Weghake, Jens; Erlei, Mathias; Keser, Claudia; Schmidt, Martin

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Jens Weghake, Mathias Erlei, Claudia Keser and Martin Schmidt

Pricing in Asymmetric Two-Sided Markets: A Laboratory Experiment

Abstract: We conducted a laboratory experiment to study the price setting behavior in two-sided markets. We seek to answer two specific research questions: Do participants charge the equilibrium prices that can be derived from a theoretical model? How is the price setting affected by the characteristics of the Nash equilibrium? Our study shows that there are hardly any realizations of the Nash equilibrium. Participants seem to use simple heuristics. The increase in complexity caused by asymmetry has two effects: On the one hand, it makes finding the optimal pricing more difficult so that, on average, we find prices that are further away from optimal prices. On the other hand, higher complexity goes along with stronger signals against non-expedient heuristics so that, on an individual level, the equilibrium is reached in more markets.

JEL Codes: C72, C91, D43, L13

Keywords: two-sided market theory, experiment, duopoly, platform competition

1. Introduction

Nowadays, the two-sided market theory rooted in Armstrong (2006), Blair and Romano (1993), Caillaud and Jullien (2001), Rochet and Tirole (2003) is an accepted part of modern industrial economics. Inter alia, it was developed to describe the price setting behavior of platforms that face two groups of users (sides of the market) that want to interact with each other (e.g., Evans 2003). For example, video game consoles bring together developers of games on one side of the market and gamers on the other. The interdependencies between the two market sides are characterized by indirect network effects as defined by Katz and Shapiro (1985): developers have an interest in producing video games for a console that is used by many gamers and gamers buy consoles for which there exist many games (and thus developers). In other words, the utility offered by a platform to users on one market side increases with the number of users on the other market side that also use this platform (and vice versa). Evans (2003) additionally require that direct, bilateral interactions (without using the platform) between the subjects of the two market sides shall not be possible or reasonable. Due to high transaction costs of bilateral interactions in real world situations, this condition is often fulfilled. Thus, platforms internalize the indirect network effects so that the interactions become possible, respectively, more efficient.

A large fraction of research on two-sided markets focuses on the price setting, because prices for the distinct market sides play an important role in the question how well platforms internalize the indirect network effects. In this context, the distinction between price level and price structure is relevant (Rochet and Tirole 2003). In a two-sided market the price level is the sum of the prices charged to the two sides, while the price structure specifies how the price level is divided between the two market sides.[1]

[1] Rochet and Tirole (2006) point out that the two-sidedness (caused by indirect network effects) can be identified by this distinction in the following way. A market is supposed to be one-sided when the number

While, to date, a huge amount of theoretical work has emerged concerning markets with two or more sides and indirect network effects, only little is known about how well real-world situations are described by the theory. In our study, we investigate price setting in a two-sided market (framed as a video-game-console market) in a controlled laboratory environment. Participants are in the role of a platform and have to charge prices for two simulated market sides (developers and gamers) that are interrelated by positive two-way indirect network effects. The platforms compete in a duopoly situation; interaction between the same two platforms is repeated (partner matching). Thus, we shall not only check for convergence to equilibrium prices but also have an eye on potential platform collusion (Selten, Mitzkewitz, and Uhlich 1997). We are particularly interested in the impact of the relative importance of indirect network effects on price setting. To this end, in two out of three treatments, we choose the indirect network effect parameters to implement asymmetric price structures in equilibrium. This means that a platform should not charge the same prices as the platform, with which it competes for demand, to maximize its individual profit.

To anticipate our results, we find, analyzing aggregate behavior, that median prices seemingly converge to equilibrium prices. However, looking at individual markets, we hardly find any realizations of the Nash equilibria in the asymmetric treatments. Surprisingly often, participants seem to use simple heuristics.

To our knowledge, there exist two other studies that investigate price setting in experimental two-sided markets, Kalaycı, Loke, and McDonald (2015) and Nedelescu (2016). Nedelescu (2016) examines the monopoly model of Armstrong (2006). Starting from a base treatment, in which one of the profit-maximizing prices lies below costs, he studies the effects of two price-setting restrictions - no prices below costs and uniform prices - and of increased costs. He finds that only in the uniform-price treatment participants reached the profit-maximizing price predicted by the underlying theory.

The experiment by Kalaycı, Loke, and McDonald (2015) builds on Armstrong's (2006) duopoly model. In four treatments, the authors vary users' transportation costs and the strength of the (one-way) indirect network effect, both of which constitute the spread between equilibrium prices, respectively, the price structure. Equilibrium prices are symmetric in that they are the same for both platforms in one market. A key finding of this study is that prices showed no convergence to the equilibrium.

Both Nedelescu (2016) and Kalaycı, Loke, and McDonald (2015) suggest that the missing convergence to the equilibrium might be driven by the high complexity of the task that involves the choice of two prices. Since we also examine asymmetric equilibria, the complexity is even higher in our experiment. Thus, it comes to no surprise that we observe, if at all, only weak convergence toward equilibrium prices.

2. Theoretical Framework and Hypotheses

Our experiment is based on a variation of the differentiated Bertrand duopoly model, which is also known as the Launhardt-Hotelling model (Hotelling 1929; Dixit 1979; Singh

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of realized transactions depends only on the price level. If, for a given aggregate price level, different price structures lead to different volumes of transactions, the market is supposed to be two-sided.

and Vives 1984; Launhardt 1993). In our model, we add indirect network effects to implement the two-sidedness of the market. Due to our video-game-console framing, we also add direct network effects. The number of users of the two market sides A (gamers) and B (developers of video games) who join platform i and platform j ($n_A^i, n_A^j, n_B^i, n_B^j$) are given by

$$
\begin{aligned}
n_A^i &= A^i - c_A^i \cdot p_A^i + cR_A \cdot \left(p_A^j - p_A^i\right) + a_A^i \cdot n_B^i + b_A^i \cdot n_A^i \\
n_A^j &= A^j - c_A^j \cdot p_A^j + cR_A \cdot \left(p_A^i - p_A^j\right) + a_A^j \cdot n_B^j + b_A^j \cdot n_A^j \\
n_B^i &= B^i - c_B^i \cdot p_B^i + cR_B \cdot \left(p_B^j - p_B^i\right) + a_B^i \cdot n_A^i - b_B^i \cdot n_B^i \\
n_B^j &= B^j - c_B^j \cdot p_B^j + cR_B \cdot \left(p_B^i - p_B^j\right) + a_B^j \cdot n_A^j - b_B^j \cdot n_B^j
\end{aligned}
$$

where $p_A^i$is the price charged by platform i to users of side A, $p_B^i$is the price charged by platform i to users of side B, and so on. The variables A^i, A^j, B^i and $B^j$are the respective intercepts of the demand functions. They can be interpreted as the stand-alone utilities of the platforms. The parameter a_A^i (a_A^j) determines the strength of the indirect network effect that users of side A receive from the number of users of side B on platform i (j). Analogously, $a_B^i$and $a_B^j$are the indirect network effects that users of side B receive from interacting with users of side A on platform i or respectively j. We assume only positive indirect network effects. Consequently, the utility that a user obtains from platform i (j) increases with an increase in the number of users of the other side that also choose platform i (j). Direct network effects are given by b_A^i, b_A^j, b_B^i and b_B^j. The positive (negative) signs in the first and second (third and fourth) equation are due to design considerations. In our experiment we use a video-game-console framing. In this context, users of side A can be seen as gamers. The positive direct network effects for this side represent the benefit of sharing games or playing together. The developers of games are the users of side B. Therefore, the negative direct network effects shall demonstrate competition between developers or a congestion effect (e.g., Aloui and Jebsi 2010). The coefficients c_A^i, c_A^j, c_B^i and c_B^jaffect the immediate reaction of the users, when the respective price of a platform is varied. The parameters cR_A and cR_B are reaction coefficients that influence how fast users switch platforms due to a relative difference in prices. To simplify the task in the experiment, we leave out any costs.

The four above equations can be simultaneously transformed to derive the demand functions depending only on prices (the calculation steps are in the appendix). In our model, we waive costs. Therefore, the revenues of both platforms are equal to their profits. By deriving the profit functions, we get the best response functions that are used to determine the equilibrium prices in Table 2. These are the unique Nash equilibria of the stage games and the unique subgame perfect equilibria of any finite repetition of the games. In order to determine the collusive prices, the joint profit functions must be established. Deriving this function and solving the resulting four first-order conditions simultaneously leads to the collusive prices in Table 2.

Table 1 provides an overview of the specific parameterization used in three treaments. The differences between the treatments are limited to differences in the variables a_A^i, a_A^j, a_B^i *and* a_B^j. In other words, the treatments differ in the indirect network effects.

