A New Price Test in Geographic Market Definition - An Application to German Retail Gasoline Market *

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Abstract

Market delineation is a fundamental tool in modern antitrust analysis. However, the definition of relevant markets can be very difficult in practice. This preliminary draft applies a new methodology combining a simple price correlation test with hierarchical clustering -a method known from machine learning- in order to analyze the competitive situation in the German retail gasoline market. Our analysis reveals two remarkable results: At first, there is a uniform pattern across stations of the same brand regarding their maximum daily prices which confirms the claim that prices are partly set centrally. But more importantly, price reactions are also influenced by regional or local market conditions as the price setting of gasoline stations is strongly affected by commuter routes.

Keywords: *market definition, gasoline market, price tests, competition, k-means clustering, hierarchical clustering*

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1 Introduction

Studying the competitive situation and defining the relevant market and the closest rivals is fundamental in modern antitrust analysis. A relevant market is needed to assess the anticompetitive effects of mergers, but also for calculating concentration ratios to be able to judge whether a firm has a dominant market position. In addition, for cartel cases it would be helpful to have an easy method to assess the competitive situation in a market.

However, because markets are multidimensional and complex, market delineation is rarely an easy task. Moreover, these analyses must often be undertaken under limited data. In many cases only prices are available which is why methods to analyze the competitive situation based on prices alone would be very helpful in merger analysis.

We are looking at the German retail gasoline market as the competitive situation of this market is object of intensive and recurring discussions. The purpose of this paper is to analyze the competitive situation and try to delineate geographically the German retail market for gasoline by using a simple price test. With this test we hope to gain some insights into the determinants of the price setting of gasoline stations. Gasoline is a relative homogeneous product and therefore, one can analyze the market by using empirical price tests, which are based on the price movement. Two regions belong to the same market when arbitrage is possible. Therefore, it can be checked whether the prices of these areas converge.

Besides that, the opportunity cost of consumers play a crucial role in the definition of local gasoline markets. Since, no one would drive 500 kilometers just to fuel up his or her car, because the opportunity costs would exceed the benefits of this arbitrage operation significantly. From this, the following question arises: How many petrol stations are considered as competitors by a specific station and is it possible to define local markets for gasoline in Germany?

The Federal Cartel Office (FCO) chooses an accessibility model and defines an area according to a driving time of 30 minutes around a gasoline station in a city (60 minutes for gasoline stations in rural areas) to identify the competitors of this specific gasoline station.[1] In doing so, the FCO assumes that a consumer is willing to drive 30 minutes from his or her starting point (preferred station) to be able to refuel at a lower price. We question whether this assumption reflects the actual behavior of consumers. Moreover, we think that it is important to identify the forces that determine the price setting behavior of the gasoline stations. Gasoline stations cannot observe an individual consumer who lives or works around

[1] The accessibility model was applied in several merger cases, for example in the case Shell Deutschland Oil GmbH /Honsel Mineralölvertriebs GmbH (B8–31-09), in the case Total Deutschland GmbH/OMV Deutschland GmbH (B8-175-08) or in the case Shell Deutschland Oil GmbH/Hanseatic Petrol Vertriebs GmbH (B8-134-07).

the specific station. However, gasoline stations are able to observe commuter routes and traffic which will possibly affect the price setting of gasoline stations along these routes. Therefore, this paper takes a different approach by using price correlation in conjunction with hierarchical clustering to analyze the competition between gasoline stations in Germany. With this procedure, the determinants considered and observed by gasoline stations which shape their price setting are taken into account.

Chapter 2 introduces already known methods to define a geographic market. At first, general methods like the SSNIP test are presented. Afterwards, several price tests are highlighted in greater detail. These quantitative tests are particularly valuable if they are used in conjunction with a thorough understanding of the industry. Therefore, the paper continues with a detailed description of the German retail gasoline market. This is necessary to assess the outcomes of the statistical tests in chapter 4.3. In the subsequent chapter we present our new approach combining hierarchical clustering -a method known from machine learning- and correlation tests to identify the closest competitors and define geographic markets for the German retail gasoline market. Results of this analysis reveal that commuter routes indeed play a crucial role in the price setting of gasoline stations. Chapter 5 compares our approach with the market definition of the FCO to verify our findings and highlighting the problems of the accessibility model as this approach cannot capture the complex competitive situation in the German retail gasoline market. The paper concludes with a summary of the findings.

2 Methods used in Geographic Market Definition / Survey of the Literature

First of all, the method applied by the Federal Cartel Office to delineate the geographic market in gasoline markets will be described. Furthermore, the hypothesis of Weizsäcker about chain of substitutions in the German gasoline market is considered briefly as gasoline stations repeatedly affirm this hypothesis.(see Franz et al. (2002))

However, these methods have some weaknesses which will be discussed in the following. For this reason, the second part of this section presents price tests which are appropriate to delineate the relevant market. We use one of these price tests and combine it with a method known from machine learning to develop a simple and comprehensive method presented in section 4.

The Federal Cartel Office has repeatedly emphasized regionally separated markets for gasoline stations in Germany and thereby rejects the proposal of the oil companies which plead for a nationwide gasoline market. For the delineation of the relevant geographic market the Federal Cartel Office uses the "Bedarfsmarktkonzept" and emphasizes that the actual behavior of consumers is a crucial factor. Thus, the geographic market for a gasoline station is determined by the distance consumers are willing to drive to buy gasoline at an alternative station if the target station increases its price. The Federal Cartel Office concludes that a radius of 25 km around the gasoline station in question is sufficient to define the relevant market. For a precise market definition on a case-by-case basis the Federal Cartel Office makes use of the accessibility model of the Federal Office for Building and Regional Planning ("Bundesamt für Bauwesen und Raumordnung").[2] With this model all stations within a specific driving time around one target station can be identified. For rural areas a driving time of 60 minutes is assumed and for urban areas a driving time of 30 minutes. The alternative petrol stations within one regional market are, however, no equal choices for the demand side. A consumer will always choose the nearer gasoline station if the price difference is smaller than the driving cost and the opportunity cost of time. To account for the different intensities of competition depending on the distances to the target station, a weighted accessibility model is applied to the gasoline market. The stations are weighted according to their distance to the target station (or the center of the regional market). Nearer stations get a higher weight which display their intensity of competition. The main problem with this approach is the arbitrarily chosen driving time which is based only on consumer surveys. Moreover, contrary to what is claimed, this approach does not seem to be suited to reflect neither the actual consumer behavior nor the behavior of gasoline stations. This problem will be discussed in detail in section 5 where our results are compared with the approach of the Federal Cartel Office.

On the contrary, oil companies claim for a nationwide market and refer to the concept of chain of substitutions. According to this approach, products (or regions) can belong to the same relevant market without competing directly with each other. This is the case when competition is passed on through a chain of substitutes. The greatest danger of the approach of chains of substitutions is that the relevant market is defined too generous since it overstates the influence of distant competitors. A hypothetical monopolist[3] needs not control over the whole substitution chain to raise his price profitably. If a sufficient amount of consumers is left after a price increase, this price increase still is profitable for the hypothetical

[2]The model is based on the digitally recorded existing network of streets.

[3]Another method, frequently used to define a geographic market, is the hypothetical monopolist test or SSNIP test (small but significant increase in price). The SSNIP test asks whether a hypothetical monopolist is able to profitably increase its price (by 5%) over a certain period. If a considerable amount of consumers switch to another product (or market) in response to a price increase, these substitutes need to be included to the relevant market. As this test is not applied to gasoline markets, we will not go into it any further here.

monopolist (Bishop and Baldauf (2006)).

The methods described so far show that market definition frequently involves rules of thumb like the assumed driving times for the accessibility model. But market delineation should not be dependent on such subjective assumptions. Therefore, econometric methods are in demand. Different econometric tests can be found in the literature that are suitable to define relevant markets and there is as well some literature that applies econometric tests to gasoline markets. Audy and Erutku (2005) and Slade (1986), for example, use price correlation and Granger causality to define geographic markets in the gasoline industry. Moreover, cointegration and stationarity tests as well as econometric models of price responses and co-movements across regions based on natural experiments are proposed for defining the relevant geographic market.

In general, price tests can be divided into two categories: short-run relationships and long-run relationships. Correlation tests and Granger causality tests belong to the first group, whereas unit root tests and cointegration tests belong to the latter. It is, however, problematic to use long-run tests for market delineation as they neglect the possibility of consumers to react to price changes. Gasoline stations in Germany, for example, change their prices several times a day and consumers will possibly react to these frequent and repeating changes.

Granger causality and price correlation, instead, are suitable for a short-run analysis which seems to be more appropriate in order to identify the closest competitors and define a relevant geographic market for gasoline stations.

A Granger causality test is able to infer whether there is a causal relationship between the price series of two products or firms (in our case gasoline stations).[4] Slade (1986) proposes a geographic market test based on Granger causality to determine whether a disturbance in price in one region have repercussions in another. The test is applied to crude oil prices of various regions of the United States. The advantage of this approach is that no specific model of price formation has to be presumed. Moreover, Granger causality tests take account of the dynamic structure of the price series as past values are used for prediction (Cartwright et al. (1989)). However, Granger causality tests focus solely on the existence of a relationship rather than its size. But for the definition of a relevant antitrust market it is of great importance whether two price series are meaningfully related. The size of a relationship is crucial to pass the requirements of the definition of an antitrust market (Boshoff, 2012). Moreover, Granger causality tests would have to be performed for each gasoline station individually which would be a very time-consuming task.

[4] The proposed test was developed by Granger (1969), Sims (1972) and others and is based on standard regression techniques, which assume that there is a cause and effect relationship between the dependent and independent variables.

As we are seeking for a method which is easy and fast to implement for competition authorities -as part of an initial market investigation- we will have a closer look at price correlation tests, which are appropriate to identify the closest competitors. Moreover, Cartwright et al. (1989) demonstrate that both, price correlation and Granger causality provide the same results in market delineation and conclude that Granger causality could be used supplementary to a price correlation analysis. Also Audy and Erutku (2005) apply both tests, price correlation and Granger causality, to the wholesale gasoline market in Canada. Both tests indicate that the relevant geographic markets can be larger than cities but can not be bigger than East and West Canada.

