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Do Daily Retail Gasoline Prices adjust Asymmetrically?

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Do daily retail gasoline prices adjust asymmetrically?

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Abstract

This paper analyzes adjustments in the Dutch retail gasoline prices. We estimate an error correction model on changes in the daily retail price for gasoline (taxes excluded) for the period 1996-2004 taking care of volatility clustering by estimating an EGARCH model. It turns out the volatility process is asymmetrical: an unexpected increase in the producer price has a larger effect on the variance of the producer price than an unexpected decrease.

We do not find strong evidence for amount asymmetry. However, there is a faster reaction to upward changes in spot prices than to downward changes in spot prices. This implies timing or pattern asymmetry. This asymmetry starts three days after the change in the spot price and lasts for four days.

Key words: Asymmetry; Retail gasoline prices, Volatility

JEL classification: D43; E31

1

1   Introduction

Starting by Bacon (1991), numerous studies have examined whether retail gasoline prices respond more quickly to upstream price increases than to decreases; see the overview in Bettendorf et al. (2003) or Eckert and West (2004). The findings on asymmetric price adjustments have been mixed. Estimations in most of these studies are based on weekly or even monthly data, whereas in reality gasoline prices are often adjusted more than once a week.[1] Recent contributions have started to use high frequency data, showing that analyzing low frequency data might lead to an improper understanding of the pricing process when upstream prices are volatile.

Bettendorf et al. (2003) demonstrate that the findings on asymmetric pricing depend on the choice of the day for which weekly changes are calculated. Our paper extends their analysis by exploring the linkage between *daily* retail gasoline prices and spot prices for the Netherlands. Price changes on this highly concentrated retail market are initiated by the market leader, which are normally followed by the other firms. Since calm and turbulent periods of price changes seem to be clustered in time, Ordinary Least Squares (OLS) estimation of an ECM results in loss of statistical efficiency. An asymmetrical EGARCH model[2] (Nelson, 1991) is therefore estimated to accommodate for volatility clustering and for asymmetry in the volatility process. We find that retail prices respond more quickly to cost increases than to decreases. Unlike some recent contributions, this paper does not aim to identify the source of the asymmetry.

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[1]For instance, the retail price in the Netherlands was adjusted two and three times a week during 22 and 3 weeks in 2004, respectively.

[2]EGARCH is short for Exponential Generalized AutoRegressive Conditional Heteroskedasticity. The GARCH process is a popular stochastic process which has been fairly successful in modeling financial time series (Engle, 2004).

The paper is structured as follows. The next section summarizes the existing asymmetry studies that use daily data. Section 3 describes the Dutch retail market for gasoline. After the data are presented in Section 4, the model is introduced in Section 5. The estimation results of the ECM are discussed in Section 6. Findings are summarized in the last section.

2   Literature

With the growing availability of detailed time series on gasoline markets and the advances in high-frequency econometric analysis, several studies have recently tested the asymmetry hypothesis with daily observations.[3] First, Bachmeier and Griffin (2003) question the robustness of the results of Borenstein et al. (1997). The latter study estimates a conventional ECM with weekly US data and finds an asymmetric response of gasoline spot prices to crude oil price changes. In contrast, Bachmeier and Griffin show that symmetry cannot be rejected when a similar specification is estimated with daily data.

Davis and Hamilton (2004) investigate the linkage between daily spot and wholesale gasoline prices set by 9 firms active in Philadelphia. They compare three types of models in estimating the probability of a price change. Following the Dixit menu-cost model, the gap between the current and the target price should be the dominant determinant in the pricing decision. Estimation of the derived specification results in implausible parameter values. Besides, this model is not consistent with the asymmetric response to positive and negative price gaps, found for 5 of the 9 firms with an atheoretical logit specification as

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[3]Borenstein and Shepard (2002, section 3) provide an early example of the estimation with daily gasoline prices. The change in the price of a gasoline *future* contract is explained by the change in the price of a crude oil futures contract on the same day and on the two prior trading days. The pass through for these competitive markets is found to be symmetric but incomplete. The latter finding is attributed to production stickiness.

well as with an autoregressive conditional duration model. In particular, when the actual price is below or above the target price by a small amount, a price increase is more likely found than a price decrease. In contrast, when the price gap is large (in absolute value), a wholesaler is more reluctant to raise prices than to lower them. Davis and Hamilton conclude that pricing decisions are more driven by strategic considerations about customers' and competitors' reactions than by explicit menu costs.

For several Canadian, US and Australian cities, retail gasoline prices are documented to exhibit a remarkable, saw-toothed pattern, even when wholesale prices are relatively stable; see Castanias and Johnson (1993) and Eckert (2003). Long periods in which prices decline gradually are succeeded by short periods with sharp price increases. These cycles can be explained by the duopoly model of Maskin and Tirole (1988). On the downward portion of the cycle, each firm undercuts prices to attract market share in the short run. When the price reaches a lower bound, one of the firms eventually restores the high price, which is quickly followed by its rivals and the cycle repeats.[4] Eckert and West (2004) test this model by constructing an unbalanced panel of daily station-specific prices for 8 regions in the Vancouver area. Simple linear regressions show that large price increases occur almost exclusively on the days of the week for which demand is lowest. Furthermore, prices increase at the same day, while prices decrease at different speeds in different regions. Prices fall more rapidly when markets are less concentrated. They stress that these features cannot be identified when using a weekly survey at a small sample of stations. Notice that the finding that retail prices adjust differently over the cycle should not be confused with asymmetric responses to cost changes. In this case, price asymmetry does not arise from

