Oldenburg Discussion Papers in Economics

Rockets and Feathers Revisited:

Asymmetric Retail Fuel Pricing in the Era of

Market Transparency

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This Version: October 2019

Abstract

In this paper, we revisit the empirical observation that prices rise like rockets when input costs increase but fall like feathers when input costs decrease. The analysis draws on a novel dataset that include daily retail prices of gasoline and diesel from virtually all fuel stations in Germany over the period from January 1, 2014 to December 31, 2018. Our findings from the national, state-specific and station-level analyses based on an asymmetric error correction model indicate that asymmetric pricing is the norm rather than exception. Specifically, we find empirical evidence that points to a pervasive rockets-and-feathers pattern. We also find that asymmetric pricing in the German retail fuel market might partly be the consequence of tacit collusion among competitors as well as disparate search intensity on the part of consumers. We further show that temporal aggregation of station-level price data might lead to inaccurate inferences and could account for the contradictory findings in the extant literature.

Keywords: Asymmetric Pricing, Market Transparency, Search Intensity, Tacit Collusion

JEL Classification Numbers: Q41, Q48, R40, L40

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1 Introduction

In this paper, we revisit the debate on the asymmetric response of retail fuel prices to crude oil price changes. Retail fuel pricing remains an area of significant interest for motorists, the media, and regulatory authorities in many countries including Germany. There exists the widespread and persistent public perception that oil companies are quick to adjust retail prices and hence profit margins in response to input cost *increases* rather than *decreases* – a behavior characterized as the *rockets-and-feathers* phenomenon (Bacon, 1991).[1] This affects the welfare of consumers as disparities regarding the speed of adjustment of retail prices to input cost increases or decreases are indicative of the fact that some market participants do not benefit fully from price changes possible under symmetric adjustment conditions.

Consequently, the retail segments of gasoline and diesel markets, in particular, have been the subject of regulatory and antitrust scrutiny in many countries, in some cases resulting in charges, convictions and hefty fines.[2] For Germany, the Federal Cartel Office (FCO) conducted an inquiry in 2008 in response to consumer concerns and found the existence of a dominant oligopoly. The oligopoly consists of five firms that not only have a nationwide network of fuel stations but have significant access to refinery capacity that further amplifies their collective dominance and market power (Bundeskartellamt, 2011).[3]

Competition and price setting behavior in gasoline and diesel retailing have also been the subject of intensive research (see Eckert, 2013; Periguero-García, 2013). With respect to the underlying causes, tacit collusion and the consumer search theory have been offered to explain the asymmetric pass-through of input cost changes to retail prices. Earlier studies such as Borenstein et al. (1997), for example, motivate the rockets-and-feathers pattern with a stylized version of the "trigger price" model of oligopolistic coordination (Green and Porter, 1984). That is, as retailers typically operate with thin margins, they respond swiftly to significant input cost increases with less regard for the pricing behavior of competitors. For a negative cost shock, on the other hand, the retail price in the previous period serves as the benchmark for price coordination. The prior retail price is maintained until one of the firms reneges on the tacit agreement and thereby triggers a price war.[4] Although rigorous theory underlying tacit collusion as a profit maximizing strategy for retailers is limited, empirical evidence lends credence to this hypothesis and is often cited as a determinant of asymmetric pricing (Verlinda, 2008; Lewis, 2011).

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[1] See Trauthig (2014), Eckert (2016) and Siedenbiedel (2018) for examples of recent discussions in the German media on the pass-through of crude oil price changes to consumers.

[2] A series of investigations in 2008, 2010 and 2012 by the Canadian Competition Bureau into a gasoline price fixing conspiracy, for example, resulted in numerous guilty pleas, substantial fines of about $ 4 million and the imprisonment of some individuals (Competition Bureau Canada, 2017).

[3] These are BP (Aral), ConocoPhilipps (Jet), ExxonMobil (Esso), Shell and Total.

[4] Asymmetric pricing due to tacit collusion has also been shown to exist in competitive markets (see Balke et al., 1998).

In a perfectly competitive market, however, firms earn zero profits and input cost changes are transmitted to consumers symmetrically. The market outcome changes, on the other hand, if consumers have imperfect information about market prices and if a significant proportion of consumers have non-zero search costs. In this case, firms are able to extract information rent from consumers. Asymmetric response of firms to input cost changes, therefore, emerges naturally as a consequence of consumer search behavior. The theoretical search-based models offer different predictions of how consumers' search efforts relate to asymmetric pricing by firms.

Yang and Ye (2008) and Tappata (2009), for example, suggest that searching activities by consumers can result in equilibrium asymmetric pricing if there is higher incentive to search for better prices when input costs are low. Although consumers have an imperfect knowledge of the input costs of firms, they learn whether the input costs are high or low by means of market search and by their purchasing decisions. At high input costs, variability in prices reduces as firms have less flexibility in setting prices. In contrast, at low input costs, retail prices are more dispersed and consumers with positive search costs anticipate higher gains from increased search activities. The intensity of search therefore increases when consumers perceive input costs to be low and vice versa. Consequently, at high input costs with lower search activities due to less price dispersion, if an unexpected negative cost shock occurs, firms may have less incentive to adjust retail prices to reflect the cost changes. The asymmetric search intensity, thus, leads to consumers being less knowledgeable about input cost decreases and enables firms to extract information rent in the short-run.

The search model by Lewis (2011), on the other hand, shows that consumers' expectations of price development are based on past realizations such that following an input cost increase, consumers anticipate lower and more dispersed prices and vice versa. In essence, consumers search more actively when prices are rising than when prices are falling. The adaptive expectation of retail prices causes asymmetric search incentive on the part of consumers and consequently leads to asymmetric pricing by firms. Cabral and Gilbukh (2019) also show that consumers search more when prices are high or increasing. Empirical evidence by Hastings and Shapiro (2013) has validated these findings by showing the increased sensitivity of consumers to price increases. Asymmetric retail pricing in equilibrium may therefore occur if consumers' search intensity soars due to increased price sensitivity.

Despite the increased traction of these two explanations in the literature, the empirical findings are rather mixed both within the same as well as across different countries, where evidence for and against asymmetric pricing has been shown (Periguero-Garía, 2013). Empirical studies on German data follow the trend in the broad empirical literature toward inconclusive findings. For example, while Kirchgässner and Kübler (1992) reject the hypothesis of symmetric adjustment for the period 1972–1979, the authors find symmetric adjustment of spot gasoline prices to retail prices between 1980 and 1989.

Other studies find evidence of asymmetric adjustment of spot and retail gasoline prices to crude oil price changes in datasets spanning a period from 1980 to the early 2000s (see Lanza, 1991; Galeotti et al., 2003; Grasso and Manera, 2007).

Moreover, recent findings for Germany by Kristoufek and Lunackova (2015) using weekly average national retail gasoline data from 1996 to 2014 find no statistically significant asymmetric gasoline pricing. Asane-Otoo and Schneider (2015) find the rockets-and-feathers pattern in the gasoline and diesel markets for the period 2003–2007. For the period 2009–2013, on the other hand, the authors find symmetric and negative asymmetric adjustment for diesel and gasoline, respectively.[5] Although, Bagnai and Ospica (2016) employ monthly average national retail gasoline data between 1999 and 2015, the results point to a negative asymmetry, reflecting the findings of Asane-Otoo and Schneider (2015) that retail prices adjust *more swiftly* to input cost *decreases* rather than *increases*.

As shown by the above-mentioned studies, the empirical findings specifically for Germany are inconclusive. The diverse findings in the extant literature may partly be attributed to the temporal and spatial aggregation of price data. Because station-level fuel prices change frequently within a given day, low frequency price data do not adequately reflects the frequency of price decisions at the station level or short-run input cost changes. This implies that the frequency of adjustment to input cost shocks or daily price volatilities cannot be detected using weekly or monthly data as is often done in the empirical literature to date.

To the best of our knowledge, all studies that focus on Germany rely on price data aggregated across fuel stations to obtain average prices at either the national level or the city level. This form of spatial aggregation ignores obvious heterogeneity across fuel stations such as differences in pricing strategy, locational competition environment and the degree of price adjustments. Spatial differences among different regional or sub-regional markets with respect to market structure might also be at odds with that of the aggregate national market.

Spatial and temporal aggregation of data might therefore compromise the validity of the estimations since time series of heterogeneous fuel stations might exhibit dynamics that differ distinctly from cross-sectionally aggregated time series data (e.g. Granger, 1980; Pesaran and Smith, 1995; Pesaran and Chudik, 2014). Moreover, while rockets-and-feathers empirical studies abound, none of the studies on Germany attempt to empirically test the underlying cause of the observed pricing pattern. They also fail to focus on the price effects of other factors such as local competition, as reflected in prices of neighboring fuel stations, and weather conditions such as ambient temperature, precipitation and snow depth. Most of the rockets-and-feathers literature relies solely on price data and largely ignores the degree of local or spatial competition and the impact of weather conditions on demand, even though such factors influence price changes and are inherent in the pricing

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[5]Negative asymmetry is defined as the reverse of the rockets-and-feathers pattern.

decisions at the station level.

While the lack of firm-level data limits the scope of previous studies in addressing the issues mentioned above, our analysis draws on price data that spans virtually all fuel stations in Germany. The advantage of using this novel dataset in a market without price restrictions is twofold. First, the data allow us to include all individual stations and conduct our analysis at the station level, where the pricing decision normally occurs. Thus, in addition to providing a comprehensive view of retail market competition at the national level, we are also able to examine differences in price adjustment across geographically diverse fuel stations following crude oil price changes. Our analysis therefore provides a complete representation of retail market competition and goes beyond the "representative agent" assumption that is implicit in all the empirical studies that focus on the German retail market.[6]

Second, it is worth noting that besides the five vertically integrated dominant oil companies, there are other integrated oil companies as well as small-to-medium sized independent retailers with varied footprints in different regions. Hence, the dataset also permits us to abstract regional market competition from nationwide competition since spatial market competition might differ across regions due to differences in market structure. Moreover, we provide a comprehensive analysis of the two most important fuel types – *gasoline (E5)* and *diesel* – that are vital for road transport in Germany.

The remainder of the paper is organized as follows. Section 2 provides a brief description of the retail fuel market in Germany and the data used for the analysis. Section 3 outlines the empirical strategy, Section 4 provides a summary of the findings and Section 5 concludes.

2 Market and Data

2.1 German Fuel Market and Station-Level Data

Fuel prices and, more generally, the market for fuel in Germany, have long been a subject of intense public debate, mostly because of their relevance to commuters. The public discourse ranges from discussion of annual price increases during holiday and vacation seasons (especially summer), to suspicion of common and coordinated pricing, all the way to a general skepticism about the composition of fuels or the ingredients used in certain fuel types. While some of these concerns and accusations are aimed at the government, others are targeted at distributors of fuel (i.e., brands) and their respective fuel stations. Gasoline and diesel are the main fuel types sold by fuel stations in Germany.[7]

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[6]In effect, we are able to examine the effect of data aggregation on the parameters and the adjustment process.

[7]Gasoline can be distinguished into "Super E5" – with up to 5% of ethanol – or "Super E10" – with up to 10% ethanol. However, the market share of E10 fuel type has been rather low in comparison with

A large share of the retail market is operated by only a small number of brands. Our data show that 49.71% of the fuel stations in Germany are run by Aral (15.41%), Shell (11.81%), Esso (6.87), Total (5.81%), AVIA (5.41%), or JET (4.40%). Another 22.37% of fuel stations are run by 9 other brands while the remaining 27.92% of fuel stations are operated by 61 smaller or independent brands. This distribution reflects a high concentration of market shares among the brand competitors and is indicative of an oligopolistic market structure. It is worth noting that the market shares do not consider station heterogeneity, e.g., in terms of sales quantity and revenues, number of pumps, opening hours, location (e.g., near a motorway or major road), or other services such as car washes. These characteristics might indeed contribute to further market concentration (Haucap et al., 2017). The FCO, for example, reports that the combined share of the five oligopolies in nationwide sales volume is more than 70% (Bundeskartellamt, 2011).