Following the reasoning of Stigler and Sherwin (1985), two geographic areas belong to the same market when their relative prices maintain a stable ratio or rather when their prices move together over time. This can be measured statistically by using price correlations. Correlation is a measure of the linear relationship between two variables and indicates the degree of contemporary linear association. A high correlation between the prices of two geographic areas (near to 1) suggests that the cross-price elasticity between those two regions (X and Y) is positive. Following this, there has to be some competitive interaction. The high correlation in prices imply that a relative price increase in region X will lead to an adjustment of the prices in both regions. This adjustment process is caused by arbitrage opportunities in conjunction with homogeneous products. Market participants (buyers as well as sellers) can move from one region to the other without incurring large costs (transportation cost, transaction cost and opportunity cost). In contrast to that, a small correlation coefficient implies that a relative price increase in region X should not affect the price in region Y. Thus, a small price correlation is an indication for separate geographic markets. In gasoline markets sellers can not shift to another market, but buyers will drive to another (nearby) gasoline station if the cost (transportation and opportunity cost) are smaller than the price difference. If the distance is too long, buyers do not switch to the other region and regional price differentials can persist, indicating separate geographical markets (see Slade (1986)).

Price correlation tests have played a prominent role in numerous antitrust and merger cases of the last decades and have been used by both the European Competition Authorities and the parties under investigation to define the relevant market.[5]

Price correlations, if used and interpreted correctly, can be a useful tool for the definition of the relevant market, at least in a first step. This is due to the pure simplicity of the method and the modest data requirements. However, price

[5]For instance, Case M190 Nestle/Perrier (1997) OJ L356/1 or COMP/M.4439 Ryanair/Aer Lingus (June 27, 2007).

correlations, if used solely, can only be applied as a first hint as they are not able to indicate a causation. Tirole (1988) argued that a high price correlation between two products or geographic areas is at best a necessary but not a sufficient condition for belonging to the same market. As we are, however, interested in identifying the closest competitors and price reactions occur very fast in the German retail gasoline market, an analysis based on short-run price correlations seems to be appropriate.

Our approach, which will be outlined in section 4, therefore uses such simple price correlations. However, as there are some shortcomings if only price correlations are used, we use the correlation results for a hierarchical clustering to identify competitors in the German retail gasoline market. The results show that the competitive situation is more complex and cannot be captured either by the model of chain of substitutions or the accessibility model applied by the Federal Cartel Office. With the method applied in section 4, we are able to identify the main driving factor for the competition between gasoline stations by using a method that takes into account the reactions of petrol stations, which in turn are triggered by actual consumer behavior. The exact approach will be further outlined in section 4.

3 The German Filing Station Network

In order to evaluate the statistical result as presented in chapter 4.3 a profound understanding of the market participants, market structure and pricing practices in the German retail gasoline industry is necessary.

The German filing station network is characterized by an oligopoly of five vertically integrated oil companies (BP (Aral), ConocoPhilipps (Jet), ExxonMobil (Esso), Shell and Total). Only these companies have access to their own refining capacities and operate a nationwide network of filling stations. The oligopolists maintain a very high share of sales in diesel and gasoline fuel, whereas the independent stations (the so-called ”Freie Tankstellen”) are only regionally active and have rather low shares of sale. In total, the German filing station network comprises 14,152 gasoline stations.[6] Aral is the largest retailer with a network size of 2,335 gasoline stations in Germany and a market share of 21.5% in terms of the total sales of fuel in Germany. Shell has 1,929 gasoline stations and a share of 20%. Total has 1,136 gasoline stations (9% share of total sales), Esso 992 stations (7.5% share of total sales) and Jet has 821 stations and a share of 10.5%. The remaining market - encompassing 6,939 filing stations - is distributed across a large number of independent stations with small and medium-sized networks. These stations to-

[6]Numbers and shares are based on the year 2017 as this corresponds to the time frame covered by our dataset which is used for the empirical analysis.

gether hold a share of total sales of only 31.5%.[7] Moreover, the competing petrol stations on the retail level which belong to smaller networks are dependent on the gasoline deliveries of the vertically integrated oil companies as only these companies have access to refinery capacities (Bundeskartellamt (2011)). Additionally, the German gasoline market is characterized by high barriers to entry. Besides missing places for new stations, newcomers need a high level of capital to get access to refinery capacities. As a result, the total number of gasoline stations has been constant over the last years. Thus, petrol stations know their competitors pretty well.

This market structure essentially allows for collusive behavior since the gasoline market exhibit many factors that facilitate a collusive arrangement between market participants. The existence of vertically integrated oligopolists and their nationwide presence is only one of the reasons why the German gasoline market has been repeatedly investigated by the German Federal Cartel Office.[8]

Another very important factor is the high product homogeneity of gasoline as petrol and diesel fuel are not substitutable for consumers. Therefore, the product market definition can be neglected as the geographic aspect is decisive in this market. The location of gasoline stations plays a crucial role for the competition in the market. Due to the high product homogeneity the price of gasoline remains the main competitive parameter. Consumers do not differentiate between petrol or diesel of different fuel stations. The diverse customer loyalty programs also point to a high product homogeneity as gasoline stations try to bind customers with such offers. As a result, the price for gasoline (diesel or petrol) is the most important competition parameter for gasoline stations.

Consequently, the pricing behavior of gasoline stations need to be investigated in great detail to understand the competition in this market. In many countries the gasoline markets feature characteristic price cycles, including the German market where the prices exhibit daily cycles: a high price is placed in the morning, then, prices decrease throughout the day and in the evening prices are increased again and remaining high until the next morning. This price-setting pattern is pursued by (nearly) all gasoline stations in Germany. The cycles are even more pronounced since the implementation of the market transparency unit for fuel ("Markttransparenzstelle für Kraftstoffe" (MTS-K)) of the Federal Cartel Office on August 31, 2013. Petrol stations are committed to report every price change in real-time to the MTS-K. This data is then provided to suppliers of information services where

[7]For detailed information on gasoline stations in Germany and their network sizes please refer to German Petroleum Industry Association (Mineralölwirtschaftsverband), 2017 `https://www.mwv.de/statistiken/tankstellenbestand/`.

[8]Other reasons are the lack of buying power, the product homogeneity and the repeated interaction and mutual dependencies between the oligopolists. For a further discussion of the market structure and the firms' behavior see Bundeskartellamt (2011), p. 50f.

consumers can easily compare prices. The MTS-K was implemented to increase the market transparency for consumers by facilitating comparison of prices, thereby increasing competition between petrol stations. But gasoline stations likewise have easier access to the prices of their competitors and price changes of competitors can be traced with very low effort. The increased horizontal market transparency facilitates collusive behavior as any deviation from a collusive (or parallel) behavior can be monitored easily and costlessly. Linder (2018) investigates the price cycles in the German retail gasoline market in great detail and evaluate their competitiveness. Moreover, Dewenter et al. (2018) discuss the possibility of tacit collusion resulting in this cyclical price setting. As the cyclical behavior plays a crucial role in the German market, the empirical analysis will take this into account which will be explained further in chapter 4.

This very specific price-setting of gasoline stations further reinforces our assumption that one should use the price of gasoline stations to analyze competition in this market. Of course, some consumers prefer petrol from brand stations, some might prefer stations with a shop and some have a preference for a station due to their location. But the main parameter for competition remains the price for petrol or diesel. This makes coordination on a collusive outcome even easier as the companies have to agree on only one parameter. But another -for this paper more important- consequence is that price tests are highly suitable for market delineation in gasoline markets. If the product is homogeneous, the possibility of arbitrage leads to uniform prices throughout the market. If consumers switch to another region due to a price increase, this price change will spill over and prices will adapt to each other. When a market is characterized by product homogeneity, the opportunity of arbitrage prevents prices from moving independently. Price tests can be used to test whether the price in one region is exogenous to the price in another region (Slade (1986) and Audy and Erutku (2005)).

In our empirical analysis in the subsequent section 4.3, we investigate the pricing behavior and price reactions of gasoline stations with a novel approach to identify competitors. This way we are able to prove our assumptions that competition is driven by the location of gasoline stations. However, the method used also allows conclusions to be drawn on other factors that have an influence on the competition between gasoline stations.

4 Methodology

The characteristics of the gasoline market, as outlined in chapter 3, in conjunction with the available price data make price tests an appropriate method to analyze the competitive situation on the German retail gasoline market. As all price tests have some weaknesses, we choose price correlation as it is an efficient method and potential issues can be solved. In addition, correlation itself is an appropriate dissimilarity measure for our hierarchical clustering method. With this method we are able to directly identify the various factors that drive the price reactions of gasoline stations without prior assumptions about the price setting behavior or the underlying model. We describe the data used in the following subsection. Afterwards, we present our approach in more detail and analyze our findings.

4.1 Data

We use data from the service provider and consumer information service „Tankerkönig“[9], that makes the price information from the „Markttransparenzstelle für Kraftstoff (MTS-K)“ publicly available. As prescribed by the Federal Cartel Office, the data set contains every price change of each individual filling station in Germany. Thus we have information about the current price of E5-gasoline, E10-gasoline and diesel for each and every point in time within the observation period. In addition, the data set contains petrol station specific information, such as the name, address, brand or geographical coordinates of all $14,714$ filling stations in the sample.

