232
WTI	0.759	0.818	0.838	0.232	1
	$x^2(10) = 920.364$				

Note: Monthly data from 1997:01 to 2017:12.

Notice that correlations in Table 2 indicate a relatively weak price relationship between the crude oil and natural gas price returns. This is a fact that has been expected, since diesel, gasoline, and heating are refined petroleum products and thus more dependent on crude oil price development. Crude oil and natural gas prices are, however, somewhat related to each other, since they are both substitutes in direct consumption but also in production of other energy sources, such as cooking, heating, and electricity generation. It should be noted that natural gas currently emerges as a considerable source of the electricity production mix, since it provides power system with significant flexibility, which complements the intermittent renewable energy sources, and therefore acts as a "bridge" to a low carbon economy (Kyritsis et. al, 2017). The correlation patterns documented in Table 2 also manifest in the different plots in Figure 1, which depict the development of the employed series over the investigated period.

Before we continue with our main analysis, we conduct some necessary unit root and stationary tests in the logarithmic energy price returns, in order to test for the presence of a stochastic trend (a unit root) in the autoregressive representation of each individual return. Our motivation stems from the fact that existence of a unit root in a series invalidates the standard assumptions for an asymptotic analysis, as for instance the usual asymptotic properties of estimators, based on which statistical inference is performed. ADF and DF-GLS are, respectively, augmented Dickey-Fuller and Phillips-Perron statistics for the null hypothesis of a unit root for the time series. KPSS denotes the stationary test for the null hypothesis of stationarity. All three tests, namely, the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller, 1981], the Dickey-Fuller GLS (DF-GLS) test [see Elliot *et al.*, 1996] and the KPSS test [see Kwiatkowski *et al.*, 1992] provide evidence that all series are stationary, or integrated of order zero, $I(0)$, and we therefore continue our analysis employing all price series in first logarithmic returns.[5] The Akaike information criterion (AIC) is used for the lag length selection in both the ADF and DF-GLS regressions, while the Bartlett kernel for the KPSS regressions is determined using the Newey-West bandwidth (NWBW). The stationarity of the logarithmic energy price returns is also verified by their historical development, which is depicted in the different plots in Figure 1.

[5]The various unit root and stationary test results are reported in Table A.1 in the appendix.

Table 3: Granger causality tests in mean between monthly WTI and energy price returns

The null hypothesis	Lag order	p-value	Decision
WTl $\nRightarrow$ Diesel	(6)	0.000	Causality
Diesel $\nRightarrow$ WTl	(6)	0.627	No causality
WTl $\nRightarrow$ Gasoline	(4)	0.000	Causality
Gasoline $\nRightarrow$ WTl	(4)	0.141	No causality
WTl $\nRightarrow$ Heating	(5)	0.002	Causality
Heating $\nRightarrow$ WTl	(5)	0.005	Causality
WTl $\nRightarrow$ Natural gas	(2)	0.016	Causality
Natural gas$\nRightarrow$ WTl	(2)	0.867	No causality

Notes: Sample Period, monthly observations, 1997:01-2017:12. The symbol $\nRightarrow$ denotes the null hypothesis of Granger non-causality. The entry "Causality" indicates that the null hypothesis is rejected at the 5% significance level, while the entry "No causality" indicates that the null hypothesis of Granger non-causality could not be rejected at the 5% significance level. Lag order is selected based on the Akaike Information Criterion.

Table 4: Granger causality tests in mean between monthly RAC and energy price returns

The null hypothesis	Lag order	p-value	Decision
RAC $\nRightarrow$ Diesel	(6)	0.000	Causality
Diesel $\nRightarrow$ RAC	(6)	0.417	No causality
RAC $\nRightarrow$ Gasoline	(4)	0.000	Causality
Gasoline $\nRightarrow$ RAC	(4)	0.047	Causality
RAC $\nRightarrow$ Heating	(6)	0.001	Causality
Heating $\nRightarrow$ RAC	(6)	0.017	Causality
RAC $\nRightarrow$ Natural gas	(2)	0.011	Causality
Natural gas$\nRightarrow$ RAC	(2)	0.968	No causality

Notes: Sample Period, monthly observations, 1997:01-2017:12. The symbol $\nRightarrow$ denotes the null hypothesis of Granger non-causality. The entry "Causality" indicates that the null hypothesis is rejected at the 5% significance level, while the entry "No causality" indicates that the null hypothesis of Granger non-causality could not be rejected at the 5% significance level. Lag order is selected based on the Akaike Information Criterion.