Gasoline and diesel products sold at the various fuel stations are fairly identical and the high degree of product homogeneity signals the vital role of prices in the retail industry. Station operators and brands are entirely responsible for all pricing decisions and the degree and frequency of price changes are not regulated.[8] In recent years, the degree to which consumers can compare prices across fuel stations in a local market has improved significantly due to the plethora of online platforms that offer such services. Market transparency in the retail fuel market is therefore much higher than in other markets, but at the cost of an increased frequency of price adjustment (BMWi, 2018).

The increased level of price transparency for both consumers and suppliers has been facilitated by the establishment of the FCO's market transparency unit (*Markttransparenzstelle für Kraftstoffe*, MTS-K). Since the end of 2013, all fuel stations are obliged to report all price changes for Super E5, Super E10, and regular diesel fuel to the MTS-K prior to an effective price change at the station-level. The price information is then transmitted to all the information service providers or platforms. These service providers then make the price information available to consumers on their websites or apps for free.[9] The MTS-K database and associated platforms offer an overview of the level and development of fuel prices with the aims of enabling consumers to make informed decision and promote competition among fuel stations and fuel brands. These services have considerably reduced the search cost for consumers and allowed consumers to access real-time prices. On the other hand, they have also improved the capability of retailers to compare prices of competitors, both within and outside their local market. Our analysis relies on this comprehensive novel dataset that covers all fuel stations with exact time stamps for all price quotes.

E5, which accounts for approximately 85% of fuel sales in Germany (BDBe, 2017)

[8]Unlike independent fuel stations, the pricing decision might be partly centralized for stations of major brands, i.e., the individual stations may have a limited role in the pricing decision.

[9]e.g., https://www.clevertanken.de, https://www.spritmonitor.de, https://www.bottledsoftware.de
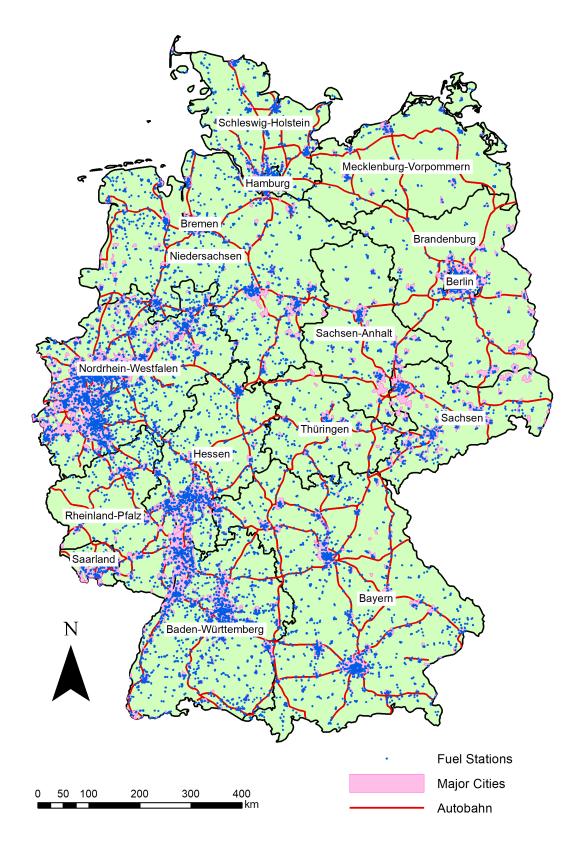
Figure 1: Spatial Distribution of Fuel Stations in Germany

Source: Own illustration based on shapefiles obtained from the Natural Earth Database

(http://www.naturalearthdata.com/downloads/10m-cultural-vectors/)

Given that fuel stations face no restrictions on the frequency of intra-day price changes, there may be multiple observations of a station per day. In order to assess price changes on an inter-day basis, daily averages are therefore calculated. In our analysis, average retail prices are nominal consumer prices at the pump in euros (cents) per liter. The prices are gross of taxes and duties – that is, they include energy taxes, value-added taxes, as well as a fee for the Petroleum Stockholding Association. Overall, we can observe daily prices for $15,228$ distinct fuel stations in Germany for the period starting from the January 1, 2014 to December 31, 2018.[10] As illustrated in Figure 1, showing the geographical distribution of all fuel stations in Germany, fuel stations are widely but unevenly distributed across cities and regions in Germany. The map shows a clear gradient between the east and west of Germany, and there is a high concentration of fuel stations in densely populated areas as well as along the *Bundesautobahn* or highway network.

In addition to the retail price data, the MTS-K dataset also provides station-specific data such as opening and closing hours, geographical coordinates, and brand affiliation of all the fuel stations.[11] To take into account the responsiveness of retail prices to variations in input cost, we use daily spot Brent (Europe) crude oil price obtained from the U.S. Energy Information Administration (EIA, 2019). The Brent crude oil prices (in dollars/barrel) are converted to euros/barrel using the exchange rate data provided by the International Monetary Fund.[12]

2.2 Neighbor Prices

The impact of local competition or neighborhood effect on station level pricing has been investigated by other authors (Hosken et al., 2008; Atkinson, 2009). To account for the role of local competition on price setting decisions at the station level, we include the average fuel prices for neighboring fuel stations in our model specification. As stations adapt their prices to those of nearby competitors within a given range, we assume that competition in the local market increases with geographic proximity. As a result, we calculate the average price of neighboring fuel stations within a range of 2 and 5 km, respectively. For all fuel stations, the complete address, as well as the georeferenced coordinates are available, so that the exact location of each station is known. This information makes it possible to compute the linear distance in kilometers between the stations using the Haversine formula (1):

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[10] The *Markttransparenzstelle* became operational as early as September 2013, but technical difficulties in the early stage led to missing observations and incomplete data for December 2013 and earlier.

[11] About 70 distinct brands can be identified in the dataset.

[12] see, https://www.imf.org/external/np/fin/ert/GUI/Pages/CountryDataBase.aspx

$$d_{ij} = 2R \ \arctan \left(\frac{\sqrt{\theta}}{\sqrt{1-\theta}} \right) \tag{1}$$

$$\text{where } \theta = \sin^2 \left(\frac{lat_i - lat_j}{2} \right) + \cos(lat_i) \cos(lat_j) \sin^2 \left(\frac{lon_i - lon_j}{2} \right)$$

The MTS-K database not only permits fuel stations to adjust their prices to reflect the real-time prices in the local market, but also allows consumers to track price movements. If significant price differences exist, it might be economical for the individual to accept a detour. Of course, whether a detour is considered economical depends on various factors, including the price difference per liter, the quantity of fuel needed, the mileage of the car, or generally if there is pressure of time. Using the Haversine formula implies considering the linear or "beeline" distance, i.e., a very simplified scenario. This approach applies mainly to a priori distance filters on price comparison websites or apps. However, it does not necessarily portray the behavior of customers with local knowledge, who are aware of actual driving routes and distances. That notwithstanding, linear distances have been used widely in prior research, mostly because of their intuitiveness and easy calculation.

We assume that fuel stations are influenced by other stations in a given radius κ, regardless of the actual driving time or distance. In the standard setting, the radius or threshold is set to $\kappa = 5$ km.[13] The influence of competitors is assumed to be decreasing with distance. The spatial weights matrix is then constructed according to the rule described in equation (2), where δ_{ij} is the pairwise weight assigned to stations i and j. By definition, the distance from any station to itself is set to 0, so that all diagonal elements of the matrix are equal to 0.

$$\delta_{ij} = \begin{cases} d_{ij}^{-1} & \text{if } 0 < d_{ij} \leq \kappa \\ 0 & \text{if } d_{ij} > \kappa \\ 0 & \text{if } d_{ij} = 0, \text{ i.e., } i = j \end{cases} \tag{2}$$

Multiplying the weight matrix by the price vector then yields the distance-weighted mean of neighbor prices within a distance of 5 km, excluding the respective station under consideration.

2.3 Public and School Holiday Data

A potential determinant of fuel price changes that is mentioned in the public discussions are public and school holidays. These periods are likely to affect fuel pricing

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[13]Choosing a distance of 5 km reduces the number of fuel stations without neighbors. In this case, we identify only 939 stations in the full sample that have no neighbor within 5 km. For further robustness testing, other truncation distances (such as $\kappa = 2$ km) are also considered.

strategies as they cause changes in commuting and travel behavior. While there is a perceived notion of increased traffic and congested roads, especially at the beginning of the holiday season, other areas show a reduction in traffic counts (Cools et al., 2007; Jun, 2010). Either way, the seasons around holidays and vacations can be expected to have an effect on the demand for fuel and overall fuel consumption. The German Federal Ministry of the Interior (*Bundesministerium des Innern*) recognizes nine national public holidays every year. Additionally, there are about eight other public holidays that are celebrated in individual federal states (e.g., "Buß- und Bettag" in Saxony) or groups of federal states. The beginning and the duration of school holidays (Christmas, winter, spring, summer, and autumn holidays), on the other hand, are decided upon every year by the Standing Conference of Ministers of Education and Cultural Affairs (*Ständige Kultusministerkonferenz*) of the individual federal states. This is done to mitigate effects such as those on traffic, demand for vehicular fuel, and leisure activities.

2.4   Weather Data

To understand the station-level pricing behavior, it is worth considering possible determinants of fuel demand. Apart from reflecting seasonality, local weather conditions play a pivotal role in the day-to-day choice of the mode of transportation. Böcker et al. (2013) conclude that favorable weather conditions promote active modes of transportation (e.g., walking or cycling), whereas, commuters tend to switch to motorized transportation (e.g., individual driving or public services) when experiencing adverse weather conditions. This is mainly for reasons of convenience and perceived safety. Several authors have shown, for example, that adverse weather conditions such as rainfall or snow tend to increase traffic and lead to increased travel times as a consequence of congested roads (Koetse and Rietveld, 2009; Rakha et al., 2012; Tsapakis et al., 2013). It has also been shown that individuals react to weather variability differently, mainly depending on their commuter status. While local residents are inclined to switch to public transportation, commuters strongly rely on independent mobility (Liu et al., 2015; Singhal et al., 2014). For them, adverse weather implies the need for trip chaining, ultimately affecting the number of kilometers traveled (Liu et al., 2016).

Daily data on weather conditions in Germany are collected as part of the European Climate Assessment and Dataset (ECA&D) (Klein Tank et al., 2002). In total, the dataset contains information on 5,617 meteorological stations which record observations including mean ambient temperature, precipitation amount and snow depth. Data availability for the different measures varies across stations, i.e., some stations have data on all three measures, while others have data on fewer measures. For all meteorological stations, the exact geographical coordinates are also given such that for each fuel station, the corresponding weather station(s) can be assigned. To cope with missing data, the information from the nearest 20 neighboring weather stations is averaged using inverse

linear distances as weights to approximate the local weather conditions.[14]

3   Estimation

To investigate the response of retail prices at the fuel station level to crude oil price changes, we first examine the degree of integration of the price series. Our retail price dataset covers 15,228 individual fuel stations that are observed over a total of 1,825 days. Of those, only stations with at least two years, i.e., 730 days of observation, are employed in the regression sample to ensure a sufficient number of observations per station. This leaves 20,398,279 data points, across a total of 11,978 stations. We adopt two strategies in testing the order of integration of the retail fuel prices. First, we apply the Augmented Dickey-Fuller unit root test to the crude oil and the retail prices of the individual stations. Optimal lag length are selected using the Akaike Information Criterion (AIC).

