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ASYMMETRIES, OUTLIERS AND STRUCTURAL STABILITY IN THE US GASOLINE MARKET

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Abstract

By using a recently developed nonlinear cointegration methodology, and a sample that encompasses more than thirty years of monthly data, we investigate whether the transmission of crude oil price variations to gasoline prices in the US market is asymmetric, i.e., depends on the sign of the change in the explanatory variable, considering both the long- and in the short-run. The model is further extended by taking separately into account the effects of extreme and mild changes in crude oil prices. This allows us to verify whether and to what extent the size and shape of any observed asymmetry in pricing is affected by the presence of outliers. Moreover, given the substantial length of the sample considered, we test for the possible presence of multiple structural breaks of unknown timing in the cointegrating vector. Our results indicate that the relationship between the prices of gasoline and crude oil has undergone a single structural break in the late 2008, and that after the break extreme observations have a non-negligible role in shaping asymmetry.

JEL classification: C22, D43, D82, E31, L71, Q41.

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1 Introduction

Asymmetric gasoline price adjustment in response to crude oil price changes has been a controversial subject in the scientific literature and public debate. Most analyses have focused on the US market (e.g. Balke *et al*., 1998, Borenstein *et al*., 1997, Honarvar, 2009, Kaufmann and Laskowski, 2005), due among other things to its relative size and to the weight of fossil fuels in the US consumption basket. Energy Information Administration data (EIA, 2015a) indicates that the US averaged over 40% of total world gasoline consumption in the last decade; according to the Bureau of Economic Analysis, the average share of gasoline and other motor fuels in total US expenditure on goods was 9.3% (BEA, 2015); according to the Bureau of Labor Statistics, the relative importance of gasoline in the CPI index was 4.5% (BLS, 2015).

Asymmetric pass-through of crude oil price changes to gasoline prices has been confirmed by a large majority of studies, thus becoming almost a stylized fact (Perdiguero-García, 2013). However, some recent studies find mixed support for asymmetry, typically suggesting that the asymmetric behaviour observed may be a statistical artefact resulting from a relatively small number of exceptional events, while in normal times gasoline pricing behaviour is roughly symmetric. In particular, Douglas (2010) claims that the observed asymmetry may be a spurious phenomenon, caused by the impact of extreme variations in crude oil prices. According to his study, once outlying observations are correctly dealt with, the pass-through to gasoline prices appears to be symmetric. Fosten (2012) presents evidence showing that asymmetric pricing behaviour only emerged after the strong exogenous shock of 2008. In a similar vein, Zhang *et al*. (2015) find that after accounting for structural breaks in long-run parameters, the relation is "almost symmetric".

A common feature of these studies is that they do not allow for asymmetries in the long-run coefficients of the estimated models. Moreover, while the issues they consider are distinct (possible dependency of price response on shock size, and structural stability of model parameters), they are interrelated. Their results are therefore conditional on the validity of untested assumptions, which may lead to biased results. For instance, ruling out asymmetries in long-run coefficients amounts to assuming that asymmetry is an intrinsically short-run feature of the process of adjustment to an exogenous shock, thus implicitly defining an untested constraint on model long-run parameters. Along the same lines, observed outliers may depend on structural shifts in estimated parameters, which will not be apparent if one imposes the untested constraint of parameter constancy.

In order to cope with this possible shortcoming, we address the empirical issue of pricing asymmetries in a comprehensive modelling framework, which takes into account the possibility of long-run asymmetries, dependence of the response on shock size, and the structural stability of the estimated equation. We build on the recent study by Atil *et al*. (2014), who analysed gasoline pricing asymmetries using a nonlinear autoregressive distributed lag model (NARDL), allowing for the possibility of asymmetries in the long-run parameters, and extend it along the lines suggested by

Greenwood-Nimmo *et al.* (2011), whose threshold-ARDL (TARDL) model allows for an unknown number of multiple regimes. This allows us to consider any possible dependence of the gasoline price response to crude price shocks exceeding endogenously determined thresholds, and hence to deal with the outlier issue stressed by Douglas (2010). The estimated equations are tested for multiple structural breaks at unknown dates, using the method proposed by Bai and Perron (1998, 2003). This allows us to determine whether any evidence of asymmetric adjustment may depend on ignoring structural breaks in the equation's parameters (as put forward by Fosten, 2012 or Zhang *et al*., 2015).

The paper is organised as follows. Section 2 provides a review of the literature focused on recent contributions regarding the US fuels market. The method used in this study is described in Section 3. The main results of our analysis are reported in Section 4 and discussed in Section 5, which also includes a series of robustness checks. The conclusions are drawn in Section 6.

2 An overview of the recent literature

Previous studies on asymmetric pricing in the fossil fuels markets have produced mixed results, though most of them indicate that adjustment of gasoline price to cost shocks is indeed asymmetric; see, for instance, the summaries contained in Wlazlowski *et al*. (2008), Clerides (2010), Polemis (2012), Perdiguero-García (2013) and Kristoufek and Lunackova (2015).

Among recent studies regarding the US market, Atil *et al*. (2014) apply the NARDL model (Shin *et al*., 2014) to estimate short- and long-run effects of variations in the price of crude oil on gasoline and natural gas prices. Using monthly data over a sample ranging from January 1997 to September 2012, they find no statistical evidence of long-run asymmetry in the response of gasoline price to crude oil price shocks. Regarding the short-run response, they find that negative crude oil variations have a greater impact on gasoline prices than positive ones. In short, their result is an indication of *negative short-run asymmetry*: the impact of a negative change in crude oil price is almost twice that of a positive variation (1.32 and 0.74, respectively). A broadly similar result was previously obtained by Adilov and Samavati (2009) using a different modelling approach. They found that although no asymmetric price adjustment can be observed for the average US gasoline price, the situation is heterogeneous across its various states, with negative asymmetry occurring in about one third of cases.

Contrary to most consumers' intuition, negative asymmetries in pricing are frequently observed (Dhyne *et al*., 2005) and have theoretical foundations (e.g. Ellingsen *et al*., 2006; Dhyne *et al*., 2011). The intuition is that in the presence of menu costs, if inflation is thriving, firms will not react to a negative shock to their costs by adjusting prices, because competitors' prices will drift upwards relatively quickly. In this way, the danger of predatory pricing policies is averted. On the other hand, if inflation is low, the firm will react more quickly to negative than to positive shocks to its costs in order to maintain its market share.

The theoretical and empirical literature stresses the fact that price adjustment may be size-dependent (Ball and Mankiw, 1995). However, the standard NARDL model only considers two regimes (defined by positive and negative changes in the explanatory variable), and as such it does not allow the effect of extreme observations to be taken into account. Pal and Mitra (2015) improve this approach by considering multiple-threshold NARDL models. The thresholds are determined by quintiles and deciles in the distribution of the explanatory variable, thereby defining five and ten regimes, respectively, each containing an equal proportion of observations. They find *positive long-run asymmetry* to large cost shocks, whereas the response to smaller ones is almost symmetric, especially in the five-regime NARDL model.[1] The picture that emerges once extreme observations are dealt with therefore differs from that of Atil *et al*. (2014).[2] However, while improving on the latter's methodology, Pal and Mitra's (2015) study suffers from two possibly related shortcomings: firstly, thresholds are determined arbitrarily and no formal testing is performed to assess the best number of regimes for data fit; secondly, estimates of single coefficients are generally statistically insignificant, suggesting overparameterisation (especially in the ten-regimes model). Moreover, while they report "overall" asymmetry tests, i.e. they test whether *all* coefficients are equal, no *pairwise* tests (symmetry tests for positive and negative shocks of comparable size, i.e. within a given regime) are reported. This is an important weakness of their analysis, since for instance the overall test could lead to rejection of the null hypothesis even when only a single coefficient is statistically different from the others, i.e. even when substantial symmetry prevails across most regimes.

Douglas (2010) deals with the issue of the arbitrary determination of thresholds using Tsay's (1989) method to estimate a threshold autoregressive error correction model (TAR-ECM) that allows endogenous determination of thresholds by looking at the deviation of gasoline price from its long-term equilibrium.[3] Each extreme regime contains on average nearly 7% of all available observations, so that the two inner regimes account for almost 86% of observations. Douglas computes the cumulative response function of a 10 cent positive and negative variation in the upstream price and finds that the difference in the predicted responses is not statistically significant. He then repeats the exercise with variations of ±25 cents: in this case, the retail price increase is significantly greater than the decrease. He also finds that prices adjust more rapidly and more asymmetrically in the extreme regimes, i.e. far from equilibrium. In short, Douglas (2010) finds *positive short-run asymmetry* but only to large crude price changes. He then estimates a standard two-regime model (where the single threshold is set at zero) and obtains a positively asymmetric price adjustment, i.e. the price of retail gasoline responds more strongly to cost increases than decreases. Douglas's conclusion is that in "normal" circumstances the adjustment to crude price is symmetric, and that the evidence of asymmetry found in estimating standard models (i.e. models that do not account properly for the existence of outliers) is driven by a relatively small number of outlying observations.

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[1] Pal and Mitra (2015) estimate their models using price levels and do not report the estimated elasticities. We calculate the implied elasticities, as explained below.

