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5 February 2018

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Abstract: This paper investigates the relationship between S&P 500 prices, viewed as a US economic barometer, and a set of energy prices, including WTI, gasoline, heating, diesel and natural gas prices, using the Quantile Autoregressive Distributed Lags (QARDL) model recently developed by Cho et al. (2015). The empirical results show a negative long-and short-run relationship between WTI crude oil and Henry Hub natural gas prices on the one side and S&P 500 stock prices on the other side, only for medium and high quantiles. The findings of Wald tests indicate a nonlinear and asymmetric pass-through from energy price shocks to aggregate US stock market prices. These results show that crude oil and natural gas are key economic variables to explain short run and long run stock market dynamics. They provide further insights into how energy price shocks are transmitted to stock market prices.

Keywords: Energy Price Shocks, Stock Market Prices, Quantile ARDL, Cointegration.
JEL Classification: C32, C5, G1

1. Introduction

Since the first oil crisis in 1973, crude oil price fluctuations have attracted much attention from researchers, policy makers, and financial market participants for two main reasons. First, variations in crude oil prices substantially affect decisions made by producers and consumers in strategic planning and project evaluation. Second, these erratic movements determine investor decisions concerning oil-related activities, portfolio allocations, and risk management. Indeed, asset prices can be calculated based on a discounted cash flows model, which is the sum of discounted expected future cash flows. Therefore, an energy price shock could affect either expected cash flows or the discount rate used in the asset pricing model. Increased oil prices affect expected cash flows, as oil is a fundamental input in firm production, whereas the discount rate is strongly affected by increased inflation driven by oil price increases. Finally, crude oil price changes may also affect firm performance through the effect on operating costs, and thus their revenues. Several trends emerge from prior analyses. Hamilton (1983) demonstrates significant correlations between crude oil prices and economic downturns, especially for the US economy, the largest oil importer in the world. Oil prices affect the economy in different ways, such as increased production costs, which in turn reduce demand for crude oil. Numerous studies investigate the effects of oil price shocks on macroeconomic aggregate indicators such as inflation rate, unemployment rate, industrial production, growth rate estimated for example by gross domestic product (GDP)[1].

Using a Markov switching VAR framework, Gronwald (2008) discriminates between large and normal oil price increases and shows that real US GDP reacted to large oil price shocks (mainly those that occurred in 1973–74, 1979, and 1991) whereas variables such as consumer and import prices were responsive to normal oil price increases. The consensus is that crude oil prices play a significant role in contemporary economic activities (e.g., Huang et al., 1996; Huntington, 1998; Hamilton and Herrera, 2004; Kilian, 2008; Kilian and Park 2009; Oladosu 2009, Boldanov et al., 2016; Broadstock et al., 2016; Guo et al., 2016; Pan et al., 2016; Zhang, 2017). In the same vein, using a structural VAR model incorporating unexpected changes of commodity prices, Gubler and Hertweck (2013) investigate the importance of commodity prices in the US economy. Their findings suggest that commodity price shocks are important drivers of macroeconomic fluctuations in the US. The authors also perform a subsample analysis and find that commodity prices mildly influence output and inflation in the post-Volcker period. Güntner (2014) investigates the effects of oil demand and supply shocks on the stock markets of oil-exporting and oil-importing countries from 1974 to 2011. The empirical results show that an increase in global oil aggregate demand increases the cumulative stock market returns, with a more persistent effect in oil-exporting countries, and that precautionary oil demand shocks have a detrimental effect on the stock markets of oil-importing countries. Similarly, Fayadd and Daly (2011) investigate the impact of oil price shocks on stock market

[1]Kilian and Vigfusson (2011) show that the responses of the US economy to negative and positive changes in real oil prices are similar. Shetty et al. (2013) find that exogenous oil price shocks impact city economics in Texas from 1995 to 2008. According to their study, the unemployment rate is not significantly influenced by oil prices in bigger cities relative to smaller cities in Texas.

returns in GCC countries, the UK, and the US using a VAR model on daily data covering the period running from September 2005 to February 2010. Their findings suggest that the predictive power of oil prices for stock returns increased following the increase in oil prices and during the global financial crisis. In addition, Qatar, UAE, and UK stock markets are found to be the most responsive to oil price shocks. Kilian and Vigfusson (2014) measure the recessionary effect of oil price shocks in the US. Findings show that oil price shocks explain a 3% decrease in real US economic growth in the late 1970s and early 1980s and a 5% decrease during the financial crisis.

The pioneering study of Jones and Kaul (1996) introduced the question of whether crude oil prices are an accurate determinant in explaining stock market returns. A strand of studies seeks to demonstrate the links between crude oil prices and stock market indices viewed as a good economic barometer. Some of these studies examine this issue for developed countries (Sadorsky, 1999; Kilian and Park, 2009; Masih et al., 2011; Lee et al., 2012, Cunado and Perez de Gracia, 2014) and others for developing countries (Basher et al. 2012, Wang and Zhang 2014). Sukcharoen et al. (2014) employ a copula approach to study the dependence between oil prices and the stock market indices of various countries covering the period from 1982 to 2007. They find evidence that the linkage between oil prices and stock indices depends on whether the country is oil-consuming or oil-producing. Wang and Liu (2016) employ GARCH-class models to test the volatility spillovers and dynamic correlations between crude oil and stock markets of seven oil-exporting countries and nine oil-importing countries. Their findings reveal evidence of volatility spillovers and dynamic correlations between the crude oil market and stock markets. The latter transmission and dependence of the two markets is tributary to the net oil position (imports or exports) of the considered country. They argue that crude oil is better hedged by investing in the stocks of oil-exporting countries than by investing in the stocks of oil-importing countries. Using a structural VAR model, Kang et al. (2016) study the impact of supply and demand shocks hitting the oil market on US bond index real returns. They find that a positive specific oil-market demand shock reduces US bond real returns for eight months, while a positive innovation in aggregate demand negatively influences US bond index real returns for 24 months. They also find that the correlation between the oil market and US bond market increased in the post-crisis period, moving from 0.381 before the crisis to 0.476 afterwards. The literature has focused on the linear relationship between oil price shocks and either economic indicators or stock market returns. Conflicting results emerge, probably due to the presence of nonlinearities, in the transmission of energy price shocks to financial markets.

Various studies have investigated this question (e.g., Anton 1989, Huntington 1998, Lardic and Mignon 2006, Kilian 2008, Wang et al. 2013). An asymmetric transmission of the oil price to stock market indices can occur if the distributions of the variables involved are nonelliptic or fat tailed, as is well-documented in the economics and finance literature. The conditional mean of the variables is only one element of an overall summary of the conditional distribution. Hence, causality in the tails of the distribution may be quite different from a causality based on the center of the distribution. Moreover, structural breaks are now considered a stylized fact in economic time series due to several major global events of recent years, such as economic, financial, and debt crises as well as terrorist attacks and political turmoil in many countries. This nonlinearity in the dynamics of time series may lead to asymmetries in the dependence between them. Hence, it is important to employ a nonlinear setting to account for the asymmetric relationship between economic and financial time series, particularly between the oil prices and stock market index in the US.

In this paper, we investigate the quantile cointegration relationship between stock prices and energy prices in the US. We extend the literature in several ways. First, we reconsider the relationship between US energy price shocks and US stock market price variations by employing the Quantile Autoregressive Distributed Lags Error Correction Model (QARDL-ECM). On the one hand, this recent econometric methodology (Cho el al. 2015) allows us to simultaneously investigate long-run relationship and short-run dynamics by accounting for any potential asymmetric and nonlinear linkages between energy price shocks and stock market prices. On the other hand, to the best of our knowledge, the effects of energy price shocks such as natural gas and retail gasoline shocks on stock market price changes have received little attention. This methodology has been employed by Lahiani et al. (2017) to investigate the pass-through of oil prices to energy prices including gasoline, heating, diesel and natural gas. The authors report an asymmetric transmission of oil price to energy prices both in the long-run and short-run. Although we use a similar framework, our methodology differs from that of Lahiani et al. (2017) in three directions. First, the research questions in the two papers are different. Indeed, Lahiani et al. (2017) studied the passthrough of oil prices to energy prices. However, we investigate in this paper the reaction of the US stock market (S&P500) to energy prices while controlling for oil price. Second, Lahiani et al. (2017) use a regression model ignoring all potential factors that could drive the dynamics of S&P500. Differently, we extend their methodology to account for more than one predictor of S&P500 returns to accurately assess the predictive power of oil-related products in forecasting the S&P500 returns. Third, while their results are important for energy policymakers, our results provide new basis for financial portfolio managers and speculators in the financial markets. In addition, Zhu et al. (2016) employed the QARDL methodology to investigate the cointegrating relation between silver and gold prices. They find a quantile-dependent (time-varying) cointegrating relationship between the two commodity prices. Particularly, cointegration is detected outside the interquartile range.

Most empirical studies have focused on crude oil price changes to explain stock market dynamics, but crude oil is not the main source of energy used by US producers and consumers. In 2015, US crude oil and other liquids produced from fossil fuel consumption totaled about 19 million barrels per day. Gasoline is the main petroleum product used by US consumers. Moreover, in 2015, motor gasoline consumption reached a peak average of about 385 gallons per day, representing about 47% of total US petroleum consumption. Distillate fuels such as diesel fuel and heating oil represent the second most-consumed refined petroleum product and correspond to 21% of total US petroleum consumption. Even if fluctuations in refined petroleum product prices have been driven largely by fluctuations in crude oil prices, disturbances in the crude oil market do not entirely explain energy price changes. As pointed out by Kilian (2008), some exogenous shocks affect crude oil prices and others affect energy prices. During the second Gulf War, the price of crude oil increased by about 40%, whereas gasoline prices increased by only about 10%. These examples show that crude oil, natural gas, and refined petroleum products are not always strongly integrated (Bachmeier and Griffin, 2006). Therefore, using alternative energy price series may help explain stock market movements (Acaravci et al., 2012; Melichar, 2016). According to Blendon and Benson (2008), Americans of all incomes cite gasoline prices as the main economic issue facing their family. The US energy market appears to have rapidly changed over the last few years. We have recently seen an unprecedented increase in US crude oil and natural gas productions due to the "Shale revolution". The level of US oil production in January 2015 roughly corresponds to that of 1973. This level is twice as high as that of the last five to six years. This rapid increase in natural gas and oil production from shale allows the US economy to be less dependent on imported energy sources.[2] Kilian (2016) provides insights into and detailed analysis of the shale revolution and its consequences for US oil prices. By revisiting these linkages in this new context, we shed light on new challenges for US producers and consumers as well as US policy makers. The origin of the asymmetry between crude oil prices and US economic activity has

[2]Readers seeking more information on the shale revolution and its consequences for the US economy are referred to the US Energy Information Agency website.

been investigated extensively in the existing literature. Previous research suggests adjustment costs, financial stresses, and/or monetary policy as possible explanations for the asymmetric responses of economic activity to crude oil shocks. Huntington (1998) attributes some of the asymmetry to the relationship between oil prices and petroleum product prices. Hamilton (1988) argues that asymmetry results from cost adjustments to changing oil prices. Tatom (1993) argues that the apparent asymmetric response of US economic activity to crude oil prices disappears when monetary policy or the misery index, which combines unemployment and inflation rates, are accounted for in the empirical model. Ferderer (1996) demonstrates that uncertainty and financial stress resulting from oil price changes could magnify the negative effect of oil price increases and offset some of the negative effects of lowered oil prices. The latter effects illustrate the asymmetric effect of oil prices on US economic activity. Balke et al. (2002) show that asymmetry is transmitted from oil markets to US economic activity through market interest rates to GDP and that monetary policy cannot be the unique source of asymmetry in real activity. Additionally, interest rates reflect increased financial stress caused by oil price changes. Interest rates are a crucial financial instrument that impacts available liquidity in financial markets and thus the volume of trade in these markets. Consequently, the interest rate is a channel through which oil market shocks could be transmitted asymmetrically to the US financial market.