Consumer surveys show that most consumers are not prepared to drive hundreds of kilometers to refuel cheaper, as this detour entails additional costs to the customer (opportunity cost of time and transportation cost) and it does not seem rational to assume that either (see for example Dewenter et al. (2012). For this reason we consider only subsamples of the original data set. We obtain the subsamples by clustering the filling stations according to their geographical location, i.e. longitude and latitude. We choose the well-known k-means method to partition our population of filling stations into 128 regional subsamples. These 128 subregions are still quite large, so we ensure that the subsamples chosen by the k-means clustering are not too restrictive

The basic idea of k-means clustering is as follows: All N observations are clustered into k clusters, such that within each cluster the average distance of the observations to the respective cluster centroid (center of a cluster) is minimized. This can be achieved by the following algorithm. First the desired number of clusters k and the features p to be clustered over are selected. In a next step, each observation is then randomly assigned a number between 1 and k. This allocation forms the starting point for an iterative descent algorithm. For each of the k clusters, the centroid is calculated as a vector of the mean values of the p features over all observations in the respective cluster. Each observation is then assigned to the cluster whose centroid is closest. The proximity between the observations and the centroids is measured by the squared Euclidean distance of the features. The algorithm proposed by Hartigan and Wong (1979) stops as soon as the within-cluster

[9] www.tankerkoenig.de

variance is minimized, i.e. there is no single switch of an observation from one cluster to another that would further minimize the within-cluster variation. The within-cluster variation can be measured as

$$\sum_{k=1}^{K} \frac{1}{N_k} \sum_{i,i' \in N_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2, \tag{1}$$

where N_k is the number of observations in cluster k, x_{ij} is the feature vector of observation i, and $x_{i'j}$ denotes the feature centroid of cluster i'[10]. Since we chose k to be 128 and clustered over the two features of latitude and longitude, we end up with 128 non-overlapping regional clusters for our gasoline stations.[11]

For our analysis we selected the cluster that includes all filling stations in the region of Stuttgart. Our subsample covers the period from 8th June 2014 to 6th June 2017 and contains 186 filling stations. We choose the region of Stuttgart as it is well known for its extremely high commuter traffic. Moreover, the cluster contains the metropolitan area which is characterized by a high station density as well as more rural areas with a rather low station density. Therefore, the chosen cluster presents a good mixture of congested urban area, rural regions and commuter routes to test our hypotheses. Chapter 5 shows results for another geographic cluster (the region around Dresden, Leipzig, and Chemnitz) which further confirms our results. The cluster containing the region of Stuttgart covers 65 km from the northernmost to the southernmost point, which corresponds to a journey time of approximately 59 minutes. The exact geographical distribution of the stations in our sample is illustrated in figure 1, whereas the number of stations per brand in the selected sample is depicted in table 1.

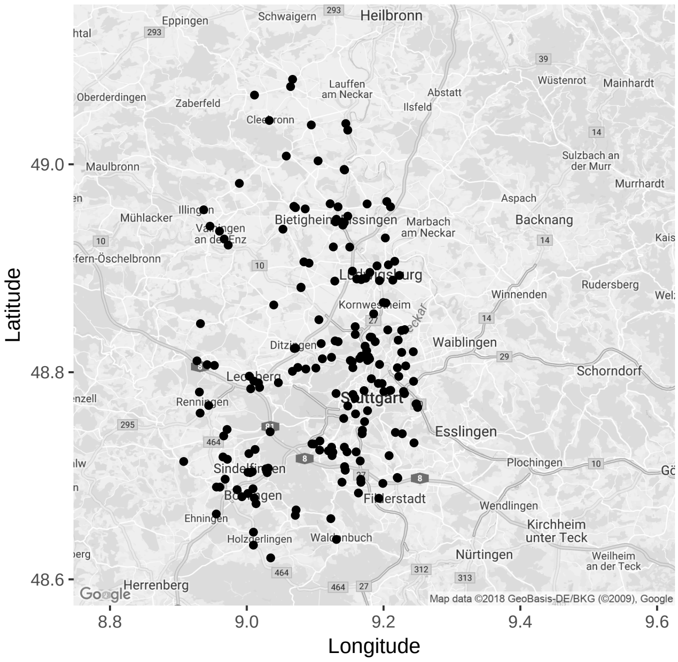
In the region of Stuttgart, the two major oil companies ARAL and Shell both have 39 filling stations. Two other oligopolists follow with ESSO 23 and JET 15 stations. TOTAL (5) is the only one of the five major retailers that is underrepresented in our sample. Nevertheless, it can be argued that the sample is representative in terms of the distribution of stations among the brands as the two major players in the market, Aral and Shell, are also the most represented in our sample. Compared to the distribution of brands throughout Germany, Agip seems to be overrepresented in our sample. This can, however, be attributed to the fact that Agip has located most of its stations across Bavaria and Baden-Wuerttemberg.

Descriptive statistics on the prices in the selected sample are provided in table 2. These are the unadjusted prices that were reported by the filling stations to

[10] See for instance Friedman et al. (2001) for a detailed discussion of the k-means meathod.

[11] We choose k to be 128 as smaller numbers all resulted in too large clusters as we take consumer behavior into account. The average cluster sizes for the respective number of clusters are: $k = 2$ clusters $\rightarrow 7,357$ stations, $k = 4 \rightarrow 3,678.5$, $k = 8 \rightarrow 1,839.25$, $k = 16 \rightarrow 919.6255$, $k = 32 \rightarrow 459.81255$, $k = 64 \rightarrow 229.91$, and $k = 128 \rightarrow 114.95$.

Figure 1: Sample of stations



Note: All 186 filling stations within the sample.

Table 1: Distribution of brands in the sample

Brand	No. of stations
ARAL	39
Shell	39
ESSO	23
JET	15
Agip	14
OMV	6
HEM	5
TOTAL	5
Others	40
N	186

Note: Number of filling stations per brand.

the MTS-K. During the observation period, the 186 stations reported $1,370,994$ prices to the transparency unit with a mean price of E5-gasoline of 137.3 and a standard deviation of 10.27 Euro Cent.

Table 2: Descriptive statistics of the prices in the sample

Feature	Statistic
No. of Obs.	$1,370,994$
Mean(price E5)	137.3
Min.(price E5)	110.4
Max.(price E5)	171.9
SD (price E5)	10.27
5%-Q. (price E5)	122.9
25%-Q. (price E5)	129.9
50%-Q. (price E5)	135.2
75%-Q. (price E5)	143.9
95%-Q. (price E5)	157.4

Note: Prices in Euro Cent.

4.2 Our Approach

We apply a method known from unsupervised machine learning to analyze whether the prices of the filling stations in our sample co-move and are therefore in close competition with each other. This method is called hierarchical clustering. In contrast to k-means clustering, the hierarchical clustering method does not require the user to specify a certain number of clusters k, but a dissimilarity measure d_{ij}. Here we use an agglomerative variant of the hierarchical clustering method. This means that we initially assume that each observation forms a separate cluster. The basic idea of hierarchical clustering is very simple and intuitive: In a first step, the two observations that have the least dissimilarity are combined into a cluster using a suitable dissimilarity measure. In the next step, the two most similar clusters are merged again[12]. This iterative procedure is carried out until all observations have been combined into one single cluster. While the chosen dissimilarity measure can be used directly with two individual observations, the question arises how the dissimilarity between clusters, containing more than one observation, should be measured. In this context, it should be briefly mentioned that the present

[12]Remember that at the beginning each observation forms its own cluster.

paper is not intended to evaluate the effectiveness of competition in the German retail gasoline market. We refer to competing stations (or competition) when stations react to each other in prices. Whether this can be attributed to effective competition or rather a collusive agreement is not subject of the following analysis. However, the identified relevant markets could be used as a starting point for further investigations of the price setting behavior of gasoline stations whose prices co-move. By following the notion of Friedman et al. (2001) a concept of linkage is defined, which measures the dissimilarity between two groups of observations, i.e. clusters. To analyze the price reactions of the filling stations within our subsample, we use the method of 'complete linkage'. This linkage method makes use of the maximum intercluster dissimilarity, which can be represented by

$$D_{complete}(A,B) = \max_{\substack{i \in A \\ j \in B}} d_{ij}, \tag{2}$$

where A and B are two distinct clusters and d_{ij} is the chosen dissimilarity measure. As can be seen from equation 2, the method of complete linkage calculates every pairwise dissimilarity between the two clusters and takes the most dissimilar pair from both clusters as the dissimilarity measure between A and B. Thus, this approach to define linkage states that two clusters can only be fused if all members of both groups are very similar. This leads to relative small and compact clusters (Friedman et al. (2001)).

Boehnke (2017) investigates the pricing strategies of German gasoline stations using a somehow similar approach. To define local geographic markets for his demand analysis, he also uses hierarchical clustering. In contrast to our approach presented below, however, he based his hierarchical clustering solely on a physical distance measure d_{ij}. It is comparable to our k-means clustering outlined in the preceding chapter. Boehnke (2017) identifies gas stations located close to each other with hierarchical clustering. In contrast, we go one step further and focus on one of the geographical clusters previously defined by the k-means algorithm to implement hierarchical clustering based on a more refined distance measure - taking the pricing pattern of gasoline stations into account - to define clusters of gasoline stations that react to each other. In applying this two-step procedure, we make use of the k-means algorithm to roughly cluster nearby gasoline stations geographically. This makes intuitive sense, since geographical proximity can be seen as a necessary condition for a close competitor in the retail gasoline market.This first clustering approach is defined to be not too restrictive, but rather provides a rough framework for the actual analysis. In the second step, hierarchical clustering based on a price-based dissimilarity measure is implemented, as price is the main competition parameter in the gasoline market. Therefore, a similar price pattern can be regarded as a sufficient condition for a close competitor in the market.[13]

[13]Of course, as already mentioned above, we only consider which stations react to each other.

We focus our analysis on the sample of filling stations in the region of Stuttgart. The analysis focuses mainly on daily average prices, whereby each price is weighted with the time in which this price was active (the longer a price was active during a day the higher his weight). Gasoline stations decrease their prices sequentially over the day until a sharp and almost simultaneous price increase interrupts this relenting phase. A weighted average price which takes the length of the different active price levels into account is appropriate to depict these characteristic price cycles and the competitive behavior of the filing stations. Such cyclical behavior of gasoline prices can be observed in many regions, like for example Canada, Australia and Norwegian. It is often attempted to explain these cycles with the concept of Edgeworth cycles (see for example Noel (2007)). Whether the cyclical pricing of German service stations is actually the result of competition or rather the result of collusive behavior is not part of this paper. We assume, however, that the analysis on basis of the weighted daily average prices is the most appropriate for our propose as they reflect the actual price setting behavior of gasoline stations. Gasoline stations in the same relevant market are expected to react to each other and with the weighted average prices we are able to capture these mutual price reactions. Additionally, we will also consider the daily highs as it is an extreme point of the price cycles and could provide additional information. Linder (2018), for example, already observed that the maximum prices are more likely to be the result of a centralized pricing by the branded stations. Our analysis as well reveals differences in the results for the weighted average price and the maximum price which will be discussed in the subsequent section.

