More New Evidence on Asymmetric Gasoline Price Responses

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ABSTRACT

There exist two possible aggregation issues in studies to asymmetric price responses: (i) an issue due to aggregation over time, and (ii) an issue due to aggregation over space. Empirical studies already confirm the existence of the first issue. This paper confirms the existence of the second issue by studying daily retail prices of individual gasoline stations. I find that 38% of the stations respond asymmetrically to changes in the gasoline spot market price. Hence, asymmetric pricing is a feature of individual firms.

Keywords: Asymmetric Price Responses, Price Setting, Gasoline Markets

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1. INTRODUCTION

Asymmetric price responses occur when prices rise more rapidly after an increase in costs than they decline after a decrease in costs (see Peltzman (2000)). Many consumers and policy makers are suspicious that this pricing behavior is common in gasoline markets. Borenstein, Cameron, and Gilbert (1997) (henceforth BCG) perform an early study to this topic and confirm the suspicion. They take the production and distribution chain of gasoline and study at each part of the chain whether the price responds asymmetrically with respect to its upstream price. The four prices in the chain are the crude oil price, spot market price, wholesale price, and retail price.

After the study of BCG, many similar papers appeared. Geweke (2004) surveys this literature. He mentions two possible aggregation issues that may arise in this literature. The first possible issue is aggregation over time. In this case, the analysis does not include all (possible) price adjustments. This problem can occur if data have a lower frequency than the frequency of price decisions or input cost changes (Geweke (1978)). For example, BCG use a weekly spot market price and a semi-monthly retail price. The second possible issue is aggregation over space. In this case, the analysis focuses on a geographic area like a national or local market instead of individual firms. This problem can occur if data are aggregated over individuals or if the estimation method does not take into account possible differences between firms. For example, BCG use the average of the retail price in 33 cities and others, Balmaceda and Soruco (2008), Hosken, McMillan, and Taylor (2008), Verlinda (2008), Noel (2009), and Lewis (2011), use data on individual firms, but pool these data and report the asymmetry in the market as a whole. However, individual firms set prices, not the market as a whole. It might be that not all gasoline stations have the same pricing strategy because, for example, they do not operate under the same conditions (competition, ownership structure, location, etc.). Moreover, even if all stations adjust prices asymmetrically, the degree to which they do may differ between stations. Finally, Robertson and Symons (1992), Pe-

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saran and Smith (1995), Hsiao (2003), and Baltagi, Bresson, and Pirotte (2008) argue that pooling across individuals may possibly give biased results in (dynamic) estimations if there exists parameter heterogeneity.

Bachmeier and Griffin (2003) study whether Geweke's first aggregation issue is relevant. More specifically, they study the first part of the chain and explain the daily spot market price by the daily price of crude oil. They do not find asymmetric price responses when they use daily data, but they do find asymmetry when they repeat the analysis with weekly data. As a consequence, the first issue that Geweke mentions is important.[1]

This paper studies Geweke's second aggregation issue. More specifically, I study the second part of the chain and explain daily retail prices of individual gasoline stations by the daily spot market price. My main interest is whether there exist differences between stations. To my knowledge, this question has not been studied before, possibly due to the large data requirements. I find that the data are not poolable across stations. A separate analysis for each individual station shows that 38% of the stations in my sample respond asymmetrically. Therefore, asymmetric pricing is a feature of individual firms. Geweke's second aggregation issue is important. Together with the results of Bachmeier and Griffin (2003), this finding shows that each decision of each decision maker is informative for understanding asymmetric price responses and the underlying motives. Subsequently, I study whether there exist differences in the characteristics of stations that do and do not adjust prices asymmetrically. I look at 35 (sometimes overlapping) characteristics. For example, I study whether stations that adjust prices asymmetrically have higher price levels, are geographically clustered, or have a certain ownership structure. I find that asymmetric pricing seems to be a phenomenon that is randomly distributed across stations.

Section 2 describes the market and data set. Section 3 specifies the model. Section 4 presents the estimation results and Section 5 studies characteristics of stations that respond asymmetrically. Section 6 contains further discussion. Section 7 concludes.

2. MARKET AND DATA

This paper studies the retail gasoline market in the Netherlands.[2] There are around 4,300 gasoline stations (BOVAG (2006)). Most stations use the brand of an oil company. There are five large oil companies. Broadly speaking, there are three ownership models: some stations are company-owned and company-operated, other stations are company-owned and dealer-operated, and the remaining stations are dealer-owned and dealer-operated. A station's operator sets the price (although oil companies publish nonbinding national suggested prices). Rough estimates indicate that around 80% of the stations are dealer-operated. Nearly all stations set prices on a daily basis. Almost all gasoline sold is bought at the Amsterdam-Rotterdam-Antwerp (ARA) spot market, which supplies large parts of western Europe. A price for this spot market is published once a day. This price is the standard spot market price in the market (see, e.g., Shell (2001)).

1. Others report similar results. Noel (2009) shows that there may exist, next to asymmetric pricing, other irregularities in a market that have an impact on asymmetric pricing, but that cannot be observed in a low frequency data set. For example, the Edgeworth cycles that he finds take approximately one week. Asplund, Eriksson, and Friberg (2000) and Eckert and West (2004) have a daily data set and conclude that a subset of observations is not sufficient for answering their research questions and can even be misleading. Bettendorf, Van der Geest, and Varkevisser (2003) also have daily data and estimate a separate model for each day of the week. For some days they find asymmetric prices responses, for others not.

2. Bettendorf, Van der Geest, and Varkevisser (2003) and Bettendorf, Van der Geest, and Kuper (2009) also study asymmetric price responses in the Dutch gasoline market.

Retail prices are published daily on the website of Athlon Car Lease. This company leases cars to other firms. When the driver fills up his car, the station electronically sends the bill to the lease company. As a result, Athlon Car Lease obtains gasoline price quotations from 120,000 drivers, who fill up on average twice a week, from all over the country. It publishes these data on its website and I downloaded the data daily over the period 30 May 2006–20 July 2008 (783 days). The data set includes about 3,600 stations. Stations that the data set does not include are randomly distributed over the country and seem to be mostly smaller or nonactive. I only use observations for the standard type of gasoline (95 RON, so-called Euro95). The data set contains approximately 2,300 unique price quotations per day for this type of gasoline.[3] During the sample period, the daily average retail price varies between 39 and 68 cents per liter (in euros, excluding taxes).[4] The spot market price that I use is the daily Platt's Barges FOB Rotterdam High (Premium Gasoline 10 PPM with 95 RON). This spot market price increases 269 times and decreases 281 times during the sample period. I convert all prices to prices per liter (excluding taxes) in euros.[5] I match individual stations in the data set to lists of station-specific characteristics and to characteristics of the area in which the station is located.[6]

3. MODEL SPECIFICATION

To study whether retail prices of individual stations respond asymmetrically to changes in the spot market price, I model for each station the relation between the retail price and spot market price. Augmented Dickey-Fuller unit root tests indicate that the spot market price and retail price of 98% of the stations are integrated of order 1. To take into account possible cointegration between these series, I estimate for each station an asymmetric error correction model. BCG and Bachmeier and Griffin (2003) use the same model. Therefore, an advantage of this model is that it is easy to compare results.[7] The long-run relationship between the retail price and spot market price is:

$$P_{i,t} = \alpha_i^* \, Spot_{t-2} + c_i^* + \tau_i^* \, Time_t + \lambda_i^* \, Mix_t + \varepsilon_{i,t}^* \tag{1}$$

3. For each station, I have a maximum of one gasoline price quotation per day. Since less busy stations have a lower probability of being visited by a driver of Athlon Car Lease, the data set contains more quotations of busier stations. Drivers do not have to pay for the gasoline (because their employers do). So drivers do not avoid more expensive stations. Casual observation shows that they also do not avoid cheaper stations.

4. There do not exist Edgeworth cycles in the market that I study. Following the methodology of Lewis (2009), I calculate the median price change of each station and search for price jumps. In case of Edgeworth cycles, the median price change of a station would be negative and a station would have large price jumps that are independent of the spot market price. I do not observe this pattern.

5. The websites of the European Central Bank and the Dutch Ministry of Finance provided respectively the dollar-euro exchange rate and tax rates.

6. I obtained lists with the ownership structure and the brand of stations from Catalist (a company collecting data on gasoline stations) and a list with highway stations from the Dutch Ministry of Finance. Data on the area around a station are from Statistics Netherlands.