This study investigates long-run and short-run relationships between a set of monthly US energy prices and monthly US aggregate stock market prices using the QARDL methodology for the period covering January 1999 to September 2015. The key results may be summarized as follows. A significantly negative long-term relationship between WTI crude oil prices and S&P 500 prices is found. This relationship prevails for natural gas as well. These findings underscore the fact that both crude oil and natural gas are key economic variables for explaining long-run stock market dynamics. At first sight, this result corroborates those of previous empirical studies that detect structural breaks in the dynamics of the time series data considered in their analyses (see, for example, Ciner (2001) for the US; Park and Ratti (2008) for the US and 13 European countries; Apergis and Miller (2009) for the most-developed countries including the US; and Zhu et al. (2016) for China). Additionally, the significance of this long-run linkage is not stable across quantiles due to the presence of nonlinearities and asymmetries. From the short-run analysis, two key findings emerge. First, our results suggest negative short-run relationships between WTI crude oil and Henry Hub natural gas prices and S&P 500 stock prices. Second, these links are found to be significant only for the medium quantiles, indicating nonlinear and asymmetric responses of aggregate stock market prices to energy price shocks. These results provide further insights into how energy price shocks are transmitted to stock market prices.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the QARDL methodology and describes the database used in this study. Section 4 reports the empirical results. Finally, the last section concludes the paper.

2. Data and methodology

2.1. Data

Our sample data consists of monthly time series for a couple of US energy prices, and we use the S&P 500 as a US stock market benchmark. We use an aggregate stock index to make our results comparable with those in the main studies carried out in the US market (Jones and Kaul 1996, Sadorski 1999, Kilian and Park 2009, Wang et al. 2013). The S&P 500 closing prices are collected from the Thomson Reuters database. The energy spot closing price series, such as for West Texas Intermediate (WTI) crude oil, regular gasoline, diesel fuel, heating oil and Henry Hub natural gas, are obtained from the website of the U.S. Energy Information Administration (EIA) and cover the period from January 1999 to September 2015. The Cushing WTI spot price is denominated in US dollars per barrel. The natural gas spot price at Henry Hub is expressed in US dollars per million British thermal units (MMBtu) and other refined petroleum products prices are expressed in US dollars per gallon. The descriptive statistics and stochastic properties of US energy prices and stock market closing price series are summarized in Table 1.

[Insert Table 1 here]

Average monthly prices range from $1.731 for gasoline to $61.372 per barrel for WTI crude oil. The Henry Hub natural gas spot prices in 2016 displayed the lowest annual average price since 1999 and averaged $2.49 per million Btu. Regular retail gasoline prices in the US averaged $2.14 per gallon in 2016, 29 cents per gallon (12%) less than in 2015 and the lowest annual average price since 2004. Lower crude oil prices in 2015 were the main cause of the lower prices for other liquid petroleum products. For example, diesel spot prices reached the historic level of approximately $0.975 per gallon in mid-January 2016. Crude oil prices fell from a peak of about $145 in July 2008 to a low of about $33 in mid-December 2008. All the US refined petroleum product spot prices follow the same trend in this period due to the 2008 financial crisis. US energy prices experienced a remarkable decrease in the post-World War II period. Concerning the stochastic properties of our monthly data, all series are positively skewed and show excess kurtosis. US energy and stock market prices exhibit fat tails; thus, the series distributions are all non-normal. The latter finding is confirmed by the results of the JB test for normality[3] that highly rejects the null of normality. When it comes to test for stationarity of time series, ignoring change points in the test procedure would lead to fallacious stationarity or equivalently to fallacious non-stationarity. Hence traditional unit root tests become inappropriate in the presence of change points in the dynamics of time series. Hence, new unit root tests with change points appeared. We thus apply two structural break unit root tests namely the Zivot-Andrews (1992) unit root test that allows for one changepoint in time series; and the Narayan-Popp (2010)[4] GARCH-based unit root test with two break points in level and slope while accounting for a trend in the models estimated to test for unit root. Indeed, Hansen (2001) argues that an undetected break point can lead to the following three major problems in a time series analysis: (a) Misinterpretation of time series model, (b) Biased estimates, and (c) Less accurate forecasting.

Table 1 reports the ZA and NP calculated statistics. All log-price series are not stationary at the 1% significance level but their first differences are stationary, meaning that all the dependent and independent variables are I(1). The QARDL-ECM approach is employed to solve the above problems caused by the stochastic properties of our data series. This new econometric specification accurately models both the asymmetric and nonlinear linkages between energy prices and stock market prices in the long and short run.

2.2. Methodology

We employ the QARDL-ECM model to investigate the cointegrating relationship between US stock market prices and a set of US energy prices (i.e., WTI, gasoline, heating, diesel and natural gas). The QARDL is an extension of the so-called “ARDL model,” allowing testing for potential asymmetries and nonlinearities between our dependent and independent variables. The first step of our empirical analysis is to estimate the linear ARDL specification, written as follows:

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[3] The JB statistic tests the null hypothesis that the time series follows a normal distribution.

[4] The ZA (NP) statistic tests the null hypothesis that the time series contains a unit root and hence is non-stationary while accounting for one (two) possible structural break(s). The NP test also accounts for heteroscedasticity of the residuals in the model.

$$SP_t = \alpha + \sum_{i=1}^{p} \varphi_i SP_{t-i} + \sum_{i=0}^{q} \omega_i WTI_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is the error term defined as $SP_t - E[SP_t / F_{t-1}]$ with F_{t-1} being the smallest $\sigma -$ field generated by $\{WTI_t, SP_{t-1}, WTI_{t-1}, SP_{t-1}, ...\}$, and p and q are lag orders selected by the Schwarz information criterion (SIC). In Equation (1), SP_t refers to the S&P 500 stock market index, used as a US economic barometer, and WTI denotes West Texas Intermediate crude oil prices.

We also consider an augmented version of Equation (1) in order to investigate the predictability of the US stock market returns while controlling for the information provided by WTI prices. The augmented model is written as follows:

$$Q_{SP_t} = \alpha + \sum_{i=1}^{p} \varphi_i SP_{t-i} + \sum_{i=0}^{q} \theta_i WTI_{t-i} + \sum_{i=0}^{q} \omega_i X_{t-i} + \varepsilon_t \tag{2}$$

where X_t represents the energy price among gasoline, heating, diesel, and natural gas. All the variables in our models are transformed into logarithm form. Cho et al. (2015) extended the model in Equation (2) to a quantile context and introduced the following basic form of the QARDL(p, q) model:

$$Q_{Y_t} = \alpha(\tau) + \sum_{i=1}^{p} \varphi_i(\tau) Y_{t-i} + \sum_{i=0}^{q} \omega_i(\tau) X_{t-i} + \sum_{i=0}^{q} \theta_i(\tau) WTI_{t-i} + \varepsilon_t(\tau) \tag{3}$$

where $\varepsilon_t(\tau) = SP_t - Q_{SP_t}(\tau / F_{t-1})$ with $Q_{SP_t}(\tau / F_{t-1})$ is the τ^{th} quantile of SP_t conditional on the information set F_{t-1} defined above (Kim and White 2003). To analyze the QARDL, we formulate Equation (3) as given below:

$$Q_{\Delta SP_t} = \alpha + \rho SP_{t-1} + \varphi_{WTI} WTI_{t-1} + \varphi_X X_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta SP_{t-i} + \sum_{i=0}^{q} \theta_i \Delta WTI_{t-1} + \sum_{i=0}^{q} \omega_i \Delta X_{t-i} + \nu_t(\tau) \tag{4}$$

Using the model in Equation (4), there is still a likelihood of a contemporaneous correlation between ν_t and ΔX_t or ΔWTI_t. The previous correlation can be avoided by employing the projection of ν_t on ΔX_t and ΔWTI_t in the form $\nu_t = \gamma_X \Delta X_t + \gamma_{WTI} \Delta WTI_t + \varepsilon_t$. The resulting innovation ε_t is now uncorrelated with both ΔX_t and ΔWTI_t. Incorporating the previous projection into Equation (4) and generalizing it to the quantile regression framework lead to the following QARDL-ECM model:

$$Q_{\Delta SP_t} = \alpha(\tau) + \rho(\tau)(SP_{t-1} - \beta_{WTI}(\tau)WTI_{t-1} - \beta_X(\tau)X_{t-1}) + \sum_{i=1}^{p} \varphi_i(\tau)\Delta SP_{t-1} + \sum_{i=0}^{q} \theta_i(\tau)\Delta WTI_{t-1} + \sum_{i=0}^{q} \omega_i(\tau)\Delta X_{t-1} + \varepsilon_t(\tau) \quad (5)$$

The cumulative short-term impact of past stock prices on the current stock prices is measured by $\varphi_* = \sum_{j=1}^{p-1} \varphi_j$, while the cumulative short-term impacts of the present and past levels of WTI and energy prices among gasoline, heating, diesel, and natural gas on the current stock prices are measured by $\theta_* = \sum_{j=0}^{q-1} \theta_j$ and $w_* = \sum_{j=0}^{q-1} w_j$, respectively. The long-term integrating parameters for WTI and energy prices are calculated as $\beta_{WTI} = -\frac{\varphi_{WTI}}{\rho}$ and $\beta_X = -\frac{\varphi_X}{\rho}$, respectively.

The cumulative short-term and long-term parameters are calculated using the conventional delta method. The ECM parameter ρ should be significantly negative. We use the Wald test to statistically investigate the short-run and long-run nonlinear and asymmetric impacts of energy prices on stock market prices. The Wald test asymptotically follows a chi-squared distribution and is used to test the null hypothesis of parameter constancy across quantiles. The Wald test is carried out for each of the following estimated parameters: φ_*, w_*, θ_*, β_{WTI}, β_X, and ρ_*. For example, considering the speed of adjustment parameter ρ_*, we test the following null hypothesis: (i) $\rho_*(0.05) = \rho_*(0.10) = \rho_*(0.20) = \rho_*(0.30) = \rho_*(0.40) = \rho_*(0.50) = \rho_*(0.60) = \rho_*(0.70) = \rho_*(0.80) = \rho_*(0.90) = \rho_*(0.95)$. The same hypothesis is tested on β_{WTI} and β_X parameters as well as on all selected lags for the short-term parameters φ, w, and θ.

The first step of our econometric methodology consists in estimating the linear ARDL(p, q) model in Eq. (1). The SIC information criterion is employed to determine the optimal length orders p and q for each model (Cho et al. 2015). Then, we run the quantile estimation in order to apply the QARDL approach. This econometric specification allows us to better understand the effect of energy price shocks on S&P 500 returns by simultaneously examining the long-run relationship between integrated time series and its associated short-run links across a range of quantiles (see Eq. 5).

3. Results

The results of the OLS and quantile estimations are reported in Tables 2 to 6. The first panel of each table displays the traditional ARDL model in Eq. 1 (Table 2) and in Eq. 2 (Tables 3-6). Following Cho et al. (2015), we employ the SIC information criterion to depict the lead-lag structure for each model. The optimal lag orders p and q differ according to the energy prices used in the model. Most of the OLS coefficients are not significant and sparse, depending on the energy price series included in the model. These findings suggest that the linear ARDL specifications cannot completely depict information about the effects of energy price shocks on stock market dynamics. In the second panel of Tables 2 to 6, all the QARDL coefficients are represented, along with their associated standard errors in brackets. Concerning the quantile coefficients, we are interested in the following kind of parameters. The ECM parameter $\rho(\tau)$, depending on the τ^{th} quantile, measures the speed of adjustment toward long-run equilibrium between US energy prices and S&P 500 stock market prices. The long-run parameters are represented by β_X and β_{WTI}, the integrating coefficient between US energy prices (gasoline, heating oil, diesel fuel, and natural gas) or WTI crude oil prices, respectively, and the S&P 500 prices. The short-run coefficient φ_* represents the cumulative impact of contemporaneous and past values of stock prices on current stock prices. Similarly, the short-term parameter θ_* reflects the cumulative impact of current and past values of WTI crude oil on the S&P 500 and w_* corresponds to the cumulative impact of energy prices on the S&P 500 index.

