Dynamic Quantile Relations in Energy Markets

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ABSTRACT

In this paper we investigate the dynamic relationships between crude oil price and and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices. This is performed by means of Granger non-causality tests for monthly US data over the period from January 1997 to December 2017. In most previous studies this has been done by testing for the added predictive value of including lagged values of one energy price in predicting the conditional expectation of another. In this study, we instead focus on different ranges of the full conditional distribution. This is done within the framework of a dynamic quantile regression model. The results constitute a richer set of findings than what is possible by just considering a single moment of the conditional distribution. We find several interesting one-directional dynamic relationships between the employed energy prices, especially in the tail quantiles, but also a bi-directional causal relationship between energy prices for which the classical Granger non-causality test suggests otherwise.

JEL classification: C22; Q41; Q47.

Keywords: Energy prices, Granger non-causality, Quantile regression.

1 Introduction

In this paper we study the relationship between crude oil price and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices 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 series, 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 test considers different locations of the conditional distribution, and therefore it provides a more complete description of the true dynamic relationship than the traditional Granger non-causality test which only investigates average relationships (in the center of the conditional distribution). This advantage is important for our study, since we have reason to believe that one energy price will affect different parts of the future distribution of another energy price to different degrees. In economic terms, this is interpreted as a different dynamic relationship in different market conditions. Thus, we avoid the need for sample splitting when we study various market situations, and therefore we do not reduce the sample size nor loose the time dependence structure in the original data.

The relationship between crude oil and energy prices has been investigated extensively in numerous research papers. Serletis and Herbert (1999) explore the existence of common trends in 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 therefore 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 and find evidence of the existence of a long-run relationship between coal, natural gas, and oil prices, while Villar and Joutz (2006) confirm the stable long-run cointegrating relationship between crude oil and natural gas prices, also suggesting that oil price is exogenous to natural gas price. Finally, Brown and Yücel (2009), similar to Asche *et al.* (2006), find cointegration between natural gas and crude oil prices and discuss substitutability and competition between the two fuels in electric power generation. In addition, they find oil price movements explaining natural gas price quite satisfactorily, as well as evidence for natural gas price Granger causing crude oil price, but only to a marginal extent.

Furthermore, there is an extended literature exploring the existence of asymmetry in the relationship between oil and 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. 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 about climate change and 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 and renewable energy returns. They also find evidence of non-linear causality running from renewable energy indices to oil prices at different time horizons, as well as mixed evidence of Granger causality running from oil to renewable energy prices. 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 they conclude that oil prices affect gasoline prices and natural gas prices in an asymmetric and non-linear transmission way. Lahiani *et al.* (2017) extend the analysis of Atil *et al.* (2014), by considering additional fuel prices and using a more advanced methodology, thereby providing evidence of a stationary equilibrium relationship between these prices.

This research adds to the extant literature related to causal relationships between crude oil price and a set of energy prices by providing empirical evidence regarding Granger causality between these prices. To the best of our knowledge, no such study has investigated Granger causality in the entire conditional distribution between these energy prices. Our study contributes to the existing literature by filling this void. The quantile approach enables us to test for non-causality between the employed monthly energy prices in different quantiles of each variable, and therefore to reveal possible non-linear causal effects between them. The same methodological approach has previously been followed by Chuang *et al.* (2009) and Ding *et al.* (2014), who investigate causal relationships between stock returns and volume and stock returns and real estate property, respectively. Our results indicate significant dynamic effects between the employed price series, particularly in the tail quantiles. We also see a bi-directional causal relationship between heating and crude oil prices, for which the classical Granger non-causality test suggests otherwise.

This rest of the paper is structured as follows. In Section 2 we introduce the classical Granger causality test and the sup-Wald test of causality in quantiles. In Section 3 we describe the data we use and present the empirical evidence, while in Section 4 we conclude with a brief discussion of our findings and their implications for an effective and sustainable energy risk management.

2 Empirical analysis

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 $F_{y_t}(.|\Omega)$ 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. 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

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

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

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 way, if the coefficients of lagged y_t, thus $\delta_1, \delta_2, ..., \delta_q$, in Equation (4) are significantly different from zero, then we conclude that y_t Granger-causes 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 interesting and influential study, investigate the causal relations between stock return and volume and define Granger non-causality in the quantile range [a, b] ⊂ (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 $\tau \in [a,b]$.

