First draft - please do not quote

Testing for price response asymmetries in the Spanish fuel market. New evidence from daily data

Jacint Balaguer[a] and Jordi Ripollés[b]

Abstract

In this work we use daily data to examine pattern asymmetries in the speed of transmission of international wholesale oil prices to Spanish retail fuel prices. Results are robust to two alternative specifications of an asymmetric error correction model, for which the presence of autoregressive conditional heteroskedasticity for disturbances is modeled by a GARCH(1,1) process. Evidence indicates that the short-term transmission of wholesale prices to retail prices is quite symmetric for both gasoline and diesel fuel. Nevertheless, in contrast to some of the results provided for an earlier period, we did not find asymmetries in the speed of retail price responses toward long-run equilibrium. Our evidence also suggests that the use of weekly (or lower frequency) data is one of the possible explanations for some of the seemingly contradictory results concerning this issue.

Keywords: Price transmission, asymmetry, daily data, fuel products.
JEL classification: D43, L71, Q40.

[a] *Department of Economics, Universitat Jaume I, Av. de Vicent Sos Baynat, s/n, 12071 Castellón, Spain; E-mail: jacint.balaguer@eco.uji.es; Telephone: 0034 964387172; Fax: 0034 964728591*

[b] *Department of Economics, Universitat Jaume I, Av. de Vicent Sos Baynat, s/n, 12071 Castellón, Spain; E-mail: jripolle@eco.uji.es; Telephone: 0034 964728615*

1. Introduction

It is well known that oil companies can be tempted to take advantage of oil price variations in international markets to generate additional revenues at the expense of reducing domestic consumer welfare. In particular, it has been broadly argued that oil companies transfer the increases in international oil prices to local markets significantly faster than the decreases. This phenomenon, commonly known in the literature as "rockets and feathers", has become an important concern in many developed countries with a high dependence on imports of oil products.

This is the case of Spain, where nearly all oil energy is imported and there is also a very high concentration of sellers of oil products on the market, which in turn naturally arouses suspicion about the existence of this phenomenon.[1] Thus, for example, in 2009 the three most important firms in the Spanish oil market (Repsol, Cepsa-Elf and British Petroleum) controlled more than 55% of the service stations around the country.[2] This particular situation could be explained basically by the fact that the fuel sector was controlled by the State monopoly for a long period (1927-1992) and the process of liberalization was only undertaken relatively recently.[3] Given this circumstance, it is not very surprising that independent Spanish consumers' associations (like the "*Organización de Consumidores y Usuarios*" – *OCU*) have often openly expressed their fear about the existence of asymmetries in the speed of oil price transmission. As a response to this concern from consumers, the Government of Spain has sometimes called for oil operating companies to be more responsible toward society.[4] Obviously, this sort of public statement contrasts sharply with those made by the Spanish

[1] Asymmetries in price transmission are usually attributed to the presence of a great power market or even a situation of collusive pricing behavior (see, for example, Borestein and Shepard, 2002).

[2] More specifically, Repsol, Cepsa-Elf and British Petroleum control 36.1%, 15.6% and 3.8%, respectively. Data for calculating the percentages were obtained from the Spanish Ministry of Industry, Tourism and Trade for June 2009.

[3] Unlike the main European retail fuel markets, the Spanish fuel sector was controlled for many years by a State monopoly ("*Compañía Arrendataria del Monopolio de Petróleos S.A.*"- *Campsa*). In spite of the liberalization and restructuring process of the industry that began in the seventies, in the early nineties the fuel sales market was still highly concentrated and vertically composed of a small number of companies.

[4] Statements made by the Spanish Minister of Industry in September 2005 in view of important increases in international oil prices are a good example (see *El País* 09/27/2005).

Association of Petroleum Product Operators (*AOP*), which has traditionally defended the sector from public accusations about non-competitive behavior.

The existing research on this issue is, in essence, within the tradition that began with the seminal paper by Bacon (1991), where the "rockets and feathers" hypothesis was empirically tested through a dynamic model in its reduced form. Although in the last two decades a large number of empirical papers on this topic have examined the hypothesis under this empirical approach, the simple partial adjustment model used early on in Bacon's paper has been mostly dropped in more recent works in favor of the *error correction model* (ECM). That is, because time series related with domestic retail oil prices and with wholesale oil prices in the international market generally contain a unit root (but both types of time series are frequently shown as being cointegrated), the ECM becomes a suitable alternative to identify possible asymmetries. In this sort of econometric models a special interest is commonly attributed to the regression coefficient associated to the error correction term since it directly captures the speed at which the price fixed by domestic retailers returns toward long-run equilibrium.

The speed of transmission of the wholesale oil price has been analyzed empirically, mainly by focusing on the commercialization chain,[5] for a wide range of industrialized countries. In some of these cases, the analysis for a particular country was conducted for a closely related period. So, for example, consistent evidence about the asymmetric response of retail oil prices is obtained for the US case from Borestein et al. (1997) and Deltas (2008). Although the frequency of the data differs (i.e., weekly versus monthly), a part of the sample periods used is common to the two works (1986-1992 and 1988-2002, respectively). In this line, consistent results in favor of asymmetric price responses are also obtained for France, Germany and Italy in Galeotti et al. (2003) and in Grasso and Manera (2007). Data frequency also differs between the two papers (i.e., weekly versus monthly), but a fairly similar period was used in both cases (1985-2000 and 1985-2003, respectively). The consistency of the empirical results obtained for these countries contrasts, however, with the seemingly puzzling results that were obtained for Spain. It is in principle surprising that, while the above-mentioned papers by Galeotti et al. (2003) and Grasso and Manera (2007) also support price transmission

[5] The use of refined oil spot prices (i.e., the commercialization chain) becomes a better approximation for the transmission of sellers' marginal cost to final prices than the use of crude oil prices (i.e., the complete distribution chain). See, for example, Bacon (1991) or Borestein et al. (1997).

asymmetries for Spain, the more recent paper by Contin-Pilart et al. (2009), based on weekly data, offers no evidence of the existence of the "rockets and feathers" phenomenon when a fairly similar period is taken into account (1993-2004).

The objective of the present paper is to provide new robust evidence for the retail price adjustments in the Spanish oil market, mainly in answer to the current social concern and the controversial results obtained in earlier empirical research. With this purpose in mind and taking two standard specifications of the ECM model used in the mentioned papers for Spain as the basis for the study, we will exploit daily data information for a recent period. Since gas stations are free to adjust their prices every day, it is reasonable to think that the use of daily data could be more appropriate for our purpose. In other words, this could be a good way to reveal more detailed information about the price adjustments of gas stations in response to rapidly changing conditions in the wholesale oil market. Failure to follow such a method could result in an important number of relevant short time lags being omitted in the regression analysis and these omitted lagged variables, in turn, can potentially generate significant estimation bias (see Geweke, 1978).

From a review of the empirical literature we can see that the use of weekly and monthly data has, however, been a habitual practice in the works on the issue.[6] This is probably because accessing information about retail oil prices at these lower frequencies is a rather straightforward matter for researchers. Hence, for instance, this type of information can be accessed for several regions from the online databases of energy institutions. Some of these institutions offer (at the highest level of temporal disaggregation) daily average prices every week (e.g., *Europe's Energy Portal* at *www.energy.eu*). Alternatively, others offer price observations for the first working day of each week (e.g., *The Energy Information Administration* at *www.eia.gov*).[7]

[6] The recent paper by Bettendorf et al. (2009) for the Dutch retail gasoline market represents an exception. One notable fact about this paper is the presence of volatility clustering in the analysis, in contrast to the habitual practice based on more temporal aggregation.

[7] Others examples of average diesel and gasoline fuel prices per week can also be obtained directly from the website of the *Australian Institute of Petroleum* (at *www.aip.com.au*) or the *UK Haulier* (at *www.ukhaulier.co.uk).* Alternatively, the *New York State Energy Research and Development Authority* (at *www.nyserda.org*) or the *California Energy Commission* (at *www.energy.ca.gov)* both select regional oil retail prices for each Monday.