We find that the null hypothesis of non-stationarity cannot be rejected for the crude oil price at the 1% significance level. Similarly, the results show that 98.58% of the individual station-level retail prices, i.e., 11,808 stations, are $I(1)$. Second, given that our dataset can be differentiated across regions (federal states or *Bundesländer*), we also exploit both the cross-sectional and time dimensions of the dataset and apply the Fisher-type panel unit root test to verify the stationarity of the panel of retail prices for the whole country as well as for all the 16 Bundesländer. The panel unit root test results again show that the null hypothesis of non-stationarity cannot be rejected at all conventional significance level for retail prices in Germany as a whole (see Table 7) as well as for all the individual federal states.[15]

Having established the order of integration of the price series, we test whether the underlying price series are cointegrated using the Engle-Granger residual-based cointegration test (Granger and Engle, 1987). The long-run relationship between the retail and the crude oil prices is first estimated as follows:

$$p_{ist} = \sigma_i + \theta w p_t + \delta d_{it} + \xi_{ist} \tag{3}$$

Here p_{ist} denotes the retail fuel price series, specific to station i in state s at time t. σ_i denotes the time-invariant station-specific fixed effect which controls out unobserved heterogeneity or time-invariant omitted variables that differ across individual fuel stations. These include brand type, ownership type, station density (number of stations within the

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[14]The number of 20 neighboring weather stations is chosen arbitrarily to ensure, on the one hand, sufficient variation across stations and on the other hand, to attain robust averages of regional weather conditions.

[15]Unit root tests for the crude oil price, station-level price series and the panel data are all specified with a linear trend. All the station- and state-level unit root and residual-based cointegration tests are available upon request.

local market), associated facilities such as convenience or kiosk-type stores, car washes etc. We are of the view that these station characteristics change little if at all over the time period under consideration.

Estimating equation (3) with the station fixed-effects also allows us to account for different long-run margins across the individual stations. wp_t denotes the underlying series of Brent crude oil prices while d_{it} denotes state-specific dummy variables for public holidays and start of school holidays (= 1 if a day is a holiday in state s and 0 otherwise). It also captures a set of dummy variables that denote the specific days of the week. These dummy variables are included to control for demand-side effects associated with specific days of the week, and with public and school holidays. In equation (3), θ denotes the cointegrating or pass-through coefficient and ξ_{ist} is the residual, which captures the gap between the retail price and its long-run equilibrium value.[16]

For the two price series to be linearly cointegrated, the estimated error term ξ_{ist} should be stationary. We apply the Augmented Dickey-Fuller unit root tests to the residuals. With respect to the individual station-level time series estimation, we find that the retail prices of about 99.82 % of the fuel stations in Germany are cointegrated with the crude oil price series. For the panel estimations, we find that all the underlying retail price series are cointegrated with the crude oil price (see Table 8 for the residual-based cointegration tests for the German panel).

Since the underlying price series are $I(1)$ and cointegrated, we can specify an error correction model (ECM) to reflect both the long-run and short-run dynamics of retail fuel prices (Granger and Engle, 1987) as follows:

$$\triangle p_{ist} = \alpha_i + \phi \xi_{ist-1} + \sum_{m=1}^{M} \beta_m \triangle p_{ist-m} + \sum_{n=o}^{N} \lambda_n \triangle wp_{ist-n} + \varepsilon_{ist} \tag{4}$$

In equation (4), $\triangle$ is the first difference operator, M and N refer to the number of lags of the underlying retail price and the crude oil price, respectively. The coefficients β_m and λ_n capture the respective short-run impacts of lagged changes in retail prices and current and lagged changes in crude oil price. ξ_{ist-1} is the error correction term – the one-period lagged residual derived from the cointegrating regression in equation (3). ξ_{ist-1} expresses the prior disequilibrium from the long-run relationship (i.e., deviation from the long-run equilibrium which occurred in the previous period). That is, if $\xi_{ist-1} \neq 0$ in equation (3), then the model is in disequilibrium and vice versa. The coefficient ϕ associated with the error correction term is the long-run equilibrium adjustment parameter and reflects the speed of convergence towards the equilibrium retail price level. Specifically, if p_{ist-1}, for example, is above its long-run equilibrium ($\xi_{ist-1} > 0$), then it should adjust back to the long-run equilibrium in the next period and vice versa.[17] Consequently, the coefficient

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[16]To control for the repeated sampling of the crude oil price, which is invariant across stations, the standard errors are clustered at the station level.

[17]$\xi_{ist-1} > 0$ implies positive deviation and hence a decrease in crude oil price, whereas $\xi_{ist-1} < 0$ implies otherwise.

associated with the error correction term should be negative.

Following Granger and Lee (1989), the symmetric ECM in equation (4) can be extended to capture asymmetric adjustments by decomposing both the error correction term and short-run dynamics into negative and positive variables. In this case, the asymmetric error correction model can be specified as follows:

$$\triangle p_{ist} = \alpha + \phi^+ \xi^+_{ist-1} + \phi^- \xi^-_{ist-1} \qquad (5)$$
$$+ \sum_{m=1}^{M} \left(\beta^+_m \triangle p^+_{ist-m} + \beta^-_m \triangle p^-_{ist-m} \right)$$
$$+ \sum_{n=0}^{N} \left(\lambda^+_n \triangle wp^+_{t-n} + \lambda^-_n \triangle wp^-_{t-n} \right)$$
$$+ \psi \triangle \overline{p}_{(-i),st-1} + \pi' \triangle \boldsymbol{W} + \gamma' \triangle \boldsymbol{H} + \delta' \boldsymbol{D} + \tau t + \varepsilon_{ist}$$

ξ_{ist} is the estimated error term from equation (3), $\xi^+_{ist-1} = max\{\xi_{ist-1}, 0\}$ and $\xi^-_{ist-1} = min\{\xi_{ist-1}, 0\}$. For each variable v in equation (5): $\triangle v^+ = max\{\triangle v, 0\}$ and $\triangle v^- = min\{\triangle v, 0\}$.[18] Note that a plus (minus) as superscript to a coefficient is indicative of an increase (decrease) change in the associated variable. This approach allows us to evaluate the presence of the rockets-and-feathers phenomenon – i.e., whether crude oil price increases are transmitted more swiftly than a corresponding price decrease. The coefficients (ϕ^+ and ϕ^-) associated with the error correction terms are therefore the long-run adjustment parameters. They reflect the speed of the adjustment process towards the long-run equilibrium. For example, positive deviations of retail prices from equilibrium in the previous period ξ^+_{ist-1} – due to a decrease in crude oil price – should return to the equilibrium in the current period at the rate of ϕ^+. Therefore, if $|\phi^+| < |\phi^-|$, then the mean reversion of retail prices to equilibrium is faster when retail prices are below their long-run equilibrium level – implying a crude oil price increase – and slower when otherwise.

The α and β coefficients reflect the short-run impact of crude oil prices (both current and lagged) and lagged retail gasoline prices, respectively. M and N are the optimal lags, which are selected using the AIC. Again, the specification allows us to test short-run asymmetry. That is, an F-test can be used to test the null hypotheses of short-run symmetry (i.e., $|\beta^+_m| = |\beta^-_m|$ or $|\lambda^+_n| = |\lambda^-_n|$).

As indicated before, local weather conditions affect the mode of transportation and hence demand for fuel. Moreover, public holidays also alter commuting behavior and perhaps, price setting behavior of fuel stations. To account for these demand-side effects, we include a vector ($\boldsymbol{W}$) of weather related variables (precipitation, snow depth and mean ambient temperature), a vector ($\boldsymbol{H}$) of holidays – particularly, the start of school

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[18]Equation (5) is estimated for (i) the entire panel for Germany, (ii) for the individual panels of the 16 Bundesländer and (iii) for the time series of individual stations.

holidays and public holidays – as well as day-of-the-week-specific dummies. We also include a vector ($\boldsymbol{D}$) of month and year dummy variables to control for seasonalities and common year-specific effects, and a linear time trend (t) is also included to account for changes in retail prices that extend over the period. Since local competition also plays a vital role in how fuel stations set and adjust prices, we further include the day-to-day changes in average prices ($\triangle \overline{p}_{(-i)}$) of neighboring fuel stations within 5 km to reflect the role of local market competition.[19]

4 Results

4.1 Main Results

Germany as a whole. In this subsection we report the estimates for the panel of Germany as a whole. We report the estimated coefficients for the long-run adjustment parameters, the day-specific dummies, holiday dummies, prices of neighbors and weather variables. Additionally, we report the F-test statistics for the long-run symmetry and short-run symmetry hypotheses.[20] Table 1 shows the estimation results of the asymmetric ECM in equation (5) for the complete sample of $11,978$ fuel stations in Germany. Column (1) shows the coefficient estimates for the baseline specification. Here, dummies for weekdays, an interaction of month and year dummies, as well as a linear time trend are included in the specification. The coefficients associated with positive and negative deviations from the long-run cointegrating relationship (ϕ^+ and ϕ^-), as well as the lags of (the respective positive and negative) changes in retail and crude oil prices are included. In the subsequent columns, we include the average price of neighbors, different holiday dummies, and weather variables, sequentially.

Focusing first on the estimates for days of the week as shown in models (1)-(4), the results point to an intra-week pricing pattern. The coefficients associated with the specific days of the week show increasing retail prices throughout the week. Specifically, we find increasing retail prices heading towards the weekend as illustrated by the magnitude of the coefficients for Friday, Saturday, and Sunday. This finding points to the presence of a weekend effect. With respect to the effect of local competition as reflected by the average prices of neighbors in Column (2), the estimated coefficient is positive and significant at the 1% level across all models. This indicates that rival fuel stations within a 5 km radius adjust prices in response to average price changes within the local market.

To assess the demand-effect of school and public holidays, we include (partly) state-

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[19]We further conduct all the analyses by reducing the radius of local market competition to 2 km and by using the price spread (max - min) within a local market in addition to the average price. The results are qualitatively consistent with the main results and are available upon request.

[20]To ensure parsimonious reporting of the estimates, we do not report the short-run coefficients, but they are available upon request.

specific public and school holidays in Column (3) and (4). As public holidays and the start of school holidays may affect fuel demand and travel behavior, there is a public perception that retail prices increase heading into the holiday period. Public holidays in Germany are mostly single-day events, i.e., they do not span a period of several days.[21] Accordingly, we include the dummy for the contemporaneous public holiday, as well as one lagged and two leaded values to account for proactive and sustained pricing effects.

The coefficients indicate that two days before the public holiday are already associated with moderate increases in retail prices. However, there is a much stronger increase in retail prices on the public holiday itself. We find an instantaneous price increase of 0.541 cents. The estimate also shows a significant price decrease (0.129 cents) a day after the public holiday, but one that is much smaller than the initial increase. As school holidays are longer episodes (e.g., the summer holidays last six to seven weeks), their influence tends to be seasonal. Consequently, we focus on the first day of the school holidays, as this is usually the day, on which the so-called *wave of vacationers* begins. Again, one lagged, two leaded and the contemporaneous dummies are included. All four estimated coefficients are positive and significant at the 1% level. In terms of their magnitude, the contemporaneous effect of the start of school holidays is smaller (approximately 0.045 cent) than that of public holidays. This is expected as school holidays apply only to a fraction of the population unlike public holidays. Moreover, retail prices continue to increase a day after the start of the school holiday period. Overall, our estimates indicate that not only do retail prices increase on public holidays and at the start of school holidays; the price increases also begin two days prior to the start of holidays.