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[4]Note that these price cycles are not observed in the highly concentrated retail gasoline market in the Netherlands.

collusive behaviour but, instead from relatively aggressive pricing.[5]

Finally, Lewis (2003) develops a theory that attributes asymmetric price adjustments to searching consumers with myopic expectations. Although the reference price search model is not yet tested on daily data, it might improve the understanding of price fluctuations. The crucial assumption is that expectations are based on prices observed in the past. When consumers observe a lower price than expected, a smaller fraction chooses to search. When the cost rises much higher than last period's price, firms have to set prices competitively to remain profitable. In contrast, when the cost falls well below last period's price, firms can keep high margins by reducing prices just enough to prevent consumers from searching. The model implies that prices do not react to cost changes during periods of high margin. Lewis (2003) tests the implications by means of a panel of weekly, station-specific prices from the San Diego area. An asymmetric ECM with one threshold is estimated, incorporating 4 sets of coefficients. Weeks for which the observed price exceeds the target price are assigned to the high margin regime. The low margin regime is identified by negative long run residuals. Next, the effects of cost increases and decreases are allowed to differ in each regime. Evidence for asymmetric responses to cost changes is found but the size of the margin seems a more important determinant of the adjustment speed. Lewis (2003) also argues that the reference price search model seems more consistent with observed patterns than two alternative explanations, suggested by Borenstein et al. (1997).[6] These alternatives are a collusion model and a standard search model.[7]

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[5]Noel (2004) examines similar cycles found with a panel of twice-daily retail prices for 22 service stations in Toronto. Results of a Markov switching regression with two regimes are consistent with predictions of the Maskin and Tirole (1988) theory. Undercutting phases, lasting on average 6.4 days, are found to be more likely triggered by small independents. Rounds of price increases take only half a day and are mostly initiated by large firms.

[6]They propose production and inventory adjustment lags as a third alternative.

[7]This search model assumes that consumers search less when facing highly variable costs. With large

3   The Dutch retail market for gasoline

The Dutch gasoline market can be characterized as a strong oligopoly (see Canoy and Onderstal, 2003). Several features support this observation. First, the market is dominated by five integrated oil companies: Shell, BP/Mobil, Exxon, Texaco and Total/Fina/Elf. As can be seen in Figure 1, these companies sell approximately 80% of the gasoline sold, with Shell having by far the largest market share (30%). The independent retailers only account for 16% of the total volume. Along the highways the market is even more concentrated as branded filling stations are mainly located at these prime locations, whereas non-branded filling stations almost never are located along the highways. Concentration on the Dutch market is much higher than in other European countries.

Second, entry barriers are high. To enter the retail gasoline market a license is required and new locations are scarce. As a result of restrictive planning, strict environmental standards and a reserved permission policy by national and local governments only a very few firms were able to enter the market. In particular along the highways the government has rarely issued licenses to new players. New licenses (with an unlimited time period) were mainly issued to incumbents who already had a strong position in the market.

Third, price formation is very transparent for petrol firms. Since the market leader Shell publicly announces changes in its recommended retail price on its website, competing oil companies can easily monitor and follow Shell's pricing policy. Although there is no clear evidence whether the oil companies do coordinate their prices, the Netherlands Competi-

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fluctuations of wholesale prices, it is costly for a consumer to check whether an observed price change is really due to a cost change, that is followed by the other suppliers. This gives the firms market power to adjust prices more slowly after a cost decrease.

Figure 1: Volume shares in 2000 (source Bettendorf et al., 2003)
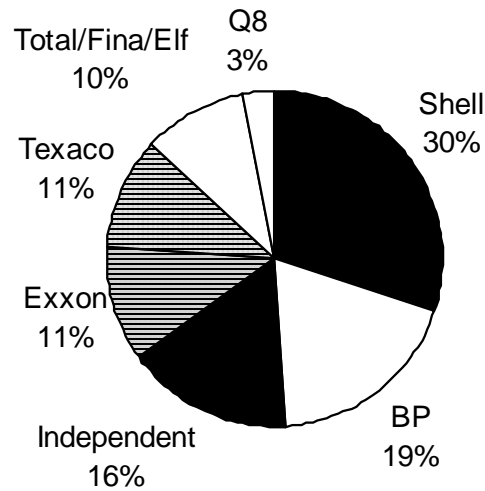
tion Authority (NMa) has concluded that the differences between the recommended prices of the various firms are marginal (NMa, 2001). Fourth, the margin on gasoline prices is higher than in other European countries. This higher margin is only partially explained by higher costs in the Netherlands such as wage and environmental costs (see European Commission, 1999).

Finally, it is argued that competition is restricted through a system of vertical agreements between oil companies and filling station owners. Oil companies financially support an affiliated filling station when faced with a price war in the neighbourhood, unless the station itself has initiated a price reduction. As a result, a station owner has less incentive to cut the price, knowing that price supports allow his rivals to follow the reduction immediately. The NMa no longer intends to prohibit these support systems because the

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evidence on the implications for retail prices is insufficient (NMa, 2003).