The original price data has to be prepared by making the prices stationary (as proposed by Cartwright et al. (1989)) and cleared of all common factors to avoid spurious correlation. Since the analysis relies heavily on calculating the empirical correlation coefficients of the prices, the price series of each filling station has to be made stationary. This is because the sample moments of stationary series converge to a constant number, whereas the sample moments of random walks converge to random variables. However, the relationship between the price series should be represented by empirical correlation coefficients, which are constant numbers and not random variables. For this reason, the reported prices of the filling stations must be made stationary by forming the log returns. The common factors influencing the retail gasoline price are especially the price for crude oil (Brent Crude) and the exchange rate (USD/EUR), since the crude oil price is usually denoted in USD per barrel. To deal with the problem of serial correlation, the common factors' lagged values have to be taken into account. This also makes sense intu-

Therefore, the similar price pattern could also be attributed to some collusive agreement or tacit collusion between this stations. In this case, the stations are as well linked to one cluster as they react to each other in a very close way.

itively, as most filling stations have some sort of long-term supply contracts with wholesalers. It is reasonable to include the common factor itself along with three lagged values, as can be seen from equation 3

$$\Delta p_{it} = \beta_1 \Delta C_t + \beta_2 \Delta C_{t-1} + \beta_3 \Delta C_{t-2} + \beta_4 \Delta C_{t-3} + \epsilon_{it}, \tag{3}$$

where Δp_{it} denotes the log difference of the price of station i for one liter E5-gasoline in Euro at time t, ΔC_t is the log difference of one liter Brent crude oil in Euro[14], and ϵ_{it} is the error term of station i at time t. Alternatively, ϵ_{it} can also be interpreted as the price adjusted by the common factor, as the error term contains everything that cannot be explained by the regressors. We argue that there are no other common factors affecting the prices[15]. For this reason, these adjusted log returns ϵ_{it} are now used to calculate the empirical correlation coefficients between each and every filling station within the region considered. As mentioned above, a dissimilarity measure is required to perform hierarchical clustering. We define the dissimilarity between the two filling stations j and k as

$$d_{ij} = 1 - |cor_{ij}|, \tag{4}$$

where $|cor_{jk}|$ is the empirical correlation coefficient of the adjusted price series ϵ_j and ϵ_k in absolute value. Thus the dissimilarity measure of a filling station i to itself is zero and the overall measure is defined between 0 and 1. By choosing correlation as the dissimilarity measure, all advantages and disadvantages associated with correlation as a price test to define markets also apply to this method. As mentioned before, the complete linkage method is used for the following analysis. This means that the dissimilarity measure of two clusters is defined as the maximum distance of all observation pairs from the clusters. Thus, the analysis starts with 186 individual clusters and merges the two most similar clusters in an iterative process until all filling stations are fused into one final group in the end. This step-by-step procedure generates the hierarchical structure, usually represented in the form of a dendrogram.

A big advantage of this analysis is that it can carried out by one step and no prior assumptions have to be made. In merger cases the parties involved often want to acquire a set of gasoline stations in a specific region. All these stations can be investigated with only one model where all the stations are analyzed jointly. This also helps to avoid not taking important factors into account. This gets obvious when the approach presented above is compared with the procedure carried out by the FCO in a specific case.

[14]Both crude oil price and exchange rate data are from the Federal Reserve Bank of St. Louis (`https://research.stlouisfed.org/`).

[15]The distances within Germany are relatively short, which means that there should not be any significant differences in transport costs.

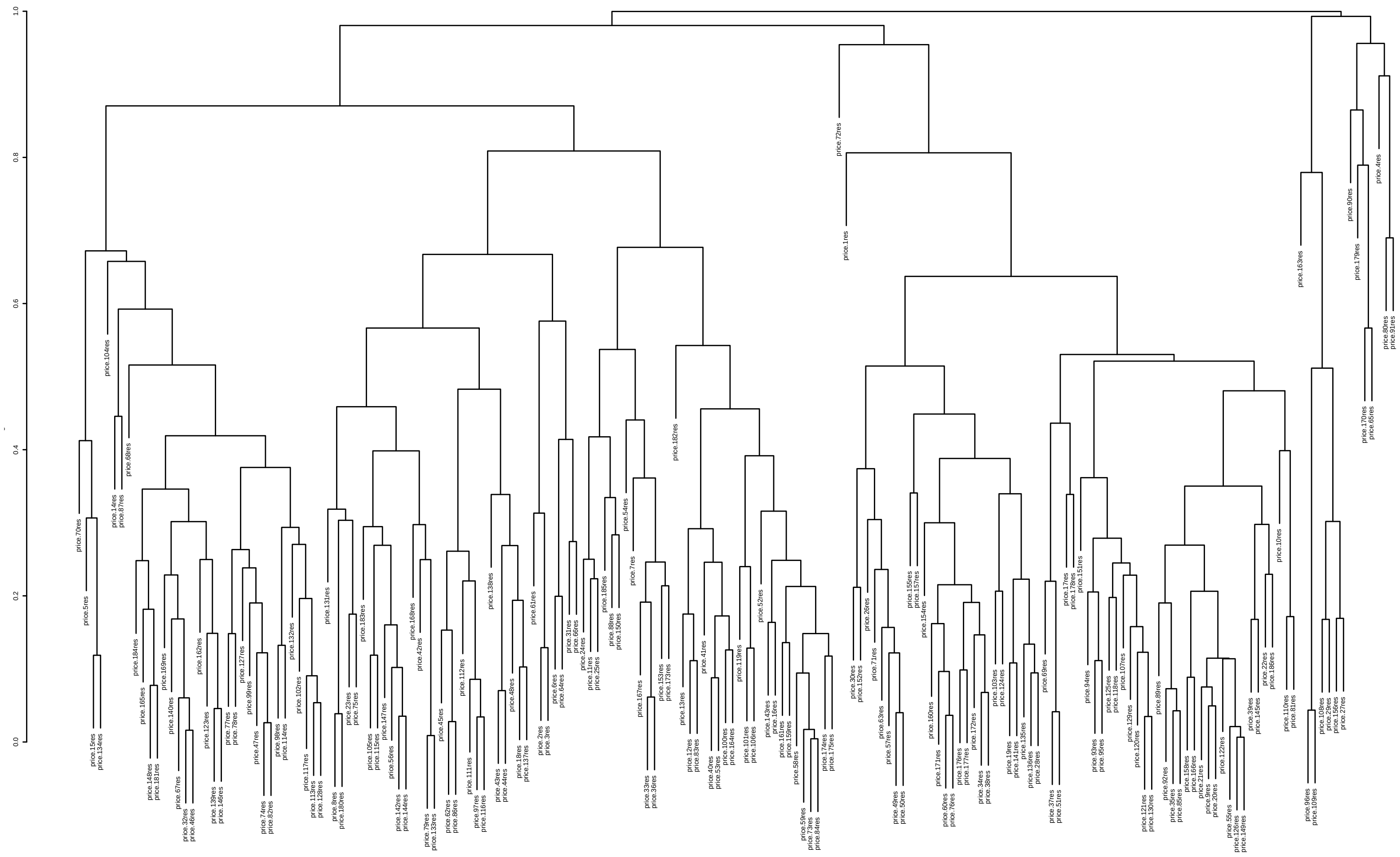
4.3 Results

In the following, results for the daily average price and the maximum price will be presented. The analysis was also carried out with the daily minimum price, but will not be presented in the following to avoid repetitions as these results do not provide any further information. This could be partly because the daily minimum price is only active for a very short time period whereas the maximum price is active over a longer time. The daily minimum price is therefore of little significance if we consider daily price cycles. As already mentioned in chapter 3, gasoline stations exhibit a cyclical price setting over the day. We use daily maximum and minimum prices as limits of these cycles. In addition, to account for the cyclical behavior, we use a weighted daily average price. Therefore, the weighted average price seems to be most suitable to depict the price reactions of gasoline stations.

Figure 2 shows the hierarchical clustering of the weighted daily average prices for the gasoline stations in our chosen cluster. This tree-like graphic should be read from the bottom to the top due to the agglomerative approach. On the very bottom of the dendrogram, each filling station has its own 'leaf'. Thus, at height equal to zero there are 186 individual clusters. The height is depicted on the far left of figure 2 and corresponds to the dissimilarity measure defined previously: $d_{ij} = 1 - |cor_{ij}|$. As soon as we move up the tree, some of those leafs begin to fuse into branches. For instance, at a height of 0.0044 the two stations with the id's 73 and 84 form a cluster. This means that the adjusted price series ϵ_{73} and ϵ_{84} show an empirical correlation of 0.9956. These two filling stations are two discount stations in the middle of an industrial area. It is therefore likely that these two stations compete with each other. If we now make a cut at a height of 0.0044, then we no longer obtain 186 individual clusters, but only 185 clusters, since two have fused. In general it can be said that the earlier two clusters merge on the way up, the more similar they are. On the other hand, clusters that fuse near the top of the dendrogram tend to be rather different. One important feature of hierarchical clustering is that once clusters have been formed according to a dissimilarity measure, they can no longer be changed. They can only be merged with other clusters as a whole.