[2] This difference may also depend on the different frequency of the data (weekly vs. monthly), as well as on inclusion of an additional control variable (volume of petroleum products).

[3] The estimated thresholds define the following regimes: $(-\infty; -14.21]$, $(-14.21; 1.94]$, $(1.94; 13.10]$ and $(13.10; \infty)$. These regimes indicate when retail price-cost margins are very low, moderately low, moderately high, and very high, respectively. It should be noted that the central threshold does not coincide with zero.

A potential weakness of Douglas's study is that estimation of the TAR-ECM is conditional on a single linear cointegration vector, thus ruling out any asymmetric long-run response. Consequently, its results may be biased whenever the implied assumption of long-run symmetry is violated by the data generating process (DGP). Nevertheless, it has the merit of stressing the role of outliers, which can be expected to be crucial in a market subject to many exogenous shocks due to events ranging from conflicts to natural disasters in oil exporting countries.[4]

Such episodes may leave the model structure unaffected, possibly leading to one or more outlying observations, or they may have permanent effects in the long-run relationship between the variables, inducing a structural break either in the DGP of the observed time series, or in the long-run parameters of the estimated equation (an issue neglected by Douglas, 2010). Atil *et al*. (2014) test the data for segmented trends and do not find evidence of structural breaks in their DGP.[5] However, as shown for instance by Gregory and Hansen (1996), the absence of breaks in the variables does not imply the absence of breaks in the estimated regression parameters. As far as the focus of our study is concerned, a change in the shape of any asymmetry is therefore not ruled out.

The issue of structural breaks in regression parameters is tackled in three further studies. Oladunjoye (2008) uses the Andrews (1993) test for structural changes with unknown change point on an asymmetric ECM (ASECM) model, and finds structural breaks in three major wholesale gasoline markets. He interprets these breaks as the results of mergers, acquisitions and joint ventures occurring between 1997 and 2002.[6] However, Andrew's (1993) test does not envisage the possibility of multiple breaks or breaks in the long-run parameters of the model. The latter feature is taken into account by Fosten (2012), who estimates a threshold vector ECM (TVECM) on a sample running from 1997:01-2012:06. He then splits his sample according to the results of segmented trend tests on the model variables, and estimates pre- and post-break models, finding that asymmetries only emerge in the post-break sample. However, the sample split does not follow from formal structural break tests on the model parameters but from indirect evidence of the properties of the univariate DGP, as in Atil *et al*. (2014) and Honarvar (2009). Formal econometric testing for structural breaks in the long-run relationship is performed by Zhang *et al*. (2015) using the Gregory and Hansen (1996) test. They find that cointegration between gasoline price and crude oil price underwent a regime shift in 2007-2008. Once this shift is taken into account, the estimated relation looks "almost symmetric", which they regard as evidence that "asymmetry is just caused by some outliers and rare exogenous shocks", a conclusion similar to that of Douglas (2010).

In our study we propose a unified approach. Starting with a NARDL model, as in Atil *et al*. (2014), we consider a number of additional regimes, as in Pal and Mitra

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[4] A brief history of the evolution of oil prices during 1947-2000 can be found in Adelman (2002); historical oil shocks since 1850s are discussed in Hamilton (2011).

[5] A similar conclusion is reached by Honarvar (2009), although through indirect evidence. He tests for unit roots in the prices of gasoline and crude oil in the full 1981:06/2007:12 sample and in two subsamples. Since the unit root tests give the same results in all cases, he concludes that a regime shift in the time series's DGP is irrelevant.

[6] Oladunjoye (2008) uses this *a priori* information to restrict his analysis to a specific subsample (January 1, 1997 and December 31, 2002) corresponding to just 34% of the available observations,

(2015), but as do Greenwood-Nimmo *et al*. (2011), we determine the number of regimes and the thresholds on the basis of statistical evidence using a sample-splitting approach proposed by Hansen (1999). The preferred specification is then tested for multiple structural breaks using the method proposed by Bai and Perron (1998, 2003). This allows us to assess any price asymmetries and their shape in a context where the role of extreme observations and structural breaks is taken into account by letting the data speak for itself, without conditioning on the location of thresholds and structural breaks, or on the number of regimes. We now present the data and describe our modelling approach.

3 Material and methods

3.1 Data

We use monthly data on gasoline and crude oil prices from January 1983 to December 2015. The price of gasoline (US dollars per gallon, excluding taxes) is the EMA_EPM0_PTA_NUS_DPG series available in EIA (2015b) from January 1983 to February 2011.[7] After February 2011 it is updated with the retail price series (excluding taxes) available in EIA (2015c). The price of crude oil is IMF's West Texas Intermediate (POILWTI) series expressed in current US dollars per barrel (IMF, 2015). Previous research (e.g. Kilian, 2010) shows that monthly data may hide asymmetries. However, as weekly pre-tax gasoline prices for the US market are only available since 1990, we opted for monthly data so as to include the "great price collapse" of 1986 in our sample (Hamilton, 2011).[8]

The data is represented in Figure 1 and descriptive statistics are reported in Table 1 along with the integration tests, carried out on the log of the variables and their first differences. The distribution of both series is negatively skewed, with a fairly large occurrence of outliers (as shown by excess kurtosis). Interestingly, the (negative) skewness coefficient is larger for gasoline than for crude oil price, suggesting that on average the former may overreact to negative changes in the latter. The unit root tests show that both series are generated by $I(1)$ processes.

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[7] Since data for 1988 is missing, for that year we used the EMA_EPM0_PTR_NUS_DPG series ("U.S. Total Gasoline Through Company Outlets Price by Refiners").

[8] In February 1986, crude price dropped by -32.6%, the largest drop since WWII.

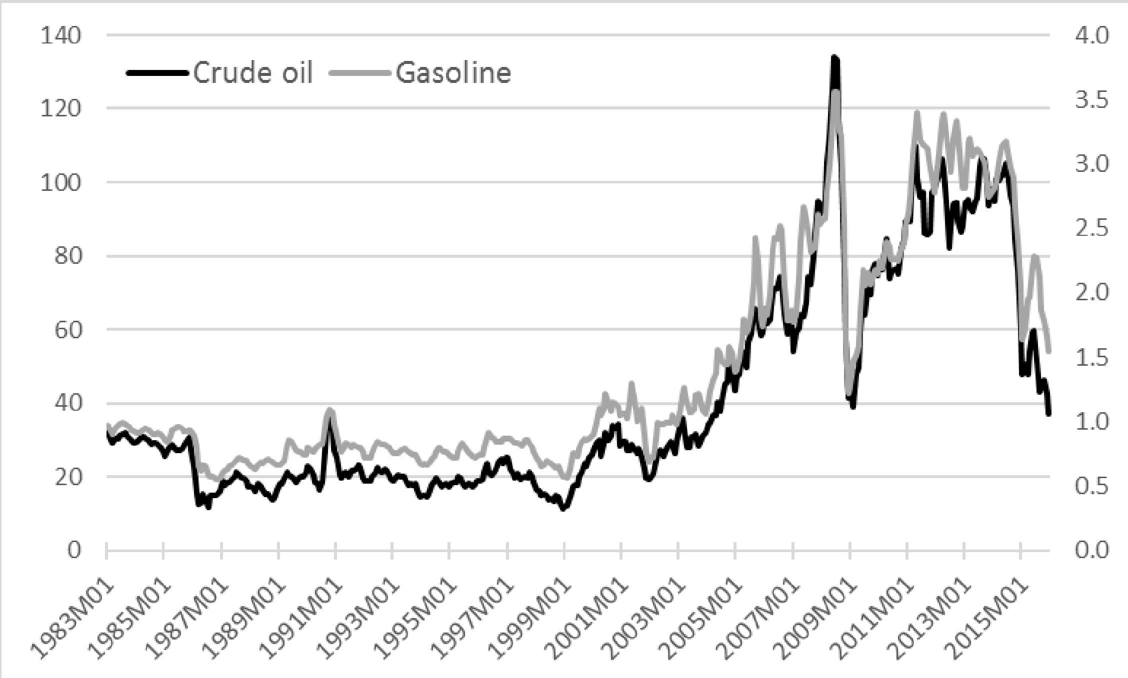

Figure 1 – Prices of crude oil (US dollars per barrel) and gasoline (US dollars per gallon; right-hand axis).

Table 1 – Descriptive statistics and test of integration, 1983:1-2015:12.

	Crude oil	**Gasoline**
Descriptive statistics		
Mean	0.000	0.001
1st quartile	-0.046	-0.026
Median	0.008	-0.001
3rd quartile	0.050	0.037
Minimum	-0.395	-0.455
Maximum	0.391	0.186
Std. deviation	0.084	0.067
Skewness	-0.436	-1.104
Kurtosis	6.015	9.722
Mean absolute deviation	0.062	0.045
Integration test (log-level)		
ADF	-1.79 (0.38)	-1.48 (0.53)
PP	-1.60 (0.48)	-1.24 (0.65)
Integration test (log-differences)		
ADF	-14.31 (0.00)	-13.97 (0.00)
PP	-13.79 (0.00)	-10.80 (0.00)

Notes: Descriptive statistics refer to price changes calculated as logarithmic differences. Integration tests were calculated on the level and on the first differences of the variables in logs; *p*-values in brackets; the number of lags in the ADF tests was automatically selected using the Schwartz Information criterion starting from 16 lags.