7. Error correction models are appropriate since gasoline stations in my data set change their price relatively gradually. A station changes its price on average on 36% of the observed days and usually these changes are small since on average 80% of a station's price changes equal 1 cent (including taxes). These numbers are representative for almost all stations. If a station would adjust its price shock wise (e.g., it adjusts prices only once a week and then makes a relatively large price change), then an error correction model could provide imprecisely estimated coefficients since it implies a gradual adjustment process (see also Lewis and Noel (2011)).

where $P_{i,t}$ is the retail price of station i on day t, $Spot_{t-2}$ is the spot market price on day $t-2$, and c_i^* is a station-specific constant (it contains, for example, the average markup). $Time_t$ is a time trend that captures a possible inflationary increase in the margin, Mix_t is a dummy variable that is 1 after 1 January 2007 (law requires the addition of biofuels from that date onward), and $\varepsilon_{i,t}^*$ is an error term. All prices are in euros per liter excluding excise duty and VAT.[8] I use the two-day lagged spot market price, since the spot market price has the highest correlation with the retail price when I use a two-day lag.[9] The one-day lagged spot market price is the most recent quotation available at the moment that a station sets its price. If I use the one-day lagged spot market price in Equation (1), then the estimated long-run impact of the spot market price is similar.

If the residuals of Equation (1) are stationary, a cointegrating relation exists. In that case, I can superconsistently estimate the coefficients in Equation (1) and define a short-run relation between the retail price and spot market price:

$$\Delta P_{i,t} = \alpha_{i,1}\Delta Spot_{t-1} + \sum_{j=0}^{k} \alpha_{i,2+j}\Delta Spot_{t-2-j} + \sum_{j=1}^{l} \beta_{i,j}\Delta P_{i,t-j} + \gamma_i \varepsilon_{i,t-1}^* + \mu_{i,t} \tag{2}$$

where $\mu_{i,t}$ is an error term. I also include the one-day lagged change in the spot market price. Thus, the model always includes *at least* the one-day and two-day lagged change in the spot market price.[10] The term $\varepsilon_{i,t-1}^*$ reflects the difference between the retail price and its equilibrium value on day $t-1$. Therefore, the coefficient γ_i measures the speed of adjustment toward the equilibrium retail price. To study asymmetric price responses, I transform Equation (2) into an asymmetric short-run relation:

$$\begin{aligned}\Delta P_{i,t} = {} & \alpha_{i,1}^{+}\Delta Spot_{t-1}^{+} + \alpha_{i,1}^{-}\Delta Spot_{t-1}^{-} + \sum_{j=0}^{v} \alpha_{i,2+j}^{+}\Delta Spot_{t-2-j}^{+} + \sum_{j=0}^{w} \alpha_{i,2+j}^{-}\Delta Spot_{t-2-j}^{-} \\ & + \sum_{j=1}^{x} \beta_{i,j}^{+}\Delta P_{i,t-j}^{+} + \sum_{j=1}^{y} \beta_{i,j}^{-}\Delta P_{i,t-j}^{-} + \gamma_i^{+}\varepsilon_{i,t-1}^{*+} + \gamma_i^{-}\varepsilon_{i,t-1}^{*-} + \mu_{i,t}\end{aligned} \tag{3}$$

where for each variable z: $\Delta z^{+} = \max\{\Delta z, 0\}$ and $\Delta z^{-} = \min\{\Delta z, 0\}$. And where $\varepsilon_{i,t-1}^{*+} = \max\{\varepsilon_{i,t-1}^{*}, 0\}$ and $\varepsilon_{i,t-1}^{*-} = \min\{\varepsilon_{i,t-1}^{*}, 0\}$. A plus (minus) as superscript to a coefficient indicates that the coefficient belongs to a variable with increases (decreases). Asymmetric price responses can exist due to a larger impact of increases than of decreases in current and lagged changes in the spot market price and lagged changes in the retail price. Asymmetry in the speed of adjustment toward the equilibrium retail price is also possible. If $|\gamma_i^{-}| > |\gamma_i^{+}|$, then the retail price returns more slowly to its equilibrium value when the retail price exceeds its equilibrium value.[11]

8. Taxes do not change substantially during the sample period and I do not consider their impact. The spot market price is published in dollars. I do not make a distinction between changes in the exchange rate and changes in the spot market price in dollars (see Asplund, Eriksson, and Friberg (2000)).

9. This finding makes sense since the two-day lagged spot market price is also the input price for the nonbinding national suggested price that oil companies publish (Shell (2001)).

10. Equation (1) and (2) can be rewritten into a standard ARDL$(k+1, l+1)$ model.

11. An asymmetric long-run relation between the spot market price and retail price cannot exist. If in the long run the pass-through of increases in the spot market price is stronger than the pass-through of decreases, then margins would increase infinitely over time.

I estimate Equation (1) and (3) for each individual station. I use the Engle-Granger two-step estimation procedure and estimate the equations by OLS.[12] The estimation results for Equation (1) are similar if I use the Johansen maximum likelihood procedure. I set the lag lengths (v, w, x, and y) via the Schwarz information criterion (SIC). To interpret the estimation results, I calculate cumulative adjustment functions (see BCG). For each station, I calculate how it changes its retail price after a 1 cent increase and a 1 cent decrease in the spot market price. I compute the cumulative changes up to and including 25 days after these shocks. The difference between the cumulative changes (that is, the adjustment after a positive shock minus the adjustment after a negative shock) reflects the extent of asymmetry of a station at a certain point in time. I use the delta method to derive the standard error of this difference.

4. ESTIMATION RESULTS

I estimate for 2,365 individual gasoline stations a separate specification.[13] The maximum value of v, w, x, and y is 3 (i.e., the maximum lag equals five days for the change in the spot market price and three days for the change in the retail price).[14] To illustrate the results, Figure 1 shows the cumulative adjustment functions of one specific station. It also reports the difference between the cumulative adjustments and its 95% confidence interval. The figure shows that the retail price of this specific station responds asymmetrically. One day after a 1 cent change in the spot market price, the cumulative adjustment of the retail price is 0.36 cent in case of a 1 cent increase and 0.18 cent in case of a 1 cent decrease. This difference is significantly different from 0. However, this asymmetry lasts for a short time. Two days after the shocks, the difference declines and is not significant anymore. The station has almost fully absorbed the shocks after approximately eight days.

How many of the 2,365 gasoline stations adjust prices asymmetrically? For each station, I calculate the number of days for which the difference between the cumulative price change after a positive shock and after a negative shock is positive and significantly different from 0 at the 5% significance level. When this significant positive difference exists at least one day, I define a station as responding asymmetrically.[15] The upper part of Table 1 shows that most stations do not adjust

12. Retail prices are not available for all stations for all days. I can only use an observation of a station's retail price for estimation if the previous $x + 1$ and $y + 1$ observations of this station are also available.

13. For 2,549 stations there are enough data to estimate both Equation (1) and (3). I exclude 7 stations because the residual-based test for cointegration could not reject the null of no cointegration in Equation (1) (all price series of the estimated stations are integrated of order 1). Furthermore, I exclude 49 stations because the estimated γ_i^+ or γ_i^- in Equation (3) is not between -2 and 0 (indicating that for these stations the retail price does not return to its equilibrium value) and 128 stations for which 20 or fewer observations that differ from 0 are available for estimating one of the parameters in Equation (3) (more restrictive conditions do not change the results much). There are 2,365 stations left. I correct the standard errors of the coefficients in Equation (3) for 1,148 stations for heteroskedasticity and for 910 stations for heteroskedasticity and serial correlation.

14. The average correlation between the change in the retail price and lags higher than the five-day lagged change in the spot market price and the three-day lagged change in the retail price is close to 0. The maximum value of 3 also seems sufficient because the SIC selects for only a few stations the maximum possible lag length (14 (7) stations use the five-day lagged increase (decrease) in the spot market price and 8 (14) stations use the three-day lagged increase (decrease) in the retail price). The average correlations between these lags and the change in the retail price are already low. There exists a trade-off when I set the maximum lag length. An advantage of considering more lags is that possibly the equation can more precisely describe the pricing behavior, but a disadvantage is that I can estimate Equation (3) for fewer stations. Later on, I show that the results do not change if I use alternative lag length selection procedures that result in both higher and lower lag lengths.

