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Manuel Frondel, Marco Horvath, Colin Vance, and Alexander Kihm[1]

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## Abstract

*Drawing on panel data on daily fuel prices covering over 5,000 filling stations in Germany, this paper documents a change in the stations' price setting behavior following the introduction of a legally mandated on-line price portal in 2013. Prior to the portal, positive asymmetry is found on the basis of error correction models, with prices following the "rockets and feathers" pattern that is typically found for fuels. In the aftermath of the portal, by contrast, negative asymmetry is observed: fuel price decreases in response to refinery price decreases are stronger than fuel price increases due to refinery price increases.*



*JEL Classification: D12, Q41*

*Keywords: Retail markets; competition; error correction model*

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# 1 Introduction

Few products elicit as much consternation among consumers as gasoline. Being almost indispensable to daily living for many people, the demand for gasoline is highly inelastic, at least in the short run. Moreover, gasoline purchases represent a significant share in many consumers' budgets. Price increases and fluctuations may therefore have substantial effects on disposable income. One type of pricing dynamic, characterized by Bacon (1991) as the "rockets and feathers" phenomenon, has piqued special attention. This is the pattern whereby gasoline prices rise quickly – like a rocket – in response to positive oil price shocks, but fall slowly – like a feather – in response to negative shocks (Noel, 2016).

This phenomenon is the basis of an extensive literature, with Borenstein et al. (1997) being an early and influential article on the topic. Support for the rockets-and-feathers hypothesis is found more often than not, but the extent varies widely, depending on the origin and time period of data (Noel, 2016). Theoretical explanations are likewise varied, but can be broadly distinguished by whether market power or some other source, such as consumer behavior, is emphasized as a driver of asymmetric pricing patterns. For example, numerous articles, such as Deltas (2008), suggest that price asymmetry is a sign of local market power.

Notably, a growing line of the literature argues that heterogeneity in consumer search intensity drives the differences in how retailers respond to positive and negative price shocks. Using a theoretic search model, Cabral and Fishman (2012), for instance, demonstrate that firms are reluctant to pass on small cost changes to consumers, as cost changes trigger consumer searching. Tappata (2009) develops a model where consumers' decision to search affects a firm's cost pass-through depending on whether the cost increases or decreases.

The present analysis draws on a related model developed by Yang and Ye (2008) in which consumers know the process with which cost evolves but, in contrast to Tappata (2009), do not know the history of cost evolution. Price asymmetry in the model by Yang and Ye (2008) arises due to heterogeneity in learning: in case of a positive cost shock, all searchers immediately learn the true cost and stop searching. Hence, search intensity reaches a minimum in the next period, with the result that prices fully adjust. In contrast, in case of a negative cost shock, non-searchers do not immediately learn the true cost state and thus search intensity increases gradually, leading to a slow fall in prices. An implication of this model is that if the net expected benefit of acquiring information increases, the adjustment of retail prices to a negative cost shock will be faster.

We test this model implication and assess changes in price setting behavior among retail filling stations in Germany, where concerns about market power came to the fore following the release of a report by the Federal Cartel Office in 2011 (FCO, 2011). The report concluded that five brands – Aral (BP), Jet (ConocoPhilipps), Esso (ExxonMobil), Shell, and Total – exercise market-dominating influence as oligopolists, leading to higher gas prices than would otherwise prevail under perfect competition. This finding led to the establishment of a publicly accessible on-line price portal in December 2013, at which gasoline retailers are legally obligated to post fuel prices in real time. By increasing market transparency for consumers, it was hoped that the portal would promote competition among stations, as would be evidenced by a speedier adjustment to negative oil price shocks.[1] We address this question by undertaking an analysis of price setting before and after the introduction of the on-line price portal, thereby contributing to a growing strand of the literature on consumer search in gasoline markets (Byrne and de Roos, 2017; Chandra and Tappata, 2011; Lewis and Marvel, 2011).

To this end, we assemble a unique data set of daily fuel prices for over 5,000 stations whose daily prices are observed over a period that includes the introduction of the price portal. The data set is correspondingly split into two nearly adjacent time intervals of equal length, one covering from January 2012 until November 2013, and

[1] A paper by Schultz (2005) points out that, theoretically, there can be two opposing effects of the portal: on the one hand, the easier monitoring of rivals can allow for easier sustainment of tacit collusion. On the other hand, as the market becomes more transparent, the temptation to undercut the competitors also increases.

the other covering from January 2014 until November 2015. Error correction models, from which impulse response functions are derived, are estimated separately on each of these intervals and for each individual filling station. This disaggregated approach facilitates exploration of whether the results are robust across branded and unbranded stations, a question for which existing pricing theory does not provide a consistent set of predictions (Besanko et al., 2005).

The impulse response functions reveal a striking change in the pattern of price pass-through: Prior to the portal's introduction, positive price asymmetry prevails, but this reverses to negative price asymmetry thereafter, providing partial validation of the theoretical model. Moreover, this pattern in reversal is found for both branded and unbranded stations. While we cannot definitively ascribe a causal effect to the price portal, the evidence strongly suggests that its introduction had positive implications for consumer welfare.

The following section describes the theoretical background of our analysis, followed by a discussion of data and methodological issues in Section 3 and Section 4. Section 5 presents the results and uses these to conduct a simple welfare analysis. Section 6 concludes.

## 2 Theoretical Background

This section presents an explanation of the rockets-and-feathers phenomenon that is based on the search model with learning developed by Yang and Ye (2008), who demonstrate that heterogeneity in learning across searchers and non-searchers is key for the emergence of price asymmetry. Based on these authors' model, we then present and prove our proposition that increased transparency in the market, as e. g. induced by the introduction of a legally mandated on-line price portal, leads to a less pronounced pattern of asymmetric pricing.

## 2.1 Summary of Yang and Ye's Search Model

Yang and Ye (2008) assume a continuum of consumers and firms in the fuel retail market, with firms offering a homogeneous good. All firms face the same unit cost $c$, as well as common cost shocks, thereby competing in prices. Common production costs $c$ can take on values at two levels, either a low level $c_L$ or a high level $c_H$, i. e. $c_L < c_H$. Furthermore, a capacity constraint $k$ common to all firms is assumed: no firm can sell more than $k$ units. It is further assumed that each consumer has a unit demand and the capacity constraint $k$ is not binding: $k > \beta$, where $\beta > 1$ denotes the number of customers per firm.

Consumers make decisions on whether to search to become informed about prices or not to search and stay uninformed. Informed consumers observe the prices charged by all firms, then purchase from those firms that offer the lowest price and, hence, always learn the true cost state $c$. Uninformed consumers shop randomly and only observe the price at which they purchase. A consumer's decision to search depends on whether the expected benefit of searching outweighs individual search cost. Thus, the search intensity, that is, the percentage of consumers who search will be determined endogenously.

There are three types of consumers, distinguished by their search cost and search intensity. The first type, whose proportion is designated by $\lambda_1$, is called the low-search-cost consumer, because they have zero search cost: $s_L = 0$. This type of consumer always searches in equilibrium. The second type, whose proportion is denoted by $\lambda_2$, encompasses the high-search-cost consumers who never search. The rest of the consumers, whose proportion amounts to $1 - \lambda_1 - \lambda_2$, are called critical consumers and have intermediate search cost $s_M \in (s_L, s_H)$. Critical consumers search depending on their belief about the cost state $c$, which, in contrast to firms, is unknown to consumers. Instead, critical consumers have to build beliefs, denoted by $\alpha$, which is the probability that $c = c_H$. $F(\alpha)$ denotes the cumulative distribution function of the beliefs among the critical consumers.

