Abstract

This paper uses spatial and temporal fluctuations in retail gasoline prices to study the effects of competition on pricing behavior and how government-mandated price restrictions impact consumers.

We use hourly price data for more than 16,500 gas stations in Austria and Germany (more than 90% of the market), collected since April 2012. This data is supplemented with manually recorded demand data for selected gas stations as well as traffic data for all German highways, and is wholly unique.

We classify the price movement of different gas stations by employing dynamic time warping and $k$-means clustering. We find that there are brand-specific pricing patterns prevailing in the German gasoline market. This suggests that there is no single dominant strategy for intertemporal price discrimination in the market. Pricing pattern deviations are highly correlated across Aral (BP) and Shell, suggesting that the each brand dynamically adjusts its prices in response to the other.

Secondly, we analyze nation-wide price fluctuations, cross-network price patterns, and price competition between gas stations that directly compete for motorists. One possible explanation for the observed price fluctuations is asymmetric information. To test this prediction, we model consumers as being informed or uninformed about the prices of all gas stations. The model illustrates that the high prices observed during the morning hours can be explained by fewer informed consumers traveling in the morning compared to the evening.

Finally, we estimate price elasticities for different groups of consumers. The data suggest that the pricing behavior observed in the Austrian and German markets cannot be explained as pure demand shocks. Rather, gas stations temporally price discriminate: in Germany, gas stations set high prices for price-inelastic business / morning consumers and low prices for the highly elastic leisure / evening consumers. In Austria, governmental regulation prevents gas stations from replicating the patterns in Germany. This leads to unintended consequences: consumers face a less volatile price with higher daily minima in Austria, forcing price-sensitive consumers to refill at higher average prices.
Gasoline and diesel prices strongly fluctuate. In different regions of Austria and Germany, there are three to seven price movements per day on average. Figure 1.1 shows the weekly gasoline price pattern of a “Jet” gas station in Germany. These daily price movements are common across all gas station networks and geographic areas. Figure 1.2 shows that all gas station networks display very similar price patterns.

The force driving these intra-day price cycles is unknown. Popular wisdom attributes gas price movements solely to changes in cost. However, changes in the price of oil can only explain long run movement of the average gasoline retail price. The frequent daily and weekly price adjustments cannot be explained by the variation of oil prices. In this paper, we address the following questions:

- What drives the daily price cycles?
- Do gas station networks follow distinct price patterns?

\[1\] Jet is owned by the U.S. oil company Phillips 66 and has about 5.5% market share. It is the 6th biggest gas station network in Germany after BP-owned Aral (17%), Shell (13%), Total (7%), Esso (7%), and Avia (6%).
• Are gas stations price discriminating against different groups of consumers?

This paper finds that gas stations engage in intertemporal price discrimination against consumers with different price elasticities, and that heterogeneous information drives the observed daily price fluctuations. First, we analyze gas stations’ pricing behavior. Using techniques from computer science, we find answers to how gasoline and diesel prices are set. We classify the price movement of different gas stations employing dynamic time warping and $k$-means clustering. These methods allow us to analyze and characterize the relationship of over 600 million price points.

Second, we find that there are network-specific price patterns prevailing in the German gasoline market, suggesting that no single dominant strategy holds in the market. Moreover, this illustrates that gas station franchises are much less independent in their pricing behavior than is broadly assumed. Prices appear to be set centrally by the network. Moreover, we find that deviations from these network-specific price patterns are highly correlated among Aral (BP) and Shell. This suggests that the each network dynamically adjusts its pattern responding to changes in the pattern of the other. More generally we find that gas stations adjust their pricing strategies in response to their competitors’ pricing behavior.
Third, this paper assess whether shifts in cost can explain price patterns at gas station. Edgeworth cycles, a theory based on exogenous cost shocks, have been used to explain fluctuations in the gasoline retail price in the United States, Canada, and Australia. The monthly price movement in these countries seems to match the patterns of alternating undercutting until price levels close to marginal costs are reached. However, the Austrian and German price patterns look very different. Prices in Germany are much more volatile; they change multiple times a day and price levels depend strongly on the hour of the day. This paper discovers alternative explanations for the observed pricing behavior.

Consumers possessing asymmetric information is one possible explanation. We model consumers as being informed or uninformed about the prices at all gas stations in their market. In this case, it is optimal for gas stations to randomize prices at every hour of the day according to some price distribution. This model reveals that the high prices in the morning hours can be explained by a lower fraction of informed consumers compared to evening hours.

Using a multinomial logit model, we estimate price elasticities for different consumer groups. The elasticity estimates show that the pricing behavior observed in the Austrian and German markets cannot be explained as pure demand shocks. In Germany, gas stations set price high for inelastic business / morning consumers and low for the elastic leisure / evening consumers. This observation can explain the price patterns existing in the data and suggests that gas stations temporarily price discriminate.

**Policy Implications**

This paper aims to inform an ongoing debate about gasoline and diesel prices in Europe. Countries search for policy measures to maximize consumer surplus and prevent price discrimination (Geradin and Petit, 2005). The popular perception that gas stations raise prices during the holiday season to extract revenue from inelastic consumers is widespread. Countries regularly debate policies to protect consumers from such pricing behavior. Germany, for example, is actively debating to limit gas stations’ ability to raise prices. Legislation to limit the number of times a gas station can increase its prices each day is being discussed. Two questions follow naturally:

- How would price patterns look if the gas stations’ ability to set prices freely is limited due to regulation?

- What impact would such a regulation have on consumers?
Austria and Germany have similar demand for gasoline and diesel, but the countries have different regulations. While market participants in Germany can freely set prices, market participants in Austria can raise prices only once a day, at 12pm noon. Moreover, for the recent holiday seasons Austria fixed prices (ARBO 2010). By comparing Austria and Germany, we can evaluate how such regulation influences consumers. Regulations limit the ability of gas stations to adjust prices optimally to fluctuations in demand, cf. figure 1.3

![Gasoline Price Chart](chart.png)

**Figure 1.3:** Gasoline price of “Jet” during a week in 2014 in Austria.

Figure 1.4 compares the average weekly gasoline price movement in Austria and Germany. As a result of pricing regulations in Austria, we see that price fluctuations occur less frequently and are smaller in magnitude. We find that Austria’s regulation impedes this behavior and yet might lead to unintended consequences: consumers face less volatile prices, forcing price sensitive consumers to refill at higher average prices.

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2 Austria gas stations can freely lower prices. They are constrained to raise prices only once a day, at 12pm.
Figure 1.4: Average gasoline price during a week in 2014 in Austria and Germany (% deviation from mean, cross-sectional average)

**Outline**

This paper uses spatial and temporal fluctuations in gas station retail prices to study the effect of competition on prices and how government-mandated price restrictions impact consumer welfare. Gas stations present a large, spatially differentiated market: consumers have close substitutes, but the cost of choosing a competitor can be measured by distance; prices are publicly displayed and are adjusted dynamically; station owners are highly heterogeneous and employ different pricing strategies; and potential demand can be directly observed through traffic counting stations. Competition takes place on a local as well as national level, with low barriers to entry and exit.

