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Melissa Bantle
University of Hohenheim

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Screen for Collusive Behavior – A Machine Learning Approach

Melissa Bantle *

February 29, 2024

Abstract

The paper uses a machine learning technique to build up a screen for collusive behavior. Such tools can be applied by competition authorities but also by companies to screen the behavior of their suppliers. The method is applied to the German retail gasoline market to detect anomalous behavior in the price setting of the filling stations. Therefore, the algorithm identifies anomalies in the data-generating process. The results show that various anomalies can be detected with this method. These anomalies in the price setting behavior are then discussed with respect to their implications for the competitiveness of the market.

Keywords: *Machine Learning, Cartel Screens, Fuel Retail Market*

JEL-Codes: *C53, K21, L44*

*University of Hohenheim, Department of Economics, Chair of Microeconomics (520C), 70593 Stuttgart, Germany, melissaulrika.bantle@uni-hohenheim.de

1 Introduction

Despite cartel enforcement and actions like the leniency program, companies still make collusive agreements. The question therefore arises as to whether punishments are not severe enough or whether the risk of detection is too low. In recent years, moreover, leniency applications have declined substantially. It might thus be time for pro-active methods to detect cartels. These include screening methods where market data is examined for evidence of collusion. These cartel screens can be used complementary to leniency programs as they can give an incentive to apply for leniency due to the higher risk of detection through such a screen.

Screening is meant to be the basis for an investigation as it does not deliver direct evidence for a cartel but identifies potential collusion. These screens could be used by competition authorities as a first screen to identify markets or firms that should be investigated further. Or to monitor suspicious firms or industries that are already under investigation to identify changes in their behavior. Competition authorities can check for suspicious behavior with a screen in order to start an investigation or prioritise cases.

Besides competition authorities, also companies should be aware of screening programs. Such screens could be used to detect anomalous behavior in the price setting of their suppliers. Firms are predestined for screening methods as they have sufficient data from their suppliers and the market knowledge to implement a screen efficiently. Screening tools can, for example, be included in antitrust compliance programs. If an anomaly is detected, the firm could renegotiate prices with the supplier and if suppliers know a screen is implemented, this could also help to prevent cartels among suppliers in the first place.

Another possible application of such a screen would be in the context of calculating damages of a cartel, for example by economic consultancies or by competition authorities. The start (and end) of a cartel is often not known exactly or is only based on statements by the cartelists themselves. A screen could detect anomalies or structural breaks that can be traced back to the start of a cartel to review the statements.

The Paper applies a machine learning method – the XGBoost model – to detect anomalies in the price setting behavior of firms. At first, an overview of screening methods is given, afterwards the screening approach is introduced. The screen is applied to the German retail gasoline prices. In order to be able to set up the screening tool efficiently, the market characteristics and the data are described in detail. Then, the XGBoost model is explained. In the last subsection the results are presented where the algorithm has classified whether certain data patterns are anomalous and worthy for further investigations. The results of such a screen are of course no direct evidence for collusion but are indications which need to be interpreted to reach a conclusion.

2 Overview of Screening Methods

There are generally two different screening approaches – structural screening and behavioral screening. Structural Screens identify markets with characteristics that are associated with collusion and which are supposed to facilitate cartel formation. These characteristics can be grouped into structural factors (e.g. a small number of firms, high entry barriers, high market transparency and frequent interaction between firms), supply factors (e.g. product homogeneity) and demand-related factors (e.g. stable demand and low demand elasticity).[1] However, this approach has several weaknesses. There is neither enough theory on these factors and their relationship to collusive markets nor enough data that could confirm these strucutral factors.

The other approach is the behavioral screening. This approach focuses on the outcomes of a cartel and identifies collusive patterns in prices and market shares, for example. These two screens can also be combined as in a first step markets that are prone to collusive behavior are identified with a sctructural screen. The flagged markets are then analysed with a behavioral screening.

Behavioral screens take advantage of the fact that a cartel leaves a change in the data-generating process. Effective behavioral screening requires readily available data and simple empirical methods that can be automated. Behavioral screens can either focus on collusive markers, structural breaks or anomalies in the data.

Collusive markers are certain behavioral patterns that are typical for collusion. These are, for example, higher prices compared to a competitive situation and more stable prices (lower variance in prices), as under collusion firms are less responsive to cost and demand shocks. Firms participating in a cartel need to coordinate and communicate before reacting to changes in their input factors, otherwise it could be misinterpreted as a deviation from a cartel agreement. This reduces the volatility of prices.

A structural break is an abrupt change in the data-generating process, which could result from a cartel begin or end. Such a structural break could, for example, stem from a change in how prices respond to cost and demand factors.

And an anomaly is a pattern in the data that cannot be explained or is in-

[1]For a detailed discussion of these factors, see for example OECD (2022)

consistent with competitive behavior. One example for such a pattern is charging lower prices when the cost is increasing. Such a behavior cannot be explained with competition. Of course, such an anomaly does not necessarily have to be due to collusive behavior, but can also have other reasons (cost shocks or similar). Such a screen is therefore a first step to uncover conspicuous behavior so that it can be investigated further (see Harrington and Imhof (2022)).

There are a number of competition authorities that already use screening methods, especially to uncover bid-rigging cartels. In 2008 the Swiss Competition Commission (COMCO) decided to design a proactive tool to screen procurement data. For this screen the COMCO makes the assumption that bid rigging affects the distribution of bids as collusive bids will differ from competitive bids as the former do not reflect the costs of each bidder. The COMCO uses collusive markers like the coefficient of variation, kurtosis, skewness and spread. These statistics were used and compared with benchmarks resulting from past investigations to identify collusive bids. In 2016 the COMCO successfully detected a cartel in the road construction sector with the help of this screening tool (see Imhof et al. (2017)). The Danish Competition and Consumer Authority as well reported that they are developing a screening tool to detect bid rigging. However, there is not much information on this, as competition authorities naturally want to keep the exact features of these screens secret in order to prevent cartelists from reacting and adjusting their behavior to avoid detection by the screen (see OECD (2022)).

Besides competition authorities, also individual companies try to fight collusive behavior between their suppliers. The Deutsche Bahn, for example, uses structural screening methods to identify markets prone to cartels. Suppliers operating in high-risk markets are then obliged to introduce effective antitrust compliance programs. Additionally, a behavioral screen is now being planned (see Beth and Reimers (2019)).

One of the most common screens (at least in the literature) is based on the assumption that price variance is lower during collusive periods than under competition, as it is costly to coordinate price changes. Abrantes-Metz et al. (2006) estimate price variance for the retail gasoline industry in Lousville and detect a substantial difference when the cartel collapsed. As this screen does not require cost data, is easy to estimate and has a known distribution and has theoretical and empirical support, the price variance is often used as an input factor for screens.

Hüschelrath and Veith (2014) apply a price screen to a data set comprising market transactions from 36 smaller and larger customers of German cement producers and show that such a price screen would have allowed the customers to detect the cement cartel in the upstream market before the investigation of the competition authority has started. For this purpose, Hüschelrath and Veith (2014) use a two-step approach. First, they apply structural break analysis on the price variance to detect anomalies in the data. In a second step, they use the findings of structural break analysis to set up a model of multivariate price and volatility analysis with regard to the end of the cartel period. With this regression they want to detect where the structural break comes from by controlling for potential drivers beside a collusive agreement.

