Rockets and Feathers Revisited: Asymmetric Retail Gasoline Pricing in the Era of Market Transparency

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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 data set that includes daily retail prices of gasoline from 12,804 stations in Germany from January 1, 2014 to December 31, 2018. Our findings based on pooled-panel asymmetric error correction models indicate that the pattern of rockets and feathers is the norm rather than the exception. Our results further show that temporal aggregation of station-level price data leads to inaccurate inferences and could account for the inconclusive findings in the literature.

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

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1. INTRODUCTION

This paper revisits the debate on the asymmetric response of retail gasoline prices to crude oil price changes. Retail fuel pricing, in general, remains an area of significant interest for motorists, the media, and regulatory authorities in many countries. This is partly due to the widespread and persistent public perception that oil companies are quick to adjust retail prices and profit margins in response to input cost *increases* rather than *decreases*—a behavior characterized as the *rockets and feathers* phenomenon (Bacon, 1991). This pricing pattern leads to consumers' welfare losses since they do not benefit from price changes possible under symmetric adjustment conditions.

Consequently, the retail segment of the fuel market, in particular, has been the subject of regulatory and antitrust scrutiny in many countries, in some cases resulting in charges, convictions, and hefty fines.[1] For Germany, the Federal Cartel Office (FCO) conducted an inquiry in 2008 in response to consumer concerns and found a dominant oligopoly that consists of five firms—BP (Aral), ConocoPhillips (Jet), ExxonMobil (Esso), Shell, and Total. The oligopoly possesses not only a nationwide network of stations but also has significant access to refinery capacity that further amplifies their collective dominance and market power (German Federal Cartel Office, 2011). Among others, this finding instigated the implementation of a price transparency regulation in 2013 that permits consumers to access real-time station-level prices.

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

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Besides the public interest and scrutiny by antitrust agencies, asymmetric retail pricing has also been the subject of intensive research (see Eckert, 2013; Periguero-Garía, 2013). However, the empirical evidence is inconclusive. The diverse findings can partly be attributed to temporal and spatial aggregation of price data (Bachmeier and Griffin, 2003; Faber, 2015). On the one hand, an aggregation that yields low-frequency price data neither adequately reflects short-run input cost changes nor the frequency of price decisions at the station level. Since station-level prices change several times within a given day, the frequency of price adjustment to input cost shocks or daily price volatilities cannot be detected using weekly or monthly data. On the other hand, an aggregation across stations that results in average prices at either the national, regional, or city level ignores station-specific characteristics and obvious heterogeneity, such as differences in pricing strategy, local competition, and demographic features of the market. These forms of aggregation could compromise the validity of estimations since time series of heterogeneous 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).

This paper examines asymmetric cost pass-through in the retail gasoline market using pooled-panel asymmetric error correction models based on a unique panel of daily E5 gasoline (i.e., with 5% bioethanol) price data that spans the vast majority of stations in Germany. The panel data from January 1, 2014, to December 31, 2018, for 12,804 stations allow us to include geographically diverse stations in rural and urban areas. Therefore, our analysis provides a complete representation of retail market competition and goes beyond the *representative agent* assumption implicit in most empirical studies. The spatial and temporal dimensions of the data also permit us to investigate the effect of aggregation on the type of asymmetry. Moreover, the analysis accounts for the price effects of spatial or local competition and demand-side fluctuations caused by the occurrence of holidays and changes in local weather conditions.

Our analysis points to a pervasive *rockets and feathers* pattern in the German gasoline market—both across brands and stations in areas of different population density. We also find that temporal data aggregation matters, as this form of aggregation yields inaccurate inferences. The results suggest that it is insufficient to abstract from determinants other than crude oil prices—as done in previous studies—when examining the rockets and feathers pattern. Given that other demand-side factors and local weather conditions are inherent in the pricing decisions, a precise model specification that accounts for these drivers is required to explain the observed price changes.

The remainder of the paper is organized as follows. Section 2 offers a concise summary of the recent literature on the retail gasoline market in Germany, while section 3 provides a brief description of the retail market and the data used for the analysis. Section 4 outlines the empirical strategy, section 5 presents the results and discussion, and section 6 concludes.

2. RELATED LITERATURE

Competition and price-setting behavior in the retail fuel market have been the focus of extensive empirical research. The literature on this subject can be categorized broadly into those that examine the determinants of retail prices, on the one hand, and those investigating price dynamics, on the other hand (see Eckert, 2013, for a comprehensive review of the different strands of the empirical literature). Empirical literature that focuses on price determinants for Germany includes those that evaluate the impact of regulatory changes on retail prices (Dewenter et al., 2017; Eibelshäuser and Wilhelm, 2017), the impact of station-specific characteristics (Haucap et al., 2017), duopoly price rivalry (LeSage et al., 2017), differential cost pass-through among major brands (Kihm et al., 2016), and the impact of local market structure (Haucap et al., 2016).

A strand of the price dynamics literature explores different aspects of recurring Edgeworth cycles (Maskin and Tirole, 1988). For Germany, Siekmann (2017) draws on a large-scale data set similar to ours to investigate recurring Edgeworth cycles and finds evidence of intra-day cycles across municipalities with cycle asymmetry and intensity more pronounced in concentrated markets. Other recent studies that employ station-level price data to investigate asymmetric price cycles in the German context include Eibelshäuser and Wilhelm (2018), Wilhelm (2019), and de Haas (2019).

Another type of price dynamics that has received considerable attention in the literature is the asymmetric response of retail prices to upstream price changes. Regarding the underlying causes, market power exploitation or tacit collusion among retailers has gained traction as a plausible driver of asymmetric pass-through of input cost changes to retail prices. Earlier studies in this research line, such as Borenstein et al. (1997), motivate the rockets and feathers pattern with a stylized version of the *trigger price* model of oligopolistic coordination (Green and Porter, 1984).[2] Although rigorous theory underlying tacit collusion as a profit-maximizing strategy for retailers is limited, empirical evidence lends credence to this hypothesis (Verlinda, 2008; Lewis, 2011).

However, in a perfectly competitive market, firms earn zero profits, and input cost changes are transmitted to consumers symmetrically. This market outcome changes when consumers have imperfect information about prices, and a significant proportion of consumers have positive search costs. In this case, firms can extract information rent from consumers. A general result from the theoretical search-based literature is that firms' asymmetric price response to input cost changes emerges naturally due to consumer search behavior. However, the models offer different mechanisms through which consumers' search efforts relate to asymmetric pricing by firms.

