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Regulation of retail gasoline prices

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ABSTRACT

Three regulatory frameworks, (i) price changes are allowed only once per day; (ii) increases are allowed once a day at a specific time, but decreases are allowed at any time; and (iii) a maximum markup is allowed, are compared in a lab experiment to an unregulated benchmark market without any regulation. We examine them in a simple spatial model with elastic demand. The results reveal that the three price regulation systems differ significantly regarding their impact on gas station profits and consumer welfare. Allowing price changes only once per day seems favorable, while restricting price increases leads to higher prices.

1. Introduction

From a theoretical point of view, government intervention in gasoline markets may be well supported because these markets show some characteristics that might entail market inefficiencies. These include the markets' combination of an oligopolistic structure, short-term inelastic aggregate demand, frequent trades, transparent prices, and relatively high search costs for consumers, which may trigger collusive behavior. Even if there is no illegal cartel in place, tacit collusion may still be present, reducing consumer welfare because the number of "big players" in the market is usually between only three and five. Therefore, the primary economic goal of regulators is often to restrict market prices in such a way that tacit collusion becomes harder to establish, prices become more competitive, volatility is decreased, and consumer welfare increases.

In general, regulators use two different approaches to protect consumer welfare: Either they influence the first moment of the distribution of retail gasoline prices by imposing a regulation on the price itself, or they implement a regulatory framework targeting the second moment and restrict the variance of prices through price-setting rules. In 2011, the Austrian government implemented a pricing rule permitting increases in retail gasoline prices only once a day at noon while allowing price cuts at any time; we will call this regulatory setup "decrease-only after fixing" (DAF). Since May 10th, 2013, a bill that proposed a regulation similar to the DAF rule has been under review by the Committee on Economic Development in the state of New York (Bill No.: A07285). Western Australia introduced measures in which companies are obliged a day ahead of time to set constant fuel prices for the entire following day, a scheme we call the "one day fixing" (ODF) rule. Both regulations are aimed at lowering the frequency of price changes while still providing considerable room for competition. Similarly, Luxembourg (along with several Canadian states) uses a maximum

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markup for retail prices on wholesale prices (the CAP rule).

We use lab experiments to investigate all three regulation systems currently in place and evaluate them in comparison to a "benchmark" market that is free of any regulation. This experimental approach appears highly suitable because it allows us to control for external country- or region-specific factors as well as for any form of illegal collusion. Thus, we can investigate consequences of applied regulations independent of the country or region where they are in force, which is a natural drawback of empirical investigations on this topic.

Our results shed new light on the dynamics of retail gasoline markets. In our experiment, no illegal cartels exist because no communication other than market prices is possible. We assume rather inelastic[1] albeit not constant aggregate demand, as we believe that inelastic demand is observable in real markets, at least in the short term, and that constant demand can be implemented without loss of generality since sellers try to maximize profits regardless of demand. We also do not differentiate between different types of gasoline stations such as discounters offering only gas with no service or large stations with attached shops. The overall setting is chosen for the sake of simplicity and to keep the experiment understandable, thus allowing us to discern the strategic behavior of participants.

2. Hypotheses

2.1. Overall profits

In line with Obradovits (2014) and Berninghaus et al. (2012), we expect that the DAF regulation increases profits. Both studies find that the DAF regulation increases prices and decreases price volatility. Regarding the CAP regulation, Engelmann and Mueller (2011) and Engelmann and Normann (2009) find in their experiments that a price ceiling has no anchoring effect on prices, although behavioral theory would expect so. Haucap and Mueller (2012) find in their experimental study no differences in the results of the ODF regulation compared to their baseline. However, we argue that we expect the levels of profits to be lower under the ODF rule. While we find no arguments for an increase in profits, it seems plausible that fixing a price for a long period of time forces retailers to set more competitive prices, as they are not allowed to lower their price for some time if they set it too high initially.

We formulate:

Hypothesis Ia\b\c : The overall level of profits is higher (T_{DAF}) than\equal (T_{CAP}) to\lower (T_{ODF}) than the benchmark treatment T_{BM}.