In view of the widespread use of weekly (or more time-aggregated) frequencies in this field of research, there are two papers that offer interesting evidence about the lack of robustness of derived estimates. On the one hand, Bachmeier and Griffin (2003) used US retail prices of gasoline and crude oil prices to compare results derived from daily data with those obtained from weekly average data. The paper revealed that the use of daily data, instead of weekly data, was sufficient to significantly reduce the evidence of price asymmetry previously obtained by Borestein et al. (1997). On the other hand, Bettendorf et al. (2003) also reached similar conclusions for the Dutch gasoline market. The authors built five datasets, one for each working day, from daily time series corresponding to retail gasoline prices and Rotterdam spot gasoline prices (for the period 1996-2001). The results concerning price asymmetries differ across these datasets, which suggests insufficient robustness derived from estimates of weekly frequencies and thereby highlighting the importance of using daily data in the research. These findings imply, as a possibility, that the presence of estimate bias with weekly or more aggregated frequencies could be a reasonable explanation for the inconclusive results obtained for Spain in earlier papers.

In the following section we will present a description of the data used in this study. In Section 3, we put forward the econometric specifications to be estimated. We will take into account both the popular asymmetric version of the ECM used in Galeotti (2003) and in Grasso and Manera (2007), and the semi-asymmetric version recently used in Contín-Pilart et al. (2009). In Section 4, we present and comment on the main results. In Section 5, we will ask ourselves whether our findings are sensitive to the transformation of our series into lower frequencies and the extent to which measuring empirical results from weekly data is robust to some of the different ways in which the dataset can be constructed. Finally, in Section 6 we will provide the summary conclusions of the paper.

2. Data and descriptive statistics

In this paper we consider two classes of petroleum energy products: gasoline and diesel fuel (unleaded 95-octane gasoline and fuel for diesel engines, respectively). Both oil products constitute the most important petroleum derivatives sold by gas stations in Spain. In July 2009, they represented 96.10% of fuel consumption according to data information obtained from the *AOP*. In particular, diesel represents close to three quarters of the total fuel oil consumption (74.33%), while gasoline accounts for nearly all the rest (21.87%).

The retail prices for each oil product that we will use in our empirical analysis are based on the average prices fixed by gas stations all over Spain. These data are collected by the Spanish *Ministry of Industry, Tourism and Trade* (in accordance with Ministerial Order ITC/2308/2007).[8] We consider daily retail prices net of taxes. Therefore, the special tax on hydrocarbons, the general tax established by the State, the taxes applied by autonomous governments and value added tax (VAT) have been excluded following information published by the Spanish *Ministry of Economy's Tax Office*.

Since we will focus on analyzing the commercialization chain, the raw oil material is taken as being the refined oil for each product. This is considered the most important direct cost for fuel retailers. So, FOB Rotterdam prices (formally, Amsterdam-Rotterdam-Antwerp) were collected from the *Energy Information Administration* for both gasoline and diesel fuels. On weekends and holidays, where observations are missing as a consequence of the spot oil market closure, the wholesale FOB prices used the day before will be applied. International wholesale prices are collected in dollar terms (per liter), and so these prices are converted into the Spanish local currency. For this purpose we used the daily US dollar/euro exchange rate obtained from the *Eurostat* database.

The sample period available for price variables ranges from November 1st 2006 to July 12th 2009, involving 985 daily observations for each type of oil product. In Figure 1 we can see the evolution of the price variables by levels throughout this period. As we can see, wholesale and retail prices (in the case of gasoline and diesel fuel) follow each other very closely (with a correlation coefficient of 0.96 and 0.98, respectively). We expect this to be derived from a strongly causal relation between both types of price variables. Moreover, retail prices are always higher than wholesale prices for refined oil products. This gap can be basically attributed to the presence of distribution and marketing costs, as well as the mark-up fixed by final sellers. With the aim of preventing misspecification in the econometric model as a consequence of the possible existence of outliers, the first differences in retail prices have also been represented in

[8] More specifically, retail prices set at the sale point must be transmitted by sellers to the Ministry every Monday and whenever prices change. In general, many service stations send information about changes in their selling prices several days per week.

Figure 1. We can now identify some extreme variations in these prices. More specifically, for both kinds of fuel products, extreme variations in data are present on December 15th 2008, January 8th 2009 and June 13th 2009.

[Please insert Figure 1 here]

Oil price volatility in our period seems relatively high. Thus, for example, standard deviation of wholesale oil prices (in euros) for our period is near four times greater than those obtained from the period June 1st 1991 to December 31st 2003. In fact, the range of rolling standard deviations (using a window-size of 30 observations) is 0.07-0.46 for gasoline and 0.14-0.56 for diesel fuel in our period, whereas ranges are between 0.00-0.10 for both types of oil products in this older period.[9]

Descriptive statistics for time series are summarized in Table 1. According to available data, it can be seen that retail prices for final products change every of days considered. In view of this, it is reasonable to think that these retail price variations could be derived from a response of sellers to the frequent daily changes in wholesale prices (in euros). In this context, the use of daily disaggregation of time series will allow us to approximate to possible response of retail prices performed within a week. Furthermore, the number of wholesale price reductions and increases available in the sample period are quite similar for intermediate refined oil products. Changes are nearly five hundreds for both upwards and downwards. The great number of both sorts of variations will ensure a better precision of the asymmetric coefficients estimates.

[Please insert Table 1 here]

3. Econometric specifications

It is reasonable to expect that, in open economies, marginal costs of domestic oil sellers are directly affected by wholesale price variations in the international market for refined oil products.[10] As in most previous research about the international oil price transmission phenomenon, we abstract from additional factors that may determine final prices (such as inventory levels, marketing costs, distribution costs or price

[9] Oil prices for this older period are also available on the *Energy Information Administration* website.

[10] We use prices for refined oil products instead of other raw material costs (such as the spot price of crude oil). In this way, we ensure the independence of the retail price to some extent from the demand for other refined products due to joint production in the industry (Borenstein et al., 1997).

expectations) and we model the international oil price pass-through as following the reduced form equation (in logs):

$$p_t = \phi_0 + \phi_1 rp_t + \varepsilon_t \qquad (1)$$

where p_t and rp_t are, respectively, the retail oil prices and the international wholesale prices for refined oil product at time *t*. The intercept ϕ_0 indicates the fixed mark-up of price over costs, and the coefficient ϕ_1 represents the cost pass-through to retail prices.

If the time series are integrated of order one I(1) and cointegrated with one another, the widely known ECM will constitute a suitable specification to study price transmission. In this case, the two-step procedure proposed by Engle and Granger (1987) becomes useful to make a direct estimation of the response of the dependent variable (p_t), both in the short and the long term, to changes in the independent variable (rp_t). In accordance with this empirical methodology, we include the (lagged) residuals obtained from the cointegrating Eq. (1) in an ECM as a measure of the error correction mechanism:

$$\Delta p_t = \sum_{m=1}^{M} \beta_m \, \Delta p_{t-m} + \sum_{n=0}^{N} \delta_n \, \Delta rp_{t-n} + \theta EC_{t-1} + u_t \qquad (2)$$

where Δ indicates the first difference operator, and *M* and *N* refers to the number of lags of the short-term impact of the retail and refined prices respectively. The regression coefficients β_m measure the short-term impact of changes in lagged retail prices, whereas δ_n measure the short-term impact of changes in refined prices. Moreover, θ represents the long-term equilibrium adjustment parameter, which is associated to the one-period lagged residuals from the cointegration relationship in Eq. (1), EC_{t-1}. The lagged error correction term is included because retail prices are not fully and instantaneously adjusted. If retail prices are above their equilibrium level, then they should fall back to the long-term equilibrium, whereas if retail prices are below the level forecast by the refined price, then they should rise. Therefore, the coefficient of error correction term (θ) should be negative.