[Insert Tables 2 to 6 here]

In the long run, the speed of the adjustment parameter (ρ_*) and cointegrating parameters (β_{WTI}, β_X) are found to behave differently across quantiles. The ECM parameters indicating the mean reversion to long-run equilibrium, are qualitatively similar regardless of the energy return series we use in the model. Concerning the relationship between WTI and the S&P 500, the ECM parameters are about -0.05 (ρ_* in Table 2) for the two highest quantiles. Similarly, the ECM coefficient is -0.066 for gasoline (ρ_* in Table 3), -0.054 for heating oil (ρ_* in Table 4), -

0.057 for diesel fuel (ρ_* in Table 5), and about -0.06 for natural gas (ρ_* in Table 6). These results indicate that the speed of adjustment is more pronounced for both the gasoline (6.6 %) and natural gas series (about 6%). Other sources of energy exhibit a similar but lower speed of adjustment parameter, corresponding to approximately 5.5 %. The empirical findings also suggest that the ECM coefficients are all significant at the 1% or 5 % level for only the two highest quantiles, $\tau = 0.9$ and $\tau = 0.95$. The cointegrating parameters β_{wti} and β_X are insignificant at all quantiles for all pairs considered[5]. The long-run coefficients β_X are positive for gasoline $(\beta_{gasoline}\ in\ Table\ 3)$, heating oil $(\beta_{heating}\ in\ Table\ 4)$, and diesel $(\beta_{diesel}\ in\ Table\ 5)$ but negative for natural gas $(\beta_{natgas}\ in\ Table\ 6)$, especially at the highest quantile. The long-term relationship between WTI and S&P 500 returns is modified when we integrate different sources of energy into the model. For example, the estimates of $\beta_{gasoline}$ and β_{wti} in Table 3 give us two distinct links. The first indicates that an increase of 1% in the gasoline price provokes an increase of 1.5% in the S&P 500 price, and the second suggests a negative long-run relationship between WTI crude oil and the S&P 500 stock market. Similar results are obtained for heating oil (Table 4) and diesel fuel (Table 5). The nature of the long-run link between WTI and the US stock market has changed because we incorporate another source of energy in Eq. 5. At this stage, the long-run relationship analysis suggests that WTI crude oil is superior to the other liquid oils in explaining US stock market dynamics. These results also underscore the finding that the behavior of natural gas is quite different from that of other sources of US energy (Table 6). This negative long-run relationship suggests that natural gas accurately models US stock market price changes. This finding corroborates the fact that oil is not the main source of energy used by producers and consumers in the US. Kilian (2008) has pointed out that US electricity has not been produced only by crude oil. In 2015, natural gas accounted for about 33% of US electricity generation (see the EIA website for more information). Overall, these findings suggest that first, crude oil has more predictive power than other refined petroleum products in explaining long-term stock market reactions and that, second, in certain situations, natural gas is a better source of energy for forecasting stock returns. Finally, our results indicate that, although a long-run relationship has been detected between stock returns and energy prices, it is not stable across quantiles due to the presence of nonlinearities and asymmetries in the links between the investigated US markets. This finding is consistent with those of recent empirical studies that incorporate asymmetric and nonlinear tools into their econometric specifications (Miller and Ratti 2009, Wang et al. 2013, and Melichar 2016 among others). For example,

[5] β_{WTI} is negatively significant at the 0.80 quantile in model including gasoline.

Baghestani (2016) investigates the dynamic relationship among real gasoline prices, the index of US current economic conditions, and US consumers' economic outlook from 1993 to 2015 using a nonlinear error-correction model. The author finds that consumers' economic outlook is negatively related to real gasoline prices in the long run while, in the short run, US consumers' outlook reacts asymmetrically to real gasoline prices: the outlook remains unchanged following a decline of real gasoline prices but deteriorates in the opposite case. Salisu and Oloko (2015) account for nonlinearities in the relationship between oil prices (WTI and Brent) and the US stock market index by incorporating endogenously determined structural breaks in the VARMA-BEKK-AGARCH model. The resulting model is then used to compute optimal portfolio weights and hedge ratios between oil prices and US stocks within the different sub-periods determined according to the break dates. The results show that volatility spillover from the oil market to the stock market became pronounced after the break, which coincides with the global economic slowdown. In addition, portfolio management shows different patterns across sub-periods. The latter findings highlight the importance of considering nonlinearities and asymmetries in the analysis of the linkage between oil prices and the US stock market index.

The results of the analysis of the short-run relationships between energy returns and S&P 500 returns differ depending on both the energy series we estimate and the quantile we use in Eq. 5. In the short run, past changes of stock prices are found to influence current realizations of stock prices in the low and medium quantiles (φ_i in Tables 2-6). Concerning the short-run relationships for liquid petroleum products and S&P returns, the findings are mixed. The S&P 500 returns have been negatively affected by past heating oil price changes (w_i in Table 4) and positively impacted by diesel price changes (w_i in Table 5) at medium quantiles. Changes in oil derivative prices fail to explain the short-run dynamics of stock market price changes. These findings suggest that oil liquid petroleum products are not good vehicles for accurately explaining current and past stock market returns in the short run.

In the short run, WTI crude oil returns negatively impact S&P returns, especially at medium quantiles. This negative response can be partly attributed to asset managers' reaction caused by uncertainty concerning future crude oil supply and demand. The same results are found for the short-term relationship between natural gas prices and S&P 500 prices (θ_i in Table 6). Not surprisingly, crude oil and natural gas are two of the best economic variables for making stock market return forecasts, especially for US financial markets. One would expect that information concerning oil and natural gas prices is easily observable by traders and asset managers all over the world. Our evidence indicates that investors react more quickly to oil and natural gas changes, in the sense that oil and gas shocks are rapidly transmitted to stock market prices. Nevertheless, this transmission is not stable across quantiles; thus, we find no evidence of symmetric effects. Rather, our evidence is consistent with locational asymmetries in the short run between oil and natural gas prices and S&P 500 stock prices. Nevertheless, our results do not support those of previous studies such as Alsalman and Herrera (2015), who find no evidence of asymmetric reaction in the US stock market to oil price innovations. They further report that even great oil price shocks do not influence the US stock market asymmetrically.

Several reasons could explain the fact that only a few quantiles contain significant relationships. First, financial markets variables show nonlinear dynamics due to exogenous economics shocks such as unexpected loss of a public company or direct state interventions in a financial market when, for example, central bank intervenes in order to influence exchange rate of the home currency. Second, nonlinear functional dependencies could create nonlinear dynamics of financial variables. For example, option prices are computed as function of the underlying price and price-earnings-ratio is function of the long-term growth prospects of the economy. Third, changing expectations of financial market participants will generally cause nonlinear dynamics of financial data. Fourth, the energy markets are sensitive and responsive to political disturbances and major events such as the recent political unrest in the Middle East and terrorist attacks. Fifth, supply and demand shocks in energy markets are causes of nonlinearity in the dynamics of energy prices via for example movements of workers between sectors. The nonlinear dynamics observed in the financial market and in the energy market pass through the relationship between financial and energy variables. The resulting nonlinearity in the link between individual variables is fed by the complexity of the world economics system.

[Insert Figures 1 to 4 here]

We also plot the dynamics of estimated parameters across quantiles in Figures 1 to 4, which display the quantile estimates of our key parameters with a 95% confidence interval using all available observations for each energy time series (i.e., speed of adjustment parameter ρ_*; long-run cointegrating parameters β_{WTI} and β_X; cumulative short-term impact of past on current S&P 500 prices φ_*; and cumulative short-term impact of WTI and energy prices on current S&P 500, θ_* and w_* respectively). The figures show that the speed of adjustment parameter is significant at the two highest quantiles only, for all models. The long-run cointegrating parameter for WTI is insignificant at all quantiles for the five considered models. Similar result is found for the respective long-run cointegrating parameter of gasoline, heating, diesel and natural gas. The S&P500 returns significantly depend on their own cumulative past returns at the low quantiles for models including respectively WTI, gasoline and natural gas and at high quantiles for heating. The graphs show that cumulative past returns of WTI and respective energy prices do not impact current S&P500 returns.

Table 7 presents the results of Wald tests of parameter constancy for the long-run and the respective short-run parameters. These tests allow testing parameters constancy across the eleven considered quantiles. Equivalently, the Wald tests check the nonlinearities in both the long-run and short-run parameters in order to evaluate locational asymmetries (Cho et al. 2015). Acceptance of the null hypothesis indicates the constancy of long-run and short-run parameters between the variables of interest across quantiles, meaning that neither nonlinearities nor asymmetries are found in the links. This is not the case here. On the whole, Wald tests reject the null hypothesis for the speed of adjustment parameter (ρ_*) in the five models. However, the Wald test fails to reject the null of parameter constancy for the long-run cointegrating parameters for both the WTI (β_{WTI}) and the involved energy prices, namely gasoline ($\beta_{gasoline}$), heating ($\beta_{heating}$), diesel (β_{diesel}) and natural gas ($\beta_{nat\ gas}$). In the short-run, findings of the Wald test indicate that current returns of S&P500 (φ_i) respond asymmetrically to their past levels in all the models. Moreover, oil returns (θ_i) pass through US stock market in an asymmetric manner in the reduced model and in models involving gasoline, diesel and natural gas. In addition, gasoline prices (w_0 in column SP-GASOLINE-WTI, Table 7) and heating prices ($w_4, \dots, w_9$ in column SP-HEATING-WTI, Table 7) influence S&P500 asymmetrically in the short-run while diesel and natural gas have a symmetric short-run effect on S&P500. Taken together, our findings indicate that the transmission of energy prices to S&P 500 stock market prices is nonlinear and asymmetric. These findings are consistent with previous research that incorporates nonlinear specifications in their models (Park and Ratti, 2008; Apergis and Miller, 2009; Zhu et al., 2016). The results shown in Table 7 may be summarized as follows. When only WTI is considered as an explanatory variable, the Wald test fails to reject the null hypothesis of parameter constancy for the long-run cointegrating parameter. The Wald test rejects the null of parameter constancy for the speed of adjustment parameter (ρ_*) and the short-run impact of past S&P500 price variations (φ_i) as well as the short-run effect of oil price variations (θ_i) on US stock market price variations. When heating and WTI are included in the model, the Wald test rejects the null hypothesis of parameter constancy as for the short-run effect of heating, and hence our results suggest an asymmetric impact of past heating price variations on current stock prices variations. The same results are obtained for all the sources of US energy.

[Insert Table 7 here]

These findings are consistent with a number of recent empirical studies in highlighting evidence of a nonlinear and asymmetric transmission of energy prices to stock market prices (Lee and Zeng 2011, Raza et al. 2016). Lee and Zeng (2011) employ a quantile regression approach that accounts for positive and negative oil price shocks. However, their approach fails to account for the cointegration that may occur between stock market and oil prices. Raza et al. (2016) use the nonlinear ARDL model to investigate the asymmetric impact of gold and oil prices on the stock markets of emerging economies. In their model, however, Raza et al. (2016) impose an exogenous zero threshold, which may be too restrictive. Our econometric specification seems to be more appropriate for assessing the adjustment of US aggregate stock market prices to US energy price shocks, as it is more flexible in its ability to account for potential cointegration between oil price shocks and stock market prices, on the one hand, and to allow for multiple data-driven thresholds as determined by quantiles, on the other hand.