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 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 can capture the quantile range from which the true causal relationships arise.

3 The data and empirical evidence

This study uses energy prices, namely crude oil, diesel, gasoline, heating, and natural gas prices for the United States. We use the U.S. refiner's acquisition cost (RAC)[3] for a composite of domestic and imported crude oil as a proxy for the price of crude oil, the Los Angeles ultra-low sulfur No 2 diesel price for the diesel price, the New York Harbour conventional gasoline price for the price of gasoline, the New York Harbour No 2 heating oil price for the price of heating, and the Henry Hub natural gas price for the price of natural gas. All prices are obtained from the U.S. Energy Information Administration (EIA) on a monthly basis,

[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).

[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.

over the period from January 1997 to December 2017.

Table A4.1 presents the summary statistics of the five price series. The average monthly prices range from \$1.591 per gallon for gasoline to \$53.968 per barrel of crude oil. On a monthly basis, the commodity prices reach their maximum values in June 2008 for diesel (\$3.894), gasoline (\$3.292), and heating (\$3.801). The highest peak in natural gas price (\$13.420) and crude oil price (\$129.03) 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 A4.1 also shows that all the series are positively skewed and deviate from normality, while natural gas price exhibits excess kurtosis indicating fatter tails, and in particular longer right tail than a normal distribution.

We present in Table A4.2 an interesting feature of the data related to the contemporaneous correlations across the logarithmic first differences[4] of the energy price series. In order to determine whether these correlations are statistically significant, we follow Pindyck and Rotemberg (1990) and we 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. The test statistic is equal to 888.782 with a p-value of 0.000 for the first differences of the logs, and therefore we can clearly reject the null hypothesis that these series are uncorrelated. We also notice the relatively weak price correlation between the crude oil and natural gas price series, a fact that has been expected since diesel, gasoline, and heating are refined petroleum products, and therefore more dependent on oil price development. Crude oil and natural gas prices, however, are also related to each other since they are both substitutes in direct consumption, and competitors in production of other energy sources such as cooking, heating, and electricity generation. The correlation patterns documented in Table A4.2 also manifest in Figures A4.1 - A4.5, which depict the development of the

[4]The terms logarithmic first differences and logarithmic returns are used interchangeably.

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 first differences of each of the employed series, in order to test for the presence of a stochastic trend (a unit root) in the autoregressive representation of each individual series. 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. As shown in Table A4.3, 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 therefore we continue our analysis employing all price series in first logarithmic differences. The Bayesian information criterion (BIC) 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 first differences of each of the price series is also verified by their historical development, depicted in Figures A4.1 - A4.5.

In the next step we use the Wald test to conduct the Granger non-causality test in mean, and 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 in 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 of y_t, beyond predictions that are based on past prices of the energy product alone, $y_{t-1}, y_{t-2}, ..., y_{t-q}$. We select the optimal lag truncation order by the Bayesian Information Criterion (BIC) and report the estimation results in Table 1.

No linear causal relationship is found propagating from any employed energy price to crude oil price, while the latter is found to Granger-cause the diesel, gasoline, and heating prices. We also notice that the selected lag order varies from one to two months, contingent on the particular investigated causal relationship between the employed fuel prices. After performing this test to all the relationships between the crude oil price and each of the other fuel prices, we conclude that the price of crude oil from the last two months improves the prediction of each of the diesel and gasoline prices, beyond predictions that are based on past prices of diesel or gasoline alone. Knowledge of the price of crude oil from only the last month improves the prediction of future heating price, compared to predictions that

Table 1: Tests for Granger causality in the mean

The null	p-value	Decision
Crude oil $\nRightarrow$ Diesel	0.000 (2)	Causality
Diesel $\nRightarrow$ Crude oil	0.456 (2)	No causality
Crude oil $\nRightarrow$ Gasoline	0.000 (2)	Causality
Gasoline $\nRightarrow$ Crude oil	0.270 (2)	No causality
Crude oil $\nRightarrow$ Heating	0.015 (1)	Causality
Heating $\nRightarrow$ Crude oil	0.376 (1)	No causality
Crude oil $\nRightarrow$ Natural gas	0.227 (1)	No causality
Natural gas$\nRightarrow$ Crude oil	0.963 (1)	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. Numbers in parentheses indicate the selected lag order based on the Bayesian information criterion.

are based only on past prices of heating price, but it does not improve the prediction of natural gas price. In the opposite direction, past information of neither diesel, gasoline, or natural gas prices improves the prediction of future crude oil price beyond predictions that are based on past prices of crude oil alone. Although the afore-mentioned results, which are based on the conditional mean represented by Equation (2), are useful to learn about causal relationships, they may not reveal all the information that describe the complete causal relationship between two time-series variables.