We can now extend the ECM specification to the case of asymmetric adjustments, following Granger and Lee (1989), by decomposing both the short-run dynamics and the error correction term into positive and negative values. Therefore, as in Galeotti

(2003) and in Grasso and Manera (2007), we can consider the following econometric specification:

$$\Delta p_t = \sum_{m=1}^{M} \beta_m^+ \Delta p_{t-m}^+ + \sum_{m=1}^{M} \beta_m^- \Delta p_{t-m}^- + \sum_{n=0}^{N} \delta_n^+ \Delta rp_{t-n}^+ + \sum_{n=0}^{N} \delta_n^- \Delta rp_{t-n}^- + \theta^+ EC_{t-1}^+ + \theta^- EC_{t-1}^- + u_t \qquad (3)$$

where, on the one hand, the short-run asymmetry is captured by breaking price changes down into Δp_{t-n}^+ and Δrp_{t-n}^+ if their respective differences are above zero, and Δp_{t-n}^- and Δrp_{t-n}^- otherwise. On the other hand, the asymmetry in the adjustment speed at which relative prices return to their long-term equilibrium is introduced by defining EC_{t-1}^+ if the one-period lagged residuals are above zero, and EC_{t-1}^- otherwise.

The sign and magnitude of the coefficients will offer information about the importance of possible asymmetries in retail price behavior. In the context of model (3), the possibility of asymmetries is contemplated in both the short and the long term. A sort of pattern asymmetry occurs when the short-term coefficients δ_n^+ and δ_n^- are different to each other. Through comparison of the aggregation of these coefficients some authors also deal with the concept of "amount asymmetry" (e.g., Von Cramon-Taubadel, 1998; Bettendorf et al., 2009). In this line, we can also refer to the existence of partial "amount asymmetry" in terms of Eq. (3) if: $\sum_{n=0}^{N-k} \delta_n^+ \neq \sum_{n=0}^{N-k} \delta_n^-,\ 0 < k < N$. That is, in a particular time period, input price increases (reductions) are transmitted more completely to retail prices than the corresponding input price reductions (increases).

Most papers are especially interested, nevertheless, in the presence of the "rockets and feathers" phenomenon in the long term. This would imply that prices return to their long-term equilibrium levels at different speeds and would be revealed if $|\theta^+| < |\theta^-|$. In other words, the mean reversion is faster when retail prices are below their long-run levels and slower when retail prices should be adjusting downwards toward their long-term levels.

As an alternative to the popular version represented in Eq. (3), we will also deal with the model used in the recent paper by Contín-Pilart et al. (2009), which is in the spirit of the models previously used by other authors (e.g., Bachmeier and Griffin, 2003; Kaufmann and Laskowski, 2005). So, we will take into account a semi-asymmetric ECM based on two regimes where the wholesale price of raw oil material is taken as a threshold variable. Specifically, symmetric behavior is assumed in the short dynamic term, but the long-run error correction term is now decomposed in accordance with the changes in the wholesale price of raw oil material:

$$\Delta p_t = \sum_{m=1}^{M} \beta_m \, \Delta p_{t-m} + \sum_{n=0}^{N} \delta_n \; \Delta rp_{t-n}$$

$$+\theta^{(\Delta rp_{t-1} \leq 0)} EC_{t-1}^{(\Delta rp_{t-1} \leq 0)} + \theta^{(\Delta rp_{t-1} > 0)} EC_{t-1}^{(\Delta rp_{t-1} > 0)} + u_t \tag{4}$$

where $EC_{t-1}^{(\Delta rp_{t-1} \leq 0)}$ refers to the one-period lagged residuals when variation of wholesale price for raw oil material is below or equal to zero, and $EC_{t-1}^{(\Delta rp_{t-1} > 0)}$ otherwise. Divergence of the associated coefficients in absolute values would indicate an asymmetric response of the pattern of adjustment toward long-run equilibrium (before the sign of shocks in wholesale prices).

We expect to confirm the existence of a close empirical relationship between long-run pattern adjustment of Eq. (3) and Eq. (4). On the one hand, the corresponding coefficient in Eq. (3) captures the retail price response obtained after their deviations above or below long-run equilibrium. On the other hand, the related coefficient in Eq. (4) indicates a response toward long-run equilibrium directly derived from positive or negative shocks in international wholesale prices. On considering both interpretations, it is reasonable to think that a positive (negative) shock in wholesale prices of raw material would lead to long-run disequilibrium and residual component moves toward negative (positive) values. Therefore, we expect the coefficient of $\theta^{(\Delta rp_{t-1}>0)}$ in Eq. (4) to be associated to θ^{-} in Eq. (3), while $\theta^{(\Delta rp_{t-1} \leq 0)}$ would, in general, be more closely linked with the coefficient θ^{+}.

4. Empirical results

4.1. Analysis of series and coefficient estimates

The error correction specifications presented by Eq. (3) and Eq. (4) are based on cointegration of time series as we mentioned above. Therefore, before performing our cointegration analysis, we check whether the different variables are stationary. We apply the *augmented* and *modified Dickey-Fuller* tests (ADF and DF/GLS, respectively) as well as the *Phillips-Perron* test (PP). As can be seen in Table 2, all prices on levels include a unit root while their first differences are stationary, so the time series are integrated of order one *I(1)*.

In this case, the retail domestic prices and wholesale international prices can be cointegrated, which would imply the existence of a stable long-run economic relationship between these variables. To test for cointegration, first we use ordinary least squares (OLS) to estimate the lineal combination between time series as expressed in Eq. (1), and later we test whether the residuals thus obtained are stationary by using the set of unit root statistics cited above. Table 2 also shows that the null hypothesis of unit root tests is clearly rejected in all cases, so we verify the existence of cointegration.

Once we have confirmed the presence of cointegration between both price variables, we now estimate the asymmetric ECM represented by Eq. (3) and Eq. (4) by OLS with White-robust standard errors. Dummy variables are considered in the regressions to account for three outliers identified in Section 2. In both cases, selection of the number of optimum lags for regressors is determined by minimizing the *Akaike information criterion* (AIC) and the *Bayesian information criterion* (BIC).[11] Figure 2 shows the standard deviations of residuals obtained for the two oil products. These graphs suggest that there are some sub-periods of low volatility which are followed by sub-periods of high volatility (basically at the end of the sample period). Therefore, it is not clear whether the standard deviations of errors can be considered constant over time. We therefore performed a robust *Lagrange multiplier* test (LM) of *autoregressive conditional heteroskedasticity* (ARCH) on residuals to know formally whether there is any volatility clustering. These results are reported in Table 3. Tests suggest that errors from Eqs. (3) and (4) follow an ARCH process for both the oil products under consideration.

[Please insert Figure 2 here]

[Please insert Table 3 here]

The existence of an ARCH process would imply that OLS estimates are inefficient and this standard estimation procedure would invalidate inference on parameters of interest.

[11] Both for gasoline and for diesel fuel, we found that Bartlett's test suggested that the error term follows a white noise process (with mean zero and variance σ^2). Additionally, Ljung-Box Q-statistics, where different numbers of lags were obtained, are in favor of the idea that errors are not serially autocorrelated. Results for this preliminary regression are available upon request.

One of the most prominent tools for capturing time variance changes is to incorporate the *generalized* ARCH process (GARCH) developed by Engle (1982) and extended by Bollerslev (1986). Therefore, our model will consist of a mean equation (i.e., ECM) and a second equation that considers the conditional variance as an ARMA process. The random disturbance can be represented as:

$$u_t = v_t \sigma_t = v_t \sqrt{h_t} \tag{5}$$

$$v_t \; i.i.d, \qquad E(v_t) = 0, \qquad E(v_t^2) = 1$$

where σ_t^2 is written as h_t and v_t represents a process of random variables that are independent and identically distributed with mean zero and unit variance. We will then consider the following GARCH (p,q) model, in which the conditional variance (h_t) is a function of the squares of the previous values of the error term (u_{t-i}^2, $i=1,\dots,P$), as well as *j* lagged conditional variances (h_{t-j}, $j = 1, \dots, Q$):

$$h_t = \alpha_0 + \sum_{i=1}^{P} \alpha_i u_{t-i}^2 + \sum_{j=1}^{Q} \gamma_j h_{t-j} \tag{6}$$

where the error term u_t, is assumed to be normally distributed with zero mean and conditional variance, h_t, and we expect the value of α_0 to be small. The effect of innovations of lagged residuals on volatility can be measured by α_i (ARCH term), whereas the γ_j (GARCH term) shows the persistence of volatility to a shock or, alternatively, the impact of innovations of lagged variance on volatility. All parameters in Eq. (6) must be positive, and $\alpha_i + \gamma_j$ is expected to be close to but less than unity (with $\gamma_j > \alpha_i$).

