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STATION HETEROGENEITY

AND

ASYMMETRIC GASOLINE PRICE RESPONSES

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Station Heterogeneity and Asymmetric Gasoline Price Responses

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Abstract

Besides temporal and spatial aggregation issues in the analysis of asymmetric response of retail gasoline prices, previous studies have also largely ignored parameter heterogeneity across fuel stations. This paper addresses the aggregation issues and the parameter homogeneity assumption by examining the responsiveness of stations to input cost changes using daily station-specific retail and wholesale gasoline prices for 12,613 geographically diverse stations. Based on individual station analysis using asymmetric error correction models, we find that 48% of stations engage in competitive pricing while the remaining 52% exhibit the rockets and feathers pricing pattern. Our findings suggest that the rockets and feathers phenomenon is a feature of individual stations and local market characteristics are important determinants. We also show that pooled panel regression techniques obscure the actual pricing pattern observed from station-level time series analysis.

Keywords: Asymmetric Pricing, Input Cost, Price Transparency, Aggregation

JEL Classification Numbers: Q41, Q48, R40, L40

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1 Introduction

The effect of input cost changes on pump prices and whether there is an asymmetric adjustment of pump prices to input cost fluctuations has been examined extensively in the literature. Constrained by data availability, earlier studies often assessed the inter-temporal price variation using pump prices aggregated across geographically diverse fuel stations. The findings are inconclusive with some studies showing that pump prices respond swiftly to crude oil or wholesale price increases than decreases – a phenomenon characterized as the *rockets and feathers* pattern – while others find the opposite (see Eckert, 2013; Periguero-Garía, 2013; Cook and Fosten, 2019, for a review of the literature). The mixed results – even for the same market – can be attributed to data aggregation and the estimation techniques employed.

Two forms of data aggregation become apparent: temporal aggregation and spatial aggregation. As to the former, because of the occurrence of intra-day pump price volatility and short-run input cost changes, low-frequency price data – for instance, weekly or monthly data – may inadequately reflect the frequency of price decisions. On the other hand, spatial aggregation ignores station-specific heterogeneity such as differences in pricing strategy and local market competition. Moreover, it may also fail to account for spatial differences – that is, market structure and population density – among local markets accurately and could compromise the validity of estimations (see, for example, Granger, 1980; Pesaran and Smith, 1995; Pesaran and Chudik, 2014).

Beyond the aggregation issues, recent empirical studies that rely on disaggregated data primarily employ pooled regression techniques. However, these types of pooled-panel regression approaches may yield biased estimates particularly if parameter heterogeneity exists across the individual stations (Baltagi et al., 2008; Hsiao, 2014). Moreover, not all stations or even stations belonging to the same brand follow the same pricing strategy due to local competition differences. Consequently, the nature and extent of asymmetry might differ among stations, and the idea of equal price adjustment across stations appears to be a strong assumption that may be at odds with the observed responses of heterogeneous retailers.

In this paper, we exploit unique station-specific retail and wholesale gasoline price data sets and revisit the debate on the asymmetric response of retail gasoline prices to fluctuations in wholesale prices.[1] We draw on daily retail and wholesale prices of 12,613 individual stations in Germany spanning from January 1, 2014 to December 31, 2018. Our analysis sheds light on whether spatial aggregation and pooled-panel estimation techniques mask the nature and extent of cost pass-through for individual stations. The theoretical literature offers market power or tacit collusion among retailers and low search

[1]Gasoline can be distinguished into "Super E5" – with up to 5% of ethanol – or "Super E10" – with up to 10% ethanol. Our analysis focuses on E5 gasoline since it accounts for approximately 85% of fuel sales in Germany (BDBe, 2017).

intensity among consumers as causal explanations for asymmetric cost pass-through (Yang and Ye, 2008; Verlinda, 2008; Tappata, 2009; Lewis, 2011). Given these explanations, our analysis does not seek to answer why asymmetric pricing exists but rather which stations engage in this pricing behavior and whether certain market features increase the tendency of price asymmetry. Moreover, recent studies have exclusively concentrated on the responsiveness of pump prices to crude oil price shocks and have mainly ignored the latter's effect on the refinery industry. Our analysis complements recent studies by assessing the adjustment of region-specific wholesale gasoline prices to crude oil price changes. Our analysis thus focuses on the responsiveness of both the retail and wholesale markets to their respective input cost changes.

Three key features of the data permit this kind of analysis. First, we rely on station-specific wholesale gasoline prices as the relevant input cost for the retail market. We compute the station-specific wholesale price using detailed information on 8 regional wholesale markets and distances from individual stations to specific refineries or depot. It should be noted that domestic wholesale gasoline prices are more relevant as input cost for stations since retail prices may be less responsive to international crude oil price shocks (Delpachitra, 2002). In the wholesale or refinery market, we use international crude oil prices as the relevant input cost since crude oil is the main input factor.

Second, our data set encompasses the universe of station-level prices from gasoline stations in Germany.[2] It therefore permits a complete representation of retail market competition across geographically diverse stations. Accordingly, we can accurately identify the empirical relationship between the retail and wholesale prices at the station-level and the response of regional wholesale prices to international crude oil price shocks. Third, previous studies mostly abstract from determinants other than crude oil or wholesale prices, and ignore the price effects of spatial competition, demand-side effects such as the occurrence of holidays, and changes in weather conditions. However, excluding these covariates could reduce the precision of estimates. Our station-level data set allows us to control these factors' impact on the pricing decision. Additionally, we are able to examine the degree to which local market characteristics impact the occurrence of the rockets and feathers pricing pattern or negative asymmetric price response at the station level.

The results show that 52% of the 12,613 stations exhibit the rockets and feathers pricing pattern while the remaining 48% of stations engage in competitive pricing behavior. Our findings suggest that price transparency regulation – that have been implemented since 2013 – alone may be ineffective at curbing anti-competition behavior in the retail gasoline market. This insight is relevant for competition authorities that implement regulations to enhance market efficiency and improve consumer outcomes in terms of competitive prices and increased welfare. The results also reveal that pooling price data across stations leads to summation bias and conceals the true nature of price

[2]The 12,613 individual stations approximately account for 87% of all functional stations observed between 2014 and 2018.

responses at the station level. The findings further point to a pervasive rockets and feathers pricing pattern in the wholesale gasoline market. This finding is not surprising given the geographic distribution of refineries and fuel depots, which increases their regional market power.

Our analysis contributes mainly to the rapidly growing rockets and feathers literature. In this strand of the literature, our analysis is related to recent studies by Faber (2015); Balaguer and Ripollés (2016); Frondel et al. (2019) and Asane-Otoo and Dannemann (2020) that use large-scale daily station-level price data set from EU member countries.[3] Frondel et al. (2019), for example, employ daily E10 gasoline prices from $5,650$ German stations observed over 23 months and identify the rockets and feathers pattern for the period 2012-2013 but negative asymmetry for the 2014-2015 period. The authors attribute the observed negative asymmetry for the 2014-2015 period to increased search activities. That is, because consumers can access real-time prices at negligible cost, the rate of retail price adjustment to crude oil price decreases is quicker than increases.

Asane-Otoo and Dannemann (2020) also draw on an extensive data set that includes daily retail prices of gasoline from $12,804$ stations in Germany observed over 5 years. With pooled-panel error correction models, the authors conclude that the pattern of rockets and feathers is the rule rather than the exception. They also show that low-frequency data, such as weekly prices, yields inaccurate inferences. Similarly, Balaguer and Ripollés (2016) examine the effect of cross-sectional aggregation of data on estimation using daily prices observed over 30 months from 468 individual stations in the Spanish metropolitan areas of Madrid and Barcelona. The authors also conclude that data aggregation overestimate the persistence of shocks and generate estimation efficiency loss that is sufficiently large to hide the existence of the rockets and feathers pattern.