Crede (2019) also uses a structural break screen to identify proven cartels in Italy and Spain for pasta products. The author estimates a reduced-form regression of the price for pasta that includes production costs, proxies for demand and controls for structural breaks in the data-generating process. As the author tests for structural breaks endogenously, this test can be used for ex ante screening.

Machine learning methods can further improve these screens and they have the advantage to can be applied at a large scale and thereby reducing the costs of screening. As machine learning is not intended to identify a causal relationship, one can use many collusive markers even if some of them are highly related as collinearity of predictors is no problem. Moreover, there is no need to set up a specific model of the underlying data-generating process. The algorithms learn from a training data set and make useful predictions on new data.[2]

Huber and Imhof (2018), for example combine machine learning techniques – lasso regression and ensemble method – with statistical screens (coefficient of variation, kurtosis, skewness, etc.) to predict collusion through bid-rigging cartels in the Swiss construction sector. In another paper, Huber and Imhof (2021) propose an approach based on deep learning. They combine convolutional neural network used for image recognition with graphs that plot the normalized bid values of some reference firm against the normalized bid of any other firms participating in the same tenders as the reference firm. They use Japanese and Swiss procurement data and construct such graphs for collusive and competitive periods and use these graphs to train the neural network distinguishing between collusive and competitive bidding.

García Rodríguez et al. (2022) applies eleven different machine learning algorithms to data sets from collusive auctions in Brazil, Italy, Japan, Switzerland and the United States. The paper investigates the ability of the various algorithms to detect collusive auctions accurately. These algorithms include linear models, ensemble models (random forest and gradient boosting), support vector machines and neural network models. Each of the eleven algorithms is tested with different

[2]The exact procedure is explained in more detail in section 3.2 as part of the method used here.

amount of information and different statistical indices as input factors (for example the coefficient of variation, skewness and kurtosis). The ensemble methods provide the best result in this study. This also includes gradient boosting which is used in the paper at hand.

All these papers present screens for bid rigging. Silveira et al. (2022) are the only ones so far to apply machine learning techniques to prices that are available to consumers which differ from public tenders and bid-rigging cases. Silveira et al. (2022) investigate the Brazilian retail market for gasoline. They combine supervised machine learning techniques with statistical moments of the price to detect cartels in this market. The authors use a dataset which contains prices from cities where collusion was already detected and prosecuted. They exploit this fact and define a binary output variable which equals 1 if the algorithm detects a cartel period and 0 for non-cartel periods. The input variables are the statistical moments of the gasoline price: the standard deviation, coefficient of variation, spread, skewness and kurtosis. Silveira et al. (2022) evaluate five supervised machine learning models – logit, LASSO logistic, ridge logistic, random forest and neural network – and conclude that all these algorithms can effectively identify cartel and non-cartel periods with only few false-positive or false-negative results.

The method presented in this paper can best be compared with the method of Silveira et al. (2022) as the aim is to find a screen that can be applied to a wide variety of markets.

3 Screening Approach

3.1 The Data and the Market

The present paper investigates the price setting behavior in the German retail gasoline market. For the analysis the paper uses a data set that contains every price change of each individual filling station in Germany from the petrol price comparison site "Tankerkönig"[3], that makes the price information from the "Markttransparenzstelle für Kraftstoff (MTS-K)" publicly available. The filling stations are obliged to report every price change to the MTS-K in real time. For the analysis in section 3.3 the price for E5-gasoline of a single filling station is used.[4]

The data set used contains as well specific information about each filling station, such as name, address, brand or geographical coordinates. With this information, the data set is extended by traffic data and information on the weather depending on the geographical location of the filling stations.

Traffic data comes from the "Bundesanstalt für Straßenwesen (bast)". These are hourly data on the traffic from automatic permanent counting stations on highways and main roads. For the analysis, the nearest counting point to the filling station in question is selected. The traffic data is used as a proxy for the demand at filling stations. The more traffic, the more likely it is that more drivers will fill up.

Data on the weather comes from the "Deutscher Wetterdienst (DWD)". Hourly data on air temperature and precipitation is available via the Climate-Data-Center portal. As with the traffic data, the relevant weather data was chosen from the

[3] www.tankerkoenig.de

[4] The analysis is conducted for a variety of filling stations, however, to avoid repetitions, the results for one example are shown below.

nearest weather stations for the filling station that is analyzed. The weather data is an additional proxy for demand. The worse the weather, the fewer drivers are on the road, which means fewer potential customers for the filling stations.

With this combined data set input features are created to build the XGBoost model (see section 3.3) in order to predict prices for filling stations and detect anomalies with these predicted values.

To select the correct input features, it is important to know the price setting behavior in the market and the key economic characteristics of the market. The gasoline market in Germany exhibit daily price cycles. Filling stations increase their prices in one or several steps and then a phase of price decreases can be observed. At least, this is the shape of the cycles at the time of the initial analysis. These cycles are repeated daily. Moreover, this specific behavior is observed for nearly all filling stations in Germany. However, over time these cycles change their shape. The present paper makes use of these changes and the model used in the next section detects the time of these changes and provides first information or hints which factors are playing a role for these changes.

Another important factor for our analysis is that the German retail gasoline market is characterized by a very high market transparency due to the real-time reporting of prices. Therefore, collusive markers like the price variance might be irrelevant or difficult to interpret in this market. Normally, it is expected that price variance is lower during cartel phases as it is costly for cartel members to coordinate price changes (see section 2). For the filling stations in Germany it is easy to observe price changes which could lead to a much higher price variance under collusion compared to a situation without this possibility. Moreover, the number of market participants is very stable as it is difficult and cost-intensive to build up a new filling station. These factors facilitate collusion in this market. Together with the consistent and parallel pricing behavior of the fillig stations, this results in repeated discussion of competition authorities about this market.

3.2 The XGBoost Model

XGBoost is short for "Extreme Gradient Boosting". This method is based on decision trees. It works well with large, complicated datasets as it uses different optimization methods. It is a scalable learning system that learns the model of interest from large datasets.[5]

XGBoost is used for a wide range of problems, including store sales prediction (see Pavlyshenko (2016)), predicting the direction of stock market price (see Dey et al. (2016)) and Gumus and Kiran (2017) forecast crude oil prices using XGBoost.

For the present case, the algorithm learns the pricing pattern with the help of a training data set. The model learned from this is used to predict future prices. A deviation of the prediction from the real values indicates an anomaly and should be examined more closely.

To set up the XGBoost model, the data is divided into a train and (several) test data sets. These data sets are then splitted into features (X) and target (Y), where Y in this case is the price for E5 gasoline and X are the input variables (see table 1) organized into a feature matrix to predict the target variable Y. These feature parameters are a major advantage of this method as a meaningful selection of these input variables helps to get sophisticated models.

For the analysis in section 3.3 a linear prediction model is used: $\hat{y}_i = \sum_j \theta_j x_{ij}$,

[5] See Chen and Guetrin (2016) for an extensive and mathematical description of the underlying algorithm.

which is a linear combination of weighted input features. The parameters θ are the undetermined part that need to be learned from the data. The training part consists of finding those parameters that best fit the training data (input features an label). To find the best parameters given the training data, an objective function is defined to measure the performance of the model given a certain set of parameters. The objective function contains of two parts: training loss and regularization: $obj(\theta) = L(\theta) + \Omega(\theta)$, where L is the training loss function and Ω is the regularization term. The training loss measures how predictive the model is on training data. For the example in this paper the mean squared error is used: $L(\theta) = \sum_i (y_i - \hat{y}_i)^2$. The regularization term controls the complexity of the model, which helps to avoid overfitting. Regularization encourages simple models and simpler models tend to have smaller variance in future predictions, making prediction more stable.