[Please insert Table 4 here]

In Table 4 we report maximum likelihood estimates of the asymmetric ECMs by incorporating a GARCH error structure. By minimizing the AIC and BIC we found that the number of optimum lags in models are 7 and 8 for retail and wholesale refined oil prices, respectively, and that the volatility cluster process in the error term can be adequately modeled as a standard GARCH(1,1). So, according to Barlett's test for white noise, the errors can be considered a sequence of independent random variables with mean zero and a constant variance σ^2. The Ljung-Box Q-statistic indicates that errors are not serially autocorrelated. Furthermore, the Q-statistic related with squared standardized residuals suggests that conditional homoskedasticity cannot be rejected.

With regard to the estimated parameters of conditional volatility, the sum of ARCH and GARCH coefficients is very close to one, thus indicating that volatility shocks are quite persistent. On the one hand, the coefficients of the lagged squared residuals (i.e., the ARCH term) are slightly positive and statistically significant for all the specifications, thereby suggesting that past innovations of error terms are moderately relevant. On the other hand, the estimated coefficients of lagged conditional variances (i.e., GARCH term) are especially high and significantly positive, which indicates the importance of the old variances within the volatility process.

As we can see at the top of Table 4, a large part of the estimated coefficients associated to the lagged retail prices are positive and statically significant. This set of results indicates that there is some sticky dependence of final prices with respect to their own past values. Sticky dependence is probably due to the presence of menu costs, information processing or stock management costs of oil sellers. The short-run effects of international wholesale prices for refined oil products are shown in Table 4. As expected, the significant coefficients are positive regardless of the specification considered. Interestingly, retail prices are not significantly affected by the contemporaneous and the first lagged period of international wholesale prices. Retail prices start to be significantly affected by international price variations as of the second lagged period. According to model selection criteria, international price changes affect retail prices up to the eighth lagged period.[12] The estimates from Eq. (3) reveal that both upward and downward variations in lagged international oil prices have a positive significant impact on the retail oil price responses. These estimates are broadly consistent with those obtained from Eq. (4), where a common effect between upward and downward variations in lagged international oil prices is assumed.

The estimated coefficients related to the error correction term can be interpreted as the speed of convergence toward long-run equilibrium. As we commented in Section 3, the coefficient associated EC_{t-1}^{+} (EC_{t-1}^{-}) in Eq. (3) can be interpreted as the speed at which retail prices return to equilibrium when they are below (above) their long-run level. In

[12] According to analyses performed by Radchenko (2005a), the number of relevant lags in response to retail prices is closely related with the type of oil shocks. The more cost shocks are perceived as transitory, the greater the number of lags is.

Eq. (4), coefficient associated to $EC_{t-1}^{(\Delta rp_{t-1} \leq 0)}$ $(EC_{t-1}^{(\Delta rp_{t-1} > 0)})$ measures the speed of convergence toward long-run equilibrium when faced with a negative (positive) variation in wholesale oil price. As expected, regardless of the type of oil product considered, the signs for both the estimated coefficients in Eqs. (3) and (4) are negative and significant.

4.2. Testing for asymmetries

A possible pattern of asymmetries in the short-run can be identified from Eq. (3), while both the equations (3 and 4) considered will allow us to identify the possible asymmetries in the adjustment towards the long run equilibrium. Table 5 shows an interesting test related with these asymmetries. Tests presented for the coefficients from Eq. (3) suggest that, in general, there is no clear pattern of asymmetries in the short term. That is, response time of positive (negative) shocks exceeds significantly negative (positive) shocks exceptionally. More specifically, positive exceeds negative in the fifth and seventh lags for gasoline and in the sixth lag for diesel fuel, whereas the opposite phenomenon is obtained in the third lag for the case of gasoline. Moreover, lack of asymmetries in the short term can be summarized by taking into account tests for amount asymmetry.

[Please insert Table 5 here]

We are especially interested in testing the null hypothesis concerning the presence of symmetry in the speed of convergence toward the long-run equilibrium level. As can be seen at the end of Table 5, it is clearly not rejected since p-values are relatively high for both types of oil products. Hence, the time required to re-establish long-run equilibrium is not statistically different in the case of a negative shock to that needed in the case of a positive shock. It is important to note that, the results of the tests are robust to two specifications of ECMs considered here. That is, these empirical results are similar if we look at the positions above and below equilibrium derived from any shock (i.e., Eq. (3)) and, alternatively, if we consider divergence from equilibrium to be closely conditioned to the sign of shocks in wholesale prices of raw material (i.e., Eq. (4)). Therefore, in view of our results, we can think that possible inefficiencies in the Spanish oil market should not be attributed to the asymmetric speed of retail price adjustment toward long-run equilibrium.

5. Would weekly data be suitable in our study case?

The availability of new data series on retail prices of fuel oil products for many countries led to a renewed interest in the empirical analysis of the response of these local prices to international oil price shocks. These series are easily obtained from official websites on a weekly basis, which is the highest frequency possible. However, as we have shown for Spain in Section 2, gas stations are free to change their prices from day to day. In this circumstance with weekly or lower data frequencies it would not be possible to obtain detailed information about the price responses that occur within a week. Therefore, weekly data might not be fully appropriate for use in ECMs since a number of time lags are probably omitted in the short term. Thus, a type of omitted variables bias can be introduced (as can be seen in Geweke, 1978).

In this section we exploit our daily database on both gasoline and diesel fuel prices with the aim of knowing whether, under our context, weekly data would be appropriate to obtain accurate estimates of reversion toward long-run equilibrium. The datasets that were used were built in two different ways (in accordance with the data information on oil retail prices offered by energy agencies). First, we consider one week day in each week and, second, we carry out averages of the seven consecutive days.

Retail price and wholesale price series contain a unit root. As in analyses with daily data, both time series are cointegrated.[13] Therefore, we can apply an ECM to measure possible transmission asymmetries. To simplify, in Table 6 we present a summary of the results that were obtained. We showed the estimates from the most popular version of ECM represented by Eq. (3) where, as in the regressions when daily data are used, three outliers identified in Section 2 are also taken into account in the corresponding observations. We start by presenting results obtained from regressions derived from information with weekly gaps. We can then see the results obtained from regressions in which the temporal average of seven consecutive daily data items is used. The number of lagged variables M and N are determined by minimizing the AIC and BIC criteria for the selection of models. Retail price changes are affected by the variations in international wholesale prices corresponding to the contemporaneous period and one lagged week. In principle it is quite compatible with the length of short-term period

[13] Unit roots and cointegration tests for weekly data are available upon request.

derived from model selection in daily data. Except in one of the cases, the Ljung-Box Q-statistics for residuals and for squared residuals, respectively, indicate that there is no problem of autocorrelation and autoregressive conditional heteroskedasticity in OLS regressions.

[Please insert Table 6 here]

Results are critically dependent on the way that we constructed the weekly sets and also on the reference day considered in the construct. Most of these results contrast with those obtained with daily data and, of fundamental importance, they contradict themselves. In the case of gasoline, for example, symmetric convergence toward long-run equilibrium is rejected in the dataset of daily averages from Mondays.[14] Nevertheless, it cannot be rejected when averages are realized from Wednesdays or from Fridays. The results thus clearly suggest the presence of estimation bias caused by the omission of relevant lagged variables. Therefore, in our case, we can think that the use of weekly data would affect the robustness of our conclusions.

6. Concluding remarks

The empirical work performed in this study was guided above all by the current social concern about the possible existence of the "rockets and feathers" phenomenon in Spain. Formal exploration of the possibility of this phenomenon is strongly encouraged bearing in mind the seemingly controversial results obtained by earlier papers. We focused on the pattern of transmission of Rotterdam spot prices to final domestic oil prices (net of tax) fixed by gas stations (i.e., the distribution chain). The work was confined to the study of the retail price behavior for both gasoline and diesel fuel, which account for almost all the oil fuel products sold in Spain. We based our empirical analysis on two standard asymmetric ECM specifications. A major difference with regard to the earlier research lies in the exploitation of daily data information over a more recent period characterized by relative price volatility. The nature of the data used here implied the application of a GARCH model in the analysis, which proved to be useful for capturing the daily volatility clustering. Our conclusions are robust to the alternative specifications of the empirical model and results are very similar between both gasoline and diesel fuel.