The analysis in this paper utilizes three years worth of data on the spatial and temporal fluctuations in Austrian and German gasoline and diesel prices. We observe hourly price information on 3,302 gas stations in Austria and 13,661 gas stations in Germany – this represents more than 90% of the Austrian and German gas station market. For Germany, the hourly prices are supplemented with manually recorded demand data for selected gas stations as well as hourly traffic data of all state streets and autbahns (highways).
The rest of the paper is organized as follows. Chapter 2 gives a short review of previous literature related to gasoline retail prices. Chapter 3 describes the data, outlines interesting price patterns observed, and reports reduced form results. Chapter 4 shows that the observed price patterns cannot be explained by Edgeworth Cycles. Chapter 5 classifies the price movement of different gas stations employing dynamic time warping and $k$-means clustering. Chapter 6 presents and analyzes a model of information asymmetry as a possible explanation for the intra-day price patterns. Chapter 7 analyzes a multinomial logit demand model. Chapter 8 concludes and discusses possible extensions.
2 Related Literature


Gasoline retail price in the United States, Canada, and Australia show cycles that begin with a large increase followed by many small price decreases over the subsequent period (compare Eckert 2003, Noel 2007, Wang 2009, and Lewis 2011). Once markups are down to the level of marginal costs, prices jump back up and the cycle begins afresh. The repeated pattern of prices is strikingly similar in appearance to “Edgeworth Cycles,” introduced by Maskin and Tirole (1988). Eckert (2003) extends the basic model to allow firms to vary in size. Atkinson (2009) uses price data to verify the predictions made in Eckert (2003). Eckert and West (2005) use daily gasoline retail price information from Vancouver to identify the role that gas station characteristics such as brand names, distance to competitors, traffic flows, etc. play in pricing choices.

A common line of criticism when analyzing the gasoline retail industry concerns the data sources used (e.g. Eckert and West 2005). Either prices are recorded with insufficient frequencies for catching short term fluctuations, or gas stations studied represent only a subset of the consumer market, or the time period of observation is too short. Haining (1983) and Barron, Taylor, and Umbeck (2000) study the gasoline retail market with survey data containing station prices updated once a month and once every two months, respectively. While this price frequency provides valuable insights into long run price trends, it will not capture daily price fluctuations (or even hourly as in Austria and Germany). The Australian Competition and Consumer Commission (2001) uses daily data from more than 2,500 sites in five major metropolitan cities in Australia to analyze the causes and implications of price cycles. It finds that the average variation of price cycles increased between 1998 and 2001. Eckert (2002, 2003) uses average weekly price information from a sample of stations in multiple markets in Ontario. Noel (2007) uses daily price information from 22 gas stations located in eastern Toronto, limiting his observations to a subset of the gasoline retail market in Toronto. Atkinson (2009) collects bi-hourly price data for 27 gas stations and three months in Guelph, Ontario. Wang (2009) uses hourly retail prices for a five-month period in the Perth area.
For measuring similarity between two temporal price sequences which vary in time or speed, we use the dynamic time warping (DTW) algorithm, compare Vintsyuk (1968), Sakoe and Chiba (1978), Myers and Rabiner (1981), and Berndt and Clifford (1994). We use FastDTW, Salvador and Chan (2007, 2012). The $k$-means clustering algorithm used to differentiate price patterns was developed by Forgy (1965), Hartigan (1975), Hartigan and Wong (1979), and Lloyd (1982) and builds on earlier work by Steinhaus (1957) and MacQueen et al. (1967).

The model of temporal price dispersion driven by informed and uninformed consumers is based on “A Model of Sales”, Varian (1980). In this model some consumers are informed of all prices and other consumers know only one price and do not look for other prices. The informed consumers purchase from the retailer with the lowest price; the uninformed consumers purchase if the price is lower than some reservation price.

The model of discrete choice demand estimation presented in this paper builds on previous work by Berry, Levinsohn, and Pakes (1995), Nevo (2001), and Thomadsen (2005). We use the Generalized Method of Moments, Hansen (1982), to estimate the demand parameters.
3 Data

3.1 Data Description

We collected three years worth of data on the spatial and temporal fluctuations in Austrian and German gasoline and diesel prices. We observe hourly price information on 3,302 gas stations in Austria and 13,661 gas stations in Germany – this represents more than 90% of the Austrian and German gas station market. The data were continuously sourced from governmental and private websites since April 2012. All gas stations observed were geocoded; a subsample is displayed figure 3.1. There are more than 600 million observations, collected and analyzed using over 24,000 lines of code programmed in Java, Python, MongoDB, MySQL, R, and Stata.

For Germany, the hourly prices were supplemented with hourly traffic data of all state streets and autobahns. This detailed traffic data was provided by the German Bundesanstalt für Straßenwesen (Federal Institute for Roadways).

Information on the quantity of gasoline and diesel sold at each gas station is needed for the demand estimation in chapter 7. To do so, we considered an 108km (67 miles) segment of autobahn A9 that stretches from Hermsdorfer Kreuz to Dreieck Bayreuth / Kulmbach (cf. figure 7.1). There are eleven gas stations in this segment. To obtain a proxy for the quantity demanded, we went to five of these gas stations and manually counted all cars and trucks refilling at the gas stations for a period of 96 hours. The dataset created is wholly unique.

3.2 Temporal Patterns
Figure 3.1: The green dots represent a subsample of the gas stations in Austria and Germany for which hourly gas prices are observed. The red dots represent a subsample of the traffic counting stations in Germany.

3.2.1 General Observations

Gasoline and diesel prices fluctuate substantially. Figure 3.2 displays the average gasoline and diesel price in Germany\(^1\) together with the gasoline wholesale market price for 2012. We see that only the gasoline and diesel price levels, but not the intra-day price fluctuations, appear to be correlated with the gasoline wholesale market price.

We also observe that the weekly patterns in Austria and Germany look very different.

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\(^1\)The average was taken cross-sectionally, i.e. across all gas stations.

\(^2\)The data from July is missing due to technical difficulties during that month.
3.2.2 Temporal Patterns in Germany

The weekly patterns of gasoline and diesel prices at various gas station networks in Germany are shown in figures 3.3 and 3.4.

**Figure 3.3:** Gasoline prices of various gas station networks during a week in 2014 in Hoyerswerda, Germany.

**Figure 3.4:** Diesel prices of various gas station networks during a week in 2014 in Hoyerswerda, Germany.
We note that all gasoline networks have common intra-day pricing behavior: morning prices are high and evening prices are low. Yet each gas station network displays idiosyncratic patterns regarding the time and shape in which prices change. While some networks raise prices in the evening, others keep them low until early morning. Shell, for example, charges 2 euro cents more than all its competitors on gasoline and diesel between 9pm and 6am. Moreover, the manner in which prices move up or down differs across network. Star, for example, first moves up once and then down three times every day. In contrast, Shell appears to employ a more fine-tuned strategy, increasing prices slightly again in the afternoon after lowering it earlier in the day.

3.2.3 Temporal Patterns in Austria

Figures 3.5 and 3.6 show the weekly gasoline and diesel price patterns at various gas station networks in Austria. While market participants in Germany can freely set prices, market participants in Austria can raise prices only once a day, at 12pm noon. Austrian regulations limit the ability of gas stations to optimally adjust prices to fluctuations in demand.

![Figure 3.5: Gasoline prices of various gas station networks during a week in 2014 in Austria.](image1)

![Figure 3.6: Diesel prices of various gas station networks during a week in 2014 in Austria.](image2)

The difference in daily price patterns suggest that Austria’s policy intervention alters firms’ pricing behavior. It seems that firms’ inability to raise prices in the morning pushes them to keep prices high until before noon. Moreover, firms reduce their prices by smaller amounts; prices stay high for longer. The figures suggest that the lowest prices are reached during weekends.

3Looking closer into Shell’s pricing, we found that Shell offers its customers a membership card. This card gives discounts for gasoline and diesel which may cancel out the premiums charged.
Price patterns appear less uniform in Austria compared to Germany. eni24, for example, prices its diesel in an ECG recording-like fashion, with discrete ‘heart-beats’ between 12pm and 1pm every day and without any weekend adjustment. Jet, on the other hand, displays more pronounced price variations around 12pm and follows an overall downward trend towards the weekend.

### 3.2.4 Comparison of Average Temporal Patterns in Austria and Germany

Figures 3.7 and 3.8 show average weekly gasoline and diesel prices in Austria and Germany.