Despite employing large-scale data sets, these studies mainly rely on panel regression techniques and present the parameter estimates as averages across stations. While this approach offers an overview of firms' average pricing behavior in the markets considered, it obscures both station and parameter heterogeneity. Our paper is most closely related to Faber (2015), who uses daily station-level data for $3,600$ individual stations in the Netherlands observed over 27 months. Based on the individual station analysis, the author concludes that about 38% of the stations respond asymmetrically to spot market price changes. The key innovation in our approach is that we do not only study retail prices of individual stations but also improve on previous studies by employing station-specific input cost that accounts for the heterogeneous transport cost of gasoline from refineries or depots to stations.

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

[3] Asane-Otoo and Schneider (2015) also employ daily retail prices, but the data set is aggregated at the city-level for four major cities in Germany.

2 Context and Data

2.1 Market and Station-Level Data

A unique feature of the German retail market is that since the last quarter of 2013, retailers are mandated to report all price changes for Super E5, Super E10, and regular diesel to the regulatory authority – Market Transparency unit (MTS-K) – before any price change. Information service providers can access this data and make it available via mobile applications and online portals to consumers in real-time.[4] The regulation aims to aid consumers in making informed decisions, enhance price competition, and improve consumer outcomes. Our analysis relies on this unique data set covering all stations with exact time stamps for all price quotes.[5] Similar to other OECD countries, the data set shows that only a small number of retailers operates a significant share of the retail market. We find 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 22.37% of stations are run by 9 other brands while 55 smaller or independent brands operate the remaining 27.9% of stations. According to the regulator, the five largest brands operate as an oligopoly with about 70% share of aggregate demand (German Federal Cartel Office, 2011).

Retail prices: In Germany, retailers or brands are entirely responsible for all pricing decisions, and the degree and frequency of price changes are not regulated. To examine price changes on an inter-day basis, daily averages are calculated since there may be multiple observations for a station per day. In our analysis, average retail prices are nominal consumer prices at the pump in euros (cents) per liter.[6] Overall, we can observe average daily prices across $15,228$ stations for the period starting from January 1, 2014 to December 31, 2018. Panel (a) of Figure 3 shows the geographical distribution of all stations, and points to the fact that stations are unevenly distributed with high concentration of stations across cities, densely populated areas and along major highways.

2.2 Network Infrastructure

Refineries and Fuel depots: There are currently 18 active refineries with different ownership structures and various degrees of vertical integration in Germany. Among the 18 refineries, 8 are either partly or fully owned by companies that also operate fuel stations and/or oil pumps. The refineries are geographically distributed across the federal states – see panel (b) of Figure 3, and their locations determine the source and mode of

[4]See for example, https://www.clevertanken.de, https://www.spritmonitor.de, https://www.bottledsoftware.de

[5]The MTS-K data set also offers station-specific information, e.g., opening and closing hours, geographical coordinates, and brand affiliation – of which we distinctively identify about 70 brands.

[6]The prices include energy taxes, value-added taxes, and a fee for the Petroleum Stockholding Association.

transport of crude oil, which serves as the main input. While road transport by tank truck is uncommon, crude oil is usually transported either by railway, pipeline or ship/vessel, in order to allow for larger quantities. Accordingly, the refinery market is bound to geographical features and network infrastructure, thus predetermining the locations for the refining of petrochemicals.

The refined products (e.g., diesel and gasoline) are transported to various fuel depots that are also distributed across federal states. The depots serve as additional storage facilities and decrease the transport distance from refineries to fuel stations. In Germany, the association of independent fuel depot operators lists 101 relevant depots dedicated to the provision of diesel and gasoline to retailers.[7] In addition, we can also identify 16 fuel depots which are run by vertically integrated companies. The fuel depots receive the refined products from the refineries by road, rail, ship, and pipeline transport, depending on their location and ownership structure. The transport of fuels to the respective fuel stations takes place by road transport in the majority of cases.

Wholesale prices: The geographic concentration of refineries and fuel depots has led to the emergence of distinct regional wholesale markets with observed price differentials. The company "Oil Market Report" (O.M.R.) distinguishes between eight different regional markets, which correspond mainly to the location of the active refineries in Germany. The approximate location of the O.M.R. market regions is shown in panel (b) of Figure 3. O.M.R. obtains daily wholesale prices of gasoline from interviews with market participants, for instance, refining, (import) trading, or wholesale trading companies.

As wholesale prices are region-specific, the main determinant for fuel stations is the transport costs. With tank trucks serving as the main mode of transport, the transport costs accruing at the individual station can be approximated by the road driving distance to the nearest fuel depot. For economic and contractual reasons, fuel stations may consider sourcing gasoline from distant depots instead of nearby depots. For example, stations belonging to vertical integrated brands may be limited to sourcing gasoline from depots of the same franchise. Accordingly, we take the weighted average of the prices at all fuel depots, weighted by their inverse road driving distance (see the appendix for additional details on the data construction). This allows us to have the actual wholesale costs for gasoline, specific to the individual fuel station.

Crude Oil Price: As to the responsiveness of wholesale prices to international crude oil price shocks, 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

[7]The association lists further depots, however these belong to the *Fernleitungs-Betriebsgesellschaft mbh*, which serves the main purpose of providing the NATO forces with fuels.

the International Monetary Fund.[8]

2.3 Other Variables

Neighbor prices: As indicated earlier, apart from the wholesale price, our analysis account for other variables that have been identified as drivers of retail price changes. One such driver is the role of local market competition in stations' pricing behavior, which increases with geographic proximity. As stations adjust their prices to those of nearby competitors within a given range, we follow Haucap et al. (2017) and Asane-Otoo and Dannemann (2020) and calculate the average inverse distant-weighted price of neighboring stations within a 5 km radius.[9] Using the exact coordinates – latitude (lat) and longitude (lon) – of all the stations, we compute the linear distance (d_{ij}) in kilometers between the stations within the range (κ =5 km) using the Haversine formula.[10]

Since the influence of competitors is assumed to be decreasing with distance, we construct the spatial weights matrix following the rule described in equation (1), where δ_{ij} is the pairwise weight assigned to stations i and j. By definition, the distance d_{ij} from any station to itself is set to 0, so that all diagonal elements of the matrix are equal to 0. 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.

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

Public and School Holiday Data: Another potential determinant of retail price changes that often features in public discourse but less in the empirical literature is the holiday period. These periods likely affect pricing strategies and demand as they cause changes in commuting and travel behavior. Besides the nine national public holidays recognized in Germany every year, there are about eight other public holidays celebrated in individual federal states or groups of federal states. In addition to public holidays, we also account for school holidays (e.g., Christmas, winter, spring, summer, and autumn holidays).

Weather Data: Local weather conditions reflect seasonality and play a vital role in the day-to-day choice of the mode of transportation since individuals react to weather variability differently (for a review of the literature, see, for example, Böcker et al.,

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

[9]For further robustness testing, other truncation distances, e.g., κ =2 km are also considered.

[10]$d_{ij} = 2R \arctan\left(\frac{\sqrt{\theta}}{\sqrt{1-\theta}}\right)$ 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 linear distance approach mirrors distance filters on price comparison websites or apps.