Summarizing, characteristics of the Dutch gasoline market seem to limit price competition. However, recently some favourable developments are observed. NMa (2004) concludes that competition has increased on local and regional roads due to the increasing number of unmanned and independent filling stations. Developments are going much more slowly on the motorway network. To reduce market concentration on the primary roads, the government has started to re-allocate 10 licenses each year over a period of 21 years using auctions. The past two auctions have resulted in few changes, for example only one new player (Samba Oil) has entered the market.

4   The data

Before analyzing the link between daily retail gasoline prices and spot prices we describe the data we use. We analyze the data and indicate why we have to use ARCH models. In the next section we test for stationarity and cointegration in order to arrive at the proper specification of the model.

Daily data are collected for the period 2 January 1996 through 7 December 2004. Prices are expressed in euros per litre.[8]

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[8]This dataset differs from the one used in Bettendorf et al. (2003) in four ways. First, this dataset contains daily data instead of weekly data. Second, variables are not expressed in guilders but in euros. Third, we use the spot price for regular instead of premium gasoline. Finally, the dataset is extended with the years 2002-2004. Only the first difference is fundamental for the findings of this study.

Sources

Retail prices (RP) of unleaded gasoline (Euro95) are taken from the website of Shell.[9] This is the price which market leader Shell recommends to its filling stations. Price changes are decided by Shell's pricing committee at 11.00 AM and implemented at 0.00 AM the next day (Shell, 2001). On Sundays the retail price is never adjusted, probably because both the Rotterdam spot market and the financial markets are closed during weekends. For that reason Sundays are excluded from the dataset. Prices often do change on Saturdays to incorporate Friday's closing spot prices and exchange rates.

We use the *Rotterdam spot price* (WP) for regular unleaded gasoline as the input cost of Euro95.[10] These spot prices are published on the website of the US Energy Information Administration.[11] Where observations are missing (in case of a holiday), the price of the previous day is used. To convert the dollar price into euros per litre we use the dollar/euro exchange rate as collected by Datastream. For the pre-euro years 1996-2001 we multiply the dollar/guilder exchange rate with the official exchange rate of 1 euro = 2.20371 guilders.

The retail price data include consumer taxes. In the sample period the *value added tax* (VAT) on gasoline has changed from 17.5% to 19.0% on 1 January 2001. Besides VAT, *excise taxes* (EXC) are levied.[12] Data on excise taxes are obtained from Statistics Nether-

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[9]www.shell.nl

[10]The technical details of the regular unleaded gasoline are ARA barge, 91 RON, 82.5 MON, 50ppm max sulfur. The prices quoted are the average of the "bid" and "offer" prices at the end of the trading day.

[11]www.eia.doe.gov/oil-gas/petroleum/info-glance/gasoline.html

[12]VAT is also imposed on excise taxes.

Figure 2: Changes in excises EXC_t and changes in retail RPE_t and spot prices WP_t
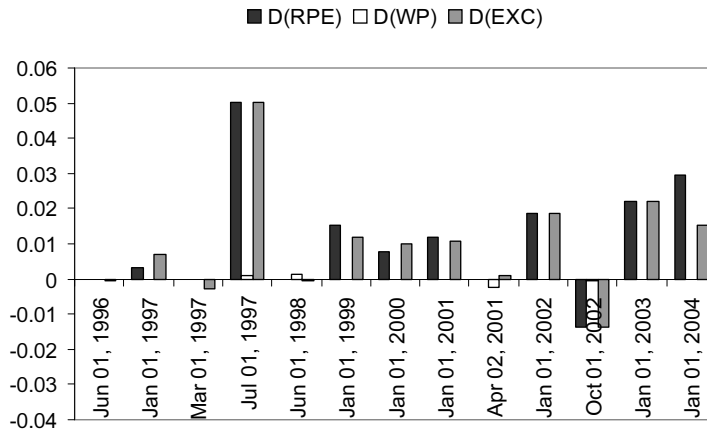
lands.[13] In the sample period there have been only 13 changes in excise taxes on unleaded gasoline (4 negative, 9 positive). The excises taxes underwent their most important change on 1 July 1997: from 0.528 to 0.578 euros per litre. Between 1 October 2002 and 1 January 2003 there was a large short-lived drop in excises from 0.630 to 0.616 euros per litre. Changes in excise taxes are usually passed on to the retail price immediately (see Figure 2), where RPE_t is defined as $RPE_t = RP_t/(1 + VAT_t)$. As we do not want our tests to be affected by the changes in excise taxes we from now on focus on producer price, defined as $PP_t = RPE_t - EXC_t$.

Descriptive statistics

The levels of the producer price and the spot price are highly correlated as the correlation coefficient of both series equals 0.988 (see Table 1). First differences are however not correlated.[14] Figure 3 illustrates that both prices follow each other closely.