![Figure 3.7: Average gasoline price during a week in 2014 in Austria and Germany (% deviation from mean, cross-sectional average)](chart1.png)

![Figure 3.8: Average diesel price during a week in 2014 in Austria and Germany (% deviation from mean, cross-sectional average)](chart2.png)

The cross-sectional average’s deviations from weekly mean confirms the following:

1. In Germany, daily price variation is greater.
2. In Germany, there exist hours with lower average prices on every day of the week.
3. In Austria, prices are lowered shortly before and after 12pm noon, and stay almost constant during the rest of the day.
4. In Germany, the lowest daily price is reached around 6:30pm.
5. In Germany, the lowest weekly price appears to be achieved on every day (around 6:30pm) except for Friday and Sunday.
6. In Austria, the lowest daily price is reached around 11am, shortly before the price increases at 12pm noon.
7. In Austria, the lowest weekly price is reached on Sunday evening.

8. In Austria, there is a general trend of decreasing prices within the week.

Observation (2) shows that price-sensitive consumers can find lower average prices on every day of the week in the unregulated (German) market. This finding holds for both types of fuel.

3.3 Reduced Form Statistics

Tables 3.1 and 3.2 show the dependence of gasoline and diesel prices on deviations from average traffic volume. The correlation between gasoline prices and traffic volume is positive, while that of diesel prices and traffic volumes is negative. Since gasoline prices are above diesel prices, the spread between the two types of fuel widens when traffic volume increases. This observation suggests that an increase in traffic

<table>
<thead>
<tr>
<th>Table 3.1: Influence of traffic on gasoline prices (OLS).</th>
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<tbody>
<tr>
<td>Gasoline price dev. from mean</td>
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<tr>
<td>Traffic total % dev. from mean</td>
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<td>Traffic cars % dev. from mean</td>
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<td>Traffic trucks % dev. from mean</td>
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<thead>
<tr>
<th>Table 3.2: Influence of traffic on diesel prices (OLS).</th>
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<tr>
<td>Diesel price dev. from mean</td>
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<tr>
<td>Traffic total % deviation from mean</td>
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<tr>
<td>Traffic cars % deviation from mean</td>
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<tr>
<td>Traffic trucks % deviation from mean</td>
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</tbody>
</table>

makes gas stations raise their gasoline prices and lower their diesel prices. This pattern appears to be independent of the traffic’s compilation of fuel types as the statement holds true for truck traffic as well which is diesel based only.

Next we looked at the relationship of demographics and the number of gas stations found in a region. The number of trucks registered in a region seems to play the biggest role in determining the number of gas stations in that region, cf. table 3.3.
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<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tr>
<td>No. gas stations /km²</td>
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<td></td>
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<td>No. Trucks /km²</td>
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<td>.00036***</td>
</tr>
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<td></td>
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<td>.00011***</td>
<td>.00014***</td>
</tr>
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<td>.00011***</td>
<td></td>
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<td>Business tax /km²</td>
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</tr>
</tbody>
</table>
4 Edgeworth Price Cycles

4.1 United States, Canada, and Australia

Edgeworth cycles have been used to explain fluctuations in the gasoline retail price in the United States, Canada, and Australia. The monthly price movements in these countries seem to match the patterns of alternating undercutting until a price level close to marginal costs are reached, compare figure 4.1 (Noel 2007).

![Figure 4.1](image)

**Figure 4.1:** Figure from Noel (2007) showing evidence for Edgeworth price cycles in the Canadian gasoline retail market. This figure depicts twelve-hourly price series for a “representative” sample of gas stations located in Toronto operated by a major brand and an independent competitor.

4.2 Austria and Germany

In Austria and Germany, prices are much more volatile than in the United States, Canada, and Australia; as seen in chapter 3 (cf. representative figure 4.2), prices change multiple times a day and price levels depend strongly on the hour of the day. We do not believe that the price fluctuations in Austria and Germany can be explained using Edgeworth cycles.

While Edgeworth cycles can explain the low-frequency price changes that occurring in the United States,
Canada, and Australia, they cannot explain the high-frequency intra-day price patterns found at gas stations in Austria and Germany. It is impossible that a cost shock influences all gas stations in Austria and Germany every evening at around 9pm to 5am as Edgeworth cycles would predict.

4.3 Pricing Behavior in Local Competition in Austria and Germany

We now look at pricing behavior among direct local competitors. We select all gas stations within a distance of 2km (1.24 miles) or less from another gas station and define this to be a ‘local market’. Comparing hourly prices at each station in a local market, we count the number of times a station undercutts or matches the price of the cheapest station in the local market. We find:

- Most gas station pairs have one firm which always goes ahead and undercutts the price of the other (ca. 80% of the time).
- The other gas station usually matches the lower price within 1 to 3 hours.
- Independent gas stations are the most fierce in competing for the lowest price (independent gas stations are the ones undercutting prices 88% of times).
- Big gas station networks (Aral, Shell, Total) are most likely to match prices set by other stations

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1Compare e.g. Eckert (2003), Noel (2007), Wang (2009), and Lewis (2011).
and do not initiate undercutting.

- Small networks (Hem, Go, ...) initiate price cuts when paired with big networks, but match prices when paired with independent stations.
5 Pricing Patterns

In this chapter, we use data mining techniques to classify the price patterns of different gas stations. We employ clustering to detect common pricing behavior. Subsequently, we will look for correlations in deviations from common pricing behavior. We choose to focus on the German market because of the availability of richer pricing data on an hourly basis.

5.1 Dynamic Time Warping

Approaching price data, we want to impose as little structure as possible. Most figures shown in this paper display price points within a week. I.e., we imposed a periodicity of one week. We will now test and verify that one week is, in fact, the correct periodicity for all gas station networks. For instance, one gas station network might follow daily price patterns while another might follow weekly price patterns. To test this, we employ dynamic time warping, a time series analysis tool which translates between time and frequency domains. Using dynamic time warping\footnote{We use the Java implementation “FastDTW” published by Salvador and Chan 2012} we find that

- Gas station networks show a 7 day time domain within a month.
- Gas station networks show a 1 day time domain for Mon – Fri.

Thus, gas station networks’ price behavior displays a periodicity of one week and of one day. Put differently, a networks’ price pattern look the most similar to itself if weekly or daily intervals are selected.

5.2 k-means Clustering

Gas stations display different pricing behavior, as discussed in chapter 3. Each gas station in figure 5.1, for example, displays idiosyncratic daily and weekly patterns in the way prices change, both in terms of time and shape. While some networks raise prices in the evening, others keep them low until early morning etc.

We want to partition the set of all gas station into $k$ clusters by selecting all gas stations with similar daily price patterns. Therefore, let $\kappa \in \{G_{E5}, G_{E10}, D\}$ denote the fuel types at each gas station $j$, i.e. gasoline
with 5% ethanol, 10% ethanol, and diesel, respectively. Let $\bar{p}_{jkd}$ denote the mean daily price of $\kappa$ at $j$ on day $d$. For every day $d$ and hour $h \in \{0, \ldots, 23\}$ of the day, define

$$
\lambda_{jkdh} := \frac{p_{dh}}{\bar{p}_{jkd}}
$$

(5.1)

Define

$$
\Omega := \left\{ \lambda_{jkdh} \bigg| h \in \{0, \ldots, 23\} \right\}_{jkd}
$$

(5.2)

the set of characteristics of fuel $\kappa$ at gas station $j$ on day $d$.

We employ $k$-means clustering on $\Omega$ for each day in our dataset using Weka [University of Waikato 2014]. Table 5.1 shows the centroid points for each of the $k = 5$ clusters.