3.2 Modelling short- and long-run asymmetry

We take the standard auto-regressive distributed-lag (ARDL) model (Pesaran and Shin, 1999) as benchmark against which to test for asymmetries. We consider the following specification:

$$\Delta g_t = \alpha + \rho g_{t-1} + \theta c_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta g_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta c_{t-j} + \varepsilon_t \qquad \textbf{(1)}$$

where g_t is the retail pre-tax price of gasoline, c_t the crude oil price (both expressed in current US dollars and as logarithms), ρ the feedback coefficient (expected to be negative), γ_j and π_j short-run coefficients (π_0 is the impact elasticity of gasoline price to crude oil price variations), and

$$\beta = -\theta / \rho \qquad \textbf{(2)}$$

is the long-run multiplier.[9] The existence of a meaningful long-run relationship can be tested through the *t_BDM* statistic (that tests for the significance of the feedback coefficient), and the *F_PSS* statistic (that tests for the joint significance of the variables in level), using the "bounds testing" approach by Pesaran *et al*. (2001).[10]

In Eq. (1) the dependent variable responds in the same way to increases and decreases in the explanatory variable, i.e. the adjustment is symmetric. The nonlinear ARDL (NARDL) by Shin *et al*. (2014) allows for asymmetric adjustment by using partial sum processes of positive and negative changes. In our case, this approach leads to the following formulation

$$\Delta g_t = \alpha + \rho g_{t-1} + \theta^+ c_{t-1}^+ + \theta^- c_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta g_{t-j} + \sum_{j=0}^{q-1} \left(\pi_j^+ \Delta c_{t-j}^+ + \pi_j^- \Delta c_{t-j}^- \right) + \varepsilon_t \qquad \textbf{(3)}$$

where the superscripts "+" and "–" indicate positive and negative changes in the variables, respectively, and the explanatory variables are expressed as partial sum processes of positive and negative changes, respectively:

[9] By gathering the terms in level and using the definition of long-run multiplier in Eq. (2), Eq. (1) can be expressed in the usual ECM form: $\Delta g_t = \alpha + \rho \left(g_{t-1} - \beta c_{t-1} \right) + \sum_{j=1}^{p-1} \gamma_j \Delta g_{t-j} + \sum_{j=0}^{q-1} \pi_j \Delta c_{t-j} + \varepsilon_t$.

[10] The "bounds test" procedure aims at establishing the existence of a meaningful long-run relationship between variables, irrespective of whether they are $I(1)$ or $I(0)$. In principle, the existence of such a relation does not imply cointegration, as the latter usually requires that all the variables be $I(1)$ and one linear combination of them be $I(0)$ (here we abstract from the literature on higher-order and mixed-order cointegration; Stock and Watson, 1993). Since in our case both variables are $I(1)$, *t_BDM* and *F_PSS* can be construed as cointegration tests, and if they reject the null hypothesis of no long-run relationship, we can conclude that a cointegrating relationship exists.

$$c_t^+ = \sum_{j=1}^{t} \Delta c_j^+ = \sum_{j=1}^{t} \max\left(\Delta c_j, 0\right)$$

$$c_t^- = \sum_{j=1}^{t} \Delta c_j^- = \sum_{j=1}^{t} \min\left(\Delta c_j, 0\right)$$

Model (3) features two long-run elasticities, one in response to positive shocks, β^+, and the other to negative shocks, β^-, defined as follows:

$$\beta^+ = -\theta^+ / \rho, \beta^- = -\theta^- / \rho \qquad \textbf{(4)}$$

Long-run symmetry occurs when $\beta^+ = \beta^-$, whereas impact symmetry requires that $\pi_0^+ = \pi_0^-$, and short-run symmetry exists when $\sum_{j=0}^{q-1} \pi_j^+ = \sum_{j=0}^{q-1} \pi_j^-$ (Brun Aguerre *et al*. 2013).

A few remarks are needed to relate this approach to the existing literature. Firstly, for q=1, impact and short-run symmetry coincide (as we shall see later, this is what occurs in our estimates, which will allow us to refer interchangeably to "impact" and "short-run" asymmetry). Secondly, the well-known "rocket and feathers" effect corresponds basically to a violation of impact symmetry, with $\pi_0^+ > \pi_0^-$, under the (implicit) assumption that the long-run multipliers be equal for positive and negative shocks, i.e. that $\beta^+ = \beta^- = \beta$ (long-run symmetry, corresponding to the existence of a single cointegrating relationship, valid under both positive and negative shocks). By relaxing this assumption, Eq. (3) provides a more general representation. Thirdly, in the NARDL model the dependent variable is not decomposed into partial sums of positive and negative changes. Therefore the model does not feature a different feedback coefficient for positive and negative shocks (say, ρ^+ and ρ^-), as in the threshold cointegration models (e.g. Chenn *et al*., 2005; Douglas, 2010), and does not distinguish between positive and negative changes in the lagged dependent variable, as in Borenstein *et al*. (1997). In principle, therefore, the NARDL model provides a less general representation of the adjustment process in response to a persistent shock, by excluding a potential source of asymmetry in the adjustment mechanism.[11] However, this limitation may be less severe than it appears, especially if evaluated against the flexibility provided by considering asymmetric multipliers.[12]

[11] We are grateful to an anonymous referee for this remark.

[12] The empirical results shown below confirm that the model can represent a very diversified range of adjustment paths even with a limited number of parameters (see Figure 2). We can obtain an intuitive explanation of how this is possible by looking at the simplest error correction specification, $\Delta g_t = \alpha + \pi_0 \Delta c_t + \rho\left(g_{t-1} - \beta c_{t-1}\right) + \varepsilon_t$. The mean lag of adjustment in this model is $l = -\left(\beta - \pi_0\right)/\left(\rho\beta\right)$. In the NARDL specification two out of three parameters involved (π_0 and β) change according to the sign of the shock, which provides a fairly large degree of flexibility in describing the respective adjustment processes. By way of comparison, also in threshold cointegration models two out of three parameters (π_0 and ρ) are allowed to change. The difference between the two approaches can be summarized as follows: in threshold cointegration models the long-run responses to a persistent positive or negative shock

3.3 Modelling the role of extreme observations

3.3.1 Defining the thresholds

The standard NARDL model considers only two regimes, corresponding to positive and negative changes in the explanatory variable c_t, thus implicitly defining a single threshold at zero. Greenwood-Nimmo *et al.* (2011) generalize the model in order to include R regimes, defined by $R-1$ thresholds, as follows:

$$\Delta g_t = \alpha + \rho g_{t-1} + \sum_{r=1}^{R} \theta^i c_{t-1}^r + \sum_{j=1}^{p-1} \gamma_j \Delta g_{t-j} + \sum_{r=1}^{R} \sum_{j=0}^{q-1} \pi_j^i \Delta c_{t-j}^r + \varepsilon_t \qquad \textbf{(5)}$$

where π_j^i and θ^i are the short- and long-run coefficients in the r-th regime (r = 1, ..., R), respectively, and the explanatory variables are defined as partial sums

$$c_t^1 = \sum_{j=1}^{t} \Delta c_j^1 = \sum_{j=1}^{t} \Delta c_j I\left(\Delta c_j \le \Delta \hat{c}^1\right)$$

$$c_t^r = \sum_{j=1}^{t} \Delta c_j^r = \sum_{j=1}^{t} \Delta c_j I\left(\Delta \hat{c}^{r-1} < \Delta c_j < \Delta \hat{c}^r\right) \text{ for } r = 2, \dots, R-1$$

$$c_t^R = \sum_{j=1}^{t} \Delta c_j^R = \sum_{j=1}^{t} \Delta c_j I\left(\Delta c_j \ge \Delta \hat{c}^{R-1}\right)$$

where $\Delta \hat{c}^r$ represents a generic bound value for $r = 1, \dots, R-1$, and $I(.)$ is the indicator function. The r-th regime long-run elasticity can be obtained as:

$$\beta^r = -\theta^r / \rho \qquad \textbf{(6)}$$

Equation (5) defines the threshold-ARDL or TARDL-n model, where $n = R - 1$ indicates the number of thresholds.

The $\Delta \hat{c}^r$ thresholds can be chosen in several ways, conditionally on a choice of some function of Δc. A possible approach uses the quantiles of Δc (see e.g. Greenwood-Nimmo *et al.*, 2011, Verheyen, 2013, and Pal and Mitra, 2015). An alternative method consists in exploiting the variance of Δc (see e.g. Fedoseeva and Werner, 2015). We use the latter strategy and define our thresholds as $\pm k_n \cdot \sigma$, where σ is the standard deviation of Δc, $k_1 = 0$, and k_n (n = 2, 3,...) are real-valued parameters, chosen by minimizing the sum of squared residuals (SSR) of the model by grid search. There are two reasons for this choice. On one hand, when $n = 1$ we obtain the TARDL-1 model, equivalent to the

converge to the same value β (long-run symmetry), possibly through different ("asymmetric") paths, whereas in NARDL models they converge to different values β^+ and β^- (long-run asymmetry), necessarily through different adjustment paths.

standard NARDL model estimated by Atil *et al*. (2014).[13] On the other hand, for n = 2, 3, … , each threshold in absolute value generates two specular regimes, bounded by $-k_n \cdot \sigma$ and $+k_n \cdot \sigma$.[14] This modelling choice allows us to separately analyse the impact of shocks of different sizes in each positive or negative regime.[15] Given the sequential bipartition of negative and positive regimes operated by each new threshold, the intuitiveness of the regimes thus obtained allows us to indicate them using increasing "+" and "–" subscripts: "+" and "–" indicate positive and negative regimes in the TARDL-1 model, respectively; "++" and "– –" indicate the two additional extreme regimes in the TARDL-2 model; "+++" and "– – –" two further external regimes in the TARDL-3 model; and so on.