2013). To account for the impact of local weather variability on price changes, we include station-specific weather variables – mean ambient temperature, precipitation amount, and snow depth – in our specification. Daily data on weather conditions is obtained from the European Climate Assessment and Dataset (ECA&D) (Klein Tank et al., 2002) which contains information on 5,617 meteorological stations. Data availability for the different measures varies across meteorological 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.[11]

3 Empirical Strategy

To investigate asymmetry in the retail and wholesale segments of the market, we first examine the unit root properties of the price series. The retail price data set covers $15,228$ individual stations that are observed over a total of $1,825$ days.[12] To ensure a sufficient number of observations per station, we use stations with at least two years, i.e., 730 days of observation, resulting in a total of $12,804$ stations. Our estimation strategy is as follows: First, we apply the Augmented Dickey-Fuller unit root test to the individual station-level prices – retail and wholesale gasoline – and the international crude oil price, with the optimal lag length selected using the Akaike Information Criterion (AIC). As to the retail price, we find that $12,661$ of the $12,804$ individual station-level retail prices are $I(1)$. Similarly, the null hypothesis of non-stationarity cannot be rejected for the wholesale and crude oil prices for $12,617$ out of the $12,661$ stations at the 10% significance level.[13]

Second, we examine whether the retail and wholesale gasoline prices are cointegrated. Following the Engle-Granger residual-based cointegration test (Granger and Engle, 1987), we specify the long-run relationship between the retail price and wholesale price for each station as follows:

$$r_t = \sigma + \theta w_t + \gamma' \boldsymbol{H} + \delta' \boldsymbol{D} + \xi_t \tag{2}$$

Here, r_t and w_t respectively correspond to the average daily retail and wholesale price specific to a station at time t. σ is a constant that captures time-invariant station-specific

[11]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.

[12]This includes stations that are out of business or entered the market during the period.

[13]Unit root tests for station-level retail and wholesale price series and the crude oil price are all specified with a linear trend. Test results, including the residual-based cointegration tests are available as online appendix.

characteristics such as brand type, ownership type, station density (number of stations within the local market), associated facilities such as convenience or kiosk-type stores, car washes etc. θ denotes the cointegration parameter or long-run cost pass-through coefficient, and ξ_t is the residual – the gap between the retail price and its long-run equilibrium value.

We include a vector ($\boldsymbol{H}$) 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 of school holiday and 0 otherwise). Vector ($\boldsymbol{D}$) is 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. For the two price series to be linearly cointegrated, the residual ξ_{ist} should be stationary. Accordingly, we apply the Augmented Dickey-Fuller unit root tests to the residuals and find the retail prices of $12,613$ out of the $12,617$ stations to be cointegrated with their wholesale price counterparts. With the underlying price series being cointegrated, we specify an asymmetric error correction model (AECM) following Granger and Lee (1989):

$$\begin{aligned}\triangle r_t = \alpha &+ \phi^+\xi^+_{t-1} + \phi^-\xi^-_{t-1} \\ &+ \sum_{l=1}^{L}\left(\beta^+_l\triangle r^+_{t-l} + \beta^-_l\triangle r^-_{t-l}\right) \\ &+ \sum_{m=0}^{M}\left(\lambda^+_m\triangle w^+_{t-m} + \lambda^-_m\triangle w^-_{t-m}\right) \\ &+ \sum_{n=0}^{N}\left(\sigma^+_n\triangle c^+_{t-n} + \sigma^-_n c^-_{t-n}\right) \\ &+ \psi\triangle\bar{r}_{(-i)t-1} + \pi'\triangle\boldsymbol{W} + \gamma'\boldsymbol{H} + \delta'\boldsymbol{D} + \tau t + \varepsilon_t\end{aligned} \tag{3}$$

In equation (3), $\triangle$ is the first difference operator, L, M and N refer to the number of lags of the retail, wholesale and crude oil price, respectively, which are selected using the AIC. The coefficients β_l and λ_m capture the respective short-run impacts of lagged changes in retail prices and current and lagged changes in wholesale prices. We include the crude oil price not as the main input cost in equation (3) but to control for price changes in the international market.[14] ξ_{ist} is the residual from equation (2) with $\xi^+_{t-1} = max\{\xi_{t-1}, 0\}$ implying $\triangle r_{-1} > 0$ or $\triangle w_t < 0$ and $\xi^-_{t-1} = min\{\xi_{t-1}, 0\}$ implying $\triangle w_{t-1} < 0$ or $\triangle w_t > 0$. For each variable v in equation (3): $\triangle v^+ = max\{\triangle v, 0\}$ and $\triangle v^- = min\{\triangle v, 0\}$. Note that a plus (minus) as superscript to a coefficient is indicative of an increase (decrease) change in the associated variable.

The one-period lagged residual ξ_{t-1} – derived from equation (2) expresses the prior disequilibrium, that is, $\xi_{t-1} \neq 0$, from the long-run relationship. The coefficients (ϕ^+ and ϕ^-) associated with the residuals or error correction terms are the adjustment parameters

[14]We also estimate variants of equation (2) and (3) where we use crude oil price as the main input cost for stations. Here, the wholesale price is excluded from equation (3). Results are shown in section 4.1.

as they reflect the speed towards the long-run equilibrium. For example, positive deviations of retail prices ($\xi_{t-1} > 0$) from equilibrium in the previous period, that is ξ^+_{t-1}, due to a decrease in wholesale price $\triangle w_t < 0$, should return to the equilibrium level 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 wholesale price increase – and slower when otherwise. Moreover, the specification in equation (3) allows us to also test short-run asymmetry, that is, an F-test of the joint null hypotheses: $|\beta^+_l| = |\beta^-_l|$ or $|\lambda^+_m| = |\lambda^-_m|$)

To account for other determinants of price changes, we include a vector ($\boldsymbol{W}$) of weather related variables – precipitation, snow depth, and heating and cooling degree days (HDD/CDD) – and a vector ($\boldsymbol{H}$) of public and the start of school holidays.[15] We also include a vector ($\boldsymbol{D}$) of day-of-the-week-specific dummies and vector ($\boldsymbol{Y}$) to denote month and year dummy variables that control for seasonalities and common year-specific effects. A linear time trend (t) is also included to account for changes in retail prices that extend over the period. Local competition is denoted by the day-to-day changes in average prices ($\triangle \bar{r}_{-i}$) of neighboring stations within 5 km.

4 Results

4.1 Station-level Pricing Patterns

All German stations: This sub-section presents the estimation results for equation (3). As indicated earlier, retail gasoline prices may be less responsive to international crude oil price changes. Accordingly, domestic wholesale gasoline price is more relevant for stations than crude oil prices that serve as the main input for refineries. However, previous studies have largely relied on crude oil prices as the retail market's relevant input cost. Against this background, two input cost measures – international crude oil and wholesale gasoline prices – are employed separately in equation (2) and (3) to test the sensitivity of the rockets and feathers hypothesis to different measures of input costs.[16]

Figure 1 visualizes the long-run adjustment parameters from the estimation of the AECM for the individual station-level time series according to equation (3) for both input cost measures separately. Here, we show the station-level difference between the absolute values of the long-run adjustment parameters, $|\phi^+| - |\phi^-|$, for all $12,613$ stations in the sample along with the associated 95% confidence band. A negative statistically significant difference at the 5% level corresponds to the *rockets and feathers* pattern, an

[15] Using the station-level daily mean ambient temperature (t_g), we calculate $HDD = \max(0, 15.5 - t_g)$ and $CDD = \max(0, t_g - 15.5)$, using 15.5 °C as the base temperature for Europe.

[16] Note that when we use crude oil price as the main input cost in equation (2), we do not include the wholesale price in the AECM specification. However, when wholesale prices are used as the input cost, we also include the crude oil price in the AECM specification, as shown in equation (3) to control for the effect of price volatility in the international market.