2.2. Intraday trading behavior

Naturally, we can observe intraday trading behavior only in markets in which intraday changes are possible, so we omit T_{ODF} in this part of the analysis. As the DAF regulation directly reduces strategic options during the period by allowing only downward price changes, we expect to see different pricing behavior than in T_{BM}. Thinking through available strategies, it seems favorable to start with a relatively high price to keep the strategic space wide. Lowering the price is always possible so there seems more danger in starting too low compared to starting too high. The CAP regulation also potentially reduces strategic options with a price ceiling. Therefore we formulate:

Hypothesis IIa\b: Intraday behavior in the DAF treatment T_{DAF}\T_{CAP} differs compared to the benchmark treatment T_{BM}.

Regarding intraday volatility, we expect to find higher levels in T_{DAF} because of the expected higher starting prices and an eventual decline. Regarding T_{CAP}, we do not expect higher volatility. If there truly is an anchoring effect, it should pull up all profits by about the same magnitude, thereby leaving volatility at about the same level as in T_{BM}. We therefore formulate our last hypothesis:

Hypothesis IIIa\b: Intraday price volatility is higher (T_{DAF})\equal (T_{CAP}) compared to the benchmark treatment T_{BM}.

3. Experimental design

3.1. Implementation of the experiments

We conduct four main treatments: a benchmark treatment with no regulations (T_{BM} and three extra treatments for each regulation approach, each consisting of six markets.[2] In each of the conducted markets, five subjects sell good A, which is not further described, for a self-defined price and try to maximize their profit. We cautiously avoided any hints or references to gasoline markets to reduce potential recognition and framing effects. A market is divided into 15 trading days,[3] each consisting of 24 trading hours. One trading hour is represented by five seconds in the experiment, with each trading day consisting of 120 s. At the beginning of each day, subjects see a screen[4] where they have to enter their initial retail selling price for the upcoming day. Additional information is provided by the wholesale costs of good A on the specific day and their closing retail price on the last day. We use a spatial model to

[1] In contrast to Haucap and Mueller (2012).

[2] For a detailed description of the implementation, please refer to Appendix A.

[3] The exact number of trading days was not known in advance by the participants to avoid end-of-experiment effects.

[4] See Screen 1 in the instructions attached in Appendix B.

determine the demand for goods by customers from each gas station.[5]

During each trading day, participants can decrease or increase their selling price at any time.[6] As in actual retail gasoline markets, each participant can see the current prices of the other players in real time on the trading screen but not the volume sold by competitors. The participant's own history of prices and corresponding volume sold at any trading hour is visible. A retailer's profit per trading hour is calculated by multiplying the markup (difference between the retail price and wholesale price) with the volume of goods sold. After 24 trading hours, the trading day is over, and the next trading day immediately starts with the first screen.

3.2. The implementation of regulations

We implement the DAF regulation into T_{DAF} by using the base of the abovementioned market but allowing subjects to increase their prices only at the beginning of the trading day. During the 24 h of a trading day, participants can only keep their initial price constant or decrease it. To introduce the CAP regulation (in T_{CAP}), we implement an upper boundary for the markup at 25 percent of the wholesale price.[7] Naturally, the best way to avoid intraday price movements is to require retailers to keep prices constant. Therefore, T_{ODF} is reduced to the start screen, at which participants are asked for the price at which they will offer good A for the whole trading day. After price-setting by the subjects, the respective market share is determined on a basis of 24,000 units of good A, thus leaving the total one-day demand for good A unaffected. Afterwards the next day starts.

4. Results

4.1. Hypothesis I: overall profits

Trading profits provide a direct measure of producer surpluses and therefore allow for the quantification of differences in market efficiency. Fig. 1 provides a first intuition of the experimental results, depicting the equally weighted mean profits per period for each individual market structure. Most noticeably, the profit in T_{ODF} seems to be consistently lowest. We find profits in T_{BM} and T_{CAP} to be rather similar, while the DAF regulation proves inefficient, with profits nearly twice as large as under the former two models.