In the final specification in Column (4), daily changes in local weather conditions are included in the regression. The rationale is that adverse weather conditions cause changes in gasoline demand and the transport costs for crude. These, in turn, affect retail prices. The results at the national level show that the coefficients associated with changes in rainfall as well as in snow depth are statistically insignificant. The result contradicts the finding that rain and snow lead to commuters switching from active modes of transportation to driving by car or public transportation (Koetse and Rietveld, 2009; Böcker et al., 2013), which is expected to entail positive price changes, due to increased fuel demand. This insignificant effect might be related to the widely varying frequency and amount of snow and precipitation across different states in Germany. Due to these variations, the net average effect on demand and hence prices might be statistically insignificant. For changes in average temperature, the opposite applies. Here, the coefficient is negative and significant at the 1% level. That is, if the average temperature rises, commuters tend to take the bicycle or walk to work, leading to less traffic and a decrease in demand for fuel, and this ultimately exerts a decreasing effect on fuel prices.[22]

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[21]The only public holidays spanning two consecutive days are Christmas and the day after Christmas.

[22]As shown in Table 1, all other results, including the various tests for symmetry, remain qualitatively unchanged despite the step-wise inclusion of neighboring prices, holiday, weather variables.

Table 1: Regression Results: Gasoline (E5) – Germany

	(1) Baseline Specification		(2) Neighbor Effects		(3) Holiday Effects		(4) Weather Effects	
Dependent Variable: $\triangle$ Retail Price of E5 Fuel								
ϕ^+	-0.061***	(0.000)	-0.060***	(0.000)	-0.059***	(0.000)	-0.059***	(0.000)
ϕ^-	-0.116***	(0.001)	-0.116***	(0.001)	-0.116***	(0.001)	-0.116***	(0.001)
Tuesday	0.061***	(0.002)	0.124***	(0.002)	0.148***	(0.002)	0.148***	(0.002)
Wednesday	0.053***	(0.002)	0.088***	(0.002)	0.107***	(0.002)	0.107***	(0.002)
Thursday	0.105***	(0.002)	0.139***	(0.002)	0.136***	(0.002)	0.137***	(0.002)
Friday	0.131***	(0.002)	0.161***	(0.002)	0.177***	(0.002)	0.177***	(0.002)
Saturday	0.263***	(0.003)	0.293***	(0.003)	0.328***	(0.004)	0.328***	(0.004)
Sunday	0.591***	(0.005)	0.613***	(0.005)	0.640***	(0.005)	0.640***	(0.005)
L1.$\triangle$ Neighbor Prices (5km)			0.117***	(0.001)	0.116***	(0.001)	0.116***	(0.001)
Public Holiday								
t+2					0.161***	(0.002)	0.161***	(0.002)
t+1					0.167***	(0.002)	0.167***	(0.002)
t					0.541***	(0.005)	0.541***	(0.005)
t-1					-0.129***	(0.002)	-0.129***	(0.002)
School Holiday Start								
t+2					0.074***	(0.002)	0.073***	(0.002)
t+1					0.038***	(0.002)	0.039***	(0.002)
t					0.045***	(0.002)	0.045***	(0.002)
t-1					0.110***	(0.002)	0.110***	(0.002)
$\triangle$ Rainfall							-0.000	(0.000)
$\triangle$ Snow Depth							0.001	(0.001)
$\triangle$ Average Temperature							-0.016***	(0.001)
F-Tests for Symmetry								
$\phi^+ = \phi^-$	5,267.80***		6,220.68***		6,619.16***		6,610.55***	
$\beta_m^+ = \beta_m^-, \quad m \in [1,7]$	621.09***		603.45***		581.82***		582.08***	
$\lambda_n^+ = \lambda_n^-, \quad n \in [0,7]$	6,821.18***		6,741.15***		5,543.63***		5,552.37***	
Cointegration Parameter	1.041***		1.041***		1.041***		1.041***	
Observations	20,398,729		20,398,729		20,398,729		20,398,729	
R^2	0.287		0.292		0.297		0.297	
Number of Fuel Stations	11,978		11,978		11,978		11,978	
Month/Year Fixed Effects	Yes		Yes		Yes		Yes	

Notes: Constant term included but not shown. Standard errors, clustered with respect to fuel stations, are reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. *Public Holiday* denotes whether the corresponding day is a public holiday, some of which vary across German states. *School Holiday Start* refers to the first day of school holidays, which in Germany are individual to the 16 federal states. *Station Fixed Effects* refer to a set of indicator variables that take a value of 1 for each individual fuel station. *Month/Year Fixed Effects* refer to a set of control variables specific to each combination of month and year. See the main text for additional details on data construction and sources. For *F-Tests for Symmetry* the following null hypotheses are tested: *Long-run symmetry* tests whether the coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-run symmetry* tests $L(i).P^+ = L(i).P^-$ for all $i \in [1,7]$ with $F(7, 12319)$ degrees of freedom and $L(j).WP^+ = L(j).WP^-$ for all $j \in [0,7]$ with $F(8, 12319)$ degrees of freedom. The *Cointegration Parameter* refers to the pass-through coefficient (θ) for equation (3) and corresponds to the long-run cointegrating relationship between the retail price (p) and the crude oil price(wp).

Across all specifications, the null hypothesis of short-run symmetry in retail ($|\beta_m^+| = |\beta_m^-|$) as well as crude oil ($|\lambda_n^+| = |\lambda_n^-|$) price changes can be rejected. This is indicative of an asymmetric response of retail prices in the short run. Focusing more on the long-run adjustment of retail prices, the results as shown in models (1)-(4) show that long-run retail prices in Germany respond asymmetrically to crude oil price changes. The long-run adjustment coefficients for both positive and negative deviations are statistically significant at the 1% level across all models. The estimates show that a day after a 1 cent change in the spot crude oil price, the corresponding adjustment of the retail price is 0.059 cent in the case of crude oil price decrease and 0.116 cent in the case of a 1 cent increase in crude oil price.

The test for equality of the long-run adjustment coefficients, i.e., $|\phi^+| = |\phi^-|$, shows that the differences between the coefficients are statistically different from zero across all

specifications. The speed of convergence towards the long-run equilibrium is therefore faster for crude oil price increases than decreases. With respect to the half-life of a deviation – the number of days required to reduce half of the deviation from the long-run equilibrium – the estimates show that it takes approximately six days for half of a negative deviation to be corrected. It, however, takes roughly twelve days in the case of a positive deviation.[23] This implies that fuel stations in the long-run adjust their retail prices more swiftly when the margin is squeezed than when it is stretched and confirms the rockets-and-feathers hypothesis.

As indicated earlier, tacit collusion among fuel stations and the extent to which information rent can be extracted from consumers have gained traction in the extant literature as important determinants of the rockets-and-feathers pattern. Given the granular nature of our data, we examine whether the asymmetric pricing pattern we find in the German retail fuel market may be the consequence of collusion and/or consumer search intensity.

Collusion and asymmetry. As to the former, the high market concentration coupled with the ease with which individual stations within a local market can monitor neighbors' prices make tacit agreement among fuel stations in a local market highly probable. Theory and empirics suggest that the focal point for tacit collusion among fuel stations is the retail price level in the previous period (Borenstein et al., 1997; Lewis, 2011; Verlinda, 2008). Fuel stations that have reached such an agreement keep the price level from the previous period when the input cost decreases. The agreement is maintained until one of the fuel stations reneges by adjusting current prices to reflect input cost decreases, thereby provoking a price war. Conversely, for input cost increases, fuel stations adjust retail prices accordingly, not only to maintain profit margins but also to signal their compliance with the agreement to their competitors. In effect, the speed of adjustment of retail prices to input cost decreases is slower than for cost increases.

To examine whether asymmetric pricing in the German market is a consequence of tacit or focal price collusion as a pricing strategy, we compute the average price of all fuel stations within 5 km radius – weighted by the inverse distance to competitors. We then use this weighted average price to identify fuel stations that frequently have retail prices above or below the local market average. That is, we consider stations relatively expensive (*"high-priced"*), if the frequency of daily prices above the local market average exceeds 75th percentile of the stations in the sample, and relatively inexpensive (*"low-priced"*) stations if their price is below the 25th percentile of stations.

Consequently, we expect the extent of asymmetry to be significantly different for *high- and low-priced* fuel stations. The emphasis here is on the speed of adjustment following an input cost decrease. In this case, retail prices should adjust more slowly for

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[23]The half-life is defined mathematically as: $ln(2)/|\phi|$.

high-priced stations than *low-priced* stations. As to input cost increase, it is difficult to predict a priori since the rate of adjustment could be similar but the underlying motivation might differ. For *low-priced* stations, it might be important to adjust prices accordingly in order to maintain positive margins while for *high-priced* stations, the underlying reason might just be to ensure compliance with the agreement.

In our analysis, we replicate the main results (Column (4) in Table 1) for these two groups and compare the magnitude of the coefficients of interest, i.e., the long-run adjustment parameters $|\phi^+|$ and $|\phi^-|$. We find that the absolute value of the adjustment coefficients for the *low-priced* fuel stations is larger than that of the *high-priced* group. Comparison of the coefficients shows that the long-run adjustment parameters for the two cases ($\phi^+_{P25} = -0.066$, $\phi^-_{P25} = -0.137$ and $\phi^+_{P75} = -0.055$, $\phi^-_{P75} = -0.103$) differ significantly, i.e., the probability of the long-run adjustment parameters being equal for *high-* and *low-priced* stations is less than 0.1%.[24]

Indeed for input cost decreases, the results show that the magnitude of the speed of adjustment is significantly larger for *low-priced* stations than *high-priced* stations. One explanation that may account for the speed of adjustment following an input cost increase for *low-priced* stations being significantly larger than that of the *high-priced* stations is that *low-priced* fuel stations have relatively thin profit margins. This implies the need to swiftly pass on cost changes. In contrast, for *high-priced* fuel stations the, relatively high prices serves as a buffer in the face of increasing costs. Accordingly, even with the smaller rate of price adjustment, the fact that the prices in these stations are consistently above the average market price enables them to maintain positive profit margins. This explanation is further supported by the observation that *high-priced* fuel stations predominantly belong to dominant brands – as illustrated in Figure 2 – that have the capacity to influence market conditions as they hold significant refinery capacities, shares of stations and sales volume.[25] These results lend support to the notion that asymmetric pricing in the German retail market might partly be due to price coordination among competitors.

Search cost and asymmetry. With respect to consumers' search activities, we focus on search-based theories that suggest that asymmetric search intensity reduces the incentive to pass on input cost decreases since consumers have less information about cost decreases than increases (Yang and Ye, 2008; Tappata, 2009). These theoretical models suggest that when input costs are low, there is higher price dispersion, and this leads to higher search intensity since consumers have an incentive to compare prices across stations if their search costs do not exceed the payoff. There is therefore less price asymmetry as individual retailers are less able to extract the informational rent from consumers.

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[24]$Pr(|\phi^+_{P25}| = |\phi^+_{P75}|) < 0.1\%$ and $Pr(|\phi^-_{P25}| = |\phi^-_{P75}|) < 0.1\%$ — Full results are available upon request.

[25]The brands listed are those, for which more than 500 fuel stations are listed in Germany. All others, including those assigned to *no brand*, are listed as *other*.
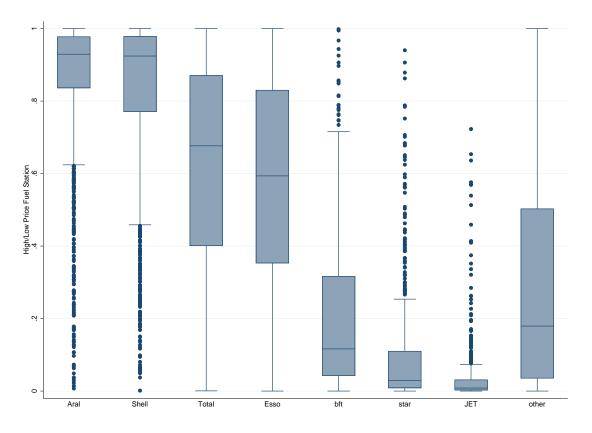
Figure 2: High and Low Price Fuel Stations by Brands

To empirically investigate whether high price dispersion and intensive searching on the part of the consumer base lead to less asymmetric pricing in the German retail market, we identify the maximum and minimum prices within a local market – again 5 km radius – to which each fuel station belongs. We calculate the price range, which is the difference between the maximum and minimum price. The range denotes the maximum gross gain a consumer can attain within the local market following a complete search across all fuel stations. We then categorize fuel stations into *"low-"* and *"high-dispersion"* groups based on the distribution of the price range. That is, the *low-dispersion* group falls below the 25th percentile of stations while those above the 75th percentile are denoted as the *high-dispersion* group.