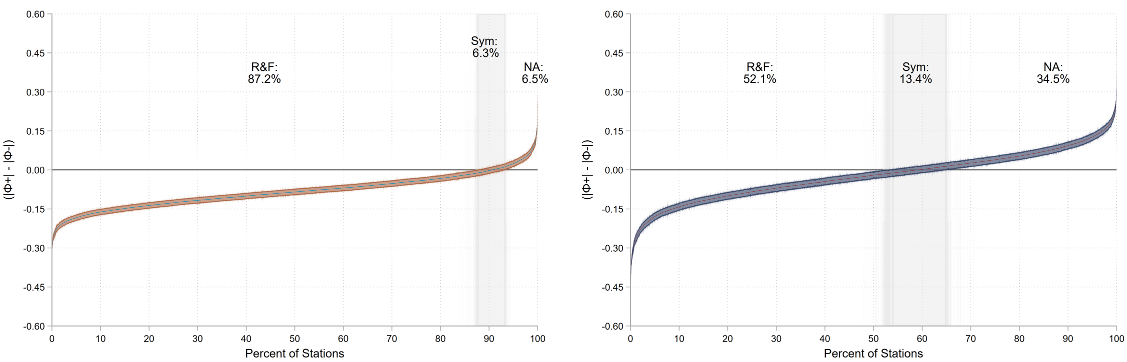
insignificant difference depicts *symmetric adjustment* of retail prices to input cost changes (gray-shaded area), whereas a positive statistically significant difference indicates the presence of *negative asymmetry.*

Regarding Figure 1a where we use crude oil prices as the relevant input cost for stations, we find an unambiguous rockets and feathers pricing pattern. Specifically, we find that 87.2% of stations show the *rockets and feathers* patterns, while only 6.3% price symmetrically. For the remaining 6.5% of fuel stations, *negative asymmetry* is found. This finding suggests that an overwhelming majority of stations swiftly adjust prices upwards following crude oil price increases than decreases, contradicting the notion of a competitive retail gasoline market. However, changing to wholesale gasoline prices as the input cost measure, as shown in Figure 1b, alters the main findings substantially. With wholesale gasoline prices, the share of stations showing the *rockets and feathers* pattern plummets to 52.1%. Simultaneously, the percentage of stations exhibiting *symmetric pricing* doubles to approximately 13.4% of stations in the sample. Moreover, 34.5% of stations show patterns of *negative asymmetry.* Therefore, a combined 48% of stations exhibit symmetric and negative asymmetric adjustment patterns, connoting a competitive market. Clearly, using international crude oil prices as the input cost overestimates the prevalence of the rockets and feathers pricing pattern.

Figure 1: Patterns of Asymmetry using Different Input Cost Measures

All brands (12, 613 stations)

(a) Crude Oil Price **(b)** Wholesale Price



Notes: The graphs shows the differences between the absolute values of the estimated long-run adjustment parameters ($|\phi^+| - |\phi^-|$) obtained from the regression of equation (3) for the 12, 613 individual fuel stations, along with its 95% confidence interval. Statistically significant negative differences suggest the presence of *rockets and feathers* (R&F), while significant positive differences suggest *negative asymmetry* (NA). Differences which do not differ significantly from zero point towards *symmetric adjustment* (Sym: gray-shaded area).

Differences by federal states: It should be noted that the distribution of fuel stations, the footprint of different brands, and sub-regional market structures vary across federal states. In terms of the density of fuel stations, for example, North Rhine-Westphalia, on the one hand, has 2,753 fuel stations in our sample, while Bremen – a federal city-state, on the other hand, has only 92 fuel stations. Since a significant number of individual stations belong to different brands that operate in different regional markets, it is also essential to test the sensitivity of our findings to regional market structure and characteristics. Figure 2 shows differences in retail price response to changes in wholesale gasoline prices across federal states. Here, the individual states are colored according to the intensity of the respective pricing pattern (see Table 5 for the full details). Red coloring indicates a higher share, whereas green visualizes lower shares.

The results show large geographic differences in the prevailing pricing patterns of stations across the federal states. While stations in the southern states exhibit the *rockets and feathers* pattern (see, Panel 2a), most states in the north and east – except Bremen, Berlin, and Schleswig-Holstein – are characterized predominantly by *negative asymmetry* (Panel 2b).[17] We should note that rockets and feathers states have high population densities – indicating higher demand – and a high share of refineries (see Figure 3b). They also have a high density of stations (see Figure 3a), which should signal a high level of competition. However, most of the stations belong to major brands. Consequently, the degree of competition among stations is limited due to the market power of major brands.

4.2 Local Market Characteristics

Competition in gasoline retailing is highly localized, with stations responding almost entirely to nearby stations' actions. However, the competition level depends largely on market-specific characteristics such as density and spatial distribution of nearby competitors, market structure, and population dynamics. We construct variables that reflect these market characteristics to provide insights into the pricing pattern determinants across the $12,613$ fuel stations. The dependent variable in our cross-sectional regression – presented in Table 1 – is the difference between the absolute values of the long-run adjustment parameters, weighted by its inverse standard error – $(|\phi^+| - |\phi^-|)/\sqrt{\frac{SE_{\phi^+}}{N} + \frac{SE_{\phi^-}}{N}}$.

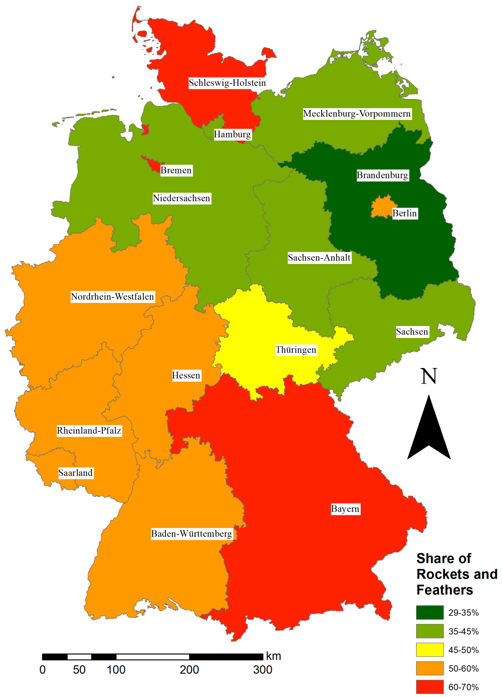
Similar to Figure 1, a negative value for the dependent variable suggests the rockets and feathers pricing pattern. In contrast, a positive value implies negative asymmetry. A negative statistically significant coefficient associated with an explanatory variable indicates that a particular market characteristic tends to increase the rockets and feathers pattern, while a positive coefficient increases the tendency of negative asymmetric pricing. To control for the geographic heterogeneity illustrated in Figure 2, all regressions include federal-state fixed effects. We also include brand fixed effects to capture brand-specific differences in pricing strategies.

Column (1) analyzes the effect of local market competition in a $5km$ radius as measured by the density of nearby competitors, i.e., total number of neighbors and its

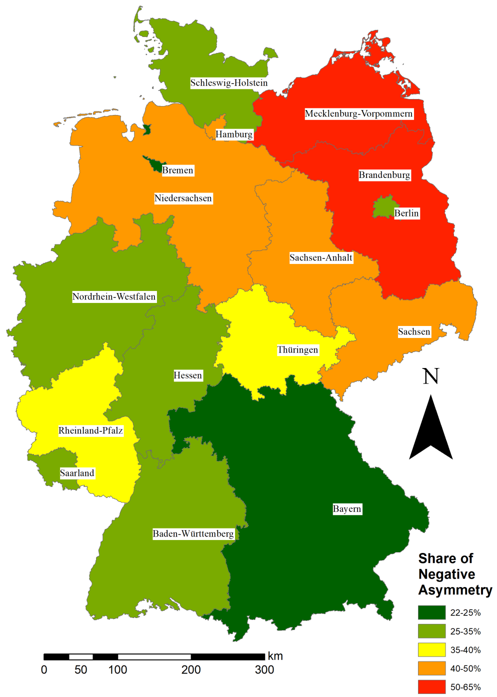
[17] Bremen and Berlin are federal city-states while Schleswig-Holstein shares a border with Denmark.