When no ambiguity arises, each specular decomposition created by the thresholds will allow us to refer to regimes in relation to the scale of positive and negative changes occurring in each partition. For instance, in the text we will refer to "extreme regime" the bipartition that contains both the most extreme positive and negative changes (i.e., extreme-positive and extreme negative regimes) in the TARDL-2 model, and consequently we will refer to "mild regime" the bipartition with the relatively small positive and negative changes.

3.3.2 Deriving the number of regimes

While most of the previous studies dealing with multiple regimes were conditional on an *a priori* number of regimes,[16] following Greenwood-Nimmo *et al.* (2011) we test for the number of regimes using a method outlined by Hansen (1999). The null hypothesis of n vs. $n-1$ thresholds is tested using the following statistic:

$$F_n = \frac{S_{n-1} - S_n}{\hat{\sigma}_n^2}$$

where S_{n-1} and S_n are, respectively, the sum of squared residuals of the model with $n-1$ and n thresholds, and $\hat{\sigma}_n^2$ is the residual variance of the latter. Given that F_n has a non-standard distribution, and that critical values cannot be tabulated as they depend on critical moments of the sample, appropriate p-values are found by the bootstrap procedure indicated in Hansen (1999). The p-value for F_n under H_0 is obtained as the percentage of draws for which the simulated F_n statistic exceeds its actual value.

3.4 Testing for long-run and short-run symmetry

Some authors (e.g. Pal and Mitra, 2015) assess long-run "overall" symmetry by testing the null hypothesis of equality of the long-term coefficients

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[13] As stressed by Greenwood-Nimmo *et al*. (2011), setting a threshold at zero may lead to loss of generality when the growth rates of the series of interest are predominantly positive or negative. As shown in Table , this is not our case, and therefore we opt for the intuitive appeal of separating positive from negative regimes.

[14] In other words, the positive threshold is equal in absolute value to the negative threshold.

[15] The k_2 threshold was obtained by grid search in the interval [0.5σ, 2σ]. The following n-th thresholds were found conditional on the values of the previous n-1.

[16] A major exception is Douglas (2010).

$$H_0: \quad \beta^1 = \ldots = \beta^r = \ldots = \beta^R$$

where the various β^r are obtained as in Eq. (6). A limit of this approach is that it may reject the null hypothesis even if a single coefficient differs from the others, or if the long-run multipliers, while symmetric within regimes, differ between regimes (e.g. if the response to mild shocks of either sign is symmetric, but differs from the equally symmetric response to large shocks of either sign).

In order to get a more precise picture of the asymmetry patterns, we therefore also tested for pairwise long-run symmetry, i.e. for equality of long-run response to positive and negative shocks within a given regime. Long-run symmetry within a regime can be assessed by testing the following hypothesis:

$$H_0: \quad \beta^r = \beta^s$$

where r = (+, ++, +++, …) indicate positive regimes and s = (−, − −, − − −, …) indicate negative regimes. Accordingly, overall short-run symmetry and symmetry within regimes exist if the following null hypotheses cannot be rejected:

$$H_0: \quad \sum_{j=0}^{q-1} \pi_j^1 = \ldots = \sum_{j=0}^{q-1} \pi_j^r = \ldots = \sum_{j=0}^{q-1} \pi_j^R$$

$$H_0: \quad \sum_{j=0}^{q-1} \pi_j^r = \sum_{j=0}^{q-1} \pi_j^s$$

The extension to overall and within impact symmetry is straightforward.

3.5 Accounting for structural breaks

In order to assess the stability of the equilibrium relationship between the price of gasoline and the price of crude oil, we apply the Bai and Perron (1998, 2003; BP hereafter) test for multiple structural breaks of unknown timing in the long-run coefficients.[17] Considering a generic TARDL-n model, the presence of b breaks in the equation parameters can be modelled as follows:

$$\Delta g_t = \alpha + \rho g_{t-1} + \sum_x \theta^x c_{t-1}^x + \sum_{j=1}^{p-1} \gamma_j \Delta g_{t-j} + \sum_x \sum_{j=0}^{q-1} \pi_j^x \Delta c_{t-j}^x + \varepsilon_t \quad t = T_{i-1}, \ldots, T_i \qquad \textbf{(7)}$$

where $i = 1, \ldots, b+1$, $(T_1, \ldots, T_b)$ are the *unknown* break points ($T_0 = 0$ and $T_{b+1} = T$), and x indicates the partitions of the explanatory variable.

By expressing Eq. (7) in matrix form, we get

[17] For a similar approach, see Bagdatoglou and Kontonikas (2011).

$$\Delta g = X\lambda + \overline{Z}\delta + \mathrm{E} \quad \textbf{(8)}$$

where X is a matrix that contains the fixed elements across regimes and $\overline{Z}$ is the matrix that diagonally partitions Z, namely the matrix that contains the lagged dependent and explanatory variables, at $(T_1, \ldots, T_b)$, i.e. $\overline{Z} = diag(Z_1, \ldots, Z_{b+1})$. By calling $S(T_1, \ldots, T_b)$ the sum of squared residuals for a generic b-partition, the estimated break-points minimize $S(T_1, \ldots, T_b)$ over all possible b-partitions, i.e. they are obtained as $(\hat{T}_1, \ldots, \hat{T}_{b+1}) = \arg\min_{T1,\ldots,Tb} S(T_1, \ldots, T_{b+1})$.

In order to test for presence and number of breaks, we use the following BP tests (see Sections 4.2 and 4.3 in Bai and Perron, 1998): the *double maximum* tests – *UDmax(B)* and *WDmax(B)* – of the null hypothesis of no breaks against the alternative of an *unknown* number of breaks (given some upper bound B); the *supF(b+1|b)* test of the null hypothesis of b breaks versus b+1 breaks. As we have no *a priori* information on the number of breaks, we follow one of Bai and Perron's (2003) recommendations: *UDmax(B)* and *WDmax(B)* are used to assess whether there is any sign of structural instability (with $B = 5$);[18] if at least one of the two statistics is significant, the sequential *supF(b+1|b)*, for $b = 0, \ldots, 4$, is used to establish the number of structural breaks.

4 Results

4.1 Deriving the number of regimes

The grid search procedure finds that the *SSR* is minimized for $k_2 = 0.732$ in the *TARDL-2* model and $k_3 = 1.930$ in the *TARDL-3* model. The results of Hansen's (1999) tests are reported in Table 2 and show that we cannot reject the null hypothesis of four regimes against the alternative of six regimes. Our preferred model is therefore the *TARDL-2*. Since the standard deviation of the logarithmic differences in crude oil price is 0.084 (Table 1), in terms of Δc the four regimes of the *TARDL-2* model are defined as $(-\infty, -0.062]$, $(-0.062, 0]$, $(0, 0.062]$, $(0.062, \infty)$. In other words, the grid search identifies observations as extreme when the percentage change in crude oil price in absolute value is greater than 6.2% (considering the approximation to percentage changes given by logarithmic differences). Thus, rather coincidentally, observations falling in the extreme positive and negative regimes are those that exceed the mean absolute deviation (see Table 1).

Table 2 – Hansen tests

	TARDL-1 vs ARDL	**TARDL-2 vs TARDL-1**	**TARDL-3 vs TARDL-2**
F_n *p*-value	0.000	0.041	0.882

Note: the values reported correspond to the bootstrapped *p*-values of the statistic (1000 replications).

[18] Basically, the *UDmax(B)* and *WDmax(B)* tests are the maximum *supF(b|0)* for $b \in \{1, \ldots, 5\}$, i.e. tests of b vs. 0 breaks. The two tests differ in weighting schemes. See Section 4.2 in Bai and Perron (1998).

Table 3 reports the full sample estimates of the ARDL and TARDL-n models.[19] In general, all the models fit the data well and the cointegration statistics indicate a long-run relationship between the variables. While there is some autocorrelation at higher lags and heteroskedasticity in the residuals, with HAC-consistent standard errors, all the explanatory variables included are highly significant. The BIC criterion selects q = 1, thus implying that impact and short-run symmetry coincide (see Section 3.2 above).

[19] For the sake of space, we do not report the estimates of the TARDL-3 model that was not supported by the data. The order of lags was chosen in each model by minimizing the Bayesian information criterion (BIC), starting from a maximum of $p = q = 7$. The values that minimize BIC are $p = 3$ and $q = 1$.

Table 3 – Estimated models, full sample. Dependent variable Δg.