A statistical investigation of the differences in the regulatory frameworks is provided by a linear regression approach. Here, each investigated model (DAF, CAP and ODF) is separately pooled with and compared to T_{BM} with an interaction dummy variable as formulated in Eq. (1). The dependent variable Profit_{ip}^{tm} is the profit of subject i in period p. To quantify the average difference between the treatments, we employ a bivariate dummy variable D_Market^{tm} that equals 0 for the BM setting and 1 otherwise. A second regression, formulated in Eq. (2), captures changing behavior over the 15 periods by including a trend variable Trend_P_p^{tm} that represents a sequence of 1, 2, 3,..., 15 and an interaction term $\text{Trend\_P}_p^{tm} \times \text{D\_Market}^{tm}$. The results are presented in Table 1.

$$\text{Profit}_{ip}^{tm} = \gamma_0 + \gamma_1 \text{D\_Market}^{tm} \tag{1}$$

$$\text{Profit}_{ip}^{tm} = \gamma_0 + \gamma_1 \text{D\_Market}^{tm} + \gamma_2 \text{Trend\_P}_p^{tm} + \gamma_3 \text{Trend\_P}_p^{tm} \times \text{D\_Market}^{tm} \tag{2}$$

Our results reveal that the DAF market model increases profits and therefore market inefficiency, while the ODF market model reduces profits, implying a more efficient market structure. These differences are also significant from an economic point of view, as profits in the T_{DAF} (T_{ODF}) market are on average increased (decreased) by roughly 79% (54%). The CAP regulatory framework has no statistically relevant influence on average profits. We find no or only very weakly significant evidence that period trends might play a role. Hence, we can confirm all parts of Hypothesis I.

4.2. Hypotheses II & III: intraday analysis

All regulatory approaches except for T_{ODF} allow subjects to adjust their prices within a trading period (i.e., a trading day). Therefore, our next analysis focuses on differences in the intraday price adjustments in T_{BM}, T_{DAF} and T_{CAP}. This allows for an analysis of coordination behavior in an oligopoly market price setting and its impact on consumer welfare. For each trading hour h=1, 2,..., 24 within each period p=1, 2,..., 15, we compute the volume weighted market price as displayed in Eq. (3). P_{iph}^{tm} is the price set by subject i in hour h of period p, and w_{iph}^{tm} is the respective market share of individual i.

$$\text{P}_{ph}^{tm} = \sum_{i=1}^{5} \text{w}_{iph}^{tm} \cdot \text{P}_{iph}^{tm} \tag{3}$$

Next, the relative markup (RMU) of the market price from the purchase price in percent is computed as outlined in Eq. (4). Here, we aim at measuring the efficiency of the market. The higher RMU_{ph}^{tm}, the better agents are able to exploit their market power at the

[5] See Appendix A for details of the model. Search costs and demand elasticity are important factors in retail pricing (Borenstein, 1991). See also Chandra and Tappata (2011), Yang and Ye (2008) and Lewis and Marvel (2011) for applications of consumer search models.

[6] See Screen 2 in the instructions attached in Appendix B.

[7] Setting this boundary is not an easy task because there is neither a published approach (reviewing, e.g., the legislation in Luxembourg) nor a theoretical approach we can follow. We therefore decided on a cap level that was not reached in pretested benchmark treatments, as we wanted to avoid unintentionally influencing prices by frequently hitting the ceiling. However, the cap is close enough to serve as a potential anchoring point.

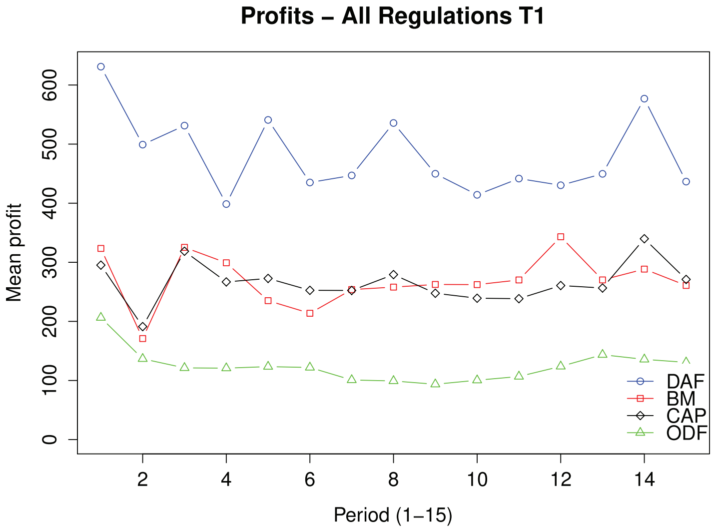

Fig. 1. The equally weighted mean profits per period for each individual regulation model under investigation.