We again replicate the main results (Column (4) in Table 1) for these two groups. Since low price dispersion is associated with low payoff from price comparison, fuel stations in this group are expected to pass cost increases to consumers more easily. Hence, we expect the magnitude of the adjustment coefficient for cost increases ϕ^- in the case of *low-dispersion* group to be significantly larger than that of the *high-dispersion* group. The estimates for the long-run adjustments show that the *low-dispersion* long-run adjustment coefficients significantly exceed their *high-dispersion* counterparts in terms of magnitude ($\phi^+_{P25} = -0.057$, $\phi^-_{P25} = -0.121$ and $\phi^+_{P75} = -0.054$, $\phi^-_{P75} = -0.102$). The probability of the long-run adjustment parameters being equal for *high-* and *low-dispersion* stations is

less than 0.1%.[26] For cost increases, the estimates are consistent with search theory and point to a negative correlation between the degree of price dispersion and asymmetry. For cost decreases, on the other hand, the estimates are not consistent with the theory since $|\phi_{P25}^{+}|$ is greater than $|\phi_{P75}^{+}|$ and significant at all conventional levels.

Individual federal states. It is worth noting that the distribution of fuel stations, the footprint of different brands as well as sub-regional market structure vary across federal states. In terms of the density of fuel stations, for example, the state of North Rhine-Westphalia has 2,753 fuel stations in our sample, while Bremen as a federal city state has only 92 fuel stations. It is, therefore, possible that the asymmetry shown in Table 1 may be driven by a few individual federal states. To rule out this possibility, we conduct the prior analysis for subsamples consisting of all the 16 individual German federal states.

Table 2 shows the results for five federal states, selected based on special features, such as area, population, or status as federal city state. We do this to show the sensitivity of the results to different characteristics of the individual states.[27] Column (1) shows the results for Bavaria – the federal state with the largest area. In Column (2), the result for Berlin, which is both the capital city as well as one of the three federal city states is presented. The result for Bremen is shown in Column (3). Bremen is the federal state with the smallest population, area, and the lowest number of fuel stations. Column (4) presents the estimates for Hamburg, a federal city state that hosts one of the main ports in Germany. Last but not least, Column (5) shows the results for North Rhine Westphalia (NRW) – the state with the largest population and the highest number of fuel stations.

From the results in Table 2, we can conclude that the state-specific findings are fairly identical to the main findings presented in Table 1. With respect to the long-run adjustment coefficients, we find that both are significant at the 1% level but the magnitude differs across states, albeit without any distinctive pattern. We find a larger magnitude for the respective long-run adjustment parameters for Hamburg, while the estimates for Bavaria are smaller as compared to all other states. Across all states, the estimates show that the speed of convergence toward the long-run equilibrium is faster for negative deviations of retail prices from equilibrium – implying increasing crude oil price – than positive deviations. Moreover, the null hypothesis of symmetric long-run adjustment is rejected at the 1% level in all states. Accordingly, deviations from the long-run equilibrium margin are rapidly corrected when the margin shrinks than when it stretches which is consistent with the widespread public perception. The state-specific and national estimates underscore the pervasiveness of the rockets-and-feathers phenomenon in Germany.

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[26] $Pr(|\phi_{P25}^{+}| = |\phi_{P75}^{+}|) < 0.1\%$ and $Pr(|\phi_{P25}^{-}| = |\phi_{P75}^{-}|) < 0.1\%$ — Full results are available upon request.

[27] The estimates for the remaining states are shown in Table 11 the Appendix.

Table 2: Regression Results: Gasoline (E5) – Federal States

	(1) Bavaria (largest area)		(2) Berlin (Federal city state)		(3) Bremen (smallest area)		(4) Hamburg (Federal city state)		(5) North Rhine Westphalia (largest population)	
Dependent Variable: △ Retail Price of E5 Fuel										
ϕ^+	-0.076***	0.001	-0.106***	0.003	-0.087***	0.005	-0.114***	(0.009)	-0.102***	(0.002)
ϕ^-	-0.114***	0.002	-0.148***	0.003	-0.124***	0.005	-0.170***	(0.005)	-0.138***	(0.002)
Tuesday	0.186***	(0.005)	0.285***	(0.008)	0.361***	(0.015)	0.293***	(0.009)	0.114***	(0.004)
Wednesday	0.140***	(0.005)	0.216***	(0.008)	0.302***	(0.016)	0.255***	(0.010)	0.069***	(0.004)
Thursday	0.175***	(0.005)	0.174***	(0.009)	0.307***	(0.016)	0.304***	(0.012)	0.127***	(0.004)
Friday	0.223***	(0.006)	0.228***	(0.010)	0.412***	(0.018)	0.363***	(0.012)	0.164***	(0.005)
Saturday	0.402***	(0.010)	0.562***	(0.019)	0.469***	(0.034)	0.509***	(0.021)	0.310***	(0.007)
Sunday	0.700***	(0.015)	0.676***	(0.018)	0.894***	(0.032)	0.831***	(0.026)	0.635***	(0.011)
L1.△ Neighbor Prices (5km)	0.099***	0.003	0.235***	(0.008)	0.175***	(0.008)	0.194***	(0.012)	0.118***	(0.003)
Public Holiday										
$t+2$	0.155***	(0.004)	0.120***	(0.010)	0.157***	(0.021)	0.112***	(0.013)	0.180***	(0.003)
$t+1$	0.103***	(0.005)	0.138***	(0.010)	0.076***	(0.020)	0.138***	(0.013)	0.279***	(0.004)
t	0.547***	(0.013)	0.766***	(0.018)	0.866***	(0.039)	0.632***	(0.036)	0.509***	(0.011)
$t-1$	-0.158***	(0.006)	-0.248***	(0.010)	-0.363***	(0.026)	-0.246***	(0.013)	-0.155***	(0.005)
School Holiday Start										
$t+2$ (before)	0.124***	(0.006)	-0.123***	(0.010)	0.017	(0.026)	-0.085***	(0.012)	0.065***	(0.005)
$t+1$	0.060***	(0.006)	0.033***	(0.008)	0.202***	(0.024)	-0.067***	(0.017)	0.082***	(0.006)
t	0.063***	(0.005)	0.042***	(0.010)	0.006	(0.016)	-0.067***	(0.011)	0.013**	(0.005)
$t-1$ (after)	0.103***	(0.007)	0.079***	(0.009)	0.008	(0.021)	0.094***	(0.015)	0.130***	(0.005)
△ Rainfall	-0.002***	(0.001)	0.006***	(0.001)	0.016***	(0.004)	0.014***	(0.002)	-0.001**	(0.000)
△ Snow Depth	0.002	(0.001)	0.060***	(0.006)	-0.044**	(0.015)	-0.045***	(0.010)	-0.019***	(0.002)
△ Average Temperature	-0.030***	(0.002)	-0.060***	(0.004)	-0.076***	(0.009)	-0.019***	(0.005)	0.005**	(0.002)
F-Tests for Symmetry										
$\phi^+ = \phi^-$	408.14***		225.13***		38.21***		39.81***		629.95***	
$\beta_m^+ = \beta_m^-,\quad m \in [1,7]$	127.29***		37.39***		30.60***		41.49***		165.66***	
$\lambda_n^+ = \lambda_n^-,\quad n \in [0,7]$	847.69***		381.50***		100.50***		103.79***		2,069.75***	
Cointegration Parameter	1.073***		1.026***		0.966***		1.025***		1.033***	
Observations	2,961,268		509,849		161,300		371,231		4,731,795	
R^2	0.306		0.290		0.324		0.334		0.313	
Number of Fuel Stations	1,773		290		92		212		2,753	
Month/Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	

Notes: Constant term included but not shown. Standard errors, clustered with respect to fuel stations, are reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. *Public Holiday* denotes whether the corresponding day is a public holiday, which partly vary across German states. *School Holiday Start* refers to the first day of school holidays, which in Germany are individual to the 16 federal states. *Station Fixed Effects* refer to a set of indicator variables that take a value of 1 for each individual fuel station. *Month/Year Fixed Effects* refer to a set of control variables specific to each combination of month and year. See the main text for additional details on data construction and sources. For *F-Tests for Symmetry* the following null hypotheses are tested: *Long-run symmetry* tests whether the coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-run symmetry* tests $L(i).P^+ = L(i).P^-$ for all $i \in [1,7]$ with $F(7, 12319)$ degrees of freedom and $L(j).WP^+ = L(j).WP^-$ for all $j \in [0,7]$ with $F(8, 12319)$ degrees of freedom. The *Cointegration Parameter* refers to the pass-through coefficient (θ) for equation (3) and corresponds to the long-run cointegrating relationship between the retail price (p) and the crude oil price(wp).

We also note that the weekly patterns of price movements are approximately identical across states, i.e., with prices peaking on the weekend. This pattern is consistent with the nation-wide trend. The estimates further show that the effect of price changes in neighboring fuel stations is more pronounced in federal city states (or smaller states in general). For example, the estimates for Berlin (0.235), Bremen (0.179), or Hamburg (0.194) are considerably larger than those of Bavaria (0.098) or North Rhine-Westphalia (0.118). The public holiday effect is qualitatively identical across federal states, with the contemporaneous effect being stronger.

In the case of the start of school holidays, the pattern varies slightly across federal states and there are differences when compared to the national pattern in terms of the direction of the effect. In Bremen in particular, significant retail price changes occur only one day before the start of school holidays. In Hamburg, retail prices start to decline two days before the start of school holidays and increase a day after. In Berlin, retail prices decrease significantly two days before the start of school holidays. The retail price then increases from the day before until the day after the start of the school holiday. The estimates for Bavaria and North Rhine-Westphalia, on the other hand, follow the national trend.

Additionally, the impact of the daily changes in local weather conditions do not

appear to have a uniform effect across all states. While the national estimates for rain and snow are statistically insignificant, they are either negative or positive and significant in most cases. For the federal city states, the effect of changes in rainfall is positive and significant at the 1% level while for the large states with a high density of stations, the effect is negative. The effects of snow on retail price changes across the different states are mixed but generally points to an inverse relationship. The estimates also show that except for the state of NRW, the negative effect of increasing temperature on price changes is consistent with the national estimates. Note, however, that the effect of changes in weather conditions on fuel price changes might differ across states because of differences in modes of transportation and transport infrastructural networks.[28] The results should, therefore, be interpreted with caution, as they are most likely confounded by state-specific geographic or other local features not accounted for in our model.