XGBoost uses the so-called tree-ensemble model, which sums the prediction of multiple trees together: $\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F$, where K is the number of trees and f is a function of F which is the space of functions containing all regression trees (see Chen (2022)).

In the tree boosting part, the objective function is optimized. In this context it means, that the model learns the functions (f), which are the parameters in the model. The training loss part of the objective function fits the function on the data points, whereby the regularization part limits the complexity of this function. XGBoost uses gradient boosting which is an additive training where training is sequentially and one new tree (function f) is added at a time, each to correct the errors of the previous one. Gradient boosting is an approach where new models are created that predict the residuals or errors of prior models and then are added together to make the final prediction.

This means that with the help of the train data set, the algorithm learns the model. In the analysis below the Root Mean Squared Error (RMSE) is used to asses the correcteness of the model. If the RMSE decreases in every round the XGBoost algorithm is adopted to the train data, the model learns the data well without exhibiting random fluctuations in the error rate. This trained model is tested against the validation data set to confirm the model. Afterwards the model is applied to the test data sets (future prices) until the predicted values deviate from the actual values. This indicates that the learned model is no longer able to predict future prices which points to a change or anomaly in the price setting behavior which cannot be explained with the given input factors. The XGBoost algorithm is able to rank the various input features based on their importance. The importance matrix builds a list of the inputs and shows the decreasing importance of features. With the importance matrix it is as well possible to identify where the anomaly in the data could come from, which is illustrated in section 3.3.

3.3 Results

This section focuses on two different time periods where anomalies were detected by the XGBoost algorithm. The first is spring 2015 where the price cycles in the German gasoline market changed. The cycles changed from one price increasing and one decreasing phase, to an interrupted cycle which exhibits one additional peak around midday. The second time period is spring 2017 where again the price cycles changed and an additional price peak is implemented by the filling stations in the afternoon.

To predict these price cycles, the XGBoost model needs the relevant input factors. A large number of input fators were tested as part of the analysis. These are listed in table A1 in the appendix. After various test runs and model tuning, the factors listed in table 1 form the relevant input features for correctly predicting the price cycles. These input factors include parameters that are directly derived from the price, moreover, cost and demand factors are included. The daily maximum and minimum price reflect the limits of the cycles, the daily mean price should help to predict the average price level. The cycle position and the daily price spread reflect the shape of the cycle and the daily number of price changes and the number of price increases capture the reactions or interactions of the fillig stations. The price variance (on a daily measure) is included as many screens make use of it and it could reflect the competitiveness of the market. However, as already outlined above, this might not hold for the German retail gasoline market. For the cost the Brent price is used and the demand side is captured with hourly traffic data and the weather.

Figure 1 shows the result of the prediction generated with the XGBoost model and the input features listed in table 1 for one gasoline station in Stuttgart.[6] The black line is the real price and the red line are the predicted values.[7] The XGBoost model is obviously very good at predicting the price and the corresponding price cycles.

The model also provides a tool for analyzing which of the input factors played the biggest role in the prediction and had the greatest influence. This can be

[6]The analysis was conducted with a variety of different gasoline stations to confirm the results. The results shown here are therefore representative for the entire petrol station market.

[7]As XGBoost does not work with a date variable, the x-axis shows the number of observations instead of a date.

Figure 1: Prediction – June 2015

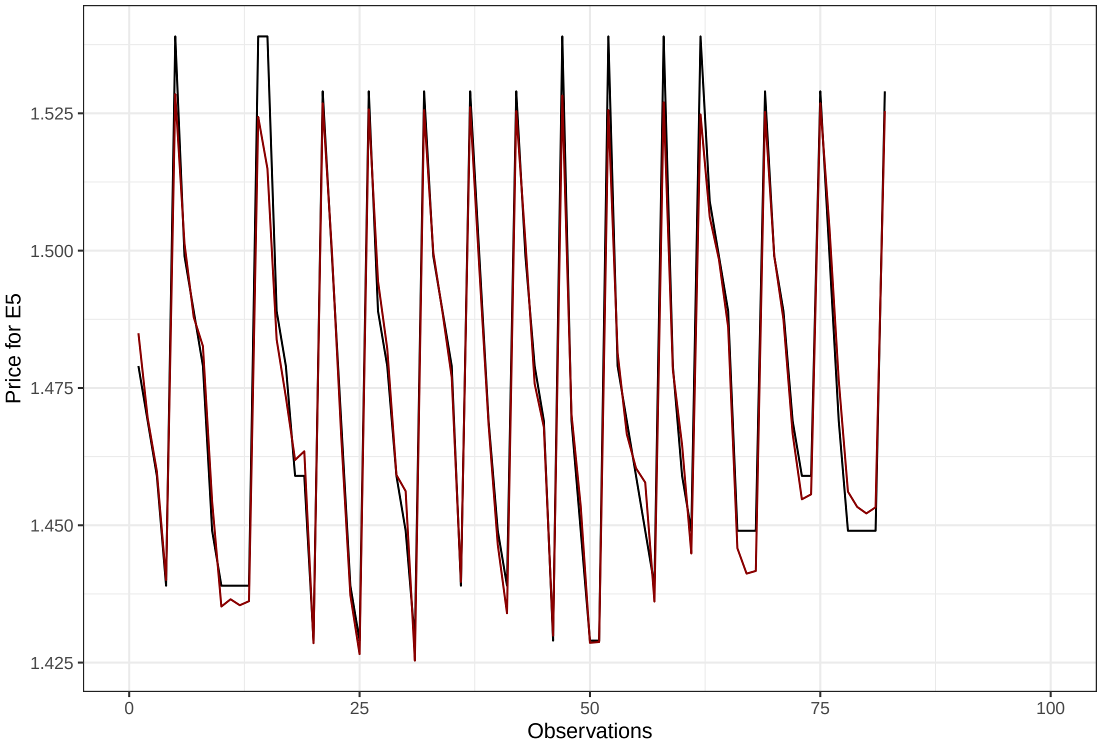


Table 1: Input Factors

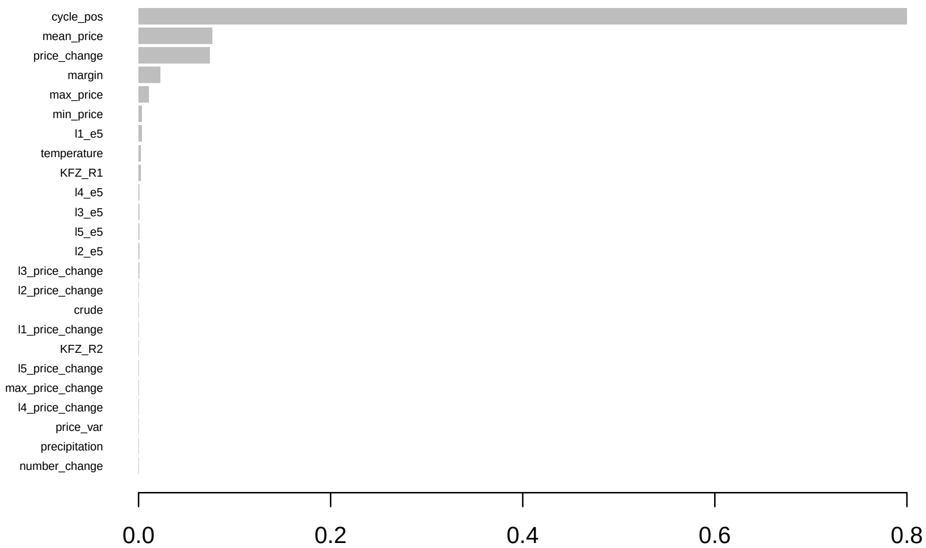
Price Factors
5 Lags of the price for E5 Daily maximum price Daily minimum price Daily mean price Price change and 5 lags Daily number of price changes Cycle position (= actual price - mean price of the day) Number of price increases by day Variance of the price Daily price spread (difference between maximum and minimum price)
Cost Factors
Daily margin (= daily mean price - Brent price) Brent price
Demand Factors
Hourly traffic data Amount of precipitation Temperature