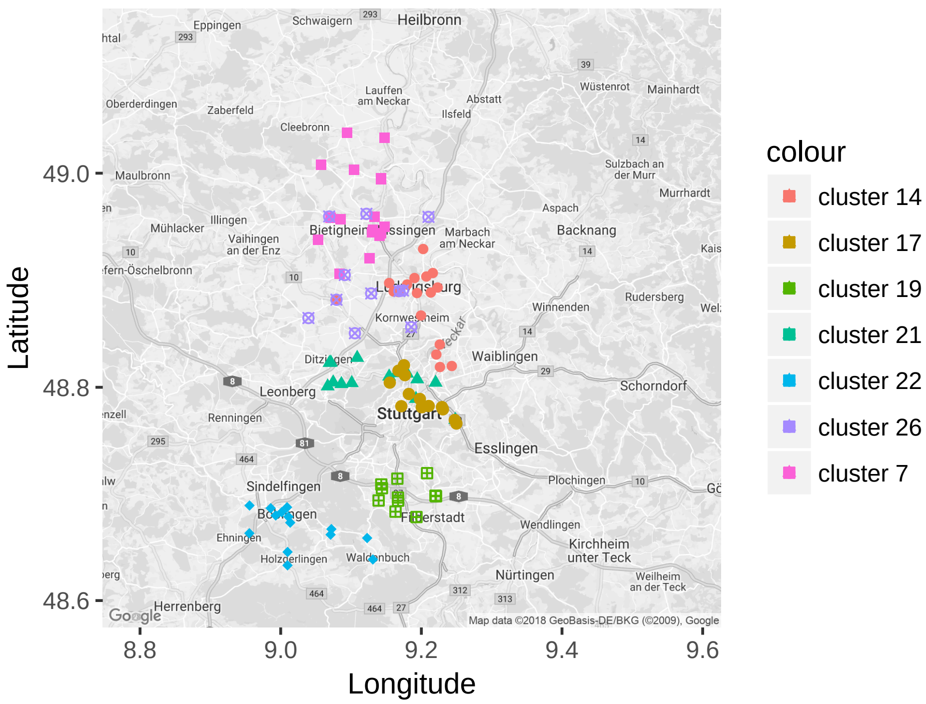
In order to delineate geographically relevant markets, a suitable cutoff value has to be determined. In that context Cartwright et al. (1989) argue that „[...] a correlation coefficient of .5 or higher is consistent with the qualitative statements that are made about market definition“. Therefore we choose two cutoff values. A slightly stricter threshold of $\bar{d}_{ij} = 0.4$, which corresponds to a correlation coefficient of 0.6, and a slightly more relaxed threshold of $\tilde{d}_{ij} = 0.6$, which is equivalent to a correlation of 0.4. Since it would be very difficult and incomprehensible to identify the individual clusters in a geographical representation of all 186 filling stations, we

Figure 2: Dendrogram Daily Average Prices



Note: Result of hierarchical clustering have only depicted the largest clusters of the sample. Figure 3 illustrates the seven largest clusters that form at a threshold value of $height = 0.4$, i.e. a correlation of 0.6. In total, the hierarchical clustering with a cutoff value at height 0.4 results in 42 clusters, whereby the seven largest clusters contain 97 of the 186 filling stations of the sample.

Figure 3: Map: Daily Average Prices – cut at 0.4



Even with this rather strict threshold, there are clearly defined geographical markets. Cluster 14, for example, is the geographically relevant market for retail gasoline in and around Ludwigsburg, whereas cluster 19 is clearly centered on Filderstadt. The two clusters 7 and 26 seem to be less clearly distinguished. This could be due to commuter routes, since both clusters tend to cover more rural areas. Since the region around the city of Stuttgart is characterized by heavy commuter traffic from smaller cities, the stations in cluster 26 confirm this as they are all located around the commuter routes. This shows that commuter traffic plays an important role for the competitive situation in the gasoline market.

Figure 4: Map: Daily Average Prices – cut at 0.6

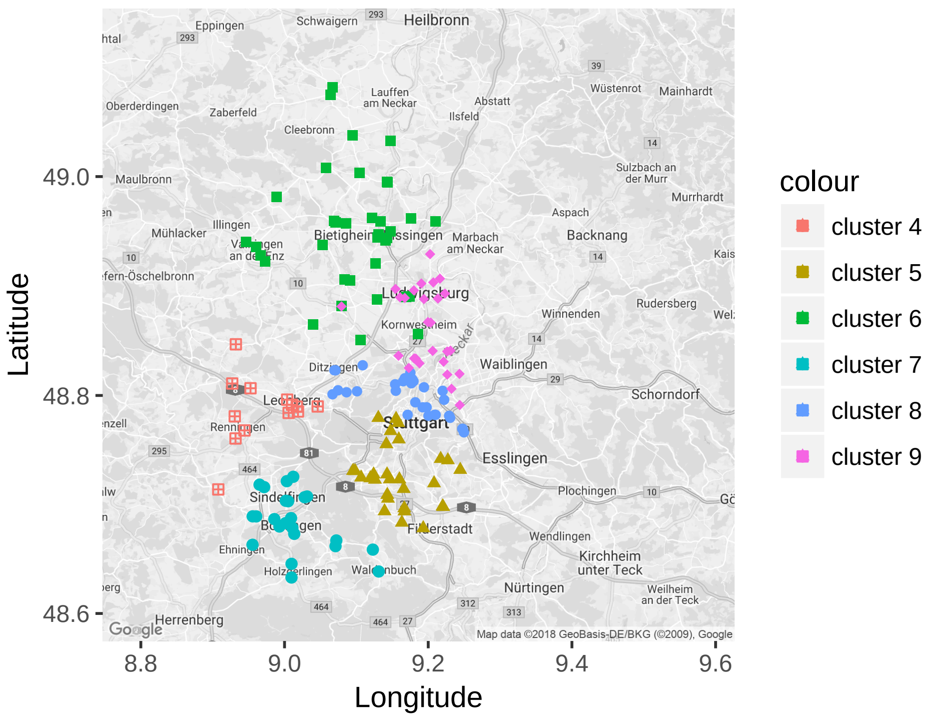


Figure 4 graphically illustrates the situation after loosening the threshold value from 0.4 to 0.6 and thus to a correlation of 0.4. Relaxing the cutoff value leads to even more clearly defined clusters. For reasons of clarity, only the filling stations that belong to the six largest clusters are depicted. These six geographic groups contain 156 of the 186 stations of the sample. As mentioned above, clusters can no longer be changed once they have been formed. This can be seen at the transition from figure 3 to figure 4. In the former, the two clusters 7 and 26 form two distinct clusters. By increasing the threshold, clusters 7 and 26 are fused into cluster 6. However, this cluster still shows the same pattern as the two distinct clusters before and contains the commuter cities around Stuttgart and Ludwigsburg.

The fusion of two clusters into one large cluster when increasing the threshold reveals an important characteristic of the retail gasoline market. The geographical markets for gasoline stations have certainly no strict boundaries, but are rather overlapping. If we allow for a lower correlation coefficient, larger clusters emerge where some stations will clearly have only limited significance for the gasoline stations in the center of the cluster (where correlation between the prices is high). For the purpose of a market definition as part of a merger analysis, however, smaller clusters seem to be more appropriate as we are interested in identifying the strongest competitors which are able to affect the pricing of the concerned parties (gasoline stations).

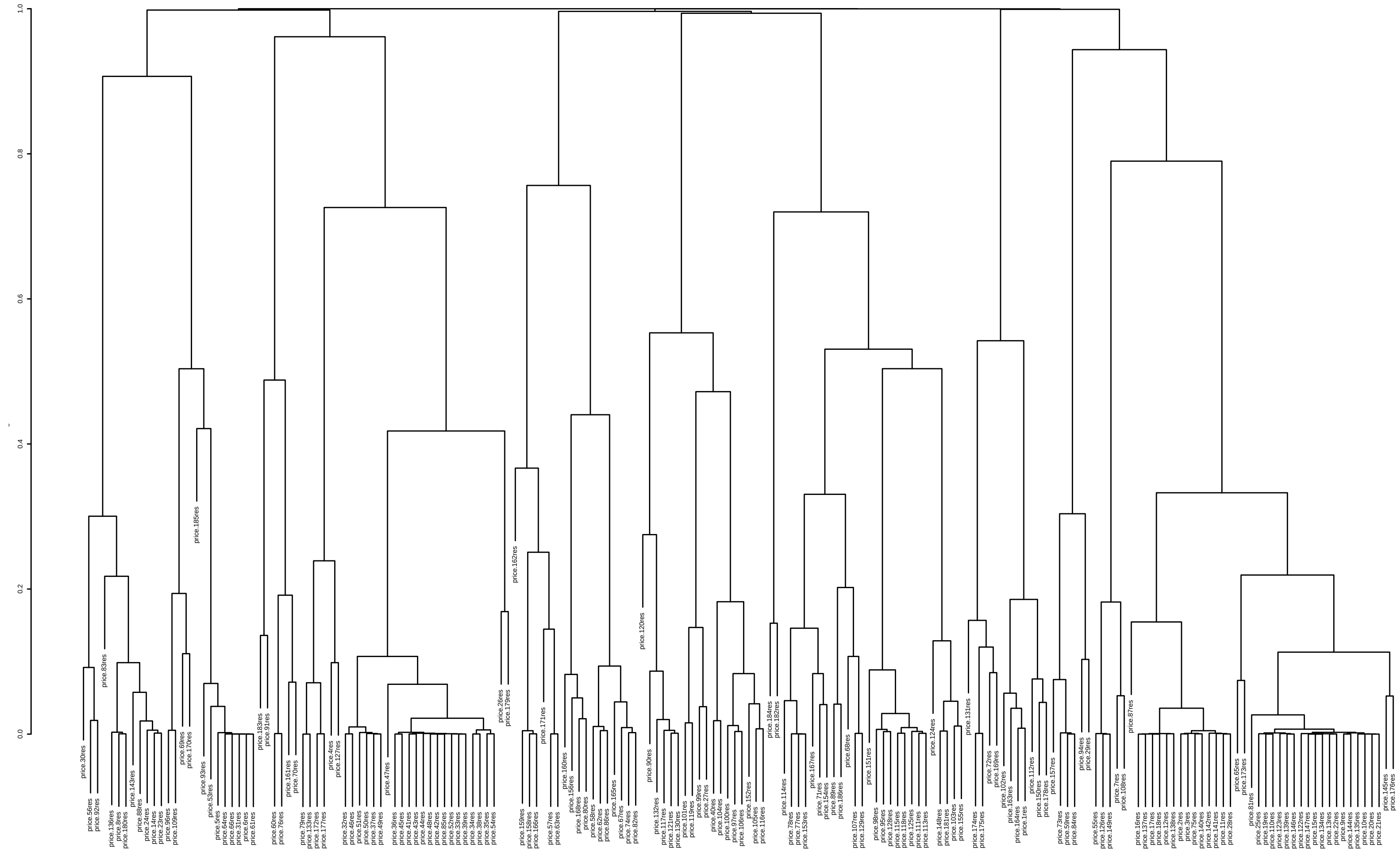
In summary, it can be said that the geographically relevant markets for retail gasoline in the sample tend to be rather small and therefore only the geographical neighbors seem to be close competitors. This is perfectly in line with our hypothesis of small regional markets. Furthermore, we do not have to worry about „special" filling stations, such as motorway rest stops, because such stations are recognized by the method and are treated accordingly. For instance, the motorway filling station 'Sindelfinger Wald' is isolated in a separate cluster for both variants, a cut at height 0.6 and 0.4, respectively. This is consistent with the general opinion that filing stations located at motorways form a separate market and do not compete with the other stations.