Figure 2: Spatial Distribution of Pricing Patterns by Federal States

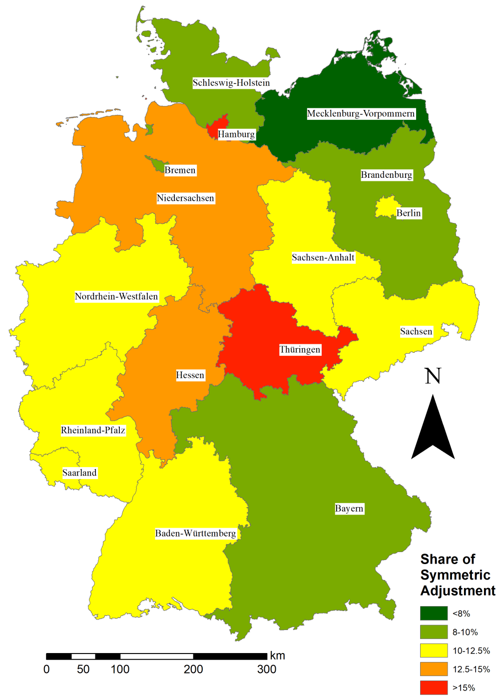
(a) Rockets and Feathers



(b) Negative Asymmetry



(c) Symmetric Adjustment



Source: Own illustration based on shapefiles obtained from the Natural Earth Database (http://www.naturalearthdata.com/downloads/10m-cultural-vectors/)

second polynomial. The estimated coefficients suggest a negative marginal effect with less than 33 neighbors. This indicates that stations with neighbors less than the threshold are likely to engage in the *rocket and feathers* pricing patterns. While the negative effect applies to stations with neighbors below the threshold, i.e., about $11,899$ stations in the sample, the impact is positive for stations with more competitors in the local market. Although the threshold in our case appears to be relatively large, the result is generally consistent with the notion that a higher number of stations in the local market assures competitive pricing behavior (Barron et al., 2004; Lewis, 2008; Bergantino et al., 2020). The result remains unchanged upon the inclusion of a dummy variable indicating the absence of neighbors in the local market – see column (2).

In column (3), we include the log of population density, which could account for the differences in purchasing behavior and demand across different markets. The coefficient is positive and statistically significant at the 1% level, implying that stations located in densely populated areas tend to exhibit *negative asymmetry* in retail pricing. That is, prices tend to be more competitive in markets with high population densities. In column (4), we investigate whether market power and concentration of brands affect an individual stations' pricing pattern in the local market. We measure these by calculating the shares of oligopoly brand stations and stations belonging to the same brand in the local market.

Regarding the share of major brands, it is important to note that these brands could have higher brand loyalty among consumers, for example, due to force of habit or the perception that they supply purer and superior gasoline. These consumers are less sensitive or inelastic to price changes across stations. The inclusion of the share of same-brand stations aims to assess whether market concentration or a higher number of same-brand stations lessens competitive pricing. After controlling for station and brand fixed effects, the results show that both variables enter the regression with significant and negative estimates. This suggests that a higher percentage of major brands or same-brand stations in the local market promotes the *rockets and feathers* pricing pattern. The competition effects of these variables accord with previous studies that show that the presence of a higher share of major brands and same-brand stations reduces price competition in the local market (Lewis, 2008; Bergantino et al., 2020).

Lastly, we include the shares of neighbors that price asymmetrically, that is, either *rockets and feathers* or *negative asymmetry*, with *symmetric adjustment* being the reference group in column (5). Here, the results clearly show that a higher share of neighboring stations showing the rockets and feathers pattern promotes anti-competitive pricing behavior. In comparison, stations with a higher percentage of negative asymmetric pricing neighbors engage in similar pricing behavior. Thus, the results suggest that the retail gasoline market is highly localized, with stations responding to their neighbors' actions.

Table 1: Local Market Characteristics and Asymmetric Pricing

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable: $(\lvert\phi^+\rvert - \lvert\phi^-\rvert)/\sqrt{\frac{SE_{\phi^+}}{N} + \frac{SE_{\phi^-}}{N}}$				
Total Number of Neighbors	-0.103***	-0.096**	-0.175***	-0.175***	-0.073*
	(0.028)	(0.029)	(0.039)	(0.039)	(0.035)
Total Number of Neighbors ^{2}	0.003***	0.003***	0.004***	0.004***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No Neighbors		0.319	0.465	-0.587	-2.767***
		(0.441)	(0.444)	(0.559)	(0.634)
ln(Population Density)			0.466**	0.504**	0.111
			(0.153)	(0.154)	(0.136)
Share of Major Brand				-1.322**	-1.868***
				(0.460)	(0.406)
Share of Same Brand				-1.276*	-0.930
				(0.540)	(0.476)
Share showing Rockets and Feathers					-10.035***
					(0.496)
Share showing Negative Asymmetry					8.334***
					(0.528)
Number of Stations	12,613	12,613	12,613	12,613	12,613
Federal State Fixed Effects?	Yes	Yes	Yes	Yes	Yes
Brand Fixed Effects?	Yes	Yes	Yes	Yes	Yes
$R^2_{Adj.}$	0.078	0.078	0.079	0.079	0.285

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.

4.3 Robustness Checks – Pooled-Panel Analysis

In this subsection, we test the sensitivity of the findings to an alternative estimation approach by estimating a pooled-panel regression across all stations. We report the estimated coefficients for the adjustment parameters, the day-specific dummies, neighbors' prices, holiday dummies, weather variables, F-test statistics for the long-run symmetry, and short-run symmetry hypotheses in Table 2.[18] Table 2 shows the pooled-panel estimation results of the asymmetric ECM in equation (3) for the complete sample of $12,613$ stations in Germany. In column (2) and (3), the relevant input cost used in equation (2) is the wholesale gasoline price while the spot crude oil price is used in column (1). Regarding the long-run adjustment parameters, the estimate show that $|\phi^-|$ exceeds $|\phi^+|$ across columns (1)-(3). The test results for the null hypothesis of equal adjustment, i.e., $|\phi^+| = |\phi^-|$ is rejected at all conventional significance level. Therefore, independent of the input cost used, the results point to the rockets and feathers pricing pattern across stations.

Averagely, a day after a 1 cent change in the crude oil price – see column (1), the corresponding adjustment for the retail price is 0.021 for crude oil price decrease and 0.056

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

Table 2: Regression Results: Gasoline (E5) – Pooled-Panel

	(1) Crude Oil Price		(2) Wholesale Price		(3) Both	
	Dependent Variable: $\triangle$ Retail Price of E5 Fuel					
ϕ^+	-0.021***	(0.000)	-0.024***	(0.000)	-0.024***	(0.000)
ϕ^-	-0.056***	(0.000)	-0.042***	(0.000)	-0.042***	(0.000)
Tuesday	0.120***	(0.001)	0.109***	(0.001)	0.107***	(0.001)
Wednesday	0.079***	(0.001)	0.087***	(0.001)	0.089***	(0.001)
Thursday	0.102***	(0.001)	0.116***	(0.001)	0.107***	(0.001)
Friday	0.139***	(0.001)	0.162***	(0.001)	0.132***	(0.001)
Saturday	0.293***	(0.001)	0.323***	(0.001)	0.280***	(0.001)
Sunday	0.609***	(0.001)	0.603***	(0.001)	0.588***	(0.001)
$\triangle\overline{p}_{(-i)t-1}$	0.116***	(0.000)	0.093***	(0.000)	0.092***	(0.000)
Public Holiday						
2 days before	0.173***	(0.002)	0.147***	(0.002)	0.149***	(0.002)
1 day before	0.169***	(0.002)	0.161***	(0.002)	0.157***	(0.002)
Same day	0.540***	(0.002)	0.529***	(0.002)	0.530***	(0.002)
1 day after	-0.105***	(0.002)	-0.078***	(0.002)	-0.073***	(0.002)
School Holiday Start						
2 days before	0.077***	(0.002)	0.043***	(0.002)	0.044***	(0.002)
1 day before	0.042***	(0.002)	0.011***	(0.002)	0.010***	(0.002)
Same day	0.043***	(0.002)	0.012***	(0.002)	0.010***	(0.002)
1 day after	0.103***	(0.002)	0.050***	(0.002)	0.051***	(0.002)
	F-Tests for Symmetry					
$\phi^+ = \phi^-$	20,022.02***		3,210.96***		3,146.30***	
$\beta_l^+ = \beta_l^-, \quad l \in [1,7]$	6,292.55***		5,150.56***		5,145.28***	
$\lambda_m^+ = \lambda_m^-, \quad m \in [0,7]$			390.63***		429.67***	
$\sigma_n^+ = \sigma_n^-, \quad n \in [0,7]$	4,522.24***				766.80***	
Cointegration based on	c_t		w_t		w_t	
N	21,621,581		21,621,581		21,621,581	
$R^2_{Adj.}$	0.286		0.332		0.332	
Number of Stations	12,613		12,613		12,613	
Month/Year Fixed Effects ($\boldsymbol{Y}$)	Yes		Yes		Yes	
Weather Controls ($\boldsymbol{W}$)	Yes		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 $\boldsymbol{D}$ in equation (3). The holiday variables represent vector $\boldsymbol{H}$. 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. $\triangle$ *Rainfall*, $\triangle$ *Snow Depth*, $\triangle$ *HDD*, and $\triangle$ *CDD* represent the vector of weather variables ($\boldsymbol{W}$). *Month/Year Fixed Effects* ($\boldsymbol{Y}$) 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 $\beta_l^+ = \beta_l^-$ for all $l \in [1,7]$ and $\lambda_m^+ = \lambda_m^-$ or $\sigma_n^+ = \sigma_n^-$, respectively, for all $m \in [0,7]$.