illustrated using the Importance Matrix (see figure 2). The score on the x-axis indicates how useful each feature was in the construction of the boosted decision trees within the model.

The most important input features are the current position in the cycle, the daily mean price and the price change. The daily mean price together with the maximum and minimum price seem to play an important role to predict the price level on average. Price changes, the cycle position and the margin seem to play a role in predicting the shape of the cycle.

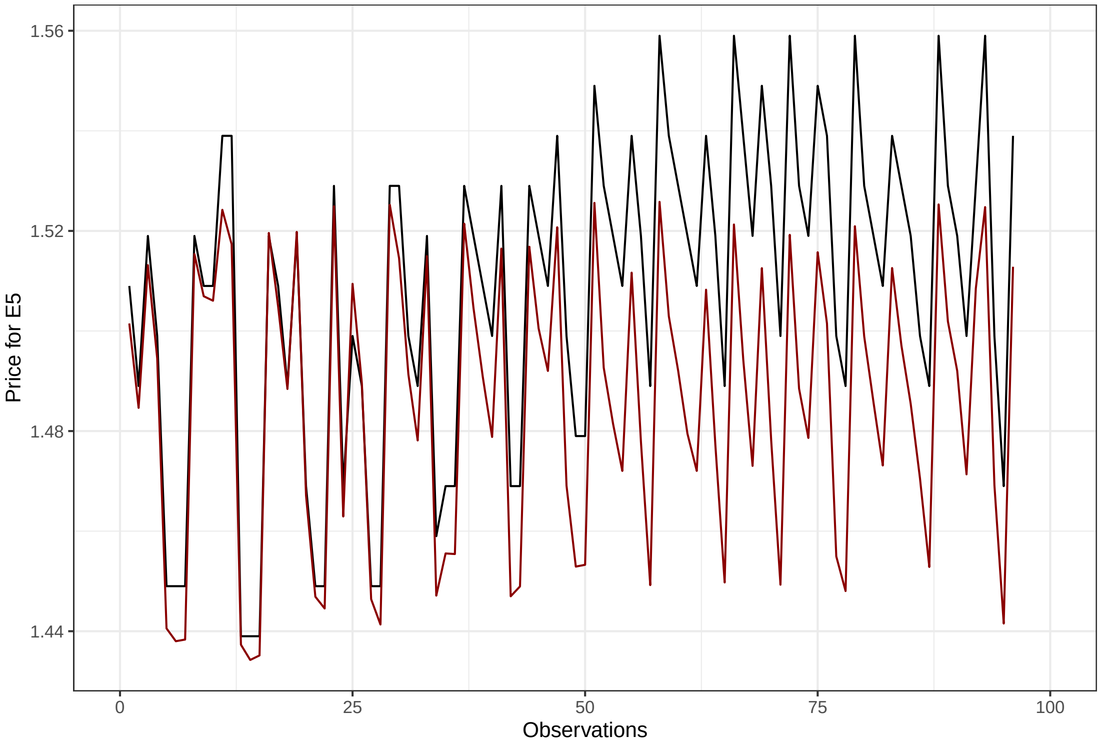
Figure 3 now shows the first anomaly detected by the model. Again, the black line is the actual price and the red line are the predicted values. The model is no longer able to predict the exact price level. Moreover, the shape of the cycles is also not depicted as accurate as before. Besides the graphical illustration, also the

Figure 2: Importance Matrix – 2015



accuracy of the forecasts can be calculated. The RMSE for the accuracy of the used model increases from 0.0056 to 0.026 in this case.[8] So the algorithm detects an anomaly in the data-generating process at the end of June 2015.

Figure 3: Prediction – July 2015



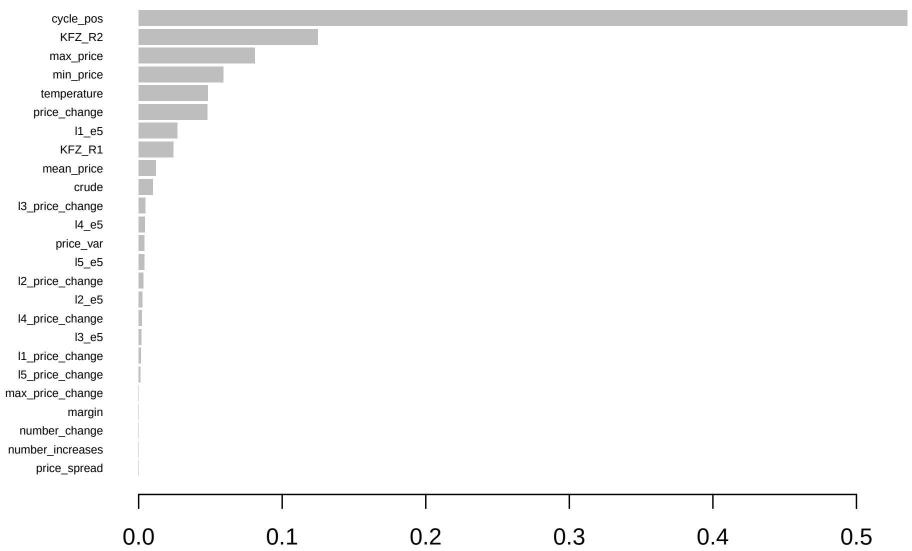
After running the XGBoost model with the new (real) data for this time period, to train a new model, the new importance matrix looks as follows (see figure 4). The cycle position is still important as well as the daily maximum, minimum and mean price. However, the demand factors (*KFZ_R1* and *KFZ_R2*) gain in importance.[9] Moreover, the price for Brent (*crude*) is listed higher in the importance matrix. Overall, significantly more factors play a role in the prediction than

[8] As the graphical representation is much clearer and illustrative, the accuracy of the prediction is shown graphically throughout this paper.

[9] The counting stations for the hourly traffic record both directions of the road traffic which is why two traffic variables are reported in the importance matrix: *KFZ_R1* and *KFZ_R2*.

before.

Figure 4: New Importance Matrix – 2015



In order to be able to assess where this anomaly comes from, whether it is caused by a change in the input factors, a changed pricing strategy or whether there is collusive behavior behind it, the conspicuous factors are now examined in more detail. These are the factors that changed their position in the importance matrix. At first the cost factor – the price for Brent – is considered. This price decreases (relatively abrupt) in July 2015. The price level of E5, however, increases. This is why the predicted level do not coincide with the real values (see figure 3). Next, the traffic intensity is also slightly higher in July than before. However, the shape of the traffic intensity throughout a day stays the same as before.[10] So this cannot

[10]The traffic intensity has as well some daily repeated cyclical shape, with peaks during rush

explain the changed shape of the price cycles with a newly implemented price increase around 12 pm.