For example, Lewis (2011) argues that for consumers with adaptive expectations of prices, rising input costs reduce the expected price distribution and cause consumers to intensify search more than they otherwise would. In essence, consumers search more actively when prices are increasing than decreasing, resulting in asymmetric price response by firms. This assertion is consistent with Cabral and Gilbukh (2020) finding that consumers search more when prices are high or increasing. Empirical evidence by Hastings and Shapiro (2013) has validated these results by showing the increased sensitivity of consumers to price increases.

In contrast, Yang and Ye (2008) and Tappata (2009) suggest that consumers' searching activities can result in asymmetric pricing if the incentive to search for better prices is high when input costs are low. Although consumers have imperfect knowledge of firms' input costs, they learn whether the input costs are high or low through search activities and purchasing decisions. Accordingly, retail prices are expected to be more dispersed at low input costs, and consumers with positive search costs anticipate higher gains from increased search activities. However, at high input costs, price dispersion decreases as firms have less flexibility in setting prices, and the benefit from search and search intensity declines. At this level, if an unexpected negative cost shock occurs, firms may have less incentive to adjust retail prices to reflect the cost changes due to the reduced search intensity. In this case, asymmetric search intensity leads to consumers being less knowledgeable about input cost decreases and enables firms to extract information rent in the short-run.

Despite the increased traction of market power and search-based theories, the empirical findings are inconclusive (Periguero-Garía, 2013). For the German retail gasoline market, studies

2. Asymmetric pricing due to tacit collusion exists not only in oligopolistic markets but also in competitive markets (see Balke et al., 1998).

based on weekly (e.g., Kristoufek and Lunackova, 2015; Asane-Otoo and Schneider, 2015) and monthly data (e.g., Bagnai and Ospica, 2016) follow a similar trend in terms of the findings being inconclusive. Frondel et al. (2020), however, employs daily E10 gasoline (i.e., with 10% bioethanol) prices from January 2014 to November 2015 for 5,650 stations and observe a negative asymmetry in the retail gasoline market. The authors draw on a search model by Yang and Ye (2008) and attribute this finding – connoting increased retail competition level – to the high proportion of consumers with low search cost following the price transparency regulation in 2013.

Note, however, that previous empirical studies—except Frondel et al. (2020)—might be vulnerable to aggregation bias which could cast doubt on the validity of estimates. Obviously, not all stations or even stations belonging to the same brand follow the same pricing strategy due to differences in local competitions or market structure. Consequently, price changes may not only occur as a result of input cost changes. Moreover, the nature and extent of asymmetry might also be sensitive to local market conditions. Our analysis provides a comprehensive overview of retail gasoline market competition by taking into account these drawbacks.

3. MARKET AND DATA

3.1 German Fuel Market and Station-Level Data

Fuel prices and, more generally, the fuel market, have long been a subject of intense public debate, mostly because of their relevance to commuters. The public discourse in Germany ranges from discussion of price increases during holiday and vacation seasons (especially in summer) to suspicion of price coordination. While some concerns and accusations are directed at the government, others are leveled against brands and their respective stations. Gasoline and diesel are the primary fuel types sold by stations in Germany. 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 has been rather low compared to E5, which accounts for approximately 85% of fuel sales in Germany (BDBe, 2017).

Like retail gasoline markets in other countries, only a small number of brands operate a large retail market share. Our data show that 49.7% of stations are run by Aral (15.4%), Shell (11.8%), Esso (6.9%), Total (5.8%), AVIA (5.4%), or JET (4.4%). Another 22.4% of stations are run by 9 other brands, while 61 smaller or independent brands operate the remaining 27.9%. This distribution reflects a concentration of market shares among the major brands. These market shares do not consider station-specific heterogeneity, e.g., sales volume and revenues, the number of pumps, opening hours, location (i.e., near a motorway or major road), or other services such as car washes, which might contribute to further market concentration (Haucap et al., 2017). Accordingly, the FCO considers the five largest brands to have formed an oligopoly as they serve more than 70% of demand (German Federal Cartel Office, 2011).

Gasoline products sold at the various stations are fairly identical, and the high degree of product homogeneity signals the vital role of prices in the retail market. Station operators and brands are entirely responsible for all pricing decisions, and the degree and frequency of price changes are not regulated.[3] Stations are, however, obliged to report all price changes for Super E5, Super E10, and regular diesel fuel to the FCO's market transparency unit (MTU) prior to an effective price change. The price information is then transmitted to information service providers or platforms,

3. 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.

who then make it available to consumers on their websites or apps for free.[4] This regulation has significantly improved the degree to which consumers can compare real-time prices across stations and considerably reduced the search cost. At the same time, it has also improved retailers' capability to compare competitors' prices, both within and outside their local market, resulting in an increased frequency of adjustment (BMWi, 2018). Our analysis relies on this comprehensive and unique data set covering all stations with exact time stamps for all price quotes.

Given that stations face no restrictions on the frequency of intra-day price changes, there may be multiple observations for a station per day. We, therefore, calculate daily averages to assess inter-day price variations. 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, and a fee for the Petroleum Stockholding Association. For the period starting from January 1, 2014, to December 31, 2018, we observe daily prices for a total of 15,228 distinct stations.[5] As illustrated in Figure 2 (see appendix), stations are widely but unevenly distributed across cities and regions. The map shows a distinct gradient between the east and west of Germany, and there is a high concentration of stations in densely populated areas and along the highway network.

In addition to the retail price data, the MTU data set also provides station-specific data such as opening and closing hours, geographical coordinates, and brand affiliation—of which we identify about 70 distinct brands. 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.[6]

3.2 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 prices for neighboring stations in our model specification. As stations adapt their prices to 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 stations within 5 km. For each station, the complete address and the georeferenced coordinates are available, so that the exact location is known. This information makes it possible to compute the linear distance or great-circle distance in kilometers between the stations using the Haversine formula—see equation (5) in the appendix.

The MTU database not only permits 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 gasoline needed, or generally, if there is time pressure. Using the linear or *beeline* distance measure corresponds to a very simplified scenario since it does not necessarily portray the behavior of customers with local knowledge, who are aware of actual driving routes and distances.

4. Notable examples include www.clevertanken.de, www.spritmonitor.de, or www.bottledsoftware.de.

5. The market transparency unit became operational as early as September 2013, but technical difficulties in the early stage led to missing observations and incomplete data. The data also capture stations that are out of business or entered the market during the observation period.

6. See, https://www.imf.org/external/np/fin/ert/GUI/Pages/CountryDataBase.aspx.

However, this approach is intuitive and applies mainly to *a priori* distance filters on price comparison websites or apps. The average of neighbor prices is calculated using their inverse distances as weights.[7]

3.3 Public and School Holiday Data

Other potential determinants of price changes that are often mentioned in the public discussions are public and school holidays. These periods are likely to affect pricing 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 affect demand and overall fuel consumption. There are nine national public holidays every year, and about eight other public holidays are unique to individual or groups of federal states. For school holidays, the beginning and duration for the individual federal states vary each year to mitigate effects on traffic, demand for vehicular fuel, and leisure activities.