Table 1 - Parameter overview

Treatment	A	B	a_A^i	a_A^j	a_B^i	a_B^j	$b_A = b_B$	c_A	c_B	$cR_A = cR_B$
symmetric (*sym*)	10	2	0.6		0.8		0.1	0.5	0.3	0.5
asymmetric (*asym*)	10	2	0.6	0.4	0.7	0.984	0.1	0.5	0.3	0.5
double asymmetric (*d-asym*)	10	2	0.01	0.92	0.99	0.2	0.1	0.5	0.3	0.5

Our study focuses on the investigation of price setting behavior. We seek to answer two specific research questions. First, do participants charge the equilibrium prices that can be derived from our theoretical model? Second, how is the price setting affected by the characteristics of the Nash equilibrium? We have designed three treatments, *symmetric (sym)*, *asymmetric (asym)* and *double-asymmetric (d-asym)*, with differing types of the Nash equilibrium by assuming different network indirect network effects. Table 2 presents the prices in equilibrium for each platform and treatment. In Treatment *sym* both platforms face identical equilibrium prices. In treatment *asym* the optimal prices for both platforms are different, but the price structures are the same (relative low price for market side A and higher price for market side B). In Treatment *d-asym* the price structure for platform i is different from platform j. This means that participants who have the role of running platform i have to charge a low price to market side A and a relative higher price to B. On the opposite, participants running platform j charge a high equilibrium price to market side A and a lower equilibrium price to B. Altogether, the task in treatment *sym* is supposed to be the easiest followed by treatment *asym*. Treatment *d-asym* is supposed to be the most difficult treatment.

Table 2: Nash equilibrium prices

			treatment *sym*		treatment *asym*		treatment *d-asym*	
			Nash	Collusion	Nash	Collusion*	Nash	Collusion
Price	Platform i	Group A	3.2	3.5	3.5	4.8	3.0	4.3
		Group B	7.0	14.4	6.8	14.3	9.0	17.9
	Platform j	Group A	3.2	3.5	0.2	0.0	8.4	12.8
		Group B	7.0	14.4	11.2	20.0	0.2	4.8

* Maximization with regard to a non-negativity condition, which we applied in the experiment according to which prices could not be negative.

As stated above, one of our central research questions is whether the theoretical equilibrium prediction is consistent with the participants' behavior in the experiment. Due to the (underlying) complex model, we conjecture that participants need some time for learning before they reach equilibrium behavior. This leads us to our first Hypothesis.

Hypothesis 1: *Pricing behavior in all three treatments converges to the Nash equilibrium of the corresponding game*.

As already explained, the cognitive demands with regard to the learning abilities of participants differ between the treatments. As a consequence, learning should be simplest in the sym treatment and most difficult in the *d-asym* treatment. Treatments *asym* and *d-asym* have yet another difficulty regarding the magnitude of one of the equilibrium prices, which is quite close to zero. In treatments *asym* und *d-asym* relative prices diverge extremely on platform j. Since we consider relative equilibrium prices p_A^j/p_B^j = 0.2/11.2 = 1/56 and p_A^j/p_B^j = 8.4/0.2 = 42 as counterintuitive and harder to learn, we expect larger deviations for those prices whose equilibrium value is 0.2.

Hypothesis 2: *There will be treatment effects with respect to the convergence paths. (a) Treatment sym will converge faster than treatment asym, which in turn converges faster than treatment d-asym. (b) There will be larger deviations from equilibrium prices which have an equilibrium value close to zero (i.e.,* $p_A^j = 0.2$ *in treatment asym and* $p_B^j = 0.2$ *in treatment d-asym).*

One of the major problems of learning equilibrium behavior consists in the underlying asymmetries of treatments *asym* and *d-asym*. In our experiment with partner matching, such asymmetries are particularly important if many participants exercise some kind of imitation learning. (Apesteguia, Huck, and Oechssler 2007) provide evidence for the relevance of imitation learning and that imitation is more pronounced when participants can observe the behavior and results of their immediate competitors. In our experiment, participants only learn their competitor's behavior and profits but not the behavior of other participants in the same session. However, due to the asymmetries, the behavior of a platform's competitor conveys little information regarding the efficient behavior of the platform itself. Therefore, we expect that there will be large differences in behavior between the treatments if imitation learning is widely applied. In turn, if there are large treatment effects, this may be due to imitation learning.

Hypothesis 3: *In the case of large treatment effects there will be a substantial part of participants whose behavior can be reconstructed by imitation learning.*

3. Experimental Design

Our laboratory experiment was run at the economic laboratories at the Clausthal University of Technology[2] (short: Cl) and the University of Göttingen[3] (short Goe) using z-Tree (Fischbacher 2007). In total 278 participants, recruited using ORSEE (Greiner 2004), took part in three different treatments, spread over thirteen sessions. An overview, containing number of sessions per laboratory and treatment can be found in

Table 3. The average session took between 70 and 80 minutes and resulted in average payoffs[4] of 16.91 €.

[2] Clausthal Laboratory of Experimental Economics (ExECUTe)
[3] Göttingen Laboratory of Behavioral Economics (GLOBE)
[4] Average payoffs by treatment: 17.82€ (symmetric), 15.45 € (double asymmetric) and 17.18 € (asymmetric).

Table 3 - Overview sessions by treatment and laboratory

Treatment	Sessions		# Groups Clausthal	# Groups Göttingen	# indep. obs
	Cl	Goe			
sym	3	2	30	24	54
asym	2	2	20	23	43
d-asym	2	2	20	21	41

The sessions were conducted following an identical protocol at both universities. Participants were welcomed and randomly allocated to computer terminals. Once everybody was seated, they were asked to read the printed instructions.[5] Questions were answered individually. The instructions described the structure of the experiment and gave a qualitative explanation of how the prices chosen by the group members affect the demand for both market sides. An exact representation of the model was not included. After all participants finished reading the instructions, a questionnaire was used to check the understanding of key features of the experiment. Each question screen was followed by an answer screen, showing their own as well as the correct answer. Afterwards the treatment started. Participants were matched in groups of two and remained in this group for all 15 periods. Matched partners received no information about each other's identities. Communication was not allowed.

Each period consisted of two stages, the pricing stage and the profit overview. In the pricing stage, participants were asked to set a price for both market sides. Those prices could range from the lower bound of zero to the upper bound of twenty-five, while negative numbers were not allowed. To avoid negative quantities to be realized, our zTree program checked price combinations before progressing to the profit stage. If platform k ($k \in i, j$) charges prices that lead to negative quantities, the prices of platform k are automatically adjusted so that platform k faces zero demand on both market sides. Technically we achieve this quasi monopoly situation by adjusting prices to equations $p_A^k = 10 + \frac{1}{2} \cdot p_A^{-k}$ and $p_B^k = \frac{5}{2} + \frac{5}{8} \cdot p_B^{-k}$ with $k \in i, j$.[6] If both platforms achieve negative quantities, the profits of both platforms are set to zero. We framed the market sides as "console", reflecting the consumer or gamer side, and "license", the producer or developer side. Additionally, a profit calculator was provided on a separate screen, which could be opened by clicking on the "test-calculator" button.[7] It included two sliders for the platform's own prices and two sliders for hypothetical prices of the competitor. To provide a better overview of the price effects, we additionally provided profits for prices close to the chosen price combination. A matrix on the lower half of the calculator screen showed profits for hypothetical platform prices ± 0.1, ± 0.2, and ± 0.3. We limited the availability of the calculator to five minutes in the first two periods and reduced the timeout to three minutes from period three on, in order to limit the duration of the experiment. There was no timeout on setting the actual prices, though. After the prices were set, a text message appeared asking the participants to confirm their choices. Once

[5] The instructions are provided in the Appendix.
[6] These equations apply to all three treatments for platform i and j.
[7] A depiction of the calculator screen can be found in the Appendix.

all participants had confirmed their decision, the profit stage started, informing everybody about their own as well as their group member's prices and profits. The same information was provided in the pricing stage for past periods. At the end of the last period, participants were informed about their total cash payoff, which was followed by an (un-incentivized) questionnaire about their socio-economic background. Each experimental session was concluded by paying one participant at a time.

4. Results

4.1 Convergence toward equilibrium prices

While the theory makes clear statements about where prices should converge to be mutually optimal (see Table 2), it is not a priori clear how well the theory describes actual human behavior. Therefore, we firstly check the development of prices on an aggregated data level. Afterwards, we show some differences in individual behavior.

The graphs in Figures 1, 2 and 3 present the median prices[8] charged by the participants over periods.[9] On the left sides of the Figures are the developments of prices for market side A while the right sides show prices for market side B. The solid lines illustrate the equilibrium levels. Because of the partner matching, we also included the dashed lines representing the (collusive) prices participants had to charge to maximize the group's profit. This allows us to see if there was any collusive behavior. In Figures 2 and 3, due to the asymmetry, there are two solid and two dashed lines each.