In the next step of our analysis we use the Wald test to conduct the classical Granger non-causality test in mean. In doing so, we test the null hypothesis that $\beta_j = 0$ (or $\delta_j = 0$) for $j = 1, 2, ..., q$, in the two linear regression models described by Equations (3) and (4). Rejection of the null hypothesis implies that knowledge of past values of x_t improves the prediction of future energy price return of y_t, beyond predictions that are based on past returns of the energy product alone, $y_{t-1}, y_{t-2}, ..., y_{t-q}$. As aforementioned, we perform the analysis twice employing each time a different proxy for the price of crude oil, namely the West Texas Intermediate (WTI) crude oil and U.S. refiner's acquisition cost (RAC) for composite crude oil. The optimal lag truncation orders are selected by the Akaike Information Criterion (AIC) and are reported together with the corresponding estimation results in Tables 3 and 4, respectively.

Several linear causal relations are found propagating between crude oil and other employed energy price returns; some exceptions however apply to this, such as for instance, from each of the diesel and natural gas returns to WTI and RAC crude oil returns, as well as from gasoline to WTI return. We also notice that the selected lag order varies from two to six months for both crude oil prices, contingent on the particular investigated causal relationship between the employed fuel price returns. After performing this test to all the bivariate relations between each of the crude oil returns, namely WTI and RAC, and each of the other returns for diesel, gasoline, heating, and natural gas, we conclude that past crude oil returns improve the predictions of all the other fuel returns, beyond predictions that are based on past returns of fuels alone. For instance, information about the returns of WTI from the last four and six months improves the prediction of future gasoline and diesel returns, respectively, compared to predictions that are based only on past returns of those fuels. The same conclusion holds for the bivariate causal relations when RAC is used as a proxy for the crude oil price, thus providing evidence for robustness to an alternative measure of the price of oil. In the opposite direction, past information of neither diesel, gasoline, or natural gas returns improves the prediction of future WTI return, beyond predictions that are based merely on its past return history. Although the aforementioned results, which are based on the conditional mean represented by Equations (3) and (4), are useful to learn about causal relations, they may not reveal all the information that describes the complete causal relationship between two time-series variables, and therefore may lead to invalid causal inferences.

Motivated by these considerations, we explore the causal relationships between the employed energy price returns, by considering the conditional quantile functions given by Equations (7) and (8) — using the longest available span of data.[6] For our empirical analysis we consider in total eight large quantile intervals for the above conditional quantile functions, similar to Ding *et al.* (2014). More precisely, we examine three large quantile intervals, namely [0.05, 0.95], [0.05, 0.5], and [0.5, 0.95], and five small quantile intervals, namely [0.05, 0.2], [0.2, 0.4], [0.4, 0.6], [0.6, 0.8], and [0.8, 0.95]. For each quantile interval, we first select the optimal lag truncation order and then conduct the sup-Wald test to evaluate the

[6]This applies to the price series of diesel, gasoline, heating, and natural gas, which start being available from January 1997.