[14] We can also note that when symmetries are rejected, the outcome of the "rockets and feathers" phenomenon (i.e. results are in favour that $|\theta^{+}| > |\theta^{-}|$).

The dataset used in the analysis allowed us to estimate the daily responses in retail oil markets, in contrast to the lower frequency data habitually used in literature dealing with the issue, which do not allow intraweek reactions to be quantified. Our short-term estimates showed that international shock costs cause, with a delay of just two days, significant adjustments in retail oil prices over the next eight days. Tests over partial amounts of retail price adjustments (derived from one of the model specifications used) clearly suggested the existence of symmetric pricing behavior in the short term.

Analyses of retail price reversion toward a long-run equilibrium level have attracted a great deal of attention in this research area. In this sense, two alternative interpretations are derived from the models used. Specifically, on the one hand, we sought to measure retail price responses to long-run equilibrium as a consequence of their deviations either above or below it. On the other hand, we attempted to obtain retail price reversion toward long-run equilibrium directly as a consequence of deviations caused by positive or negative shocks in international wholesale prices. Regardless of the specification model that was used, evidence suggests that there is a symmetric response of retail prices in the rate of adjustment toward long-run equilibrium. Hence, our findings are consistently in favor of an efficient price transmission mechanism.

To know whether lower frequencies in our price series could be an important source of poor estimates of the pattern of responses toward long-run equilibrium, we built several weekly datasets. First, we constructed some datasets by choosing one working day for each week. We showed that results are critically dependent on the working day that is selected. The outcome is in line with the findings obtained by Bettendorf et al. (2003), where price series for Netherlands were analyzed. Second, we also built a new set of time series using the averages of daily prices per week. Results were clearly affected by the first day for which each week was defined. This outcome suggests that estimates from average data per week suffers from the presence of temporal aggregation bias. This is in line with the conclusions of the paper by Bachmeier and Griffin (2003) concerning non-standard ECM.

It should be noted that our work refers to a more recent period than the previous papers in which Spain was considered. Hence, our findings are not directly contradictory to the earlier results obtained by Galeotti et al. (2003) and by Grasso and Manera (2007). The existence of some structural changes in the retail oil market, which implied a more efficient price transmission mechanism, could be conjectured. A more believable explanation of changes toward symmetries could be attributed to the great degree of international oil price volatility in the more recent period. Interestingly, as Radchenko (2005b) revealed, a higher degree of price volatility may contribute significantly to reduce the degree of asymmetries. However, even accepting these or other possibilities, results from both papers seemingly conflict with those obtained by Contín-Pilart et al. (2009) for a similar period. Therefore, it is plausible to think that the lack of robustness derived from weekly or more aggregated data would be able to explain the differences. In any case, our findings reinforce the idea that further research is needed in this area as more daily data on retail oil prices become available.

Acknowledgements

The authors wish to thank to Juan A. Máñez, José C. Pernías and the participants of the INTECO conference at the University of Valencia (2010) for helpful comments on an earlier version of this paper. Facilities for data information from the Spanish *Ministry of Industry, Tourism and Trade*, as well as financial support from the Spanish *Ministry of Science and Technology* (ECO2008-06057/ECON), *Generalitat Valenciana* (VALi+D Program, ACIF/2010) and *Fundació Caixa Castelló-Bancaixa* (P1-1A2007-19) are also gratefully acknowledged.

References

Bachmeier, L.J., Griffin, J.M., 2003. New evidence on asymmetric gasoline price responses. Review of Economics and Statistics 95, 772-776.

Bacon, R.W., 1991. Rockets and feathers: the asymmetric speed of adjustment of UK retail gasoline prices to cost changes. Energy Economics 13, 211-218.

Bettendorf, L., Van der Geest, S., Varkevisser, M., 2003. Price asymmetry in the Dutch retail gasoline market. Energy Economics 25, 669-689.

Bettendorf, L., Van der Geest, S., Kuper, G., 2009. Do daily retail gasoline prices adjust asymmetrically? Journal of Applied Statistics 36, 385-397.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-327.

Borenstein, S., Cameron, A.C., Gilbert, R., 1997. Do gasoline prices respond asymmetrically to crude oil price changes? Quarterly Journal of Economics 112, 305-339.

Contín-Pilart, I., Correljé, A.F., Palacios, M.B., 2009. Competition, regulation, and pricing behaviour in the Spanish retail gasoline market. Energy Policy 37, 219-228.

MacKinnon, J.G., 1996. Numerical distribution functions for unit root and cointegration tests. Journal of Applied Econometrics 11, 601-618.

Deltas, G., 2008. Retail gasoline price dynamics and local market power. The Journal of Industrial Economics 61, 613-628.

Enders, W., Granger, C.W.J., 1998. Unit root tests and asymmetric adjustment with an example using the term structure of interest rates. Journal of Business and Economic Statistics 16, 304-311.

Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of United Kingdom inflation. Econometrica 50, 987-1008.

Engle, R.F., Granger, C.W.J., 1987. Cointegration and error correction: representation, estimation, and testing. Econometrica 55, 251-276

Galeotti, M., Lanza, A., Manera, M., 2003. Rockets and feathers revisited: an international comparison on European gasoline markets. Energy Economics 25, 175-190.

Geweke, J., 1978. Temporal aggregation in the multiple regression model. Econometrica 46, 643-661.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance 48, 1779-1801.

Granger, C.W.J., Lee, T.H., 1989. Investigation of production, sales and inventory relationships using multicointegration and non-symmetric error correction models. Journal of Applied Econometrics 4, S145–S159.

Grasso, M., Manera, M., 2007. Asymmetric error correction models for the oil-gasoline price relationship. Energy Policy 35, 156-177.

Griffith, G.R., Piggott, N.E., 1994. Asymmetry in beef, lamb and pork farm-retail price transmission in Australia. Agricultural Economics 10, 307-316.

Kaufmann, R.K., Laskowski, C., 2005. Causes for an asymmetric relation between the price of crude oil and refined petroleum products. Energy Policy 33, 1587-1596.

Peltzman, S., 2000. Prices rise faster than they fall. Journal of Political Economy 108, 466-502.

Phillips, P.C.B., Perron, P., 1988. Testing for a unit root in time series regression. Biometrika 75, 335-346.

Radchenko, S., 2005a. Lags in the response of gasoline prices to changes in crude oil prices: The role of short-term and long-term shocks. Energy Economics 27, 573-602.

Radchenko, S., 2005b. Oil price volatility and the asymmetric response of gasoline prices to oil price increases and decreases. Energy Economics 27, 708-730.

Romain, R., Doyon, M., Frigon, M., 2002. Effects of State regulations on marketing margins and price transmission asymmetry: evidence from the New York City and Upstate New Work fluid milk markets. Agribusiness 18, 301-315.

Von Cramon-Taubadel, S., 1998. Estimating asymmetric price transmission with the error correction representation: an application to the German pork market. European Review of Agricultural Economics 25, 1-18.

Table 1. Descriptive statistics

Prices of:	Minimum values	Maximum values	Total changes	Number of increases	Number of decreases
Retail gasoline	0.296	0.685	984	545(55.39%)	439(44.61%)
Wholesale gasoline	0.152	0.578	973	481(49.43%)	492(50.57%)
Retail diesel fuel	0.387	0.817	984	519(52.74%)	465(47.26%)
Wholesale diesel fuel	0.229	0.709	977	480(49.13%)	497(50.87%)

All prices are expressed in euros per liter and retail prices are net of taxes. The relative percentages of changes are reported in parenthesis.