4. Conclusion

We investigate potential locational asymmetry in the reaction of US stock market to energy prices while controlling for the influence of oil price on US stock market using the quantile autoregressive distributed lags model. Our quantile estimations offer several important results. The ECM parameters are significant only for higher quantiles for all pairs of energy prices considered in the model. The speed of adjustment is more pronounced for both gasoline and natural gas. The long-run relationships between US energy prices and S&P 500 stock prices are found to be insignificant for all quantiles. The results clearly indicate negative and significant short-run relationship between WTI crude oil and S&P 500 stock prices on the one hand and between Henry Hub natural gas prices and S&P 500 stock prices on the other hand, at the medium quantiles. Our first finding suggests that neither the long-run nor the short-run relationships between the variables of interest are stable across quantiles. This result underscores the presence of nonlinearities and locational asymmetries in these links. The second finding is that natural gas and crude oil are both substitutes and complements in driving S&P 500 stock returns. Consequently, oil and natural gas prices are important drivers of stock market returns in both the long and short run. For some quantiles, the predictive power of Henry

Hub natural gas is higher than that of WTI crude oil in explaining future S&P 500 stock price variations. Conversely, in some circumstances, crude oil is better than natural gas for predicting future stock market price variations, meaning that natural gas has gained an increasingly important role in the US energy market (Kilian, 2016). The third finding indicates that the presence of alternative energy products improves the fit of the model containing WTI crude oil prices. All these empirical data are therefore exploitable by various economic agents, such as asset managers to manage their commodity portfolios and minimize their exposure to oil price risk, or energy policy makers to consider stock market reactions to energy price shocks. In particular, WTI and energy-related products constitute instruments for portfolio diversification and hedging in the long-run as these assets are found to not influence S&P 500 index. However, in the short-run the diversification and hedging power of WTI and the related oil products is different depending on the time horizon and the quantile. Portfolio and risk managers should select suitable assets according to the horizon of their portfolios to develop appropriate diversification and hedging strategies. Stock market participants in the US such as traders should pay attention to past oil and natural gas market dynamics in order to formulate more effective risk management strategies. Indeed, since traders and speculators build up their trading activities on the basis of expectations regarding the future dynamics of asset prices, it seems crucial to accurately forecast the future movements of asset prices. We find that energy prices do not significantly predict S&P 500 prices in the long-run while they significantly predict the US stock price index in the short-run. Furthermore, the oil and stock markets are positively correlated, since oil prices are now determined by oil demand rather than by oil supply. Stock index futures could be a good way for traders to hedge crude oil risk in case of unavailability of crude oil futures or if stock index futures contracts are cheaper than those of crude oil. The fact that the transmission of energy prices to the US stock market is not very strong provides an opportunity to promote the "green public fiscal system," which uses an environmental tax and carbon tax to reflect the real social costs of energy production and consumption. Nevertheless, to avoid extreme volatility in the stock market price index due to responses to energy price changes, reform should be carried forward prudently and by stages. Regarding portfolio management, the results of the quantile ARDL model differ from those of the linear ARDL model estimated on the full sample period. For instance, the respective relationships between oil prices and natural gas and the S&P 500 index are shown to be significant if one considers the full sample, while they are significant at very high quantiles if one considers the quantiles. Ignoring these asymmetries may thus aggregate hedging effectiveness. Finally, financial practitioners should be aware of the increasing connectedness between the oil and financial markets and make their decision accordingly.

References

Acaravci, A., Ozturk, I. and Kanadir, S. K. (2012). Natural gas prices and stock prices: Evidence from EU-15 countries. Economic Modelling, 29, 1646-1654.

Alsalman, Z. and Herrara, A. M. (2015). Oil price shocks and the US stock market: do sign and size matter? The Energy Journal, 36, 171-188.

Anton, M. K. (1989). Oil and the macroeconomy when prices go up and down: an extension of Hamilton’s results. Journal of Political Economics, 97, 740-744.

Apergis, N. and Miller, S. M. (2009). Do structural oil-market shocks affect stock prices? Energy Economics, 31, 569–575.

Bachmeier, L. J.and Griffin, J. M. (2006). Testing for market integration crude oil, coal, and natural gas. Energy Journal, 27, 55-71.

Baghestani, H. (2016). Do gasoline prices asymmetrically affect US consumers’ economic outlook? Energy Economics, 55, 247-252.

Balke, N. S., Brown, S. P. A. and Yücel, M. K. (2002). Oil prices shock and the US economy: where does the asymmetry originate? Energy Journal, 23, 27-52.

Basher, S.A., Haug, A. A. and Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. Energy Economics, 34, 227–240.

Blendon, R. and Bensen, J. (2008). Americans worry: how they view their lives in an economic downturn? Challenge, 51, 5-26.

Boldanov, R., Degiannakis, S. and Filis, G. (2016). Time-varying correlation between oil and stock market volatilities: evidence from oil-importing and oil-exporting countries. International Review of Finance Analysis, 48, 209-220.

Broadstock, D. C., Fan, Y., Ji, Q. and Zhang, D. (2016). Shocks and stocks: a bottom-up assessment of the relationship between oil prices, gasoline prices and the returns of Chinese firms. The Energy Journal, 37, 55-86.

Ciner, C. (2001). Energy shocks and financial markets: nonlinear linkages. Studies in Nonlinear Dynamics and Economics, 5, 203–212.

Cho, J.S., Kim, T.-H. and Shin, Y. (2015). Quantile cointegration in the autoregressive distributed-lag modeling framework. Journal of Econometrics, 188, 281–300.

Cunado, J. and Perez de Gracia, F. (2014).Oil price shocks and stock market returns: evidence for some European countries. Energy Economics, 42, 365–377.

Fayadd, A. and Daly, K. (2011). The impact of oil price shocks on stock market returns: Comparing GCC countries with the UK and USA. Emerging Market Review, 12, 61-78.

Ferderer, J. P. (1996). Oil price volatility and the macroeconomy: a solution to the asymmetry puzzle. Journal of Macroeconomics, 18, 1-16.

Gronwald, M. (2008). Large oil shocks and the US economy: infrequent incidents with large effects. The Energy Journal, 29, 151-171.

Gubler, M. and Hertweck, M. S. (2013). Commodity price shocks and the business cycle: Structural evidence for the US. Journal of International Money and Finance, 37, 324-352.

Güntner, J. H. F. (2014). How do international stock markets respond to oil demand and supply shocks? Macroeconomic Dynamics, 18, 1657-1682.

Guo, J., Zheng, X. and Chen, Z-M. (2016). How does coal price drive up inflation? Reexamining the relationship between coal price and general price level in China. Energy Economics, 57, 265-276.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. Journal of Political Economy, 91, 228–248.

Hamilton, J. D. (1988). A neoclassical model of unemployment and the business cycle. Journal of Political Economy, 96, 593-617.

Hamilton J. D. and Herrera A. M. (2004). Oil shocks and aggregate macroeconomic behavior: The role of monetary policy. Journal of Money, Credit and Banking, 36, 265-286.

Hansen, B. E. (2001). The new econometrics of structural change: dating breaks in U.S labor productivity. Journal of Economic Perspectives, 15, 117-128.

Huang, R. D., Masulis, R.W. and Stoll, H. R. (1996). Energy shocks and financial markets. Journal Future Markets, 16, 1–27.

Huntington, H. G. (1998). Crude oil prices and U.S. economic performance: Where does the asymmetry reside? The Energy Journal, 19(4), 107-132.

Jones, C. M. and Kaul, G. (1996).Oil and the stock markets. Journal of Finance, 51, 463–491.

Kang, W., Ratti, R. A. and Vespignani, J. (2016). The impact of oil price shocks one the US stock market: A note on the roles of U.S. and non-U.S. oil production. Economics Letters, 145, 176-181.

Kilian, L. (2016). The impact of the Shale oil Revolution on US oil and gasoline prices. Manuscript. University of Michigan. CEPR.

Kilian, L. (2008). The economic effects of energy price shock. Journal of Economic Literature, 46, 871-909.

Kilian, L. and Park, C. (2009). The impact of oil price shocks on the U.S. stock market. International Economic Review, 50, 1267-1287.

Kilian, L. and Vigfusson, R. J. (2011). Are the responses of the U.S. economy asymmetric in energy price increases and decreases? Quantitative Economics, 2, 419-453.

Kilian, L. and Vigfusson, R. J. (2014). The role of oil price shocks in causing US recessions. CEPR discussion paper N. DP10040. https://ssrn.com/abstract=2501512

Kim, T. and White, H. (2003). Estimation, inference, and specification testing for possibly misspecified quantile regression. In: Fomby, T., Hill, R. (Eds.), Maximum Likelihood Estimation of Misspecified Models: Twenty Years Later, vol. 17. Elsevier, New Yok, pp. 107–132.

Lahiani, A., Miloudi, A., Benkraiem, R and Shahbaz, M. (2017). Another look on the relationships between oil prices and energy prices. Energy Policy, 102, 318-331.

Lardic, S. and Mignon, V. (2006). The impact of oil prices on GDP in European countries: An empirical investigation based on asymmetric cointegration. Energy Policy, 34, 3910-3915.

Lee, B.J., Yang, C.W. and Huang, B. N. (2012). Oil price movements and stock markets revisited: A case of sector stock price indexes in the G-7 countries. Energy Economics, 34, 1284–1300.

Lee, C. C. and Zeng, J. H. (2011). The impact of oil price shocks on stock market activities: asymmetric effect with quantile regression. Mathematical and Computational Simulation, 81, 1910–1920.

Masih, R., Peters, S. and Mello, L. (2011). Oil price volatility and stock price fluctuations in an emerging market: evidence from South Korea. Energy Economics, 33, 975–986.

Melichar, M. (2016). Energy price shocks and economic activity: which energy price series should we be using? Energy Economics, 54, 431–443

Miller, J. I. and Ratti, R. A. (2009). Crude oil and stock markets: stability, instability and bubbles. Energy Economics, 31, 559–568.

Narayan, P. K. and Popp, S. (2010). A new unit root test with two structural breaks in level and slope at unknown time. Journal of Applied Statistics, 37, 1425-1438.

Oladosu, G. (2009). Identifying the oil price-macroeconomy relationship: An empirical mode decomposition analysis of US data. Energy Policy, 37, 5417-5426.

Pan, Z., Wang, Y. and Liu, L. (2016). The relationships between petroleum and stock returns: an asymmetric equi-correlation approach. Energy Economics, 56, 453-463.

Park, J. and Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. Energy Economics, 30, 2587–2608.

Raza, N., Shahzad, S. J. H., Tiwari, A. K. and Shahbaz, M. (2016). Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. Resources Policy, 49, 290-301.

Sadorsky, P. (1999). Oil price shocks and stock market activity. Energy Economics, 21, 449–469.

Salisu, A. A. and Oloko, T. F. (2015). Modeling oil price-US stock nexus: A VARMA-BEKK-AGARCH approach. Energy Economics, 50, 1-12.

Shetty, S., Iqbal, Z. and Alshamali, M. (2013). Energy price shocks and economic activity in Texas cities. Atlantic Economic Journal, 41, 371-383.

Sukcharoen, K., Zohrabyan, T., Leatham, D. and Wu, X. (2014). Interdependence of oil prices and stock market indices: A copula approach. Energy Economics, 44, 331–339.

Tatom, J. A. (1993). Are there useful lessons from the 1990-91 oil price shock? The Energy Journal, 14, 129-150.

Wang, X. and Zhang, C. (2014). The impacts of global oil prices hocks on China's fundamental industries. Energy Policy, 68, 394–402.

Wang, Y., Wu, C. and Li, Y. (2013).Oil price shock and stock market activities: Evidence from oil-importing and oil-exporting countries. Journal of Comparative Economics, 41, 1220-1239.

Wang, Y. and Liu, L. (2016). Crude oil and world stock markets: volatility spillovers, dynamic correlations and hedging. Empirical Economics, 50, 1481-1509.

Zhang, D. (2017). Oil shocks and stock markets revisited: measuring connectedness from a global perspective. Energy Economics, 62, 323-333.

Zhu, H., Guo, Y., You, W. and Xu, Y. (2016). The heterogeneity dependence between crude oil price changes and industry stock market returns in China: Evidence from a quantile regression approach. Energy Economics, 55, 30-41.

Zhu, H., Cheng, P. and You, W. (2016). Quantile Behaviour of cointegration between silver and gold prices. Finance Research Letters, 19, 119-125.

Table-1: Descriptive Statistics and Unit Root Analysis

	S&P500	WTI	Gasoline	Heating oil	Diesel	Natural Gas
Mean	1278.599	61.372	1.731	1.769	1.886	4.895
Minimum	735.090	12.010	0.317	0.304	0.391	1.771
Maximum	2067.560	133.880	3.292	3.801	3.894	13.422
Std Dev	262.598	29.731	0.836	0.904	0.903	2.235
Skewness	0.792	0.196	0.145	0.228	0.172	1.284
Kurtosis	3.850	1.868	1.702	1.823	1.814	4.974
JB	27.080 [0.000]	12.012 [0.002]	14.805 [0.001]	13.346 [0.001]	12.769 [0.002]	87.856 [0.000]
ZA (level)	-3.539	-4.121	-3.919	-3.563	-3.204	-4.706
ZA (Δlevel)	-7.848***	-7.766***	-8.494***	-8.081***	-8.432***	-8.281***
NP (level/M1)	-1.978	-1.297	-1.219	-0.992	-2.580	-3.460
NP (level/M2)	-2.518	-2.225	-3.078	-2.238	-3.086	-4.189
NP (Δlevel/M1)	-13.480***	-13.730***	-11.430***	-11.920***	-12.210***	-13.100***
NP (Δlevel/M2)	-13.140***	-13.830***	-12.070***	-8.037***	-11.990***	-13.020***

Notes: JB and ZA denote the empirical statistics of the Jarque–Bera test for normality and Zivot–Andrews (1992) unit root test with structural break, respectively. ZA critical values are -5.57, -5.08, and -4.82 at the significance levels of 1%, 5%, and 10%, respectively. NP denotes the Narayan-Popp (2010) GARCH-based unit root test with two structural breaks in level and slope at unknown time. M1 and M2 in Narayan-Popp (2010) unit root test denote Model 1 that allows for two breaks in level and Model 2 that allows for two breaks in level as well as slope. For the ZA and NP unit root tests time series were analyzed with a trend. *** indicates rejection of the null hypothesis of normality and unit root at the 1% significance level.