Individual station-level time series.   The use of weekly or monthly time series data at the national level is a common practice in the extant literature, particularly in studies that relate to the retail fuel market in Germany. This is perhaps due to difficulties associated with obtaining station-level data. Notwithstanding, it is obvious that even for established brands with a nationwide network of fuel stations, the pricing decision is partly made at the station level taking into account local market conditions. As compared to previous studies, our analysis reflects station-level pricing decisions by drawing on station-level data instead of aggregate data. We have so far conducted our panel data analysis for the whole of Germany and all the 16 federal states in Germany. Since the response of retail prices to input cost changes at the station level could differ from the average response across a panel of stations, we further exploit our granular and extensive station-level dataset to investigate whether the average long-run asymmetric responses at the national and state levels also exist at the station level. To do this, we estimate a variant of the asymmetric error correction model in equation (5) for all the individual fuel stations in our sample.[29]

Focusing on just the long-run adjustment coefficients, we find that for 95.01% of the 11,787 fuel stations in our sample, retail gasoline prices respond asymmetrically in the long run to crude oil price changes. In contrast to the panel estimates in Tables 1–2, the type of asymmetry differs across the fuel stations. Specifically, the estimates show

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[28]Our estimation approach only partially controls out unique state-specific characteristics. There might therefore still be some other state-specific features related to the transport network that are not captured by our specification.

[29]For all 11,978 individual fuel stations that we consider in our sample, ADF unit root tests for the station-level retail price series show that the retail prices for only 170 fuel stations are stationary. These stations are excluded from this analysis. Out of the remaining 11,808 fuel stations, the residual-based cointegration test shows that for 99.87 % of the 11,808 fuel stations, the retail fuel prices are cointegrated with the crude oil price. We exclude the 21 fuel stations where the null hypothesis of no cointegration could not be rejected.

that for 88.42% of all the fuel stations, the response of retail prices to crude oil price changes follows the rockets-and-feathers pricing pattern. For the remainder of the fuel stations, we find either symmetric or negative asymmetric response. Since only a small proportion of stations exhibits a pricing pattern that signifies a high level of competition, i.e., symmetric or negative asymmetric adjustments, our analysis at the individual station level confirms the prevalence of the rockets-and-feathers phenomenon.

Table 3: Regression Results: Gasoline (E5) – Individual Stations (by brand)

Brand Name	(1)	(2)	(3)	(4)
		Type of Adjustment? (%)		
	Negative asymmetry	Rockets & Feathers	Symmetry	Σ
Aral	12.97	78.78	8.26	100
	(267)	(1,622)	(170)	(2,059)
Esso	1.71	95.73	2.56	100
	(16)	(896)	(24)	(936)
JET	4.22	92.21	3.57	100
	(26)	(568)	(22)	(616)
Shell	5.32	89.74	4.94	100
	(85)	(1,434)	(79)	(1,598)
Total	8.98	85.12	5.9	100
	(67)	(635)	(44)	(746)
bft	7.29	86.79	5.92	100
	(32)	(381)	(26)	(439)
star	3.64	93.13	3.23	100
	(18)	(461)	(16)	(495)
other	5.35	90.42	4.23	100
	(262)	(4,429)	(207)	(4,898)
Σ	6.56	88.45	4.99	100
	(773)	(10,426)	(588)	(11,787)

Notes:

The table shows the percentage of individual fuel station time series depending on whether $|\phi^+| > |\phi^-|$ (negative asymmetry), $|\phi^+| = |\phi^-|$ (symmetric adjustment) or $|\phi^+| < |\phi^-|$ (rockets and feathers). The absolute number of fuel stations is shown in parentheses.

The brands listed are those for which more than 500 fuel stations are listed in Germany. All others, including those assigned to *no brand*, are listed as *other*.

The results as shown in Tables 3 – 4 also depict differences in retail price response to input cost changes across different brands and federal states. Again, the results confirm the widespread existence of the rockets-and-feathers phenomenon across all branded and unbranded fuel stations. Particularly, we find that for major brands such as Esso, Star, and Jet, more than 90% of their respective fuel stations pass on input cost increases at a faster rate than input cost decreases. Compared to other brands, retail pricing appears to be more competitive for a significant proportion of fuel stations that belong to major brands such as Total, Aral and bft. For the individual federal states (see Table 4), the estimates also show that the rockets-and-feathers pricing pattern is more prevalent in the states of Saarland, Rhineland-Palatinate, and Baden-Württemberg. In the state of Thuringia and the three city-states – Berlin, Hamburg, and Bremen – on the other hand – we find a higher share of fuel stations with negative asymmetric adjustment or

Table 4: Regression Results: Gasoline (E5) – Individual Stations (by Federal State)

Federal State	(1)	(2) Adjustment? (%)	(3)	(4)
	Negative asymmetry	Rockets & Feathers	Symmetry	Σ
Baden-Württemberg	2.96	93.52	3.52	100
	(47)	(1,487)	(56)	(1,590)
Bavaria	3.56	92.82	3.62	100
	(62)	(1,615)	(63)	(1,740)
Berlin	10.69	83.79	5.52	100
	(31)	(243)	(16)	(290)
Brandenburg	7.65	85.63	6.73	100
	(25)	(280)	(22)	(327)
Bremen	10.87	83.70	5.43	100
	(10)	(77)	(5)	(92)
Hamburg	10	84.76	5.24	100
	(21)	(178)	(11)	(210)
Hesse	6.77	89.53	3.70	100
	(64)	(847)	(35)	(946)
Mecklenburg-Vorpommern	4.05	89.88	6.07	100
	(10)	(222)	(15)	(247)
Lower Saxony	6.64	87.6	5.76	100
	(91)	(1,201)	(79)	(1,371)
North Rhine-Westphalia	7.08	86.20	6.71	100
	(191)	(2,324)	(181)	(2,696)
Rhineland-Palatinate	2.48	95.05	2.48	100
	(15)	(576)	(15)	(606)
Saarland	2.13	96.45	1.42	100
	(3)	(136)	(2)	(141)
Saxony	6.75	87.58	5.66	100
	(31)	(402)	(26)	(459)
Saxony-Anhalt	8.76	86.50	4.74	100
	(24)	(237)	(13)	(274)
Schleswig-Holstein	9.63	85.27	5.11	100
	(49)	(434)	(26)	(509)
Thuringia	34.26	57.79	7.96	100
	(99)	(167)	(23)	(289)
Σ	6.56	88.45	4.99	100
	(773)	(10,426)	(588)	(11,787)

Notes:

The table shows the percentage of individual fuel station time series depending on whether $|\phi^+| > |\phi^-|$ (negative asymmetry), $|\phi^+| = |\phi^-|$ (symmetric adjustment) or $|\phi^+| < |\phi^-|$ (rockets and feathers). The absolute number of fuel stations is shown in parentheses.

symmetric response to input cost changes than all the other states. This could be due to the close proximity of fuel stations from one another, thereby increasing the degree of local competition.

4.2 Further Analyses

Aggregation over space: State-level time series. Since the dynamics of time series of heterogeneous fuel stations might be markedly different from those derived from spatially aggregated data, we ascertain whether the average adjustment process in Tables

1–2 are sensitive to spatial data aggregation. We calculate daily average prices for the whole of Germany and for the respective federal states and present the nationwide and state-level time series estimates in Columns (1) to (3) of Table 5.[30]

Table 5: Further Results: Gasoline (E5) – Spatial and Temporal Aggregation

	Spatial			Temporal			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
State	ϕ^+	ϕ^-	$\|\phi^+\| = \|\phi^-\|$	ϕ^+	ϕ^-	$\|\phi^+\| = \|\phi^-\|$	N
Whole Country	-0.043***	-0.106***	12.19***	-0.322***	-0.309***	174.24***	2,865,990
Baden-Württemberg	-0.046***	-0.121***	12.95***	-0.407***	-0.384***	74.41***	387,504
Bavaria	-0.050***	-0.099***	7.21***	-0.408***	-0.372***	207.02***	432,141
Berlin	-0.097***	-0.141***	2.68	-0.353***	-0.395***	49.65***	69,047
Brandenburg	-0.074***	-0.132***	5.31**	-0.350***	-0.366***	5.24**	80,125
Bremen	-0.114***	-0.199***	5.60**	-0.353***	-0.380***	7.95***	22,464
Hamburg	-0.122***	-0.156***	1.41	-0.443***	-0.399***	10.66***	50,047
Hesse	-0.037**	-0.125***	15.86***	-0.429***	-0.422***	2.72*	229,603
Mecklenburg-Vorpommern	-0.110***	-0.193***	8.32***	-0.463***	-0.441***	5.22**	58,719
Lower Saxony	-0.060***	-0.139***	12.75***	-0.433***	-0.412***	30.93***	331,685
North Rhine-Westphalia	-0.060***	-0.123***	9.52***	-0.467***	-0.460***	3.54*	651,889
Rhineland-Palatinate	-0.035**	-0.118***	17.00***	-0.430***	-0.426***	0.40	151,596
Saarland	-0.052***	-0.125***	10.49***	-0.416***	-0.404***	1.84	35,121
Saxony	-0.071***	-0.160***	14.81***	-0.466***	-0.458***	1.07	115,230
Saxony-Anhalt	-0.110***	-0.188***	7.28***	-0.424***	-0.433***	0.74	61,826
Schleswig-Holstein	-0.088***	-0.161***	8.29***	-0.431***	-0.403***	15.56***	118,661
Thuringia	-0.077***	-0.113***	2.94*	-0.475***	-0.452***	14.71***	70,332

Notes: *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. The number of observations for the spatial aggregation estimation is 1825 in all cases.

In Table 5, we show the long-run adjustment coefficients ϕ^+ and ϕ^- in Columns (1) and (2), and the F statistic for the null hypothesis of long-run symmetric adjustment is reported in Column (3). The long-run adjustment coefficients for Germany and the 16 individual federal states show that the absolute value of ϕ^- exceeds that of ϕ^+. The test for symmetric adjustment also shows that the difference between the two coefficients is statistically different from zero in 15 out of the 17 cases. That is, the only states in which the null hypothesis of symmetric adjustment cannot be rejected are Berlin and Hamburg. The rejection of the symmetric adjustment for the whole of Germany and 14 states is consistent with the results from the panel data and station-specific time series analyses. The results show that crude oil price changes that shrink the retail margin are passed on to consumers more swiftly than a corresponding price change that increases the margin. The findings show that the long-run rockets-and-feathers phenomenon is not sensitive to spatial data aggregation and holds for daily national or state-specific time series.

Aggregation over time: Average weekly prices across stations. We also examine whether temporal aggregation of station-level data matters with respect to the long-run adjustment of retail price response to input cost changes. To illustrate the sensitivity of the results to temporal data aggregation, we aggregate the *daily* station-level retail

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[30]Note that daily country- and state-level time series are non-stationary and cointegrated with the spot crude oil prices – results for unit root and cointegration tests are available upon request.

prices to station-level *weekly* prices. The results are presented in Table 5 (Columns 4-7). Focusing on the long-run speed of convergence, the findings differ from the previous results obtained by using daily data. In contrast to the national estimates in Table 1 and Columns 1-3 of Table 5, we find that the absolute value of the average long-run adjustment parameter for positive deviations is larger than that of negative deviations. The coefficients are also statistically different at the 1% level. This indicates that retail prices adjust more swiftly to crude oil price decreases than to crude oil price increases. For the state-specific estimates, symmetric adjustment towards the long-run equilibrium is rejected in 12 out of 16 cases. Out of the 12 states with asymmetric adjustments, the speed of adjustment towards the long-run equilibrium is faster for crude oil price decreases than price increases in 10 cases. We also find symmetric adjustment in 4 out of the 16 cases and the rockets-and-feathers pattern in only two states.

The results using station-level weekly panel data point primarily to a high degree of competition in the retail market and are consistent with recent findings in the empirical literature on the German market (Kristoufek and Lunackova, 2015; Asane-Otoo and Schneider, 2015; Bagnai and Ospica, 2016). The long-run speed of adjustments from the weekly data, however, diverge from those obtained using the daily station-level data. Our findings suggest that temporal data aggregation or the use of low frequency data are critical to the accurate assessment of the type of adjustment towards the long-run equilibrium.