In the next step, the adjusted daily maximum prices are used as the basis for hierarchical clustering with the complete linkage method. The results of the clustering process is again illustrated as a dendrogram in figure 5. Compared to the results for the weighted daily average prices, the dendrogram looks much more consistent in the sense that most clusters can be fused at the very bottom of the graph (which corresponds to a higher correlation value).

Since the daily highs and lows represent the limits of the Edgeworth-cycles and are not necessarily the long-term results of a competitive situation, it is sufficient to look at the somewhat stricter cutoff height of 0.4. The five largest clusters, resulting from the threshold value of 0.4 are depicted in figure 5. It turns out that the individual filling stations were not combined geographically, but rather by brand. The clusters 1 and 5 consists almost exclusively of Shell stations, whereas the clusters 13 and 15 consist mainly of ARAL stations. Therefore, the daily maximum prices for E5-gasoline seem to be set uniformly across the stations of a brand.

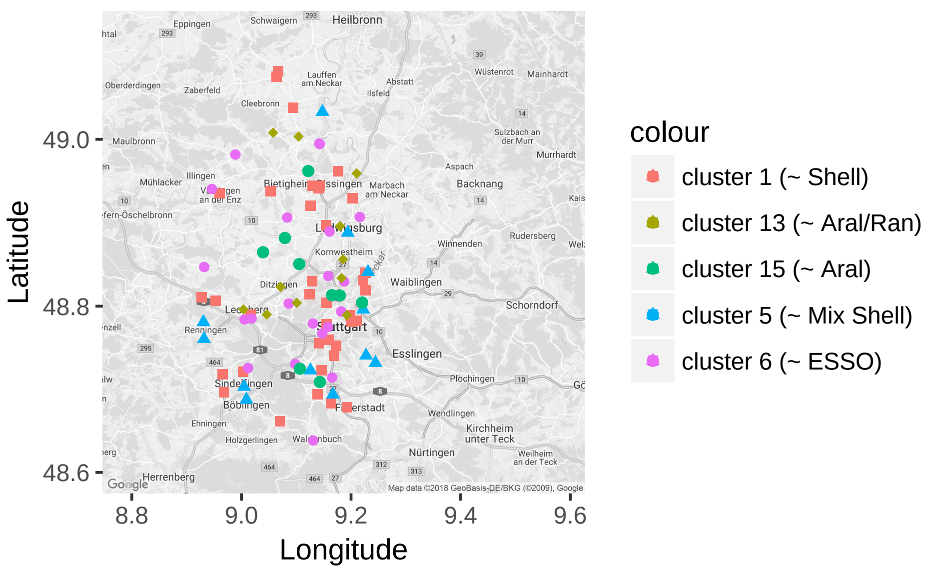
Boehnke (2017) reaches a similar conclusion by using k-means clustering in order to detect common pricing behavior between the stations. The hourly prices of gasoline stations in Germany are used to define clusters including stations with a similar pricing pattern. He identifies that three of his five clusters contain a dominant number of gas stations from one network only (Aral, Shell and Esso,

Figure 5: Dendrogram Daily Maximum Prices



Note: Result of hierarchical clustering respectively) and concludes that these brands exhibit a network-wide pricing behavior (prices appear to be set centrally by a network). This is also in line with the findings of the sector inquiry of the FCO (Bundeskartellamt (2011)) which concludes that many oil companies quote a maximum price for their filing stations. A short descriptive analysis as well reveals that stations of the same brand increase their prices on the same level, which especially holds for distinct regional markets (see also Linder (2018) or Dewenter et al. (2018)). Therefore, in contrast to the daily average price which results in geographical markets, a hierarchical clustering based on the maximum price reveals the uniform behavior of the branded stations with regard to their daily price increases.

Figure 6: Map: Daily Maximum Prices – cut at 0.4



In summary, our analysis of the weighted daily average prices indicates relatively small geographic relevant markets for retail gasoline. Accordingly, the geographical k-means clustering at the beginning of the analysis has no implications for the final results and is not restrictive. The geographical markets are much smaller and the competitive situation more complex and is highly influenced by the demand behavior and the road network. It is obvious that regional factors have an impact on the competitive situation. The analysis carried out with the weighted daily average prices shows a very specific pattern for the clusters. The resulting clusters comply to a large extent with the typical commuter routes in the respective region as gasoline stations along heavily frequented routes are clustered together due to their similar pricing patterns. Thus, commuter routes and thereby commuters have a strong influence on the price setting behavior of gasoline stations and determine the price reactions. The results based on the maximum prices show the centralized pricing of the gasoline brands for their gasoline stations where the companies seem to dictate the price increases. One could argue that the results of the analysis with the weighted daily average prices are precisely the consequence of the uniform pricing of filling stations across brands and the demand-driven price competition due to commuter routes.

Our results show that both, the chain of substitution approach as well as the accessibility model used by the FCO do not properly depict the competitive situation in the German gasoline market which is much more complex. The FCO claims that it takes consumer behavior into account by assuming a driving time of 30 minutes for an individual consumer which live or work near the target station as a basis for their market delineation. Petrol stations, though, are not in a position to observe individual consumers. Instead, however, it is quite possible for them to take commuter flows into account.

5 A Comparison with the Market Definition based on the Accessibility Model

In order to affirm our results presented in chapter 4.3 and to outline the problems when using the accessibility model applied by the FCO in several cases, we compare our approach with one of the market definitions carried out during a merger analysis by the FCO. One of the main difficulties with the accessibility model is that it neglects commuter routes and thereby ignores an important determinant for the price setting behavior of gasoline stations. In the previous section, however, we found out that commuters determine which filling stations react to each other as price reactions of stations along a commuter route are co-moving.

The accessibility model applied by the FCO has already been briefly described in chapter 2. A detailed description of the procedure for the market delineation by the FCO is now explained based on the case Total Deutschland GmbH/OMV Deutschland GmbH (B8-175-08).[16] Information about the final market definition and the exact procedure of the delineation is quite different between the various merger cases of the FCO, whereby the provision of information is in all cases rather sparse. We chose the case Total/OMV as the decision report still is the most informative.

In 2009 Total Deutschland GmbH notified its proposal to acquire 59 filling stations of the OMV Deutschland GmbH located in the federal states Saxony and Thuringia. About half of the filling stations were located in the cities Chemnitz, Dresden, Erfurt and Leipzig whereas the other stations were spread over the rural regions of the federal states concerned.

In general, the accessibility model determines those filling stations that can be reached by car within a certain travel time starting from the target (starting) station. For urban areas, the FCO assumes that consumers are willing to drive 30 minutes to an alternative station to refuel there at a lower price. For rural areas the FCO even determines a longer driving time of 60 minutes for relevant stations. In the present case, the FCO only examined the urban areas because it assumes a priori that competitive problems will arise in areas with a higher petrol station density. According to the accessibility model, one would have to determine the relevant market for each of the concerned stations in the case. As the procedure is time-consuming and a multitude of relevant markets should have been determined, the FCO abstains from defining relevant markets for each gasoline station separately, but defines four regional markets for the four cities mentioned above. The four relevant markets are therefore delineated around the geographical city centers of Chemnitz, Dresden, Erfurt and Leipzig. With this approach the FCO identifies 104 stations in the relevant regional market Chemnitz, 86 stations

[16] See Bundeskartellamt (2009).

for Dresden, 75 stations for Erfurt and 75 stations for Leipzig.[17] The gasoline stations are weighted according to their distance to the city center. On the basis of the market shares resulting from this market definition, the FCO has prohibited the proposed merger as it would further strengthen the position of the dominant oligopoly. In the following, however, the Higher Regional Court of Düsseldorf (OLG) opposed the decision of the Federal Cartel Office and decided that the takeover of the 59 OMV petrol stations by Total was not contrary to cartel law. The OLG Düsseldorf argues that the petrol stations of OMV and Total are in strong competition with the other market participants in the respective regional markets and concludes that the takeover of the 59 petrol stations would not create or strengthen a dominant position. The FCO, in turn, has lodged a complaint against this decision of the OLG at the Federal Supreme Court (BGH). In the course of the appeal procedure, OMV sold 56 of the 59 petrol stations to Orlen Deutschland AG and closed the others.