Table 2. Unit roots and cointegration tests

	ADF	Lags ADF	DF/GLS	Lags DF/GLS	PP	Lags PP
Unit roots tests for time series of prices						
Gasoline						
p_t	-2.154	21	-1.806	21	-0.776	6
Δp_t	-3.868***	20	-3.779***	20	-22.475***	6
rp_t	-1.751	21	-1.508	21	-0.427	6
Δrp_t	-5.390***	20	-4.066***	20	-29.209***	6
Diesel fuel						
p_t	-0.303	21	-1.068	21	-0.161	6
Δp_t	-4.671***	20	-4.616***	20	-22.273***	6
rp_t	-0.042	20	-0.991	21	-0.009	6
Δrp_t	-5.583***	20	-4.366***	20	-33.973***	6
Cointegration tests for residuals from long-run Eq.(1)						
Gasoline	-2.735***	21	-3.448**	21	-5.027***	6
Diesel fuel	-0.061***	18	-4.031***	18	-5.302***	6

Number of lags in ADF test is based on the Schwarz Information Criterion. The DF/GLS is implemented using the optimum lags obtained by the Ng-Perron procedure and the PP test uses Newey-West lags. We use ***, ** and * to indicate the rejection of the null hypothesis (the variable has a unit root) at 1%, 5% and 10% significance levels, respectively, on the basis of the critical values by Mackinnon (1996).

Table 3. ARCH LM test for residuals

Lags and degrees of freedom	1	2	3	4	5	6	7
Eq. (3)							
Gasoline	12.124***	14.541***	14.795	18.890***	23.404***	24.656***	26.245***
	[0.001]	[0.001]	[0.002]	[0.001]	[0.000]	[0.000]	[0.000]
Diesel fuel	3.954**	10.308***	10.321**	14.316***	16.752***	16.945***	17.470**
	[0.047]	[0.006]	[0.016]	[0.006]	[0.005]	[0.010]	[0.015]
Eq. (4)							
Gasoline	31.849***	33.638***	33.606***	38.060***	44.483***	45.061***	48.213***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Diesel fuel	4.985**	15.059***	15.136***	22.245***	24.668***	24.635***	25.820***
	[0.026]	[0.001]	[0.002]	[0.000]	[0.000]	[0.001]	[0.001]

The p-values are reported in brackets, and we use ***, ** and * to indicate the rejection of the null hypothesis (no ARCH errors) at the 1%, 5% and 10% significance levels, respectively.

Table 4. Asymmetric ECMs with GARCH(1,1) specification

Variables and statistics	Eq. (3) Gasoline		Diesel fuel	
Δp^{+}_{t-1}	0.215***	(0.040)	0.228***	(0.046)
Δp^{-}_{t-1}	0.001	(0.047)	0.009	(0.039)
Δp^{+}_{t-2}	-0.040	(0.047)	-0.025	(0.061)
Δp^{-}_{t-2}	0.162***	(0.047)	0.132***	(0.050)
Δp^{+}_{t-3}	0.001	(0.040)	0.037	(0.036)
Δp^{-}_{t-3}	0.073*	(0.044)	0.094*	(0.049)
Δp^{+}_{t-4}	0.029	(0.037)	0.002	(0.039)
Δp^{-}_{t-4}	0.087*	(0.048)	0.057*	(0.041)
Δp^{+}_{t-5}	0.013	(0.041)	0.010	(0.042)
Δp^{-}_{t-5}	0.109***	(0.041)	0.101**	(0.041)
Δp^{+}_{t-6}	0.093**	(0.037)	0.136	(0.031)
Δp^{-}_{t-6}	-0.035	(0.035)	0.001	(0.044)
Δp^{+}_{t-7}	0.129***	(0.042)	0.127***	(0.037)
Δp^{-}_{t-7}	0.187***	(0.047)	0.116***	(0.040)
Δrp^{+}_{t}	-0.001	(0.009)	-0.002	(0.009)
Δrp^{-}_{t}	-0.011	(0.010)	-0.001	(0.009)
Δrp^{+}_{t-1}	0.008	(0.011)	0.008	(0.011)
Δrp^{-}_{t-1}	-0.008	(0.009)	-0.003	(0.011)
Δrp^{+}_{t-2}	0.017**	(0.008)	0.013	(0.011)
Δrp^{-}_{t-2}	0.023**	(0.009)	0.013*	(0.009)
Δrp^{+}_{t-3}	0.010	(0.008)	0.014*	(0.009)
Δrp^{-}_{t-3}	0.036***	(0.011)	0.027***	(0.010)
Δrp^{+}_{t-4}	0.033***	(0.011)	0.034***	(0.012)
Δrp^{-}_{t-4}	0.040***	(0.009)	0.032***	(0.010)
Δrp^{+}_{t-5}	0.045***	(0.011)	0.024**	(0.010)
Δrp^{-}_{t-5}	0.013*	(0.008)	0.047***	(0.011)
Δrp^{+}_{t-6}	0.033***	(0.009)	0.055***	(0.011)
Δrp^{-}_{t-6}	0.029***	(0.009)	0.023**	(0.010)
Δrp^{+}_{t-7}	0.033***	(0.009)	0.033***	(0.009)
Δrp^{-}_{t-7}	0.008	(0.010)	0.024**	(0.011)
Δrp^{+}_{t-8}	0.027***	(0.010)	0.024**	(0.011)
Δrp^{-}_{t-8}	0.035***	(0.011)	0.027**	(0.011)
$EC^{(a)}_{t-1}$	-0.013**	(0.006)	-0.014**	(0.006)
$EC^{(b)}_{t-1}$	-0.009**	(0.004)	-0.012***	(0.005)
Constant	0.000	(0.000)	0.000	(0.000)
GARCH	0.960***	(0.012)	0.980***	(0.013)
ARCH	0.037***	(0.011)	0.019*	(0.011)
Adj. R^2	0.629		0.609	
BIC	-8116.363		-8346.986	
AIC	-8301.935		-8532.558	
Bartlett	0.668	[0.764]	0.551	[0.922]
LB(7)	1.452	[0.984]	1.939	[0.963]
$LB^2(7)$	4.854	[0.678]	8.895	[0.260]

Variables and statistics	Eq. (4) Gasoline		Diesel fuel	
Δp_{t-1}	0.112***	(0.032)	0.117***	(0.030)
Δp_{t-2}	0.057*	(0.033)	0.051*	(0.037)
Δp_{t-3}	0.007	(0.032)	0.038	(0.033)
Δp_{t-4}	0.040	(0.030)	0.014	(0.029)
Δp_{t-5}	0.068**	(0.028)	0.064**	(0.028)
Δp_{t-6}	0.037*	(0.025)	0.071**	(0.028)
Δp_{t-7}	0.181***	(0.032)	0.147***	(0.028)
Δrp_{t}	-0.008	(0.006)	-0.002	(0.005)
Δrp_{t-1}	0.001	(0.006)	0.002	(0.007)
Δrp_{t-2}	0.021***	(0.005)	0.013**	(0.006)
Δrp_{t-3}	0.023***	(0.006)	0.022***	(0.006)
Δrp_{t-4}	0.035***	(0.007)	0.036***	(0.007)
Δrp_{t-5}	0.031***	(0.006)	0.039***	(0.007)
Δrp_{t-6}	0.032***	(0.006)	0.042***	(0.007)
Δrp_{t-7}	0.022***	(0.006)	0.030***	(0.006)
Δrp_{t-8}	0.031***	(0.007)	0.027***	(0.007)
$EC^{(a)}_{t-1}$	-0.012***	(0.004)	-0.014***	(0.005)
$EC^{(b)}_{t-1}$	-0.011***	(0.004)	-0.013***	(0.004)
Constant	0.000	(0.000)	0.000	(0.000)
GARCH	0.958***	(0.012)	0.978***	(0.015)
ARCH	0.039***	(0.011)	0.020*	(0.011)
Adj. R^2	0.600		0.601	
BIC	-8182.046		-8426.14	
AIC	-8284.599		-8528.693	
Bartlett	0.738	[0.648]	0.590	[0.878]
L-B(7)	1.394	[0.986]	1.825	[0.969]
$L\text{-}B^2(7)$	5.273	[0.627]	8.750	[0.271]

White's heteroskedasticity consistent standard errors are in parenthesis and p-values are reported in brackets. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively. LB(7) and $LB^2(7)$ are, respectively, the Ljung-Box statistics for standardized and squared standardized residuals (using 7 lags). The superscripts (a) and (b) refer respectively to (+) and (-) in the case of Eq. (3), and $(\Delta rp_{t-1} \leq 0)$ and $(\Delta rp_{t-1} > 0)$ in the case of Eq. (4).