Figure 1 shows that in treatment *sym* median prices in later periods are relatively close to the equilibrium. However, median prices, charged to market side A are consistently too high and, from period 4 onwards, prices charged to market side B are too low. Given that equilibrium prices are $p_A^i = p_A^j = 3.2$ and $p_B^i = p_B^j = 7$ median prices are somewhat biased towards the middle. The large distance to the collusive price level of group B prices suggests that collusive behavior was of little relevance in treatment *sym.*

Median prices of platform-i-participants in treatment *asym* tend to be too high but are near the equilibrium prices. However, median prices of platform-j-participants for market side A are clearly too high and prices for market side B were too low. Since all four prices must correspond to the equilibrium level this aggregated data view suggests that participants in treatment *asym* did not coordinate to the Nash-equilibrium.

[8] We use median prices because the median is robust to outliers. However, mean and median are quite similar.

[9] We tested the null Hypothesis that mean prices charged by participants in Göttingen and Clausthal are equal by applying Wilcoxon–Mann–Whitney tests for the four prices in each treatment. We were not able to reject the null hypothesis at any level of significance lower than 9.8%. However, most test results lay clearly above this value. Therefore it should be reasonable that we pooled the observations collected in Göttingen and Clausthal.

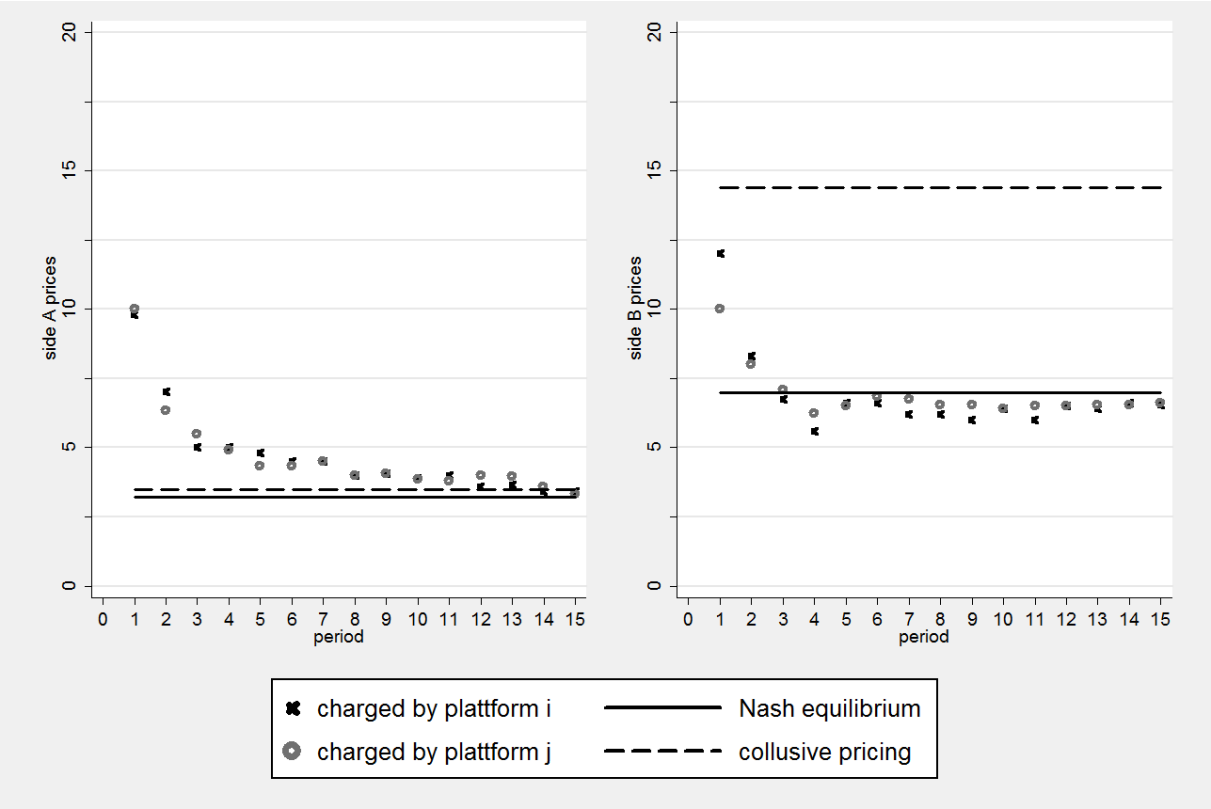

Figure 1: Median prices over periods in treatment sym.

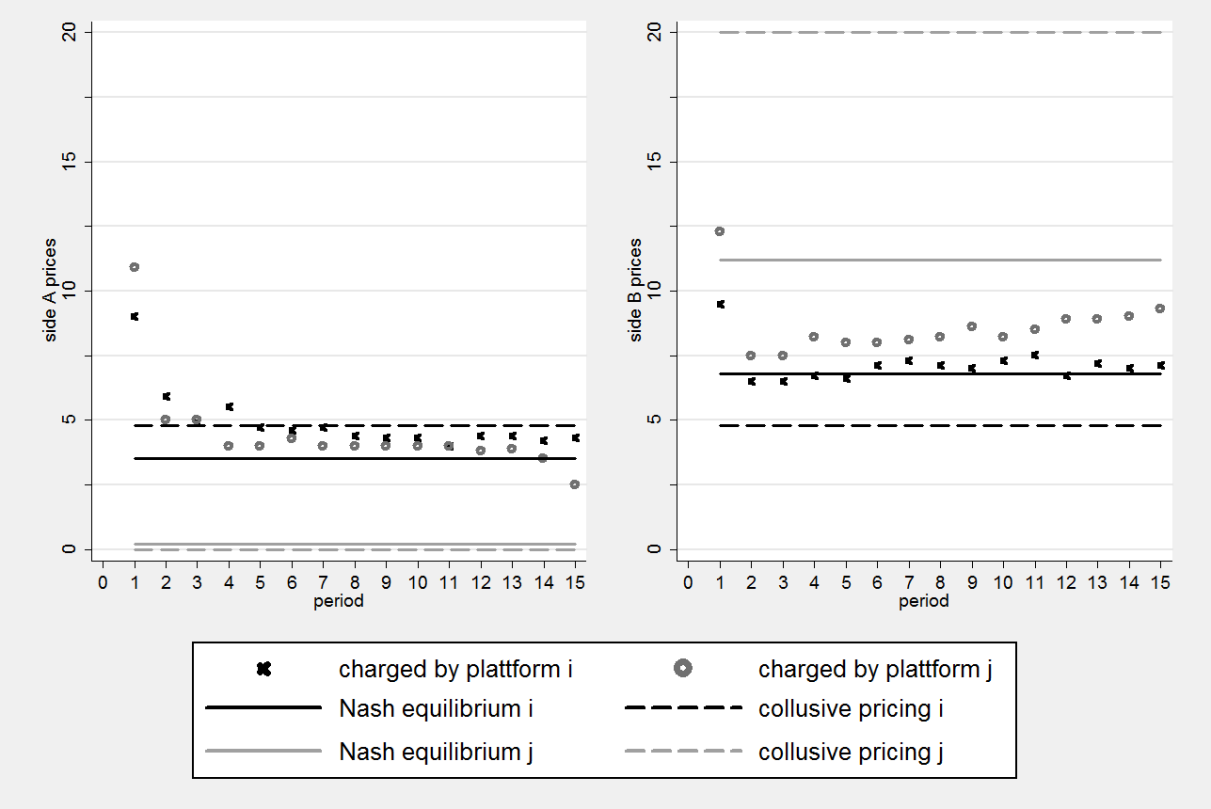

Figure 2: Median prices over periods in treatment asym.

Figure 2 also suggests that there is no collusive behavior in treatment *asym*.

Figure 3 shows that in treatment *d-asym* median prices are biased toward the middle. Nevertheless the prices seem to converge to the respective equilibrium prices. For a joint profit maximum, median prices are too low.