Resulting from the static model of Yang and Ye (2008), the unique equilibrium search intensity $\mu^*$ is given by

$$\mu^* = \lambda_1 + (1 - \lambda_1 - \lambda_2)F(\hat{\alpha}), \tag{1}$$

provided that firms correctly anticipate $F(\hat{\alpha})$, where $\hat{\alpha} \in (0,1)$ is the cutoff value for which all critical consumers with beliefs below $\hat{\alpha}$ search, but not those with beliefs above this cutoff value. Expression (1) is highly intuitive: the equilibrium search intensity $\mu^*$ is the sum of the percentage $\lambda_1$ of those consumers who always search and the fraction $F(\hat{\alpha})$ of those critical consumers who search given cutoff value $\hat{\alpha}$.

While critical consumers hold heterogeneous beliefs with respect to the firms' production cost $c$, according to formula (1), for given $\lambda_1$ and $\lambda_2$, the equilibrium search intensity $\mu^*$ only depends on the distribution $F(.)$ of the beliefs among the critical consumers. Two polar cases resulting from formula (1) deserve noting: the lower bound $\underline{\mu}$ of search intensity results if $F(\hat{\alpha}) = 0$, that is, if none of the critical consumers search: $\mu^* = \lambda_1 = \underline{\mu}$, whereas the upper bound $\bar{\mu}$ emerges from $F(\hat{\alpha}) = 1$, i. e. all critical consumers search: $\mu^* = 1 - \lambda_2 = \bar{\mu}$.

According to this static analysis, changes in equilibrium prices originate from two causes, changes in search intensity and cost shocks. To explain the discrepancy in price adjustments in response to either positive or negative cost shocks, Yang and Ye (2008) extended their static analysis to a dynamic setting where in each period $t = 1, 2, ...$ the static model applies and common costs evolve according to a Markov process: $P(c_{t+1} = c_H | c_t = c_H) = P(c_{t+1} = c_L | c_t = c_L) = \rho$, where the persistence parameter $\rho$ is positive: $\rho > 1/2$. The authors demonstrate that the asymmetry in price adjustment arises because the learning behavior of the critical consumers depends upon whether a cost shock is positive, $c_{t+1} = c_H > c_t = c_L$, or negative: $c_{t+1} = c_L < c_t = c_H$.

As the consumers do not observe any realization of the cost level $c$, their beliefs and search intensity $\mu^*$ do not adjust as quickly as the cost changes. A positive cost shock can be said to be fully adjusted when in state $c = c_H$ no critical consumer searches, that is, when $\mu^* = \underline{\mu}$. A negative cost shock is fully adjusted when in state $c = c_L$ all critical consumers search, that is, when $\mu^* = \bar{\mu}$. According to this logic, the lowest price across periods results when $c = c_L$ and all critical consumers search, i. e. $\mu^* = \bar{\mu}$, whereas the highest possible price results when $c = c_H$ and no critical consumer searches, i. e. $\mu^* = \underline{\mu}$.

The asymmetry in price adjustments in response to positive and negative cost shocks is summarized in the following propositions presented by Yang and Ye (2008).

*Proposition on the Response to Positive Cost Shocks*: If a positive cost shock occurs in period $t+1$ and persists thereafter, then, regardless of $F_{t+1}(\hat{\alpha})$,

$$F_{t+2}(\hat{\alpha}) = 0 \tag{2}$$

and

$$\mu^*_{t+2} = \underline{\mu}. \tag{3}$$

(For a proof, see the proof of Proposition 4 of Yang and Ye (2008:557).) In other words, regardless of previous history, if the cost states $c_t = c_L$ and $c_{t+1} = c_H = c_{t+2}$ are realized in the periods $t, t+1$, and $t+2$, prices fully adjust to the highest level in period $t+2$, that is, within two periods, ultimately because in period $t+2$ no critical consumer searches: $F_{t+2}(\hat{\alpha}) = 0$.

The intuition for this result is as follows: While in period $t+1$ only a fraction of firms adjust their prices upward, those critical consumers who search immediately learn that the cost realization is $c_H$ and thus stop searching in period $t+2$. Non-searchers among the critical consumers remain non-searchers if they happen to observe a higher price in $t+1$ and, hence, learn that the cost state is $c_H$. Likewise, if non-searchers happen to observe a low price in $t+1$, they remain non-searchers, as they do not observe a change in price. Aggregating over all critical consumers, search intensity then reaches its lower bound in $t+2$: $\mu^*_{t+2} = \underline{\mu}$, and, hence, all firms pass on the higher cost in period $t+2$.

*Proposition on the Response to Negative Cost Shocks*: If a negative cost shock occurs in period $t+1$ and persists thereafter, then[2]

$$F_{t+2}(\hat{\alpha}) = \frac{\underline{\mu}\beta}{k - \beta + \underline{\mu}\beta} < 1 \tag{4}$$

and

$$\mu^*_{t+2} < \bar{\mu}. \tag{5}$$

The latter result implies that prices do not fully adjust downward within two periods, as the search intensity does not reach its upper bound $\bar{\mu}$ in period $t+2$, just because not all of the critical consumers are searching in $t+2$: $F_{t+2}(\hat{\alpha}) < 1$.[3] Instead, this proposition implies that prices decrease gradually upon a persistent negative cost shock $c_t = c_H, c_{t+1} = c_L = c_{t+2}$. The underlying reason is that in period $t+1$ only those critical consumers who happen to observe the lower price learn the true cost state $c_{t+1} = c_L$ and start searching in period $t+2$. Consumers who observe the high price do not learn the true cost state $c_L$ and remain non-searchers in $t+2$. In short, not all critical consumers search in $t+2$ and, hence, $\mu^*_{t+2} < \bar{\mu}$. In other words, it takes longer than two periods for prices to fully adjust downward.

In sum, according to the search model of Yang and Ye (2008), the major reason underlying price asymmetry is the disparity in learning between searchers and non-searchers: the group of searchers learns the current cost state quicker than non-searchers, leading to a differential adjustment in search intensity. Most notably, searchers immediately learn about a positive cost shock and stop searching, leading to a quick price adjustment, whereas the group of non-searchers slowly learns about a ne-

[2]This proposition is based on the following transition equation for the beliefs of critical consumers:

$$\text{if } c_t = c_L: \qquad F_{t+1}(\hat{\alpha}) = F_t(\hat{\alpha}) + \frac{\mu^*_t \beta}{k - \beta + \mu^*_t \beta}[1 - F_t(\hat{\alpha})],$$

where $\frac{\mu^*_t \beta}{k-\beta+\mu^*_t \beta}$ is the proportion of firms that charge the lowest price. (For a proof, see the proof of Proposition 5 of Yang and Ye (2008:558).) This result is intuitive: The fraction $F_{t+1}(\hat{\alpha})$ of searchers among critical consumers in period $t+1$ is the sum of the respective fraction $F_t(\hat{\alpha})$ in period $t$ plus a fraction of the proportion $1 - F_t(\hat{\alpha})$ of non-searchers who happen to be customers of those firms that charge the lowest price in $t$.

[3]Note that $F_{t+2}(\hat{\alpha}) = \frac{\underline{\mu}\beta}{k-\beta+\underline{\mu}\beta}$ is lower than unity because it is assumed that $k > \beta$.

gative price shock and this group only gradually increases search intensity, leading to a decelerated price adjustment.

## 2.2 Implication of Increased Market Transparency

We now use the model from Yang and Ye (2008) to demonstrate that increased transparency in the market, as e. g. induced by the introduction of a legally mandated on-line price portal, may increase the proportion $\lambda_1$ of low-search-cost consumers, as the cost and barriers to searching decrease. Furthermore, with the introduction of such a price portal, the perceived quality of the information increases, in turn raising the benefit-cost ratio of searching. Yet, Yang and Ye's model implies that an increase in the proportion $\lambda_1$ of low-search-cost consumers does not affect price adjustments in response to positive cost shocks, but only to negative shocks, a conclusion that we summarize in the following proposition.

*Proposition:* An increase in the proportion $\lambda_1$ of consumers with low search costs does not affect price adjustments in response to positive cost shocks, but only to negative shocks.