for an increase. Using the wholesale gasoline price as the relevant input cost – see column (1), the adjustment parameters $|\phi^+|$ and $|\phi^-|$ are 0.024 and 0.042, respectively. These adjustment parameters remain unchanged when we control for changes in crude oil price – see column (3) – as specified in equation (3). In terms of the half-life of a deviation from the long-run equilibrium – calculated as $ln(2)/|\phi|$ – half of a unit crude oil price increase is adjusted within 12 days while it takes approximately 33 days for a decrease. For wholesale price as the input cost – column (2) and (3), the half-life of a 1 cent deviation is approximately 17 days for an increase and 29 days for a decrease. Thus, using the crude oil price results in a swift adjustment of input cost increases and slower adjustment of cost decreases to retail prices compared to using the wholesale gasoline prices as the relevant input cost. Overall, the results based on the pooled-panel regression are identical to a recent finding by Asane-Otoo and Dannemann (2020), which shows that the "pattern of rockets and feathers is the norm rather than the exception".

In summary, the results show that the type of input cost considered in the analysis affects the prevalence of the rockets and feathers pattern across stations and the magnitude of the adjustment coefficients. Moreover, even with wholesale prices as the relevant input cost, employing pooled-panel regression techniques may mask the nature and extent of asymmetry, leading to inaccurate inferences. In our analysis, pooling across stations leads to a definite conclusion that wholesale price increases are passed through faster than decreases. This contrasts to the station-specific time series regression counterpart, which shows that anti-competitive pricing patterns are relatively moderate.

Concerning the estimates for days of the week, our results suggest increasing retail prices throughout the week with a strong weekend effect, independent of the type of input cost used. Across all columns, we also find that the effect of local competition as measured by average neighbors' prices is positive and significant at the 1% level, indicating that stations are responsive to neighbors' actions in the local market (5 km radius). On the demand-effect of public and school holidays, the results again tie well with the finding of Asane-Otoo and Dannemann (2020).

In Table 3, we disaggregate the results in column (3) of Table 2 based on the type of pricing pattern from the individual station time series regression analysis. Column (1) presents the pooled panel regression results for only stations that exhibit the rockets and feathers pattern, column (2) for stations that price symmetrically, and column (3) for stations that portray the negative asymmetric adjustment pattern. As expected, the pooled panel AECM results confirm the rockets and feathers pattern for individual stations that engage in this type of pricing pattern.

In contrast, we find that the adjustment coefficients point to a *rockets and feathers* pricing pattern for symmetric adjustment stations. Although these individual stations symmetrically adjust their prices to cost changes, the average adjustment coefficients based on the panel regression reveal otherwise. Similarly, we also find an average symmetric adjustment for stations that individually pass on wholesale price decreases more swiftly than increases (see, column 2). In a nutshell, the pooled panel regression findings support the notion of summation bias due to pooling across stations. Accordingly, estimation approaches that yield average coefficients across stations may obscure the actual pricing pattern observed from station-level time series analysis.

4.4 Wholesale price response

In this sub-section, we complement our analysis of the retail market by examining region-specific wholesale gasoline prices' responsiveness to international crude oil price

Table 3: Pooled Panel by Pricing Patterns

	(1) Rockets & Feathers Stations		(2) Symmetry Stations		(3) Negative Asymmetry Stations	
	Dependent Variable: △ Retail Price of E5 Fuel					
ϕ^+	-0.019***	(0.000)	-0.028***	(0.001)	-0.031***	(0.000)
ϕ^-	-0.049***	(0.000)	-0.040***	(0.001)	-0.032***	(0.000)
Tuesday	0.106***	(0.002)	0.111***	(0.004)	0.107***	(0.002)
Wednesday	0.085***	(0.002)	0.085***	(0.004)	0.095***	(0.002)
Thursday	0.103***	(0.002)	0.104***	(0.004)	0.114***	(0.002)
Friday	0.133***	(0.002)	0.132***	(0.004)	0.131***	(0.002)
Saturday	0.274***	(0.002)	0.288***	(0.004)	0.288***	(0.002)
Sunday	0.570***	(0.002)	0.591***	(0.004)	0.613***	(0.002)
$\triangle\overline{p}_{(-i)t-1}$	0.095***	(0.001)	0.091***	(0.001)	0.088***	(0.001)
Public Holiday						
2 days before	0.144***	(0.002)	0.156***	(0.005)	0.153***	(0.003)
1 day before	0.152***	(0.002)	0.160***	(0.005)	0.163***	(0.003)
Same day	0.495***	(0.003)	0.540***	(0.006)	0.580***	(0.003)
1 day after	-0.078***	(0.002)	-0.058***	(0.005)	-0.068***	(0.003)
School Holiday Start						
2 days before	0.036***	(0.003)	0.057***	(0.007)	0.052***	(0.004)
1 day before	0.004	(0.003)	-0.002	(0.007)	0.023***	(0.004)
Same day	0.007*	(0.003)	0.010	(0.006)	0.016***	(0.003)
1 day after	0.039***	(0.003)	0.050***	(0.006)	0.070***	(0.004)
	F-Tests for Symmetry					
$\phi^+ = \phi^-$	4,887.60***		179.18***		1.89	
$\beta_l^+ = \beta_l^-, \quad l \in [1,7]$	2,115.47***		618.19***		2,527.68***	
$\lambda_m^+ = \lambda_m^-, \quad m \in [0,7]$	230.27***		45.84***		177.30***	
$\sigma_n^+ = \sigma_n^-, \quad n \in [0,7]$	425.37***		87.40***		267.95***	
Cointegration based on	w_t		w_t		w_t	
N	11,480,801		2,428,496		7,712,284	
$R^2_{Adj.}$	0.328		0.336		0.339	
Number of Stations	6,718		1,421		4,474	
Month/Year Fixed Effects ($\boldsymbol{Y}$)	Yes		Yes		Yes	
Weather Controls ($\boldsymbol{W}$)	Yes		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 $\boldsymbol{D}$ in equation (3). The holiday variables represent vector $\boldsymbol{H}$. 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. △ *Rainfall*, △ *Snow Depth*, △ *HDD*, and △ *CDD* represent the vector of weather variables ($\boldsymbol{W}$). *Month/Year Fixed Effects* ($\boldsymbol{Y}$) 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 $\beta_l^+ = \beta_l^-$ for all $l \in [1,7]$ and $\lambda_m^+ = \lambda_m^-$ or $\sigma_n^+ = \sigma_n^-$, respectively, for all $m \in [0,7]$.

changes. As illustrated in Figure 3b, we obtain the wholesale gasoline prices from 8 spatially differentiated regional markets that host the 18 refineries in Germany. Note that for these regional wholesale markets, the relevant input cost is the international crude oil price. Table 8 shows the results of the AECM estimated using variants of equation (2) and (3) as follows:

$$w_t = \sigma + \theta c_t + \xi_t \tag{4}$$

$$\triangle w_t = \alpha + \phi^+ \xi^+_{t-1} + \phi^- \xi^-_{t-1} + \sum_{m=1}^{M} \left(\beta^+_m \triangle w^+_{t-m} + \beta^-_m \triangle w^-_{t-m} \right) \quad (5)$$
$$+ \sum_{n=0}^{N} \left(\lambda^+_n \triangle c^+_{t-n} + \lambda^-_n \triangle c^-_{t-n} \right) + \tau t + \varepsilon_t$$

Here, w_t and c_t are daily region-specific wholesale prices and Brent crude oil price, respectively. Note that the wholesale price series are cointegrated with the crude oil price. σ is the region fixed effect, θ denotes the long-run crude oil price pass-through coefficient, and ξ_t is the residual.