	ARDL		**TARDL-1**		**TARDL-2**	
	coeff.	*s.e.*	*coeff.*	*s.e.*	*coeff.*	*s.e.*
const.	-0.405 ***	[0.064]	0.004	[0.005]	0.010 *	[0.006]
g_{-1}	-0.148 ***	[0.024]	-0.220 ***	[0.025]	-0.221 ***	[0.024]
c_{-1}	0.123 ***	[0.020]				
c_{-1}^{+}			0.161 ***	[0.018]	0.184 ***	[0.024]
c_{-1}^{-}			0.155 ***	[0.017]	0.165 ***	[0.022]
c_{-1}^{++}					0.154 ***	[0.018]
c_{-1}^{--}					0.154 ***	[0.016]
Δg_{-1}	0.451 ***	[0.037]	0.441 ***	[0.033]	0.446 ***	[0.034]
Δg_{-2}	-0.219 ***	[0.040]	-0.178 ***	[0.040]	-0.176 ***	[0.039]
Δc	0.467 ***	[0.045]				
Δc^{+}			0.402 ***	[0.054]	0.031	[0.141]
Δc^{-}			0.492 ***	[0.091]	0.840 ***	[0.167]
Δc^{++}					0.356 ***	[0.052]
Δc^{--}					0.530 ***	[0.094]
Adj. R^2	0.647		0.665		0.669	
t_BDM	-6.112 ***		-8.768 ***		-9.094 ***	
F_PSS	19.874 ***		27.537 ***		20.084 ***	
SC(2)	0.713	(0.491)	0.901	(0.407)	1.160	(0.315)
SC(12)	3.946	(0.000)	3.347	(0.000)	3.480	(0.000)
HET	11.127	(0.000)	11.400	(0.000)	8.032	(0.000)
FF	3.817	(0.023)	3.450	(0.051)	2.964	(0.053)
NOR	110.846	(0.000)	106.158	(0.000)	103.15	(0.000)
Long-run coefficients						
β	0.83 ***	[0.019]				
β^{+}			0.73 ***	[0.020]	0.83 ***	[0.094]
β^{-}			0.71 ***	[0.023]	0.75 ***	[0.060]
β^{++}					0.70 ***	[0.031]
β^{--}					0.70 ***	[0.036]

Notes: the subscripts "+" and "−" indicate positive and negative sum processes, respectively, in the *TARDL-1* model, and partial sums of mild increases/decreases in the TARDL-2 model; the partial sums of extreme increases/decreases are indicated by the subscripts "++" and "− −", respectively; *, **, and *** indicate statistical significance at 1%, 5% and 10% levels, respectively; standard errors (*s.e.*) are robust to heteroskedasticity and autocorrelation and are reported in brackets; *t_BDM* and *F_PSS* are Banerjee *et al*. (1998) and Pesaran *et al*. (2001) cointegration statistics, respectively; *SC(i)* is the serial correlation LM statistic with *i* lags, *HET* is White's heteroskedasticity test, *FF* is Ramsey's functional form test and *NOR* is Jarque-Bera's normality test; *p*-values for *SC(i)*, *HET*, *FF* and *NOR* and *FF* are reported in parentheses; long-run elasticities are obtained as indicated in Eq. (6); significance levels for long-run elasticities are calculated by the Delta method (for an overview see Davidson and MacKinnon, 2004) and reported in brackets.

Table 4 reports the symmetry tests on our preferred specification, the TARDL-2 model. Starting with short-run symmetry, the tests strongly reject this hypothesis in the mild regime, with a *p*-value of 0.002. A glance at Table 3 shows that this outcome does not depend on a "rocket and feathers" effect. On the contrary, the response to mild shocks features *negative* asymmetry: while the impact elasticity to mild positive shocks Δc^{+} is π_0^{+} = 0.031 and does not differ significantly from zero, that to negative shocks is π_0^{-} = 0.840 and is significant at 1% level. Short-run symmetry to extreme shocks, on the other hand, is not rejected, with a *p*-value of 0.185. A look at the coefficient in Table 3 shows that there is some hint of negative asymmetry (the coefficient of Δc^{++} is equal to 0.356, smaller than the coefficient of Δc^{--}, equal to 0.530), but this difference is not statistically significant. Since short-run symmetry tests provide different outcomes in different regimes, the hypothesis of overall short-run symmetry is also rejected at 5% level (with a *p*-value of 0.011; Table 4, fourth row).

Conversely, the hypothesis of long-run symmetry is not rejected for any regime. However, Table 3 shows that the long-run responses to mild shocks are larger (reaching 0.83 for positive shocks and 0.75 for negative shocks) than to extreme shocks (0.70 for both positive and negative shocks). Consequently, even in this case the test for overall (long-run) symmetry rejects the null hypothesis at any significance level. In other words, while there is no evidence of asymmetric response within either regime (mild and extreme), there is significant evidence that extreme shocks to crude price are passed through to gasoline prices to a lesser extent than mild shocks. Before interpreting these results, we check whether they are stable across the sample.

Table 4 – Symmetry tests, full sample

Short run		
$\pi_0^{+} = \pi_0^{-}$	9.655	(0.002)
$\pi_0^{++} = \pi_0^{--}$	1.759	(0.185)
Overall	3.757	(0.011)
Long run		
$\beta^{+} = \beta^{-}$	1.200	(0.274)
$\beta^{++} = \beta^{--}$	0.001	(0.979)
Overall	14.828	(0.000)

Notes: *p*-values are reported in brackets; significance levels are calculated by the Delta method (for an overview see Davidson and MacKinnon, 2004).

4.2 Testing for structural stability

The long-run coefficients of the preferred specification were then tested for structural stability, and the results are shown in Table 5. Both *UDmax* and *WDmax* are significant at 5% and therefore signal structural instability. The sequential *supF*(b+1|b) test is significant at 5% for $k = 1$ which implies a single structural break. It dates to 2008:10, coinciding with the sharp drop in crude oil price visible in Figure 1.

Table 5 – Bai and Perron structural breaks tests

UDmax	WDmax	SupF(1|0)	SupF(2|1)	SupF(3|2)	SupF(4|3)	SupF(5|4)	Break date
47.86	**76.97**	**20.24**	19.89	11.00	7.78	9.37	2008:10

Notes: the maximum number of breaks is five; the trimming parameter is 0.15; statistics in boldface are significant at 5%.

Accordingly we re-estimate the model in the two subsamples 1983:1-2008:10 and 2008:11-2015:12. The results are shown in Table 6.

Table 6 – TARDL-2 pre- and post-break estimates. Dependent variable Δg.

	1983:1 – 2008:10		2008:11 – 2015:12	
	coeff.	*s.e.*	*coeff.*	*s.e.*
const.	0.005	[0.008]	0.363 ***	[0.070]
g_{-1}	-0.222 ***	[0.025]	-0.396 ***	[0.079]
c^{+}_{-1}	0.186 ***	[0.022]	0.497 ***	[0.165]
c^{-}_{-1}	0.142 ***	[0.028]	0.719 ***	[0.193]
c^{++}_{-1}	0.156 ***	[0.022]	0.338 ***	[0.077]
c^{--}_{-1}	0.168 ***	[0.019]	0.228 ***	[0.046]
Δg_{-1}	0.440 ***	[0.045]	0.378 ***	[0.057]
Δg_{-2}	-0.166 ***	[0.036]	-0.158 *	[0.087]
Δc^{+}	0.149	[0.098]	-0.039	[0.359]
Δc^{-}	0.739 ***	[0.230]	1.081 ***	[0.358]
Δc^{++}	0.389 ***	[0.042]	0.419 ***	[0.146]
Δc^{--}	0.466 ***	[0.105]	0.576 ***	[0.130]
Adj. R^2	0.646		0.740	
t_BDM	-8.778 ***		-5.042 ***	
F_PSS	47.592 ***		6.626 ***	
SC(2)	2.785	(0.063)	1.956	(0.149)
SC(12)	3.812	(0.000)	0.957	(0.498)
HET	4.244	(0.000)	6.841	(0.000)
FF	0.705	(0.495)	5.218	(0.008)
NOR	69.292	(0.000)	0.358	(0.836)
Long-run coefficients				
β^{+}	0.84 ***	[0.083]	1.25 ***	[0.383]
β^{-}	0.64 ***	[0.069]	1.81 ***	[0.399]
β^{++}	0.70 ***	[0.026]	0.85 ***	[0.108]
β^{--}	0.76 ***	[0.042]	0.58 ***	[0.080]

Notes: the subscripts "+" and "–" indicate positive and negative variations, respectively, in the *TARDL-1* model, and extreme increases and extreme decreases in the TARDL-2 model; *, **, and *** indicate statistical significance at 1%, 5% and 10% level, respectively; standard errors (*s.e.*) are robust to heteroskedasticity and autocorrelation and are reported in brackets; *t_BDM* and *F_PSS* are Banerjee *et al*. (1998) and Pesaran *et al*. (2001) cointegration statistics, respectively; *SC(i)* is the serial correlation LM statistic with *i* lags, *HET* is White's heteroskedasticity test, *FF* is Ramsey's functional form test and *NOR* is Jarque-Bera's normality test; *p*-values for the *SC(i), HET, FF* and *NOR* and *FF* are reported in brackets; long-run elasticities are obtained as indicated in Eq. (6); s.e. and significance levels for the long-run elasticities have been calculated with the Delta method (for an overview see Davidson and MacKinnon, 2004) and reported in brackets.