**Proof:** Recalling that $\underline{\mu} = \lambda_1$, the latter part of the proposition can be seen from equation (4), from which follows that the number of critical consumers who search is higher with a larger $\lambda_1$:

$$F_{t+2}(\hat{\alpha}^0) = \frac{\lambda_1^0 \beta}{k - \beta + \lambda_1^0 \beta} < \frac{\lambda_1^1 \beta}{k - \beta + \lambda_1^1 \beta} = F_{t+2}(\hat{\alpha}^1) \quad \text{if} \quad \lambda_1^0 < \lambda_1^1.$$

Hence, in line with the larger number of critical consumers who search, the downward price adjustment in response to a negative shock is faster. In contrast, as $F_{t+2}(\hat{\alpha}) = 0$ according to equation (2), the proportion $\lambda_1$ of low-search-cost consumers does not affect the number $F_{t+2}(\hat{\alpha})$ of critical consumers who search and, hence, does not affect price adjustments in response to positive cost shocks.

The difference summarized in our proposition leads to a less pronounced pattern of asymmetric pricing. Based on these theoretical considerations, in what follows, we empirically test the hypothesis that the introduction of the price portal leads to a faster adjustment in response to a negative cost shock and a reduced asymmetry in price adjustment.

# 3 Data

The data used for this analysis comprises two variables, daily retail fuel prices for E10, a 10% bioethanol fuel mixture, and the wholesale price of refined fuel out of Rotterdam, where one of the major pipelines into Germany originates. Data on daily refined prices was taken from the EID, a trade magazine.[4] Data on retail E10 fuel prices was drawn from two sources. One was established as of December 2013, when legislation required stations to post prices on an on-line portal, referred to as the Market Transparency Unit for Fuels (MTU).[5] In addition to fuel prices, the MTU records sundry station characteristics, such as the station's geographical coordinates, brand name, and opening hours. This information allows consumers who visit the site to assess price offerings in their vicinity. To access the data, we wrote a script that continuously retrieves entries from the site and stores these on a server (Frondel et al. , 2016). From the raw data, a panel of daily station-level prices for E10 was created for the approximately 14,000 filling stations in Germany over a 23-month interval from January 2014 through November 2015.[6]

The accuracy of the MTU data is high, and it has served as the basis for a growing body of research that analyzes fuel price setting in Germany (e.g. Frondel et al. , 2016; LeSage et al. , 2017). From a motorist perspective, the MTU is also user friendly. It can be accessed from several on-line sites, one being Clevertanken.de (see below). Upon visiting the site, the user need only enter a zip code, desired fuel type, and search

[4]For more information on the *Energie Informationsdienst* (EID), see `http://www.eid-aktuell.de/`.

[5]For more information on the Market Transparency Unit (MTU) for Fuels, see `http://www.bundeskartellamt.de/EN/Economicsectors/MineralOil/MTU-Fuels/mtufuels_node.html`.

[6]Along with E5, which has a 5% ethanol mix, E10 is a very common fuel type in Germany. Petrol cars comprise about 65.5% of the German car fleet, compared with a share of 32.9% for diesel cars.

radius, ranging from one to 25 kilometers. The site thereupon produces a list of stations in increasing order of the fuel price, each with the brand name and the street address. An app is also available for smart phones.

To pursue our aim of comparing how price setting changed for individual stations before and after the introduction of the MTU, we draw on another data set that was assembled by Kihm et al. (2016) covering the 23-month interval from January 2012 through November 2013. This data set comprises retail fuel prices retrieved from the site www.clever-tanken.de, which is currently one of a handful of sites in Germany that publishes real time data from the MTU. Prior to the MTU, the Clevertanken site relied on price postings voluntarily provided by customers of the stations via mobile apps. Kihm et al. (2016) created a panel of daily fuel prices from these postings covering 13,701 stations, i. e. about 95% of the market.

In assembling the data used in the present analysis, we sought to ensure that an identical set of stations appears in the pre- and post-MTU periods. To this end, we were able to unambiguously match about 9,410 stations in the Clevertanken and MTU data sets by linking the street addresses provided in the former with the geographical coordinates provided in the latter. We eliminated another 3,760 stations from the Clevertanken data owing to spotty temporal coverage, which particularly applied to smaller independent stations that registered fewer app readings from customers. The resulting sample of 5,650 stations, which are observed both before and after the introduction of the MTU, is consequently over-represented by major brands, which comprise about 60% of the sample.

As several studies have documented, markets for retail gasoline may exhibit price evolutions that resemble the Edgeworth price cycle equilibria, whereby prices jump periodically and then fall gradually before the cycle repeats itself. Lewis and Noel (2011) have shown that prices in markets with cycles respond much more quickly to wholesale cost fluctuations than in markets without cycles and, moreover, that cycling markets have faster pass-through even after controlling for features that could influence the speed of price response. As such dynamics can bear on the appropriate modeling technique, it is consequently important to test for the existence of Edgeworth cycles, both for individual stations as well as across the periods preceding and following the introduction of the price portal. To this end, we follow the suggestion of Lewis (2009), who inspects the median daily price change as an indicator for Edgeworth cycles. Because a cycling market is characterized by negative retail price changes on most days, with big price increases occurring only periodically, Lewis (2009) suggests that the median price change is negative in the presence of an Edgeworth cycle. A median close to zero, conversely, would indicate a non-cycling market. For the period prior to the price portal, we found that the average station had a median price change that was only slightly above zero, at 0.0003, without a single station falling below the threshold of -0.1 identified by Lewis and Noel (2011) to indicate cycling. The same pattern is seen in the post-portal period, when the average station had a median price change of 0.0006. We thereby consistently fail to find evidence for Edgeworth cycles in the German market over the daily time interval of the present analysis.

A final empirical concern relates to the Clevertanken data and the fact that it is assembled from the voluntary postings of motorists, raising the potential of a selection problem from the possibility that such motorists search more intensively and thus frequent stations where competition is higher. To assess the accuracy of the Clevertanken data, Kihm et al. (2016) compared the data with price postings from the German automobile club ADAC and found a strong correlation, confirming Atkinson's (2008) conclusion that internet data can be reliable for answering questions requiring daily station prices. Further evidence for the accuracy of the Clevertanken data is seen by comparison with the MTU data. Figure 1 shows the recorded price trajectories for an interval when the two data sets briefly overlapped between September 21 and November 21, 2013, which corresponds to a test period of the MTU before its official launch. The figure additionally includes the trajectory of the cost variable used in our analysis, the wholesale price of refined fuel out of Rotterdam. The correspondence between the Clevertanken and MTU data is tight, with a correlation coefficient of 99.7%. While the price level of the MTU is slightly lower throughout the interval, the difference varies on average by less than 1%.

Figure 1: **Refinery prices and retail prices reported by Clevertanken and the MTU**.

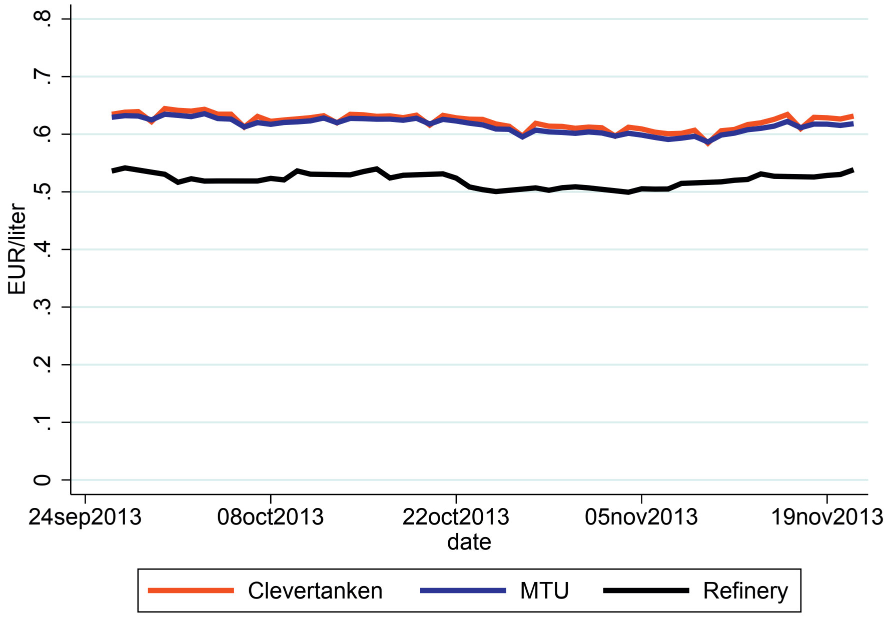



Figure 1 also reveals a high correlation between retail and wholesale fuel prices. The results of an augmented Dickey-Fuller test (not shown) indicate that both series are integrated of order one. For each station in the data, we additionally established that the gasoline and refinery price series are cointegrated using the approach of Engle and Granger (1987). The distributions of the test-statistics of the individual cointegration tests for both the pre- and post-portal period are shown in Figure A1 of the appendix.