3.4 Weather Data

To further understand the station-level pricing behavior, it is worth considering possible determinants of demand. Generally, petroleum products processed in refineries, such as heating oil and gas, are subject to cyclical demand fluctuations, with significant implications for refined products' wholesale price (Chouinard and Perloff, 2007; Mu, 2007). Regarding gasoline, in particular, regional heterogeneity of demand elasticities is sometimes attributed to weather conditions (Liu, 2014; Arzaghi and Squalli, 2015). However, these studies fail to confirm this hypothesis empirically, mainly due to shortcomings in the data.[8]

Apart from reflecting seasonality, local weather conditions play a pivotal role in the day-to-day choice of transportation mode. Böcker et al. (2013) conclude that favorable weather conditions promote active modes of transportation, e.g., walking or cycling. In contrast, commuters tend to switch to motorized transport, e.g., individual driving or public services, when experiencing adverse weather conditions, mainly for convenience and perceived safety. Several authors have shown that adverse weather conditions such as rainfall or snow tend to increase traffic and lead to increased travel times due to congested roads (Koetse and Rietveld, 2009; Rakha et al., 2012; Tsapakis et al., 2013). Liu et al. (2015) and Singhal et al. (2014) also show that individuals react to weather variability differently, mainly depending on their commuter status.

We obtain daily data on weather conditions from the European Climate Assessment and Dataset (ECA&D) (Klein Tank et al., 2002). In total, the data set contains information on 5,617 meteorological stations, which record observations, including mean ambient temperature, rainfall amount, and snow depth.[9] Data availability for the different measures varies across stations, i.e., some stations have data on all three measures while others have few. 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 20 nearest

7. See appendix for details on the calculation of the neighborhood average prices.

8. While Liu (2014) has no explicit measure for weather variability across U.S. federal states, Arzaghi and Squalli (2015) find no significant impact of temperature on gasoline demand in a panel data set of 32 countries.

9. We use the station-level daily mean ambient temperature (t_g) to calculate heating degree days—HDD = max(0,15.5-t_g)—and cooling degree days—CDD = max(0,t_g–15.5)—using 15.5 C as the base temperature for Europe.

neighboring weather stations is averaged using inverse linear distances as weights to approximate the local weather conditions.[10]

4. ESTIMATION

To investigate the response of retail prices at the station level to crude oil price changes, we first examine the degree of integration of the price series. Our retail price data set covers 15,228 individual stations observed over 1,825 days. Among these, only stations with at least two years of data are employed in the regression sample to ensure a sufficient number of observations per station. Overall, we observe 21,781,789 data points across 12,804 stations. We adopt two strategies in testing the order of integration of the price series. First, we apply the Augmented Dickey-Fuller unit root test to the crude oil price and select the optimal lag length 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, indicating that the crude oil price series is $I(1)$. Second, we exploit both the cross-sectional and time dimensions of the data set and apply the Fisher-type panel unit root test to verify the stationarity of the panel of retail prices for the 12,804 stations. The test results show that the null hypothesis of non-stationarity cannot be rejected at all conventional significance level (see Table 6).[11]

After establishing the order of integration of the prices, we test whether the retail and crude oil prices are cointegrated using the Engle-Granger residual-based cointegration test (Granger and Engle, 1987) as follows:

$$p_{it} = \sigma_i + \theta c_t + \gamma' \mathbf{H} + \delta' \mathbf{D} + \xi_{it} \tag{1}$$

Here p_{it} denotes the retail price, specific to station i at time t. σ_i denotes the station-specific fixed effect, which controls out unobserved heterogeneity or time-invariant omitted variables that differ across individual stations. These include brand type, ownership type, station density (number of stations within the local market), associated facilities such as, for example, convenience or kiosk-type stores, car washes, or the number of pumps. These characteristics, in our view, change little if at all over the period under consideration. Estimating equation (1) with the station fixed-effects also allows us to account for different long-run margins across the individual stations.

c_t denotes the Brent crude oil prices, and θ is the cointegration parameter or long-run pass-through coefficient, estimated to be 1.041 for the complete panel of 12,804 stations. We include a vector (**H**) denoting state-specific dummy variables for holidays, particularly the start of school holidays and public holidays (=1 if a day is a holiday/start of school holiday and 0 otherwise). Vector (**D**) is a set of day-specific dummy variables—included to control the associated demand-side effect, and ξ_{ist} in equation (1) is the residual, defined as:[12]

$$\xi_{it} = p_{it} - \sigma_i - \theta c_t - \gamma' \mathbf{H} - \delta' \mathbf{D} \tag{2}$$

ξ_{it} captures the gap between the retail price and its long-run equilibrium value. For the two price series to be linearly cointegrated, the residual ξ_{it} should be stationary. Again, we apply the Fisher-type

10. The number is chosen arbitrarily to ensure, on the one hand, sufficient variation across stations and, on the other hand, to attain robust averages of local weather conditions.

11. Unit root tests for the crude oil price and the panel data are all specified with a linear trend.

12. To control for the repeated sampling of the crude oil price, which is invariant across stations, the standard errors in equations (1) and (4) are clustered at the station level.

panel unit root test to the residuals and find that the retail price is cointegrated with the crude oil price (see Table 6 in the appendix).

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:

$$\Delta p_{it} = \alpha + \phi \xi_{it-1} + \sum_{m=1}^{M} \beta_m \Delta p_{it-m} + \sum_{n=0}^{N} \lambda_n \Delta c_{t-n} + \varepsilon_{it} \tag{3}$$

In equation (3), Δ is the first difference operator, M and N refer to the number of lags of the retail price and the crude oil price, respectively, selected using the AIC. The coefficients β_m and λ_n capture the respective short-run impacts of retail and crude oil prices. ξ_{it-1} is the error correction term from equations (1) and (2)—the one-period lagged residual, which expresses the prior disequilibrium ($\xi_{it-1} \neq 0$) from the long-run relationship. The coefficient ϕ associated with ξ_{it-1} is the symmetric adjustment parameter and reflects the convergence speed towards the equilibrium retail price level. Specifically, if p_{it-1}, for example, is above its long-run equilibrium, i.e., $\xi_{it-1} > 0$, it should decrease by ϕ in the next period to attain its long-run equilibrium level.[13] Consequently, the coefficient associated with the error correction term should be negative.