Looking deeper into the price setting behavior for this time period, the number of price increases per day show a relevant change which is the reason for the detected anomaly. It seems to be that the filling stations had a transition phase where they had either two or three price increases per day. After some time, they settled on two price increases (see figure A1 in the appendix).

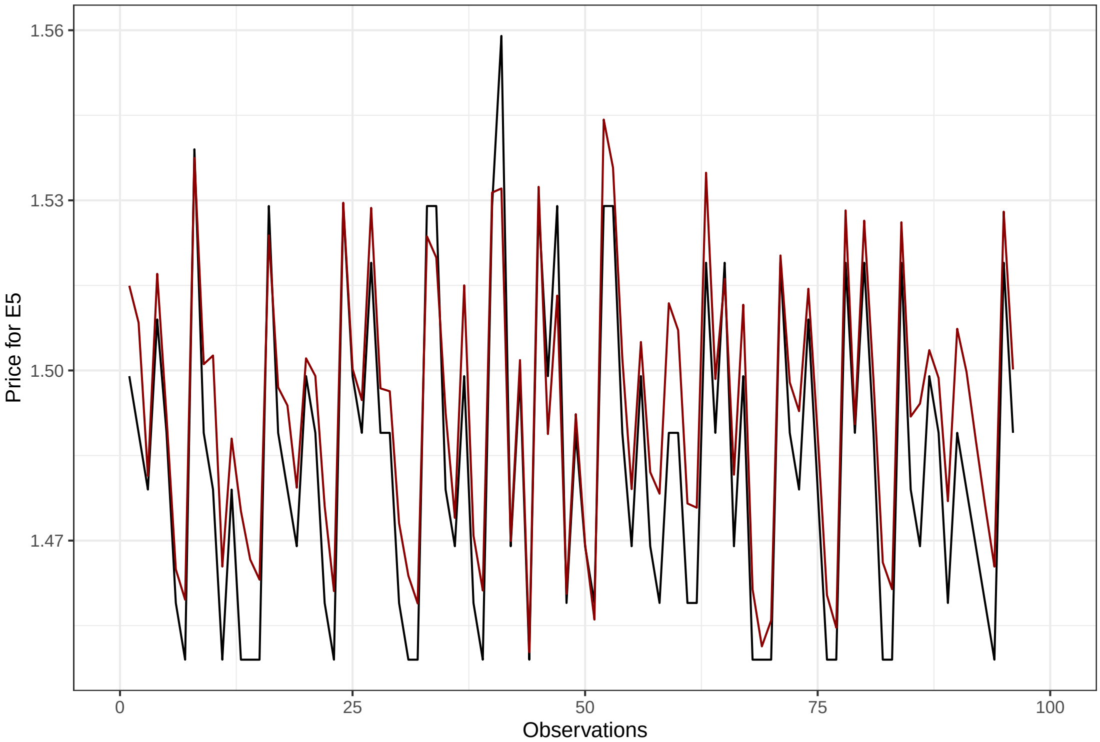
It could be that the filling stations changed their price setting to better react to fluctuating demand. As there seems to be some transition phase until they settled to have two price increases per day, this could be an indication for some tacit agreement between the firms. Or they tested some rules for their price settings in order to check which one gives the highest profit. Such temporal price increases, that are always at the same time of a day could be an indication for a strategy of price discrimination, where filling stations for example exploit inelastic demand (e.g. consumers that fill up their car always on their way to work and do not react to price changes). This would also explain the higher listing of the demand factors in the importance matrix. Without further information it is difficult to state whether the filling stations simply react to their competitors or whether they collude to act uniform. However, this screen provides a reference point for further investigations.

After learning this new model, the XGBoost algorithm is able to predict the changed price cycles, shown in figure 5.

In order to confirm the power of this model, another anomaly example is illustrated. Until April 2017 the cycles remain more or less unchanged and the above

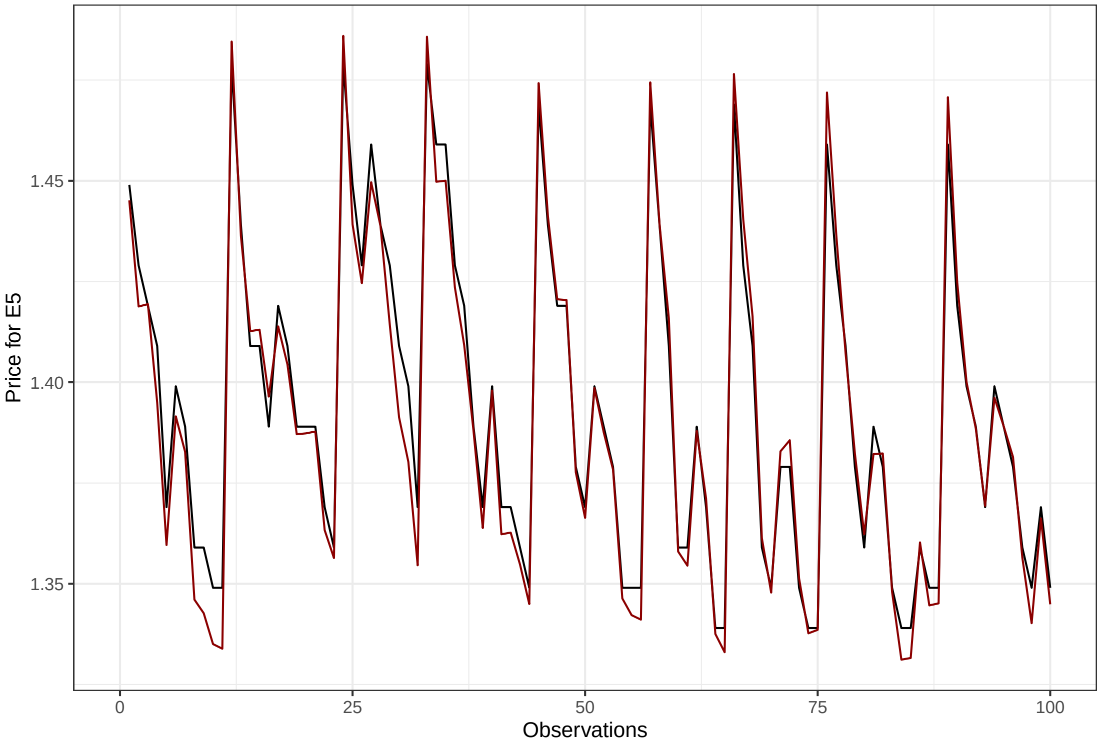
hours.

Figure 5: New Prediction – July 2015



presented XGBoost model is able to predict the price cycles throughout this period (see figure 6).

Figure 6: Prediction – 2017



In May 2017, however, the model detects an anomaly and can no longer predict the price cycles accurately, which is illustrated in figure 7.

As before, a new model is trained with the changed price setting behavior. The importance matrix given this new model is depicted in figure 8. It seems somewhat surprising that significantly fewer input factors play a role in the prediction of the price cycles, although the price cycles are more pronounced and have more price increases than before. However, this new trained model is confirmed by the prediction results it delivered, which is illustrated in figure 9.