# 4 Methodological Issues

To model the transmission of refinery prices, $PC$, to gasoline prices, $PG$, we follow Bachmeier and Griffin (2003:773) and estimate a standard ECM:

$$\Delta PG_t = \sum_{i=0}^{k} \beta_{ci} \Delta PC_{t-i} + \sum_{i=1}^{n} \beta_{gi} \Delta PG_{t-i} + \theta z_{t-1} + \varepsilon_t, \tag{6}$$

where $\beta_{ci}$ and $\beta_{gi}$ measure the short-run impact of refinery prices and lagged gasoline prices, respectively. $\theta$ is the long-run equilibrium parameter and

$$z_t = PG_t - \gamma_0 - \gamma_1 PC_t \quad (7)$$

measures the long-run disequilibrium between gasoline and refinery prices. $\gamma_1$ reflects the long-run effect of a permanent change in refinery prices. In line with LeSage et al. (2017), $\Delta PG_t$ and $\Delta PC_t$ are defined as changes from the same day last week to eliminate day-of-the-week pricing variation: $\Delta PG_t := PG_t - PG_{t-7}$ and $\Delta PC_t := PC_t - PC_{t-7}$.

An important step in estimating an ECM is the specification of the lag lengths $k$ and $n$ so as to obtain unbiased estimates while at the same time avoiding overfitting. Various techniques can be availed for determining lag length, including direct testing of the statistical significance of the lagged terms (Borenstein et al., 1997) and expert discretion (Lewis and Noel, 2011). Perhaps the most common technique for determining lag length is the application of information criteria (Bachmeier and Griffin, 2003), such as the AIC and Bayes information criterion (BIC). The latter has been employed by Frondel et al. (2016) in a pooled analysis of the MTU data, yielding an extremely long lag specification and an associated pass-through that exceeds 150 days, which the authors deem implausible. They consequently recommend a shorter lag specification that is in line with the literature. Our application differs from that of Frondel et al. (2016) because, rather than pooling the data, we estimate the model separately on each station.

Based on both the AIC and the BIC, we find that this approach yields optimal lag orders of two for both $PC$ and $PG$ for the majority of stations, which is within the range found by several other studies (e.g. Borenstein et al., 1997; Lewis, 2011). As we have empirically found that the $PC$ and $PG$ time series are cointegrated, the long-run relationship follows a stationary process.Hence, inference on functions of the coefficients, such as the impulse response function (IRF), is standard.

As derived in detail by Frondel et al. (2016), based on Borenstein et al. (1997), the general formula for the impulse response function $IRF_t$ reads for $t = j$:

$$IRF_j = \beta_{c_j} + \sum_{i=1}^{j} \beta_{gi}(IRF_{j-i} - IRF_{j-i-1}) + \theta(IRF_{j-1} - \gamma_1) + IRF_{j-1}. \tag{8}$$

It bears noting that $\beta_{c_j} = 0$ if $j > k$ and $\sum_{i=1}^{j} \beta_{gi}(IRF_{j-i} - IRF_{j-i-1}) = \sum_{i=1}^{n} \beta_{gi}(IRF_{j-i} - IRF_{j-i-1})$ if $j > n$. Finally, the long-term equilibrium $IRF := \lim_{k\to\infty} IRF_k$ is given by $IRF = \gamma_1$, as can be seen from formula (8) by setting $IRF_j = IRF$ for all $j$.

In case of asymmetry, instead of ECM (6), the following asymmetric ECM has to be estimated:

$$\begin{aligned} \Delta PG_t = \sum_{i=0}^{k} [\beta_{ci}^{+} \Delta PC_{t-i}^{+} + \beta_{ci}^{-} \Delta PC_{t-i}^{-}] + \\ \sum_{i=1}^{n} [\beta_{gi}^{+} \Delta PG_{t-i}^{+} + \beta_{gi}^{-} \Delta PG_{t-i}^{-}] + \theta^{+} z_{t-1}^{+} + \theta^{-} z_{t-1}^{-} + \varepsilon_t, \end{aligned} \tag{9}$$

where $z_t^+ := \max\{z_t, 0\}$, $z_t^- := \min\{\Delta z_t, 0\}$, $\Delta PC_t^+ := \max\{\Delta PC_t, 0\}$, $\Delta PC_t^- := \min\{\Delta PC_t, 0\}$, and $\Delta PG_t^-$ and $\Delta PG_t^-$ are defined similarly. The distinction between the coefficients $\beta_{ci}^+$ and $\beta_{ci}^-$, as well as $\beta_{gi}^+$ and $\beta_{gi}^-$ and $\theta^+$ and $\theta^-$, respectively, allows an asymmetric response to changes in refinery prices and the error correction term.

For an initial refinery price increase, all of the coefficients $\beta_{ci}$ and $\beta_{gi}$ emerging in equation (8) are replaced by $\beta_{ci}^+$ and $\beta_{gi}^+$, respectively:

$$\begin{aligned} IRF_j^+ = \beta_{c_j}^+ + IRF_{j-1}^+ + \theta^+(IRF_{j-1}^+ - \gamma_1) + \\ \sum_{i=1}^{j} (\beta_{gi}^+ \max\{0, (IRF_{j-i}^+ - IRF_{j-i-1}^+)\} + \beta_{gi}^- \min\{0, (IRF_{j-i}^+ - IRF_{j-i-1}^+)\}). \end{aligned} \tag{10}$$

Similar adjustments are made for an initial refinery price decrease.

# 5 Empirical Results

We estimated individual error correction models for each of the 5,650 filling stations in the data corresponding to the period before and after the establishment of the MTU.

One virtue of this approach is that we control for station-specific fixed effects such as those related to location, which have been found to be important in the setting of gas prices (Deltas, 2008; Iyer and Seetharman, 2008). Table 1 consolidates the results of this exercise by presenting the mean-group (MG) estimates, which result from averaging the estimated coefficients across the stations (Pesaran and Smith, 1995).[7]

## 5.1 Model Estimates

Although the coefficient estimates from ECM (9) are not straightforward to interpret, two general patterns can be discerned. First, while all estimates on the adjustment rates $\theta^{+}$ and $\theta^{-}$ to the long-run equilibrium are negative, the higher magnitude of the estimates in the pre-portal period suggests that convergence towards the long-run equilibrium is faster in this period than in the post-portal period. Second, the coefficients on the refinery prices have the expected positive signs. Moreover, the estimates of the coefficients $\beta^{+}_{c_j}$ on the positive wholesale price changes are higher in magnitude than those of the coefficients $\beta^{-}_{c_j}$ on the negative wholesale price changes in the pre-portal period, suggesting positive price asymmetry in the price pass-through. This pattern is reversed in the post-portal period, when negative asymmetry prevails.