15. I discuss significant negative differences at the end of this section.

Figure 1: Cumulative Adjustments of the Retail Price of Shell Station Maasboulevard Rotterdam

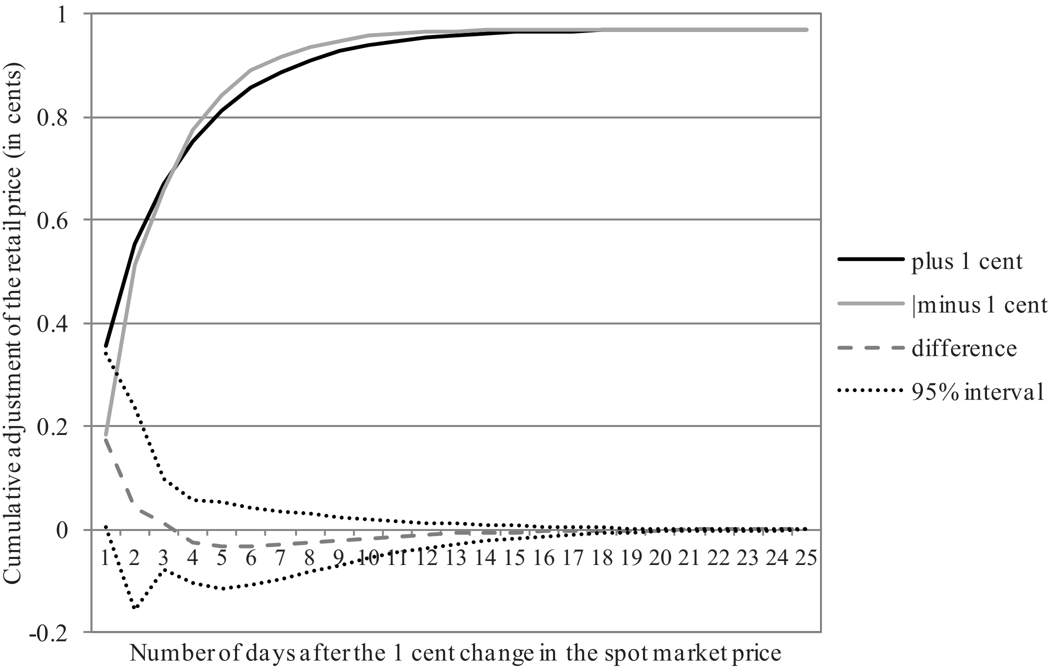


Table 1: Percentage of Stations That Respond Asymmetrically and the Duration of the Asymmetry

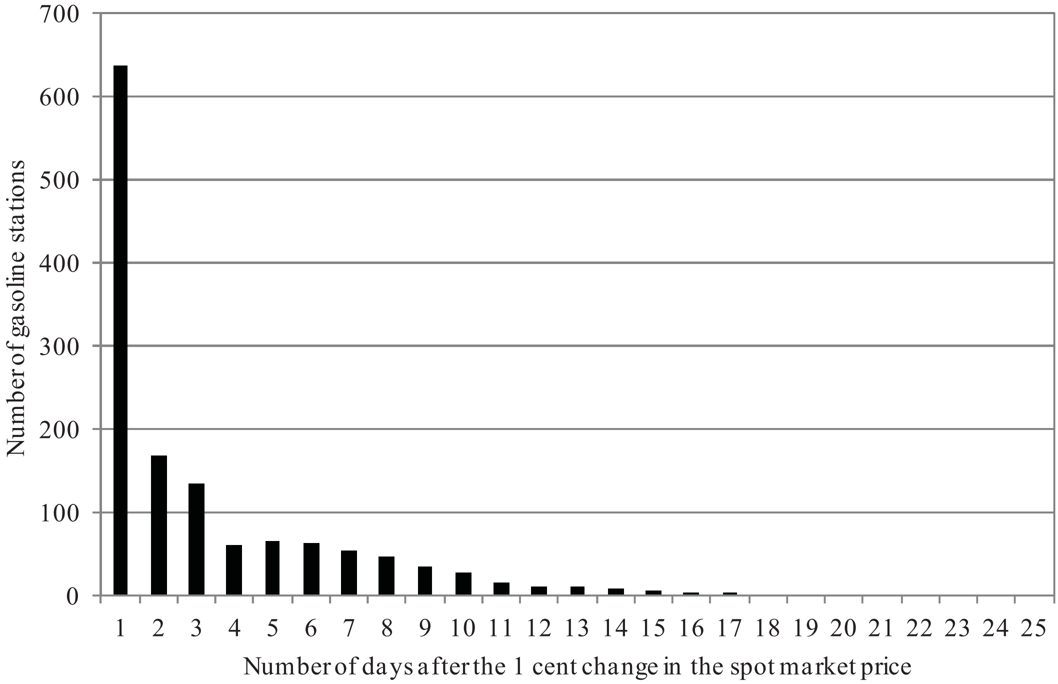
	Number of stations	% of stations
Total	2,365	
0 days asymmetrically	1,468	62%
1 day or more asymmetrically	897	38%
Duration of the asymmetry:		
1 day	686	29%
2 days	135	6%
3 days	20	1%
4 days	19	1%
5 days	9	0%
6 days or more	28	2%

prices asymmetrically. However, 38% of the stations do. There exist differences between stations. Hence, Geweke's second aggregation issue (the issue of aggregation over space) is important.

In the following paragraphs, I study the degree of asymmetry. First, I report the *duration* of the asymmetry. The lower part of Table 1 shows that the duration differs between stations, although for most stations that adjust prices asymmetrically the asymmetry exists for only one or two days.

Second, I study on *which days* the stations respond asymmetrically. Does asymmetry arise directly after the shocks or only after a couple of days? For each day after the shocks, I calculate

Figure 2: Per Day after the Shocks, the Number of Stations That Respond Asymmetrically

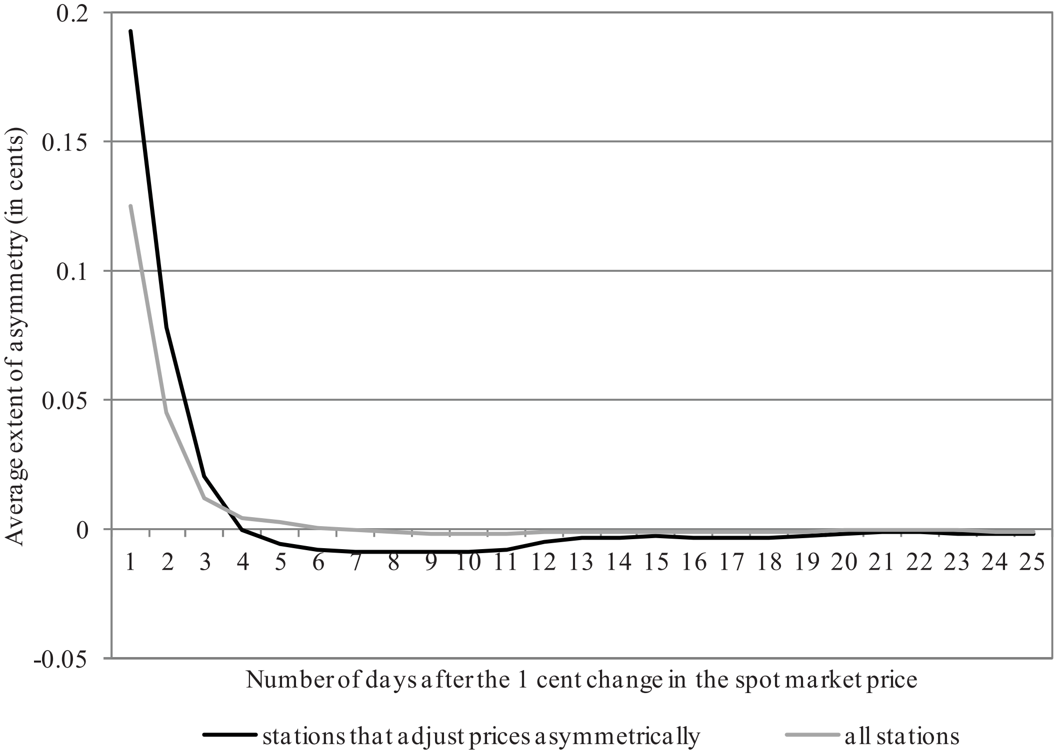


the number of stations for which the difference between the cumulative price changes is positive and significantly different from 0. Figure 2 shows the results.[16] Most asymmetry takes place on the first days after the shocks. On the first day, for 637 out of 2,365 gasoline stations (27%) the difference between the cumulative price changes is positive and significantly different from 0. On the second day, 169 stations respond asymmetrically. This number decreases further after the second day.

Third, I calculate the extent of the asymmetry. For each day, I compute for the 38% of the stations that respond asymmetrically the average difference between the cumulative price changes. Figure 3 shows the result. The asymmetry is on average 0.19 cent on the first day, but declines over time. One day after a 1 cent shock, the price of asymmetrically pricing stations increases on average by 0.35 cent in case of a positive shock and decreases on average by 0.15 cent in case of a negative shock. This asymmetry means that a consumer pays on average 0.19 cent more after a positive shock than what the consumer saves after a negative shock. On the third day, the difference is close to 0. To place these numbers in perspective, Figure 3 also contains the average difference for all 2,365 stations (so including the stations that respond asymmetrically). One day after the shocks, the estimated extent of the asymmetry is on average 0.07 cent (54%) larger when I only consider stations that adjust prices asymmetrically.

16. If according to Table 1 the duration of the asymmetry of a station is two days, then this station adjusts its price asymmetrically on two different days and thus shows up in two separate bars in Figure 2.