Table 5: Test results for quantile causality between monthly WTI and energy price returns

$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
(a) WTI $\nRightarrow$ energy prices								
Diesel	55.34***	56.14***	4.96	60.05***	37.04***	8.73**	3.59	1.91
	(2)	(2)	(1)	(2)	(2)	(1)	(1)	(1)
Gasoline	20.86**	17.27***	18.49**	17.48***	5.60*	7.53*	17.28**	18.50**
	(4)	(2)	(4)	(2)	(1)	(2)	(4)	(4)
Heating	41.21***	41.21***	2.86	47.01***	14.18***	2.60	1.53	2.86
	(5)	(5)	(1)	(5)	(2)	(1)	(1)	(1)
Natural gas	71.37***	1.28	71.37***	1.30	8.54*	1.05	10.98**	71.37***
	(7)	(1)	(7)	(1)	(2)	(1)	(2)	(7)
(b) Energy prices $\nRightarrow$ WTI								
Diesel	6.09	0.86	6.16	0.94	0.69	1.97	5.82*	6.16*
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Gasoline	4.05	0.71	4.19	0.77	13.13*	0.29	0.59	4.19
	(1)	(1)	(1)	(1)	(4)	(1)	(1)	(1)
Heating	34.29***	34.29***	29.11***	34.29***	17.95***	14.43**	11.86*	29.11***
	(5)	(5)	(4)	(5)	(4)	(4)	(4)	(4)
Natural gas	3.28	0.81	3.38	10.29	0.83	0.77	0.71	3.38
	(1)	(1)	(1)	(4)	(1)	(1)	(1)	(1)

Notes: Sample Period, monthly observations, 1997:01-2017:12. Each interval in the square brackets is the quantile interval on which the null hypothesis of Granger non-causality, as per Equuation (7) and (8), holds. The sup-Wald test statistics and the selected lag orders (in parentheses) are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

Table 6: Test results for quantile causality between monthly RAC and energy price returns

$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
(a) RAC $\nRightarrow$ energy prices								
Diesel	73.78***	73.78***	5.56	73.78***	45.89***	11.32***	9.58**	2.77
	(2)	(2)	(1)	(2)	(2)	(1)	(2)	(1)
Gasoline	52.22***	52.22***	26.64***	52.65***	4.83	0.83	0.12	26.64***
	(4)	(4)	(4)	(4)	(1)	(1)	(1)	(4)
Heating	68.52***	68.52***	5.61	68.52***	19.56***	2.19	0.53	20.37***
	(7)	(7)	(1)	(7)	(2)	(1)	(1)	(4)
Natural gas	40.45***	17.94**	12.25**	18.16**	2.08	2.14	9.01*	24.74***
	(4)	(4)	(2)	(4)	(1)	(1)	(2)	(6)
(b) Energy prices $\nRightarrow$ RAC								
Diesel	6.10	2.32	7.20*	2.32	1.10	1.03	1.24	7.20*
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Gasoline	3.43	3.43	1.91	3.47	1.35	1.96	1.78	1.84
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Heating	5.13	5.13	16.67**	33.63***	19.53***	3.60	12.21*	16.67**
	(1)	(1)	(4)	(6)	(4)	(1)	(4)	(4)
Natural gas	5.25	1.79	5.25	8.87	1.62	1.79	0.89	5.25
	(1)	(1)	(1)	(4)	(1)	(1)	(1)	(1)

Notes: Sample Period, monthly observations, 1997:01-2017:12. Each interval in the square brackets is the quantile interval on which the null hypothesis of Granger non-causality, as per Equuation (7) and (8), holds. The sup-Wald test statistics and the selected lag orders (in parentheses) are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

joint significance of all coefficients of lagged crude oil or fuel price returns.