Three of the five clusters contain a dominant number of gas stations from one network only (“Aral”, “Shell”, or “Esso”). For instance, about 97% of the gas stations in the cluster we denote by “Aral” are Aral gas stations. The two clusters “Mixed 1” and “Mixed 2” contain a variety of brands. Especially smaller networks and privately owned gas stations appear to be very diverse in their intra-day pricing behavior.
Table 5.1: Cluster centroids for $k = 5$ in deviation from daily mean price / cents. These values can be thought of as a prototype for each cluster.

<table>
<thead>
<tr>
<th>$h$</th>
<th>Aral (BP)</th>
<th>Shell</th>
<th>Esso (ExxonMobil)</th>
<th>Mixed 1</th>
<th>Mixed 2</th>
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<td>−6</td>
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</tr>
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<td>8</td>
<td>3.4188</td>
<td>8</td>
</tr>
<tr>
<td>22</td>
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<td>0</td>
<td>8</td>
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<td>8</td>
</tr>
<tr>
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<td>0</td>
<td>0</td>
<td>5</td>
<td>0.3419</td>
<td>0</td>
</tr>
</tbody>
</table>

5.3 Deviations from Network’s ‘Normal Pricing Patterns’

We established that Aral, Shell, and Esso exhibit network-wide pricing behavior. Now, we analyze how networks react to a competitor’s deviation from its standard price pattern. We compute the deviations from network-specific pricing behavior (centroids) recorded in table 5.1. Figure 5.2 shows average deviations from the ‘centroid behavior’ conditional on observing a deviating behavior from at least one market participant.

The two biggest German gas station networks, Aral (BP) and Shell, display strongly correlated deviations from their respective standard price pattern. Esso’s (ExxonMobil’s) prices almost never deviate from its ‘centroid behavior.’ It is not surprising that the mixed network cluster fluctuates more intensively, considering the large number of different networks and owners that is grouped into it.
Figure 5.2: Average deviations from the network-specific pattern conditional on observing a deviating behavior from at least one market participant. Green = Aral (BP), (light) blue = Shell, purple = Esso (ExxonMobil), and red = all others.
6 Information Asymmetry

Consumers possessing asymmetric information can explain the price patterns observed in Austria and Germany. In this chapter, we develop a model of temporal price dispersion driven by informed and uninformed consumers similar to Varian (1980). We model consumers as being informed or uninformed about the prices at all gas stations in their market. In this case, it is optimal for gas stations to randomize prices at every hour of the day according to some price distribution. This model reveals that the high prices in the morning hours can be explained by a lower fraction of informed consumers compared to evening hours.

6.1 Model

Consumers drive vehicles that run on either gasoline ($\kappa = G$) or diesel ($\kappa = D$), but not both.

For each hour of the week $h(t)$, let $m_{h(t)}$ denote the average number of motorists at $h(t)$. Furthermore, let $\rho_{kh(t)} \in [0, 1]$ represents the fraction of motorists that need to refill their vehicle, i.e. $\rho_{kh(t)}m_{h(t)}$ is the number of motorists that need to refill. Let $t_{kh(t)} \in (0, 1)$ be the fraction of informed motorists and $1 - t_{kh(t)}$ be the fraction of uninformed motorists. Uninformed motorists will pick a gas station in the market at random as long as the price is below some reservation price $r_{kh(t)}$. Informed consumers, on the other hand, know the prices of all gas stations in the market and will refill at the gas station with the lowest available price.

Let $J$ be the number of gas stations in the market and $\frac{1 - t_{kh(t)}}{J} \rho_{kh(t)}m_{h(t)}$ be the number of uninformed motorists per gas station buying fuel $\kappa$ at hour $h(t)$. Each gas station has a density function $f_{kh(t)}(p)$ representing the probability of the gas station charging price $p$. Each gas station takes the demand behavior of the motorists as well as the pricing strategies of the other gas stations as given.

Subsequently, we will only consider the case of a symmetric equilibrium. At every time $t$, each gas station sets a price at random according to $f_{kh(t)}(p)$. The gas station with the lowest price receives

---
[1] Informed consumers can be thought of as consumers who have installed a price comparison app on their phone. At any time $t$, the informed consumers can query the prices of all gas stations in her proximity. The two most popular gas price comparison apps in Germany, “clever-tanken” and “mehr-tanken”, have both been installed between 1 million and 5 million times on Google’s Android OS alone. It seems reasonable to assume that there is a large group of ‘informed consumers’ in the German market.

[2] $h : N_+ \to \{1, ..., 7\} \times \{0, ..., 23\}$ maps time $t$ to its hour of the week.
If two or more gas stations charge the lowest price it is considered a tie and each get an equal share of the informed motorists. All gas stations with a higher price get

\[ \frac{1 - \tau_{kh}(t)}{J} \rho_{kh(t)} m_{h(t)} \] motorists.

All gas stations are characterized by identical, strictly declining average cost curves for fuel \( \kappa \) at hour \( h(t) \), denoted \( c_{kh}(t)(q) \). We assume all gas stations to operate at zero profit. Define \( I_{kh} := \tau_{kh} \rho_{kh} m_{h} \) and \( U_{kh} := \frac{1 - \tau_{kh}}{J} \rho_{kh} m_{h} \) the number of informed and uninformed motorists. For continuous prices \( p_{\kappa t} \), Varian (1980) proves:

- \( f_{kh}(p) = 0 \) for \( p < p^{*}_{kh} := \frac{c_{kh}(I_{kh} + U_{kh})}{I_{kh} + U_{kh}} \) or \( p > r_{kh} \) (the motorists’ reservation price).
- There is no symmetric equilibrium where all gas stations charge the same price.
- There are no point masses in the equilibrium pricing strategies.
- If \( f_{k}(p_{\kappa t}) > 0 \), then the equilibrium cumulative distribution function of \( p_{\kappa t} \) is

\[ 1 - F_{kh}(p) = \left( \frac{\pi_{kh,g}(p)}{\pi_{kh,g}(p) - \pi_{kh,l}(p)} \right)^{\frac{1}{J-1}} \] (6.1)

where \( \pi_{kh,l}(p) = p(I_{kh} + U_{kh}) - c_{kh}(I_{kh} + U_{kh}) \) and \( \pi_{kh,g}(p) = pU_{kh} - c_{kh}(U_{kh}) \) represent the profits for gas station(s) with the lowest price and those with greater prices.

- \( \frac{\pi_{kh,g}(p)}{\pi_{kh,g}(p) - \pi_{kh,l}(p)} \) is strictly decreasing in \( p \).
- \( F_{kh}(p^{*}_{kh} + \varepsilon) > 0 \) for any \( \varepsilon > 0 \).
- \( F_{kh}(r_{kh} - \varepsilon) < 1 \) for any \( \varepsilon > 0 \).
- There are no \( p_{1}, p_{2} \in (p^{*}_{kh}, r_{kh}) \) such that \( f_{kh}(p) \equiv 0 \) for all \( p \in (p_{1}, p_{2}) \).

For gas stations it is natural to assume a cost function with a (high) fixed and constant marginal cost, i.e. \( c_{kh}(q) = D + d_{kh} q \) for all \( \kappa \) and \( h \). Then equation (6.1) simplifies to
\[
1 - F(p) = \left( \frac{p^{1-i} \rho m - d^{1-i} \rho m - D}{-p_i \rho m + d_i \rho m} \right)^{\frac{1}{1-i}} \\
= \left( \frac{(p - d)^{1-i} \rho m - D}{-p + d} \right)^{\frac{1}{1-i}} \\
= \left( \frac{D \rho m}{(p - d) i - \frac{1}{J}} \right)^{\frac{1}{1-i}} 
\]

### 6.2 Market Definition

The model developed in section 6.1 relies on the definition of ‘a market.’ A market needs to capture all gas stations that are directly competing with each other in prices. In order to define the market for 13,661 gas stations in Germany objectively, we employ hierarchical clustering \[\text{Ward Jr} \, 1963\].