Further insight into this distinction can be gained from comparing Figure 2a with Figure 2b. Figure 2a shows the IRF and associated 95% confidence interval for the pre-portal period, when the pattern is clearly consistent with the rockets-and-feathers pattern. By the second day, a 1 Euro per liter increase in the refinery cost induces a 0.98 Euro per liter increase in the retail price, after which there is a gradual decrease in the trajectory until reaching the long-run equilibrium of 0.79 Euro by day ten. By contrast, a 1 Euro per liter decrease in the refinery price induces only a 0.68 Euro per liter decrease in the retail price by the second day. The adjustment duration until the long-run equilibrium for a negative cost shock likewise takes ten days.

[7]To test the robustness of the results, we also estimated ECM (9) by pooling the data and thereby estimating a single model. The results, presented in Table A1 in the appendix, are very similar to those presented in Table 1.

Table 1: **Mean-Group Estimation Results for the Asymmetric ECM (9) prior to and after the Introduction of the MTU**

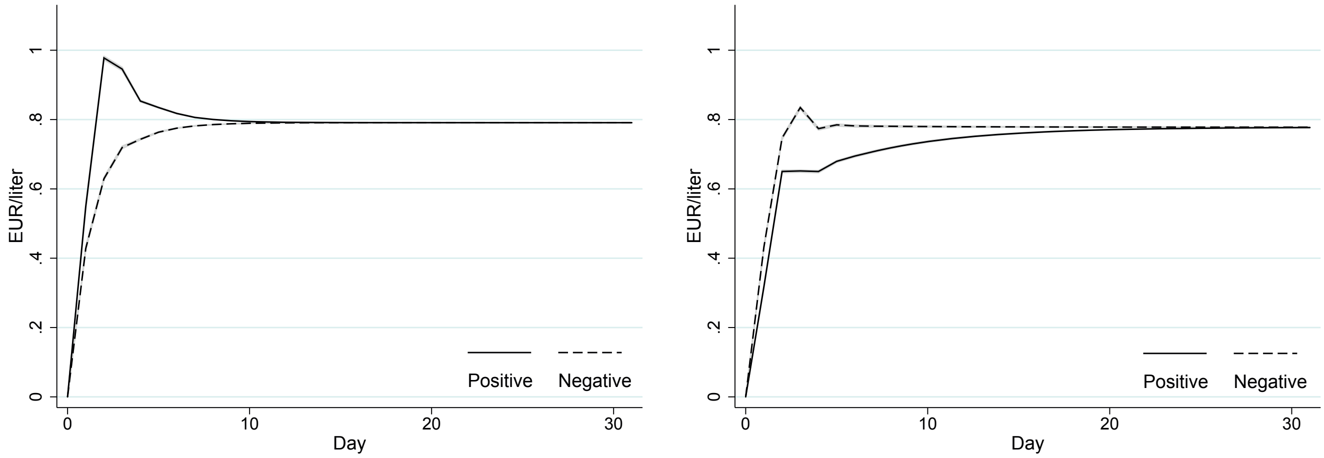
| | Pre-Portal | | Post-Portal | |
|---|---|---|---|---|
| | Coeff. s | Std. Errors | Coeff. s | Std. Errors |
| $\theta^{+}$ | -0.562** | (0.0020) | -0.224** | (0.0018) |
| $\theta^{-}$ | -0.495** | (0.0021) | -0.202** | (0.0013) |
| $\beta_{c0}^{+}$ | 0.559** | (0.0019) | 0.318** | (0.0012) |
| $\beta_{c0}^{-}$ | 0.434** | (0.0018) | 0.432** | (0.0010) |
| $\beta_{c1}^{+}$ | 0.355** | (0.0020) | 0.306** | (0.0014) |
| $\beta_{c1}^{-}$ | 0.065** | (0.0017) | 0.348** | (0.0013) |
| $\beta_{c2}^{+}$ | 0.133** | (0.0019) | 0.082** | (0.0013) |
| $\beta_{c2}^{-}$ | 0.030** | (0.0017) | 0.196** | (0.0009) |
| $\beta_{g1}^{+}$ | -0.106** | (0.0016) | -0.241** | (0.0017) |
| $\beta_{g1}^{-}$ | -0.180** | (0.0016) | -0.295** | (0.0016) |
| $\beta_{g2}^{+}$ | -0.019** | (0.0013) | -0.090** | (0.0012) |
| $\beta_{g2}^{-}$ | -0.058** | (0.0013) | -0.016** | (0.0010) |
| *Constant* | 0.047** | (0.0020) | -0.070** | (0.0007) |
| Number of stations | 5,650 | | 5,650 | |

Note: Standard errors are in parentheses. * denotes significance at the 5%-level and ** at the 1%-level, respectively.

Presenting the IRF and 95% confidence interval for the post-portal period, Figure 2b indicates a reverse pattern characterized by negative asymmetry. A 1 Euro per liter increase in the refinery price is matched by a 0.32 Euro per liter increase in the refinery price after the first day, rising to 0.65 Euro by the second and third day. The continuing adjustment until the long-run equilibrium of 0.78 Euro now reaches about 24 days. Conversely, a 1 Euro per liter decrease in the refinery price induces a 0.43 Euro decrease in the retail price the first day, peaking at an 0.83 Euro decrease by the third day, after which adjustment towards the long-run equilibrium is nearly complete by day seven.

Concerning the adjustment to a negative cost shock, this change in the asymmetry pattern is consistent with the hypothesis derived from the theoretical model. Indeed, the relative speed of the price adjustment to a negative cost shock is quicker after the introduction of the MTU: It seems that more consumers are searching after the intro-

Figure 2: **Impulse Response Functions for the Pre- and Post Portal Period**




(a) Pre Portal Period

(b) Post Portal Period

duction, which induces firms to pass on price reductions faster, even given the overshooting at day three along the path to the long-run equilibrium. On the other hand, we also see a change in the adjustment to a positive cost shock, which is at odds with the theoretical predictions: The price adjustment after a positive cost shock is slower after the introduction of the MTU. In fact, contrasting with the pre-portal period, the price-adjustment in the post-portal period undershoots the long-rung equilibrium in the days following the shock (see Figure 2).

To probe the robustness of the results, we undertook a series of placebo tests that set alternative cut-off dates. In one such test, documented in Figure A2 of the Appendix, we estimated the model on data limited to the year 2012. The pattern yielded is very similar to Figure 2a, providing further evidence that a rockets and feathers pattern prevailed prior to the introduction of the MTS in September 2013.

## 5.2 Influence of Branding

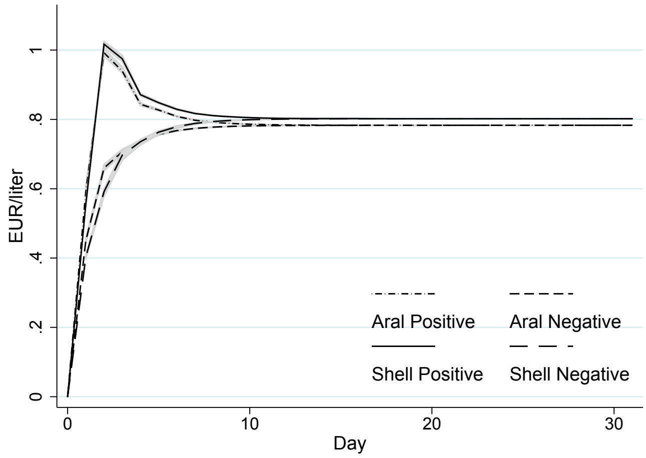
The question arises as to whether these patterns hold across branded and unbranded stations. While numerous studies have found that large brands can demand significantly higher prices than unbranded filling stations (for example Barron et al., 2000), few have explored differences in the pass-through of cost shocks across fuel or station types. Exceptions are Bajo-Buenestado's (2017) analysis of four types of fuels from 38 filling stations located in Northern Spain and Verlinda's (2008) study of the retail gas market in Southern California, which compares the impulse response functions for branded and unbranded stations. This comparison is motivated by the expectation that branding is associated with greater market power via the relatively lower demand elasticity of brand customers. Verlinda (2008) finds that the maximum difference in the degree of asymmetry between branded and unbranded stations amounts to about 14 cents, which he cautiously interprets as weak evidence supporting tacitly cooperative price setting from branding.