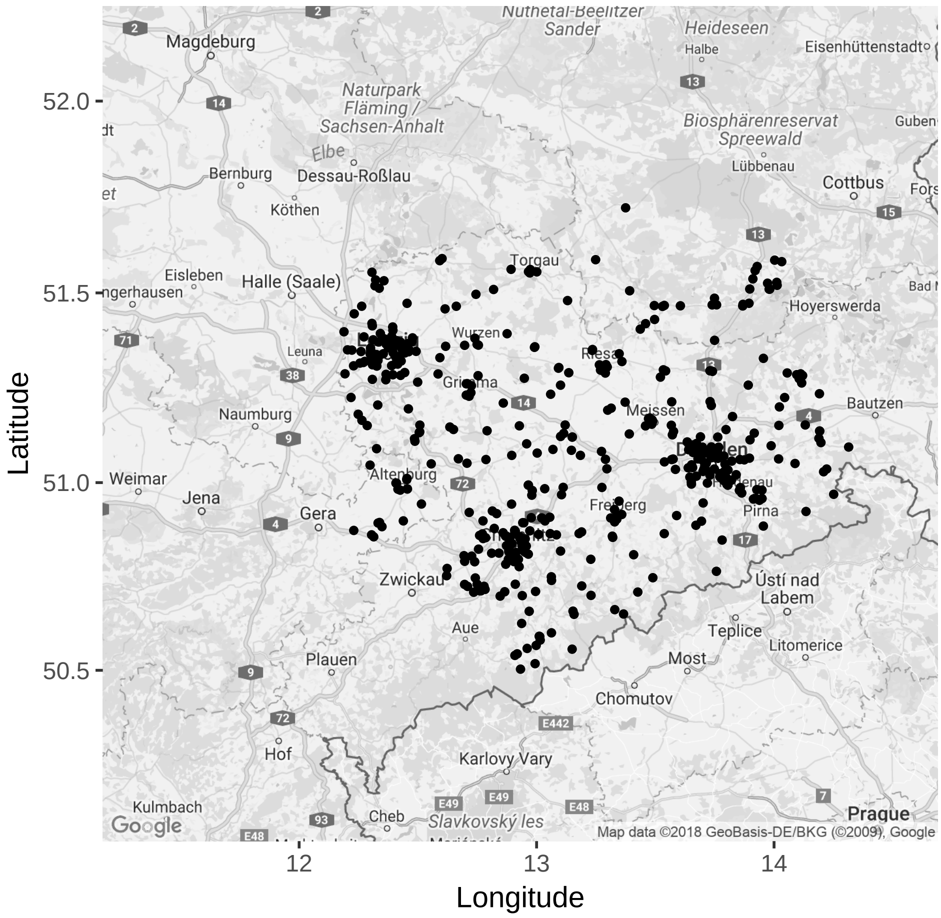
In the following, we choose a sample from our data set that contains the concerned region mentioned in the case report of the FCO. The FCO performs its market definition for each city separately resulting in four disjuncted geographic regions for the cities Chemnitz, Dresden, Erfurt and Leipzig. However, the analysis in chapter 4.3 has shown that commuters play a crucial role. As the three cities Chemnitz, Dresden and Leipzig are geographically close, we choose a sample that contains all three cities. The sample therefore includes all filling stations up to a distance of 85 km from one of the three cities, a total number of 465 stations. Figure 7 shows the location of these stations.

The composition of brands within the sample is shown in table 3. In particular the brands Aral (79 stations), Total (69), Shell (50), Star (41), and Esso (32) must be pointed out. However, Jet as part of the big five oligopolists is somewhat underrepresented in the given sample with only 16 stations.

The joint consideration of the three cities allows us to investigate urban as well as rural areas with a single analysis. With the method presented in chapter 4.2 it is possible to run only one model for the whole sample. This is an important difference from the approach taken by the FCO. The FCO restricts its analysis in advance as it investigates the four cities not together but each separately despite the geographical proximity. Due to these a priori assumptions, however, the FCO is not able to take important factors like commuter flows and thus demand behavior into account. With the method described in section 4.2 it is not necessary to subdivide the sample under consideration into subsamples in advance as

[17] The report does not include more detailed information on the location of these stations. Moreover, the exact numbers of different brands are not reported. Market shares are only available for Total and OMV. In Chemnitz Total has a market share of 10-15% as well as OMV. In Dresden Total has a market share of 17-22% and OMV has 4-9%. In Erfurt Total has a share of 18-23% and OMV 7-12 % which is comparable to the market shares in Leipzig.

Figure 7: Sample of stations (BKartA)



Note: All 465 filling stations within the sample.

Table 3: Distribution of brands in the BKartA sample

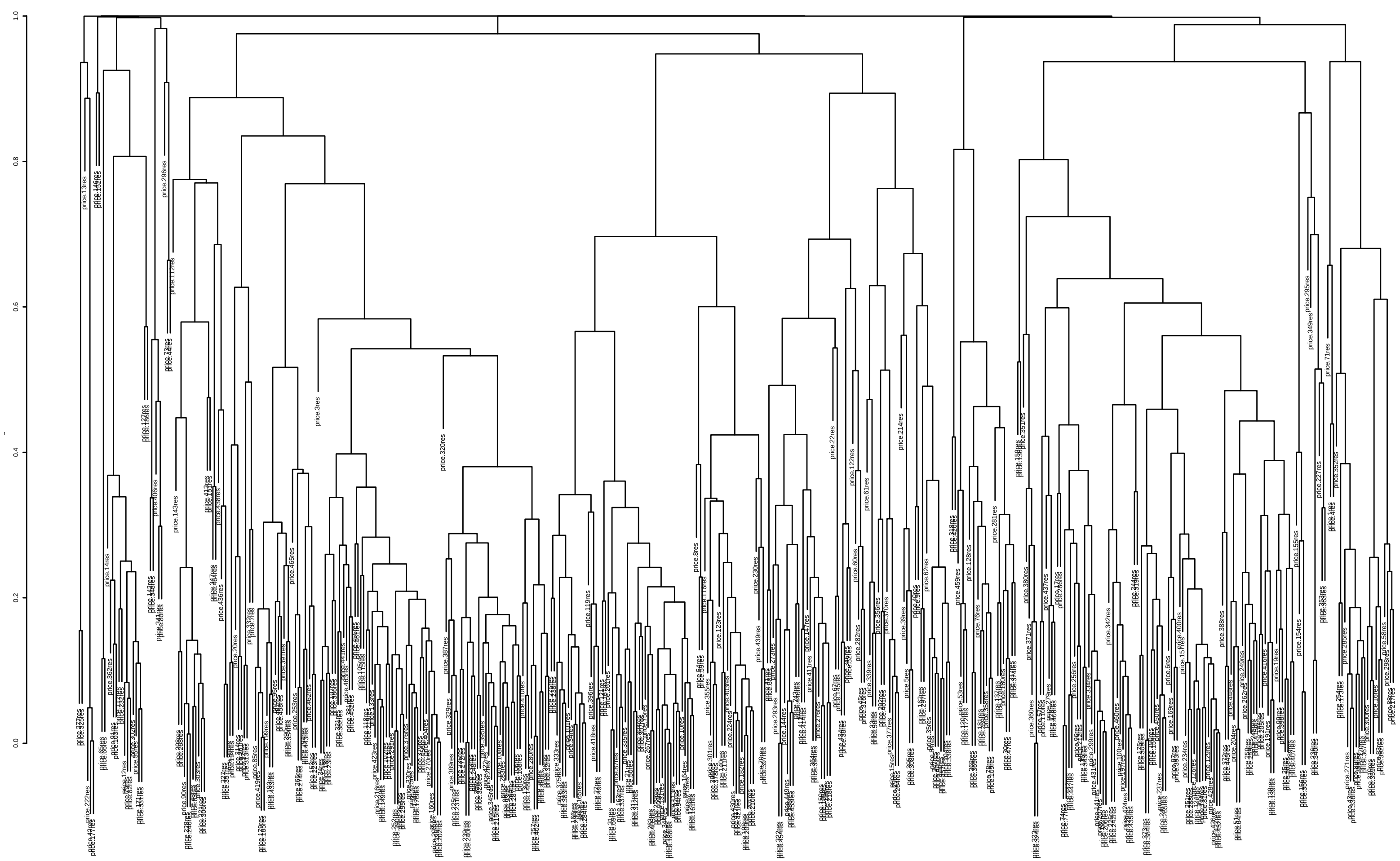
Brand	No. of stations
ARAL	79
TOTAL	69
Shell	50
Star	41
ESSO	32
HEM	19
JET	16
Agip	13
Others	146
N	465

Note: Number of filling stations per brand.

all gasoline stations can be analyzed in one step. This is a big advantage of our analysis as we do not have to make any further assumptions about the extent of the relevant markets in advance. Therefore, we are able to take commuter routes into account and we can consider areas with low as well as high station density at the same time. Moreover, the approach is not time-consuming and can therefore easily be applied by competition authorities during a merger investigation. For a detailed description of the method, please refer to chapter 4. Figure 8 shows the dendogram which presents the hierarchical clustering of the weighted daily average prices for the 465 gasoline stations in our sample. In contrast to chapter 4.3, for this case only results with the weighted average price are presented below. As outlined above, the maximum price leads to a clustering based on the different brands and reflects the centralized price setting of the oil companies. The weighted daily average price, however, is the most appropriate for the analysis and represents the cyclical behavior of the gasoline stations.

The height is depicted on the far left of figure 8 and corresponds the dissimilarity measure defined previously: $d_{ij} = 1 - |cor_{ij}|$. Considering the clusters formed in the dendogram, we choose a slightly stricter threshold of $d_{ij} = 0.4$, which corresponds to a correlation coefficient of 0.6. Besides that, a higher correlation coefficient coincides with our intent to identify the closest competitors as the relevant market should contain the closest substitutes. Especially for merger analysis it seems to be appropriate to focus on those rivals which really have an influence on the pricing of the concerned companies. With a threshold value of 0.4 ninety distinct clusters are identified. There is a number of clusters which contain only a few stations (or

Figure 8: Dendrogram FCO–Sample



even only one). These stations are either highway filing stations which obviously have a different price setting behavior and form a separate market or, on the other hand, there are smaller clusters especially in the rural areas where the station density is very low.