Estimates in both subsamples have a good statistical fit, the *t_BDM* and *F_PSS* test statistics are significant at 1% level of confidence, and the residual diagnostic improves considerably. Taking the structural shift in parameters into account, the results of the symmetry tests (Table 7) give a somewhat different picture.

In the short run, negative asymmetry to mild shocks continues to prevail both before and after the break (although only marginally in the post-break sample, with a *p*-value of 0.052). As in the full sample case, impact elasticity to mild-positive variations of crude price, Δc^{+}, is not significant at any reasonable level. Impact elasticity to mild negative changes in crude price , Δc^{-}, is much larger and increases from π_0^{-} = 0.739 to π_0^{-} = 1.081 after the break. In other words, there is evidence that after 2008:10, negative changes in crude prices are entirely passed through to gasoline prices in the first month.

Regarding long-run elasticities, before the break the results are similar to those of the full-sample estimates. The symmetry tests do not detect any significant asymmetry within any regime, although some positive symmetry seems to prevail for mild changes, with β^{+} = 0.84 larger than β^{-} = 0.64 (the corresponding symmetry test has a *p*-value of 0.068; see Table 6 for the coefficients and Table 7 for the test). However, the overall symmetry test rejects the null hypothesis for the same reason as in the full-sample estimates.

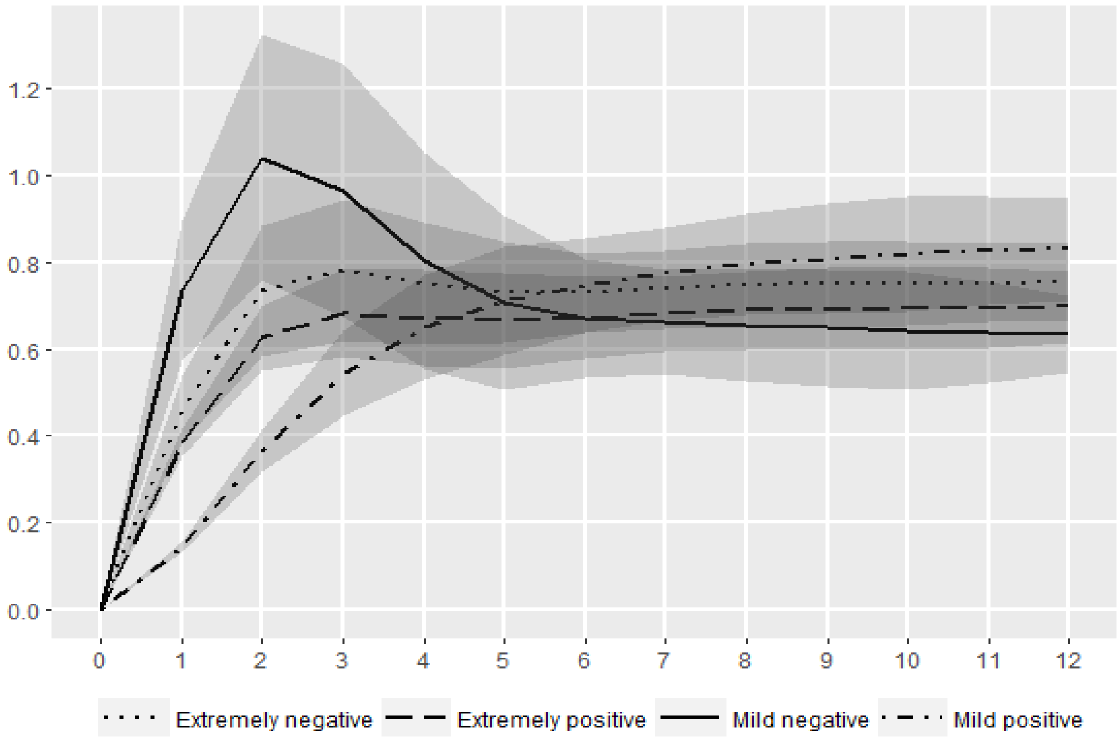
After the break the situation changes: the asymmetry to mild shocks becomes significant, with a *p*-value of 0.014 (Table 7) and negative, with β^{+}= 1.25 and β^{-} = 1.81. The response to extreme shocks, which was symmetric in all the previous estimates, now becomes significantly asymmetric with a *p*-value of 0.011, and the asymmetry is positive, with β^{++} = 0.85 and β^{--} = 0.58. While the presence of asymmetries distinguishes the results of the pre-break and the full sample, again we find that the overall test à la Pal and Mitra (2010) rejects the hypothesis of symmetry. In this case, however, this overall result is expected, because we do not find symmetry in any regime.

Table 7 – Asymmetry tests pre- and post-break

		1983:1 – 2008:10		**2008:11 – 2015:12**	
Short-run					
	$\pi_0^{+} = \pi_0^{-}$	4.631	(0.032)	3.895	(0.052)
	$\pi_0^{++} = \pi_0^{--}$	0.431	(0.512)	0.506	(0.479)
	Overall	3.287	(0.021)	1.322	(0.274)
Long-run					
	$\beta^{+} = \beta^{-}$	3.356	(0.068)	6.383	(0.014)
	$\beta^{++} = \beta^{--}$	1.298	(0.256)	6.798	(0.011)
	Overall	10.984	(0.000)	6.903	(0.000)

Notes: *p*-values are in brackets; significance levels are calculated by the Delta method (for an overview see Davidson and MacKinnon, 2004).

Figure 2 reports the dynamic multipliers in response to 1% shocks in the various regimes for pre- and post-break TARDL-2 models (in the upper and lower part of the Figure, respectively). The figure helps explain the meaning of short- and long-run asymmetries in the framework of a NARDL model. Considering for instance the extreme regime in the post-break sample (bottom panel of Figure 2), the short-negative asymmetry is demonstrated by the fact that the dashed line (depicting the dynamic multiplier for large positive changes) lies below the dotted line (depicting the dynamic multiplier for large negative changes) in the first month. Starting in the second month, the difference between the two effects is no longer statistically significant. However, the negative dynamic multiplier then settles on a lower path, and after 12 months the situation is reversed. The positive dynamic multiplier, β^{++}, has converged to its long-run value of 0.85, and the negative dynamic multiplier, β^{--}, to its long-run value of 0.58, thus showing positive long-run asymmetry.



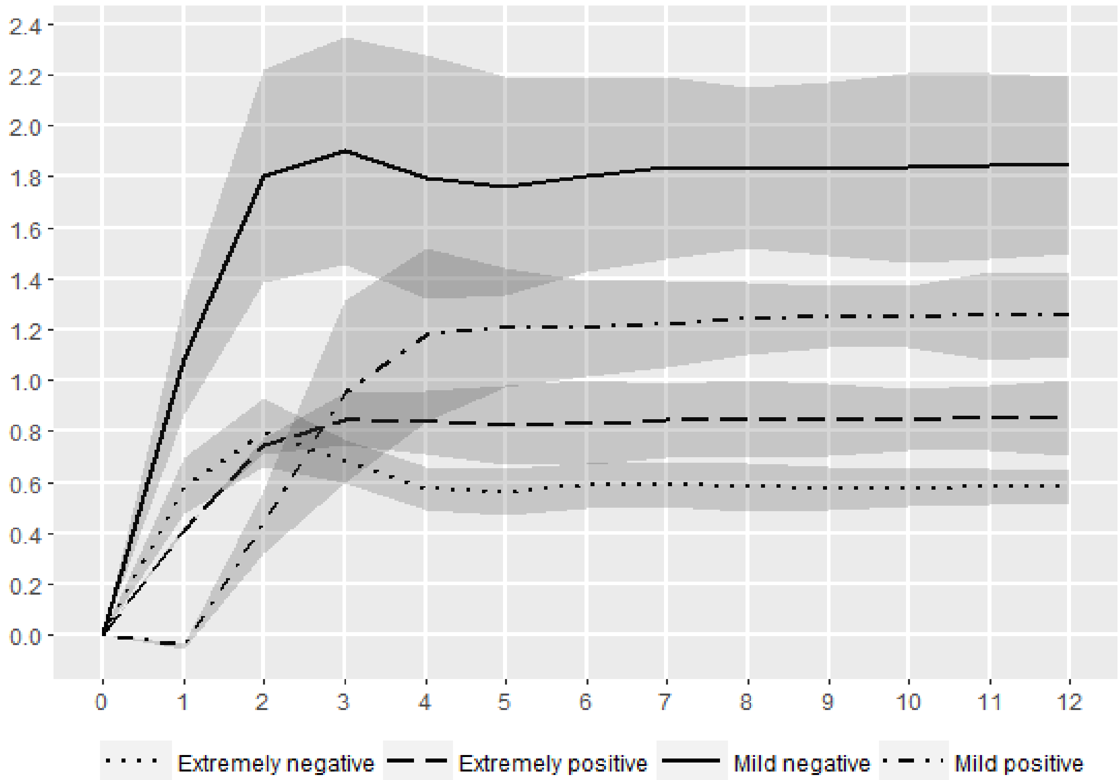


Figure 2 – Dynamic multipliers of a 1% change in crude oil prices, in TARDL-2 pre- and post-break models (upper and lower panel, respectively); shaded areas are 95% confidence intervals.