Having estimated an ECM for each station individually, we can readily follow Verlinda's lead by calculating impulse response functions for subsets of stations, an exercise that reveals a highly homogeneous pattern across groups. For illustrative purposes, we focus here on a comparison between three station-types: Aral stations (n=1862), the brand with the highest market share in Germany, Shell stations (n=1393), the brand with the highest market share globally, and unbranded stations (n=2288). Figure 3 and 4 show pairwise comparisons of the IRFs for these groups before and after the introduction of the price portal.[8] The shape of the curves is very similar to those of Figure 2, with positive asymmetry in the pre-portal period for all Aral, Shell, and unbranded stations, and negative asymmetry in the post-portal period. Referring to Figure 3, differences in the IRFs between Aral and Shell are hardly discernible in both periods. For the pre-portal period, Figure 4 indicates that the overshooting of the IRF for Aral appears slightly more pronounced than that of the unbranded stations.

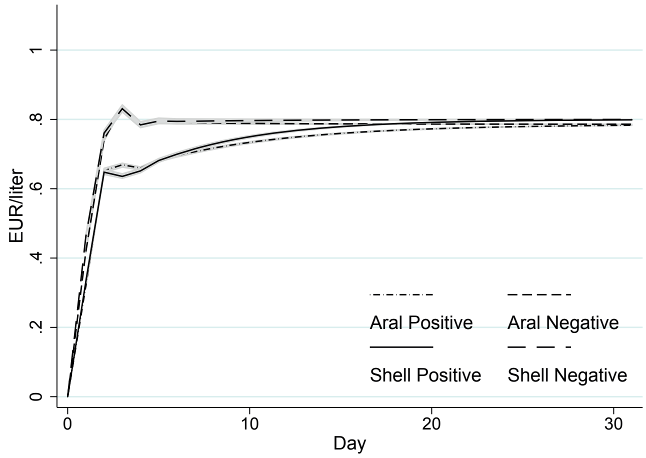
To pursue this further, Figure 5 plots the degree of asymmetry between Aral and the unbranded stations, which results from subtracting the IRF corresponding to a negative shock from that corresponding to a positive shock. This figure reveals that the response to shocks is highly similar across the Aral and the unbranded stations. In

[8] Figure A3 in the Appendix presents the same graph for all of the five major station brands (Aral, Jet, Esso, Shell, and Total) in addition to the unbranded stations.

Figure 3: **IRF for the Pre- and Post-Portal Period, Aral and Shell**

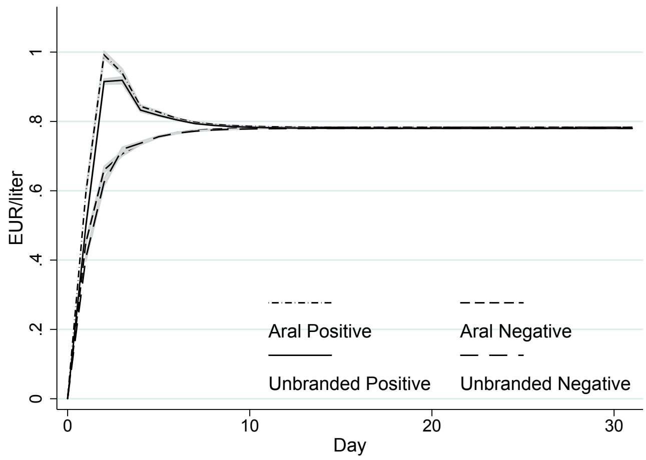



(a) Pre-Portal Period

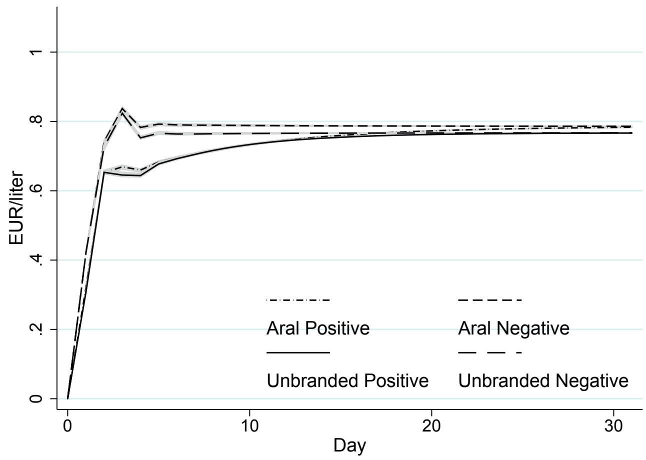



(b) Post-Portal Period

Figure 4: **IRF for the Pre- and Post-Portal Period, Aral and Unbranded**



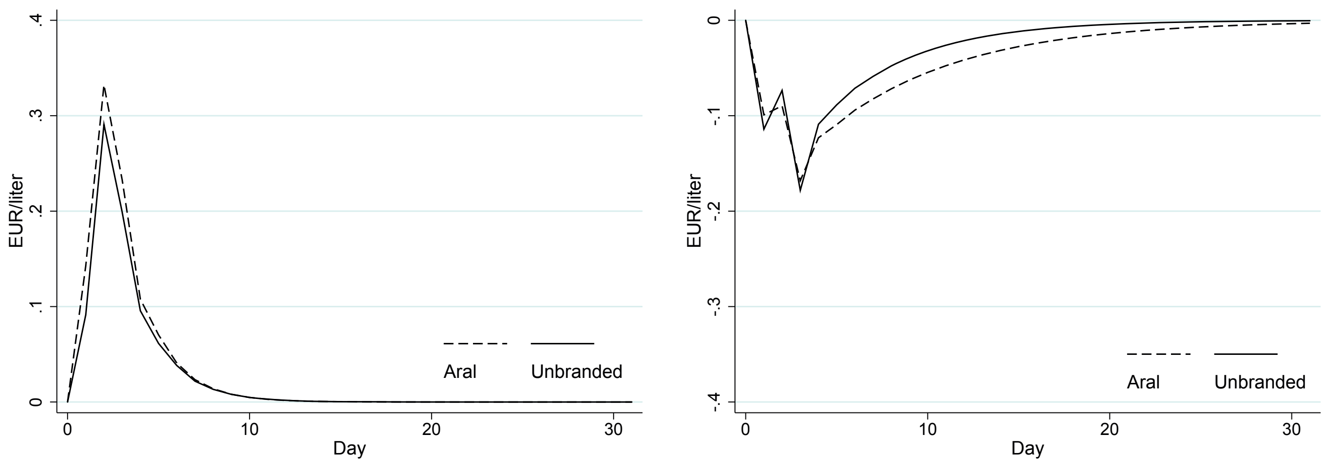

(a) Pre-Portal Period




(b) Post-Portal Period

the pre-portal period, the maximum difference between the two curves occurs at day two and amounts to only four cents, or about 5.8% of the pre-tax retail fuel price of 68 cents. The maximum difference is even smaller in the post-portal period, reaching 2.4 cents at day eight, which amounts to 4.3% of the pre-tax fuel price of 55 cents. By way of comparison, the corresponding figure that can be derived from Verlinda's results is considerably higher, at about 11%.[9] Taken together, these results suggest that the difference in price pass through between branded and unbranded stations in Germany is relatively small, and declined even further with the introduction of the price portal.