Table 1
The estimation results of the regression model depicted in Eqs. (1) and (2), where D_Market^{tm} is a dummy variable that equals 0 for T_{BM} and 1 for either T_{DAF}, T_{CAP} or T_{ODF}. $Trend\_P_p^{tm}$ represents a sequence of 1, 2, 3,..., 15. Standard errors are given in parentheses.

	T_{DAF}		T_{CAP}		T_{ODF}	
	Mean	Trend	Mean	Trend	Mean	Trend
Intercept	269.129***	258.318***	269.129***	258.318***	269.129***	258.318***
	(10.233)	(21.492)	(5.822)	(12.255)	(4.825)	(10.142)
D_Market^{tm}	212.075***	266.087***	−3.651	−0.077	−144.783***	−119.334***
	(14.471)	(30.394)	(8.233)	(17.331)	(6.824)	(14.343)
$Trend\_P_p^{tm}$		1.351		1.351		1.351
		(2.364)		(1.348)		(1.115)
$Trend\_P_p^{tm} \times D\_Market^{tm}$		−6.752*		−0.447		−3.181*
		(3.343)		(1.906)		(1.578)
R^2	0.193	0.198	0.000	0.002	0.334	0.337
Adj_R^2	0.192	0.195	−0.001	0.002	0.333	0.335
Num_obs	900	900	900	900	900	900

***$p < .001$, **$p < .01$, *$p < .05$.

expense of consumer welfare, implying a less efficient market. WP_{ph} is the wholesale price at which the agents can purchase the product being offered, and P_{ph}^{tm} represents the volume-weighted market prices.

$$\text{Relative Markup}_{ph}^{tm} = \frac{P_{ph}^{tm} - WP_{ph}}{WP_{ph}} \cdot 100 \tag{4}$$

Fig. 2 provides a first graphical inspection of the average intraday development of the relative markups on wholesale prices. We find that at the end of a trading day markups are very similar for all regulations, a little below 7%. Descriptive statistics of the investigated market settings are depicted in Table 3. While T_{BM} and T_{CAP} arrive at this price via a very stable intraday pricing behavior, T_{DAF} shows initially high markups that decrease over the period, leading to more overall market inefficiency. The specific pattern is a result of the strategic restrictions for the retailers introduced by the DAF regulation. As retailers are only allowed to decrease prices during the trading day, they would limit their strategical pricing space if they set low prices from the start of the day. It is therefore rational to start with high prices, knowing decreases are always possible. As this is a rational approach for all retailers, most of them choose this strategy, and the market starts with high prices that only slowly reach the level of the treatments without these strategy limitations.[8]

The statistical difference among the three market setups is evaluated in analogy to the previous section by comparing T_{DAF} and T_{CAP} to T_{BM} and running linear regressions with the relative markup from the wholesale price (RMU_{ph}^{tm}) as the dependent variable.[9] As

[8] There were hardly any learning effects over time.
[9] We use clustered standard errors at the period level, as observations are not independent within a period.

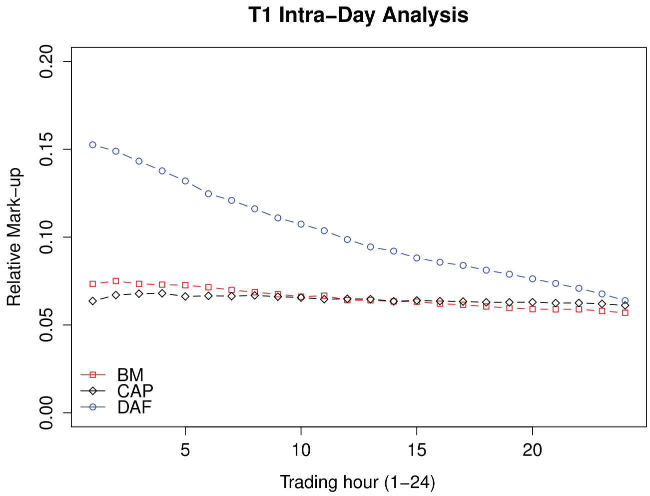

Fig. 2. The intraperiod development of the average relative markup of the volume weighted market price from the wholesale price. In a first step, we compute the volume-weighted market price and the relative markup. In a next step, the average relative markup is computed for each trading hour.