Table 5. Tests for symmetric adjustments

Null hypothesis	Gasoline		Diesel fuel		Null hypothesis	Gasoline		Diesel fuel	
Eq. (3)									
Pattern of short-term adjustment in *n*					Partial amount of short-term variations in *n*				
$\delta_0^+ = \delta_0^-$	0.43	[0.510]	0.01	[0.935]	-	-		-	
$\delta_1^+ = \delta_1^-$	1.03	[0.311]	0.33	[0.565]	$\Sigma_{n=0}^{n=1}\delta_n^+ = \Sigma_{n=0}^{n=1}\delta_n^-$	1.72	[0.189]	0.18	[0.670]
$\delta_2^+ = \delta_2^-$	0.22	[0.639]	0.00	[0.998]	$\Sigma_{n=0}^{n=2}\delta_n^+ = \Sigma_{n=0}^{n=2}\delta_n^-$	0.75	[0.385]	0.13	[0.722]
$\delta_3^+ = \delta_3^-$	2.79*	[0.095]	0.84	[0.359]	$\Sigma_{n=0}^{n=3}\delta_n^+ = \Sigma_{n=0}^{n=3}\delta_n^-$	0.05	[0.819]	0.02	[0.880]
$\delta_4^+ = \delta_4^-$	0.20	[0.657]	0.01	[0.905]	$\Sigma_{n=0}^{n=4}\delta_n^+ = \Sigma_{n=0}^{n=4}\delta_n^-$	0.22	[0.642]	0.01	[0.941]
$\delta_5^+ = \delta_5^-$	4.72**	[0.030]	1.96	[0.162]	$\Sigma_{n=0}^{n=5}\delta_n^+ = \Sigma_{n=0}^{n=5}\delta_n^-$	0.41	[0.521]	0.57	[0.452]
$\delta_6^+ = \delta_6^-$	0.08	[0.781]	4.26**	[0.039]	$\Sigma_{n=0}^{n=6}\delta_n^+ = \Sigma_{n=0}^{n=6}\delta_n^-$	0.56	[0.454]	0.04	[0.832]
$\delta_7^+ = \delta_7^-$	2.93*	[0.087]	0.29	[0.593]	$\Sigma_{n=0}^{n=7}\delta_n^+ = \Sigma_{n=0}^{n=7}\delta_n^-$	2.30	[0.129]	0.20	[0.655]
$\delta_8^+ = \delta_8^-$	0.25	[0.620]	0.03	[0.866]	$\Sigma_{n=0}^{n=8}\delta_n^+ = \Sigma_{n=0}^{n=8}\delta_n^-$	1.52	[0.218]	0.15	[0.703]
Speed of convergence toward long-run equilibrium									
$\theta^{(a)} = \theta^{(b)}$	0.19	[0.660]	0.08	[0.777]					
Eq. (4)									
$\theta^{(a)} = \theta^{(b)}$	0.06	[0.814]	0.06	[0.811]					

The p-values are reported in brackets and we use ***, ** and * to indicate the rejection of the null hypothesis (symmetry) at the 1%, 5% and 10% significance levels, respectively. The superscripts (a) and (b) refer respectively to (+) and (-) in the case of Eq. (3), and ($\Delta rp_{t-1} \leq 0$) and ($\Delta rp_{t-1} > 0$) in the case of Eq. (4).

Table 6. Results from weekly data

	Gasoline			Diesel fuel		
Day of the week:	Monday	Wednesday	Friday	Monday	Wednesday	Friday
Δp^{+}_{t-1}	0.213*** (0.073)	0.217** (0.095)	0.171** (0.090)	0.446*** (0.093)	0.172** (0.075)	0.338*** (0.089)
Δp^{-}_{t-1}	0.239*** (0.072)	0.287*** (0.104)	0.249** (0.102)	0.204** (0.092)	0.550*** (0.097)	0.185** (0.084)
Δrp^{+}_{t}	0.103*** (0.029)	0.135** (0.057)	0.134** (0.066)	0.071* (0.040)	0.125*** (0.046)	0.068** (0.027)
Δrp^{-}_{t}	0.185*** (0.047)	0.078** (0.032)	0.048 (0.038)	0.176*** (0.041)	0.055* (0.032)	0.103*** (0.035)
Δrp^{+}_{t-1}	0.337*** (0.044)	0.197*** (0.069)	0.194*** (0.055)	0.325*** (0.060)	0.222*** (0.069)	0.323*** (0.048)
Δrp^{-}_{t-1}	0.077 (0.073)	0.151*** (0.048)	0.141*** (0.045)	0.048 (0.070)	0.143*** (0.044)	-0.070 (0.088)
EC^{+}_{t-1}	-0.227*** (0.059)	-0.215*** (0.055)	-0.231*** (0.061)	-0.305*** (0.073)	-0.127** (0.057)	0.423*** (0.104)
EC^{-}_{t-1}	-0.051* (0.039)	-0.137*** (0.046)	-0.122** (0.054)	-0.054* (0.042)	-0.188*** (0.065)	-0.050 (0.041)
Num. Obs.	140	141	141	140	141	141
Adj. R^2	0.813	0.704	0.662	0.747	0.750	0.755
BIC	-801.329	-731.737	-721.624	-802.989	-802.525	-812.187
AIC	-824.747	-755.213	-745.100	-826.408	-826.000	-835.662
Barlett	0.507 [0.959]	1.156 [0.138]	0.842 [0.478]	1.188 [0.119]	2.217*** [0.000]	0.995 [0.276]
L-B(1)	0.183 [0.668]	3.455 [0.178]	0.005 [0.945]	3.339 [0.188]	10.491*** [0.001]	1.962 [0.161]
L-B^2(1)	1.953 [0.162]	1.824 [0.402]	0.062 [0.803]	0.676 [0.411]	8.792*** [0.003]	4.320 [0.115]
H_0: $\theta^{+} = \theta^{-}$	4.75** [0.031]	0.99 [0.323]	1.44 [0.233]	6.60** [0.011]	0.36 [0.551]	9.87*** [0.002]

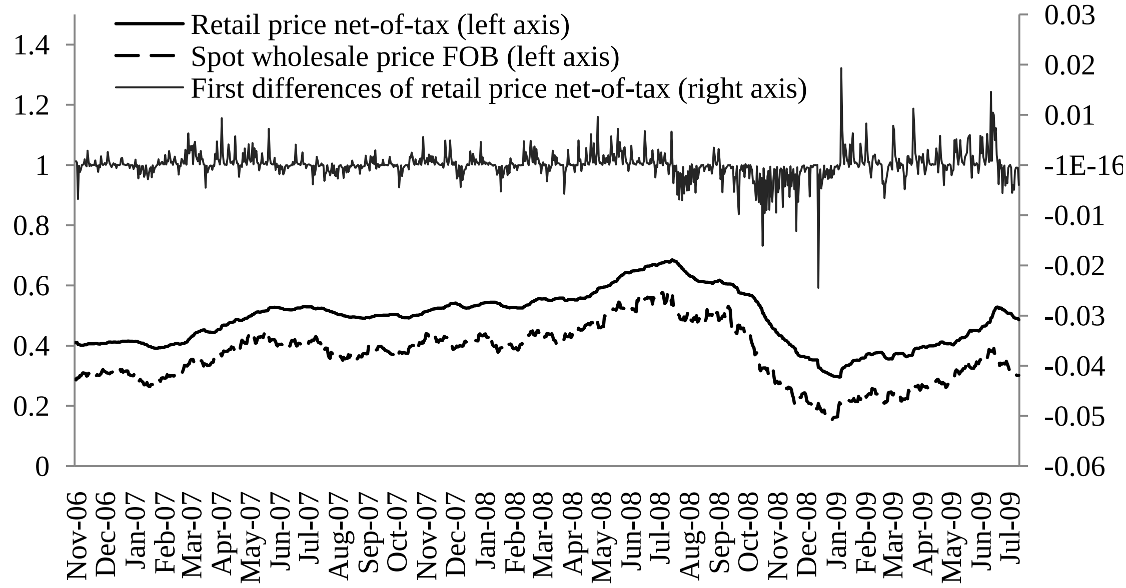
Table 6. Results from weekly data (continued)