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[13]statline.cbs.nl, Table "Heffingen (totaal) op energiedragers".
[14]Prefix Δ denotes the backward difference $\Delta X_t = X_t - X_{t-1}$

Table 1: Correlations

	PP_t	WP_t	ΔPP_t	ΔWP_t
PP_t	1.000			
WP_t	0.988	1.000		
ΔPP_t	0.025	0.035	1.000	
ΔWP_t	-0.039	0.029	0.021	1.000

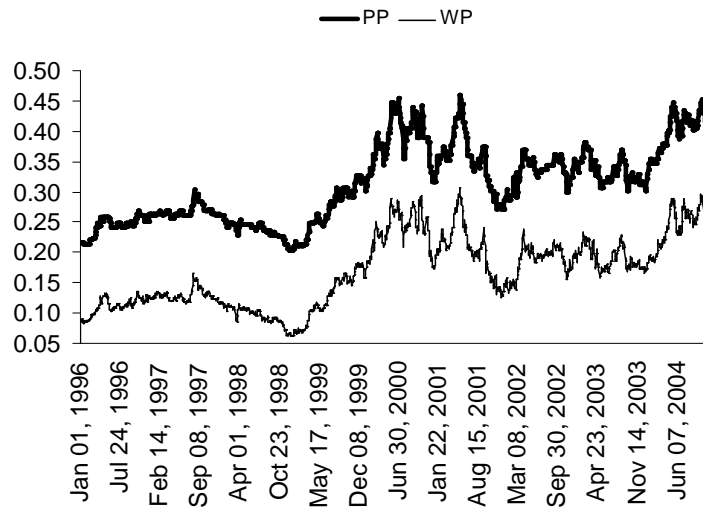Figure 3: Time series (daily data for the period 1996-2004) of producer prices PP_t and spot prices WP_t

Table 2: Number of adjustments of ΔPP_t, categorized by values of $\Delta PP_t \neq 0$ and ΔWP_t. Listed are the mean and the number of observations in each category, respectively

		ΔWP_t		
		[-0.02, 0)	[0, 0.02)	All
	[-0.06, -0.04)	NA	-0.042	-0.042
		0	1	1
	[-0.04, -0.02)	NA	NA	NA
		0	0	0
	[-0.02, 0)	-0.008	-0.008	-0.008
ΔPP_t		87	146	233
	(0, 0.02)	0.009	0.007	0.008
		88	165	253
	[0.02, 0.04)	NA	0.029	0.029
		0	1	1
	All	0.000	0.000	0.000
		175	313	488

Table 2 shows the number of producer price adjustments. There have been 488 changes in the producer price. This implies that, on average, there is about one change in the producer price per week. There have been 254 (52%) increases and 234 (48%)decreases. In 88 (18%) cases the producer price rose while the spot price fell. On the other hand there are 147 (30%) days in which producer price fell despite a rise in the spot price. In only 87 (18%) cases both the producer price and the spot price decreased, whereas in 166 (34%) cases both prices rose.

Volatility clustering

Table 3 shows significant autocorrelations of ΔPP_t and $[\Delta PP_t]^2$ indicating volatility clustering (autocorrelations larger than 0.038 in absolute values would be significant at a 5% level). Volatility clustering is also indicated in Figures 4 and 5.

Table 3: Autocorrelations of first differences and squared first differences in PP_t

	First differences	Squared first differences
1	0.047	-0.033
2	0.096	0.062
3	0.075	0.030
4	0.057	0.053
5	0.029	0.011
6	0.019	0.022
7	-0.004	0.037
8	-0.003	0.022
9	-0.003	0.005
10	0.004	0.035

Two standard error bounds are computed as $\pm 2/\sqrt{T} = \pm 0.038$, with T=2797

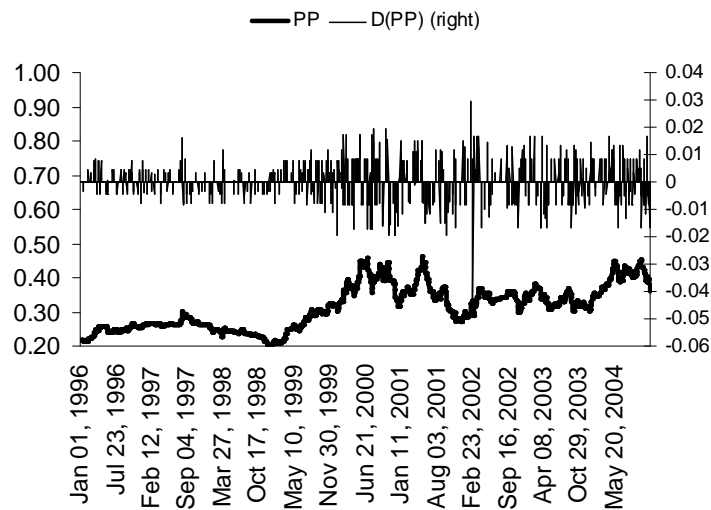Figure 4: Level and differences in producer price of gasoline PP_t

Figure 5: Level and differences in gasoline spot prices WP_t
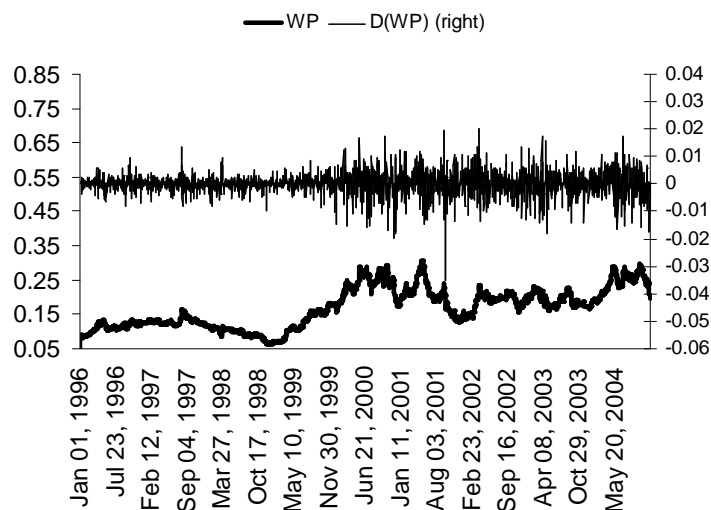
In Figures 4 and 5 prices are shown on the left axis and daily changes of prices are shown on the right axis. These figures show an increase in prices in the second halve of the sample. Moreover, price changes are becoming more volatile and the amplitude of the prices changes is changing as well. The magnitude of the price change is small for extended periods and then low for extended periods. This is what has been called volatility clustering and is the effect ARCH models are designed to measure.[15]

Assuming, as is done in OLS regressions, that the variance of the error term is constant results in loss of statistical efficiency (Engle 1982, Bollerslev et al. 1994, for an overview see Engle 2004).