4.3 Robustness check

In order to check whether (and eventually to what extent) our results are sensitive to the exclusion of some variables that may influence the price of gasoline, we extend the full sample TARDL-1 and TARDL-2 models as well as the pre- and post-break TARDL-2 models by adding further explanatory variables. We include: 1) volatility, measured by the conditional standard deviation of the crude oil price estimated through a GARCH(1,1) model (see Romano and Scandurra, 2012); 2) seasonal idiosyncratic factors, given by seasonal dummy variables (see Kaufmann and Laskowski, 2005);[20] 3) petroleum stocks (see Kaufmann and Laskowski, 2005); 4) consumer willingness to spend, proxied by the consumer confidence indicator; 5) a specific demand-related variable, measured by the index of new passenger car registrations; 6) a demand-related variable, given by the real consumption of energy goods and services. The alternative models are labelled *Volatility*, *Seasonality*, *Stocks*, *Confidence*, *New cars* and *Consumption*, respectively, in Table 8, which contains asymmetry tests, and Table 9, which contains the values of the long-term and impact coefficients. To facilitate comparison with our previous results, the benchmark values from Table 3 and 6 are also reported in the upper part of each table.

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[20] Besides seasonal dummies (winter, spring, summer and autumn), monthly dummies are also tested. Results remain qualitatively similar.

As can be seen from Table 8, the long-term asymmetry results are robust to alternative specifications. The only test which contrasts with the benchmark case is that for asymmetry in the inner regimes in the pre-break TARDL-2 model when seasonal and industry-specific factors (“Seasonality” and “Stock”) are added to the baseline model. In these cases, there is some indication of asymmetry between the mild-negative and mild positive regimes, though the value of the coefficients is not very different from the benchmark (see Table 9).

Table 8 – Robustness checks: asymmetry tests with various specifications

Specification	TARDL	Long-run					Short-run				
		Overall	$\beta^{++} = \beta^{--}$	$\beta^{++} = \beta+$	$\beta^{--} = \beta^{-}$	$\beta^{+} = \beta^{-}$	Overall	$\pi^{++} = \pi^{--}$	$\pi^{++} = \pi^{+}$	$\pi^{--} = \pi^{-}$	$\pi^{+} = \pi^{-}$
Benchmark	1	0.000					0.490				
	2	0.000	0.979	0.246	0.510	0.274	0.011	0.186	0.008	0.029	0.002
	2-pre	0.000	0.256	0.181	0.232	0.068	0.021	0.512	0.016	0.063	0.032
	2-post	0.000	0.011	0.384	0.006	0.014	0.274	0.479	0.147	0.180	0.052
Volatility	1	0.000					0.582				
	2	0.000	0.825	0.281	0.419	0.368	0.010	0.248	0.009	0.027	0.002
	2-pre	0.000	0.368	0.216	0.332	0.122	0.012	0.591	0.017	0.050	0.033
	2-post	0.000	0.010	0.372	0.008	0.013	0.291	0.485	0.167	0.171	0.056
Seasonality	1	0.000					0.403				
	2	0.000	0.882	0.274	0.958	0.140	0.028	0.173	0.010	0.064	0.006
	2-pre	0.000	0.086	0.167	0.018	0.010	0.042	0.657	0.013	0.130	0.045
	2-post	0.000	0.001	0.675	0.001	0.001	0.339	0.286	0.143	0.311	0.081
Stocks	1	0.000					0.527				
	2	0.000	0.831	0.327	0.938	0.218	0.023	0.225	0.016	0.031	0.004
	2-pre	0.000	0.083	0.149	0.096	0.008	0.067	0.680	0.048	0.080	0.042
	2-post	0.003	0.031	0.539	0.003	0.001	0.215	0.498	0.079	0.193	0.043
Confidence	1	0.000					0.459				
	2	0.000	0.452	0.579	0.356	0.829	0.011	0.175	0.011	0.023	0.002
	2-pre	0.000	0.504	0.355	0.484	0.218	0.069	0.431	0.034	0.082	0.024
	2-post	0.002	0.007	0.645	0.017	0.012	0.214	0.475	0.073	0.308	0.056
New cars	1	0.000					0.381				
	2	0.000	0.859	0.272	0.641	0.290	0.020	0.144	0.017	0.048	0.003
	2-pre	0.001	0.226	0.174	0.237	0.045	0.054	0.489	0.025	0.086	0.022
	2-post	0.001	0.015	0.298	0.001	0.009	0.425	0.553	0.150	0.265	0.110
Consumption	1	0.005					0.508				
	2	0.020	0.935	0.253	0.624	0.514	0.012	0.201	0.011	0.030	0.002
	2-pre	0.693	0.322	0.373	0.755	0.469	0.052	0.569	0.030	0.086	0.022
	2-post	0.000	0.009	0.286	0.000	0.009	0.345	0.405	0.130	0.223	0.080

Note: p-values are in brackets; significance levels are calculated by the Delta method (for an overview see Davidson and MacKinnon, 2004).

Table 9 – Robustness checks: long-run elasticities from various specifications

Specification	TARDL	β^{+}	β^{-}	β^{++}	β^{--}	π^{+}	π^{-}	π^{++}	π^{--}
Benchmark	1	**0.73**	**0.71**			**0.40**	**0.49**		
	2	**0.83**	**0.75**	**0.70**	**0.70**	0.03	**0.84**	**0.36**	**0.53**
	2-pre	**0.84**	**0.64**	**0.70**	**0.76**	0.15	**0.74**	**0.39**	**0.47**
	2-post	**1.25**	**1.81**	**0.85**	**0.58**	-0.04	**1.08**	**0.42**	**0.58**
Volatility	1	**0.73**	**0.71**			**0.41**	**0.48**		
	2	**0.82**	**0.75**	**0.70**	**0.69**	0.04	**0.84**	**0.37**	**0.52**
	2-pre	**0.83**	**0.65**	**0.70**	**0.75**	0.15	**0.74**	**0.40**	**0.46**
	2-post	**1.30**	**1.90**	**0.86**	**0.57**	-0.03	**1.10**	**0.42**	**0.58**
Seasonality	1	**0.74**	**0.71**			**0.37**	**0.48**		
	2	**0.82**	**0.72**	**0.72**	**0.72**	0.02	**0.76**	**0.33**	**0.52**
	2-pre	**0.84**	**0.61**	**0.72**	**0.79**	0.15	**0.63**	**0.38**	**0.43**
	2-post	**1.07**	**1.83**	**0.93**	**0.56**	-0.05	**0.90**	**0.37**	**0.59**
Stocks	1	**0.73**	**0.71**			**0.41**	**0.49**		
	2	**0.82**	**0.72**	**0.71**	**0.71**	0.06	**0.83**	**0.36**	**0.53**
	2-pre	**0.82**	**0.61**	**0.71**	**0.77**	**0.21**	**0.72**	**0.40**	**0.45**
	2-post	**1.10**	**1.82**	**0.84**	**0.59**	-0.11	**1.06**	**0.41**	**0.56**
Confidence	1	**0.74**	**0.72**			**0.40**	**0.49**		
	2	**0.79**	**0.77**	**0.72**	**0.69**	0.02	**0.85**	**0.35**	**0.52**
	2-pre	**0.82**	**0.65**	**0.71**	**0.75**	0.13	**0.75**	**0.37**	**0.46**
	2-post	**1.08**	**1.63**	**0.88**	**0.60**	-0.13	**0.99**	**0.42**	**0.58**
New cars	1	**0.73**	**0.71**			**0.40**	**0.51**		
	2	**0.82**	**0.74**	**0.71**	**0.70**	0.07	**0.83**	**0.36**	**0.54**
	2-pre	**0.85**	**0.64**	**0.70**	**0.76**	0.15	**0.74**	**0.39**	**0.46**
	2-post	**1.32**	**1.93**	**0.88**	**0.59**	-0.01	**1.03**	**0.44**	**0.57**
Consumption	1	**0.73**	**0.70**			**0.40**	**0.49**		
	2	**0.83**	**0.75**	**0.70**	**0.70**	0.05	**0.83**	**0.36**	**0.52**
	2-pre	**0.84**	**0.75**	**0.73**	**0.78**	0.17	**0.71**	**0.39**	**0.45**
	2-post	**1.26**	**2.16**	**0.83**	**0.54**	0.03	**1.06**	**0.41**	**0.59**

Note: long-run coefficients are calculated as reported in Eq. (6); coefficients significant at 5% are reported in boldface.

5 Discussion

We now highlight the main features of the above results in the light of the previous empirical research, focusing in turn on the three features considered in our modelling approach: the presence of structural shifts in model parameters, the role of shock size, and the presence and sign of observed asymmetries.

The results of Hansen's (1999) sequential test show that the TARDL-2 model, featuring four regimes (extreme and mild shocks of both signs) provides the best description of our data. While suggesting that models with a larger number of regimes, such as Pal and Mitra's (2015), might actually be overparameterised, this finding confirms the intuition expressed in a number of previous studies that the shape of gasoline price adjustment might be size-dependent. The preferred model is then tested for the presence of multiple structural breaks of unknown timing, revealing a single structural break in 2008:10, as in Fosten (2012). While these findings are broadly consistent with those of previous studies, when we simultaneously consider structural shifts, the size of shocks, and the long-run behaviour of the model, we get a picture that differs from the one emerging from the literature, especially as far as the presence and sign of the asymmetries is concerned.