Table 2: WTI

	α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	φ_4	θ_0	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
Linear ARDL																
	0.053	-0.013	0.779	0.080	-0.097	0.126*	0.111	0.043	0.003	-0.014	-0.040	-0.015	-0.041	0.049	0.044	0.103***
	(0.134)	(0.019)	(1.148)	(0.05)	(0.074)	(0.073)	(0.073)	(0.038)	(0.039)	(0.039)	(0.039)	(0.039	(0.039)	(0.039)	(0.040)	(0.039)
QARDL																
	α_*	ρ_*	β_{WTI}	φ_1	φ_2	φ_3	φ_4	θ_0	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
0.05	-0.463	0.045	-0.364	0.296	-0.086	0.085	0.132	0.060	0.052	-0.030	0.074	-0.015	-0.044	-0.039	0.114	0.114
	(0.286)	(0.042)	(0.533)	(0.187)	(0.208)	(0.113)	(0.142)	(0.092)	(0.080)	(0.065)	(0.145)	(0.114)	(0.086)	(0.100)	(0.105)	(0.080)
0.10	0.017	-0.18	0.745	0.198	-0.037	0.145	0.376***	0.073	0.058	-0.115	-0.051	-0.056	0.021	-0.010	0.050	0.112*
	(0.274)	(0.039)	(1.696)	(0.149)	(0.188)	(0.103)	(0.087)	(0.089)	(0.072)	(0.085)	(0.120)	(0.089)	(0.064)	(0.096)	(0.083)	(0.059)
0.20	0.192	-0.041	0.414	0.140	0.043	0.298***	0.208*	0.058	0.0003	-0.065	-0.094	-0.076	0.047	-0.014	0.038	0.084
	(0.204)	(0.030)	(0.384)	(0.135)	(0.151)	(0.114)	(0.115)	(0.057)	(0.066)	(0.066)	(0.085)	(0.080)	(0.071)	(0.072)	(0.067)	(0.076)
0.30	0.007	-0.013	1.303	0.065	-0.065	0.242	0.069	0.082	0.042	0.004	-0.081	-0.075	-0.036	0.059	0.027	0.127**
	(0.195)	(0.027)	(2.527)	(0.113)	(0.094)	(0.147)	(0.109)	(0.065)	(0.055)	(0.045)	(0.070)	(0.059)	(0.057)	(0.073)	(0.065)	(0.064)
0.40	0.183	-0.036	0.483	0.119	-0.071	0.098	0.064	0.039	0.009	0.019	-0.079	-0.012	-0.105*	0.094	-0.0002	0.120*
	(0.200)	(0.028)	(0.466)	(0.107)	(0.087)	(0.129)	(0.074)	(0.059)	(0.048)	(0.038)	(0.051)	(0.059)	(0.062)	(0.068)	(0.057)	(0.059)
0.50	0.151	-0.030	0.598	0.104	-0.029	0.102	0.043	0.074	-0.030	-0.013	-0.028	-0.019	-0.099*	0.107	0.006	0.051
	(0.175)	(0.024)	(0.559)	(0.107)	(0.095)	(0.095)	(0.083)	(0.059)	(0.042)	(0.041)	(0.050)	(0.042)	(0.060)	(0.065)	(0.062)	(0.053)
0.60	0.145	-0.029	0.634	0.027	-0.063	0.052	0.056	0.055	-0.045	-0.022	-0.004	-0.014	-0.074	0.089	0.014	0.053
	(0.136)	(0.020)	(0.458)	(0.105)	(0.093)	(0.080)	(0.092)	(0.065)	(0.051)	(0.043)	(0.051)	(0.048)	(0.063)	(0.069)	(0.059)	(0.052)
0.70	0.124	-0.021	0.584	-0.013	-0.077	0.033	-0.070	0.026	-0.033	0.002	0.0001	0.029	-0.072	0.059	0.056	0.062
	(0.142)	(0.020)	(0.635)	(0.099)	(0.089)	(0.052)	(0.106)	(0.076)	(0.047)	(0.048)	(0.050)	(0.056)	(0.062)	(0.069)	(0.051)	(0.048)
0.80	0.235	-0.034	0.303	-0.060	-0.109	0.051	0.019	-0.027	-0.007	-0.032	0.013	0.025	-0.034	0.083	0.005	0.060
	(0.174)	(0.022)	(0.417)	(0.120)	(0.088)	(0.074)	(0.099)	(0.094)	(0.060)	(0.039)	(0.062)	(0.063)	(0.068)	(0.075)	(0.054)	(0.049)
0.90	0.378***	-0.049***	0.142	-0.289***	-0.225***	0.020	-0.039	-0.054	0.034	-0.030	0.065	0.013	-0.027	0.029	0.024	0.059
	(0.142)	(0.018)	(0.201)	(0.106)	(0.075)	(0.077)	(0.079)	(0.086)	(0.034)	(0.048)	(0.056)	(0.059)	(0.055)	(0.065)	(0.051)	(0.048)
0.95	0.408***	-0.055***	0.187	-0.290***	-0.230***	0.045	-0.083	-0.075	0.045	-0.043	0.054	0.030	-0.038	0.021	0.031	0.049
	(0.148)	(0.019)	(0.159)	(0.101)	(0.083)	(0.106)	(0.084)	(0.081)	(0.051)	(0.067)	(0.049)	(0.051)	(0.054)	(0.067)	(0.042)	(0.058)

Note: Table 2 reports the estimation results of the linear ARDL and QARDL models including only WTI as explanatory variable. Numbers between brackets are standard deviations. ***, ** and * indicate rejection at the 1%, 5% and 10% significance levels, respectively.

Table 3: GASOLINE-WTI

Linear ARDL

α_*	ρ_*	$\beta_{gasoline}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	φ_5	w_0	θ_0
0.474** (0.193)	-0.021 (0.019)	4.943 (4.764)	-4.404 (4.376)	0.046 (0.074)	-0.121* (0.073)	0.131* (0.072)	0.103 (0.072)	0.100 (0.072)	0.103*** (0.036)	-0.061 (0.053)

QARDL

	α_*	ρ_*	$\beta_{gasoline}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	φ_5	w_0	θ_0
0.05	-0.377 (0.390)	0.015 (0.031)	2.356 (6.541)	-3.711 (10.703)	0.184 (0.189)	-0.155 (0.0255)	0.095 (0.144)	0.260 (0.206)	0.042 (0.141)	0.161 (0.130)	-0.129 (0.171)
0.10	0.170 (0.326)	-0.013 (0.031)	3.580 (10.664)	-2.923 (9.398)	0.179 (0.169)	-0.063 (0.205)	0.157 (0.167)	0.339 (0.187)	0.117 (0.098)	-0.002 (0.128)	0.098 (0.176)
0.20	0.403 (0.330)	-0.035 (0.029)	2.141 (2.637)	-1.596 (1.878)	0.100 (0.167)	0.012 (0.170)	0.268* (0.160)	0.159 (0.133)	0.069 (0.078)	0.098 (0.076)	-0.041 (0.119)
0.30	0.400 (0.289)	-0.028 (0.028)	2.915 (3.739)	-2.234 (2.320)	-0.006 (0.163)	-0.061 (0.156)	0.180 (0.129)	0.121 (0.123)	0.066 (0.100)	0.106* (0.057)	-0.065 (0.084)
0.40	0.544* (0.320)	-0.042 (0.029)	2.047 (2.058)	-1.681 (1.465)	0.055 (0.121)	-0.054 (0.127)	0.150 (0.119)	0.036 (0.092)	0.065 (0.080)	0.032 (0.047)	-0.020 (0.084)
0.50	0.430* (0.222)	-0.030 (0.018)	2.566 (3.501)	-2.038 (2.185)	0.095 (0.130)	-0.064 (0.111)	0.085 (0.094)	0.030 (0.090)	0.032 (0.085)	0.054 (0.037)	-0.007 (0.062)
0.60	0.441** (0.210)	-0.022 (0.017)	4.278 (5.254)	-3.419 (3.276)	-0.075 (0.121)	-0.078 (0.122)	-0.031 (0.098)	0.008 (0.078)	-0.006 (0.089)	0.069 (0.043)	-0.001 (0.066)
0.70	0.563*** (0.186)	-0.030* (0.018)	3.716 (2.972)	-3.093 (2.490)	-0.133 (0.124)	-0.066 (0.117)	-0.042 (0.097)	0.029 (0.093)	0.038 (0.066)	0.100*** (0.037)	-0.038 (0.067)
0.80	0.621** (0.258)	-0.027 (0.026)	4.651 (3.610)	-4.210*** (1.271)	-0.158 (0.118)	-0.150 (0.105)	-0.136 (0.103)	-0.007 (0.098)	0.029 (0.079)	0.115* (0.067)	-0.110 (0.083)
0.90	0.809*** (0.274)	-0.061** (0.027)	1.684 (1.103)	-1.488 (1.163)	-0.213 (0.136)	-0.250** (0.105)	-0.006 (0.112)	0.061 (0.101)	0.040 (0.083)	0.103 (0.092)	-0.174* (0.103)
0.95	0.808** (0.335)	-0.066** (0.026)	1.452 (1.092)	-1.197 (1.117)	-0.270** (0.136)	-0.262*** (0.081)	-0.014 (0.095)	0.050 (0.096)	0.042 (0.081)	0.122 (0.098)	-0.188* (0.100)

Linear ARDL

θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
0.004 (0.038)	-0.007 (0.038)	-0.048 (0.038)	-0.008 (0.038)	-0.024 (0.039)	0.054 (0.039)	0.051 (0.039)	0.129*** (0.039)

QARDL

	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
0.05	-0.129 (0.171)	0.101 (0.097)	-0.107 (0.102)	0.009 (0.072)	-0.028 (0.092)	-0.093 (0.083)	0.042 (0.069)	0.192* (0.101)
0.10	0.049 (0.076)	-0.087 (0.086)	-0.040 (0.072)	-0.067 (0.074)	-0.021 (0.084)	-0.001 (0.080)	0.029 (0.085)	0.153 (0.092)

0.20	-0.009 (0.062)	-0.055 (0.074)	-0.077 (0.053)	-0.027 (0.058)	0.022 (0.069)	-0.001 (0.062)	0.010 (0.076)	0.098 (0.090)
0.30	0.037 (0.038)	0.015 (0.061)	-0.079 (0.050)	-0.062 (0.046)	-0.031 (0.070)	0.052 (0.068)	0.012 (0.039)	0.141** (0.063)
0.40	0.008 (0.043)	-0.008 (0.043)	-0.066 (0.044)	-0.011 (0.044)	-0.101* (0.057)	0.111* (0.065)	0.008 (0.046)	0.101* (0.058)
0.50	-0.018 (0.041)	0.014 (0.036)	-0.052 (0.045)	-0.019 (0.041)	-0.110* (0.060)	0.120** (0.056)	0.010 (0.054)	0.079 (0.058)
0.60	-0.034 (0.043)	-0.001 (0.066)	-0.010 (0.041)	-0.009 (0.044)	-0.089 (0.062)	0.124*** (0.042)	0.024 (0.064)	0.062 (0.056)
0.70	-0.026 (0.046)	0.039 (0.042)	-0.044 (0.032)	0.005 (0.044)	-0.040 (0.057)	0.082** (0.040)	0.067 (0.059)	0.083 (0.054)
0.80	-0.110 (0.083)	0.034 (0.058)	0.008 (0.046)	0.011 (0.053)	-0.012 (0.062)	0.078 (0.057)	0.044 (0.058)	0.114** (0.057)
0.90	0.071 (0.044)	-0.079 (0.049)	0.040 (0.060)	0.005 (0.059)	-0.013 (0.070)	0.069 (0.054)	0.046 (0.065)	0.065 (0.063)
0.95	0.070 (0.054)	-0.073 (0.055)	0.044 (0.071)	0.053 (0.061)	-0.054 (0.059)	0.067 (0.049)	0.063 (0.066)	0.028 (0.049)

Note: Table 3 reports the estimation results of the linear ARDL and QARDL models including WTI and gasoline as explanatory variables. Numbers between brackets are standard deviations. ***, ** and * indicate rejection at the 1%, 5% and 10% significance levels, respectively.