We define markets employing Ward’s hierarchical clustering procedure on the physical distance between all gas stations in Germany. This approach identifies clusters of gas stations located close to each other, competing for consumers in the same geographic vicinity. This method of cluster analysis seeks to agglomeratively build a hierarchy of clusters. This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy. The “height” parameter represents the value of the average distance of clusters to each other.

Applying Ward’s hierarchical clustering procedure on all gas station in Germany results in the dendrogram (clustering tree) displayed in figure 6.1. The dotted red lines indicate the “height” to partition the 13,661 gas stations into approximately 500, 1,500, and 5,500 groups (top to bottom, respectively). The resulting clusters of gas stations in Germany are displayed in figures 6.2 and 6.3 respectively. Appendix A shows the clustering results for the Austrian and German gas station market combined.

### 6.3 Estimation Results

We estimate \( F_{\kappa h}(\cdot) \) using equation 6.2. To gain precision on the empirical distribution of prices, we pool all markets of common size \( J \). As the level of prices varies on a weekly basis, we modulate the gas station

---

\[Ward \text{ introduced a general agglomerative hierarchical clustering procedure, where the criterion for choosing the pair of clusters to merge at each step is minimizing the within-cluster sum of squared distances, also known as Ward’s minimum variance method.}\]
specific price movement on top of each market size $J$’s average price. Table A.1 in the appendix provides the estimates for $\frac{D_{pm}}{m}$, $d$, and $\iota$ resulting from the modulated price data for $J = 2$ (two direct competitors) and $\kappa = G$ (gasoline). Figure A.4 in the appendix shows the difference between the empirical CDF and the $F_{\kappa h}(\cdot|\hat{\theta})$.

Figure 6.4 shows the marginal cost $d$ over the course of a week. The marginal cost $d$ is close to constant, fluctuating only within the range of 1.4 to 1.5 euro per liter. As gas stations’ largest variable cost component is the cost of fuel they sell, it appears intuitive that costs stay constant across hours.

Figure 6.5 shows the fraction of informed motorists, $\iota_{\kappa}$, over the course of a week for $J = 2$ and $\kappa = G$ (gasoline). We can see an increase in the number of informed consumers from about 70% in the morning to about 80% in the evening during weekdays, and a constantly high level on weekends. The estimates

\footnote{The downwards spikes in $d$ close to midnight are computational errors arising due to imprecisions from our estimation procedure lacking data points in this area.}
imply that there are less informed consumers frequenting gas stations in the morning than in the evening.

\footnote{The downwards spikes in \( t_\kappa \) close to midnight are computational errors arising due to imprecisions from our estimation procedure lacking data points in this area.}
Figure 6.1: The dendrogram resulting from applying Ward's hierarchical clustering procedure on all gas station in Germany. The dotted red lines indicate the "height" to partition the 13,661 gas stations into approximately 500, 1,500, and 5,500 groups (top to bottom, respectively).
Figure 6.2: Clusters of gas stations in Germany resulting from “cutting the dendrogram” for approximately 500 groups.
Figure 6.3: Clusters of gas stations in Germany resulting from “cutting the dendrogram” for approximately 5,500 groups.
Figure 6.4: The marginal cost $d$ over the course of a week. The marginal cost $d$ is close to constant, fluctuating only within the range from 1.4 to 1.5 euro per liter. The downwards spikes in $d$ close to midnight are computational errors arising due to imprecisions from the estimation procedure with the limited number of data points there.
Figure 6.5: The fraction of informed motorists, $\iota_{\kappa}$, over the course of a week for $J = 2$ (two direct competitors) and $\kappa = G$ (gasoline). We can see an increase in the number of informed consumers from morning to evening on weekdays and a constant high level. The downwards spikes in $\iota_{\kappa}$ close to midnight are computational errors arising due to imprecisions from the estimation procedure with the limited number of data points there.
7 Demand Analysis

7.1 Logit Model

Consumers drive vehicles that run on either gasoline \((\kappa = G)\) or diesel \((\kappa = D)\), but not both.

The utility of consumer \(i\) from buying fuel \(\kappa\) at gas station \(j\) at time \(t\) is given by a linear specification with an additively random component.

\[
U_{ij\kappa,t} = X_j'\beta - P_{jk,t}\rho_k + \varepsilon_{ij\kappa,t} \tag{7.1}
\]

\[
U_{i0\kappa,t} = \beta_0 + \varepsilon_{i0\kappa,t}
\]

where \(X_j\) is the vector of dummies indicating gas station \(j\)'s characteristics. \(\beta\) and \(\rho_k\) are parameters that need to be estimated and \(\varepsilon_{ij\kappa,t}\) is the unobserved portion of the utility of consumer \(i\) at station \(j\). \(\beta_0\) represents consumer \(i\)'s outside option of refilling her car at a gas station that is not in \(\{1, \ldots, J\}\). Without loss of generality, we normalize \(\beta_0 = 0\) going forward. We assume that consumers know all prices and that they can reach all gas stations including the outside option. This assumption restricts our definition of markets as consumers are assumed to not run out of fuel within the market. Specifically, the market cannot be too big in spatial size.

Each consumer has measure zero and thus acts as a price taker. The consumer will purchase fuel \(\kappa\) from the gas station from which she derives the highest utility, or not consume in this market if \(U_{i0\kappa,t} > U_{ij\kappa,t}\) for all \(j \in \{1, \ldots, J\}\) (outside option, i.e. obtaining fuel somewhere else). She selects \(j \in \{0, \ldots, J\}\) which maximizes utility.

\[
\arg\max_j U_{ij\kappa,t} \tag{7.2}
\]

We assume that \(\varepsilon_{i\kappa,t} \equiv (\varepsilon_{i1\kappa,t}, \ldots, \varepsilon_{iJ\kappa,t})\) are drawn independently across consumers \(i\) and times \(t\) according to

\[
\varepsilon_{i\kappa,t} \sim F(\varepsilon_{i,t}). \tag{7.3}
\]
We can write down the expected share of gas station \( j \) among consumers as a function of prices, station characteristics, and taste parameters:

\[
S_{j,k,t}(X, P; \theta) = \int_{E_{j,k,t}} dF(\varepsilon_{i,k,t}),
\]

(7.4)

where \( P \) is the vector of prices for every gas station in the market, \( \theta = \{\beta, \rho\} \), and \( E_{j,k,t} \) is the set of \( \varepsilon_{i,t} \) that corresponds to the greatest utility value \( U_{ij,k,t} > U_{i0,k,t} \).

We assume

\[
\varepsilon_{i,t} \sim T1EV.
\]

(7.5)

Then the share of consumers with vehicle \( T \) choose to refill their car at station \( j \) is

\[
S_{j,k,t}(X, P; \theta) = \frac{e^{X_{j}^{\beta} - P_{j,k,t} \rho_{k}}}{1 + \sum_{r=1}^{J} \sum_{s \in \{G,D\}} e^{X_{r}^{\beta} - P_{r,s,t} \rho_{s}}},
\]

(7.6)

and its derivative is

\[
\frac{\partial S_{j,k,t}(X, P; \theta)}{\partial P_{op,q}} = \frac{-\rho_{k} e^{\Lambda_{j,k,t}} \left( 1 + \sum_{r=1}^{J} \sum_{s \in \{G,D\}} e^{\Lambda_{r,s,t}} \right) \delta_{jo} + \rho_{k} e^{\Lambda_{j,k,t}} e^{\Lambda_{op,q}}}{\left( 1 + \sum_{r=1}^{J} \sum_{s \in \{G,D\}} e^{\Lambda_{r,s,t}} \right)^{2}} \delta_{kp} \delta_{tq},
\]

(7.7)

with \( \Lambda_{j,k,t} := X_{j}^{\beta} - P_{j,k,t} \rho_{k} \) and \( \delta_{jo} \) and \( \delta_{kp}, \delta_{tq} \) Kronecker delta\(^1\) (representing ‘same station’ and ‘same fuel type and market’, respectively).