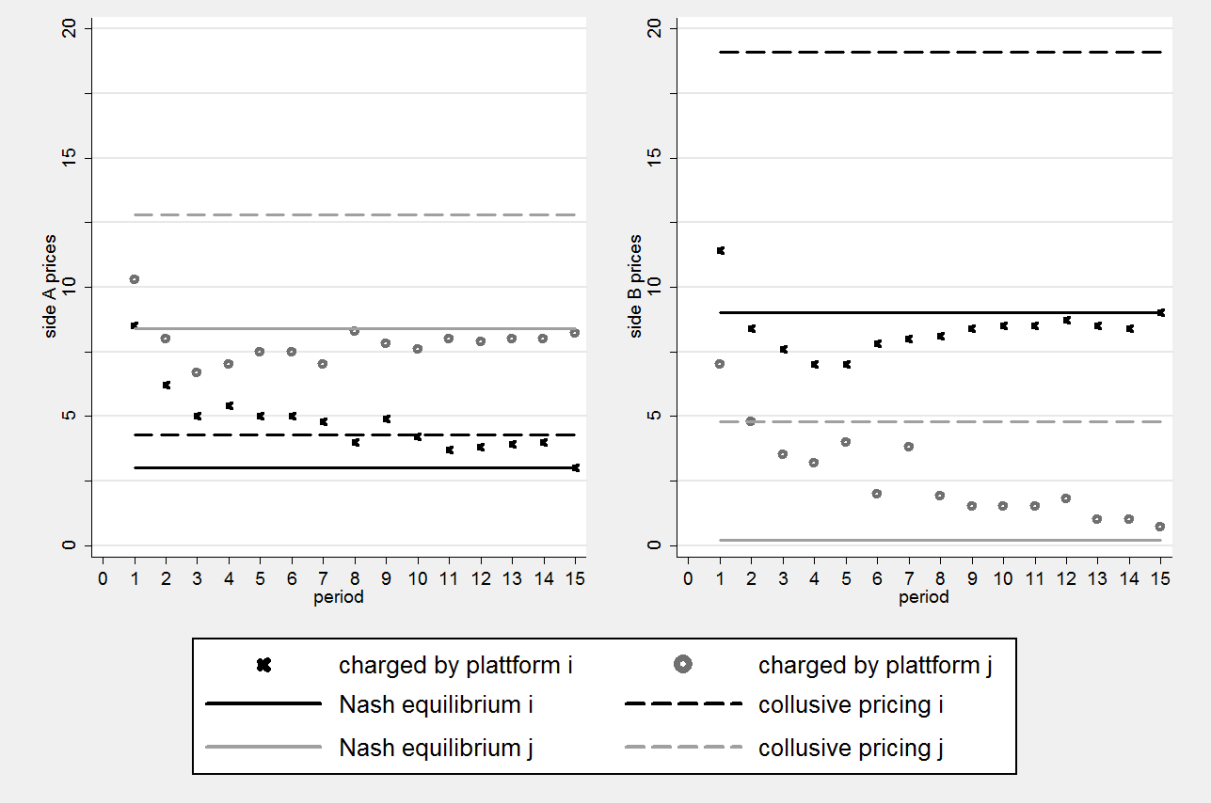

Figure 3: Median prices over periods in treatment d-asym.

As far as Hypothesis 1 is concerned, the development of median prices in treatment *sym* shows the most pronounced trend toward the Nash equilibrium, followed by the development in treatment *d-asym*. In treatment *asym* the deviations from the equilibrium of platform-j-participants are striking. With a pooled OLS-regression of the following model we test if prices converge to the respective equilibrium prices (for this purpose we use the **d**eviations from the respective **e**quilibrium **p**rice (**dep**)):

$$dep_l^k = \beta_{l,0}^k + \beta_{l,1}^k \cdot \frac{1}{period} + \epsilon_l^k \; with \; l \in A, B \; and \; k \in i, j$$

If $\beta_{l,1}^k$ is unequal to zero, $\beta_{l,1}^k \cdot \frac{1}{period}$ goes against zero with increasing number of periods. Thus the model indicates that prices converge to the equilibrium level as long as the constant ($\beta_{l,0}^k$) is not significantly different from zero.[10] We tested each price individually. The test statistics are reported in Table 4. It can be seen that in all treatments and for all prices the influence of the period is significantly different from zero. Consequently $\beta_{l,1}^k \cdot \frac{1}{period}$ drops with increasing periods.

[10] That means the models intercept is of interest. Therefore we use a pooled OLS regression although we have panel data. With a Hausman-test we checked if a random effects model is permitted. Since this is the case, pooled OLS is permitted, too (Cameron and Trivedi (2005)). To take into account the intra-group correlation we use cluster robust standard errors.

Table 4: Test of trend towards the equilibrium prices (OLS regression with cluster robust standard errors).

treatment *sym*	p^i_A	p^i_B	p^j_A	p^j_B
period$^{(-1)}$	7.202*** (0.754)	5.566*** (0.580)	7.987*** (0.904)	5.029*** 0.836
constant	0.269 (0.219)*	-1.252*** (0.303)	0.188 (0.222)	-1.167*** (0.306)
observations	810	810	810	810
F-Stat	91.29	92.15	78.09	36.21
R-squared	0.332	0.169	0.316	0.136
treatment *asym*	p^i_A	p^i_B	p^j_A	p^j_B
period$^{(-1)}$	5.892*** (0.834)	2.596*** (0.872)	8.360*** (0.963)	3.387*** (0.949)
constant	0.250 (0.281)	0.197 (0.333)	2.644*** (0.363)	-3.192 (0.485)
observations	645	645	645	645
F-Stat	49.94	8.856	75.34	12.73
R-squared	0.220	0.0369	0.284	0.0498
treatment *d-asym*	p^i_A	p^i_B	p^j_A	p^j_B
period$^{(-1)}$	4.557*** (0.757)	3.455*** (0.781)	4.856*** (0.930)	5.993*** (1.142)
constant	1.121** (0.328)	-2.026*** (0.519)	-1.936*** (0.376)	2.286*** (0.415)
observations	615	615	615	615
F-Stat	36.28	19.56	27.25	27.56
R-squared	0.121	0.0451	0.132	0.118

Standard errors in parentheses
* p < 0.05, ** p< 0.01, *** p< 0.001

In treatment *sym* prices for side A converge to the equilibrium level, so do the prices of platform-i-participants in treatment *asym*. In treatment *d-asym* all four constants are significantly different from zero. Since all four prices have to reach the equilibrium level in order to achieve a mutually optimal state, these tests suggest that there is no overall convergence toward the equilibrium in any treatment.

In this context the interdependencies between the prices are important and the missing consideration of these interdependencies is a shortcoming of the regression and of the descriptive Figures 1, 2 and 3. A participant may charge the equilibrium price for one side

and a price for the second side that is tremendously far away from the equilibrium level. Figures 1, 2 and 3 do not mirror such possible situations.

However, we are interested if participants play equilibrium prices in later periods more often. For this purpose we calculate the logit quantal response equilibrium (LQRE) (for the theoretical basics see Goeree, Holt, and Palfrey 2016 and McKelvey and Palfrey 1995). For this calculation we use the normal form of the game, which has been adjusted by the following points:

- Participants in the treatments had to set two prices between 0 and 25 and one decimal place. Thus each type has got 63001 strategies. Consequently the normal form of the game is a 63001x63001 matrix. Although we used a computer algebra system the dimension of the matrix led to problems in computing. Therefore we calculated the LQRE for prices between 0 and 25 and a step size of 0.5 (each type of participant has got 2601 strategies). For our intended purpose this lack of accuracy should not be crucial.
- In the treatments losses (because of negative quantities) were excluded. If one participant charged prices (given the prices of the second participant in the group) leading to negative quantities this participant gets zero profit and the second participant gets the monopoly profit. If both participants had negative quantities both players earned zero profits. We have also taken this aspect into account in the calculation of the LQRE.

We used the variant in which each strategy j of a subject i is chosen with the probability

$$\pi_{ij} = \frac{e^{\lambda x_{ij}(\pi)}}{\sum_{k=1}^{n} e^{\lambda x_{ik}(\pi)}} \; with \; x_{ij}(\pi): expected \; profits$$

That means, if λ equals zero each strategy is chosen with the same probability. If λ goes against ∞ the probability of playing the Nash-strategy goes against 1. Table 5[11] illustrates the key findings of the LQRE.

In the "random-columns" there are the log likelihoods that result when each strategy is chosen with the same probability. The first entries in the "LQRE-columns" are the log likelihoods that result in the best possible fit of the aggregate data. The λs in brackets are the corresponding values that lead to these maximum likelihoods. Therefore the "random-columns" and the first entries in the "LQRE-columns" give impressions of the accuracy of the LQRE. The comparisons between these log likelihoods show that the LQRE represents the data better than a model that implies a decision-maker that randomizes uniformly.

However, more interesting are the λ-values in the LQRE-columns. While the absolute values cannot be interpreted, the developments in the rows allows inferences with regard to the price-setting behavior. An increasing λ-value implies that in later periods more charged prices equal the equilibrium prices, respectively, are closer to the equilibrium than in earlier periods. Since both prices were considered simultaneously in this

[11] For the calculation we used a uniform distribution as initial distribution. Computing was stopped when all differences of all probabilities between iteration t and $t-1$ were ≤ 0.0000001. To find the maximum likelihoods some kind of bisection method was used.

evaluation the increasing λ-values in treatment *sym* and *asym* suggest learning and a tendency to the equilibrium.