The results show, as expected that the regional wholesale markets exhibit the rockets and feathers phenomenon. We find that for almost all regional wholesale markets – except the *South* market where we find a symmetric adjustment – increases in Brent crude oil prices are transmitted more swiftly to wholesale prices than an equivalent Brent crude oil price decrease.[19] As shown in Figure 3b, refineries – some of which are also owned by vertically integrated firms with control over depots – have regional market power that allows them to price asymmetrically. Thus, contrary to the retail market where we observe a large number of stations engaging in competitive pricing, anti-competitive pricing is rather a common feature of the wholesale market.

5 Concluding Remarks

Anti-competitive pricing in the retail gasoline market is largely attributed to market inefficiencies, e.g., market power, information asymmetry. In this paper, we examine the prevalence of anti-competitive pricing in the German retail market following the price transparency regulation in 2013. Specifically, we investigate whether retail fuel prices adjust more swiftly to input cost increases than decreases – a phenomenon characterized as the *rockets and feathers* pricing pattern. Previous studies have investigated this pricing pattern by employing data aggregated across stations and time or adopted estimation techniques that ignore parameter heterogeneity across stations. However, to provide a comprehensive understanding of asymmetric price responses, it is crucial to conduct the analysis at the station level, where pricing decisions are actually implemented.

Accordingly, our analysis draws on a unique data set of daily retail and wholesale gasoline prices, spanning across 12,613 individual stations over the period from January 1, 2014 to December 31, 2018. Our detailed station-level data set allows us to analyze each station individually, therefore allowing parameter heterogeneity and overcoming potential problems associated with data aggregation across space and time. Using asymmetric error correction models for each station, we find that 52% of stations respond asymmetrically to wholesale gasoline price changes by swiftly passing the price change to consumers when it decreases the retail margin than when it increases it.

[19] The symmetric adjustment finding in the *South* market is not surprising since this market has more refineries and depots than all other regional markets.

The remaining 48% of stations either respond symmetrically to wholesale gasoline price changes or pass on wholesale price decreases faster to consumers than increases. Our finding suggests that the rockets and feathers pricing pattern is a feature of individual stations, and it is not unique to specific brands or sub-regional markets. Although a majority of stations engage in anti-competitive pricing behavior, the results suggest that the high level of price transparency and the ease with which consumers can access real-time price information in a local market appear to enhance price competition among stations.

We also find that the type of input cost and the estimation approach used to evaluate asymmetric responses at the station-level matters. Using the international crude oil price as the retail market's relevant input cost leads to pervasive rockets and feathers pattern, with over 87% of stations engaging in this pricing pattern. Moreover, employing pooled panel regression techniques obscure the actual pricing pattern observed from station-level time series analysis. Beyond temporal and spatial aggregation issues, which have been confirmed in previous studies, parameter heterogeneity exists across individual stations. Therefore, pooling across individual stations leads to estimation or summation bias that conceals the actual price responses at the station level. Overall, our findings offer a comprehensive view of the retail gasoline market in a major OECD country following the price transparency regulation, thereby allowing us to generalize our findings to typical national retail gasoline markets.

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Appendix

Driving Distances

Wholesale price data from Oil Market Report is presented for 8 distinct regions in Germany, for which only approximate coordinates are given. To illustrate, the O.M.R. region "Nord" is described on their website as the region around Hamburg, without stating the spatial extent. Accordingly, the center of the respective city is employed as the geographic coordinate for the market regions, as presented in Table 4. The 18 refineries and 117 fuel depots, for which the exact geographic coordinates and the postal address are known, are then assigned to the market regions by proximity, as measured by linear distance (air distance).

We employ the routing software *Open Source Routing Machine* (OSRM)[20] using OpenStreetMaps data[21] to run a batch calculation of driving distances and durations between the exact georeferenced positions of the fuel stations in Germany and the 135 refineries and fuel depots. The calculation of the route considers characteristics (e.g., road type, speed limit, routing restrictions) based on the standard car profile for the navigation and routing software. Further, the profile is set to avoid ferries, as their use would entail additional costs. The inverse distance is then used to calculate the station-level averages of the wholesale prices.

Table 4: Assignment of O.M.R. Market Region Centroids

Region	Near City	Latitude	Longitude
North	Hamburg	53° 34' 3.3816"	9° 59' 44.6748"
Seefeld	Seefeld	52° 51' 49.0752"	13° 53' 41.9532"
East	Berlin	52° 30' 58.428"	13° 23' 56.6592"
West	Duisburg, Essen, Gelsenkirchen	51° 29' 29.8932"	6° 56' 59.352"
South-East	Leuna	51° 19' 21.1404"	12° 1' 28.7868"
Rhine-Main	Frankfurt	50° 6' 52.2216"	8° 40' 59.466"
South-West	Karlsruhe	49° 0' 5.9328"	8° 23' 36.7656"
South	Ingolstadt, Neustadt, Vohburg	48° 45' 42.0156"	11° 25' 31.2168"

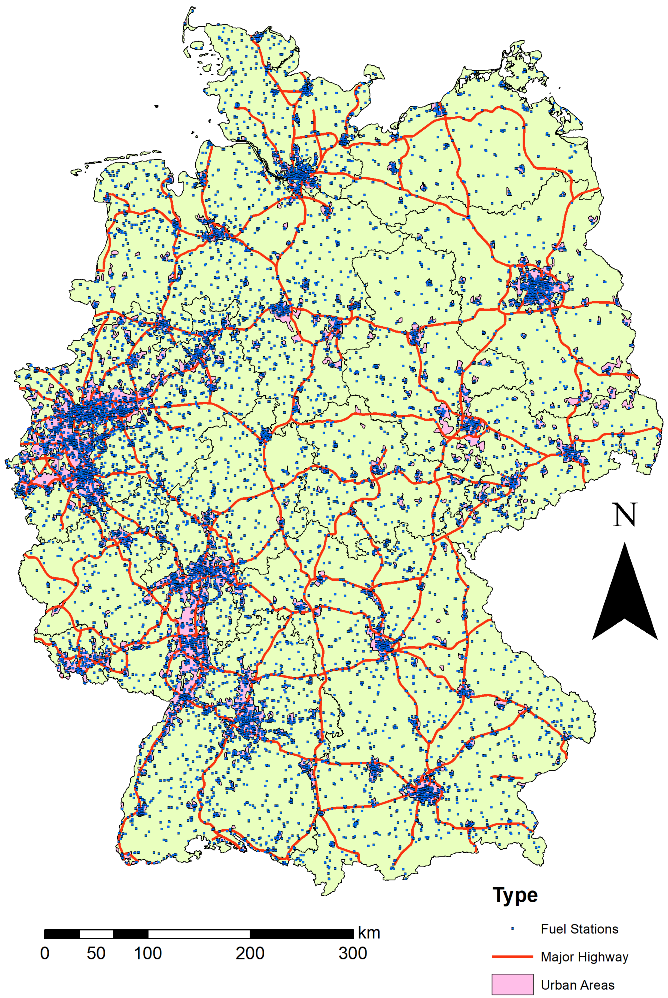
Notes: In the case of more than one city mentioned (i.e., regions *West* and *South*), the center-point between the given cities is used to determine the regions' centroids.