Figure 3: Average Extent of Asymmetry (difference between the cumulative adjustments)

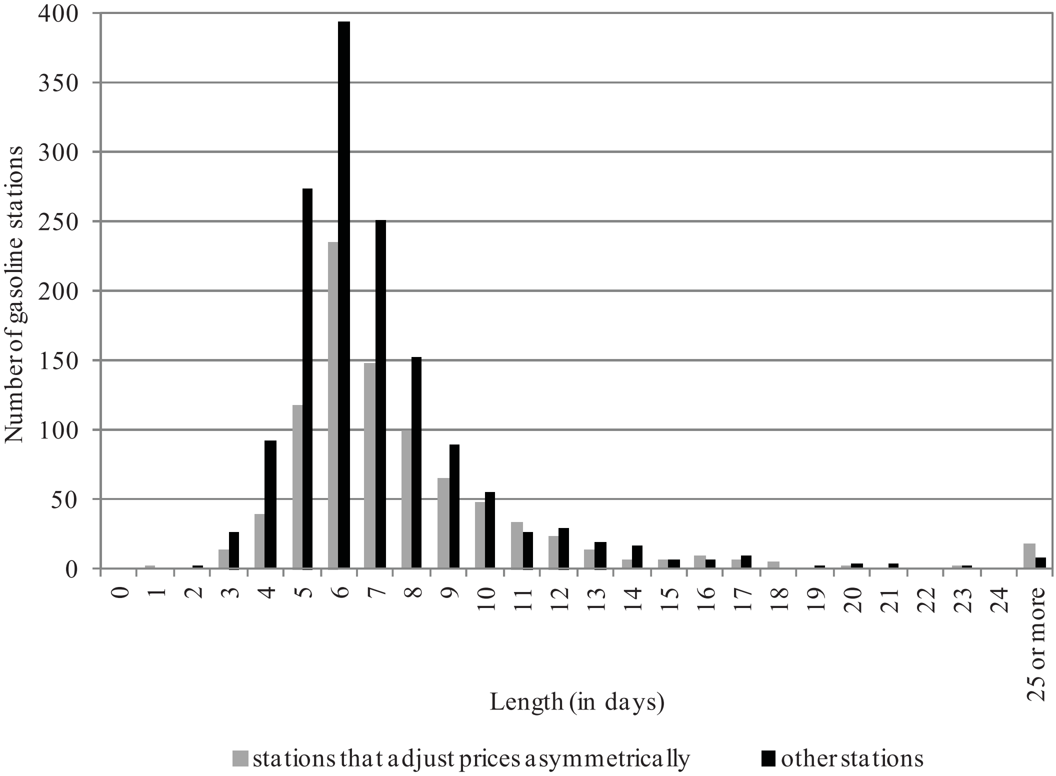


Fourth, to measure the length of the full transmission process, I calculate the number of days that it takes before the cumulative change in the retail price almost equals the long-run pass-through α_i^*. The mean of the estimated long-run pass-through is 0.99 (standard deviation equals 0.05). Thus, in the long run there is for most stations almost a full pass-through of changes in the spot market price into the retail price. I calculate the number of days that the retail price is outside the interval $[0.95\alpha_i^*, 1.05\alpha_i^*]$. Figure 4 shows the length of the transmission process after a positive shock. For asymmetrically pricing stations it takes on average 7.9 days and for other stations 7.1 days.[17] I calculate the length of the transmission process after a negative shock as well. For most stations, it takes about the same amount of time to absorb a negative shock as it takes to absorb a positive shock.

As a robustness check, I show that stations are statistically significant due to a relatively large estimated difference between the cumulative price adjustments and not just due to a relatively narrow confidence interval. Table A1 in Appendix A shows for each individual station the extent of asymmetry on the first three days after the shocks in the spot market price (on these days there are the most stations that respond asymmetrically, see Figure 2). It shows that stations that respond

17. If I use the interval $[0.99\alpha_i^*, 1.01\alpha_i^*]$, then the full transmission process takes on average 12.1 days for asymmetrically pricing stations and 11.0 days for other stations. I also calculate for each station the number of days that the 95% confidence interval of the cumulative adjustment after a positive shock does not contain the point estimate of the long-run pass-through of the spot market price. This number equals on average 8.0 days for stations that adjust prices asymmetrically and 7.1 days for other stations.

Figure 4: Length of the Full Transmission Process after a Positive Shock



asymmetrically on a particular day have in general a larger difference between the cumulative price adjustments than the other stations on that day. Moreover, there is no relation between the extent of asymmetry and the size of the confidence interval. The correlations for the first, second, and third day after the shocks in the spot market price are respectively −0.02, −0.01, and −0.12.[18] The results are similar for the other days. Hence, stations that respond asymmetrically do not just have a more precise estimate of the difference. If I define a station as responding asymmetrically when it has a significant positive difference between the cumulative adjustment functions on at least one of the 25 days and the sum of these positive significant differences is larger than 0.15 (0.20) cent, then 36% (27%) of the stations respond asymmetrically. These percentages are relatively close to the 38% that I find when I only take statistical significance into account.

As an additional robustness check, I also estimate Equation (3) with $\gamma_i^+ = \gamma_i^-$, higher and lower maximum values for v, w, x, and y (see Footnote 14), and the Akaike information criterion (AIC) to set the lag lengths (the AIC tends to include more lags than the SIC if the number of observations ≥ 8). The maximum lag lengths for changes in the spot market price vary between 0 and 10.[19] Table 2 reports the results. The percentage of stations that adjust prices asymmetrically

18. I exclude from these calculations stations with a significant negative difference between the cumulative adjustments on a particular day. These stations have a low extent of asymmetry but might also have a narrow confidence interval. The qualitative results are independent of the used sample.

19. A maximum lag length of 10 seems sufficient for the AIC as it selects the twelve-day lag of the increase (decrease) in the spot market price for only 1% (1%) of the stations.

Table 2: Percentage of Stations That Respond Asymmetrically in case of Alternative Specifications and Alternative Lag Length Selection Procedures for Equation (3)

	% of stations
max $v = w = x = y = 3$	39%
max $v = w = x = y = 1$	39%
max $v = w = x = y = 0$	37%
max $v = w = 3$, $x = y = 0$	43%
max $v = w = 10$, $x = y = 3$	39%
max $v = w = 3$, $x = y = 0$; $\gamma_i^+ = \gamma_i^-$	39%
max $v = w = x = y = 0$; $\gamma_i^+ = \gamma_i^-$	31%
max $v = w = x = y = 3$; AIC	41%
max $v = w = 10$, $x = y = 3$; AIC	49%

Note: For all specifications I use the same 2,026 stations. Therefore, the percentage for the specification with a maximum value of v, w, x, and y of 3 differs from the 38% in Table 1 (I base this latter percentage on 2,365 stations).

is between 31% and 49%, depending on the exact specification and selection procedure for the lag lengths. Therefore, the conclusion that there exist differences between firms does not change.

As a final robustness check, I also study whether retail prices respond faster to *decreases* than to *increases* in the spot market price. If the previous results would mainly be a statistical artifact, then I would expect that this type of pricing would occur as regularly as asymmetric pricing. However, I find that stations do not often practice this type of pricing. For only 7% of the stations, there is a significant negative difference between the cumulative price changes on at least one day. For most of these stations, this negative difference exists just for one day and takes place about six days after the shocks in the spot market price. Around this day, the average difference between the cumulative price changes is small. Thus, the asymmetric price responses that I find do not seem to result from the statistical method.

The Market as a Whole

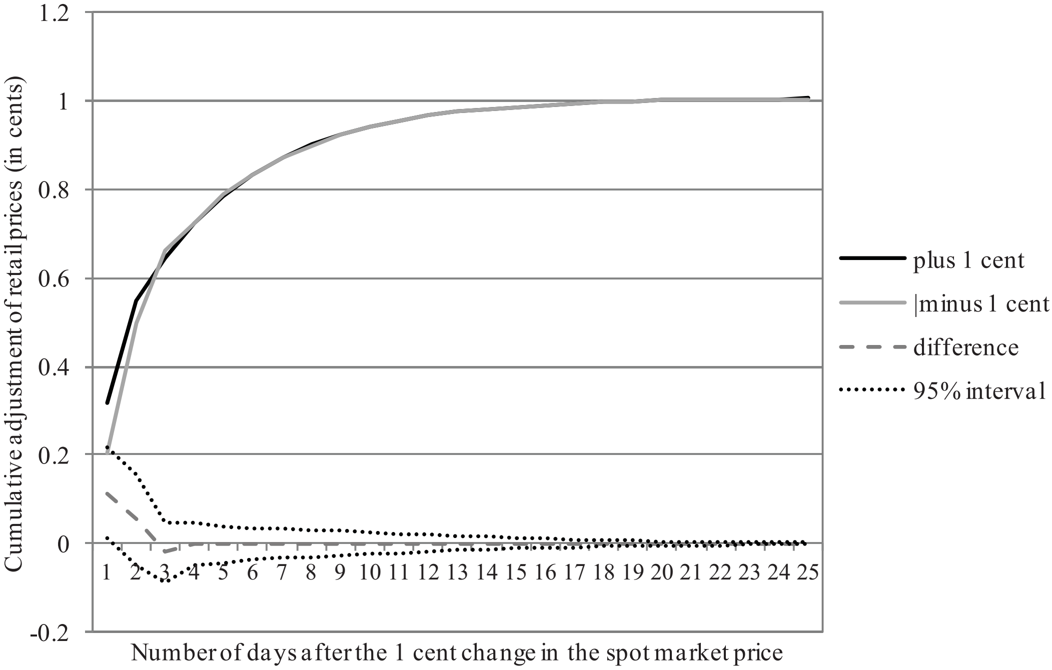
To further study the effect of aggregation over space, I estimate asymmetric price responses of the market as a whole. Aggregation over space can have two effects. First, it can obscure differences between firms. Second, pooling across individual firms may possibly give biased results in (dynamic) estimations if there exists parameter heterogeneity (see, e.g., Robertson and Symons (1992), Pesaran and Smith (1995), Hsiao (2003), and Baltagi, Bresson, and Pirotte (2008)).