Table 5: Key findings of the LQRE.

Sum of log likelihoods	**random *sym***	**LQRE *sym***	**random *asym***	**LQRE *asym***	**random *d-asym***	**LQRE *d-asym***
Periods 2-15	-11,889.84	-9,429.68 (λ = 0.04)	-9,467.84	-7,548.82 (λ = 0.04)	-9,027.47	-7,907.58 (λ = 0.04)
Periods 11-15	-4,246.37	-3,076.05 (λ = 0.075)	-3,381.37	-2,598.04 (λ = 0.05)	-3,224.10	-2,777.96 (λ = 0.05)
Periods 13-15	-2,547.82	-1,813.72 (λ = 0.085)	-2,028.82	-1,539.88 (λ = 0.06)	-1,934.46	-1,672.53 (λ = 0.05)
Period 15	-849.27	-584.07 (λ = 0.115)	-676.27	-507.25 (λ = 0.07)	-644.82	-553.91 (λ = 0.05)

In treatment *d-asym* there is almost no increase of the λ-value. Thus on the aggregate data level we cannot find evidence for learning in treatment *d-asym*. At first glance, this finding seems to contradict the development of prices in Figure 3. However, this apparent contradiction can be explained by the fact that in Figure 3 the prices for the two sides A and B are considered individually and the LQRE is calculated with strategies that include both prices simultaneously. Consequently the developments in Figure 3 are only possible if there are participants who charged prices to one side that converge to the equilibrium level and prices for the second side that diverge from the equilibrium level over periods. Figure 4 illustrates this. In this Figure the sum of the absolute deviations from the respective equilibrium prices of each participant are shown in a boxplot. The declining position of the 25%-quantile implies that in later periods some participants succeeded in setting prices close to the equilibrium level. However, with an almost constant median and a slightly increasing position of the 75%-quantile, other participants have moved away from the equilibrium level at least on one side of the market.

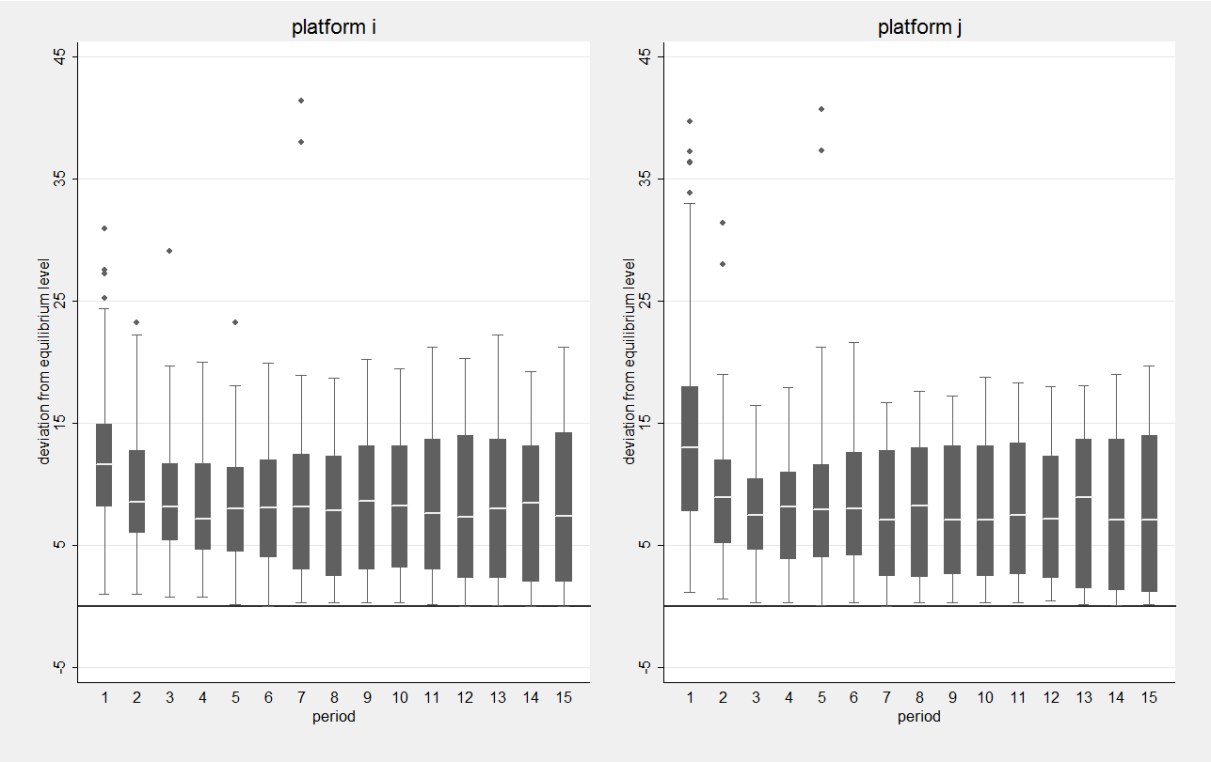

Figure 4: Absolute deviations (sum of p_A and p_B) from the equilibrium level over periods.

4.2 Classification of individual prices

Overall, this shows that there must have been significant differences at the individual level. Therefore, we have classified the individual decisions of all participants according to the following criteria that are illustrated in Figure 5.

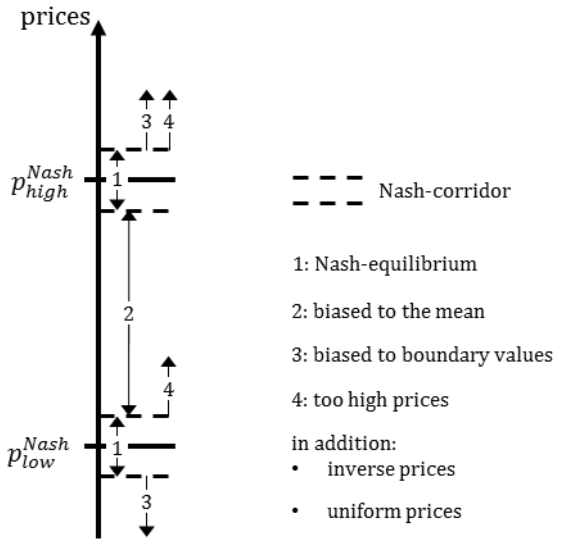

Figure 5: Classification of individual decisions.

First of all, we classify prices as Nash-equilibria when all prices (of both players in one pairing) lay in the so-called "Nash-corridor". For our classification, the Nash corridor in Figure 5 has three different widths. In the strictest demarcation all four prices in one

pairing must be equal to the equilibrium prices ± no more than 0.5. Building on this, we have two further demarcations in which prices must be equal to the equilibrium prices ±] 0.5, 1], respectively, ±] 1, 1.5]. That means the first three parts in the Figures 6, 7 and 8 are cumulative. Moreover, since we use all four prices in the groups, the height of these parts must be equal for platform i and platform j. For all further classifications, only the two prices of each participant are taken into account. The classification "biased to the mean" is chosen if both prices of a participant lay between the upper bound of the Nash-corridors[12] of the relative lower equilibrium price and the lower bound of the Nash-corridor of the relative higher equilibrium price. Furthermore, the price structure has to be "correct" in these cases. This means that relative prices must be in line with the price structure in equilibrium. Cases in which participants charged prices with the "wrong" price structure were classified as "inverse prices". Next, we use the classification "bias-to boundary-values" if the price structure is correct, one price is above the Nash-corridor and simultaneously the other one is below the Nash-corridor. That means charged prices have to be closer to 0 and 25 than prices in the equilibrium are. We call prices "too high" if both prices lie above the upper bound of the Nash-corridor of the related equilibrium prices. If a participant charged equal prices for side A and side B we choose "uniform prices" as classification. "Other" includes three cases: (1) one player has prices in the Nash-corridor, while the second player in the pairing has his prices outside of our definition of equilibrium prices. (2) One player has one price in the corridor and the second price lays outside the corridor. (3) Too low prices, which have occurred only very rarely.

Against the background of the importance of the price structure we consider inverse prices and uniform prices to be the clearest violations of the behavior that is derived theoretically.

[12] This refers to the size 3 Nash-corridors, which is done to have a clearly defined separation.