Firstly, in contrast with Zhang *et al*. (2015), once we take shifts in the long-run parameters into account, we do not obtain an "almost symmetric" adjustment. On the contrary, once the structural break is accounted for, a sizeable and statistically significant degree of asymmetry persists, although the pre- and post-break models behave quite differently. In particular, before 2008:10 there is strong evidence of short-run asymmetry in response to mild shocks, while from 2008:11 onwards long-run asymmetry prevails (see Table 7). As suggested in Section 2, this difference may be explained by the fact that Zhang *et al*. (2015) do not allow for asymmetries in the long-run parameters.

Secondly, in contrast with Douglas (2010), once we allow for different responses to large shocks, the asymmetry in the adjustment does not evaporate. In particular, before the structural break our estimates feature an asymmetric short-run response to mild, rather than to extreme shocks, contrary to what Douglas finds. After the break, a strongly significant long-run asymmetry to both mild and above all to extreme shocks emerges. While this result is more consistent with Douglas's (2010) findings, accounting for size dependency does not completely remove the asymmetry in the short-run adjustment parameters: the hypothesis of short-run asymmetry in response to mild shocks is still significant at 6%, with a *p*-value of 0.052 (see Table 7).

Thirdly, as far as the sign of the asymmetries is concerned, interesting differences emerge between the pre- and post-break samples. In particular, the pre-break estimates confirm the negative short-run asymmetry reported by Atil *et al*. (2014). As shown in the first column of Table 6, the impact elasticity to positive mild changes in crude prices is small (0.15) and not statistically significant, while the impact elasticity to negative mild changes is large (0.74) and statistically significant. A similar pattern persists after the structural break, although the difference between the impact coefficients turns out to be statistically significant only at 6% level (as mentioned above). In the post-break sample, however, a different picture emerges. Unlike Atil *et al*. (2014) we find strong evidence of negative long-run asymmetry to mild shocks (with elasticities of 1.25 and

1.81 to positive and negative shocks, respectively) and even stronger evidence of positive long-run asymmetry to extreme shocks (with elasticities of 0.85 and 0.58, respectively). In other words, after the 2008:10 break, the model conforms to "rocket and feathers" effects in the long-run, but only in the case of unusually large changes in crude price, while in normal times negative asymmetry prevails. As recalled in Section 2, negative asymmetry is not an entirely new finding and is consistent with Taylor's (2000) endogenous mark-up model and its further development by Ellingsen *et al*. (2006). In these models, characterized by costly price adjustment in a monopolistic competition setting under stochastic costs, pricing behaviour depends on the perceived price "drift", i.e. on perceived inflation. The basic intuition is that a relatively large "drift" reduces the need to quickly adjust prices downward in the case of a negative shock to costs, because competitors' prices will drift upward anyway, thus reducing the scope for predatory policies. Conversely, in a low inflation environment, firms lose market power and therefore adjust prices downward more quickly if costs decrease, in order to keep their market shares. Indeed, the post-break sample features much lower consumer price inflation than the pre-break one (average 1.39% and 3.13% respectively), with one year of outright deflation (2009). This significant change in the macroeconomic environment may explain the change in pricing behaviour. At the same time, it may also explain why firms behave differently in relation to the size of the shock. Indeed, a large increase in crude price raises inflation expectations, signalling the onset of a high inflation environment in which prices are more responsive to cost increases than to cost decreases (Ellingsen *et al*., 2006).

Fourthly, as far as the size of the asymmetries is concerned, our results suggest that after 2008:10 the pass-through is larger for shocks in the inner regimes than in the extreme ones. This contrasts with the results implied by Pal and Mitra's (2015) estimates: in their five- and ten-regime models, these authors find that elasticities tend to follow a U-shaped pattern, where extreme variations in the price of crude oil have a greater long-term impact on the price of gasoline.[21] However, the results of Hansen's (1999) test show that these models are overparameterised, which is also evident in the reported results. For instance, in the ten-regime model, less than half the parameters are significantly different from zero. Moreover, our results are consistent with the possible presence of a band of inattention in consumers' perceptions similar to that documented in Chen *et al*. (2008): when crude oil price changes are relatively small they are ignored by consumers; when prices go up consumers are encouraged to find alternatives. Thus a rational strategy for retailers is to contain the price increase so as not to lose their market shares; in the case of a price decrease, consumers do not engage in intensive price search behaviour, and retailers therefore have an incentive to further reduce prices.

[21] As mentioned previously, Pal and Mitra (2015) do not report elasticities. In order to have results that could be compared with our estimates and with other author's models (e.g. Atil *et al*, 2014), we estimated the implied elasticities in Pal and Mitra's work on the basis of their results as $-\sigma_{k+2}/\sigma_1 \times CR(k)/P$, where $CR(k)$ is the average price of crude oil during regime k, P is the average price of gasoline over the whole sample (as reported in their Table 1), σ_{k+2} is the coefficient associated with crude oil during regime k and σ_1 is the error-correcting coefficient. The values of σ_1 and σ_{k+2} are Pal and Mitra's estimates of "Gulf Coast" and "New York Harbor" spot prices. In the five-regime model, extreme positive and extreme negative variations have nearly unit elasticity, while the inner regimes have an average elasticity of 0.68. The average elasticities in the ten-regime model are 0.69 in the two more extreme negative regimes, 0.5 in the two more extreme positive regimes, and 0.38 in the inner regimes.

6 Conclusions

The aim of this paper was to analyze the adjustment mechanism of the (pre-tax) retail gasoline price in the US market in response to crude oil price variations, in an endeavour to reconcile conflicting evidence from some recent studies that separately raised a number of interrelated issues, including possible differences between short- and long-run adjustment, the impact of outlying observations and the constancy of model parameters. We united all these features in a consistent modelling framework that builds on the recent methodological contributions of Greenwood-Nimmo *et al*. (2011) and Shin *et al*. (2014), while adopting the multiple break testing methodology of Bai and Perron (1998, 2003). We used an extended monthly data set, ranging from January 1983 to December 2015. We used series of alternative specifications to assess the robustness of our findings and no substantial deviations from the benchmark model were found.

Our results confirm some stylized facts emerging from the previous studies, such as the pervasive presence of asymmetries and the importance of the structural break that occurred in the second half of 2008. At the same time, the picture emerging from our study differs in many respects from that provided by the literature, and in the previous section we discussed how these differences can be explained by our use of more flexible methodology. The main conclusion is that while the adjustment process was characterized by short-run *negative* asymmetry and long-run symmetry before 2008:10, after the structural break the nature of asymmetry changed: short-run adjustments somehow became symmetric (though asymmetry persists at the 6% significance level), while in the long run mild changes show *negative* asymmetry and extreme regimes show *positive* asymmetry. These two features are consistent with the behaviour that Taylor's (2000) model predicts after onset of a low-inflation environment, such as the one starting in 2009 with deflation in the US and with an inattention band in consumers' perception, along the lines set out in the model of Chen *et al*. (2008).

Our empirical analysis can be extended in several directions. First of all, it could be interesting to check whether these results are confirmed with higher frequency (e.g. weekly) data. Another stimulating strand of research could be the application of our method to single-state markets or Petroleum Administration for Defense Districts, in order to investigate whether the relationships observed at aggregate level are confirmed in a more geographically homogeneous setting. Moreover, while our robustness checks control for oil market volatility, it might be worthwhile repeating this analysis endogenising uncertainty by a GARCH-M modelling approach, as in Chang and Serletis (2016).

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ASYMMETRIES, OUTLIERS AND STRUCTURAL STABILITY IN THE US GASOLINE MARKET

Abstract

By using a recently developed nonlinear cointegration methodology, and a sample that encompasses more than thirty years of monthly data, we investigate whether the transmission of crude oil price variations to gasoline prices in the US market is asymmetric, i.e., depends on the sign of the change in the explanatory variable, considering both the long- and in the short-run. The model is further extended by taking separately into account the effects of extreme and mild changes in crude oil prices. This allows us to verify whether and to what extent the size and shape of any observed asymmetry in pricing is affected by the presence of outliers. Moreover, given the substantial length of the sample considered, we test for the possible presence of multiple structural breaks of unknown timing in the cointegrating vector. Our results indicate that the relationship between the prices of gasoline and crude oil has undergone a single structural break in the late 2008, and that after the break extreme observations have a non-negligible role in shaping asymmetry.

JEL classification: C22, D43, D82, E31, L71, Q41.

Keywords: asymmetric cointegration, nonlinear autoregressive distributed lag model, asymmetric price adjustment, pass-through, gasoline price, US gasoline market.

Research Highlights

- Analysis of price asymmetries US gasoline market
- Decomposition of positive and negative shocks in mild/extreme shocks
- Pervasive presence of asymmetries, and 2008 structural break
- Short run negative asymmetry and long run symmetry before 2008
- After the structural break the nature of asymmetry changed

Simulation Code and Data (.ZIP)

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