Tables 5 and 6 report the sup-Wald test statistics and selected lag truncation orders for non-causality in quantiles between each of the WTI and RAC crude oil returns and other energy price returns. In particular, Panel (a) of Table 5 reports the tests results for non-causality from WTI crude oil return to diesel, gasoline, heating, and natural gas price returns. For the quantile interval [0.05, 0.95], WTI crude oil return Granger-causes all the other energy returns at the 5% significance level, while the quantile sub-intervals indicate significant causality propagating solely from the lower- and/or upper- level quantiles, [0.05, 0.2] and [0.8, 0.95], for three out of the four relationships. In particular, for the case of gasoline we find no evidence of causality arising from WTI crude oil returns over the middle quantile intervals [0.2, 0.4] and [0.4, 0.6]. Hence, WTI crude oil return does not improve the prediction of gasoline return, beyond predictions that are based on its own past return history alone, when the latter fluctuates around its median. However, by considering causal relations in the tail region of the conditional distribution [0.05, 0.2] and [0.8, 0.95], we find significant Granger causality from WTI crude oil return to gasoline return. For the case of heating, there is Granger causality propagating over the lower quantile intervals [0.05, 0.2] and [0.2, 0.4] at the 1% significance level, while investigation of causality for the case of natural gas indicates the opposite pattern, thus causality arising only over the upper quantile intervals [0.6, 0.8] and [0.8, 0.95] at the 5% significance level. Hence, WTI crude oil return improves the predictions of heating and natural gas returns, beyond predictions that are based on their own past return history alone, only when the latter fluctuate around their lower- and upper- level quantiles, respectively. Finally, knowledge of the WTI crude oil return from only the last month improves the prediction of diesel return, beyond predictions that merely account its past return development, when the latter fluctuates around its median. The test results for non-causality over quantiles from RAC crude oil return to the other energy price returns, reported in Panel (a) of Table 6, are very similar to the above results in terms of significance, but also lag truncation order. For instance, knowledge of the two previous RAC oil returns improves the prediction of diesel return over the lower quantile intervals [0.05, 0.2] and [0.2, 0.4], while knowledge of the four past RAC oil returns improves the prediction of gasoline return, when the latter fluctuates over the upper quantile interval [0.8, 0.95].

Panel (b) of Table 5 reports the sup-Wald test statistics for non-causality from each of the diesel, gasoline, heating, and natural gas returns to WTI crude oil return, over the eight investigated quantile intervals. None of the test results is significant at the 5% significance level over the first quantile interval [0.05, 0.95], except for the case of the heating return which reveals existence of a feedback mechanism between heating and crude oil markets. The results are in accordance with previous findings in the literature that support (weakly) exogeneity of crude oil price, at least with respect to gasoline and natural gas prices. See, for instance, Asche et al. (2003) and Villar and Joutz (2006). When we explore causal relationships in the context of smaller quantile intervals, we find no causality running from the diesel, gasoline, and natural gas returns to WTI crude oil return, but statistically significant causality, in the context of Granger, propagating from the heating return to the WTI crude oil return over most parts of the conditional distribution. These test results are very similar in terms of

Table 7: Granger causality tests in mean between daily WTI and energy price returns

The null hypothesis	Lag order	p-value	Decision
WTl $\nRightarrow$ Diesel	(8)	0.003	Causality
Diesel $\nRightarrow$ WTl	(8)	0.012	Causality
WTl $\nRightarrow$ Gasoline	(8)	0.001	Causality
Gasoline $\nRightarrow$ WTl	(8)	0.088	No causality
WTl $\nRightarrow$ Heating	(8)	0.000	Causality
Heating $\nRightarrow$ WTl	(8)	0.139	No causality
WTl $\nRightarrow$ Natural gas	(6)	0.000	Causality
Natural gas$\nRightarrow$ WTl	(6)	0.505	No causality

Notes: Sample Period, daily observations, January 2, 1997 to December 29, 2017. The symbol $\nRightarrow$ denotes the null hypothesis of Granger non-causality. The entry "Causality" indicates that the null hypothesis is rejected at the 5% significance level, while the entry "No causality" indicates that the null hypothesis of Granger non-causality could not be rejected at the 5% significance level. Lag order is selected based on the Akaike Information Criterion.

significance and lag truncation order with the reported results in Panel (b) of Table 6, which refer to the same causal relations, but with RAC being used as a proxy for the price crude oil. In particular, we find no statistical evidence in favor of feedback mechanisms, except for the case of heating and RAC crude oil returns where heating return Granger-causes RAC oil return over the quantile invervals [0.05, 0.2], [0.2, 0.4], and [0.8, 0.95]. Considering the results from Tables 5 and 6, we conclude that energy price returns Granger cause each other mostly under extreme market conditions, and therefore consideration of these relationships only under normal market situations may lead to invalid causal inferences, and thus inefficient risk management strategies or unintended policy outcomes. Finally, comparison of Tables 5 and 6 provides evidence for robustness to alternative measures of the price of oil.