I estimate Equation (1) and (3) when all gasoline stations are pooled. Pooling implies that none of the coefficients are station-specific anymore, except the constant c_i^* (which is now a fixed

20. The long-run specification is not fully pooled because it is a priori clear that a common intercept is not appropriate as the average price level differs between stations (an F-test confirms this). A common coefficient for the long-run impact of the spot market price is not implausible as for most stations there is almost a full pass-through of changes in the spot market price in the long run.

21. The OLS estimator is superconsistent, but can possibly have a substantial bias if the cross-sectional dimension of the panel is large (Pedroni (2000)). To estimate Equation (1) via panel DOLS (Kao and Chiang (2000) and Mark and Sul (2003)), I include 6 leads and lags of changes in the two-day lagged spot market price in the regression. That is, I add to the right hand side of the equation: $\sum_{j=-6}^{6}\theta_j \Delta Spot_{t-2+j}$. Results do not change much if I use another length. The impact of the leads and lags is homogeneous across stations to limit the number of coefficients that I have to estimate. Subsequently, I define: $\varepsilon_{i,t}^* = P_{i,t} - \alpha^* Spot_{t-2} - c_i^* - \tau^* Time_t - \lambda^* Mix_t$. Results are similar if I use the OLS estimator.

Figure 5: Cumulative Adjustments of Retail Prices of the Market as a Whole



effect).[20] I use a panel DOLS estimator and Newey-West standard errors to estimate Equation (1).[21] The estimated coefficient for the long-run impact of the spot market price is 1.01 (standard error equals 0.00).[22]

To estimate Equation (3), I use the pooled OLS estimator and Driscoll-Kraay standard errors that are robust to heteroskedasticity, serial correlation, and cross-sectional correlation (see Driscoll and Kraay (1998) and Hoechle (2007)). Both an F-test and the Pesaran and Yamagata (2008) tests ($\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$) reject the null hypothesis of common slopes across stations in Equation (3).[23] Hence, the parameters vary across stations and the data are not poolable. Nevertheless, I study whether the results of the pooled estimation differ from the individual estimates from the previous subsection.

Figure 5 shows the cumulative adjustment functions for the specification with $v = w = x = y = 1$ (other specifications provide similar results).[24] There is significant asymmetry in the market as a whole. However, this asymmetry lasts for a short time. The difference between the cumulative change in the retail price after a 1 cent increase and a 1 cent decrease in the spot market

22. An augmented Dickey-Fuller Fisher panel unit root test indicates that retail prices are, like the spot market price, integrated of order 1. The panel cointegration test of Kao (1999) reveals homogeneous cointegration between retail prices and the spot market price.

23. The tests also reject if I only use the 2,365 stations or the 2,549 stations that I use in the previous subsection (see Footnote 13). The results hold for different lag lengths as well. Like Pesaran and Yamagata (2008), I include a station-specific constant in the pooled equation when I perform their tests. Pesaran and Yamagata (2008) separately study strictly exogenous regressors and dynamic models. The tests also reject when I exclude from Equation (3) the lagged differences of the spot market price or the lagged differences of the retail price and the lagged residuals of Equation (1).

24. This specification uses 3,658 stations and 1,052,741 observations.

price is significantly different from 0 on the first day after the shocks (these changes are respectively 0.32 cent and 0.21 cent, thus the difference is 0.11 cent). After the first day, the difference is not significantly different from 0 anymore. Retail prices have absorbed more than 95% of the estimated long-run pass-through of both the positive and negative shock after the eleventh day.

Of course, the analysis for the market as a whole does not detect differences between individual stations. Although the tests reject poolability of the data, in general, the pooled estimation provides an overview of the average pricing behavior of stations. For example, the average extent of asymmetry on the first day according to the pooled estimation is close to the average difference between the cumulative adjustment functions of all stations in Figure 3 (0.114 cent versus 0.125 cent). However, the individual estimations consistently show on average a shorter transmission process than the pooled estimation. This finding possibly indicates a summation bias. For example, the length of the transmission process after a positive shock is according to the pooled estimation 11 days. According to the individual estimations, this number is on average 7.4 days.

5. CHARACTERISTICS

This section studies whether stations that adjust prices asymmetrically have different characteristics than other stations. For each gasoline station, I have 35 (sometimes overlapping) characteristics. Roughly, there are five kinds of station-specific characteristics: brand indicators (e.g., the specific brand and the ownership structure), location indicators (e.g., a location along the highway, a location near the border, and the population size of the area in which the station is located), competitor indicators (e.g., the number of stations in the area in which the station is located), price indicators (e.g., the price level of the station), and consumers' search intensity indicators (e.g., income per capita in the area where the station is located). This classification is rough, since many characteristics have a link with several groups. I take the 3 digit zip code area in which a station is located as a proxy for its direct market and the 2 digit zip code area as a proxy for its broader market.[25]

Theoretical studies often explain asymmetric price adjustments by tacit collusion between retailers or a low search intensity of consumers (see, e.g., Verlinda (2008), Yang and Ye (2008), Tappata (2009), Lewis (2011), and Cabral and Fishman (2012)). Some of the characteristics that I use are broad proxies (or conditions) for the existence of tacit collusion and/or a low search intensity. However, often it is possible to link a characteristic to asymmetric pricing via both theoretical explanations. For example, Verlinda (2008) links market power to asymmetric pricing via tacit collusion and Deltas (2008) via a low search intensity. For that reason, I do not try to answer *why* stations adjust prices asymmetrically, but I look at *which* stations adjust prices asymmetrically.

I divide all tested gasoline stations into two groups: one group with stations that adjust prices asymmetrically and one group with all other stations. I study whether stations in these two groups have similar characteristics. For both groups, I calculate for each characteristic the average value of this characteristic over all stations in the group or the share of stations in the group with this characteristic. Afterward, I test for equality of the averages or shares via a t-test.

25. The Netherlands consists of 90 areas at the 2 digit zip code level (average size 375 km^2, average number of stations 44) and 829 areas at the 3 digit zip code level (average size 41 km^2, average number of stations 5). Some 3 digit zip code areas do not contain many stations. However, the 3 digit zip code characteristics provide similar results as all their nonreported 2 digit equivalents.

Table 3: Characteristics of the Group with Asymmetrically Pricing Stations and the Group with All Other Stations