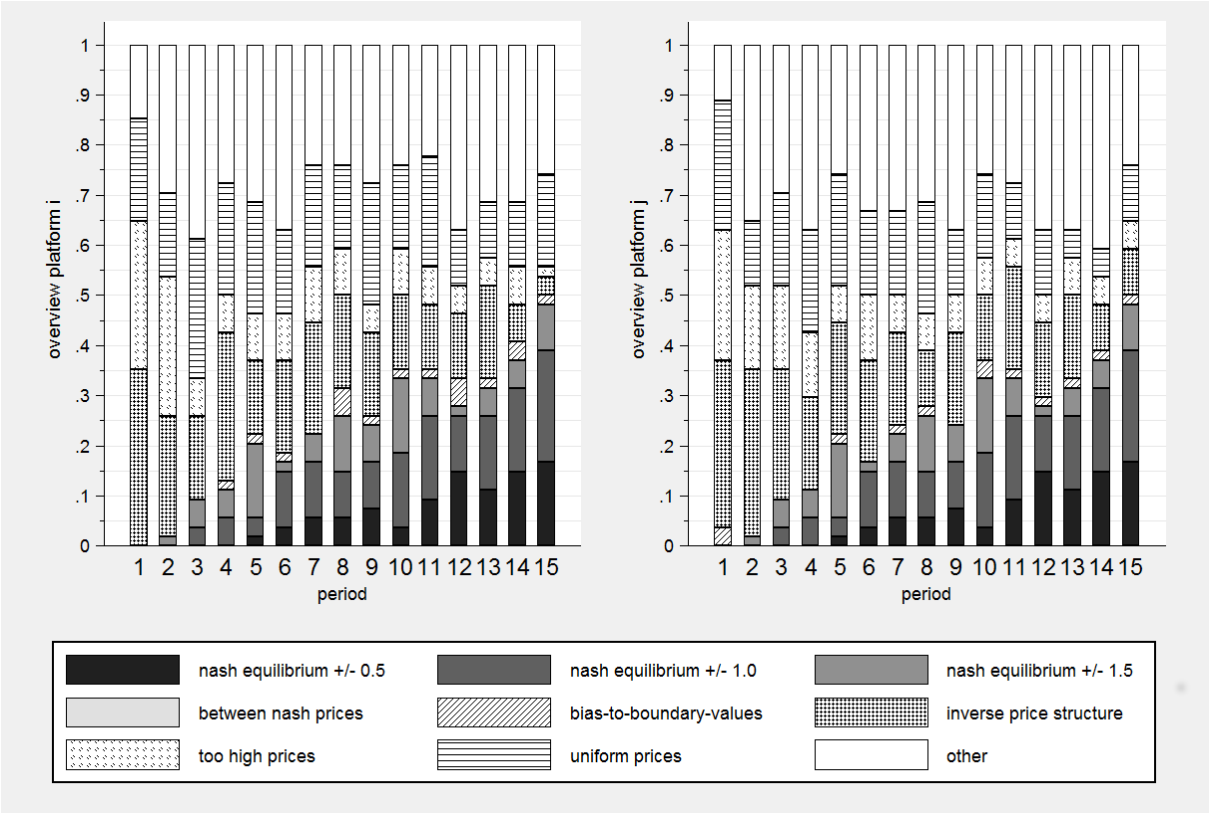

Figure 6: Proportion of the classified decisions in treatment sym.

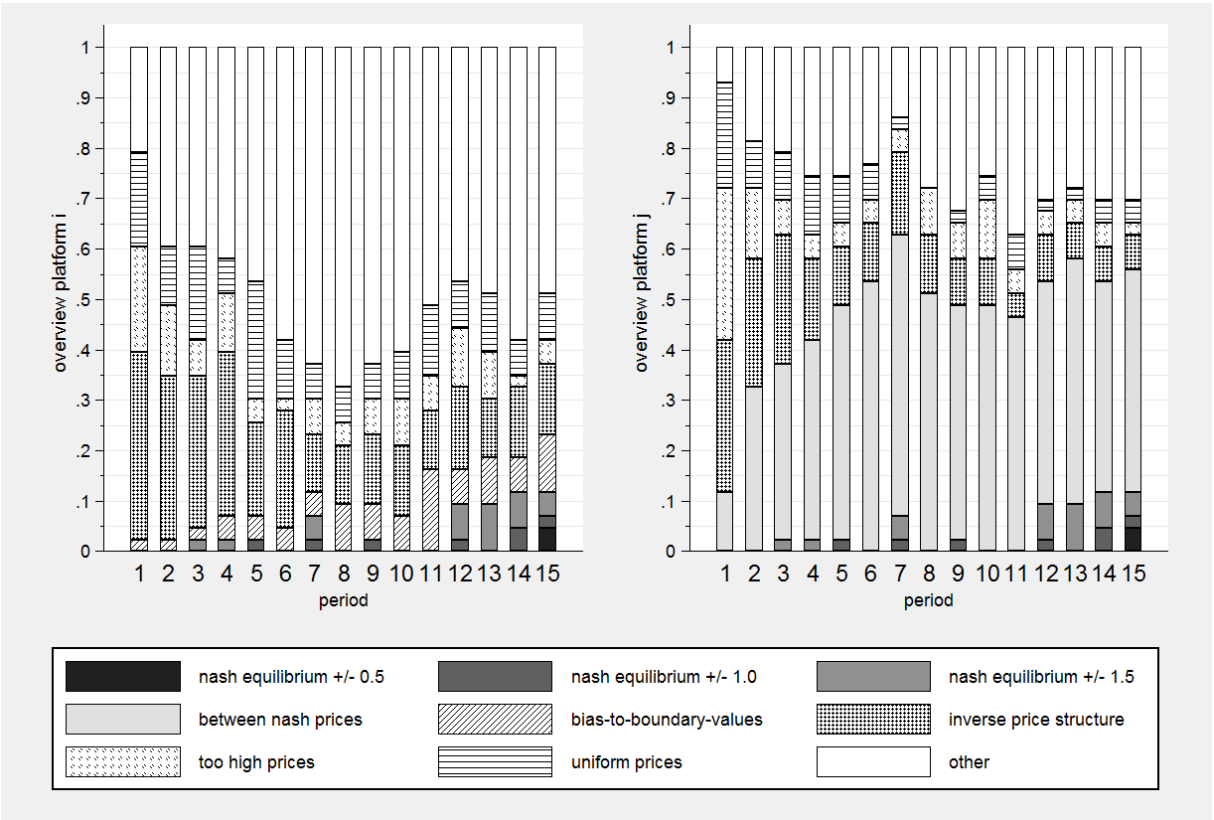

Figure 7: Proportion of the classified decisions in treatment asym.

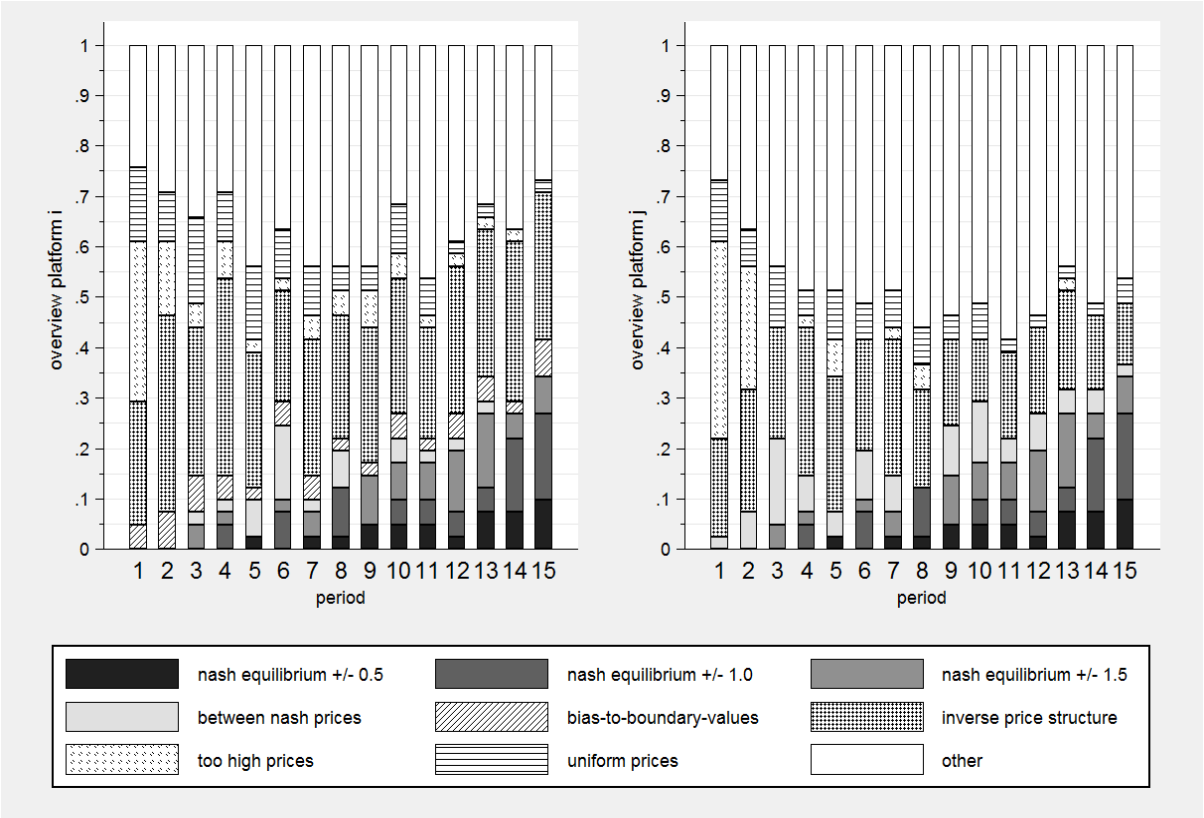

Figure 8: Proportion of the classified decisions in treatment d-asym.