Figure 5: **Degree of Asymmetry by Branding for the Pre- and Post-Portal Period**




(a) Pre-Portal Period

(b) Post-Portal Period

## 5.3 Welfare Implications

A final question concerns what these patterns imply for consumers. Borenstein et al. (1997) suggest a simple analytical approach – also employed by Balmaceda and Soruco (2008) – for addressing this question, which involves integrating the difference bet-

[9]We calculate this figure by dividing Verlinda's estimated difference of 14 cents by the pre-tax price of gas in California in 2003 of 130 cents (Lockyer, 2004).

ween the two response functions over the entire adjustment process:

$$\Delta \text{ Consumer Cost} = \int_{j=0}^{n} (IRF_j^{+} - IRF_j^{-}). \tag{11}$$

Referring to the results for the entire sample from the pre-portal period (Figure 2a), when positive asymmetry prevails, this integral yields the extra costs to consumers relative to the case of a symmetric price response, while for the post-portal period (Figure 2b), when negative asymmetry prevails, it yields the savings. Turning first to the former case, we calculate that a 1 cent per liter increase in the refinery price would have resulted in a 0.27 cent per liter extra cost, while a 1 cent per liter decrease would have resulted in a 0.71 cent pert liter extra cost in the pre-portal period. For a consumer whose daily consumption is 6 liters, this implies that the rockets phenomenon costs 1.63 cents while the feathers phenomenon costs 4.21 cents over the whole adjustment time.

By contrast, in the post-portal period, our calculations suggest that relative to a situation of symmetric price responses, consumers enjoy a cost saving of 1.46 cent given a 1 cent per liter increase in the refinery price, and incur a cost of 0.3 cents given a 1 cent per liter decrease in the price.[10] Given a daily consumption of six liters, over the whole adjustment time these figures translate into a saving of 8.77 cents and a cost of 1.79 cents, respectively. We thereby conclude that on net, the portal has contributed to welfare gains for consumers.

# 6 Summary and Conclusion

Concerns about market power in the German gasoline market led to the establishment of a publicly accessible on-line price portal in December 2013, at which gasoline retailers are legally obligated to post fuel prices in real time. By increasing market transparency for consumers, it was hoped that the portal would promote competition among

[10]This latter effect emerges despite the overshooting in the IRF by day three, and owes to the undershooting in the IRF over days one and two.

stations. Drawing upon a unique data set of daily fuel prices for over 5,000 stations that covers two periods, a period prior to the introduction of the portal, from January 2012 until November 2013, and a second nearly adjacent period covering January 2014 until May 2015, this article has investigated the pass-through of refinery prices, the primary cost factor for fuel retailers.

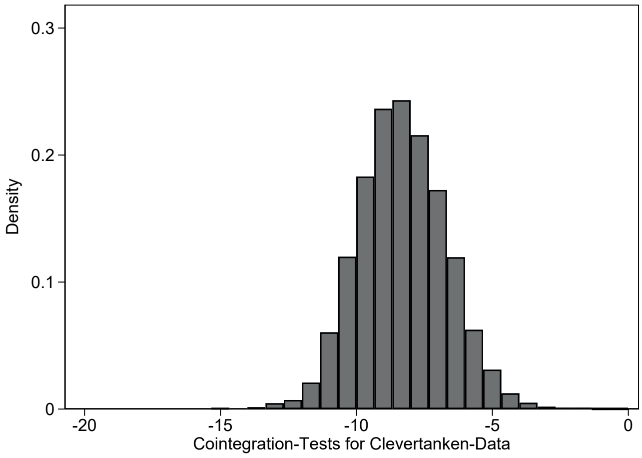
Drawing on the search model developed by Yang and Ye (2008), we have tested the model's implication that if the net expected benefit of acquiring information increases, the adjustment of retail prices to a negative cost shock will be faster. By estimating impulse response functions for standard error correction models, we have explored whether the price setting behavior of retail filling stations in Germany has changed following the introduction of the price portal.

Two principle findings emerge from our analysis. First, we do not uncover economically significant differences in the pricing response of branded (Aral and Shell) and unbranded fuel types to cost shocks, either before or after the introduction of the price portal. Second, we find that prior to the portal's introduction, a time during which an informal system existed for posting prices on-line via mobile apps, positive asymmetry prevailed, with prices following the rockets-and-feathers pattern frequently documented for retail fuel markets. This results in extra costs incurred by consumers relative to the case of price symmetry.

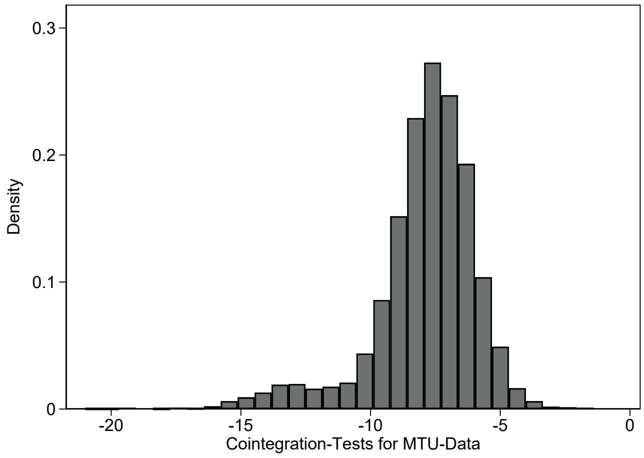
In the aftermath of the portal's introduction, by contrast, negative asymmetry is observed. Fuel price decreases in response to refinery price decreases are stronger than fuel price increases due to refinery price increases, which results in cost savings to consumers. Although our analysis does not isolate a causal role of the portal in this reversal in price pass-through, it does demonstrate that the period following the portal's introduction was marked by welfare gains for consumers.

# 7 Appendix

Figure A1: **Cointegration-Tests for Clevertanken and MTU-Data**




(a) Clevertanken-Data




(b) MTU-Data

Figure A2: **IRF if clevertanken data is limited to the year 2012**

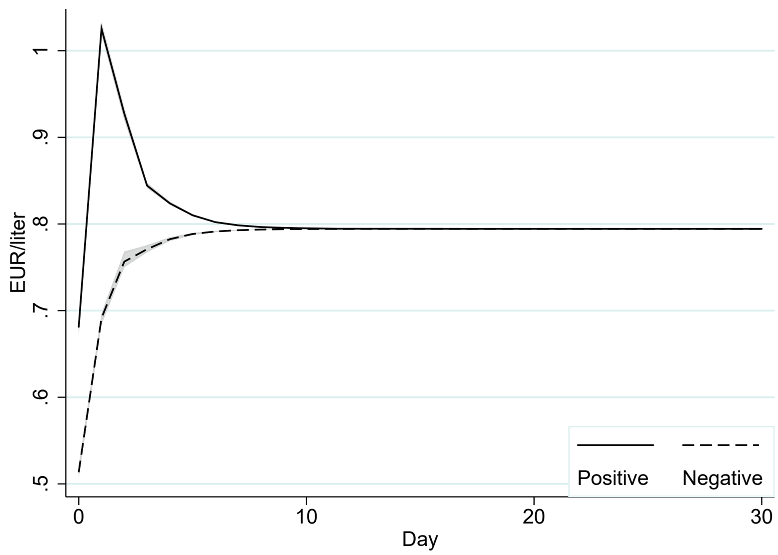
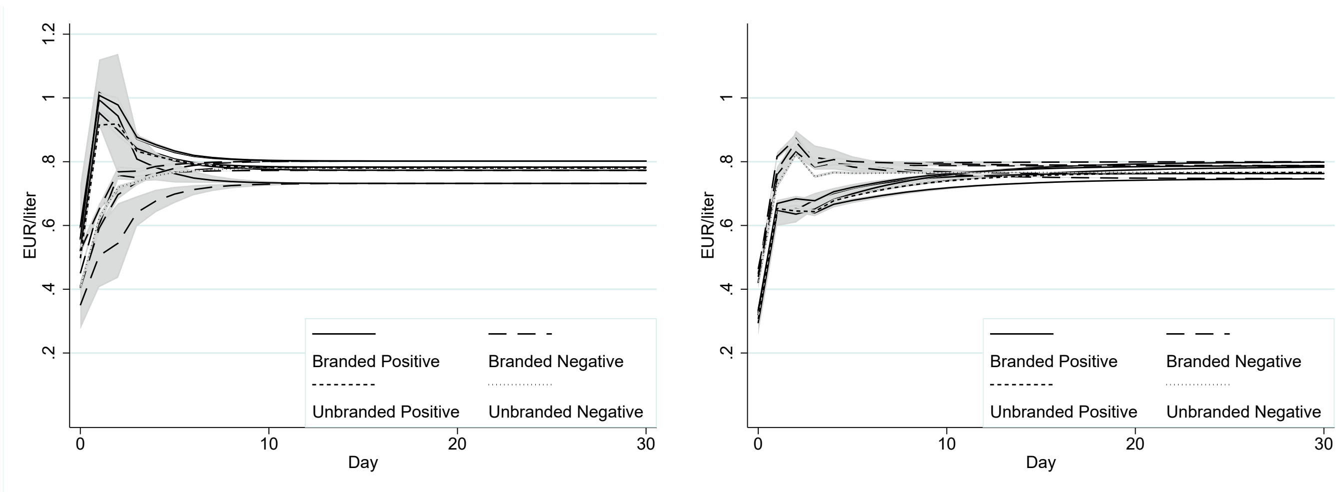