explanatory variables, we employ a combination of dummy variables and trend variables to quantify differences between the treatments. The two trend variables are $\mathrm{Trend\_P}_p^{tm}$ for periods and $\mathrm{Trend\_H}_{ph}^{tm}$ for hours within a period. Moreover, we include a dummy variable $\mathrm{D\_\Delta WP}_p^{tm}$ equaling 1 if the change in the wholesale price is positive and 0 otherwise to measure asymmetry in responses to positive and negative price changes.[10] We also use a treatment dummy $\mathrm{D\_Market}^{tm}$ and build interaction terms. We formulate and present our results in Table 2:

$$\mathrm{RMU}_{ph}^{tm} = \gamma_0 + \gamma_1 \mathrm{D\_Market}^{tm} \tag{5}$$

$$\begin{aligned} \mathrm{RMU}_{ph}^{tm} = {} & \gamma_0 + \gamma_1 \mathrm{D\_Market}^{tm} + \gamma_2 \mathrm{D\_\Delta WP}_p^{tm} + \gamma_3 \mathrm{Trend\_P}_p^{tm} + \gamma_4 \mathrm{Trend\_H}_{ph}^{tm} \\ & + \gamma_5 \mathrm{D\_\Delta WP}_p^{tm} \times \mathrm{D\_Market}^{tm} + \gamma_6 \mathrm{Trend\_P}_p^{tm} \times \mathrm{D\_Market}^{tm} \\ & + \gamma_7 \mathrm{Trend\_H}_{ph}^{tm} \times \mathrm{D\_Market}^{tm} \end{aligned} \tag{6}$$

Looking first at T_{DAF}, the most striking findings are the coefficients of the market dummy ($\mathrm{D\_Market}^{tm}$), which indicates that the intraday price deviation in T_{DAF} starts at a higher level. This suggests that agents are well aware of the limitations the regulatory framework sets on their usable strategies. They consequently try to charge significantly higher prices at the beginning of the trading day. While the price deviation in the BM market slightly decreases over the trading day (γ_4), we find a highly pronounced negative trend for T_{DAF} ($\gamma_4 + \gamma_7$), as the high initial prices are corrected over the time span of a day. T_{DAF} also has a small negative trend in price deviations throughout the experiment. From Table 3, we also know that volatility is higher in T_{DAF}. As T_{DAF} clearly shows different behavior of participants, we confirm Hypothesis IIa.

Regarding T_{CAP}, we observe no difference from T_{BM} except for a less pronounced intraday trend in T_{CAP}. This observation is surprising: Theory would predict that the setting of an anchor point should lead prices to gravitate towards it. We therefore reject Hypothesis IIb.

In all tested frameworks (T_{BM}, T_{DAF}, T_{CAP}), we observe that wholesale price changes do not influence profits. In other words, retailers in our experiments do not charge relatively higher (lower) markups when wholesale prices fell (increased) from the last period.[11]

Regulators prefer a low intraday volatility of prices (c.p.) because it reduces search costs of consumers and does not discriminate against customers who are only able to buy at certain times of day. Table 3 reports the mean markups and standard deviation as a measure of price volatility. We find volatility to be lowest in T_{CAP} and a little higher in T_{BM}, while in T_{DAF}, it is more than four times higher. We can therefore confirm Hypothesis IIIa but must reject Hypothesis IIIb.

5. Discussion and concluding remarks

We experimentally test three currently used regulation systems for retail gasoline pricing in the lab with a spatial model. Our approach allows us to reevaluate the findings in existing empirical, theoretical and experimental studies. In contrast to other studies

[10] For an overview of the drivers of the rockets and feathers effect, see, e.g., Verlinda (2008), Lewis (2011) and Peltzman (2000).

[11] We refrain from analyzing this matter known as "rockets and feathers". Although the transmission of prices from the wholesale to the retail level is interesting and heavily researched, we believe it is not important for our target of an analysis of consumer welfare. Additionally, we do not find evidence for asymmetric price transmission.