In the last step of our analysis, we investigate the robustness of our results to the use of higher frequency data. In particular, we use daily returns for the above diesel, gasoline, heating, and natural gas prices for the period from January 2, 1997 to December 29, 2017. Regarding the price of oil we use daily WTI crude oil return, since RAC crude oil is not available on a higher frequency than monthly. We report the estimation results in Tables 7 and 8, exactly in the same fashion as those in the previous tables for the case of monthly returns. By looking at Table 7 we conclude, similarly to the previous cases, that daily WTI crude oil return Granger causes all other energy returns, while gasoline, heating, and natural gas returns do not Granger cause WTI crude oil return. In the next step, we conduct the sup-Wald test in order to investigate Granger causality from daily WTI crude oil return to diesel, gasoline, heating, and natural gas returns over different quantile intervals. The results of these tests are reported in Panel (a) of Table 8 and lead to similar conclusions to those of

Table 8: Test results for quantile causality between daily WTI and energy price returns

$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
(a) WTI $\nRightarrow$ energy prices								
Diesel	17.96***	8.55**	18.38***	9.54**	1.71	1.94	13.35	18.45***
	(1)	(1)	(1)	(1)	(1)	(1)	(5)	(1)
Gasoline	38.30***	32.48***	22.83**	32.48***	1.33	2.15	16.52**	23.07***
	(6)	(4)	(6)	(4)	(1)	(1)	(4)	(6)
Heating	56.68***	67.64***	42.81***	67.64***	18.22***	2.83	2.92	42.81***
	(10)	(10)	(10)	(10)	(4)	(1)	(1)	(10)
Natural gas	54.52***	54.50***	42.24***	35.57***	55.03***	39.56***	39.20***	47.06***
	(3)	(1)	(3)	(1)	(1)	(1)	(1)	(4)
(b) Energy prices $\nRightarrow$ WTI								
Diesel	25.82**	25.82**	17.17*	26.21**	19.04*	11.64	0.68	17.71**
	(8)	(8)	(5)	(8)	(8)	(8)	(1)	(5)
Gasoline	21.14	21.14	3.89	21.14*	17.62	4.96	0.68	3.95
	(9)	(9)	(1)	(9)	(8)	(1)	(1)	(1)
Heating	72.12***	72.12***	2.09	74.80***	15.93	0.36	2.08	10.85
	(9)	(9)	(1)	(9)	(9)	(1)	(1)	(6)
Natural gas	51.18***	1.87	51.18***	33.28***	1.23	0.60	7.93*	54.44***
	(10)	(1)	(10)	(4)	(1)	(1)	(2)	(10)

Notes: Sample Period, daily observations, January 2, 1997 to December 29, 2017. Each interval in the square brackets is the quantile interval on which the null hypothesis of Granger non-causality, as per Equuation (7) and (8), holds. The sup-Wald test statistics and the selected lag orders (in parentheses) are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.

the previous cases. In fact, for the case of gasoline we find evidence of causality propagating from daily WTI crude oil return over the lower- and upper- level quantiles [0.05, 0.2], [0.6, 0.8], and [0.8, 0.95], thus being identical to the results from the case of monthly WTI crude oil return in Table 5. Moreover, we find evidence of WTI crude oil return Granger causing heating return over the quantile intervals [0.05, 0.2], [0.2, 0.4] and [0.8, 0.95], thus verifying robustness of our results to the employment of a different oil price and particularly to the use of monthly RAC crude oil in Table 6. It is worth noting that use of daily energy returns provides us with evidence of WTI crude oil return Granger causing natural gas return over the full conditional distribution. This result may have practical implication for investors who operate in these energy markets with different investment horizons, since horizon-specific information regarding causality may be useful for portfolio diversification and value-at-risk estimation. Moreover, we find several interesting causal relations propagating from the different daily energy returns to WTI crude oil return outside the interquartile range, which cannot be captured by the classical Granger non-causality test — see Panel (b) of Table 8. In particular, we find evidence of heating and natural gas returns Granger causing WTI crude oil over the lower level quantile of [0.05, 0,2], thus verifying the existence of a bi-directional causal relation for which the classical Granger non-causality test suggests otherwise (see Table 7). Hence, we conclude that a failure to reject the null hypothesis of Granger causality in the mean does not preclude causality in other moments of the distribution, and therefore it is important to investigate causality on different ranges of the full conditional distribution.