Motivated by these considerations, we explore the causal relationships between the employed energy price series, by considering the conditional quantile functions given by Equations (7) and (8) — using the longest available span of data.[5] 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]. Table 2 reports the sup-Wald test statistics and the selected lag truncation order.

[5]This applies to the price series of diesel, gasoline, heating, and natural gas, which starting being available in January 1997.

Panel (a) of Table 2 reports the tests results for non-causality from crude oil price to diesel, gasoline, heating, and natural gas prices. For the quantile interval [0.05, 0.95] crude oil price Granger-causes all the energy prices at the 1% significance level, while the quantile sub-intervals indicate significant causality deriving from the lower and upper levels of quantiles, for three out of the four relationships. For instance, there is no Granger causality over the quantile levels, [0.2, 0.4], [0.4, 0.6], and [0.6, 0.8], for gasoline and natural gas prices. Similarly, for the case of heating, the middle quantile intervals [0.4, 0.6] and [0.6, 0.8] do not show any causality arising from the crude oil price changes. To put it differently, there is causality from crude oil to gasoline, heating, and natural gas prices arising only over the low or high quantile intervals. Hence, crude oil does not improve the predictions of these energy products, beyond predictions that are based on their own past price development alone, when the latter fluctuate around their median. For the case of diesel there is causality from crude oil price changes over all the quantile intervals, except for the upper interval of [0.8, 0.95].

Panel (b) of Table 2 reports the sup-Wald test statistics for non-causality from diesel, gasoline, heating, and natural gas price to oil price. None of the test results for the quantile interval [0.05, 0.95] are significant at our significance levels. This might be partly a result of the fact that diesel, gasoline, and heating are refined petroleum products, and therefore cannot improve the prediction of future oil price development. However, by considering causal relationships in the context of quantiles, we find significant Granger causality from heating price to crude oil price for the quantile intervals [0.05, 0.2], [0.2, 0.4], and [0.8, 0.95]. This implies that, similar to most of the results of the panel (a), no causality arises around the conditional median, namely [0.4, 0.6], but only from the tail region of the conditional distribution. It is only between crude oil and heating price changes that we find statistically significant bi-directional causality. Combining the results from both panels of Table 2, we conclude that the investigated energy markets depend more on each other under extreme market conditions, and therefore consideration of these relationships during only normal market situations may lead to an inefficient risk management strategy, or unintended energy policy outcome.

Table 2: The sup-Wald tests of non-causality in different quantile ranges.

$\tau \in$	[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). Crude oil price $\rightarrow$ 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 $\rightarrow$ crude oil price								
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 Equation (7) and (8), holds. The sup-Wald test statistics and the selected lag orders (in parentheses) are reported.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

4 Conclusion

The interaction between the crude oil price and other energy prices, also other than natural gas price which is mostly studied in the literature, is an important research topic yet to be fully addressed. This paper investigates the non-linear causal relationships between the crude oil price and a set of other energy prices, namely diesel, gasoline, heating, and natural gas prices for the United States. To the best of our knowledge, no study has used the quantile Granger non-causality methodology to model the relationships of these energy price series. Our results suggest significant causal relationships between the employed price series, especially in the tail quantiles, but also a bi-directional causal relationship between heating and crude oil prices, for which the classical Granger non-causality test suggests otherwise. Interdependence between energy prices on different locations of the conditional distribution renders risk hedging across fuels even more challenging when fuel prices are extreme volatile. Policy makers should also be cautious and limit the risk exposure by constructing well-diversified energy portfolios in different sectors, such as transportation, heating, agriculture, and particularly electricity, where natural gas accounted for the first time in 2017 more than 27% of total gross electricity production in OECD countries, substituting largely crude oil (IEA, 2017).