Table 4: HEATING-WTI

Linear ARDL											
	α_*	ρ_*	$\beta_{heating}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	w_0	w_1	w_2
		0.414*	3.228	-2.966	0.095	-0.084	0.126*	0.114	0.163***	0.006	-0.035
		(0.236)	(2.718)	(2.640)	(0.077)	(0.073)	(0.073)	(0.072)	(0.056)	(0.039)	(0.038)
QARDL											
	α_*	ρ_*	$\beta_{heating}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	w_0	w_1	w_2
0.05	-0.079	0.015	-3.888	2.019	0.115	-0.192	0.160	0.130	0.279**	0.033	-0.076
	(0.488)	(0.058)	(14.523)	(9.375)	(0.152)	(0.175)	(0.197)	(0.144)	(0.124)	(0.073)	(0.061)
0.10	0.473	-0.035	3.058	-2.319	0.144	-0.089	0.277	0.232**	0.191	-0.022	-0.049
	(0.556)	(0.049)	(3.520)	(3.399)	(0.126)	(0.174)	(0.195)	(0.112)	(0.117)	(0.059)	(0.077)
0.20	0.522	-0.019	6.454	-6.045	0.030	-0.033	0.247	0.152	0.204*	0.059	-0.069
	(0.495)	(0.034)	(12.867)	(8.468)	(0.146)	(0.162)	(0.177)	(0.135)	(0.114)	(0.069)	(0.064)
0.30	0.350	-0.018	4.523	-3.968	0.137	-0.099	0.192*	0.081	0.143	0.066	-0.085*
	(0.514)	(0.033)	(10.985)	(4.522)	(0.138)	(0.180)	(0.116)	(0.104)	(0.091)	(0.062)	(0.051)
0.40	0.229	-0.018	2.207	-1.772	0.156	0.036	0.090	0.130	0.166*	0.039	-0.097**
	(0.456)	(0.027)	(4.403)	(3.201)	(0.123)	(0.145)	(0.120)	(0.083)	(0.094)	(0.054)	(0.047)
0.50	0.547	-0.048	1.596	-1.226	0.097	0.033	0.061	0.075	0.144**	0.018	-0.057
	(0.500)	(0.031)	(0.960)	(1.225)	(0.130)	(0.114)	(0.113)	(0.090)	(0.073)	(0.047)	(0.040)
0.60	0.421	-0.039	1.387	-0.937	0.006	-0.034	-0.002	0.064	0.154***	0.003	-0.037
	(0.418)	(0.029)	(0.923)	(1.331)	(0.085)	(0.080)	(0.126)	(0.084)	(0.058)	(0.036)	(0.058)
0.70	0.400	-0.036	1.526	-0.991	-0.105	-0.055	-0.003	0.046	0.117	0.030	-0.010
	(0.298)	(0.022)	(1.171)	(1.455)	(0.069)	(0.089)	(0.122)	(0.065)	(0.072)	(0.039)	(0.058)
0.80	0.429*	-0.033	1.742	-1.409	-0.052	-0.100	-0.016	0.028	0.156*	0.037	0.008
	(0.259)	(0.023)	(2.026)	(1.631)	(0.100)	(0.114)	(0.102)	(0.068)	(0.090)	(0.060)	(0.074)
0.90	0.535***	-0.053**	0.797	-0.587	-0.267**	-0.241**	-0.006	-0.049	0.089	0.012	-0.062
	(0.192)	(0.021)	(0.909)	(0.622)	(0.124)	(0.102)	(0.091)	(0.061)	(0.081)	(0.064)	(0.041)
0.95	0.481**	-0.054***	0.338	-0.208	-0.261**	-0.215***	0.007	-0.065	0.070	0.003	-0.056
	(0.208)	(0.019)	(0.989)	(0.622)	(0.114)	(0.072)	(0.087)	(0.078)	(0.081)	(0.064)	(0.045)

Linear ARDL								
	w_3	w_4	w_5	w_6	w_7	w_8	w_9	θ_0
	-0.027	-0.043	0.019	0.041	0.033	0.144***	-0.065	-0.070
	(0.038)	(0.038)	(0.038)	(0.037)	(0.038)	(0.039)	(0.040)	(0.043)
QARDL								
	w_3	w_4	w_5	w_6	w_7	w_8	w_9	θ_0
0.05	0.046	-0.111	-0.065	-0.029	0.057	0.236**	0.104*	-0.109
	(0.057)	(0.080)	(0.085)	(0.072)	(0.082)	(0.090)	(0.061)	(0.132)
0.10	0.024	-0.176**	-0.014	-0.029	0.059	0.153	0.086	-0.029
	(0.049)	(0.076)	(0.063)	(0.060)	(0.073)	(0.127)	(0.062)	(0.133)

0.20	-0.022 (0.047)	-0.058 (0.077)	0.024 (0.051)	0.012 (0.075)	0.064 (0.072)	0.111 (0.092)	0.010 (0.072)	-0.095 (0.118)
0.30	-0.009 (0.050)	-0.064 (0.061)	-0.010 (0.059)	0.044 (0.047)	0.046 (0.074)	0.118* (0.065)	-0.034 (0.058)	-0.057 (0.082)
0.40	-0.008 (0.041)	-0.058 (0.066)	0.006 (0.066)	0.046 (0.055)	-0.029 (0.068)	0.095* (0.057)	-0.108** (0.049)	-0.117 (0.082)
0.50	-0.035 (0.043)	-0.011 (0.067)	-0.054 (0.061)	0.063 (0.048)	0.027 (0.057)	0.054 (0.056)	-0.072** (0.035)	-0.086 (0.078)
0.60	-0.013 (0.048)	-0.024 (0.055)	-0.024 (0.066)	0.047 (0.045)	0.012 (0.047)	0.074 (0.054)	-0.051 (0.041)	-0.089 (0.076)
0.70	-0.040 (0.049)	-0.016 (0.059)	-0.015 (0.800)	0.074 (0.059)	0.030 (0.049)	0.073 (0.056)	-0.058 (0.050)	-0.096 (0.072)
0.80	-0.020 (0.046)	-0.010 (0.033)	0.043 (0.052)	0.048 (0.045)	-0.014 (0.052)	0.132** (0.056)	-0.058 (0.058)	-0.159* (0.093)
0.90	0.057 (0.047)	-0.002 (0.045)	-0.010 (0.057)	0.010 (0.044)	0.017 (0.065)	0.125** (0.054)	-0.054 (0.053)	-0.141 (0.100)
0.95	0.037 (0.055)	0.001 (0.049)	-0.011 (0.059)	0.008 (0.051)	0.019 (0.073)	0.123* (0.063)	-0.072 (0.052)	-0.104 (0.081)

Note: Table 4 reports the estimation results of the linear ARDL and QARDL models including WTI and heating as explanatory variables. Numbers between brackets are standard deviations. ***, ** and * indicate rejection at the 1%, 5% and 10% significance levels, respectively.

Table 5: DIESEL-WTI

	α_*	ρ_*	β_{diesel}	β_{WTI}	w_0	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	θ_0
Linear ARDL														
	0.425*	-0.013	8.297	-7.387	0.181***	0.002	-0.037	-0.032	0.005	0.046	0.019	0.031	0.115***	-0.097**
	(0.219)	(0.019)	(11.127)	(10.044)	(0.049)	(0.034)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.033)	(0.034)	(0.039)
QARDL														
0.05	-0.692	0.086*	-0.162	0.019	-0.002	0.134	-0.086	0.038	0.074	-0.048	-0.006	0.193*	0.130	-0.004
	(0.792)	(0.047)	(1.249)	(1.611)	(0.0138)	(0.004)	(0.077)	(0.081)	(0.086)	(0.083)	(0.077)	(0.098)	(0.101)	(0.128)
0.10	0.256	0.034	-5.286	4.691	0.147	-0.008	-0.058	0.025	0.006	0.038	-0.039	0.087	0.139	0.045
	(0.370)	(0.036)	(7.745)	(5.491)	(0.095)	(0053)	(0.056)	(0.074)	(0.079)	(0.085)	(0.069)	(0.099)	(0.088)	(0.100)
0.20	0.428*	0.005	-33.657	29.519	0.070	0.012	-0.114**	0.020	-0.029	0.029	-0.002	0.0003	0.173**	0.034
	(0.250	(0.034)	(244.243)	(200.477)	(0.082)	(0.060)	(0.045)	(0.049)	(0.051)	(0.083)	(0.059)	(0.067)	(0.070)	(0.073)
0.30	0.0471**	-0.010	12.647	-11.530	0.120	0.024	-0.061	-0.026	-0.010	-0.010	0.031	0.008	-0.131	-0.051
	(0.0238)	(0.034)	(46.618)	(39.470)	(0.069)	(0.058)	(0.047)	(0.053)	(0.059)	(0.078)	(0.053)	(0.065)	(0.065)	(0.072)
0.40	0.486**	-0.023	5.166	-4.198	0145**	0.039	-0.040	-0.013	0.002	0.004	0.001	0.064	0.056	-0.070
	(0.202)	(0.0119)	(7.112)	(5.983)	(0.060)	(0.043)	(0.031)	(0.047)	(0.042)	(0.079)	(0.036)	(0.055)	(0.053)	(0.079)
0.50	0.242	-0.014	4.463	-2.966	0.110*	0.053	-0.040	-0.004	-0.006	0.013	0.023	0.040	0.028	-0.078
	(0.255)	(0.030)	(9.170)	(7.397)	(0.064)	(0.047)	(0.037)	(0.046)	(0.028)	(0.059)	(0.029)	(0.045)	(0.038)	(0.083)
0.60	0.460*	-0.035	2.109	-1.648	0.137**	-0.007	-0.016	-0.034	0.012	-0.006	0.033	0.034	0.042	-0.102
	(0.267)	(0.027)	(2.004)	(1.930)	(0.066)	(0.039)	(0.035)	(0.043)	(0.032)	(0055)	(0.023)	(0.038)	(0.039)	(0.074)
0.70	0.417	-0.033	2.055	-1.504	0.155***	0.00006	-0.011	-0.014	-0.001	-0.006	0.046	0.037	0.042	-0.134*
	(0.0288)	(0.028)	(2.498)	(2.120)	(0.054)	(0.039)	(0.032)	(0.057)	(0.038)	(0.056)	(0.038)	(0.042)	(0.037)	(0.068)
0.80	0.284	-0.027	0.921	-0.631	0.151*	0.004	0.036	-0.020	0.013	-0.009	0.036	-0.001	0.050	-0.149
	(0.354)	(0.028)	(2.453)	(2.462)	(0.086)	(0.043)	(0.051)	(0.046)	(0.045)	(0.050)	(0.039)	(0.045)	(0.059)	(0101)
0.90	0.369	-0.057	-0.290	0.413	0.101	0.016	-0.035	0.027	-0.052	0.022	0.034	0.0001	0.007	-0.132*
	(0.273)	(0.025)	(0.993)	(0.960)	(0.076)	(0.056)	(0.068)	(0.052)	(0.075)	(0.048)	(0.059)	(0.054)	(0.063)	(0.078)
0.95	0.562**	-0.055**	0.504	-0.571	0.075	-0.044	-0.119	0.070	0.036	0.069	0.055	-0.014	0.095	-0.033
	(0.280)	(0.02)	(1.006)	(0.916)	(0.053)	(0.058)	(0.075)	(0.062)	(0.072)	(0.048)	(0.058)	(0.043)	(0.081)	(0.122)

Note: Table 5 reports the estimation results of the linear ARDL and QARDL models including WTI and diesel as explanatory variables. Numbers between brackets are standard deviations. ***, ** and * indicate rejection at the 1%, 5% and 10% significance levels, respectively.