Figure 9 looks more closely at the 20 largest clusters that form with a cutoff value of $height = 0.4$, i.e. a correlation of 0.6. As these are regions with a higher station density, we expect that competition problems are more probable in these areas. Moreover, for the present paper an illustration of all clusters in one map would not be very informative. However, in a merger analysis one could easily look at all clusters. The 20 largest clusters include 320 gasoline stations of our 465 stations in the sample. Where the largest cluster contains 43 filing stations and the smallest 9.

At first, it can be noted that a multitude of relevant geographic markets are identified for the geographical area around Chemnitz, Dresden and Leipzig. Many clusters can be identified for each city.[18]

Taking into account the findings of our analysis in chapter 4.3, we assume that commuter routes play a major role for the price responses of petrol stations. Unfortunately, we do not have access to specific statistics on commuter flows in this area which could be used directly. However, we use data from the automatic road traffic counting of the „Federal Highway Research Institute“.[19] The automatic counting points record all cars driving on the monitored „Bundesstraßen“ and „Autobahnen“. We are looking at routes with a traffic volume above-average. The identified roads are used as a proxy for commuter routes and are highlighted in figure 10. The routes marked in figure 10 all count between 9,000 and 46,000 vehicles per day on average and are therefore appropriate as a proxy for commuter routes. We scrutinised our assumption by investigating the reports of the „Institute for Employment and Research“ which carries out regular studies on commuter flows. The findings of these reports are consistent with the routes identified with the data of the traffic census. Therefore, the traffic-intensity measured by the counting stations offers a good possibility to make ex ante assumptions about commuter flows.

Comparing the commuter routes highlighted in figure 10 with the results of the hierarchical clustering in figure 9, one can clearly see that several clusters coincide with the commuter routes. If we look at Chemnitz for example (bottom center in figure 9), gasoline stations along the commuter flows from city districts and from nearby smaller cities are clustered together. Another very clear example is the

[18]Unfortunately the city names are partly difficult to read due to the high number of gasoline stations located in the cities. However, the map is consistent with the one in figure 7 which can serve as orientation if needed.

[19]`https://www.bast.de/BASt_2017/DE/Verkehrstechnik/Fachthemen/v2-verkehrszaehlung/zaehl_node.html`

Figure 9: Sample of stations (BKartA)

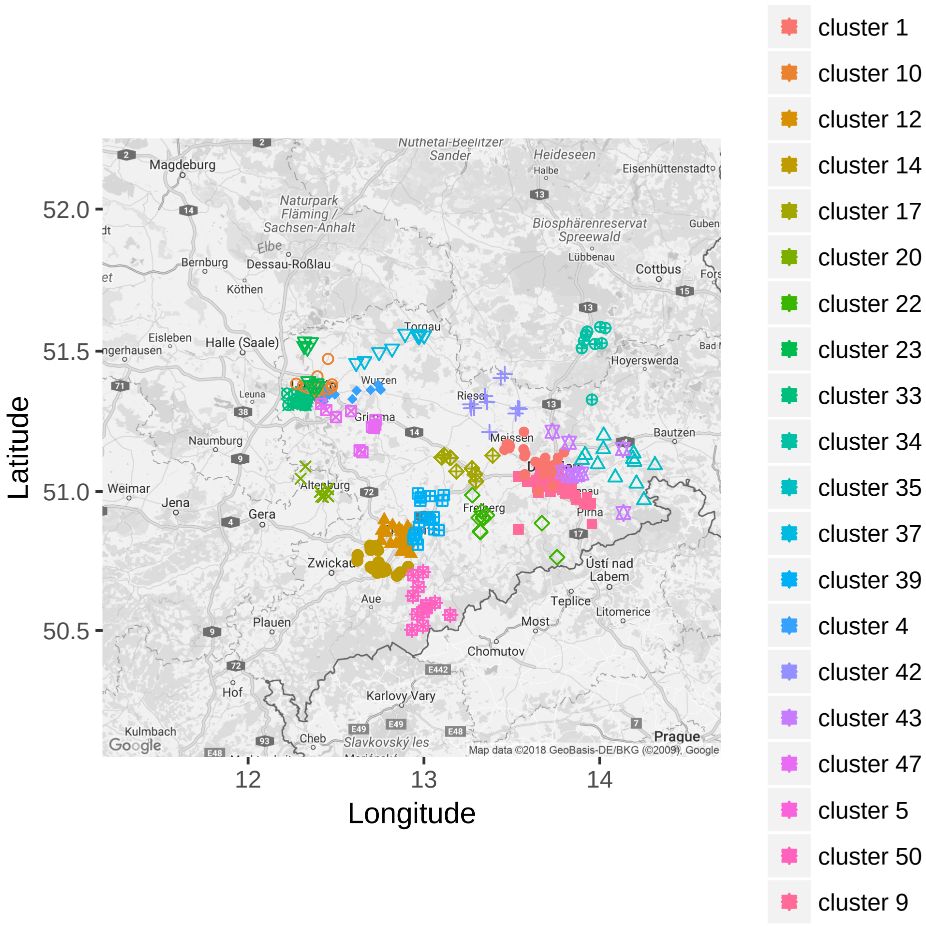
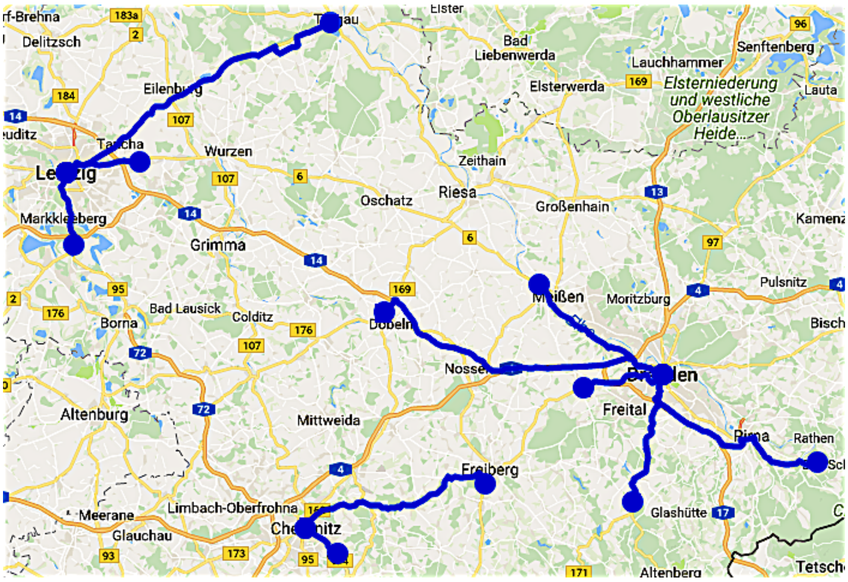


Figure 10: Commuter Routes in Saxony



route from Leipzig to Torgau (top-centre of figure 9 and top-left in figure 10). The filling stations along this commuter route are clustered together and demonstrate a very high correlation of their price setting behavior. These results confirm our findings in chapter 4.3 and verify our assumption that commuters are an important determinant for the price setting of gasoline stations as price reactions are triggered by commuter routes. In contrast to the presented approach, the FCO only looks at the competitive situations in the cities. The risk of neglecting commuter routes is therefore high which could possibly lead to wrong conclusions about the relevant rivals for the concerned gasoline stations.

The FCO takes the demand behavior of an individual car driver as a basis for its market definition. However, a driving time around a target (starting) station of 30 minutes does not seem to reflect the actual demand behavior of car drivers. Most car drivers refuel during their travel from work to their home place, which is as well stipulated by the FCO. It does not seem to be a reasonable behavior of a consumer to drive 30 minutes to a cheaper station starting from the target station. Moreover, gasoline stations are not able to observe individual (local) consumers which live or work near the station. It seems to be more reasonable that the pricing of gasoline stations is influenced by general fluctuations in demand like commuter flows. In contrast to the behavior of individual consumers, commuting traffic and commuter routes can be observed by gasoline stations and can be taken into account in the price setting. The timing of the price cycles further confirms this presumption. Gasoline stations increase prices in the evening when commuter traffic is as well increasing (see for example Dewenter et al. (2018)) which also shows that commuters are a driving force for the price reactions of gasoline stations. As commuters know the stations and their prices along their route, these gasoline stations will react to each other in their pricing and thereby belong to one market.

The results of our analysis show that with the approach presented in section 4.2, a different market delineation results when compared with the investigation of the FCO. Of course, due to lack of information, we cannot make a final conclusion what this would mean for the antitrust assessment of the present case. However, it is of course quite possible that a different market delineation would also result in a different merger decision.

6 Conclusion

We combine the simple and intuitive concept of price correlations and hierarchical clustering, a method from the rich toolkit provided by unsupervised machine learning, to a new and efficient price test in order to define geographically relevant markets for retail gasoline in Germany and to identify the closest competitors.

The method used is very attractive, especially for antitrust authorities, since one can extract any number of clusters from one single dendrogram based on the preferred correlation coefficient. As we are interested in the closest competitors, in most cases a higher correlation coefficient is recommended. Further advantages of hierarchical clustering with price correlation as a dissimilarity measure are first that the method is easy to use and very intuitive. Secondly, we do not have to worry about special filling stations, such as motorway rest stops as these are identified as separate markets by our method.

Our analysis reveals that the relevant geographic markets are rather small. Moreover, commuter routes play a crucial role for the competitive behavior in the German retail gasoline market. Gasoline stations cannot observe the refuel behavior of individual consumers as assumed by the FCO. Rather, it is the case that the price reactions are strongly affected by commuter routes along which gasoline stations are competing. The results show that the competitive situation is complex and cannot be captured neither by the chain of substitution model nor by the accessibility model applied by the Federal Cartel Office. As the accessibility model neglects commuter routes, conclusions based on this approach could be misleading. Gasoline stations cannot observe the behavior of individual consumers which live or work near the station. However, they are able to observe commuting traffic and commuter routes. Our analysis reveals that besides local market conditions, these frequently used routes and thus the commuters are a driving force in the price setting of gasoline stations. Stations along these routes react strongly to price changes of their neighbouring stations.

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