4 Conclusions and policy implications

The present paper investigates the causal relations and dynamic interactions between crude oil and a set of energy price returns, namely diesel, gasoline, heating, and the natural gas, within the framework of a dynamic quantile regression model. To the best of our knowledge, no study has previously investigated Granger causality between these energy markets on different ranges of the full conditional distribution. Our paper contributes to the existing literature by filling this void and provides insights on information dynamics that are of high importance for robust economic policy, as well as for optimal hedging strategies and sustainable risk management. The quantile approach enables us to test for non-causality between the price returns in different quantiles of each variable, and thereby identify the quantile ranges from which causality arises. The latter is the greatest strength of the quantile causality test, which makes it possible for us to draw valid causal inferences and undertake effective policy measures, for instance fuel taxes and import tariffs with the aim of transforming successfully the energy sector and increasing national energy security. Moreover, through the use of quantile causality tests, we provide detailed information about dispersion of energy return distributions, which can complement conventional volatility measures, such as conditional variance.

The paper employs monthly crude oil, diesel, gasoline, heating, and natural gas price data from U.S. wholesale markets, for the period from January 1997 to December 2017. Our results indicate significant one-directional causal relations between the employed energy price returns, especially in the tail quantile intervals, which cannot by identified by the classical

Granger non-causality test. Interdependence between energy returns outside the interquartile range of the conditional distributions implies that investors are incapable of hedging the risk across these energy markets during extremely volatile bear and bull periods. It also suggests that policy-makers should be cautious of increasing systemic risk when extreme returns are observed in these energy markets, and thereby should implement economic policies that minimize systemic risk. Moreover, policy-makers should aim at reducing the oil price risk in different sectors, such as transportation, heating, and agriculture, for instance by constructing well-diversified energy portfolios. It is worth noting that natural gas emerges as a considerable source in the power production mix, substituting largely crude oil and thus decreasing dependence of electricity sector on crude oil price fluctuations. Finally, we find the existence of bi-directional causal relations and therefore feedback mechanisms, for instance between heating and crude oil price returns, for which the classical Granger non-causality test suggests otherwise. Our results are robust to a number of alternative oil prices and data frequencies.

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5 Appendix

Table A.1: Unit roots and stationary tests

Series	Test: ADF	DF-GLS	KPSS	Decision
		A. Log levels		
Diesel	-2.097	-2.146	0.333***	$I(1)$
Gasoline	-1.887	-2.076	0.364***	$I(1)$
Heating	-1.835	-1.911	0.339***	$I(1)$
Natural gas	-2.223	-2.214	0.413***	$I(1)$
RAC	-2.356	-2.400	0.346***	$I(1)$
WTI	-1.988	-2.279	0.364***	$I(1)$
		B. Logarithmic returns		
Diesel	-13.630***	-13.634***	0.055	$I(0)$
Gasoline	-4.811***	-2.662*	0.045	$I(0)$
Heating	-12.733***	-2.267*	0.066	$I(0)$
Natural gas	-15.438***	-1.560	0.033	$I(0)$
RAC	-9.529***	-8.291***	0.060	$I(0)$
WTI	-12.043***	-2.134	0.056	$I(0)$

Note: Sample Period, monthly observations, 1997:01-2017:12.
***, **, and * indicate significance at the 1%, 5%, and 10% significance levels, respectively.