Following Granger and Lee (1989), the symmetric ECM in equation (3) 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 is specified as follows:

$$\begin{aligned} \Delta p_{it} = {} & \alpha + \phi^{+} \xi^{+}_{it-1} + \phi^{-} \xi^{-}_{it-1} + \sum_{m=1}^{M} (\beta^{+}_{m} \Delta p^{+}_{it-m} + \beta^{-}_{m} \Delta p^{-}_{it-m}) + \sum_{n=0}^{N} (\lambda^{+}_{n} \Delta c^{+}_{t-n} + \lambda^{-}_{n} \Delta c^{-}_{t-n}) + \delta' \mathbf{D} \\ & + \psi \Delta \overline{p}_{(-i)t-1} + \gamma' \mathbf{H} + \pi' \Delta \mathbf{W} + \eta' \mathbf{Y} + \tau t + \varepsilon_{it} \end{aligned} \tag{4}$$

Again, ξ_{it} is the estimated error term from equation (2), with $\xi^{+}_{it-1} = max\{\xi_{it-1}, 0\}$ implying $\Delta p_{it-1} > 0$ or $\Delta c_t < 0$ and $\xi^{-}_{it-1} = min\{\xi_{it-1}, 0\}$ implying $\Delta p_{it-1} < 0$ or $\Delta c_t > 0$. For each variable v in equation (4): $\Delta v^{+} = max\{\Delta v, 0\}$ and $\Delta v^{-} = min\{\Delta v, 0\}$. Note that a plus (minus) as superscript to a coefficient is indicative of an increase (decrease) change in the associated variable.

The coefficients (ϕ^{+} and ϕ^{-}) associated with the error correction terms are the adjustment parameters as they reflect the speed of adjustment towards the long-run equilibrium. For example, positive deviations of retail prices in the previous period ξ^{+}_{ist-1}—due to a decrease in crude oil price $\Delta c_t < 0$—should return to the equilibrium level at the rate of ϕ^{+} in the current period. 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 specification in equation (4) allows us to evaluate the rockets and feathers phenomenon, i.e., whether crude oil price increases are transmitted more swiftly than a corresponding price decrease. Moreover, it also allows us to test short-run asymmetry, i.e., an F-test of the joint null hypotheses: $|\beta^{+}_{m}| = |\beta^{-}_{m}|$ or $|\lambda^{+}_{n}| = |\lambda^{-}_{n}|$.

In equation (4), we include a vector (**W**) of weather-related variables (precipitation, snow depth, and temperature measures—calculated as heating (HDD) and cooling (CDD) degree days), a vector (**H**) of the start of school holidays and public holidays, and a vector (**D**) of day-of-the-week-specific dummies. Vector (**Y**) is the interaction of month and year dummy variables—included to account for seasonalities and common year-specific effects. A linear time trend (t) is also included

13. From equation (2), $\xi_{it-1} > 0$ implies a positive deviation, i.e., $\Delta p_{it-1} > 0$ or a decrease in crude oil price ($\Delta c_t < 0$) whereas $\xi_{it-1} < 0$ implies otherwise.

to control changes in retail prices that extend over the period. Since local competition additionally plays a vital role in how stations set and adjust prices, we further include the day-to-day changes in the weighted average prices ($\Delta\overline{p}_{(-i)}$) of neighboring stations within 5 km to reflect the role of local market competition.[14] Equation (4) is estimated using a pooled-panel regression approach for the entire panel of 12,804 stations, for subsamples based on different population densities and for major brands.

5. RESULTS AND DISCUSSION

5.1 National Estimates

In this subsection, we present the estimates for the pooled-panel regression for Germany as a whole. We report the estimated coefficients for the adjustment parameters, the day-specific dummies, neighbors' prices, holiday dummies, and weather variables. Additionally, we show the F-test statistics for the long-run symmetry and short-run symmetry hypotheses.[15] Table 1 shows the estimation results of the asymmetric ECM in equation (4) for the complete sample of 12,804 stations. Column (1) shows the coefficient estimates for the baseline specification—included to illustrate the adjustment parameters' sensitivity to the inclusion of other variables, i.e., day of the week dummies, neighbor prices, public and school holidays, or weather variables. We report only the coefficients associated with positive and negative deviations from the long-run cointegrating relationship (ϕ^+ and ϕ^-) for brevity. The second column reports the estimates from the full specification in equation (4).

Focusing on the long-run adjustment of retail prices, the estimate from equation (1) suggests that a 1 cent change in crude oil price leads in the long-run to a 1.041 cents change in the retail gasoline price. The results in Table 1, however, reveal that the daily adjustment to the long-run retail price level is asymmetric and that the adjustment coefficients for both positive and negative deviations are statistically significant at the 1% level in both specifications. The estimates also show that $|\phi^-|$ clearly exceeds $|\phi^+|$. Based on column (2), a day after a 1 cent change in the spot crude oil price, the retail price's corresponding adjustment is 0.059 cents for a decrease and 0.117 cents for an increase.

The test for equality of the adjustment coefficients, i.e., $|\phi^+|=|\phi^-|$, shows that the difference between the coefficients are statistically different from zero across both specifications. Therefore, the speed of convergence towards the long-run equilibrium is faster for crude oil price increases than decreases. Concerning the half-life of a deviation—the number of days required to reduce half of the deviation from the long-run equilibrium, calculated as $ln(2)/|\phi|$—we find that it takes approximately six days for half of a negative deviation to be corrected. As opposed, it takes roughly twelve days in the case of a positive deviation. The result suggests that stations in the long-run adjust their prices more swiftly when the retail margin is squeezed than stretched, confirming the rockets and feathers hypothesis. Across both 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, indicating an asymmetric response of retail prices in the short run.

14. Note that we follow equations (5) and (6)—see appendix—in calculating the weight matrix for $\overline{p}_{(-i)t}$. As robustness checks, we further conduct all the analyses by reducing the local market's radius to 2 km and using the price spread ($p_{max}-p_{min}$) within a local market. The results are qualitatively consistent with the main results and are available upon request.

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

Focusing on the estimates for days of the week, as shown in column (2), the results point to an intra-week pricing pattern. The coefficients associated with the specific days of the week suggest 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. As to the effect of local competition as reflected by average neighbors' prices, the estimated coefficient is positive and significant at the 1% level. The result indicates that stations adjust prices in response to price changes of rival stations within the local market (5 km radius).