4.3 Analysis for Diesel

Since gasoline and diesel are the main transport fuel types in Germany, we also repeated the analysis for diesel.[31] With respect to the national estimates in Table 9, the results for the long-run speed of convergence are consistent with the findings for gasoline (E5). In general, the rockets-and-feathers phenomenon is also confirmed in the case of diesel. The day-of-week, holiday, and neighboring price effects are all consistent with the findings for gasoline. Again, as evidenced by the estimates of the weather variables, the results for diesel also show that retail prices are influenced by changes in weather conditions but the effects –as in the case of gasoline – also differ across different states (see Table 10).

5 Conclusions

In this paper, we reexamine the perception that retail fuel prices respond more swiftly to crude oil price increases than decreases – a pricing pattern characterized as the *rockets-and-feathers* phenomenon. This is often associated with market inefficiencies

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[31]The main results are presented in Tables 9 - 10 in the Appendix and the remaining results are available upon request.

(e.g., collusion among retailers) and/or disparities in consumer search intensity following input cost changes. Our analyses explore the adjustment of retail fuel prices to crude oil price changes using a novel dataset of station-level daily retail prices for 11,978 fuel stations spanning the period January 1, 2014 to December 31, 2018. To the best of our knowledge, none of the previous studies in the rockets-and-feathers literature has examined the phenomenon using daily prices from virtually all geographically diverse fuel stations in a major OECD country. In addition to using these extensive and granular station-level retail price data, our analysis also accounts for the demand-side effects of changes in weather conditions, intra-week pricing patterns, holiday effects, as well as pricing decisions of neighboring fuel stations.

Contrary to recent findings for Germany, we find that asymmetric pricing is the norm rather than exception and the *rockets-and-feathers* phenomenon is very prevalent in the German retail fuel market. Specifically, we find evidence in support of the perception that input cost changes that squeeze the retail margin are passed on more swiftly to consumers than equivalent input cost change that increase firms' retail margins. On the one hand, this finding is surprising given the high level of market transparency and the reduced search cost for consumers since they can easily obtain price information across fuel stations in real time. On the other hand, the transparent nature of the retail market and the low search cost benefit not only consumers, but also firms, that can effortlessly compare prices both within and outside their local markets and adjust prices accordingly – making the potential for tacit collusion or price coordination more likely. In fact, our analysis shows not only that the pervasiveness of the rockets-and-feathers pattern might partly be due to disparities in search intensity, but also that price coordination among retailers might play a role.

Our findings also suggest that temporal aggregation of station-level data matters in assessing the type of long-run adjustment as there are substantial differences with respect to the type of adjustment exhibited by low- and high-frequency data. In essence, temporal aggregation obscures the nature of adjustment and can lead to inaccurate inferences. This might explain the diverse findings in the extant literature as well as why our results differ from recent findings, particularly for Germany. Overall, the granular and extensive nature of the data used in the empirical analysis permits a comprehensive analysis of the entire retail fuel market, including both rural and urban areas. This affords the opportunity to generalize our findings to typical national retail fuel markets.

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Appendix

Table 6: Descriptive Statistics

Variable	Stations	N.Obs.	Mean	S.D.	Min.	Max.
		Regression Sample				
p	11,978	20,398,729	140.912	10.171	88.800	194.900
wp	11,978	20,398,729	33.544	8.609	14.998	53.191
$\triangle p$	11,978	20,398,729	-0.007	1.470	-55.417	40.600
$\triangle wp$	11,978	20,398,729	-0.011	0.533	-2.773	2.584
$\triangle$ Neighbor Prices (5km)	11,978	20,398,729	-0.009	1.245	-30.667	56.900
Public Holiday	11,978	20,398,729	0.030	0.169	0	1
School Holiday Start	11,978	20,398,729	0.015	0.122	0	1
$\triangle$ Rainfall	11,978	20,398,729	0	1.210	-38.033	40.191
$\triangle$ Snow Depth	11,978	20,398,729	0	0.494	-357.188	357.188
$\triangle$ Average Temperature	11,978	20,398,729	0	0.307	-2.987	5.549
Reduced Sample: Stations for which p is $I(1)$ and cointegrated with wp						
p	11,787	20,179,154	140.924	10.173	88.800	194.900
wp	11,787	20,179,154	33.569	8.623	14.998	53.191
$\triangle p$	11,787	20,179,154	-0.007	1.466	-55.417	40.600
$\triangle wp$	11,787	20,179,154	-0.011	0.533	-2.773	2.584
$\triangle$ Neighbor Prices (5km)	11,787	20,179,154	-0.009	1.243	-30.667	33.000
Public Holiday	11,787	20,179,154	0.030	0.169	0	1
School Holiday Start	11,787	20,179,154	0.015	0.122	0	1
$\triangle$ Rainfall	11,787	20,179,154	0	1.210	-38.033	40.191
$\triangle$ Snow Depth	11,787	20,179,154	0	0.496	-357.188	357.188
$\triangle$ Average Temperature	11,787	20,179,154	0	0.307	-2.987	5.549

Table 7: Panel Unit Root Test for Retail Price

H_0: All panels contain unit roots			
H_a: At least one panel is stationary			

Number of Panels			11,978
Number of Periods		min	722
		mean	1,695
		max	1,813
		Statistic	p-Value
Inverse Normal	Z	67.18	1.000
Inverse Logit t()	L^*	60.60	1.000

Table 8: Panel Unit Root Test for Residuals from Cointegration Equation

H_0: All panels contain unit roots			
H_a: At least one panel is stationary			

Number of Panels:			11,978
Number of Periods:		min	722
		mean	1,696
		max	1,812
		Statistic	p-Value
Inverse Normal	Z	-349.37	0.000
Inverse Logit t()	L^*	-445.79	0.000

Table 9: Regression Results: Diesel – Germany

	(1) Baseline Specification		(2) Neighbor Effects		(3) Holiday Effects		(4) Weather Effects	
Dependent Variable: △ Retail Price of Diesel Fuel								
ϕ^+	-0.056***	(0.001)	-0.055***	(0.001)	-0.055***	(0.001)	-0.055***	(0.001)
ϕ^-	-0.122***	(0.001)	-0.122***	(0.001)	-0.121***	(0.001)	-0.121***	(0.001)
Tuesday	0.061***	(0.001)	0.124***	(0.002)	0.150***	(0.002)	0.150***	(0.002)
Wednesday	0.061***	(0.002)	0.096***	(0.002)	0.115***	(0.002)	0.115***	(0.002)
Thursday	0.130***	(0.002)	0.162***	(0.002)	0.159***	(0.002)	0.159***	(0.002)
Friday	0.167***	(0.002)	0.195***	(0.002)	0.212***	(0.002)	0.211***	(0.002)
Saturday	0.292***	(0.004)	0.320***	(0.004)	0.357***	(0.004)	0.356***	(0.004)
Sunday	0.603***	(0.005)	0.623***	(0.005)	0.653***	(0.006)	0.653***	(0.006)
L1.△ Neighbor Prices (5km)			0.111***	(0.001)	0.111***	(0.001)	0.111***	(0.001)
Public Holiday								
t+2					0.187***	(0.002)	0.187***	(0.002)
t+1					0.169***	(0.002)	0.169***	(0.002)
t					0.570***	(0.005)	0.569***	(0.005)
t-1					-0.147***	(0.002)	-0.147***	(0.002)
School Holiday Start								
t+2					0.052***	(0.002)	0.051***	(0.002)
t+1					0.007**	(0.002)	0.008***	(0.002)
t					0.036***	(0.002)	0.036***	(0.002)
t-1					0.074***	(0.002)	0.074***	(0.002)
△ Rainfall							-0.001***	(0.000)
△ Snow Depth							0.002**	(0.001)
△ Average Temperature							-0.024***	(0.001)
F-Tests for Symmetry								
$\phi^+ = \phi^-$	6,043.30***		7,021.63***		6,959.91***		6,957.61***	
$\beta_m^+ = \beta_m^-, \quad m \in [1,7]$	621.79***		618.31***		599.77***		599.48***	
$\lambda_n^+ = \lambda_n^-, \quad n \in [0,7]$	4,164.28***		4,135.33***		3,144.11***		3,150.18***	
Cointegration Parameter	1.246***		1.246***		1.246***		1.246***	
Observations	20,428,731		20,428,731		20,428,731		20,428,731	
R^2	0.304		0.309		0.314		0.314	
Number of Fuel Stations	11,984		11,984		11,984		11,984	
Month/Year Fixed Effects	Yes		Yes		Yes		Yes	

Notes: Constant term included but not shown. Standard errors, clustered with respect to fuel stations, are reported in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. *Public Holiday* denotes whether the corresponding day is a public holiday, which vary to some extent across German states. *School Holiday Start* refers to the first day of school holidays, which in Germany are specific to the 16 federal states. *Station Fixed Effects* refer to a set of indicator variables that take a value of 1 for each individual fuel station. *Month/Year Fixed Effects* refer to a set of control variables specific to each combination of month and year. See the main text for additional details on data construction and sources.

For *F-Tests for Effect Symmetry* the following null hypotheses are tested: *Long-Run Symmetry* tests whether the coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-Run Symmetry* tests $L(i).P^+ = L(i).P^-$ for all $i \in [1,7]$ with $F(7, 12319)$ degrees of freedom and $L(j).WP^+ = L(j).WP^-$ for all $j \in [0,7]$ with $F(8, 12319)$ df.

The *Cointegration Parameter* refers to the coefficient estimate of θ for equation (3) and corresponds to the long-run cointegrating relationship between p and wp.

Table 10: Regression Results: Diesel – Federal States

	(1) Bavaria (largest area)		(2) Berlin (Federal city state)		(3) Bremen (smallest area)		(4) Hamburg (Federal city state)		(5) North Rhine Westphalia (largest population)	
Dependent Variable: △ Retail Price of Diesel Fuel										
ϕ^+	-0.075***	(0.002)	-0.136***	(0.004)	-0.150***	(0.009)	-0.120***	(0.015)	-0.088***	0.002
ϕ^-	-0.121***	(0.002)	-0.156***	(0.004)	-0.100***	(0.005)	-0.175***	(0.007)	-0.137***	0.002
Tuesday	0.199***	(0.005)	0.259***	(0.008)	0.333***	(0.015)	0.218***	(0.008)	0.113***	0.004
Wednesday	0.157***	(0.005)	0.218***	(0.008)	0.284***	(0.016)	0.209***	(0.010)	0.091***	0.004
Thursday	0.197***	(0.005)	0.190***	(0.009)	0.313***	(0.017)	0.314***	(0.012)	0.159***	0.004
Friday	0.255***	(0.006)	0.298***	(0.010)	0.387***	(0.018)	0.324***	(0.013)	0.198***	0.005
Saturday	0.439***	(0.010)	0.529***	(0.021)	0.443***	(0.037)	0.471***	(0.023)	0.336***	0.007
Sunday	0.715***	(0.015)	0.654***	(0.019)	0.857***	(0.035)	0.857***	(0.025)	0.655***	0.011
L1.△ Neighbor Prices (5km)	0.094***	(0.003)	0.217***	(0.009)	0.184***	(0.009)	0.135***	(0.013)	0.110***	0.003
Public Holiday										
$t+2$	0.194***	(0.004)	0.081***	(0.008)	0.127***	(0.019)	0.120***	(0.014)	0.179***	0.003
$t+1$	0.101***	(0.004)	0.207***	(0.014)	0.144***	(0.017)	0.134***	(0.013)	0.244***	0.004
t	0.538***	(0.013)	0.785***	(0.023)	0.921***	(0.044)	0.649***	(0.038)	0.549***	0.011
$t-1$	-0.167***	(0.005)	-0.265***	(0.010)	-0.310***	(0.031)	-0.240***	(0.012)	-0.195***	0.005
School Holiday Start										
$t+2$	0.092***	(0.006)	-0.098***	(0.012)	-0.009	(0.019)	-0.089***	(0.013)	0.046***	0.005
$t+1$	0.023***	(0.005)	-0.124***	(0.011)	0.090***	(0.023)	-0.080***	(0.017)	0.046***	0.006
t	0.028***	(0.006)	0.010	(0.008)	-0.095***	(0.017)	0.034**	(0.012)	-0.024***	0.004
$t-1$	-0.088***	(0.006)	0.179***	(0.009)	0.070**	(0.021)	0.182***	(0.013)	0.066***	0.005
△ Rainfall	-0.004***	(0.001)	0.008***	(0.001)	0.000	(0.004)	0.010***	(0.002)	-0.002***	0.000
△ Snow Depth	0.006***	(0.002)	0.103***	(0.006)	-0.072***	(0.015)	-0.014	(0.010)	-0.017***	0.002
△ Average Temperature	-0.021***	(0.002)	-0.048***	(0.006)	-0.102***	(0.010)	-0.058***	(0.006)	-0.017***	0.002
F-Tests for Effect Symmetry										
$\phi^+ = \phi^-$	534.46***		31.08***		28.52***		12.95***		783.36***	
$\beta_m^+ = \beta_m^-, \quad m \in [1,7]$	139.92***		48.44***		18.02***		28.74***		188.67***	
$\lambda_n^+ = \lambda_n^-, \quad n \in [0,7]$	509.94***		175.76***		64.05***		78.44***		869.72***	
Cointegration Parameter	1.271***		1.230***		1.172***		1.251***		1.240***	
Observations	2,968,641		510,058		161,619		371,050		4,732,928	
R^2	0.320		0.309		0.335		0.372		0.333	
Number of Fuel Stations	1,777		290		92		212		2,752	
Month/Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	