According to the importance matrix, the price factors cycle position and mean

Figure 7: Prediction after Change – 2017

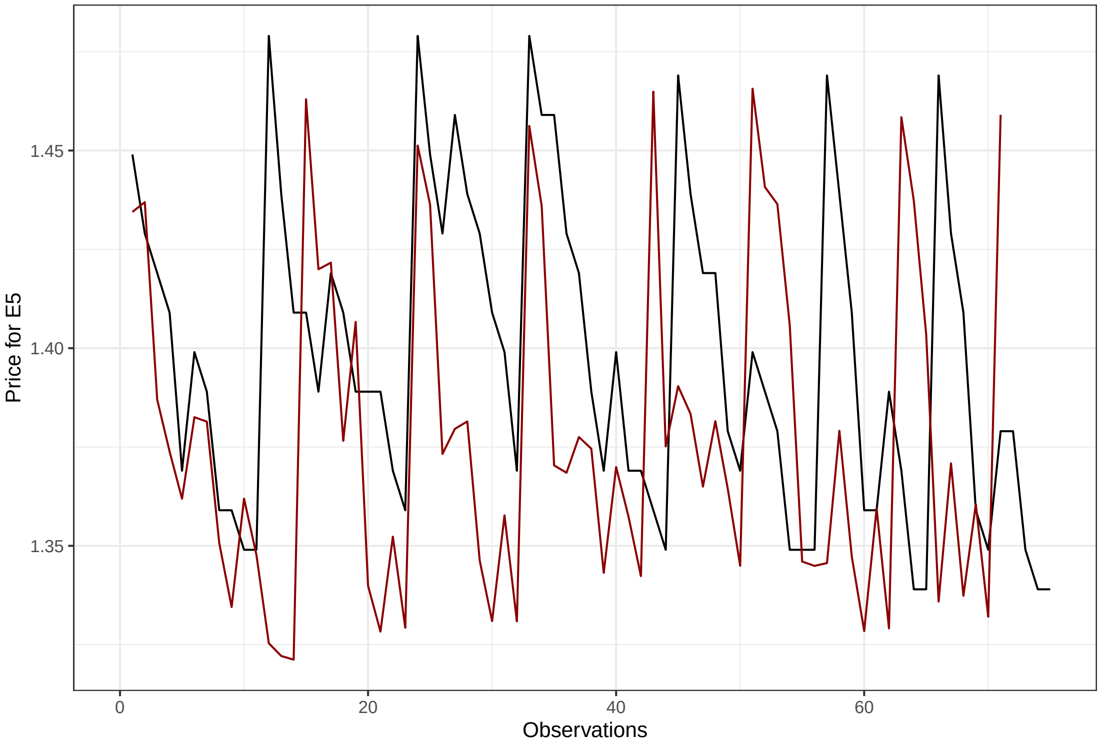


Figure 8: Importance Matrix 2017

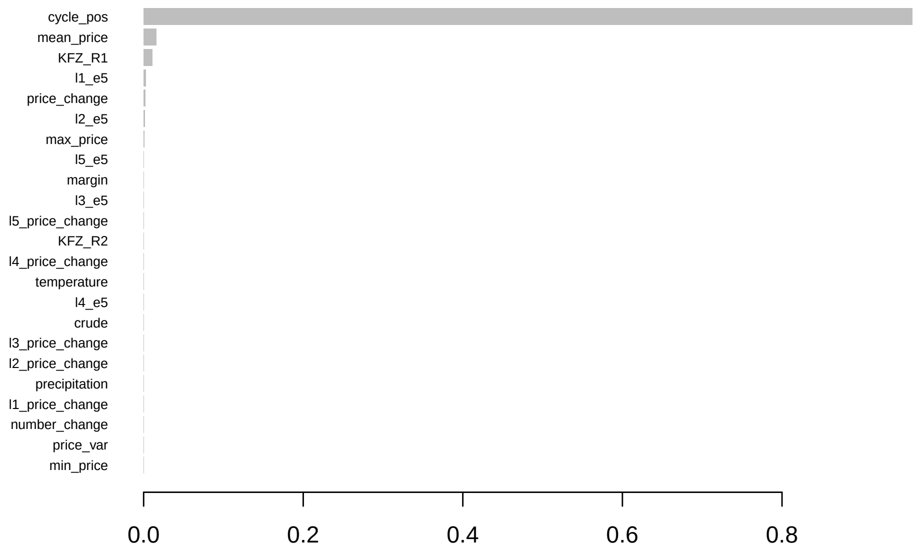
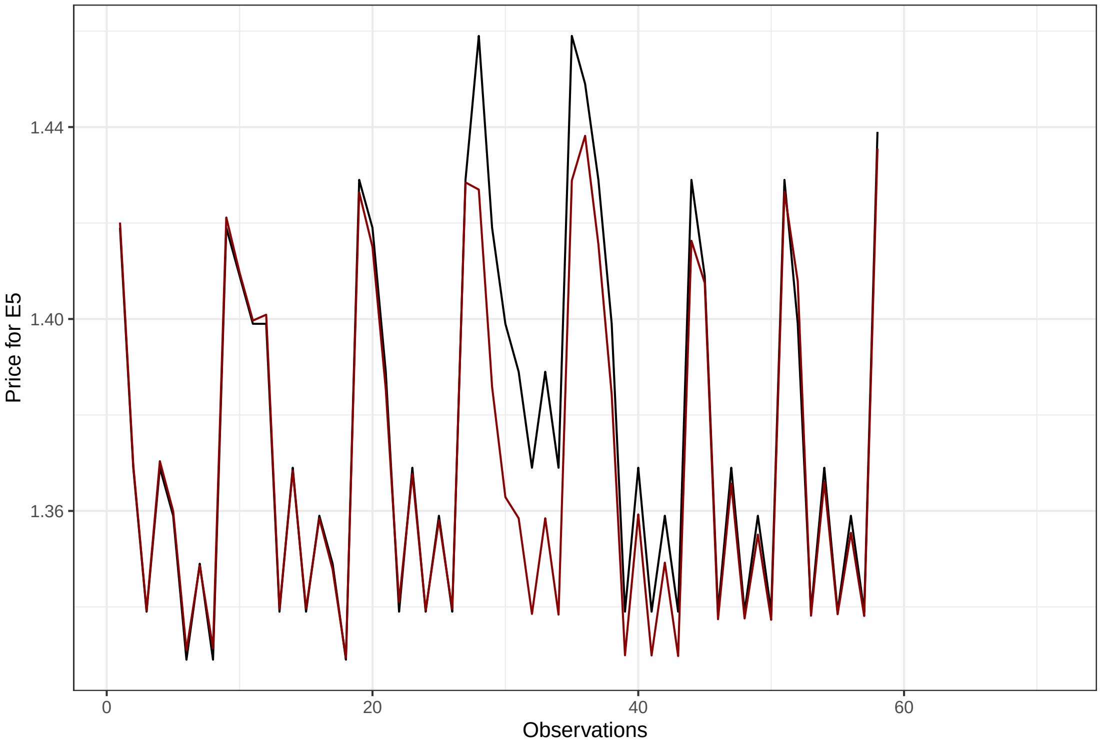