To assess the school and public holidays' demand-effect, we include (partly) state-specific public and school holidays. As public holidays and the start of school holidays may affect demand and travel behavior, there is a general perception that retail prices increase heading into the holiday period. Public holidays in Germany are mostly single-day events and do not span several days. Accordingly, we include the dummy for the contemporaneous public holiday, as well as one lagged and two leading values to account for proactive and sustained pricing effects. The coefficients suggest moderate increases in retail prices two days before the public holiday. However, there is a more substantial increase in retail prices on the public holiday itself, where we find an increase of 0.539 cents. The estimate also shows a significant price decrease (0.126 cents) a day after the public holiday, but it 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 leading, and the contemporaneous dummies are included. All four estimated coefficients are positive and significant at the 1% level. In terms of magnitude, the start of school holidays' contemporaneous effect is smaller (0.045 cents) than that of public holidays (0.539 cents). This is expected as school holidays apply only to a fraction of the population, unlike public holidays. Moreover, retail prices continue to increase the day after the start of the school holiday period. Overall, our estimates suggest that not only do retail prices increase on public holidays and at the beginning of school holidays, the price increases also begin two days before to the start of the holidays.

Furthermore, the full specification in column (2) includes daily changes in local weather conditions in the regression. The rationale is that adverse weather conditions cause changes in gasoline demand and transport costs for crude oil. These, in turn, affect retail prices. The results at the national level for the coefficients associated with rainfall and snow depth are mixed. Increases in snow depth positively affect price changes, confirming that adverse weather conditions cause commuters to switch from active modes of transportation to driving by car (Koetse and Rietveld, 2009; Böcker et al., 2013).

At first glance, the negative coefficient associated with changes in the amount of rainfall does not support the notion of increased demand and seems puzzling. However, the negative price effect of increasing rainfall might be related to the tendency to switch to public transport due to safety concerns. For temperature variations, the estimates indicate that only changes in CDD affect price changes. Here, the coefficient is negative and significant at the 1% level. The estimate suggests that for an increase in average temperature above 15.5 °C, commuters perhaps tend to use active modes of transportation, leading to less traffic and a decrease in demand for gasoline, which ultimately exerts a decreasing effect on prices.[16]

16. As shown in Table 1, all other results, including the various symmetry tests, remain qualitatively unchanged despite the inclusion of neighbors' prices, holiday, and weather variables.

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

	(1) Baseline Model		(2) Further Controls	
	Dependent Variable: Δ Retail Price of E5 Fuel			
ϕ^+	–0.060***	(0.000)	–0.059***	(0.000)
ϕ^-	–0.114***	(0.001)	–0.117***	(0.001)
Tuesday			0.142***	(0.002)
Wednesday			0.103***	(0.002)
Thursday			0.131***	(0.002)
Friday			0.172***	(0.002)
Saturday			0.322***	(0.004)
Sunday			0.631***	(0.005)
$\Delta\overline{p}_{(-i)t-1}$			0.114***	(0.001)
Public Holiday				
2 days before			0.162***	(0.002)
1 day before			0.166***	(0.002)
Same day			0.539***	(0.005)
1 day after			–0.126***	(0.002)
School Holiday Start				
2 days before			0.073***	(0.002)
1 day before			0.039***	(0.002)
Same day			0.045***	(0.002)
1 day after			0.109***	(0.002)
Δ Rainfall			–0.001**	(0.000)
Δ Snow Depth			0.001*	(0.001)
Δ HDD			–0.000	(0.000)
Δ CDD			–0.001***	(0.000)
	F-Tests for Symmetry			
$\phi^+ = \phi^-$	5,586.86***		7,233.14***	
$\beta_m^+ = \beta_m^-,\ \ m \in [1,7]$	744.21***		609.49***	
$\lambda_n^+ = \lambda_n^-,\ \ n \in [0,7]$	7,589.93***		5,830.29***	
Observations	21,781,789		21,781,789	
R^2	0.277		0.296	
Number of Stations	12,804		12,804	
Month/Year Fixed Effects (**Y**)	Yes		Yes	

Notes: Constant term included but not shown. Standard errors are clustered at the fuel station level and reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

The dummy variables for the days of the week correspond to vector **D** in equation (4). The holiday variables represent vector **H**. Here, *Public Holiday* denotes whether the corresponding day is a public holiday, some of which vary across federal states. *School Holiday Start* refers to the first day of school holidays, which are individual to the 16 federal states. Δ *Rainfall*, Δ *Snow Depth*, Δ *HDD*, and Δ *CDD* represent the vector of weather variables (**W**). *Month/Year Fixed Effects* (**Y**) 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 adjustment coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-run symmetry* tests $\beta_m^+ = \beta_m^-$ for all $m \in [1,7]$ and $\lambda_n^+ = \lambda_n^-$ for all $n \in [0,7]$.

5.2 Rural vs. Urban Areas

Table 2 replicates column (2) of Table 1 for subsamples based on the respective postal code region's population density. A possible concern is that the prior results are driven mainly by stations in sparsely populated or rural areas. On the one hand, the distance of these stations from competitors gives them sub-regional market power. On the other hand, these stations are often characterized by shorter opening hours, such as closing earlier on weekends or not operating at all times.

Table 2: Regression Results: Gasoline (E5)—Population Density

	(1) $\geq P_{10}$	(2) $\geq P_{25}$	(3) $\geq P_{75}$	(4) $\geq P_{90}$
	Dependent Variable: Δ Retail Price of E5 Fuel			
ϕ^{+}	–0.060***	–0.061***	–0.065***	–0.062***
	(0.000)	(0.001)	(0.001)	(0.001)
ϕ^{-}	–0.117***	–0.118***	–0.122***	–0.121***
	(0.001)	(0.001)	(0.001)	(0.002)
Tuesday	0.150***	0.165***	0.235***	0.262***
	(0.002)	(0.002)	(0.004)	(0.006)
Wednesday	0.108***	0.118***	0.166***	0.194***
	(0.002)	(0.002)	(0.004)	(0.006)
Thursday	0.138***	0.150***	0.205***	0.231***
	(0.002)	(0.002)	(0.004)	(0.006)
Friday	0.180***	0.191***	0.238***	0.266***
	(0.002)	(0.003)	(0.004)	(0.007)
Saturday	0.334***	0.349***	0.418***	0.454***
	(0.004)	(0.004)	(0.007)	(0.011)
Sunday	0.650***	0.681***	0.789***	0.850***
	(0.006)	(0.006)	(0.010)	(0.015)
$\Delta\overline{p}_{(-i)t-1}$	0.122***	0.137***	0.184***	0.191***
	(0.002)	(0.002)	(0.002)	(0.004)
	F-Tests for Symmetry			
$\phi^{+} = \phi^{-}$	6,345.75***	5,232.52***	1,943.14***	874.08***
$\beta_m^{+} = \beta_m^{-},\ \ m \in [1,7]$	577.27***	522.57***	250.19***	144.94***
$\lambda_n^{+} = \lambda_n^{-},\ \ n \in [0,7]$	5,475.55***	4,758.51***	1,922.53***	810.12***
Observations	19,605,528	16,342,601	5,446,332	2,181,291
R^2	0.298	0.303	0.315	0.320
Number of Stations	11,489	9,514	3,130	1,250
Holiday Controls (**H**)	Yes	Yes	Yes	Yes
Weather Controls (**W**)	Yes	Yes	Yes	Yes
Month/Year Fixed Effects (**Y**)	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.