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[15]Volatility clustering is still present if we include time dummies in the model for the period 1999-2004.

5 Model specification

Most models in this literature are error correction models (ECM). Before estimating an ECM we have to test stationarity and cointegration. If producer prices and spot prices are integrated of order one, and if these prices are cointegrated then an ECM is applicable. Before presenting any estimation results we first describe the outcomes of the various stationarity and cointegration tests.

Stationarity and cointegration

We use the Augmented Dickey-Fuller (ADF) unit root tests as well as the Phillips-Perron (P-P) test to test for stationarity. The P-P test has been shown to be more powerful in the presence of heteroscedasticity and serial correlation under a wide range of circumstances (Phillips and Perron, 1988). Both tests in Table 4 clearly indicate that the producer price PP_t and the spot price WP_t are I(1), i.e. the prices are stationary after taking first differences. The null hypothesis that PP_t has a unit root is not rejected (p-value is 0.211), whereas the null that ΔPP_t has a unit root is rejected (p-value is 0.000). The same conclusion holds for WP_t. The null that WP_t has a unit root is not rejected (p-value is 0.224). First differencing WP_t clearly rejects the null of a unit root in ΔWP_t (p-value is 0.000).

We assume that our prices share a uniform volatility process and that cointegration is robust with respect to ARCH innovations.[16] So, we use the familiar Johansen cointegration

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[16]See Rahbek et al., 2002. There is some evidence for stock market indices sharing a uniform volatility process (see Engle and Kozicki, 1993). An alternative cointegration test with GARCH effects is provided by Gannon (1996).

Table 4: Augmented Dickey-Fuller and Phillips-Perron unit root tests

	PP_t	ΔPP_t	WP_t	ΔWP_t
Augmented Dickey-Fuller test				
Exogenous	constant	none	constant	none
Lag length (SIC)	3	2	1	0
ADF test statistic	-2.187	-26.218	-2.153	-49.114
Critical values 5% level	-2.862	-1.941	-2.862	-1.941
p-value*	0.211	0.000	0.224	0.000
Observations	2794	2794	2795	2795
Null of unit root	not rejected	rejected	not rejected	rejected
Phillips-Perron test				
Exogenous	constant	none	constant	none
Bandwidth	17	16	11	9
P-P test statistic	-2.183	-51.487	-2.236	-49.366
Critical values 5% level	-2.862	-1.941	-2.862	-1.941
p-value*	0.213	0.000	0.193	0.000
Observations	2794	2794	2795	2795
Null of unit root	not rejected	rejected	not rejected	rejected
*MacKinnon (1996) one-sided p-values				

Table 5: Johansen cointegration test

Series	$RPE_t, EXC_t\ WP_t$			
Trend assumption	no deterministic trend			
Lags	4			
Observations	2792			
Unrestricted cointegration rank test (trace)				
Hypothesized no. of CE(s)	eigenvalue	trace statistic	5% critical value	p-value**
None *	0.073	224.500	35.193	0.000
At most 1	0.003	13.743	20.262	0.308
At most 2	0.002	4.558	9.165	0.335
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized no. of CE(s)	eigenvalue	max-eigen statistic	5% critical value	p-value**
None *	0.073	210.757	22.300	0.000
At most 1	0.003	9.186	15.892	0.414
At most 2	0.002	4.558	9.165	0.335
* Denotes rejection of the hypothesis at the 0.05 level				
** MacKinnon-Haug-Michelis (1999) p-values				

test. The Johansen cointegration test in Table 5 indicates 1 cointegrating equation at the 0.05 level (both the Trace test and the Max-eigenvalue test yield consistent results). This implies that the relationship between cointegrated series can be considered to be generated by an error correction model (Granger and Weiss, 1983): a system not in equilibrium has a tendency to converge to equilibrium in the long run. This implies that the retail price RPE_t, excises EXC_t and the spot price WP_t cannot drift apart in the long run.

Error correction model

The model consists of regressors that explain short run dynamics of gasoline retail prices and the error correction part (OLS errors from the levels equation). The short run allows for asymmetric adjustment.