Table A1: **Pooled Mean-Group Estimation Results for the Asymmetric ECM prior to and after the Introduction of the MTU**

| | Pre Portal Period | | Post Portal Period | |
|---|---|---|---|---|
| $\theta^{+}$ | -0.235** | (0.001) | -0.554** | (0.001) |
| $\theta^{-}$ | -0.170** | (0.001) | -0.476** | (0.001) |
| $\beta_{c0}^{+}$ | 0.320** | (0.001) | 0.552** | (0.002) |
| $\beta_{c0}^{-}$ | 0.436** | (0.001) | 0.435** | (0.001) |
| $\beta_{c1}^{+}$ | 0.332** | (0.001) | 0.361** | (0.002) |
| $\beta_{c1}^{-}$ | 0.347** | (0.001) | 0.074** | (0.001) |
| $\beta_{c2}^{+}$ | 0.100** | (0.001) | 0.137** | (0.002) |
| $\beta_{c2}^{-}$ | 0.198** | (0.001) | 0.037** | (0.001) |
| $\beta_{g1}^{+}$ | -0.309** | (0.001) | -0.123** | (0.001) |
| $\beta_{g1}^{-}$ | -0.264** | (0.001) | -0.190** | (0.001) |
| $\beta_{g2}^{+}$ | -0.119** | (0.001) | -0.022** | (0.001) |
| $\beta_{g2}^{-}$ | -0.016** | (0.001) | -0.061** | (0.001) |
| *Constant* | -0.086** | (0.001) | 0.069** | (0.002) |
| Number of stations | 5,650 | | 5,650 | |
| Number of observations | 3,396,980 | | 2,039,119 | |

Note: Standard errors are in parentheses. * denotes significance at the 5%-level and ** at the 1%-level, respectively.

Figure A3: **IRF for the Pre- and Post-Portal Period, Branded and Unbranded**




(a) Pre-Portal Period (b) Post-Portal Period

# References

Atkinson, B. (2008) On Retail Gasoline Pricing Websites: Potential Sample Selection Biases and Their Implications for Empirical Research. *Review of Industrial Organization* 33(2), 161-175.

Bachmeier, L. J., and J. M. Griffin, (2003) New Evidence on Asymmetric Gasoline Price Responses. *Review of Economics and Statistics* 85(3), 772-776.

Bacon, R. W. (1991) Rockets and Feathers: the Asymmetric Speed of Adjustment of UK Retail Gasoline Prices to Cost Changes. *Energy Economics* 13(3) 211-218.

Bajo-Buenestado, R. (2017) Does a Gas Tax Cut Reduce Retail Fuel Prices? *Journal of Transport Economics and Policy* 51(3), 157-172.

Balmaceda, F., and P. Soruco, (2008) Asymmetric Dynamic Pricing in a Local Gasoline Retail Market. *Journal of Industrial Economics*, 56(3), 629-653.

Barron, J. M., B. A. Taylor, and J. R. Umbeck (2000) A Theory of Quality-Related Differences in Retail Margins: Why there is a 'Premium' on Premium Gasoline. *Economic Inquiry* 38(4), 550-569.

Besanko, D., J.-P. Dube, and S. Gupta (2005) Own-Brand and Cross-Brand Retail Pass-Through. *Marketing Science*, 24(1), 123-137.

Borenstein, S., A. C. Cameron, and R. Gilbert (1997) Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes? *Quarterly Journal of Economics* 112(1), 305-339.

Byrne, D. P., and N. de Roos (2017). Consumer Search in Retail Gasoline Markets. *Journal of Industrial Economics*, 65(1), 183-193.

Cabral, L., and A. 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.

Chandra, A., and M. Tappata (2011). Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets. *RAND Journal of Economics*, 42(4), 681-704.

Deltas, G. (2008). Retail Gasoline Price Dynamics and Local Market Power. *Journal of Industrial Economics*, 56(3), 613-628.

FCO (2011) Fuel Sector Inquiry - Final Report (May 2011), Federal Cartel Office. `http://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Sector%20Inquiries/Fuel%20Sector%20Inquiry%20-%20Final%20Report.html?nn=4143316`

Engle, R. F. , and C. W. J. Granger (1987) Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, 55(2), 251-276.

Frondel, M., C. Vance, and A. Kihm (2016) Time Lags in the Pass-Through of Crude-Oil Prices - Big Data Evidence from the German Gasoline Market. *Applied Economics Letters* 23(10), 713-717.

Iyer, G., and P. B. Seetharaman (2008) Too Close to be Similar: Product and Price Competition in Retail Gasoline Markets. *Quantitative Marketing & Economics*, 6(3), 205.

Kihm, A., N. Ritter, and C. Vance (2016) Is the German Retail Gas Market Competitive? A Spatial-temporal Analysis Using Quantile Regression. *Land Economics* 92(4), 718-736.

LeSage, J. P., C. Vance, and Y. Chih (2017) A Bayesian Heterogeneous Coefficients Spatial Autoregressive Panel Data Model of Retail Fuel Price Rivalry. *Regional Science and Urban Economics* 62, 46-55.

Lewis, M. 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.

Lewis, M. S. (2011) Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market. *Journal of Economics & Management Strategy* 20(2), 409-449.

Lewis, M. S., and H. P. Marvel (2011). When do Consumers Search? *Journal of Industrial Economics*, 59(3), 457-483.

Lewis, M. S., and M. Noel (2011) The Speed of Gasoline Price Response in Markets With and Without Edgeworth Cycles. *Review of Economics and Statistics* 93(2), 672-682.

Lockyer, B. (2004) Report on California Gasoline Prices by the Attorney General. `https://oag.ca.gov/sites/all/files/agweb/pdfs/antitrust/gasstudy/gasoline.pdf`

Noel, M. (2016) Retail Gasoline Markets. *Handbook on the Economics of Retailing and Distribution*, 392-412. Editor: Emek Basker.

Pesaran, H. M., and R. P. Smith (1995) Estimating Long-run Relationships from Dynamic Heterogenous Panels. *Journal of Econometrics* 68(1), 79-113.

Schultz, C. (2005). Transparency on the consumer side and tacit collusion. *European Economic Review*, 49(2), 279-297.

Tappata, M. (2009) Rockets and Feathers: Understanding Asymmetric Pricing. *RAND Journal of Economics* 40(4), 673-687.

Verlinda, J. A. (2008) Do Rockets Rise Faster and Feathers Fall Slower in an Atmosphere of Local Power? Evidence from the Retail Gasoline Market. *Journal of Industrial Economics* 56(3), 581-612.

Yang, H., and L. Ye (2008) Search with Learning: Understanding Asymmetric Price Adjustments. *RAND Journal of Economics* 39(2), 547-564.