The dummy variables for the days of the week correspond to vector **D** in equation (4). *Holiday Controls* (**H**) refers to controls for public holidays and the start of school holidays. *Weather Controls* (**W**) refer to a set of control variables for changes in precipitation, snow depth, HDD, and CDD. *Month/Year Fixed Effects* (**Y**) 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 adjustment coefficients of the ECM are equal, i.e., $\phi^{+} = \phi^{-}$. *Short-run symmetry* tests $\beta_m^{+} = \beta_m^{-}$ for all $m \in [1,7]$ and $\lambda_n^{+} = \lambda_n^{-}$ for all $n \in [0,7]$.

Column (1) shows the subsample, where stations below the 10th percentile of population density are excluded. This corresponds to all postal code regions with less than 85 people per km^2. Column (2) excludes stations in postal codes with less than 163 inhabitants per km^2, that is, below the 25th percentile. In column (3), only those stations which are located in postal codes with a population density higher than 1,250 people per km^2 (75th percentile) are used. Last, column (4) reduces the sample to stations located in the most densely populated urban clusters above the 90th percentile, with more than 3,021 people per km^2.

The overall results remain qualitatively unchanged upon splitting the sample by population density.[17] First, all four models exhibit a strong rockets and feathers pattern, as is visible from the

17. For brevity and compactness, holiday and weather variables are not reported since the estimates do not diverge from the estimates in Table 1.

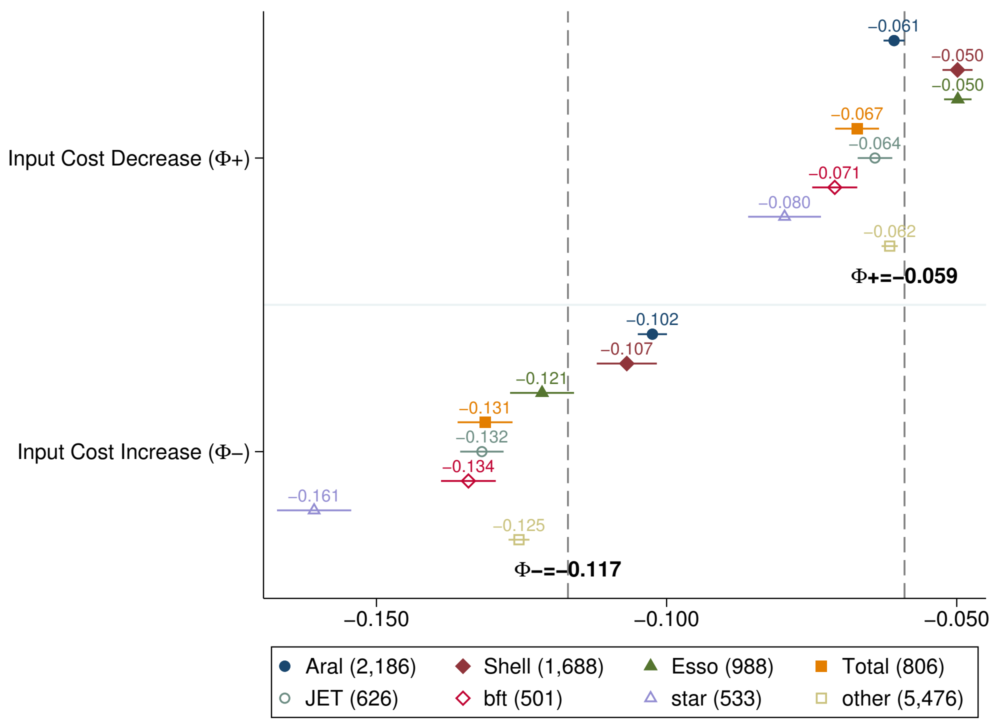
stable adjustment parameters ϕ^+ and ϕ^-, as well as the corresponding F-test for symmetry, which is rejected at the 1% level in all cases. Second, the effect of neighbor price changes is significant across all four specifications and increases with increasing population density. Third, the intra-week pricing pattern remains unchanged throughout all subsamples. However, in contrast to the initial concerns, the pattern is even more pronounced in densely populated areas where we observe a high number of stations and a high share of major brands.

5.3 Major Brands

For major brands with a nationwide network of fuel stations, pricing decisions might be centralized, and individual stations may have only a limited role in adjusting prices to reflect local market conditions. Major brands may also charge higher prices than unbranded stations due to their market power, which emanates partly from their customers' relatively low demand elasticity. Accordingly, we examine whether the pattern of asymmetry observed holds across brands and unbranded stations.

We again estimate a pooled-panel regression for the different brands based on equation (4) and show the adjustment parameter estimates in Figure 1. The results depict differences in retail price response to input cost changes across different brands. The absolute values of the adjustment coefficient for input cost increase for major brands and *others*—except Aral and Shell—exceed the nationwide average (|–0.117|) while only Shell and Esso adjust prices downwards more than the national average (|–0.059|) following an input cost decrease.

Figure 1: Regression Results: Gasoline (E5)—Asymmetric Adjustment by Brand



Notes: The plot shows the adjustment parameters and their 90% confidence intervals obtained from estimating equation (4) for individual brands. The number of fuel stations is shown in parentheses. The results are shown for brands with more than 500 stations in the sample, the remaining brands and independent stations are pooled as *other*. The vertical lines correspond to the estimates of ϕ^+ and ϕ^- for the pooled sample presented in Table 1, column 2.

A test for equality of the adjustment parameters $|\phi^+|=|\phi^-|$ shows a rejection of the symmetric adjustment hypothesis across brands, implying that, on average, both branded and unbranded fuel stations pass on input cost increases at a faster rate than input cost decreases. Contrary to the findings of Frondel et al. (2020), our results confirm a widespread existence of the rockets and feathers phenomenon across all branded and unbranded fuel stations. The significant heterogeneity regarding the pass-through of cost variations to consumers across brands ties well with the result by Kihm et al. (2016). It is indicative that the notion of perfect competition does not hold in the gasoline market.