Figures 6, 7 and 8 show that the proportion of price decisions that can be classified as uniform prices and inverse prices tend to decrease. This can be evaluated in favor of the theory. Nonetheless even in period 15, especially in treatment *d-asym*, several inverse prices were charged by the participants.

Another interesting aspect is the development of decisions that can be classified as equilibrium prices. First of all, it is noticeable that the proportion of equilibrium prices increases most markedly in treatment *sym*. Furthermore, it is remarkable that in treatment *d-asym* some cases can be classified as equilibrium, whereas in treatment *asym* hardly any cases can be classified as equilibrium, although the LQRE suggests learning in treatment *asym* and no learning in treatment *d-asym*. Therefore this is a case in which an evaluation based on aggregated data does not reveal all important aspects. Specifically, it must be stated that although there was an overall tendency to the equilibrium in treatment *asym* the deviations from the equilibrium prices must be large. In contrast, the prices of the majority of the participants in treatment *d-asym* do not converge to the equilibrium or even move away from the equilibrium, but some pairings actually achieve the mutually optimal state.

Conclusion of Subsections 4.1 and 4.2: Considering the entire evaluation so far, it is not possible to make a definitive judgement regarding Hypothesis 1. In all treatments we found some evidence for convergence to the Nash equilibrium. However, in no treatment the equilibrium was reached and the convergence differs markedly between treatments. In treatment *sym*, the trend towards equilibrium is the most pronounced. When comparing treatment *asym* and treatment *d-asym* a judgement can only be made if it has been clarified whether the average behavior or individual behavior is used as a criterion. Gigerenzer and Brighton (2016) state: “Do not test what the average individual does,

because systematic individual differences may make the average meaningless." (Gigerenzer and Brighton 2016, S. 22). Nevertheless, averages (and medians) are regularly used to evaluate results. We don't want to answer the question what the correct way is. In addition, we do not want to make a final judgement whether it is better when the average converges to equilibrium but remains far from it (as in treatment *asym*) or the case in which some participants actually reach the equilibrium and the majority of participants miss the equilibrium (treatment *d-asym*). Therefore it is also difficult to give a final answer regarding Hypothesis 2. Once again, our results suggest that symmetry favors convergence. But it is not clear whether prices converge more quickly in the case of asymmetry or double asymmetry.

Result 1: Summarizing, we reject Hypothesis 1. Although median prices, viewed in isolation, tend towards the respective equilibrium level in all treatments, the complete equilibrium, consisting of four prices, is rarely realized.

Result 2a: We reject Hypothesis 2 (part a). Our analysis suggests that learning is simplest in the symmetric treatment. However, we find no evidence that learning is more difficult under double asymmetry than under simple asymmetry.

4.3 Equilibrium prices close to the lower bound

There is another feature in the asymmetric and double-asymmetric treatment worth mentioning. Participants running platform j had to charge a price of 0.2 to one of the sides in equilibrium (participants could set prices between 0 and 25). That means one price was close to the lower bound. Equilibrium prices of participants of role i were more centered. Altogether, we supposed that participants who had to charge a price close to the bound could have bigger difficulties with finding the profit maximizing price structure.

Therefore, we tested the null Hypothesis that prices charged by participants running platform i and j in the asymmetric treatment and double-asymmetric treatment have the same absolute deviation from the corresponding equilibrium levels by applying a Wilcoxon Matched-Pairs Signed-Ranks Test.[13] Table 6 reports the mean absolute deviations from the respective equilibrium, the z-values of the test, the corresponding p-values and Pearson's r. We report the results for all periods, the last five periods and the last three periods. Table 6 must be read column by column.

There are significant differences between the participants in both treatments. In the double-asymmetric treatment over all 15 periods the platform j prices for market side A are closer to the equilibrium prices than the platform i prices for market side A. Measured by Pearson's r the significant effects are small to medium.[14] For side B, the significant difference in the deviations vanishes toward the end of the experiment. For side A, the significant difference remains. Considering that participants running platform j had to charge a price of 0.2 to side B, these results suggest that the task to charge a price close to the bound was not a problem in the double-asymmetric treatment.

[13] We use the Wilcoxon Matched-Pairs Signed-Ranks Test due to the dependency of the two prices which results from the partner matching. The tests were conducted using subject means.
[14] We use Cohen's (1992) classification with r = 0.1 for a small effect, r = 0.30 for a medium effect and r = 0.50 for a large effect.

Table 6: Testing for identical deviations from equilibrium

		asymmetric						double-asymmetric					
Periods		1-15		11-15		13-15		1-15		11-15		13-15	
Price		group A*	group B	group A*	group B	group A*	group B	group A	group B*	group A	group B*	group A	group B*
Mean absolute deviation from equilibrium	i	2.28	2.25	1.66	1.90	1.59	1.72	2.84	2.99	2.09	2.65	2.10	2.57
	j	4.51	3.56	3.27	3.02	3.04	2.95	2.26	3.80	1.66	2.64	1.60	2.37
|z|		15.76	10.55	8.72	5.55	6.23	4.73	4.42	3.47	2.38	0.09	2.31	0.89
Prob > |z|		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.93	0.02	0.38
Pearson's r		0.62	0.42	0.59	0.38	0.55	0.42	0.18	0.14	0.16	0.01	0.21	0.08

h_0: no differences between platform i and platform j

* group with equilibrium price = 0.2

In the asymmetric treatment the deviations from the equilibrium prices of platform j were significantly greater on both market sides over the whole experiment, over the last five periods and over the last three periods.
However, the difference between the asymmetric and the double-asymmetric treatment does not allow for clear conclusions with respect to the importance of the relative prices in equilibrium. Consequently it is also unclear whether the border position of one equilibrium price impedes the convergence to the equilibrium.

Given that prices charged by participants running platform i and participants running platform j do not conform to equilibrium prices the results in Table 6 do not provide information with regard to profit maximizing behavior. It is possible that participants give best-responses to the non-equilibrium prices of the second participants in the respective pairing. Therefore we tested the null Hypothesis that prices charged by participants running platform i and j have the same absolute deviation from the best-responses to the prices in the prior period. Due to the same reason as before we again use the Wilcoxon Matched-Pairs Signed-Ranks Test. To ensure that the test results give an impression of profit maximizing behavior we compare the sums of deviations (both prices must be best-responses to maximize the own payoff). As there are no best-responses to the prior period in the first period the first column of each treatment covers the periods 2-15. Table 7 reports the results.

In all three treatments there are significant differences between participants running platform i and j. In the symmetric and double-asymmetric treatment the deviations of platform-j-participants are smaller. However, in these two treatments the effects are small to medium. That means, the actual extent of the differences are rather small. In the asymmetric treatment the prices charged by participants running platform i are significantly closer to the best-responses and the effects are large. Thus only few prices charged by platform-j-participants are best-responses.

Table 7: Testing for identical deviations from best-responses to prior period

		symmetric			double-asymmetric			asymmetric		
Periods		2-15	11-15	13-15	2-15	11-15	13-15	2-15	11-15	13-15
Mean absolute deviation from best-response	i	3.25	2.33	2.22	6.40	5.09	5.04	3.25	2.92	2.72
	j	3.17	2.09	1.92	6.11	4.73	4.39	7.92	6.65	6.31
|z|		2.16	2.59	1.88	2.05	1.35	1.95	17.49	9.48	7.28
Prob > |z|		0.03	0.01	0.06	0.04	0.09	0.05	0.00	0.00	0.00
Pearson's r		0.08	0.16	0.15	0.09	0.09	0.18	0.71	0.65	0.64

h_0: no differences between platform i and platform j

Conclusion of Subsection 4.3: All things considered it can be concluded that participants running platform j in the asymmetric treatment got the biggest problems finding the best response prices for side A and side B. A possible explanation might be the combination of the border position of one equilibrium price and the comparatively weaker incentives for best-responses against imitation as discussed previously.