[20] Latest stable version, v5.16.0

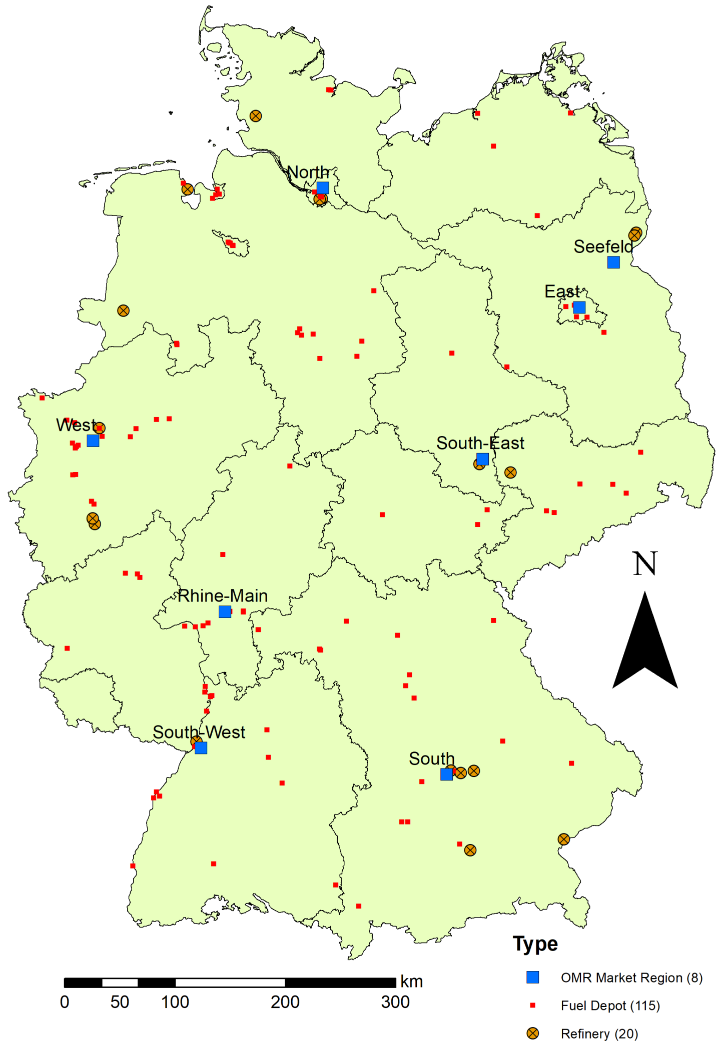
[21] Available online from geofabrik.de, Version from February 2019

Figure 3: Spatial Distribution of Fuel Stations, Depots, and Refineries in Germany

(a) Fuel Stations and Urban Areas



(b) Refineries and Fuel Depots



Source: Own illustration based on shapefiles obtained from the Natural Earth Database (http://www.naturalearthdata.com/downloads/10m-cultural-vectors/)

Table 5: Adjustment Patterns by Federal States

State	Rockets and Feathers	Symmetric Adjustment	Negative Asymmetry	Total
Baden-Württemberg	951	174	531	1,656
%	(57.43)	(10.51)	(32.07)	(100.00)
Bayern	1,266	179	466	1,911
%	(66.25)	(9.37)	(24.39)	(100.00)
Berlin	163	32	95	290
%	(56.21)	(11.03)	(32.76)	(100.00)
Brandenburg	111	38	232	381
%	(29.13)	(9.97)	(60.89)	(100.00)
Bremen	63	8	21	92
%	(68.48)	(8.70)	(22.83)	(100.00)
Hamburg	80	33	98	211
%	(37.91)	(15.64)	(46.45)	(100.00)
Hesse	548	137	299	984
%	(55.69)	(13.92)	(30.39)	(100.00)
Mecklenburg-Vorpommern	108	24	174	306
%	(35.29)	(7.84)	(56.86)	(100.00)
Niedersachsen	626	186	654	1,466
%	(42.70)	(12.69)	(44.61)	(100.00)
Nordrhein-Westfalen	1,495	315	956	2,766
%	(54.05)	(11.39)	(34.56)	(100.00)
Rheinland-Pfalz	336	76	244	656
%	(51.22)	(11.59)	(37.20)	(100.00)
Saarland	80	18	49	147
%	(54.42)	(12.24)	(33.33)	(100.00)
Sachsen	225	61	232	518
%	(43.44)	(11.78)	(44.79)	(100.00)
Sachsen-Anhalt	134	35	158	327
%	(40.98)	(10.70)	(48.32)	(100.00)
Schleswig-Holstein	373	51	145	569
%	(65.55)	(8.96)	(25.48)	(100.00)
Thüringen	159	54	120	333
%	(47.75)	(16.22)	(36.04)	(100.00)
All States	6,718	1,421	4,474	12,613
%	(53.26)	(11.27)	(35.47)	(100.00)

Notes:

Table 6: Variables used

Variable	Unit	Source
Retail Price of Fuel Type Gasoline E5 - (p)	Cents per Liter	MTS-K
Wholesae Price of Fuel Type Gasoline E5 - (w)	Cents per Liter	O.M.R.
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	—
Public Holiday Dummy	binary	—
Day of the Week Dummies	binary	—

Table 7: Descriptive Statistics: Regression Sample

Variable	Stations	Obs.	Mean	S.D.	Min.	Max.
p	12,613	21,621,581	140.925	10.168	88.800	194.900
w	12,613	21,621,581	109.375	8.201	90.280	128.640
c	12,613	21,621,581	33.567	8.622	14.998	53.191
dp	12,613	21,621,581	-0.007	1.461	-55.417	40.600
dw	12,613	21,621,581	-0.008	0.495	-7.773	6.793
dc	12,613	21,621,581	-0.011	0.533	-2.773	2.584
rr	12,613	21,621,581	-0.001	0.999	-0.471	39.880
sd	12,613	21,621,581	-0.006	0.965	-0.632	368.119
HDD	12,613	21,621,581	60.098	57.612	0.000	336.000
CDD	12,613	21,621,581	10.243	21.960	0.000	154.000

Table 8: Regression Results: Wholesale Market Regions

	(1)	(2)	(3)	(4)	(5)	(6)
			Tests for Symmetry			
O.M.R. Market Region	ϕ^{+}	ϕ^{-}	Long-Run	Short-Run (w)	Short-Run (c)	R^2
North	-0.084***	-0.163***	6.75***	0.48	2.14**	0.304
	(0.021)	(0.024)				
East	-0.087***	-0.155***	5.07**	1.09	1.70*	0.287
	(0.022)	(0.021)				
Seefeld	-0.101***	-0.172***	4.81**	0.95	1.53	0.295
	(0.023)	(0.024)				
Southeast	-0.062**	-0.142***	8.86***	1.28	1.59	0.294
	(0.019)	(0.020)				
West	-0.081**	-0.161***	5.41**	0.78	2.02**	0.283
	(0.025)	(0.025)				
Rhine-Main	-0.059***	-0.143***	8.59***	0.53	2.23**	0.270
	(0.016)	(0.024)				
Southwest	-0.099***	-0.156***	2.95*	0.83	2.25**	0.281
	(0.027)	(0.024)				
South	-0.088**	-0.128***	1.36	0.50	1.59	0.271
	(0.029)	(0.024)				

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.
All Specifications comprise of $1,826$ Observations The dummy variables for the days of the week correspond to vector $\boldsymbol{D}$ in equation (3).
Month/Year Fixed Effects ($\boldsymbol{Y}$) 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 $n \in [0, 7]$.

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