5.4 Spatial and Temporal Aggregation

As indicated earlier, while spatial aggregation ignores potential differences across individual stations, temporal aggregation leading to low-frequency data also fails to adequately reflect the frequency of price adjustment to input cost changes at the station level. Given that the dynamics of time series of heterogeneous stations might be markedly different from those derived from spatially aggregated data, we examine the sensitivity of the average adjustment process in Table 1 to both spatial and temporal aggregation. As to aggregation across space, we compute a time series of daily average retail prices for Germany. We then estimate a time series variant of equation (4) and report the results in Table 3.[18]

Table 3: Regression Results: Gasoline (E5)—Spatial and Temporal Aggregation

	Spatial Aggregation		Temporal Aggregation	
	Dependent Variable: Δ Retail Price of E5 Fuel			
ϕ^+	–0.043***	(0.011)	–0.318***	(0.001)
ϕ^-	–0.104***	(0.014)	–0.304***	(0.002)
$\Delta\bar{p}_{(-i)t-1}$	–1.898***	(0.411)	–0.003***	(0.000)
Δ Rainfall	–0.009	(0.011)	–0.014***	(0.001)
Δ Snow Depth	–0.028	(0.055)	0.023***	(0.001)
Δ HDD	–0.000	(0.001)	–0.004***	(0.000)
Δ CDD	–0.001	(0.001)	0.001***	(0.000)
	F-Tests for Symmetry			
$\phi^+ = \phi^-$	12.10***		185.67***	
$\beta^+_m = \beta^-_m,\ \ m \in [1,7]$	1.14		5.76**	
$\lambda^+_n = \lambda^-_n,\ \ n \in [0,7]$	1.29		27,661.53***	
Observations	1,816		2,594,258	
R^2	0.547		0.993	
Number of Stations	—		12,804	
Day of the Week Controls (**D**)	Yes		No	
Holiday Controls (**H**)	Yes		No	
Month/Year Fixed Effects (**Y**)	Yes		Yes	

Notes: Constant term included but not shown. Standard errors are clustered at the fuel station level and reported in parentheses. *: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.
Δ Rainfall, *Δ Snow Depth*, *Δ HDD*, and *Δ CDD* represent the vector of weather variables (**W**). *Day of the Week Controls* (**D**) refers to dummy variables for the individual days of the week. *Holiday Controls* (**H**) refers to controls for public holidays and the start of school holidays. *Month/Year Fixed Effects* (**Y**) 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 adjustment coefficients of the ECM are equal, i.e., $\phi^+ = \phi^-$. *Short-run symmetry* tests $\beta^+_m = \beta^-_m$ for all $m \in [1,7]$ and $\lambda^+_n = \lambda^-_n$ for all $n \in [0,7]$.

18. Note that daily country-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.

The results show that the absolute value of ϕ^{-} exceeds that of ϕ^{+}. The symmetric adjustment test also indicates that the difference between the two coefficients is statistically different from zero. The rejection of the symmetric adjustment of national daily average retail gasoline prices to crude oil price changes is consistent with the results from the pooled-panel data analysis presented in Table 1. This finding suggests that the long-run rockets and feathers phenomenon is not sensitive to spatial data aggregation. However, the weather variables are sensitive to spatial aggregation as they are all statistically insignificant—an indication that this form of aggregation might lead to imprecise estimates (see, for instance, Arzaghi and Squalli, 2015).

As to aggregation over time, we examine whether the frequency of station-level data matters for the adjustment of retail prices to input cost changes. We aggregate the *daily* station-level retail prices to *weekly* station-level prices. Again, we estimate a pooled-panel variant of equation (4) and report the results in Table 3. Note that we do not include the day-specific and holiday dummies in this specification since we employ average weekly station-specific data. Again, focusing on the adjustment parameters, the findings differ from the previous results obtained using daily data.

Contrary to the pooled-panel estimates in Table 1 and the time series estimates in Table 3, we find that the absolute value of the adjustment parameter for positive deviations is larger than that of negative deviations. The coefficients are also statistically different from each other at the 1% level. This indicates that retail prices adjust more swiftly to crude oil price decreases than increases. The result using station-level weekly panel data points falsely to a high degree of competition in the retail market and is consistent with recent findings for Germany (Kristoufek and Lunackova, 2015; Asane-Otoo and Schneider, 2015; Bagnai and Ospica, 2016). Our findings suggest that temporal data aggregation or the use of low-frequency data yields inaccurate inferences and is therefore relevant for the accurate appraisal of the type of long-run equilibrium adjustment.

6. CONCLUSION

This paper re-examines the perception that retail gasoline prices respond more swiftly to crude oil price increases than decreases—a pricing pattern characterized as the *rockets and feathers* phenomenon. This pattern is often associated with market inefficiencies, prominently collusion among retailers, and search intensity disparities following input cost changes. Our analyses explore the adjustment of retail gasoline prices to crude oil price changes using a novel panel data set of station-level daily retail prices for 12,804 stations spanning from January 1, 2014, to December 31, 2018. In addition to using the extensive and unique 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, and pricing decisions of neighboring stations.

Contrary to recent findings, we find that the *rockets and feathers* phenomenon is the norm in the German retail gasoline market rather than the exception. Specifically, based on national, population density, and brand analyses using pooled-panel asymmetric error correction models, we find evidence supporting the perception that input cost changes that squeeze the retail margin are passed on to consumers more swiftly than equivalent changes that stretch the margin. On the one hand, this is surprising, given the high level of price transparency and the negligible search cost since consumers can easily obtain price information across stations in real-time. On the other hand, increased market transparency also works to the advantage of firms since they can effortlessly compare prices both within and outside their local markets and adjust prices accordingly, making tacit collusion or price coordination more likely.

Our findings also suggest that temporal aggregation of station-level data matters in appraising the type of adjustment. As evidenced by our results, substantial differences exist between the nature of adjustment exhibited by low- and high-frequency data. The former obscures the inherent adjustment mechanism and lead to inaccurate inferences. Essentially, this might explain the diverse findings in the literature and why our results differ from recent findings for Germany. In addition to the observed intra-week price patterns, our findings also support the public perception that retail prices increase heading into the holiday period. Overall, the unique data set permits a comprehensive analysis of the entire retail gasoline market, including markets in both densely and sparsely populated areas. Therefore, the scale of the data and empirical analysis allows generalizing our findings to typical national retail gasoline markets.