Table 6: NATURAL GAS-WTI

Linear ARDL											
α_*		ρ_*	$\beta_{nat\ gas}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	w_0	w_1	w_2
0.108*** (0.040)		-0.014 (0.019)	-0.223 (0.660)	0.817 (1.120)	0.104 (0.75)	-0.088 (0.075)	0.101 (0.073)	0.129* (0.073)	0.057** (0.026)	-0.038 (0.025)	0.042* (0.025)
	α_*	ρ_*	$\beta_{nat\ gas}$	β_{WTI}	φ_1	φ_2	φ_3	φ_4	w_0	w_1	w_2
0.05	-0.371** (0.179)	0.037 (0.025)	-0.097 (0.387)	-0.222 (0.341)	0.397* (0.206)	0.013 (0.164)	0.056 (0.102)	0.148 (0.156)	0.086* (0.047)	-0.043* (0.025)	0.086* (0.047)
0.10	-0.121 (0.203)	0.010 (0.029)	0.341 (0.856)	0.793 (0.919)	0.375** (0.189)	0.083 (0.141)	0.127 (0.111)	0.285** (0.138)	0.061 (0.040)	-0.036 (0.034)	0.098 (0.050)
0.20	0.052 (0.250)	-0.021 (0.036)	0.263 (0.938)	0.660 (1.052)	0.238 (0.158)	-0.019 (0.156)	0.252** (0.105)	0.187 (0.126)	0.072 (0.046)	-0.068* (0.039)	0.063 (0.040)
0.30	0.108 (0.233)	-0.027 (0.036)	0.039 (0.560)	0.596 (0.578)	0.208 (0.136)	0.008 (0.151)	0.171 (0.128)	0.128 (0.114)	0.081* (0.045)	-0.079** (0.038)	0.013 (0.031)
0.40	0.107 (0.516)	-0.023 (0.035)	-0.072 (0.495)	0.600 (0.645)	0.169 (0.106)	-0.048 (0.115)	0.033* (0.124)	0.073 (0.107)	0.054 (0.033)	-0.057* (0.031)	0.029 (0.024)
0.50	0.053 (0.188)	-0.018 (0.030)	-0.143 (0.620)	1.116 (1.554)	0.171 (0.106)	-0.021 (0.112)	0.050 (0.116)	0.042 (0.091)	0.059 (0.035)	-0.039 (0.031)	0.028 (0.030)
0.60	0.133 (0.179)	-0.023 (0.027)	-0.496 (0.475)	0.724 (0.680)	0.006 (0.085)	-0.077 (0.114)	0.008 (0.113)	0.075 (0.085)	0.036 (0.028)	-0.048** (0.024)	0.024 (0.027)
0.70	0.161 (0.153)	-0.029 (0.022)	-0.389 (0.435)	0.738 (0.557)	-0.028 (0.071)	-0.084 (0.128)	0.003 (0.124)	0.062 (0.082)	0.031 (0.031)	-0.062** (0.026)	0.040 (0.034)
0.80	0.241* (0.142)	-0.030 (0.021)	-0.737 (0.570)	0.376 (0.383)	-0.154 (0.123)	-0.154 (0.112)	-0.057 (0.119)	-0.038 (0.095)	0.024 (0.034)	0.011 (0.030)	0.045 (0.034)
0.90	0.532*** (0.150)	-0.064*** (0.021)	-0.321 (0.233)	0.018 (0.159)	-0.134 (0.120)	-0.067 (0.122)	-0.016 (0.100)	0.006 (0.098)	0.041 (0.045)	0.027 (0.037)	0.027 (0.037)
0.95	0.0483*** (0.134)	-0.059*** (0.020)	-0.275 (0.190)	0.084 (0.146)	-0.160 (0.099)	-0.180* (0.102)	0.083 (0.099)	-0.080 (0.112)	0.011 (0.048)	0.012 (0.030)	0.039 (0.036)

Linear ARDL									
θ_0		θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
0.029 (0.038)		0.016 (0.040)	-0.046 (0.040)	-0.028 (0.038)	-0.026 (0.039)	-0.033 (0.038)	0.029 (0.040)	0.041 (0.040)	0.108*** (0.040)
QARDL									
	θ_0	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	θ_7	θ_8
0.05	0.021 (0.078)	-0.011 (0.097)	-0.039 (0.067)	0.119 (0.078)	-0.143* (0.073)	0.031 (0.083)	0.003 (0.057)	0.059 (0.074)	0.108* (0.071)
0.10	0.050 (0.058)	-0.005 (0.074)	-0.125** (0.062)	0.085 (0.077)	-0.130 (0.084)	0.053 (0.083)	0.016 (0.051)	0.084 (0.054)	0.064 (0.080)
0.20	0.062	-0.026	-0.077	-0.018	-0.128	-0.003	0.008	0.023	0.090

	(0.054)	(0.072)	(0.060)	(0..075)	(0.082)	(0.089)	(0.071)	(0.063)	(0.059)
0.30	0.038 (0.054)	0.017 (0.061)	-0.032 (0.050)	-0.073 (0.052)	-0.036 (0.078)	-0.036 (0.087)	0.040 (0.064)	0.001 (0.046)	0.120* (0.072)
0.40	0.033 (0.054)	0.014 (0.055)	-0.050 (0.042)	-0.023 (0.040)	-0.002 (0.058)	-0.097 (0.086)	0.050 (0.059)	0.013 (0.07)	0.072 (0.068)
0.50	0.042 (0.059)	0.013 (0.042)	-0.050 (0.045)	-0.009 (0.046)	0.001 (0.056)	-0.118* (0.066)	0.061 (0.058)	0.035 (0.041)	0.065 (0.070)
0.60	0.048 (0.048)	0.001 (0.039)	-0.062 (0.041)	0.004 (0.054)	0.020 (0.046)	-0.064 (0.045)	0.082 (0.042)	0.023 (0.047)	0.060 (0.067)
0.70	0.015 (0.051)	-0.002 (0.044)	-0.050 (0.043)	0.018 (0.071)	0.011 (0.059)	-0.061 (0.042)	0.080 (0.063)	0.031 (0.049)	0.064 (0.048)
0.80	-0.017 (0.049)	-0.011 (0.046)	-0.005 (0.066)	-0.006 (0.056)	0.008 (0.051)	-0.006 (0.055)	0.035 (0.060)	0.046 (0.057)	0.025 (0.053)
0.90	-0.063 (0.046)	0.016 (0.051)	-0.058 (0.068)	0.043 (0.036)	-0.010 (0.070)	-0.027 (0.047)	0.061 (0.048)	0.026 (0.050)	0.049 (0.064)
0.95	-0.060 (0.051)	0.027 (0.057)	-0.049 (0.068)	0.060 (0.043)	0.030 (0.068)	-0.056 (0.052)	0.032 (0.039)	0.033 (0.051)	0.052 (0.064)

Note: Table 6 reports the estimation results of the linear ARDL and QARDL models including WTI and natural gas as explanatory variables. Numbers between brackets are standard deviations. ***, ** and * indicate rejection at the 1%, 5% and 10% significance levels, respectively.

Table 7: WALD Tests

SP-WTI		SP-GASOLINE-WTI		SP-HEATING-WTI		SP-DIESEL-WTI		SP-NATGAS-WTI	
ρ_*	6.040*** [0.000]	ρ_*	3.360*** [0.000]	ρ_*	2.060** [0.030]	ρ_*	5.960*** [0.000]	ρ_*	3.280*** [0.000]
β_{WTI}	0.800 [0.627]	$\beta_{GASOLINE}$	0.260 [0.989]	$\beta_{HEATING}$	0.400 [0.945]	β_{DIESEL}	0.890 [0.544]	β_{NATGAS}	0.150 [0.999]
φ_1	3.750*** [0.000]	β_{WTI}	0.180 [0.997]	β_{WTI}	0.350 [0.964]	β_{WTI}	0.270 [0.987]	β_{WTI}	0.870 [0.567]
θ_0	1.720* [0.080]	φ_1	3.690*** [0.000]	φ_1	3.230*** [0.001]	φ_8	3.690*** [0.000]	φ_1	8.220*** [0.000]
θ_3	2.070** [0.029]	w_0	1.050 [0.404]	φ_2	3.520 [0.000]	θ_0	2.210** [0.019]	φ_3	1.970** [0.040]
θ_4	1.850* [0.055]	θ_0	1.740* [0.075]	w_4	2.230** [0.018]			θ_4	4.210** [0.000]
θ_6	3.090*** [0.001]	θ_1	1.660* [0.094]	w_5	3.230*** [0.001]			θ_5	2.080** [0.028]
θ_7	2.180** [0.021]	θ_3	2.290** [0.015]	w_7	5.540*** [0.000]				
		θ_8	2.080** [0.028]	w_8	1.850* [0.056]				
				w_9	1.660* [0.094]				

Note: This table reports the results of the Wald test of parameter constancy across the quantiles 0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, 0.95. p-values are between [ ]. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. Only parameters for which the null of parameters constancy is rejected are reported in the table.