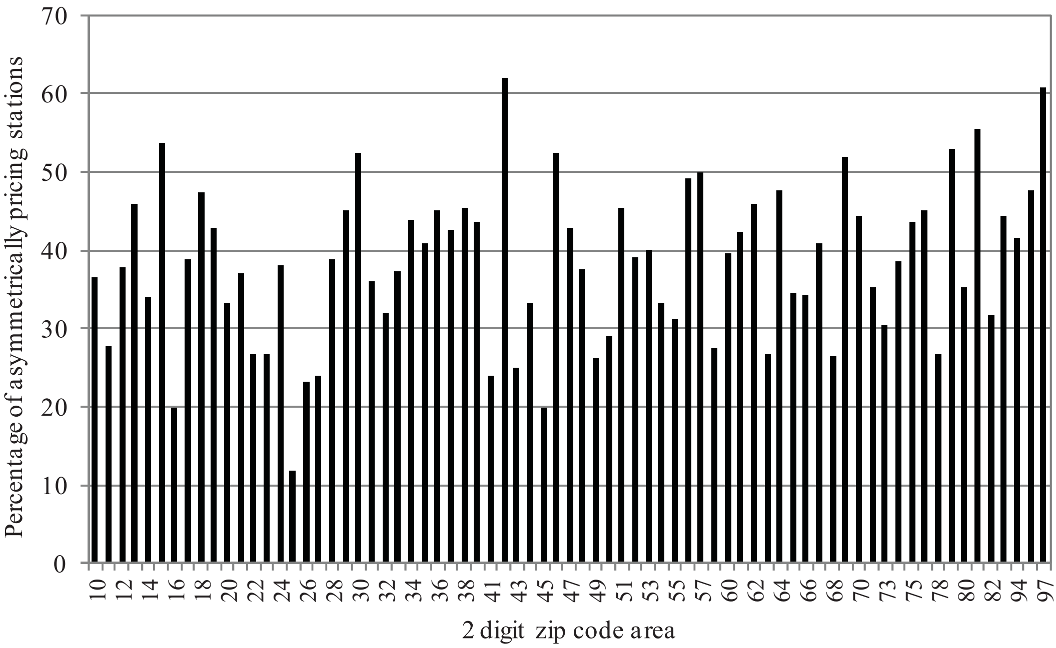
	Asymmetrically pricing group	All other stations group	Equality: p-value
Number of stations in group	897	1,468	
Brand indicators			
Share of comp-owned stats	53%	55%	0.18
Av % of comp-owned stats in 3 dig zip	45%	47%	0.14
Share of Brand A stats	11%	15%	0.02*
Share of Brand B stats	14%	10%	0.00**
Share of Brand C stats	27%	23%	0.04*
Share of Brand D stats	10%	13%	0.13
Share of Brand E stats	10%	12%	0.03*
Share of branded stats	73%	74%	0.81
Av concentration ratio five largest brands in 3 dig zip	0.62	0.62	0.79
Av % of stats with same brand as stat in 3 dig zip	31%	30%	0.52
Av % of stats with largest brand in 3 dig zip	33%	33%	0.63
Location indicators			
Share of highway stats	14%	11%	0.05
Av % of highway stats in 3 dig zip	10%	8%	0.00**
Av size of population in 3 dig zip	34,358	34,492	0.89
Av car/population ratio in 3 dig zip	0.61	0.61	0.65
Share of stats in 2 dig zip next to German border	18%	16%	0.28
Share of stats in 2 dig zip next to Belgian border	13%	13%	0.76
Competitor indicators			
Av % of other asym pricing stats in 2 dig zip	39%	37%	0.01*
Av % of other asym pricing stats in 3 dig zip	40%	37%	0.00**
Av nr of stats in 2 dig zip	51	50	0.05*
Av nr of stats in 3 dig zip	8	8	0.93
Av nr of stats per 1,000 inhab in 2 dig zip	0.26	0.25	0.32
Av nr of stats per 1,000 inhab in 3 dig zip	0.29	0.30	0.86
Price indicators			
Av (retail price − spot price) of stat	€ 0.116	€ 0.114	0.23
Av (retail price − spot price) of other stats in 2 dig zip	€ 0.112	€ 0.113	0.06
Av (retail price − spot price) of other stats in 3 dig zip	€ 0.112	€ 0.112	0.64
Av % of days with price change	36%	36%	0.12
Search intensity indicators			
Av rank reversal of a stat's area in 2 dig zip	0.051	0.050	0.07
Av rank reversal of a stat's area in 3 dig zip	0.055	0.056	0.47
Av spread of prices other stats in 2 dig zip	€ 0.028	€ 0.028	0.88
Av spread of prices other stats in 3 dig zip	€ 0.026	€ 0.026	0.92
Av % aged 60 or older in 3 dig zip	21%	21%	0.52
Av % unemployed in municipality	3%	3%	0.90
Av % immigrants in 3 dig zip	17%	17%	0.22
Av income per capita in 3 dig zip	€ 2,029	€ 2,033	0.70

Notes: * and ** indicate significance at the 5% and 1% levels, respectively. "Share of *x* stats" means share of stations in the group with characteristic *x*. "Av *x*" means average of characteristic *x* over all stations in the group.

Results

Table 3 presents the results. The interpretation of the first line of the table is as follows: the first and second column show that 53% of all stations that adjust prices asymmetrically are company-owned while, of all other stations, 55% are company-owned. The third column shows the

Figure 6: Percentage of Asymmetrically Pricing Stations per 2 Digit Zip Code Area



Note: The figure depicts only areas with 15 or more stations.

p-value of the t-statistic (null hypothesis of the t-test: the two percentages are equal). There is no significant difference between the two groups at all usual significance levels, so oil company ownership does not have a higher incidence in one of the two groups.

None of the characteristics show a substantial difference between the group of asymmetrically pricing stations and the group of all other stations. Of the 35 characteristics in the table, only three are significantly different at the 1% significance level. However, the economic impact of these three differences is small. Asymmetric pricing seems to be a phenomenon that occurs randomly in the population of gasoline stations. I will first discuss the statistically significant results and then a few others.

First, I discuss whether asymmetrically pricing stations are closely located to each other. I look at three levels of geographic concentration: the 3 digit zip code level, the 2 digit zip code level, and the national level. I calculate the percentage of other stations that price asymmetrically in the zip code area of a station. Table 3 shows that this percentage is on average significantly higher for stations that adjust prices asymmetrically themselves (for both the 2 and 3 digit zip code level). Although statistically significant, the geographic concentration is very low. To illustrate, stations that *do not* set prices asymmetrically are located in 3 digit zip code areas where on average 37% of the other stations set prices asymmetrically, while stations that *do* set prices asymmetrically are located in areas where on average 40% of the other stations price asymmetrically. To study clustering at the national level, Figure 6 shows the percentage of stations that adjust prices asymmetrically in each 2 digit zip code area. Zip codes with numbers that are close to each other are roughly in the same part of the country. The figure shows that in all zip code areas a substantial part of the stations adjust prices asymmetrically and that areas with a high percentage are not close to each other. So asymmetrically pricing stations are present all over the country.

The second characteristic that is statistically different is the percentage of highway stations in the 3 digit zip code area of a station. For asymmetrically pricing stations the average percentage of highway stations in the 3 digit zip code area is significantly higher than for all other stations. The size of the effect is moderate (10% versus 8%). The final significant result is that stations that adjust prices asymmetrically are significantly more likely to use certain brands, although differences are not substantial.

All other characteristics in the table do not statistically differ between asymmetrically pricing stations and all other stations. Most of these characteristics and their intuition are relatively straightforward. Therefore, I elaborate on just a few of them. First, I discuss the price level of stations. Table 3 shows the average difference between the retail price and the two-day lagged spot market price for stations that do and do not set prices asymmetrically. Stations that adjust prices asymmetrically do not have a significantly higher price on average.[26] Also the other stations in the zip code area of an asymmetrically pricing station do not have a higher price.

Second, I look at the *rank reversal of a station's area*. Retailers can increase search costs via their pricing behavior. If there is not a consistent price ranking of stations (i.e., stations often become cheaper or more expensive compared to each other), then there is a higher degree of imperfect information among consumers (higher search costs). To measure this temporal price dispersion across stations (or say: the degree to which consumers are uncertain about which firms are cheap), I calculate the *rank reversals* (Chandra and Tappata (2011)). The rank reversal between two stations is the fraction of days on which the station that has most often the lowest price charges the highest price. Hence, a rank reversal of 0.05 means that the station which has on the most days the lowest price, has on 5% of the days the highest price. More specifically, I calculate for each gasoline station the average of the rank reversals between all possible pairs of competitors in the zip code area where the station is located. This average rank reversal (say: the rank reversal of a station's area) is a proxy for the degree of uncertainty about prices in the market of this station.[27] Table 3 presents the average rank reversal of a station's area for both groups of stations. There is no difference between the groups.

The third characteristic that I look at is the average spread of prices of other stations in an area. A proxy for station-specific search costs for a consumer is the price spread between stations. If there are still high potential gains of search in the area around a station, search costs in the market of that station must be high.[28] For each station I take the mean of the average price spread between all possible pairs of competitors in the zip code area. The table shows that there is no difference between the two groups.

The final characteristics that I discuss are the characteristics of consumers in the area around a gasoline station. The share of people in an area that are 60 years or older, unemployed, or immigrant might be related to the number of searchers (for example, Aguiar and Hurst (2005) and Lach (2007) argue that respectively retirees and immigrants can have different search costs). Income per capita of an area may be a measure of consumers' opportunity costs of search. The results are similar for stations in both groups.

26. Verlinda (2008) notes that stations with similar retail prices do not necessarily have similar margins, because it is possible that oil companies do not charge all stations the same wholesale price.

27. Asymmetric pricing can lead to a higher rank reversal. Therefore, I exclude the station itself because the rank reversal may be higher by definition if the station adjusts prices asymmetrically.

28. Chandra and Tappata (2011) show that in general the relation between search intensity and price dispersion is nonmonotonic.

Appendix B presents robustness checks. The results of this section do not change when I use, next to statistical significance, the extent of asymmetry of a station to define the two groups or when I use the extent of asymmetry as the measure for asymmetric pricing.