The ECM is estimated in two rounds following Engle and Granger (1987). First, we estimate the long-run equation using OLS:

$$RPE_t = \mu_0 + \mu_1 WP_t + \mu_2 EXC_t + \eta_t \tag{1}$$

The specification can be derived from the maximization of static profits by an oligopolist (see Bettendorf et al., 2003). Under the assumption that marginal costs are independent of the output level and that the mark-up ratio is constant, the parameters μ_2 and μ_1/μ_2 are interpreted as the mark-up ratio and the effect of spot price changes in costs, respectively.[17]

Second, we capture the short-run dynamics including asymmetries in first differences as:

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[17]This price setting relation requires the model to be estimated in absolute price changes and not in rates of growth. Moreover, this is the common procedure in the gasoline asymmetry literature which makes it easier to compare the results.

$$\Delta(PP_t) \quad = \quad \sum_{i=0}^{n} \lambda_i^+ \Delta W P_{t-i}^+ + \sum_{j=0}^{m} \lambda_j^- \Delta W P_{t-j}^- +$$
$$\omega^+ RES_{t-1}^+ + \omega^- RES_{t-1}^- + \epsilon_t \tag{2}$$

where RES are the residuals from Equation (1). The superscripts $+$ and $-$ refer to the positive part and negative part of the time series, so that

$$X_t^+ = \begin{cases} X_t & \text{if } X_t > 0 \\ 0 & \text{if } X_t < 0 \end{cases} \tag{3}$$

and

$$X_t^- = \begin{cases} 0 & \text{if } X_t > 0 \\ X_t & \text{if } X_t < 0 \end{cases} \tag{4}$$

The first two terms in Equation (2) are current and lagged spot price increases and decreases, respectively. The number of lags for decreases m and increases n is determined by minimizing the Akaike Information Criterion. Also the adjustment process toward the long run can be asymmetrical.

EGARCH specification

ARCH LM-tests of OLS estimates of Equation (2) (not reported here) indicate that volatility is serially correlated over time (p-value is 0.024).[18] Defining ϵ_t^2 as the variance of the error term ϵ_t in Equation (2), also known as the mean equation, one can

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[18]This implies that OLS estimates are not efficient and that neglecting volatility clustering affects the tests for asymmetry.

test whether the conditional variance σ_t^2, is affected by conditional variances p periods in the past $(\sigma_{t-j}^2, j = 1, \ldots, p)$ as well as by q lags of the unconditional variance terms $(\epsilon_{t-i}^2, i = 1, \ldots, q)$. This is done by determining the significance of the parameters in a GARCH model.

To allow for asymmetry in the volatility process we use the Exponential GARCH (EGARCH) model (Nelson 1991):

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \left(\frac{\epsilon_{t-k}}{\sigma_{t-k}} \right) \tag{5}$$

In EGARCH, the natural log of the conditional variance $\ln \sigma_t^2$, is affected by the natural log of conditional variances p periods in the past $(\ln \sigma_{t-j}^2, j = 1, \ldots, p)$ as well as by q lags of the unconditional normalized standard deviations in absolute values $(|\epsilon_{t-i}/\sigma_{t-i}|, i = 1, \ldots, q)$. Asymmetry is introduced by including r lags of the unconditional normalized standard deviations $(\epsilon_{t-k}/\sigma_{t-k}, k = 1, \ldots, r)$. Unlike GARCH and threshold GARCH, the log specification does not require non-negativity constraints on the parameters to ensure positive conditional variances. However, restrictions on β_j are required to ensure stationarity. If the coefficients $\gamma_k \neq 0$, the response of volatility to shocks is asymmetrical. For instance if $p = q = r = 1$: negative shocks have an impact of $\alpha_1 - \gamma_1$ on the log of the conditional variance and positive shocks have an effect of $\alpha_1 + \gamma_1$. Stationarity of EGARCH(1,1) requires $|\beta_1| < 1$.[19]

Summarizing, GARCH models consist of a "mean equation," which in our case is the ECM presented in Equation (2). The second equation describes the "conditional variance" which

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[19]It should be noted that threshold GARCH (TGARCH) models produce similar results.

Table 6: Long-run OLS results

$RPE_t = \mu_0 + \mu_1 WP_t + \mu_2 EXC_t + \eta_t$		
	Coefficient	(t-value)
μ_0	0.081	(25.829)
μ_1	1.045	(258.963)
μ_2	1.093	(183.951)
Observations	2797	
Adjusted R^2	0.991	
S.E. of regression	0.009	
F-statistic (p-value)	146011.7	(0.000)
Durbin-Watson	0.360	
Wald tests	F-statistic	(p-value)
$H_0 : \mu_2 = 1$ (df=2794)	245.921	(0.000)
$H_0 : \mu_1/\mu_2 = 1$ (df=2794)	29.523	(0.000)

in our case is an EGARCH(p, q) model.

We have to determine the number of ARCH and GARCH terms (using z-tests). In all models presented below the EGARCH(1,1) model explains most of the variability of the changes in producer prices. The z-test for significance and the Akaike Information Criterion are used to determine the number of periods with rising and falling spot prices.

6 Estimation results

The ECM is estimated in two rounds. First, we estimate the Equation (1) using OLS. These results are unaffected by volatility clustering (asymptotically). Table 6 indicates that the mark-up ($\mu_2 = 1.093$) is significantly bigger than 1 (p=0.000) and the effect of spot price changes in costs ($\mu_1/\mu_2 = 0.956$) is significantly smaller than 1 (p=0.000).

In the second round we include the lagged long-run residuals in the short-run equation. We

estimate Equation (2) with and without asymmetry in the adjustment towards the long run to find evidence for asymmetries. There are various types of asymmetries (see Geweke, 2004). If the retail price and the spot price are cointegrated, these variables will not drift apart in the long run. Hence, there is no *amount asymmetry* in the long run, but perhaps there is amount asymmetry in the short run. We define short-run amount asymmetry if $\sum \lambda_i^+ \neq \sum \lambda_j^-$. *Timing* or *pattern* asymmetry refers to differences in estimates of λ_j^+ and λ_j^- at the same lags j. There is another type of asymmetry, which has to do with the speed of adjustment towards the long run. *Adjustment* asymmetry is present if $\omega^+ \neq \omega^-$. Finally, the effects of volatility to shocks can be asymmetrical. This *shock* asymmetry is present if in the variance equation $\gamma_k \neq 0$.