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5 Appendix

Table A4.1: Summary statistics

Series	Mean	Variance	Minimum	Maximum	Skewness	Kurtosis	Normality
Crude oil	53.968	957.025	9.810	129.030	0.476***	-0.995***	19.910***
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***

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

Table A4.2: Contemporaneous correlations

Series	Crude oil	Diesel	Gasoline	Heating	Natural gas
Crude oil	1	0.762	0.808	0.816	0.235
Diesel	0.762	1	0.716	0.809	0.207
Gasoline	0.808	0.716	1	0.728	0.208
Heating	0.816	0.809	0.728	1	0.346
Natural gas	0.235	0.207	0.208	0.346	1
	$x^2(10) = 888.782$				

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

Table A4.3: Unit roots and stationary tests

Series	Test			Decision
	ADF	DF-GLS	KPSS	
Crude oil	-9.529***	-8.291***	0.060	$I(0)$
Diesel	-13.630***	-13.634***	0.055	$I(0)$
Gasoline	-11.616***	-11.902***	0.045	$I(0)$
Heating	-12.733***	-6.408***	0.066	$I(0)$
Natural gas	-15.438***	-2.381	0.033	$I(0)$

Note: Sample Period, monthly observations, 1997:01-2017:12.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

Figure A4.1: Crude oil price and its logarithmic returns

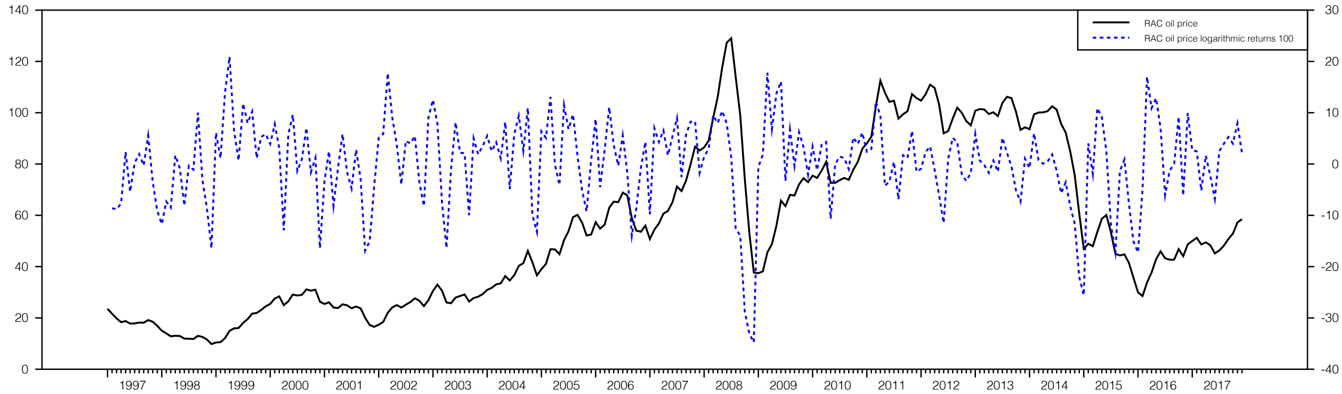

Figure A4.2: Diesel price and its logarithmic returns

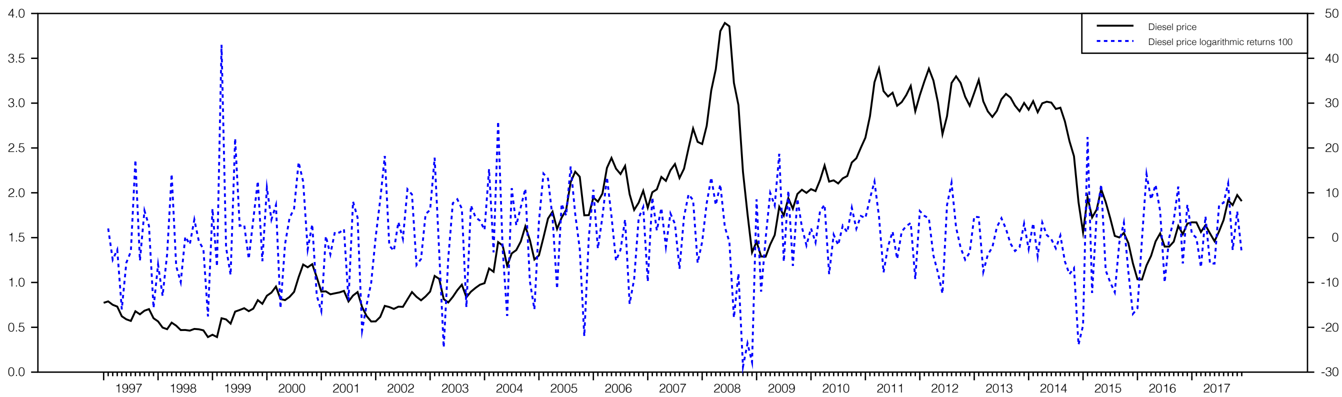

Figure A4.3: Gasoline price and its logarithmic returns

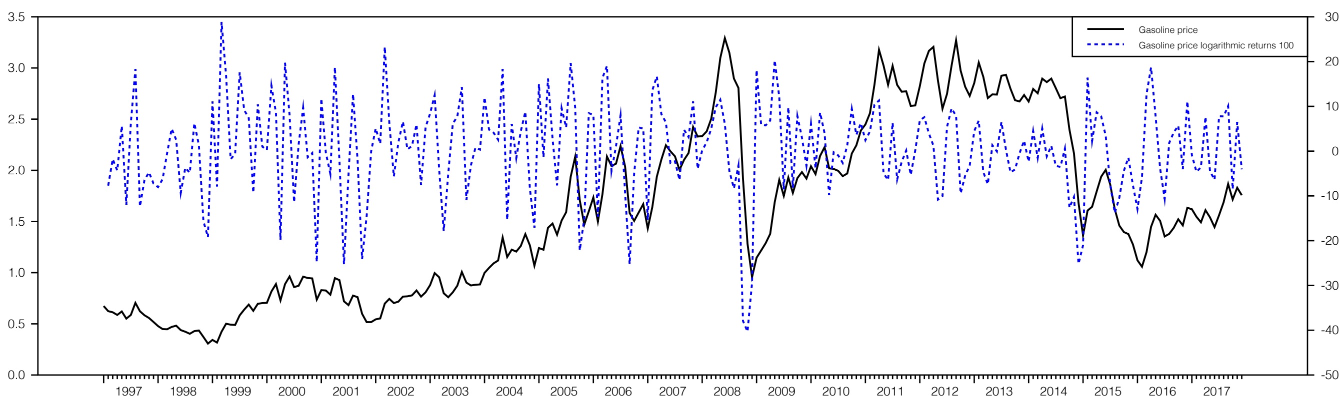

Figure A4.4: Heating price and its logarithmic returns

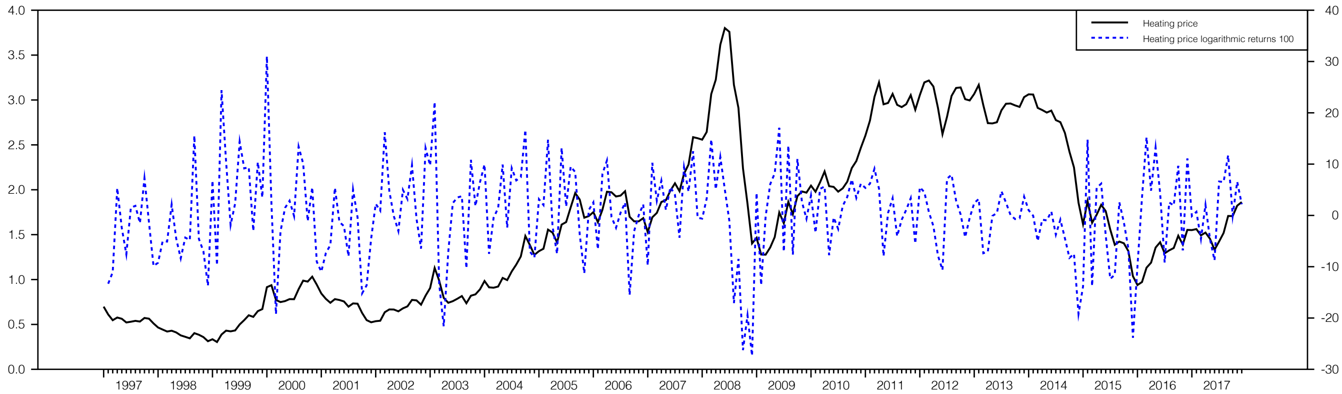

Figure A4.5: Natural gas price and its logarithmic returns