6. DISCUSSION

In the previous sections, I find a relatively moderate degree of asymmetry. Some other studies (e.g., BCG and Verlinda (2008)) find a higher degree of asymmetry. In these studies, asymmetry lasts several weeks and full pass-through of cost shocks takes even longer. Do I find a relatively moderate degree because I do not use aggregated data (see Bachmeier and Griffin (2003)) or because I study another market?

To get an idea about this issue, I repeat the exercise with aggregated data. I aggregate over space (the pooled estimation in Section 4), over time (weekly data), and over space and time (pooled estimation with weekly data). Although the transmission process takes longer in these estimations (see, e.g., Section 4), the degree of asymmetry does not increase enormously.

Another explanation might be a specific property of the market that I study. Remember that oil companies publish daily nonbinding national suggested prices for stations. These suggested prices respond symmetrically to the spot market price (Faber (2009)). Possibly, stations do not want to deviate too much or too long from these suggested prices (see Faber and Janssen (2013)). Therefore, the degree of asymmetry in the market that I study may be relatively moderate in comparison to the degree in other markets. However, there is no reason to think that differences between firms are specific to the market that I study.

7. CONCLUSION

Geweke (2004) states that there are two possible aggregation issues in the literature on asymmetric price responses: (i) a possible issue due to aggregation over time, and (ii) a possible issue due to aggregation over space. I study the second issue via daily retail prices of individual gasoline stations. The data of the stations are not poolable and therefore I analyze each station individually. I find that 38% of the stations respond asymmetrically to changes in the daily gasoline spot market price. Therefore, Geweke's second aggregation issue is important. Asymmetric pricing is a feature of individual firms. Bachmeier and Griffin (2003) show that the first aggregation issue is relevant. Therefore, to fully understand asymmetric price responses, it is important to analyze decisions at the most detailed level.

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REFERENCES

Aguiar, Mark and Erik Hurst (2005). "Consumption versus Expenditure." *Journal of Political Economy* 113(5): 919–948. http://dx.doi.org/10.1086/491590.

Asplund, Marcus, Rickard Eriksson, and Richard Friberg (2000). "Price Adjustments by a Gasoline Retail Chain." *Scandinavian Journal of Economics* 102(1): 101–121. http://dx.doi.org/10.1111/1467-9442.00186.

Bachmeier, Lance J. and James M. Griffin (2003). "New Evidence on Asymmetric Gasoline Price Responses." *Review of Economics and Statistics* 85(3): 772–776. http://dx.doi.org/10.1162/003465303322369902.

Balmaceda, Felipe and Paula Soruco (2008). "Asymmetric Dynamic Pricing in a Local Gasoline Retail Market." *Journal of Industrial Economics* 56(3): 629–653. http://dx.doi.org/10.1111/j.1467-6451.2008.00349.x.

Baltagi, Badi H., Georges Bresson, and Alain Pirotte (2008). "To Pool or Not to Pool?" In *The Econometrics of Panel Data: Fundamentals and Recent Developments in Theory and Practice*, edited by László Mátyás and Patrick Sevestre, Third Edition, 517–546. Berlin: Springer. http://dx.doi.org/10.1007/978-3-540-75892-1_16.

Bettendorf, Leon, Stéphanie A. van der Geest, and Gerard H. Kuper (2009). "Do Daily Retail Gasoline Prices Adjust Asymmetrically?" *Journal of Applied Statistics* 36(4): 385–397. http://dx.doi.org/10.1080/02664760802466468.

Bettendorf, Leon, Stéphanie A. van der Geest, and Marco Varkevisser (2003). "Price Asymmetry in the Dutch Retail Gasoline Market." *Energy Economics* 25(6): 669–689. http://dx.doi.org/10.1016/S0140-9883(03)00035-5.

Borenstein, Severin, A. Colin Cameron, and Richard Gilbert (1997). "Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?" *Quarterly Journal of Economics* 112(1): 305–339. http://dx.doi.org/10.1162/003355397555118.

BOVAG (2006). *Tankstations in cijfers 2006–2007*. Bunnik.

Cabral, Luís and Arthur Fishman (2012). "Business as Usual: A Consumer Search Theory of Sticky Prices and Asymmetric Price Adjustment." *International Journal of Industrial Organization* 30(4): 371–376. http://dx.doi.org/10.1016/j.ijindorg.2012.01.003.

Chandra, Ambarish and Mariano Tappata (2011). "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets." *RAND Journal of Economics* 42(4): 681–704. http://dx.doi.org/10.1111/j.1756-2171.2011.00150.x.

Deltas, George (2008). "Retail Gasoline Price Dynamics and Local Market Power." *Journal of Industrial Economics* 56(3): 613–628. http://dx.doi.org/10.1111/j.1467-6451.2008.00350.x.

Driscoll, John C. and Aart C. Kraay (1998). "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *Review of Economics and Statistics* 80(4): 549–560. http://dx.doi.org/10.1162/003465398557825.

Eckert, Andrew and Douglas S. West (2004). "Retail Gasoline Price Cycles across Spatially Dispersed Gasoline Stations." *Journal of Law and Economics* 47(1): 245–273. http://dx.doi.org/10.1086/380474.

Faber, Riemer P. (2009). "Asymmetric Price Responses of Gasoline Stations: Evidence for Heterogeneity of Retailers." Tinbergen Institute Discussion Paper 09-106/1.

Faber, Riemer P. and Maarten C.W. Janssen (2013). "On the Effects of Suggested Prices in Gasoline Markets." Working Paper.

Geweke, John (1978). "Temporal Aggregation in the Multiple Regression Model." *Econometrica* 46(3): 643–661. http://dx.doi.org/10.2307/1914238.

Geweke, John (2004). "Issues in the Rockets and Feathers Gasoline Price Literature." Report to Federal Trade Commission.

Hoechle, Daniel (2007). "Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence." *Stata Journal* 7(3): 281–312.

Hosken, Daniel S., Robert S. McMillan, and Christopher T. Taylor (2008). "Retail Gasoline Pricing: What Do We Know?" *International Journal of Industrial Organization* 26(6): 1425–1436. http://dx.doi.org/10.1016/j.ijindorg.2008.02.003.

Hsiao, Cheng (2003). *Analysis of Panel Data*, Second Edition. Cambridge: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511754203.

Kao, Chihwa (1999). "Spurious Regression and Residual-Based Tests for Cointegration in Panel Data." *Journal of Econometrics* 90(1): 1–44. http://dx.doi.org/10.1016/S0304-4076(98)00023-2.

Kao, Chihwa and Min-Hsien Chiang (2000). "On the Estimation and Inference of a Cointegrated Regression in Panel Data." In *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, edited by Badi H. Baltagi, Advances in Econometrics, 15, 179–222. New York: Elsevier. http://dx.doi.org/10.1016/S0731-9053(00)15007-8.

Lach, Saul (2007). "Immigration and Prices." *Journal of Political Economy* 115(4): 548–587. http://dx.doi.org/10.1086/521529.

Lewis, Matthew S. (2009). "Temporary Wholesale Gasoline Price Spikes Have Long-Lasting Retail Effects: The Aftermath of Hurricane Rita." *Journal of Law and Economics* 52(3): 581–605. http://dx.doi.org/10.1086/592056.

Lewis, Matthew S. (2011). "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market." *Journal of Economics and Management Strategy* 20(2): 409–449. http://dx.doi.org/10.1111/j.1530-9134.2011.00293.x.

Lewis, Matthew S. and Michael Noel (2011). "The Speed of Gasoline Price Response in Markets with and without Edgeworth Cycles." *Review of Economics and Statistics* 93(2): 672–682. http://dx.doi.org/10.1162/REST_a_00176.

Mark, Nelson C. and Donggyu Sul (2003). "Cointegration Vector Estimation by Panel DOLS and Long-Run Money Demand." *Oxford Bulletin of Economics and Statistics* 65(5): 655–680. http://dx.doi.org/10.1111/j.1468-0084.2003.00066.x.

Noel, Michael (2009). “Do Retail Gasoline Prices Respond Asymmetrically to Cost Shocks? The Influence of Edgeworth Cycles.” *RAND Journal of Economics* 40(3): 582–595. http://dx.doi.org/10.1111/j.1756-2171.2009.00078.x.

Pedroni, Peter (2000). “Fully Modified OLS for Heterogeneous Cointegrated Panels.” In *Nonstationary Panels, Panel Cointegration, and Dynamic Panels*, edited by Badi H. Baltagi, Advances in Econometrics, 15, 93–130. New York: Elsevier. http://dx.doi.org/10.1016/S0731-9053(00)15004-2.

Peltzman, Sam (2000). “Prices Rise Faster than They Fall.” *Journal of Political Economy* 108(3): 466–502. http://dx.doi.org/10.1086/262126.

Pesaran, M. Hashem and Ron Smith (1995). “Estimating Long-Run Relationships from Dynamic Heterogeneous Panels.” *Journal of Econometrics* 68(1): 79–113. http://dx.doi.org/10.1016/0304-4076(94)01644-F.