Before discussing the results and testing the various types of asymmetry we note that the model in Table 7 is an EGARCH(1,1) model with standard normal distributed errors. The ARCH-LM test in Table 7 indicates that the EGARCH(1,1) model properly accounts for heteroscedasticity and that the volatility process is stationary. The Durbin-Watson statistic indicates that there is no autocorrelation.

Table 7 yields the following conclusions:

1. The volatility process is asymmetrical. Since $\alpha_1 > \gamma_1 > 0$ and $0 < \beta_1 < 1$, shocks increase volatility and positive shocks have a larger effect on volatility than negative shocks of the same size. An unexpected increase in the producer price has a larger effect on the variance of the producer price than an unexpected drop in the producer price. This evidence of shock asymmetry might have a search cost explanation. Consumers who observe a turbulent world oil market are more reluctant to start a costly

21

Table 7: EGARCH(1,1) estimation results

$\Delta PP_t = \sum_{i=0}^{n} \lambda_i^+ \Delta WP_{t-i}^+ + \sum_{j=0}^{m} \lambda_j^- \Delta WP_{t-j}^- + \omega^+ RES_{t-1}^+ + \omega^- RES_{t-1}^- + \epsilon_t$ with $\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left| \frac{\epsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \left(\frac{\epsilon_{t-k}}{\sigma_{t-k}} \right)$				
	Coefficient	(z-value)	Coefficient	(z-value)
λ_0^+	-0.008	(-0.348)	-0.008	(-0.347)
λ_1^+	-0.035	(-1.430)	-0.035	(-1.487)
λ_2^+	0.197	(8.991)	0.197	(9.593)
λ_3^+	0.223	(10.651)	0.223	(10.901)
λ_4^+	0.075	(3.461)	0.075	(3.531)
λ_5^+	0.080	(3.113)	0.080	(3.213)
λ_6^+	0.109	(4.452)	0.109	(4.450)
λ_7^+	0.024	(0.869)	0.024	(0.869)
λ_0^-	0.007	(0.283)	0.007	(0.284)
λ_1^-	-0.052	(-2.126)	-0.052	(-2.158)
λ_2^-	0.176	(8.206)	0.176	(8.388)
λ_3^-	0.125	(6.396)	0.125	(6.485)
λ_4^-	0.093	(3.904)	0.093	(3.932)
λ_5^-	0.079	(3.104)	0.079	(3.122)
λ_6^-	0.060	(2.132)	0.060	(2.129)
λ_7^-	0.079	(3.478)	0.079	(3.468)
λ_8^-	0.042	(1.646)	0.042	(1.676)
ω^+	-0.110	(-10.676)		
ω^-	-0.110	(-9.625)		
ω			-0.110	(-17.809)
α_0	-0.090	(-10.354)	-0.090	(-10.345)
α_1	0.078	(18.798)	0.079	(18.809)
β_1	0.997	(1511.600)	0.997	(1504.503)
γ_1	0.016	(4.119)	0.016	(5.420)
Observations	2788		2788	
Adjusted R^2	0.272		0.273	
S.E. of regression	0.003		0.003	
Durbin-Watson	2.282		2.281	
ARCH LM-test (p-value)	0.341	(0.559)	0.339	(0.560)
Wald tests	F-statistic	(p-value)	F-statistic	(p-value)
$H_0 : \beta_1 \geq 1$ v $H_1 : \beta_1 < 1$	26.142	(0.000)	26.179	(0.000)
$H_0 : \alpha_1 \leq \lambda_1$ v $H_1 : \alpha_1 > \lambda_1$	110.571	(0.000)	134.585	(0.000)
$H_0 : \lambda_i^+ = \lambda_i^- \forall i$ v $H_1 : \lambda_i^+ \neq \lambda_i^-$	1.750	(0.073)	2.336	(0.013)
$H_0 : \lambda_\Sigma^+ = \lambda_\Sigma^-$ v $H_1 : \lambda_\Sigma^+ \neq \lambda_\Sigma^-$	0.667	(0.414)	2.373	(0.124)
$H_0 : \omega^+ = \omega^-$ v $H_1 : \omega^+ \neq \omega^-$	0.001	(0.972)		

price comparison when faced with a price change. Firms can benefit from reduced search incentives by adjusting retail prices more rapidly upwards than downwards in periods with uncertain costs.

2. The adjustment parameter is about -0.11 and highly significant which implies that it takes about 0.5/0.11=4.5 days to close half the gap between the current state and the long-run equilibrium. The final test reported in Table 7 does not reject to null of adjustment symmetry.

Because of the last conclusion, we focus on the second model in Table 7 in which the adjustment speed is symmetrical. This leads to the following conclusions:

3. For most lags j spot price increases and spot price decreases affect the producer price significantly. Contemporaneous spot prices changes are not significant. One-day lagged spot price decreases increase the producer price (this is what is expected from Table 2 above).