Daily averages from:	Gasoline Monday	Gasoline Wednesday	Gasoline Friday	Diesel fuel Monday	Diesel fuel Wednesday	Diesel fuel Friday
Δp_{t-1}^{+}	0.346*** (0.089)	0.256*** (0.095)	0.207** (0.099)	0.384*** (0.084)	0.392*** (0.068)	0.377*** (0.057)
Δp_{t-1}^{-}	0.251*** (0.075)	0.361*** (0.103)	0.435*** (0.089)	0.336** (0.073)	0.328*** (0.090)	0.319*** (0.081)
Δrp_{t}^{+}	0.173*** (0.036)	0.134*** (0.025)	0.149*** (0.030)	0.158*** (0.033)	0.133*** (0.025)	0.114*** (0.028)
Δrp_{t}^{-}	0.072** (0.030)	0.102*** (0.033)	0.134*** (0.041)	0.072** (0.030)	0.090** (0.037)	0.131*** (0.047)
Δrp_{t-1}^{+}	0.228*** (0.028)	0.264*** (0.050)	0.308*** (0.056)	0.363*** (0.050)	0.356*** (0.036)	0.333*** (0.052)
Δrp_{t-1}^{-}	0.208*** (0.063)	0.137*** (0.034)	0.168*** (0.040)	0.149*** (0.051)	0.098 (0.080)	0.120** (0.072)
EC_{t-1}^{+}	-0.188*** (0.054)	-0.176*** (0.063)	-0.098** (0.045)	-0.257*** (0.077)	-0.278*** (0.083)	-0.186*** (0.052)
EC_{t-1}^{-}	-0.040* (0.026)	-0.053* (0.030)	-0.039* (0.034)	-0.022* (0.035)	-0.016* (0.029)	-0.028* (0.029)
Num. Obs.	140	140	140	140	140	140
Adj. R^2	0.819	0.845	0.872	0.842	0.871	0.874
BIC	-818.898	-845.741	-873.931	-907.332	-916.205	-920.354
AIC	-842.316	-869.159	-897.349	-930.750	-939.623	-943.772
Barlett	0.558 [0.914]	1.249 [0.088]	0.709 [0.696]	0.782 [0.573]	0.883 [0.416]	0.982 [0.289]
L-B(1)	0.300 [0.584]	1.444 [0.230]	1.682 [0.195]	1.240 [0.266]	1.521 [0.217]	3.334 [0.189]
L-B^2(1)	0.002 [0.969]	1.637 [0.201]	0.618 [0.432]	0.491 [0.484]	4.576 [0.101]	3.337 [0.189]
H_0: $\theta^{+} = \theta^{-}$	5.08** [0.026]	2.48 [0.118]	0.85 [0.357]	8.36*** [0.004]	8.41*** [0.004]	5.56** [0.020]

White's heteroskedasticity consistent standard errors are in parenthesis and the p-values are reported in brackets. We use ***, ** and * to indicate the significance of the coefficients and the rejection of the null hypothesis (long-run symmetry) at the 1%, 5% and 10% levels, respectively.

Figure 1. Level and first difference of fuel prices (euros per liter)

a) Gasoline



b) Diesel fuel

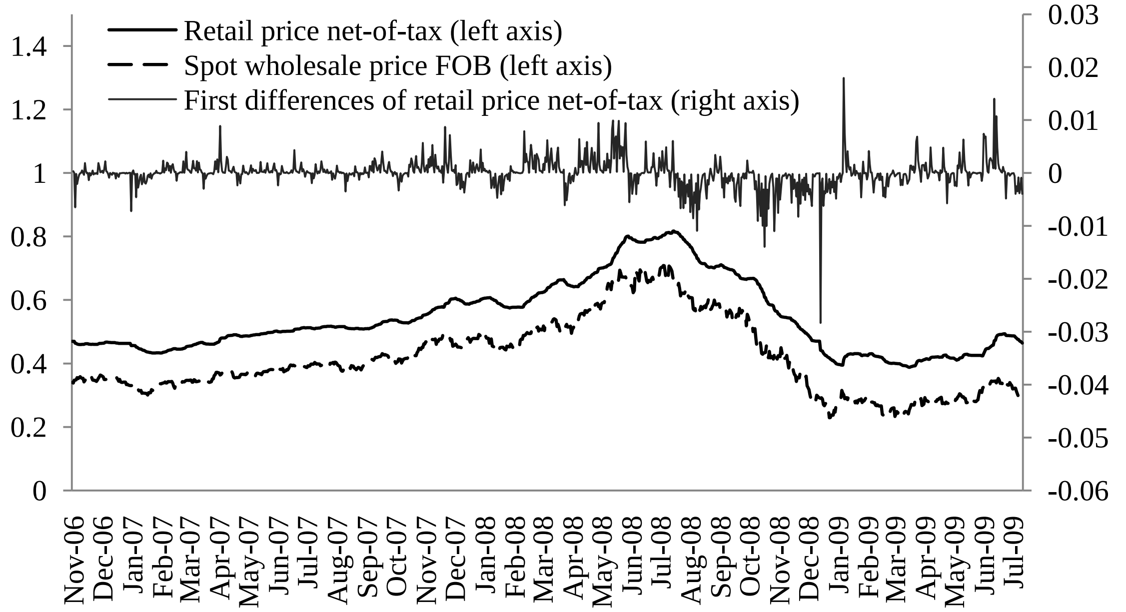
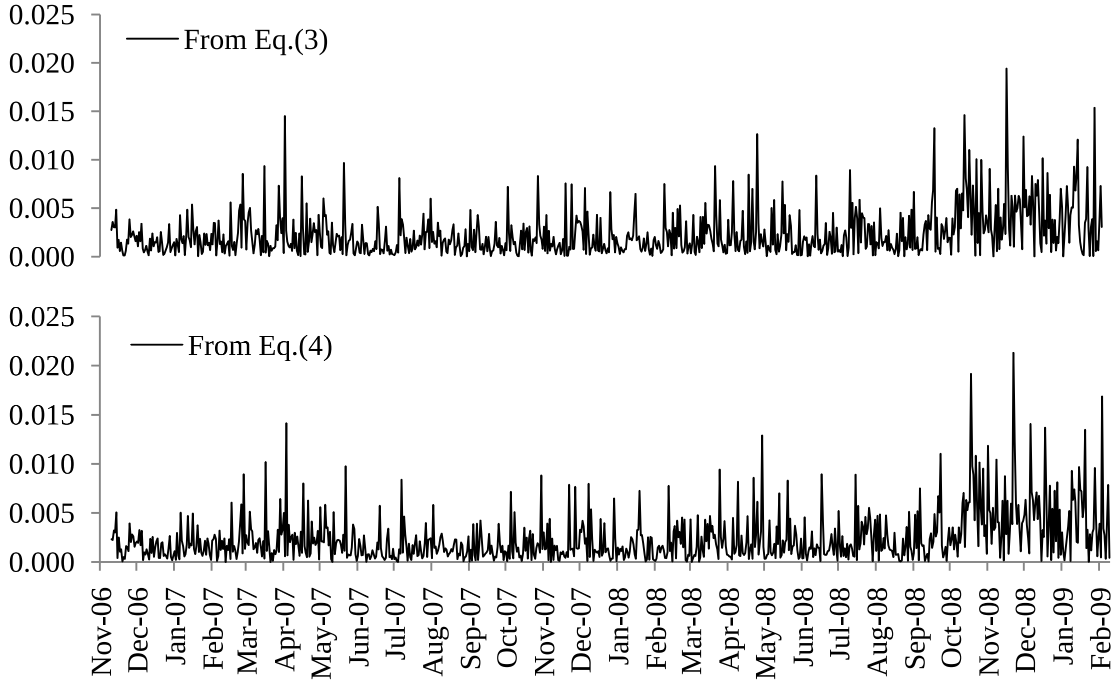


Figure 2. Standard deviation of residuals

a) Gasoline



b) Diesel fuel