The total demand for fuel \( t \) at gas station \( j \) is

\[
Q_{j,k,t}(X, P; \theta) = \sum_{l} \chi_{\kappa,t}(l) S_{j,k,t}(X, P; \theta)
\]

(7.8)

where \( \chi_{\kappa,t}(l) \) denotes the vehicle’s tank volume corrected mass of consumers potentially demanding \( \kappa \) at time \( t \).

\(^1\)Kronecker delta is defined \( \delta_{jo} = \begin{cases} 1 & \text{if } j = o \\ 0 & \text{if } j \neq o. \end{cases} \)
7.2 Estimation

Given observed demand $Q$ and $\hat{Q}(P, X|\theta)$ from formula (7.8), we set

$$\eta := Q - \hat{Q}(P, X|\theta).$$ \hfill (7.9)

We estimate $\theta$ using that, at the optimum, $\eta$ needs to be zero in expectation (generalized method of moments), i.e.,

$$E[\eta(\theta^*)] = 0.$$ \hfill (7.10)

7.2.1 Market Definition

For estimating the demand parameter vector $\theta^*$, we define the market to be the segment of autobahn A9 (highway A9) displayed in figure 7.1 at every hour. The length of this segment is 108km (67 miles) and it stretches from Hermsdorfer Kreuz to Dreieck Bayreuth / Kulmbach.

For this length it is reasonable to assume that most consumers can reach all of the gas stations on their side of the autobahn. We selected a stretch of autobahn as it offers an interesting feature: gas stations in direct proximity are serving different customers; separated by medians and crash barriers, the two sides of the road are impossible to cross without big detours.\(^2\) Thus, the traffic going north and south on the selected stretch of autobahn can be viewed as consumers on different markets. We selected this particular segment of the A9 because

- it has traffic counting stations at its beginning and end,
- it is the main autobahn used for north-south transit (by both cars and trucks),
- traffic volume greatly fluctuates, depending on the time of day, day of week, and season, and
- there is only one major autobahn crossing it, which we also observe traffic for.

The selected segment of the A9 has eleven gas stations in direct proximity to the autobahn:

\(^2\)In order to cross over to the other side of an autobahn, one has to drive to the next exit, change sides, drive to the gas station, refill, drive to the next exit, and change sides again. This can easily account for a 20km (12 miles) detour.
• 6 gas stations are bi-directional (can be accessed by north- and south-bound vehicles),

• 3 gas stations are accessible to north-bound vehicles only, and

• 2 gas stations are accessible to south-bound vehicles only.

We manually counted all cars and trucks refilling at five of the eleven gas stations for 96 hours (08/05 2014 to 08/08 2014). The five selected gas stations included the three north-bound and two bi-directional stations.

7.2.2 Results

We used Nelder-Mead, a widely used gradient free optimization method, to estimate the demand parameters. We selected all hours from 08/05 2014 to 08/08 2014, 4 days = 96 different markets / hours. The price coefficients corresponding to the selected markets are listed in table 7.1.
Table 7.1: Price coefficients of multinomial logit model for cars and trucks.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{\text{diesel, car}}$</td>
<td>$-2.57^{**}$</td>
</tr>
<tr>
<td>$\rho_{\text{gasoline, car}}$</td>
<td>$-2.25^{**}$</td>
</tr>
<tr>
<td>$\rho_{\text{diesel, truck}}$</td>
<td>$-3.15^{***}$</td>
</tr>
</tbody>
</table>

7.3 Interpretation

The negative price elasticities in table 7.1 show that price and quantity are countercyclical. This means that the Austrian and German price patterns cannot be explained as pure demand shocks. Explaining the observed pricing behavior using demand shocks implies prices and quantity to go in the same direction (assuming an upwards sloping supply curve). Figure 7.2 illustrates the price and quantity oscillation in the observed times period.

Figure 7.2: Price and quantity are countercyclical. This rejects the hypothesis that the observed price patterns are mainly driven by demand shifts.
8 Conclusion and Outlook

Gas stations are interesting and important markets to study. Consumers have close substitutes, yet choosing one gas station over another requires physically traveling to the corresponding station. Moreover, while the (main) product sold is homogeneous, stations face different demand profiles throughout the day. As a result, store owners employ a range of pricing strategies, many of which involve dynamically changing posted prices throughout the day. Finally, characteristics that differentiate gas stations are mostly observable: we directly observe the location of the station and its nearest competitors, traffic flows, station ownership, and additional amenities that the station offers. While there are unique aspects of this market, we believe that the analysis presented in this paper can help us understand industries well outside of the gasoline retail business.\footnote{An example of a similar industry is the mobile app market: there are big corporate as well as small independent app developers, each employing their own pricing strategy (free + ads / for pay); customers have closely substitutable products, with search and time cost deterring from sampling every alternative.}

Using this market, we consider how competition – both at the nation-wide macroeconomic level and between adjacent gas stations at the microeconomic level – affects pricing behavior. Furthermore, by comparing Austria and Germany, we are able to evaluate how policies which limit the frequency at which stations can change their prices influence consumers. We use hourly price data for more than 16,500 gas stations in Austria and Germany, collected since April 2012. This data is supplemented with manually recorded demand data for selected gas stations as well as traffic data for all German highway, providing insights into the market that were not previously possible in the literature.

Using dynamic time warping and $k$-means clustering, this paper classifies the price movement of various gas stations. We find that there are network-specific price patterns prevailing in the German gasoline market. This suggests that there is no single dominant strategy for intertemporal price discrimination in the market. Pricing pattern deviations are highly correlated across Aral and Shell, suggesting that the each network dynamically adjusts its pricing in response to the other.

This paper rejects Edgeworth cycles as a possible explanation for the price volatility observed in Austria and Germany. Instead, we model consumers possessing asymmetric information: consumers being informed or uninformed about the prices at all gas stations in their market. Here it is optimal for gas stations to randomize prices at every hour of the day according to some price distribution. This model reveals that
the high prices in the morning hours can be explained by a lower fraction of informed consumers compared to evening hours.

We estimate the price elasticity for different consumer groups and show that the pricing behavior observed in the Austrian and German market cannot be explained as pure demand shocks. The data suggest that gas stations temporally price discriminate: in Germany, gas stations set high prices for price-inelastic business/morning consumers and low prices for the highly elastic leisure/evening consumers. In Austria, governmental regulation prevents gas stations from replicating the patterns in Germany, and might lead to unintended consequences: consumers face a less volatile price with higher daily minima in Austria, forcing price-sensitive consumers to refill at higher average prices.

It is a fundamental goal of this work to fully understand pricing behavior. While the characterization of the price patterns in the German market is an essential and valuable step towards achieving this goal, we cannot stop here. Important questions that have not yet been answered include: Is the deviation from the network-specific pricing pattern strategic, competitive or collusive, anti-competitive behavior? Also, why do Austria’s gas station networks employ considerably different pricing approaches; is it because the equilibrium strategy is non-symmetric or because gas stations have not yet fully converged to a symmetric equilibrium strategy?
A Information Asymmetry: Tables and Figures

Applying Ward’s hierarchical clustering procedure on all gas station in Austria and Germany results in the dendrogram (clustering tree) displayed in figure A.1. The dotted red lines indicate the “height” to partition the 16,500 gas stations into approximately 500, 1,500, and 5,500 groups (top to bottom, respectively). The resulting clusters of gas stations in Austria and Germany are displayed in figures A.2 and A.3 respectively.