4. The number of lags for spot price increases and spot price decreases, 8 and 9 days respectively, is determined by minimizing the Akaike Information Criterion. So there is a faster reaction to upward changes in spot prices than to downward changes in spot prices. Simultaneous testing equality of all parameters for the same lags (the third reported Wald test in Table 7) rejects the null of equality. This implies that for at least one lag the parameters differ significantly. The Wald test reveals that the parameters for changes are significantly bigger for the third lag (the null of $\lambda_3^+ = \lambda_3^-$ is rejected at 5%). This implies timing or pattern asymmetry three days after the
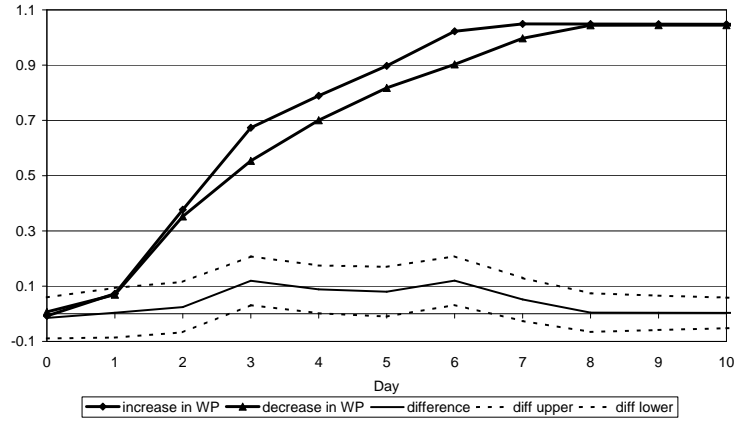
change in the spot price.

5. Already from Table 5 we concluded that there is no amount asymmetry in the long run. From Table 7 we conclude that the sum of all upward price change parameters is not significantly different from the sum of all downward price change parameters (two-sided test) at 5%. The difference between the sum of upward and downward parameters $(\lambda_\Sigma^+ - \lambda_\Sigma^-)$ equals 0.057. The table reports two-sided tests. However, for a one-sided test, the appropriate probability is one-half that reported in the table. So, if we would test $H_0 : \lambda_\Sigma^+ \leq \lambda_\Sigma^-$ v $H_1 : \lambda_\Sigma^+ > \lambda_\Sigma^-$, the p-value is 0.062 and we would reject the null at 10%. This implies that there is some evidence for short-run amount asymmetry.

6. In the introduction we have indicated that OLS estimates are inefficient affecting the asymmetry tests. To illustrate this we have re-estimated the ECM using OLS. Again, adjustment symmetry is not rejected (the p-value drops from 0.972 to 0.906). The tests for short-run asymmetry, however, give different results. Now, the null of $\lambda_i^+ = \lambda_i^- \forall i$ is not rejected (p-value=0.312). Also the p-value of the test of $H_0 :$ $\lambda_\Sigma^+ = \lambda_\Sigma^-$ v $H_1 : \lambda_\Sigma^+ \neq \lambda_\Sigma^-$ increases, from 0.124 to 0.744. Neglecting volatility clustering turns the conclusions upside down: there is no evidence for timing or pattern asymmetry and the probability of incorrectly rejecting the null of short-run amount symmetry increases.

We characterize the adjustment path of the model by examining the cumulative adjustment function. It should be noted that this function is non-linear in the parameters, as the

Figure 6: Cumulative adjustment in PP_t after changes in the spot price WP_t

adjustment in the i-th period after a change in the spot price will be the sum of the estimated response parameters from Equation (2) and the error correction effects over i-th period.[20] Figure 6 presents the calculated producer price response (in eurocents per litre) to a one-time one eurocent per litre increase or decrease in the spot price. To ease comparison we give the absolute value of the price responses. Also the difference between the two adjustment paths and its two standard error bounds are shown.[21]

The significant differences between the cumulative adjustment functions illustrate the finding of pattern asymmetry by the Wald-test. A one eurocent increase in the spot price leads to a 0.67 eurocents increase of the producer price after three days, whereas the estimated response to a one eurocent decrease is only 0.55 eurocents. This difference in the responses after three days is significant and remains (almost) significant for about four days. After six days the difference is no longer significant and the long-run equilibrium price is reached.

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[20]The calculation of the cumulative adjustment function can be found in Borenstein et al. (1997, p.337).
[21]The standard errors are approximated using the Delta method (see Judge et al., 1985, p.205-207). In the calculation we consider the long run effect μ_1 as predetermined.

7   Conclusions

Analyzing high frequency data leads to a better understanding of the pricing process when upstream prices are volatile as others have argued. However, using high frequency data in OLS regressions leads to a loss of statistical efficiency if volatility is serially correlated over time. In this paper we take care of volatility clustering by estimating an EGARCH model. As a by-product we introduce a new type of asymmetry in the literature on asymmetric price adjustments, namely shock asymmetry: an unexpected increase in the producer price has a larger effect on the variance of the producer price than an unexpected drop in the producer price.

We conclude that an ECM is an appropriate way to model retail gasoline price changes. Cointegration leads us to conclude that there is no amount asymmetry in the long run. However, there is some evidence for short-run amount asymmetry. Also, there is a faster reaction to upward changes in spot prices than to downward changes in spot prices: 8 and 9 days, respectively. The parameters for upward changes are also significantly larger for the third lag. This implies timing or pattern asymmetry three days after the change in the spot price.

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