Figure 9: New Prediction 2017

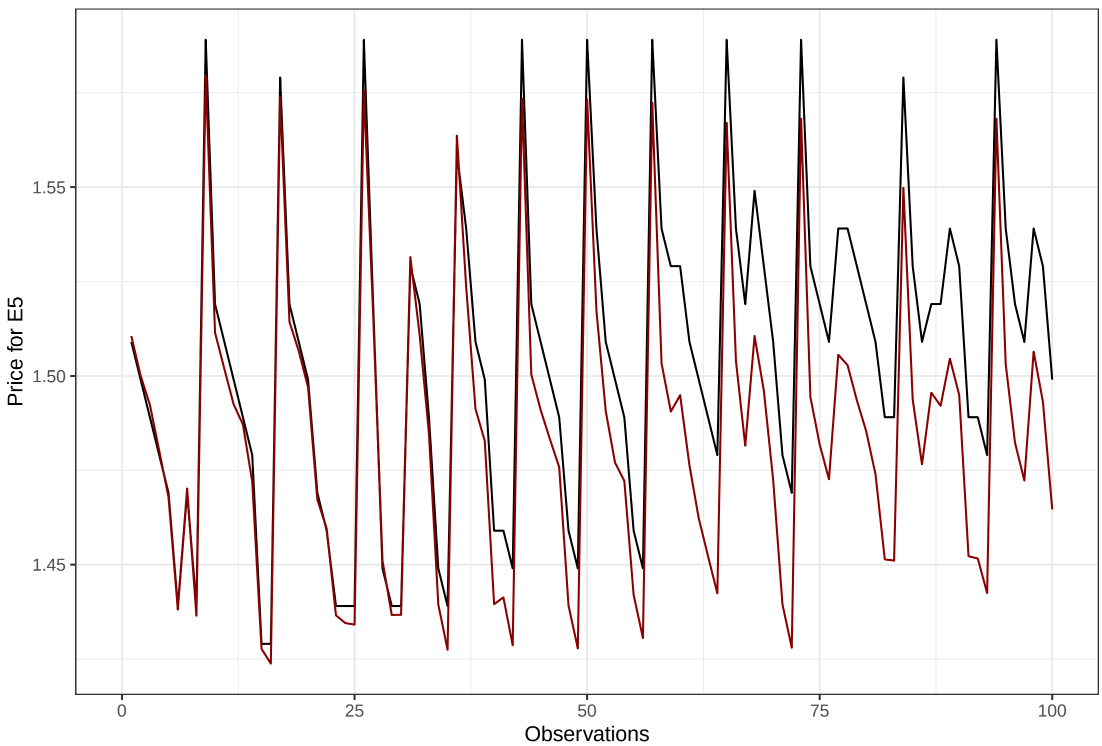


price remain important. When taking a closer look at these variables, a significant change can be detected. The cycle position is much less pronounced than before due to a significant lower overall price spread. Looking at the other input features, again a change in the number of price increases per day can be detected. It is a similar behavior as in the example above. Now the number of price increases jump from two increases on one day to three in a similar way as before. In addition to these price factors, however, demand also remains an important input factor.

In addition to these changes in the given input factors, there could also be disruptions in factors that are not yet included in the model. From spring or summer 2017, filling stations increasingly make use of algorithmic pricing software. Assad et al. (2020) investigate the implementation of algorithmic pricing on competition and detect as well the structural breaks mid-2017. Providers of these algorithmic pricing software (for example Kalibrate, or a2i) emphasize the ability of their algorithms to incorporate market conditions, own and competitor prices, sales volumes, costs, and weather and traffic data into their decision-making. These are as well the factors that were used for predicition of the price cycles in the XGBoost model. The XGBoost model clearly detects a change in the price setting behavior, eventually triggered by the change from rule-based pricing to algorithmic pricing. This assumption is supported by the development of the cycles in the following months. The cycles get flatter and at the same time the number of price changes per day increases significantly. One possible reason for this could be that the use of software enables even faster price reactions to competitors. The cycles differ greatly from the pricing behavior before the (probable) introduction of such pricing algorithms.

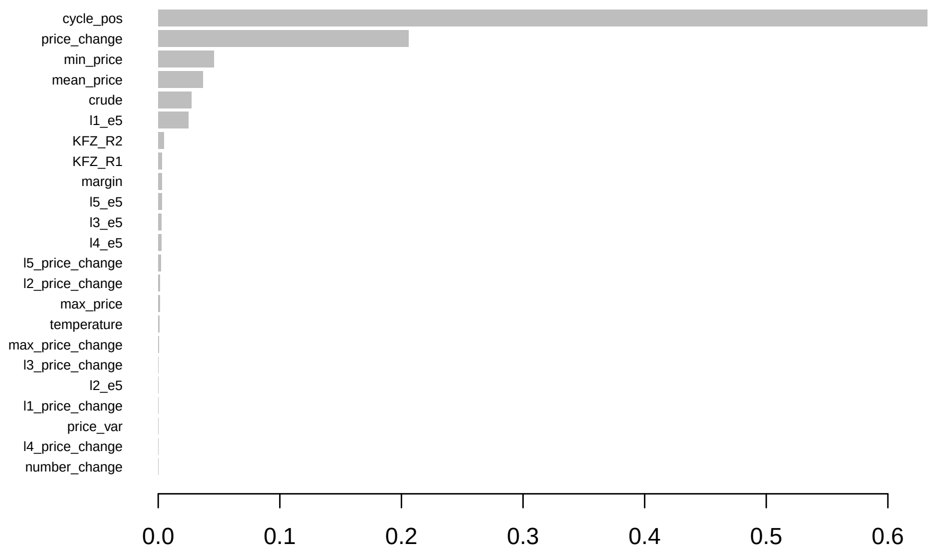
The results shown so far are based on the pricing behavior of an Aral filling station in the city of Stuttgart. The analysis was also carried out with other branded filling stations located in the vicinity of this Aral filling station. These analyses are not shown here as the results are the same. The branded filling stations show uniform behavior. Now these results are compared with the nearest independent station (so called „Freie Tankstelle“) in order to better understand the competitive situation. Figure 10 shows the prediction of the XGBoost model for the time where the first anomaly in 2015 was detected for the Aral station above. The black line shows again the real price and the red line the predicted values.

Figure 10: Prediction for the „Freie Tankstelle“– 2015



The XGBoost model as well detects an anomaly in the price series. However, this anomaly is detected two weeks later for the independent station compared to the competing Aral station. This could be a first indication that the independent filling stations are merely reacting to the branded filling stations, as the branded filling stations dominate the market, at least in terms of size. In order to examine the pricing behavior of independent filling stations in more detail, the importance matrix of the independent station is shown (after the change in the cycles) in figure 11.

Figure 11: Importance Matrix 2015 – „Freie Tankstelle“



Compared to the importance matrix for the Aral station in figure 4, the demand factors play a minor role for the independent station. This could be an indication that the independent filling stations do not pursue such a sophisticated pricing strategy or pricing rules as the branded filling stations, but rather react to them. The branded stations would therefore be the so-called leaders in the market, who first determine their pricing strategy, which is then adopted by the followers (the independent filling stations).

This leader-follower relationship is supported by another factor. As part of the change in the cycles, it was observed for the Aral filling station, that the number of price increases per day went through a transition phase until they leveled off at one price increase per day (see figure A1). This picture can also be seen at other branded filling stations. However, this behavior cannot be observed at independent filling stations. These stations have no transition phase but jump to a price increase at lunchtime, some time after this was implemented by the branded filling stations.