Figure A.4 shows a comparison between the empirical CDF and the CDF estimated by equation 6.2 in section 6.3 for \( J = 2 \) (two direct competitors) and \( \kappa = G \) (gasoline).

Table A.1 shows the coefficients from the estimation of equation 6.2 in section 6.3 for \( J = 2 \) (two direct competitors) and \( \kappa = G \) (gasoline). The standard deviations are computed using bootstrap.

**Table A.1**: Coefficients from the estimation of equation 6.2 in section 6.3 for \( J = 2 \) (two direct competitors) and \( \kappa = G \) (gasoline). The standard deviations are computed using bootstrap (continued on next page).

<table>
<thead>
<tr>
<th>time</th>
<th>( d ) (SD)</th>
<th>( \frac{\Delta \rho}{\rho} ) (SD)</th>
<th>( \iota ) (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mon 06:00</td>
<td>1.480 (0.004)</td>
<td>0.026 (0.002)</td>
<td>0.721 (0.017)</td>
</tr>
<tr>
<td>Mon 07:00</td>
<td>1.473 (0.001)</td>
<td>0.027 (0.000)</td>
<td>0.725 (0.004)</td>
</tr>
<tr>
<td>Mon 08:00</td>
<td>1.459 (0.003)</td>
<td>0.029 (0.002)</td>
<td>0.705 (0.040)</td>
</tr>
<tr>
<td>Mon 09:00</td>
<td>1.460 (0.003)</td>
<td>0.025 (0.002)</td>
<td>0.750 (0.014)</td>
</tr>
<tr>
<td>Mon 10:00</td>
<td>1.451 (0.001)</td>
<td>0.025 (0.001)</td>
<td>0.755 (0.010)</td>
</tr>
<tr>
<td>Mon 11:00</td>
<td>1.443 (0.674)</td>
<td>0.025 (0.314)</td>
<td>0.762 (0.247)</td>
</tr>
<tr>
<td>Mon 12:00</td>
<td>1.436 (0.001)</td>
<td>0.025 (0.001)</td>
<td>0.750 (0.017)</td>
</tr>
<tr>
<td>Mon 13:00</td>
<td>1.429 (0.001)</td>
<td>0.026 (0.001)</td>
<td>0.725 (0.015)</td>
</tr>
<tr>
<td>Mon 14:00</td>
<td>1.425 (0.001)</td>
<td>0.025 (0.001)</td>
<td>0.733 (0.013)</td>
</tr>
<tr>
<td>Mon 15:00</td>
<td>1.422 (0.001)</td>
<td>0.024 (0.001)</td>
<td>0.736 (0.012)</td>
</tr>
<tr>
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<td>0.022 (0.001)</td>
<td>0.765 (0.026)</td>
</tr>
<tr>
<td>Mon 17:00</td>
<td>1.419 (0.001)</td>
<td>0.021 (0.001)</td>
<td>0.768 (0.052)</td>
</tr>
<tr>
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<td>0.021 (0.001)</td>
<td>0.786 (0.022)</td>
</tr>
</tbody>
</table>
Table A.1: Continued.

<table>
<thead>
<tr>
<th>Market</th>
<th>( d ) (SD)</th>
<th>( \Delta ) (SD)</th>
<th>( \varepsilon ) (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tue 06:00</td>
<td>1.486 (0.001)</td>
<td>0.022 (0.001)</td>
<td>0.812 (0.014)</td>
</tr>
<tr>
<td>Tue 07:00</td>
<td>1.479 (0.001)</td>
<td>0.023 (0.001)</td>
<td>0.812 (0.011)</td>
</tr>
<tr>
<td>Tue 08:00</td>
<td>1.471 (0.002)</td>
<td>0.022 (0.001)</td>
<td>0.821 (0.006)</td>
</tr>
<tr>
<td>Tue 09:00</td>
<td>1.468 (0.004)</td>
<td>0.020 (0.002)</td>
<td>0.822 (0.010)</td>
</tr>
<tr>
<td>Tue 10:00</td>
<td>1.458 (0.007)</td>
<td>0.021 (0.004)</td>
<td>0.804 (0.015)</td>
</tr>
<tr>
<td>Tue 11:00</td>
<td>1.449 (0.456)</td>
<td>0.022 (0.214)</td>
<td>0.785 (0.228)</td>
</tr>
<tr>
<td>Tue 12:00</td>
<td>1.442 (0.005)</td>
<td>0.022 (0.009)</td>
<td>0.790 (0.019)</td>
</tr>
<tr>
<td>Tue 13:00</td>
<td>1.435 (0.003)</td>
<td>0.022 (0.007)</td>
<td>0.776 (0.020)</td>
</tr>
<tr>
<td>Tue 14:00</td>
<td>1.431 (0.003)</td>
<td>0.022 (0.002)</td>
<td>0.780 (0.019)</td>
</tr>
<tr>
<td>Tue 15:00</td>
<td>1.428 (0.003)</td>
<td>0.021 (0.001)</td>
<td>0.771 (0.017)</td>
</tr>
<tr>
<td>Tue 16:00</td>
<td>1.425 (0.007)</td>
<td>0.020 (0.004)</td>
<td>0.782 (0.037)</td>
</tr>
<tr>
<td>Tue 17:00</td>
<td>1.422 (0.003)</td>
<td>0.020 (0.001)</td>
<td>0.785 (0.017)</td>
</tr>
<tr>
<td>Tue 18:00</td>
<td>1.419 (0.006)</td>
<td>0.020 (0.004)</td>
<td>0.797 (0.033)</td>
</tr>
</tbody>
</table>