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APPENDIX

Distance Calculation

The Haversine formula allows for the calculation of great circle distances between two given sets of geographic coordinates on a sphere with radius *R*. Applying the latitude (*lat*) and longitude (*lon*) of two stations (*i* and *j*) to equation (5) yields their linear distance in kilometers. The calculations employ the earth's mean radius of 6,371 km.

$$d_{ij} = 2R\arctan\left(\frac{\sqrt{\theta}}{\sqrt{1-\theta}}\right) \tag{5}$$

where

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

We assume that stations in a given radius κ influence each other regardless of the actual driving time or distance. In the standard setting, the radius or threshold is set to $\kappa = 5$ km. Choosing a distance of 5 km reduces the number of stations without neighbors. In this case, we identify only 939 stations in the full sample with no neighbor within 5 km and may be considered local monopolists. For further robustness testing, other truncation distances (such as $\kappa = 2$ km) are also considered. The influence of competitors is assumed to be decreasing with distance. Accordingly, the spatial weights matrix is constructed following equation (6), where elements of the matrix (δ_{ij}) are 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.

$$\delta_{ij} = \begin{cases} d_{ij}^{-1} & \text{if } 0 < d_{ij} \leq \kappa \\ 0 & \text{if } d_{ij} > \kappa \\ 0 & \text{if } d_{ij} = 0, \text{ i.e., } i = j \end{cases} \tag{6}$$

Multiplying the weight matrix by the price vector then yields the inverse-distance-weighted mean price ($\overline{p}_{(-i)t}$) of neighboring stations within a distance of 5 km, excluding the respective station under consideration.

Table 4: Variables used

Variable	Unit	Source
Retail Price of Fuel Type Gasoline E5—(p)	Cents per Liter	MTU
Brent (Europe) Crude Oil Price—(c)	Cents per Liter	EIA (2019)
Surface Air Temperature (Daily Average)	0.1 Degree Celsius	ECA&D, Klein Tank et al. (2002)
Heating Degree Days—(HDD)	0.1 Degree Celsius	Calculation based on Surface Air Temperature (Daily Average)
Cooling Degree Days—(HDD)	0.1 Degree Celsius	Calculation based on Surface Air Temperature (Daily Average)
Rainfall Amount	standardized $\mathcal{N}(0,1)$	ECA&D, Klein Tank et al. (2002)
Snow Depth	standardized $\mathcal{N}(0,1)$	ECA&D, Klein Tank et al. (2002)
School Holiday Start Dummy	binary	https://www.schulferien.org/deutschland/ferien/
Public Holiday Dummy	binary	https://www.schulferien.org/deutschland/feiertage/
Day of the Week Dummies	binary	—
Population Density	Population per km^2 of postal code region	https://www.suche-postleitzahl.org/

Table 5: Descriptive Statistics: Regression Sample

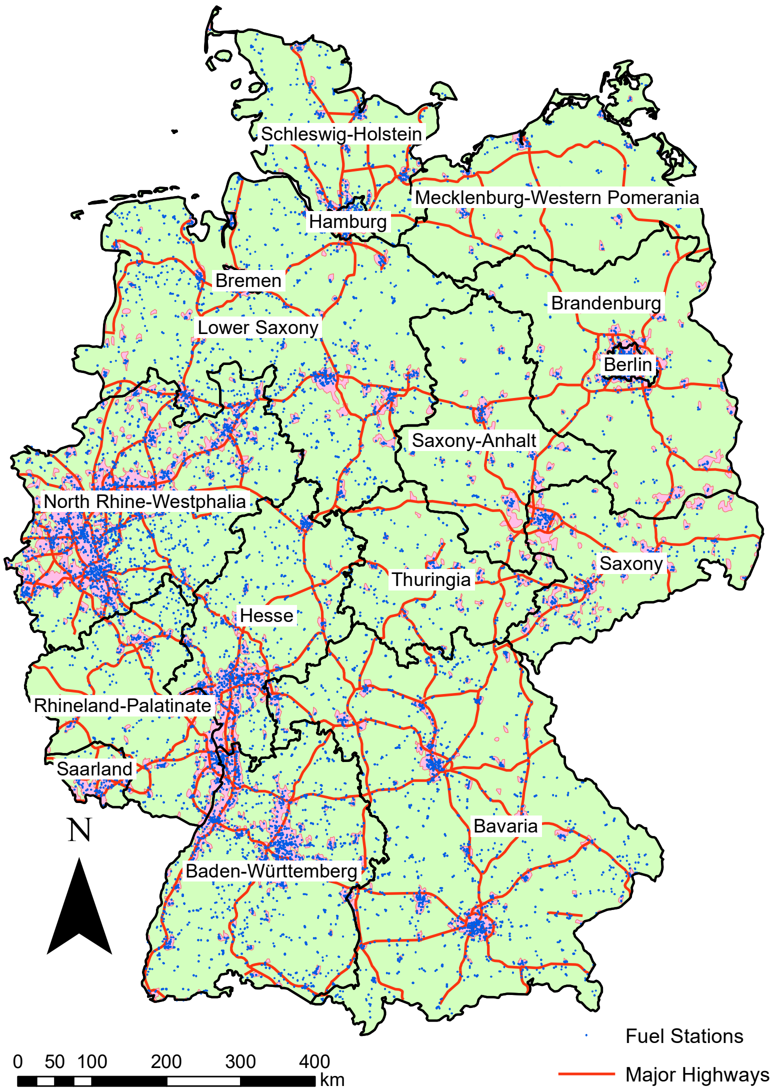
Variable	Stations	Obs.	Mean	S.D.	Min.	Max.
p	12,804	21,781,789	140.911	10.166	88.800	194.900
c	12,804	21,781,789	33.542	8.607	14.998	53.191
Δp	12,804	21,781,789	–0.007	1.468	–55.417	40.600
Δc	12,804	21,781,789	–0.011	0.533	–2.773	2.584
$\Delta\overline{p}_{(-i)}$	12,804	21,781,789	–0.008	1.196	–30.667	56.900
Public Holiday	12,804	21,781,789	0.029	0.169	0.000	1.000
School Holiday Start	12,804	21,781,789	0.236	0.425	0.000	1.000
Δ Rainfall	12,804	21,781,789	0.000	1.215	–38.141	40.305
Δ Snow Depth	12,804	21,781,789	–0.000	0.526	–368.268	368.268
Δ HDD	12,804	21,781,789	0.029	17.884	–334.996	171.643
Δ CDD	12,804	21,781,789	0.003	11.394	–128.747	117.875

Table 6: Panel Unit Root Test: Retail Price and Residuals

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

Number of Panels			12,804		
Number of Periods		min	722		
		mean	1,694		
		max	1,813		
		Retail price		Residuals	
		Statistic	p-Value	Statistic	p-Value
Inverse Normal	Z	69.65	1.000	–361.25	0.000
Inverse Logit t()	L^*	62.86	1.000	–461.06	0.000

Figure 2: 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/)