Figures of long-run parameters & cumulative short-run parameters

Firgure-1: S&P 500 – WTI crude oil

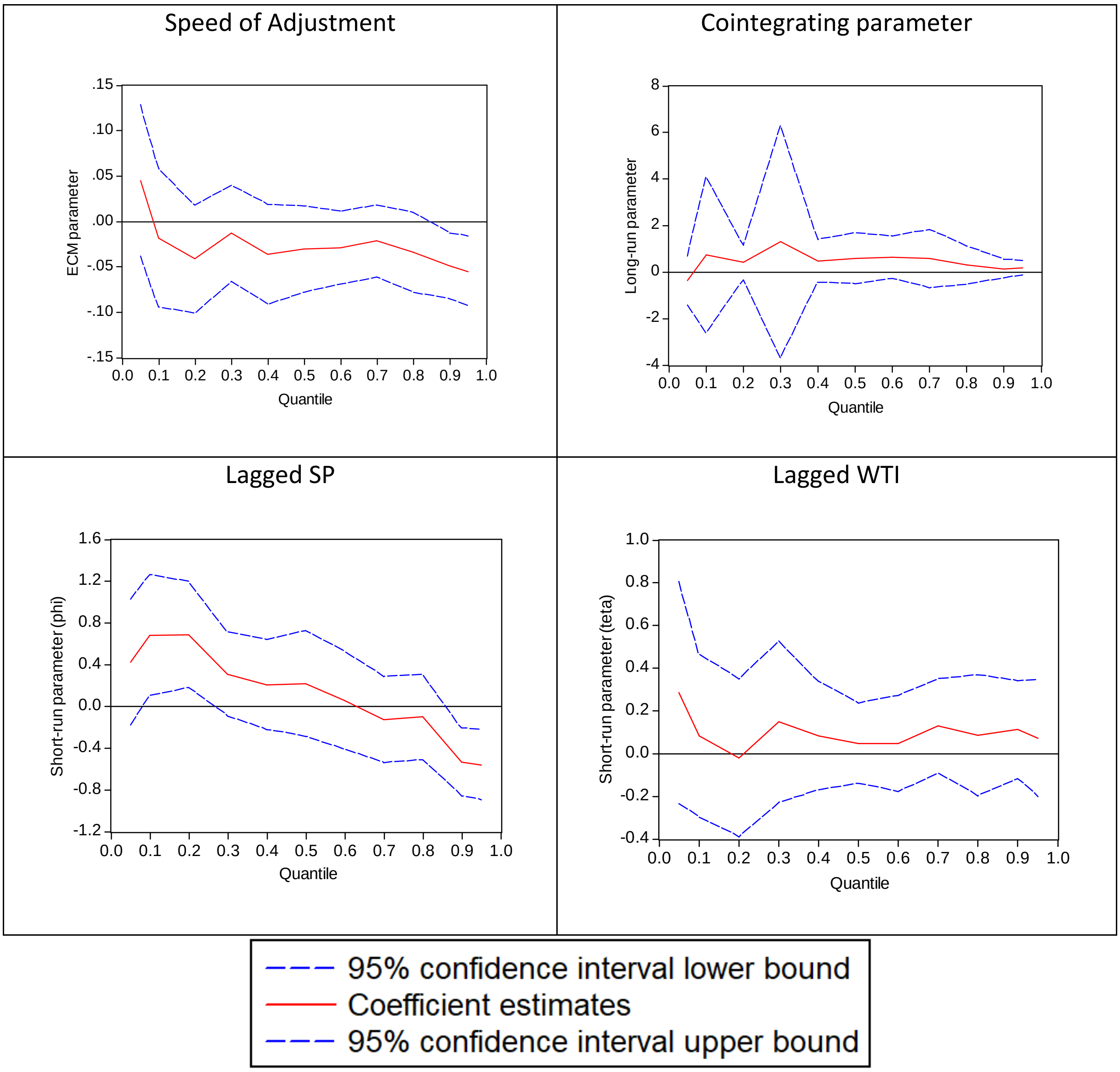

Figure-2: S&P 500-Gasoline-WTI

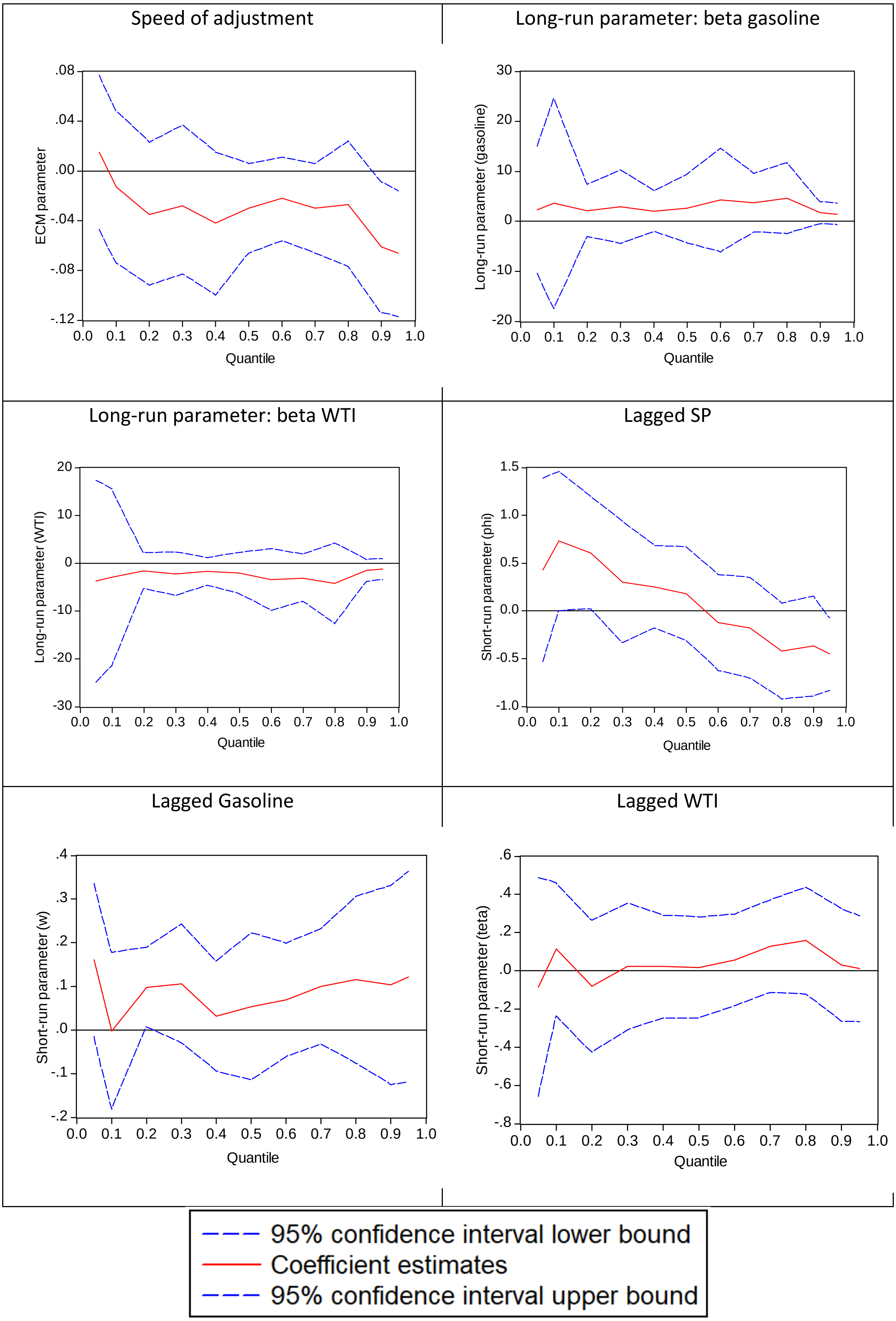

Figure-3: S&P 500-heating-WTI

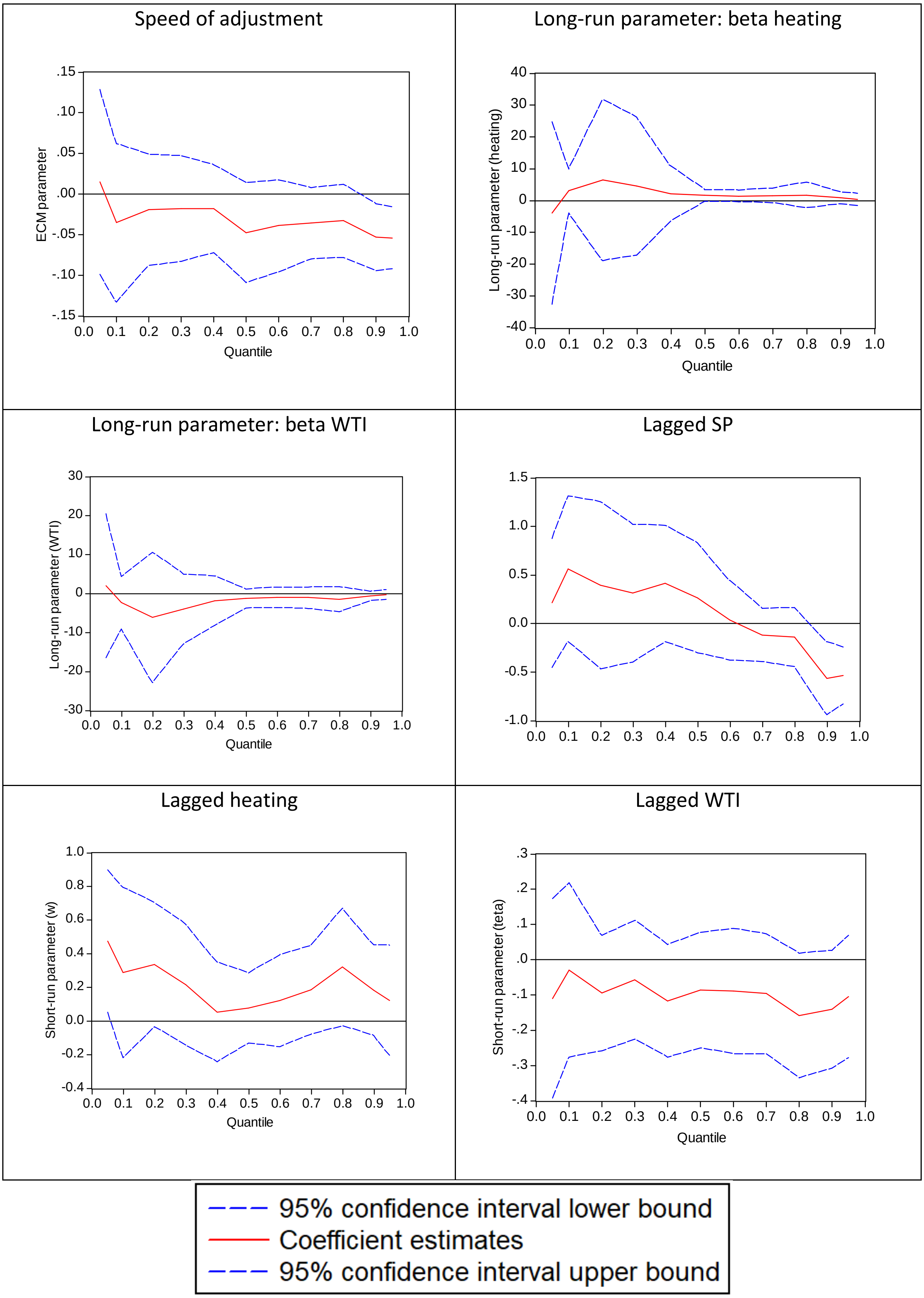

Figure-4: SP&500-diesel-WTI

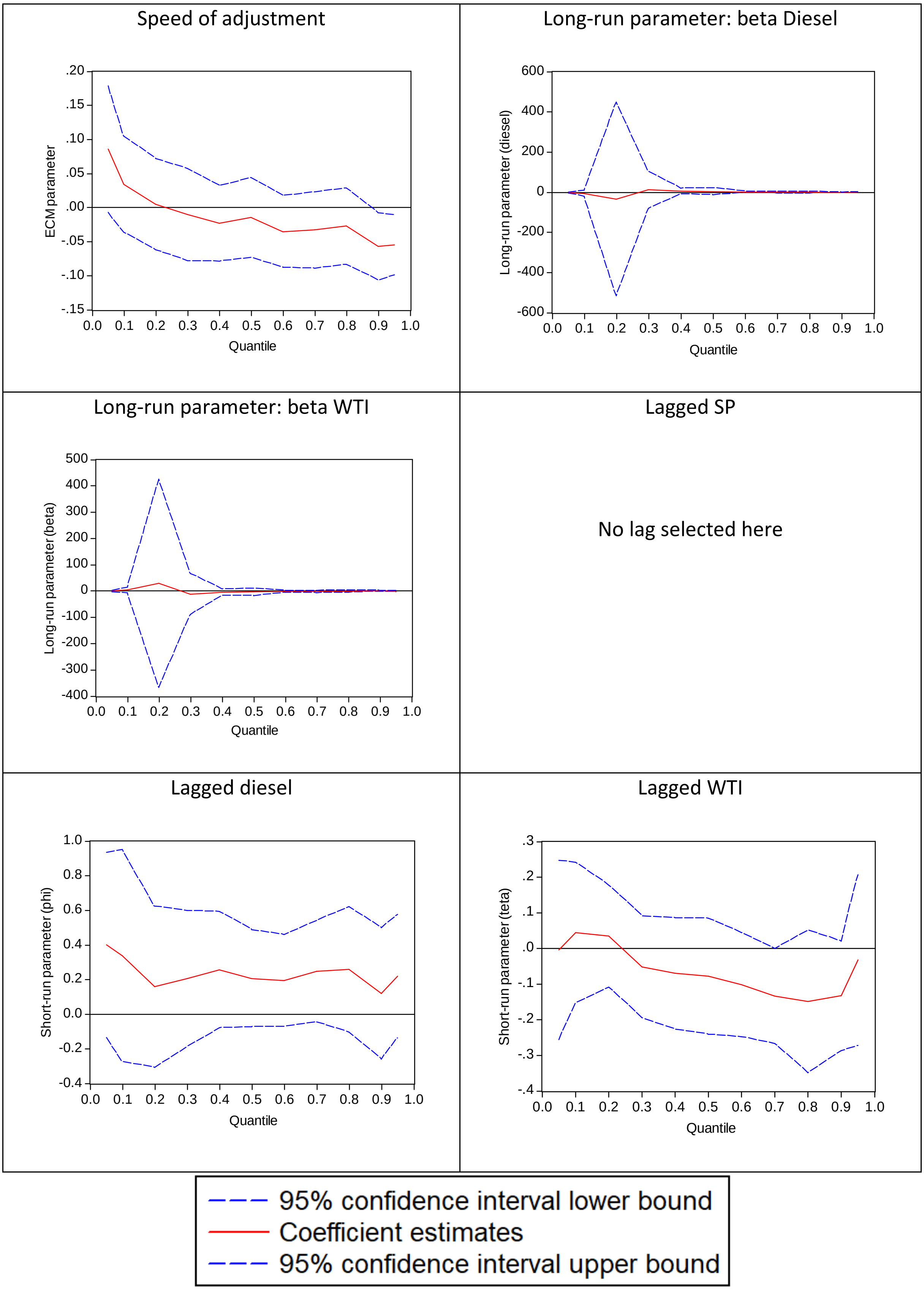

Figure-5: SP&500-Natural Gas-WTI