Notes: Constant term included but not shown. Standard errors, clustered with respect to fuel stations, are reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. *Public Holiday* denotes whether the corresponding day is a public holiday, which vary to some extent across German states. *School Holiday Start* refers to the first day of school holidays, which in Germany are specific to the 16 federal states. *Station Fixed Effects* refer to a set of indicator variables that take a value of 1 for each individual fuel station. *Month/Year Fixed Effects* refer to a set of control variables specific to each combination of month and year. See the main text for additional details on data construction and sources.

For *F-Tests for Effect Symmetry* the following null hypotheses are tested: *Long-Run Symmetry* tests whether the coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-Run Symmetry* tests $L(i).P^+ = L(i).P^-$ for all $i \in [1,7]$ with $F(7, 12319)$ degrees of freedom and $L(j).WP^+ = L(j).WP^-$ for all $j \in [0,7]$ with $F(8, 12319)$ *df*.

The *Cointegration Parameter* refers to the coefficient estimate of θ for equation (3) and corresponds to the long-run cointegrating relationship between p and wp.

Table 11: Regression Results: Gasoline (E5) – Federal States (Full)

	(1) Baden-Württemberg	(2) Brandenburg	(3) Hesse	(4) Mecklenburg-Vorpommern	(5) Lower Saxony	(6) Rhineland-Palatinate	(7) Saarland	(8) Saxony	(9) Saxony-Anhalt	(10) Schleswig-Holstein	(11) Thuringia
Dependent Variable: Δ Retail Price of E5 Fuel											
ϕ^+	-0.081*** (0.002)	-0.077*** (0.006)	-0.072*** (0.002)	-0.106*** (0.006)	-0.089*** (0.003)	-0.070*** (0.002)	-0.076*** (0.003)	-0.111*** (0.006)	-0.111*** (0.006)	-0.103*** (0.005)	-0.097*** (0.005)
ϕ^-	-0.125*** (0.002)	-0.132*** (0.005)	-0.116*** (0.003)	-0.156*** (0.006)	-0.135*** (0.003)	-0.118*** (0.004)	-0.133*** (0.006)	-0.150*** (0.007)	-0.160*** (0.005)	-0.154*** (0.005)	-0.115*** (0.005)
Tuesday	0.161*** (0.006)	0.201*** (0.011)	0.234*** (0.008)	0.088*** (0.010)	0.090*** (0.005)	0.094*** (0.007)	0.216*** (0.015)	0.179*** (0.010)	0.179*** (0.013)	0.117*** (0.008)	0.133*** (0.013)
Wednesday	0.137*** (0.006)	0.206*** (0.011)	0.210*** (0.007)	0.012 (0.012)	0.031*** (0.005)	0.074*** (0.007)	0.181*** (0.014)	0.172*** (0.010)	0.129*** (0.014)	0.062*** (0.010)	0.058*** (0.014)
Thursday	0.171*** (0.006)	0.197*** (0.013)	0.241*** (0.008)	0.091*** (0.011)	0.062*** (0.005)	0.078*** (0.008)	0.218*** (0.014)	0.158*** (0.011)	0.118*** (0.015)	0.094*** (0.010)	0.045** (0.015)
Friday	0.230*** (0.006)	0.213*** (0.015)	0.266*** (0.008)	0.060*** (0.013)	0.141*** (0.006)	0.118*** (0.009)	0.211*** (0.015)	0.177*** (0.011)	0.169*** (0.013)	0.093*** (0.016)	0.120*** (0.015)
Saturday	0.405*** (0.010)	0.415*** (0.021)	0.467*** (0.012)	0.230*** (0.022)	0.207*** (0.009)	0.267*** (0.014)	0.467*** (0.030)	0.360*** (0.020)	0.159*** (0.021)	0.128*** (0.025)	0.300*** (0.019)
Sunday	0.800*** (0.016)	0.895*** (0.031)	0.853*** (0.019)	0.350*** (0.029)	0.494*** (0.014)	0.449*** (0.021)	0.651*** (0.036)	0.721*** (0.025)	0.350*** (0.033)	0.356*** (0.030)	0.459*** (0.042)
L1.Δ Neighbor Prices (5km)	0.108*** (0.003)	0.102*** (0.007)	0.130*** (0.006)	0.101*** (0.005)	0.106*** (0.004)	0.094*** (0.007)	0.121*** (0.006)	0.124*** (0.007)	0.145*** (0.010)	0.129*** (0.005)	0.107*** (0.007)
Public Holiday											
$t+2$	0.144*** (0.004)	0.202*** (0.008)	0.137*** (0.005)	0.229*** (0.013)	0.178*** (0.005)	0.186*** (0.006)	0.083*** (0.011)	0.114*** (0.007)	0.115*** (0.009)	0.150*** (0.009)	0.226*** (0.010)
$t+1$	0.152*** (0.005)	0.018* (0.008)	0.164*** (0.007)	0.240*** (0.012)	0.109*** (0.006)	0.168*** (0.008)	0.100*** (0.015)	0.120*** (0.007)	0.161*** (0.011)	0.145*** (0.010)	0.235*** (0.013)
t	0.589*** (0.016)	0.796*** (0.031)	0.689*** (0.017)	0.520*** (0.023)	0.490*** (0.013)	0.405*** (0.017)	0.418*** (0.033)	0.512*** (0.023)	0.452*** (0.041)	0.333*** (0.025)	0.589*** (0.045)
$t-1$	-0.130*** (0.006)	-0.113*** (0.010)	-0.182*** (0.008)	0.007 (0.013)	-0.107*** (0.007)	-0.112*** (0.009)	-0.105*** (0.015)	-0.089*** (0.009)	-0.099*** (0.015)	-0.034* (0.013)	-0.047** (0.017)
School Holiday Start											
$t+2$	0.157*** (0.006)	-0.004 (0.013)	0.089*** (0.009)	-0.039*** (0.010)	0.098*** (0.006)	-0.065*** (0.009)	0.082*** (0.024)	-0.042*** (0.009)	0.079*** (0.013)	-0.068*** (0.010)	0.149*** (0.011)
$t+1$	-0.010 (0.007)	0.097*** (0.014)	-0.071*** (0.010)	0.118*** (0.012)	0.011 (0.006)	0.033*** (0.009)	-0.083*** (0.020)	0.063*** (0.010)	0.250*** (0.014)	0.037*** (0.011)	0.078*** (0.014)
t	0.110*** (0.006)	-0.050*** (0.010)	0.060*** (0.009)	0.164*** (0.016)	0.057*** (0.005)	0.063*** (0.008)	0.103*** (0.018)	0.071*** (0.010)	0.032** (0.012)	-0.023* (0.009)	0.183*** (0.016)
$t-1$	0.146*** (0.007)	0.123*** (0.012)	0.091*** (0.009)	0.144*** (0.015)	0.154*** (0.006)	0.101*** (0.009)	0.011 (0.018)	0.062*** (0.009)	0.174*** (0.019)	0.079*** (0.011)	0.173*** (0.013)
Δ Rainfall	0.002** (0.001)	-0.001 (0.001)	-0.003* (0.001)	0.001 (0.002)	0.002** (0.001)	0.001 (0.001)	-0.003* (0.002)	-0.002 (0.001)	0.005** (0.002)	-0.002 (0.001)	-0.003* (0.001)
Δ Snow Depth	-0.004 (0.002)	-0.003 (0.002)	-0.043*** (0.004)	-0.030*** (0.005)	0.026*** (0.004)	-0.030*** (0.005)	-0.070*** (0.009)	0.008* (0.003)	0.033*** (0.007)	0.003*** (0.001)	0.018*** (0.004)
Δ Average Temperature	-0.014*** (0.003)	-0.049*** (0.005)	0.001 (0.003)	0.052*** (0.005)	-0.038*** (0.002)	-0.035*** (0.003)	-0.060*** (0.007)	-0.014*** (0.004)	-0.021*** (0.005)	-0.038*** (0.004)	-0.015** (0.005)
F-Tests for Symmetry											
$\phi^+ = \phi^-$	452.84***	86.85***	266.59***	118.83***	509.22***	256.38***	137.22***	59.42***	50.01***	254.57***	7.58***
$\beta_m^+ = \beta_m^-$, $m \in [1,7]$	116.96***	50.32***	87.49***	17.74***	35.94***	36.88***	36.90***	43.28***	35.81***	11.34***	20.50***
$\lambda_n^+ = \lambda_n^-$, $n \in [0,7]$	1,035.06***	189.34***	674.12***	126.62***	722.04***	382.05***	98.70***	256.97***	96.69***	166.48***	114.56***
Cointegration Parameter	1.058***	1.021***	1.043***	1.016***	1.01***	1.077***	1.045***	1.029***	1.046***	1.046***	1.045***
Observations	2,717,507	577,249	1,637,840	435,561	2,340,940	1,049,242	238,463	808,055	463,775	890,467	504,187
R^2	0.324	0.340	0.317	0.268	0.280	0.273	0.301	0.319	0.274	0.271	0.292
Number of Fuel Stations	1,611	332	960	249	1,390	622	142	462	280	515	295
Month/Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Constant term included but not shown. Standard errors, clustered with respect to fuel stations, are reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level. *Public Holiday* denotes whether the corresponding day is a public holiday, which partly vary across German states. *School Holiday Start* refers to the first day of school holidays, which in Germany are individual to the 16 federal states. *Month/Year Fixed Effects* refer to a set of control variables specific to each combination of month and year. See the main text for additional details on data construction and sources. For *F-Tests for Effect Symmetry* the following null hypotheses are tested: *Long-run symmetry* tests whether the coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-run symmetry* tests $L(i).P^+ = L(i).P^-$ for all $i \in [1,7]$ with $F(7, 12319)$ degrees of freedom and $L(j).WP^+ = L(j).WP^-$ for all $j \in [0,7]$ with $F(8, 12319)$ df.

The *Cointegration Parameter* refers to the coefficient estimate of θ for equation (3) and corresponds to the long-run cointegrating relationship between p and wp.

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