The analysis above was also conducted in other regions (urban and rural areas). The results are confirmed, which is why no further illustrations are shown in order to avoid repetition. At this point, however, important similarities and differences should be emphasized: The comaprison with other regions shows that the behavior of the branded stations and the independent stations as well as their relationship can be observed throughout Germany and is not unique to the example illustrated above. In all regions the branded stations are the first that introduce a change in the cycles and the independent stations follow this change with some delay. Moreover, the importance matrices show that the same factors are relevant for the predictions. However, the time of the anomalies differ. Whereas in Stuttgart the cycles change, for example, in June 2015, in Bonn the midday price increase was first introduced in August 2015. In 2017 the change in the cycles is detected almost at the same time, which would support the assumption of the use of software for the pricing strategy at least in the case of the branded stations.

The strategy of a price leader is not new for gasoline markets. Byrne and Roos (2019) show in a descriptive analysis how the firms in the Australian gasoline market learn to coordinate without any explicit communication. The Australian market as well has a price transparency program called *Fuelwatch*. Gasoline retailers have to submit their next day's station-level prices to the government and have to commit to these prices for 24 hours. The government posts today's prices online for every gasoline station. This implicates that retailers set their prices simultaneously and they can perfectly monitor each other's prices, like the firms in the German gasoline market. The gasoline prices as well exhibit asymmetric price cycles with price jumps and an undercutting phase. In contrast to the German market these cycles last several days.[11] In this market BP (the dominant firm) establishes itself as a price leader by April 2009. Before April 2009, the price jumps were dispersed throughout the week and last 7 to 35 days. After BP uses price leadership to create focal points that coordinate market prices, the cycles always start on Thursdays with a price jump and have a length of 7 days. BP as the leader increases its price always on Wednesday which is a signal to the rivals. In periods where BP does not engage in Wednesday-jumps, the rivals fail to coordinate on Thurday jumps. After 3 years, firms were able to coordinate on Thursday-jumps without a price leader. With this strategy the firms were able to limit price undercutting between jumps and raise margins overall.

As shown above, also in the German retail gasoline market the dominant branded firms, like Aral, act as price leaders. They initiate the changes in the cycles and are the first that introduce, for example, the midday price increase. Like in the Australian market, there is a transition phase, where the price leaders engage in price increases until the other firms follow. In the German market it is the phase where the branded firms test out different numbers of price increases (see

[11] This is partly due to the legal requirement that a price must be valid for 24 hours.

figure A1). After this transition phase, the firms in the market settled on the new „equilibrium“ and the price setting stays stable for some time.

4 Conclusion

The paper showed that the XGBoost model is able to detect various anomalies in the price series. Moreover, with a deeper investigation of the input features and the market characteristics, it was possible to identify the reasons for these anomalies. The results show that the filling stations pursue a price discrimination strategy that is enforced on the market with the help of a leader-follower relationship.

The model can also be extended if additional information is available. When companies use such a screening tool for their suppliers, they usually have a fixed number of suppliers. In this case, the competitors' prices or the price gap to the competitors' prices can also be included in the XGBoost model as an input factor.[12]

As there is no need to set up a specific model of the market or the price setting for this screen, this method can also be applied relatively easily to other markets or industries. Of course, knowledge of the market is needed to identify the right input factors, but then the screen can be applied easily and at low cost.

[12] This was also tested in the example presented in this paper. In addition to the price differences to neighboring filling stations, the reaction time to price changes was included. However, according to the model, these did not play a role and the results remain unchanged.

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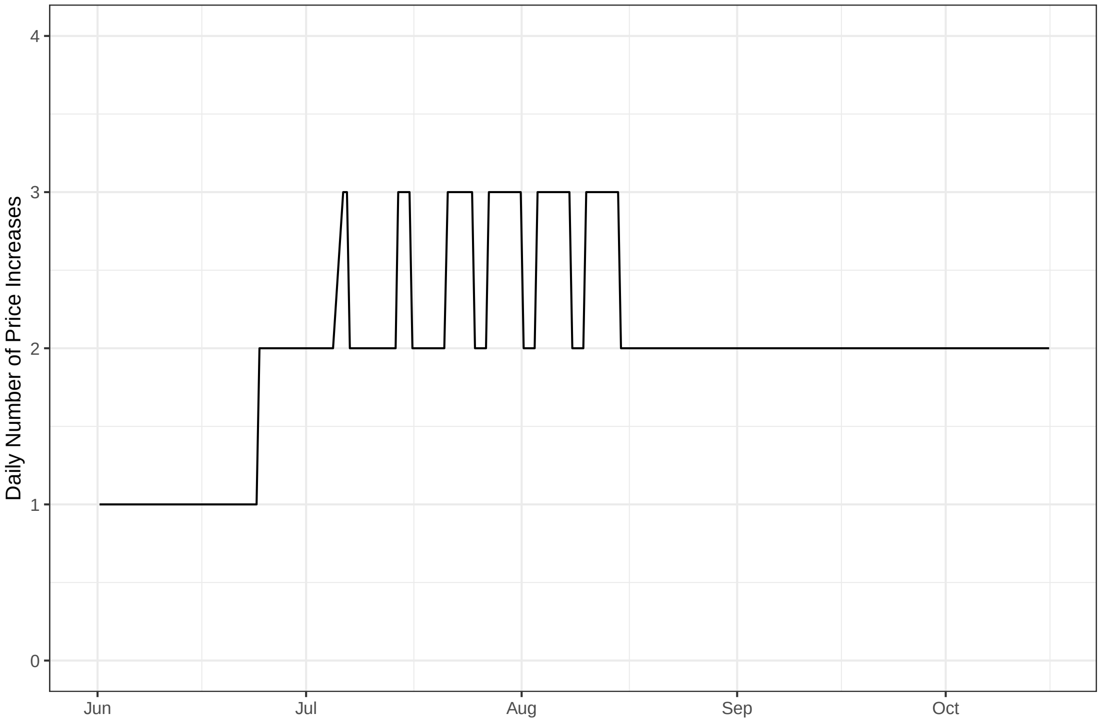
Appendix

Table A1: Input Factors – Complete List

Price Factors
5 Lags of the price for E5
Daily maximum price
Daily minimum price
Daily mean price
Price change and 5 lags
Maximum price change by day
Minimum price change by day
Mean price change by day
Median of price changes by day
Time of the maximum price change by day
Time of the minimum price change by day
Daily number of price changes
Daily number of price decreases
Daily number of price increases
Time of price increases
Cycle position (= actual price - mean price of the day)
Price spread (= maximum price of the day - minimum price of the day)
Standard deviation by day
Skewness
Kurtosis
Variance of the Price
Daily price spread (difference between maximum and minimum price)
Cost Factors
Daily margin (= daily mean price - Brent price)
Brent price
Weekly average Brent price
Monthly average Brent price
Demand Factors
Hourly traffic data
Amount of precipitation
Temperature

Figure A1: Number of Price Increases 2015



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University of Hohenheim
Dean’s Office of the Faculty of Business, Economics and Social Sciences
Palace Hohenheim 1 B
70593 Stuttgart | Germany
Fon +49 (0)711 459 22488
Fax +49 (0)711 459 22785
wiso@uni-hohenheim.de
wiso.uni-hohenheim.de