Table 2
The estimation results of the two regression models depicted in Eqs. (6) and (6). D_Market^{tm} is a dummy variable that equals 0 for T_{BM} and 1 for either T_{DAF} or T_{CAP}. $D\_\Delta WP_{ph}^{tm}$ is a dummy variable equaling 1 if the change in the wholesale price is positive and 0 otherwise. $Trend\_P_{p}^{tm}$ represents the period trend and thus a sequence of 1, 2,..., 15, while $Trend\_H_{ph}^{tm}$ is the intraday trend and therefore a sequence of 1, 2,..., 24. Clustered standard errors at the period level are used and given in parentheses.

	T_{DAF}		T_{CAP}	
	Mean	Trend	Mean	Trend
Intercept	6.534***	8.185***	6.534***	8.185***
	(1.091)	(2.252)	(1.091)	(2.252)
D_Market^{tm}	3.688***	9.277***	−0.077	−0.659
	(0.357)	(0.579)	(0.150)	(0.395)
$D\_\Delta WP_{p}^{tm}$		−0.304		−0.304
		(2.216)		(2.216)
$Trend\_P_{p}^{tm}$		−0.064		−0.064
		(0.195)		(0.195)
$Trend\_H_{ph}^{tm}$		−0.080***		−0.080***
		(0.009)		(0.009)
$D\_\Delta WP_{p}^{tm} \times D\_Market^{tm}$		−1.046		−0.153
		(0.543)		(0.319)
$Trend\_P_{p}^{tm} \times D\_Market^{tm}$		−0.173**		−0.005
		(0.064)		(0.037)
$Trend\_H_{ph}^{tm} \times D\_Market^{tm}$		−0.297***		0.056***
		(0.027)		(0.009)
R^2	0.084	0.189	0.000	0.124
Adj_R^2	0.084	0.187	0.000	0.108
Num_obs	4320	4320	4320	4320

***$p < .001$, **$p < .01$, *$p < .05$.

Table 3
The mean relative markup and its average intraday volatility for each treatment. For the average standard deviation we first compute the per-period standard deviations and then compute the mean across all periods and markets in each treatment.

	T_{BM}	T_{DAF}	T_{CAP}
Mean markup	6.534	10.221	6.457
Mean of intraday S.D.	0.947	2.825	0.649

(e.g., Haucap and Mueller, 2012), our study allows multiple continuous price changes per day and implement search costs.

We find most hypotheses grounded in the literature to be confirmed except for the one regarding the CAP regulation, which does not show an anchoring effect. From a consumers point of view, the ODF regulation offers the largest increase in consumer welfare and a favorable interperiod price development. The CAP framework did equally well as the benchmark. This finding is good news for regulators: CAP frameworks are often used to eliminate price peaks with the drawback of anchoring effects, which we could not find here. The DAF regulation did far worse than the benchmark in all important factors. Compared to the benchmark, it produced more inefficient prices, had more intraday volatility, and systematically discriminated against customers who are not able to buy at the end of the day. Although the regulation might sound favorable to the general public ("only increase once but decrease throughout the day"), we deliver evidence that its implementation is not favorable.

Acknowledgments

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Appendix A. Implementation and experimental details

A1. Experimental implementation

The data for every treatment is drawn from six independent market repetitions with a new cohort of five participants for every market in every treatment. Therefore we have in total 120 participants within our study. Each session had a duration of about 90 minutes (60 min for ODF markets) and the average payment was around 21 (16 for ODF markets) euros. All treatments were programmed and conducted with zTree 3.3.12 (Fischbacher, 2007). The recruitment of the students was carried out using ORSEE (Greiner, 2004). Each subject is paid according to the profit individually accumulated during the whole experiment, divided by a constant conversion factor of 150 to calculate the final payment in euros.

A2. The demand for goods

The total maximum market demand for good A is 1000 units per trading hour. This demand only holds if selling prices are perfectly competitive. In this case the retail selling price equals the cost (the wholesale price) of the good, and profits are zero. However, the more prices deviate from the wholesale price, the lower the overall demand, with an elasticity of 0.5, so that a 1% increase in price decreases demand by 0.5%. The choice of a rather inelastic demand is because the demand for gasoline, at least from a short-term perspective, is also rather inelastic in the real world. The maximum total market demand of 1000 units of the good is represented by 50 potential customers on the market with a maximum demand of 20 units each. A customer takes search costs, driving costs to a retailer, and the selling price into account, buying at the retailer at the lowest total costs. Driving costs are between 0 and 0.09 monetary units (five customers with 0, five with 0.01, etc.). Search costs are either 0; 0.025; 0.05; 0.075 or 0.1 monetary units, with each level populated by ten customers. The values are assigned to the customers in a way that every gas station faces the same range of customers. As a last factor we implement a small normally distributed (0; 0.005) random element that is added to the price, accounting for customers not always starting at the same point.