Pesaran, M. Hashem and Takashi Yamagata (2008). “Testing Slope Homogeneity in Large Panels.” *Journal of Econometrics* 142(1): 50–93. http://dx.doi.org/10.1016/j.jeconom.2007.05.010.

Robertson, Donald and James Symons (1992). “Some Strange Properties of Panel Data Estimators.” *Journal of Applied Econometrics* 7(2): 175–189. http://dx.doi.org/10.1002/jae.3950070206.

Shell (2001). “Het is echt heel transparant. Hoe ontstaan de adviesprijzen voor benzine?” *Shell Venster* July/August: 16–18.

Tappata, Mariano (2009). “Rockets and Feathers: Understanding Asymmetric Pricing.” *RAND Journal of Economics* 40(4): 673–687. http://dx.doi.org/10.1111/j.1756-2171.2009.00084.x.

Verlinda, Jeremy A. (2008). “Do Rockets Rise Faster and Feathers Fall Slower in an Atmosphere of Local Market Power? Evidence from the Retail Gasoline Market.” *Journal of Industrial Economics* 56(3): 581–612. http://dx.doi.org/10.1111/j.1467-6451.2008.00351.x.

Yang, Huanxing and Lixin Ye (2008). “Search with Learning: Understanding Asymmetric Price Adjustments.” *RAND Journal of Economics* 39(2): 547–564. http://dx.doi.org/10.1111/j.0741-6261.2008.00027.x.

APPENDIX A. EXTENT OF ASYMMETRY PER STATION

Table A1: Extent of Asymmetry per Station

Extent of asymmetry	Day 1		Day 2		Day 3	
	Number of stations that respond asymmetrically	Number of other stations	Number of stations that respond asymmetrically	Number of other stations	Number of stations that respond asymmetrically	Number of other stations
less than −0.325		9		23		12
−0.3		1		8		8
−0.25		9		14		5
−0.2		12		24		18
−0.15		27		61		49
−0.1		52		125		125
−0.05		98		239		303
0	0	173	0	425	0	818
0.05	0	311	0	547	2	689
0.1	0	457	1	430	34	165
0.15	69	406	42	191	50	34
0.2	255	103	47	70	34	4
0.25	157	38	32	21	5	0
0.3	78	17	25	8	5	1
0.35	36	6	13	6	2	0
0.4	14	3	3	2	1	0
0.45	11	2	2	0	0	0
0.5	6	2	1	0	1	0
0.55	6	0	1	1	0	0
0.6	1	1	1	1	0	0
0.625 or more	4	1	1	0	0	0
Total number of stations	637	1,728	169	2,196	134	2,231

APPENDIX B. CHARACTERISTICS: ROBUSTNESS

This appendix presents robustness checks for the characteristics analysis in Section 5. Some stations that do not respond asymmetrically do have a positive difference between the cumulative price changes that is not statistically significant (see Table A1 in Appendix A). Therefore, I compare the characteristics of stations that adjust prices asymmetrically to the characteristics of subsets of the group with all other stations. These subsets consist of stations with a relatively small difference between the cumulative price changes. As an additional change with respect to the methodology that I use in the main text, I start by only studying the first day after the shocks in the spot market price since the most stations respond asymmetrically on this day (see Figure 2).

The first two columns of Table B1 show that the characteristics of stations that respond asymmetrically on the first day after the shocks are similar to the characteristics of all other stations.[29] The third and fourth column show that there are also no substantial differences between the characteristics of stations that respond asymmetrically on the first day and the characteristics of two subsets of all other stations (the exact definition of the subsets is in the notes below the table). For most characteristics there is no statistically significant difference. When the difference is statistically significant, the economic impact is small or the result depends on how I define the subset. Compared to Table 3, the main difference is that in Table B1 the percentage of highway stations and the percentage of stations near the German border are higher in the group with asymmetrically pricing stations than in the two subsets. However, the difference between these percentages is relatively small and depends on the definition of the subset (the table does not report all subsets that I study). The results in Table B1 are similar for the second and third day after the shocks in the spot market price and for other subsets of the group with all other stations. The qualitative results also do not change when I take a subset of the group with asymmetrically pricing stations by requiring a minimum extent of asymmetry (e.g., more than 0.15, 0.20, or 0.30 cent).

As a second robustness check, I use the extent of asymmetry of a station as the measure for asymmetric pricing instead of whether or not a station adjusts its price asymmetrically. More specifically, I relate via regression analysis the characteristics of a station to the sum of the significant differences between the cumulative price changes on the first 25 days after the shocks in the spot market price. Moreover, for the first three days after the shocks, I relate in the same way the characteristics of a station to the difference between the cumulative price changes on a specific day (I weigh the observations with the standard error of the difference to take into account that differences with smaller standard errors are more informative). These analyses provide the same qualitative conclusions and therefore I do not report the results.

29. Relatively many (few) stations that respond asymmetrically on the first day after the shocks in the spot market price use Brand C (Brand E). However, on the other days, the group with stations that respond asymmetrically contains relatively few (many) additional stations that use Brand C (Brand E). Hence, overall there is no substantial difference between stations that adjust prices asymmetrically and other stations concerning the use of these two brands (see the first column of Table 3).

Table B1: Characteristics of the Group with Stations That Respond Asymmetrically on the First Day and (subsets of) the Group with All Other Stations

	Asymmetrically pricing group	All other stations group	Subset 1	Subset 2
Number of stations in group	637	1,728	705	327
Brand indicators				
Share of comp-owned stats	53%	55%	60%*	56%
Av % of comp-owned stats in 3 dig zip	46%	47%	50%**	48%
Share of Brand A stats	11%	15%*	16%**	17%**
Share of Brand B stats	12%	12%	10%	11%
Share of Brand C stats	35%	21%**	22%**	19%**
Share of Brand D stats	11%	12%	13%	11%
Share of Brand E stats	5%	14%**	15%**	15%**
Share of branded stats	73%	74%	77%	73%
Av concentration ratio five largest brands in 3 dig zip	0.62	0.62	0.63	0.61
Av % of stats with same brand as stat in 3 dig zip	31%	30%	30%	30%
Av % of stats with largest brand in 3 dig zip	33%	33%	33%	32%
Location indicators				
Share of highway stats	14%	11%	10%*	6%**
Av % of highway stats in 3 dig zip	10%	8%*	8%*	7%**
Av size of population in 3 dig zip	35,704	33,975	36,025	34,724
Av car/population ratio in 3 dig zip	0.61	0.61	0.61	0.60
Share of stats in 2 dig zip next to German border	18%	16%	11%**	12%*
Share of stats in 2 dig zip next to Belgian border	13%	13%	12%	13%
Competitor indicators				
Av % of other asym pricing stats in 2 dig zip	39%	38%	37%*	38%
Av % of other asym pricing stats in 3 dig zip	40%	37%*	36%**	34%**
Av nr of stats in 2 dig zip	52	50*	50	50
Av nr of stats in 3 dig zip	8	8	8	8
Av nr of stats per 1,000 inhab in 2 dig zip	0.26	0.25	0.25	0.25
Av nr of stats per 1,000 inhab in 3 dig zip	0.29	0.30	0.28	0.28
Price indicators				
Av (retail price − spot price) of stat	€ 0.115	€ 0.115	€ 0.115	€ 0.113
Av (retail price − spot price) of other stats in 2 dig zip	€ 0.112	€ 0.112	€ 0.113*	€ 0.113*
Av (retail price − spot price) of other stats in 3 dig zip	€ 0.112	€ 0.112	€ 0.112	€ 0.112
Av % of days with price change	36%	36%	36%	36%
Search intensity indicators				
Av rank reversal of a stat's area in 2 dig zip	0.051	0.050	0.050	0.050
Av rank reversal of a stat's area in 3 dig zip	0.054	0.056	0.056	0.059
Av spread of prices other stats in 2 dig zip	€ 0.028	€ 0.028	€ 0.029*	€ 0.029
Av spread of prices other stats in 3 dig zip	€ 0.025	€ 0.026	€ 0.025	€ 0.025
Av % aged 60 or older in 3 dig zip	21%	21%	21%	21%
Av % unemployed in municipality	3%	3%	3%	3%
Av % immigrants in 3 dig zip	17%	17%	18%	18%
Av income per capita in 3 dig zip	€ 2,025	€ 2,034	€ 2,036	€ 2,030

Notes: * and ** indicate that the value differs from the value in the first column at the 5% and 1% significance levels, respectively. "Share of *x* stats" means share of stations in the group with characteristic *x*. "Av *x*" means average of characteristic *x* over all stations in the group. The third and fourth column contain subsets of the group of stations in the second column. The third (fourth) column contains stations of which the difference between the cumulative adjustment functions is in the interval [−0.1,0.1] ([−0.05,0.05]). Furthermore, these stations also do not respond asymmetrically on one of the other 24 days.