Wed 06:00 | 1.481 (0.004) | 0.025 (0.002) | 0.731 (0.018) |

Wed 07:00 | 1.476 (0.001) | 0.025 (0.000) | 0.743 (0.004) |

Wed 08:00 | 1.473 (0.002) | 0.022 (0.001) | 0.825 (0.035) |

Wed 09:00 | 1.469 (0.001) | 0.019 (0.001) | 0.847 (0.023) |

Wed 10:00 | 1.460 (0.001) | 0.020 (0.001) | 0.849 (0.021) |

Wed 11:00 | 1.450 (0.445) | 0.021 (0.221) | 0.847 (0.253) |

Wed 12:00 | 1.443 (0.064) | 0.021 (0.031) | 0.851 (0.067) |

Wed 13:00 | 1.437 (0.002) | 0.020 (0.001) | 0.855 (0.030) |

Wed 14:00 | 1.431 (0.001) | 0.021 (0.000) | 0.803 (0.004) |

Wed 15:00 | 1.427 (0.001) | 0.021 (0.000) | 0.825 (0.009) |

Wed 16:00 | 1.425 (0.001) | 0.020 (0.000) | 0.835 (0.009) |

Wed 17:00 | 1.421 (0.001) | 0.019 (0.000) | 0.829 (0.003) |

Wed 18:00 | 1.419 (0.001) | 0.019 (0.000) | 0.835 (0.003) |

Thu 06:00 | 1.484 (0.001) | 0.023 (0.000) | 0.757 (0.017) |

Thu 07:00 | 1.478 (0.001) | 0.024 (0.000) | 0.763 (0.004) |

Thu 08:00 | 1.469 (0.002) | 0.024 (0.001) | 0.757 (0.007) |

Thu 09:00 | 1.467 (0.006) | 0.020 (0.003) | 0.794 (0.012) |

Thu 10:00 | 1.457 (0.009) | 0.021 (0.001) | 0.794 (0.002) |

Thu 11:00 | 1.447 (0.350) | 0.022 (0.163) | 0.793 (0.212) |

Thu 12:00 | 1.440 (0.038) | 0.022 (0.019) | 0.785 (0.072) |

Thu 13:00 | 1.436 (0.003) | 0.021 (0.001) | 0.798 (0.019) |

Thu 14:00 | 1.430 (0.002) | 0.022 (0.004) | 0.759 (0.021) |

Thu 15:00 | 1.433 (0.009) | 0.017 (0.003) | 0.940 (0.004) |

Thu 16:00 | 1.422 (0.006) | 0.021 (0.003) | 0.777 (0.003) |

Thu 17:00 | 1.419 (0.009) | 0.020 (0.004) | 0.791 (0.004) |

Thu 18:00 | 1.415 (0.005) | 0.021 (0.001) | 0.751 (0.004) |

Fri 06:00 | 1.481 (0.001) | 0.025 (0.001) | 0.725 (0.010) |

Fri 07:00 | 1.474 (0.001) | 0.025 (0.001) | 0.732 (0.017) |

Fri 08:00 | 1.468 (0.002) | 0.024 (0.001) | 0.768 (0.017) |

Fri 09:00 | 1.463 (0.001) | 0.022 (0.000) | 0.759 (0.007) |

Fri 10:00 | 1.453 (0.001) | 0.023 (0.001) | 0.745 (0.019) |

Fri 11:00 | 1.445 (0.041) | 0.023 (0.020) | 0.754 (0.055) |

Fri 12:00 | 1.438 (0.001) | 0.023 (0.001) | 0.764 (0.014) |

Fri 13:00 | 1.434 (0.001) | 0.023 (0.000) | 0.746 (0.007) |

Fri 14:00 | 1.439 (0.005) | 0.016 (0.003) | 0.976 (0.109) |

Fri 15:00 | 1.434 (0.005) | 0.016 (0.003) | 0.976 (0.118) |

Fri 16:00 | 1.430 (0.012) | 0.016 (0.006) | 0.976 (0.107) |

Fri 17:00 | 1.427 (0.004) | 0.016 (0.002) | 0.977 (0.106) |

Fri 18:00 | 1.423 (0.004) | 0.016 (0.002) | 0.977 (0.095) |
**Table A.1:** Continued.

<table>
<thead>
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<th>Market</th>
<th>$d$ (SD)</th>
<th>$\hat{d}$ (SD)</th>
<th>$\sigma$ (SD)</th>
</tr>
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<tbody>
<tr>
<td>Sat 06:00</td>
<td>1.490 (0.015)</td>
<td>0.018 (0.008)</td>
<td>0.975 (0.153)</td>
</tr>
<tr>
<td>Sat 07:00</td>
<td>1.486 (0.024)</td>
<td>0.019 (0.011)</td>
<td>0.972 (0.154)</td>
</tr>
<tr>
<td>Sat 08:00</td>
<td>1.481 (0.008)</td>
<td>0.019 (0.005)</td>
<td>0.999 (0.146)</td>
</tr>
<tr>
<td>Sat 09:00</td>
<td>1.475 (0.051)</td>
<td>0.018 (0.026)</td>
<td>0.974 (0.164)</td>
</tr>
<tr>
<td>Sat 10:00</td>
<td>1.467 (0.011)</td>
<td>0.018 (0.006)</td>
<td>0.974 (0.144)</td>
</tr>
<tr>
<td>Sat 11:00</td>
<td>1.460 (0.024)</td>
<td>0.017 (0.013)</td>
<td>0.974 (0.160)</td>
</tr>
<tr>
<td>Sat 12:00</td>
<td>1.448 (0.057)</td>
<td>0.018 (0.024)</td>
<td>0.973 (0.164)</td>
</tr>
<tr>
<td>Sat 13:00</td>
<td>1.442 (0.007)</td>
<td>0.018 (0.004)</td>
<td>0.974 (0.135)</td>
</tr>
<tr>
<td>Sat 14:00</td>
<td>1.438 (0.014)</td>
<td>0.017 (0.007)</td>
<td>0.975 (0.130)</td>
</tr>
<tr>
<td>Sat 15:00</td>
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<td>0.016 (0.003)</td>
<td>0.976 (0.120)</td>
</tr>
<tr>
<td>Sat 16:00</td>
<td>1.430 (0.008)</td>
<td>0.017 (0.004)</td>
<td>0.976 (0.112)</td>
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<tr>
<td>Sat 17:00</td>
<td>1.427 (0.014)</td>
<td>0.016 (0.007)</td>
<td>0.976 (0.109)</td>
</tr>
<tr>
<td>Sat 18:00</td>
<td>1.425 (0.005)</td>
<td>0.016 (0.003)</td>
<td>0.977 (0.109)</td>
</tr>
<tr>
<td>Sun 06:00</td>
<td>1.483 (0.007)</td>
<td>0.019 (0.004)</td>
<td>0.975 (0.116)</td>
</tr>
<tr>
<td>Sun 07:00</td>
<td>1.483 (0.009)</td>
<td>0.019 (0.005)</td>
<td>0.974 (0.134)</td>
</tr>
<tr>
<td>Sun 08:00</td>
<td>1.480 (0.008)</td>
<td>0.020 (0.005)</td>
<td>0.972 (0.033)</td>
</tr>
<tr>
<td>Sun 09:00</td>
<td>1.474 (0.007)</td>
<td>0.020 (0.003)</td>
<td>0.972 (0.016)</td>
</tr>
<tr>
<td>Sun 10:00</td>
<td>1.467 (0.013)</td>
<td>0.019 (0.006)</td>
<td>0.972 (0.088)</td>
</tr>
<tr>
<td>Sun 11:00</td>
<td>1.457 (0.044)</td>
<td>0.020 (0.022)</td>
<td>0.972 (0.108)</td>
</tr>
<tr>
<td>Sun 12:00</td>
<td>1.447 (0.018)</td>
<td>0.020 (0.009)</td>
<td>0.972 (0.074)</td>
</tr>
<tr>
<td>Sun 13:00</td>
<td>1.439 (0.007)</td>
<td>0.020 (0.004)</td>
<td>0.972 (0.064)</td>
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<tr>
<td>Sun 14:00</td>
<td>1.434 (0.007)</td>
<td>0.020 (0.004)</td>
<td>0.973 (0.071)</td>
</tr>
<tr>
<td>Sun 15:00</td>
<td>1.430 (0.013)</td>
<td>0.019 (0.007)</td>
<td>0.973 (0.073)</td>
</tr>
<tr>
<td>Sun 16:00</td>
<td>1.427 (0.005)</td>
<td>0.019 (0.003)</td>
<td>0.974 (0.116)</td>
</tr>
<tr>
<td>Sun 17:00</td>
<td>1.426 (0.007)</td>
<td>0.018 (0.004)</td>
<td>0.975 (0.133)</td>
</tr>
<tr>
<td>Sun 18:00</td>
<td>1.424 (0.009)</td>
<td>0.018 (0.005)</td>
<td>0.975 (0.112)</td>
</tr>
</tbody>
</table>
Figure A.1: The dendrogram resulting from applying Ward’s hierarchical clustering procedure on all gas station in Austria and Germany. The dotted red lines indicate the “height” to partition the 16,500 gas stations into approximately 500, 1,500, and 5,500 groups (top to bottom, respectively).
Figure A.2: Clusters of gas stations in Austria and Germany resulting from “cutting the dendrogram” for approximately 1,000 groups.
Figure A.3: Clusters of gas stations in Austria and Germany resulting from “cutting the dendrogram” for approximately 7,000 groups.
Figure A.4: Comparison between the empirical CDF and the CDF estimated by equation 6.2 in section 6.3 for $J = 2$ (two direct competitors) and $\kappa = G$ (gasoline).
References


Hartigan, J. A. (1975): “Clustering algorithms,”.