Appendix B

The following provides the instructions for T_{DAF} and TR_{DAF}. The screens shown are for TR_{DAF}. The other instructions only differed slightly in the section discussing the regulation, and the screens differ slightly in their description fields where needed.

B1. Instructions for treatment 1 DAF - Translated to English

Dear participant.

We would like to welcome you to this experiment. From now on you are asked not to speak to anyone except for those conducting the experiment. If you have a question, please raise your hand and wait at your seat until an instructor approaches you.

Background of the experiment

The underlying experiment replicates a goods market in which “good A” is traded. Trading of this good is carried out in 13–20 rounds (representing trading days). This means the computer will stop the experiment randomly between Period 13 and 20, with each period having the same probability of being the last one. Each period is subdivided into 24 trading hours. You are a retailer of good A and will try to maximize your profit by trading this good.

At the beginning of each period (trading day) you can observe your purchase price of good A in that period. This price covers your total costs of buying good A. You do not need to decide on the quantity of good A you want to buy as this is automatically done by the computer for you. Based on your observation of the purchase price you need to determine the initial price at which you are willing to start selling good A. Within each round you are able to decrease your selling price at any time, but you are only allowed to increase it at the beginning of a period. As additional information, you will be able to observe the current prices of the other market participants.

At the end of each trading hour (1 h corresponds to 5 s in the experiment), a specific quantity of good A is sold in the market. The allocation of how many units each retailer sells depends on the prices of the market participants (see next section). In general, the sales volume of a market participant is larger the lower the selling price is. However, a lower selling price implies a lower profit per unit. After each trading hour (=5 s) you will see the quantity of good A you have sold and the corresponding profit.

The experiment randomly stops between rounds 13 and 20 with an equal probability. Your monetary payoff depends on how much profit you made during the experiment. Your total profit will be divided by 150. The result is your payout in euros. Your personal goal is to maximize your payoff.

Sales volume

How much you sell depends on the factors below:

- Generally, there is a demand for 1000 units of the good on the market if selling prices are low (close to the own costs of the retailers). The more the prices deviate from the own costs, the lower the overall demand. For each percentage point the price increases, demand decreases by half a percentage point.
- There are 50 potential customers on the market with a general demand of 20 units each.
- Your personal quantity of goods sold depends on how expensive your goods are compared to the other retailers. A customer takes driving costs to a shop and selling price into account and buys at the retailer with the lowest total costs for him. Driving costs are between 0 and 0.9 monetary units (five costumers with 0, five with 0.1, ⋯)
- You might therefore try on the one hand to use a low price to convince costumers to come to your shop, although they might be closer to another shop. On the other hand, your profit per unit sold decreases with lower prices and therefore the lowest price can also be a bad strategy.
- The last factor is a small random element accounting for costumers not always starting at the same point. However, in 65% of all cases this factor is very small and below $+/-0.005$ units.

Table A1
Exemplary allocation of sales volume and profit.

Player	Selling price V	Volume	Profit
1	1.10	265.14	26.51
2	1.13	222.68	28.95
3	1.14	192.33	26.93
4	1.15	157.54	23.63
5	1.16	105.33	16.85
	Total	943.02	

Calculating profits

Example: The purchasing price of the current period is 1.00 monetary units (MU). You are Player 3 and set your price at 1.14. Based on the prices of all other market participants your sales volume is 192.33 units of good A. This corresponds to a profit of 26.93 MU (Profit = (1.14-1.00)*192.33 = 26.93).

When you look at Player 1 you can also see, that selling the most goods is **not necessarily** the strategy with the highest profits (although it could be).

Your Payout

Your final payout depends on the amount of profit you earn during the experiment. Your total profit will be divided by 150 to convert it into euros. Your personal goal is to maximize your payout.

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