Result 2b: We reject Hypothesis 2 (part b). We do not find sufficient evidence that an equilibrium value close to zero leads to larger deviations from equilibrium prices.

4.4 Decision heuristics

Further examination of the individual decisions shows that there are many price decisions that can be reproduced by two simple explanations:

1. Best responses to previous period prices of the other player in the pairing.
2. Imitation of the other player's prizes if the other player was more successful.

Figure 9 is an example of 1. The dots show the actual prices charged by the participants in treatment *d-asym* session 4 that formed group 3. The connected circles indicate what prices participants should have chosen to give best responses to the respective other's previous period prices. It is striking that the prices charged by the participants are identical or at least very similar to these hypothetical prices. In consequence participants in this group reached the mutual optimal equilibrium state.

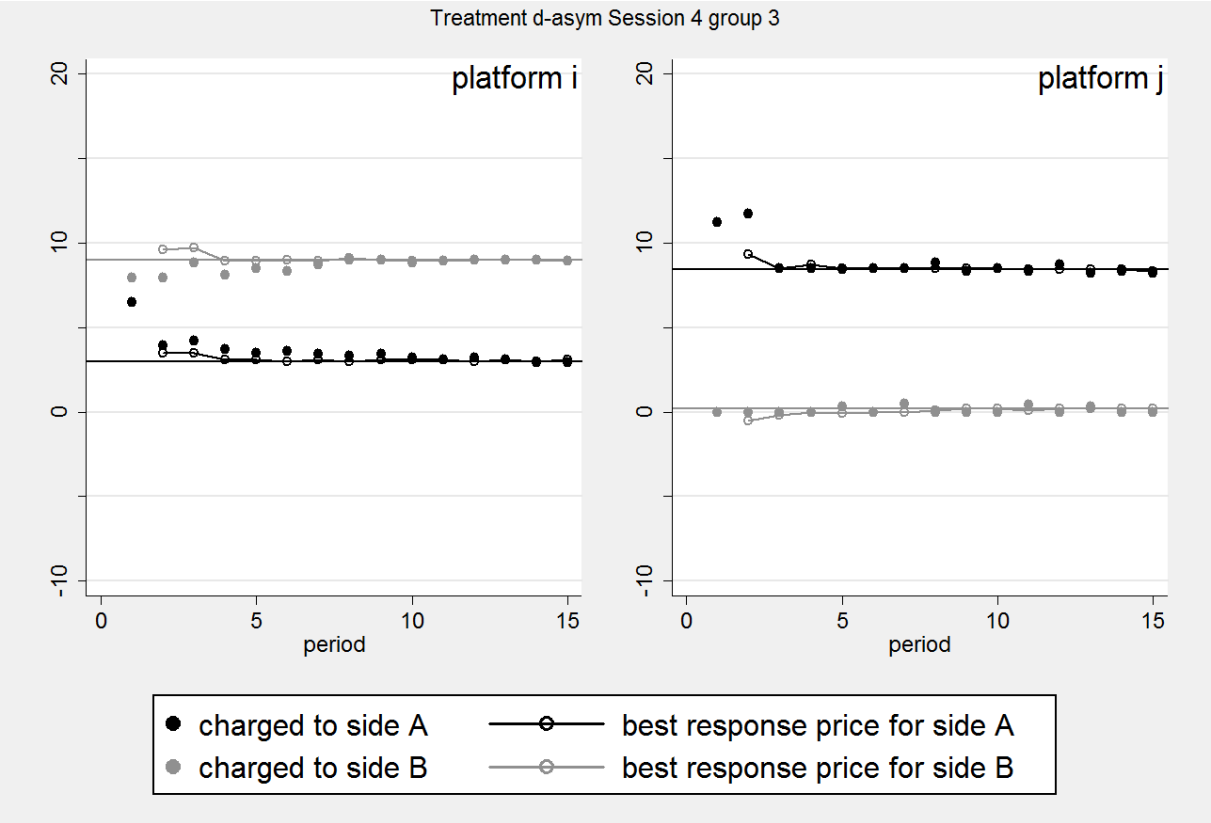

Figure 9: Actual price decisions in the experiment (dots) and prices that participants should have charged if they wanted to give best responses to the prices of the previous period (connected circles) in treatment d-asym session 4 group 3. The solid lines show the equilibrium prices.

Figure 9 is a prime example of a pairing in which both players give best responses. Figure 10 is some kind of counterexample. While the prices of platform i are still quite close to the best responses, prices of platform j do not fit to this explanation at all. In fact, this is a case of an inverse price structure, so that platform j achieves a significantly lower payoff than the best-response-player.

In Figure 11 is the same group as in Figure 10. The difference is, that in Figure 11 the connected circles indicate the prices participants should have charged if they follow the simple rule "imitate-if-better". In this explanatory approach, we assume that one participant takes over the prices of the other participant if his or her own profit is lower. Otherwise, he keeps his prices. Even though not all dots and circles are perfectly identical, it can be seen that the observations of platform j are much better represented by imitation. Thus the comparison between these two Figures suggests that the platform-j-participant in this pairing imitates the more successful platform-i-participant. In the next chapter we discuss why participants might have imitated and to what extent imitation is a useful heuristic in the treatments.

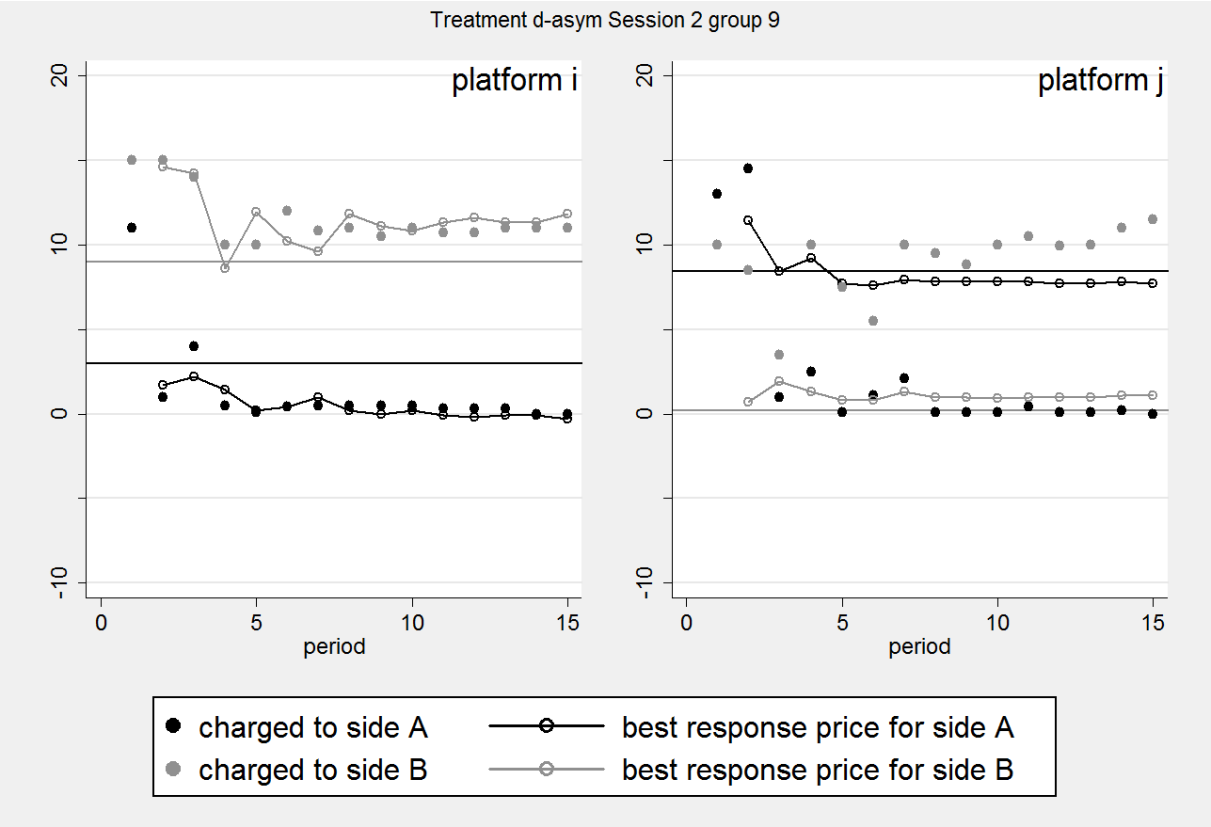

Figure 10: Actual price decisions in the experiment (dots) and prices that participants should have charged if they wanted to give best responses to the prices of the previous period (connected circles) in treatment d-asym session 2 group 9. The solid lines show the equilibrium prices.

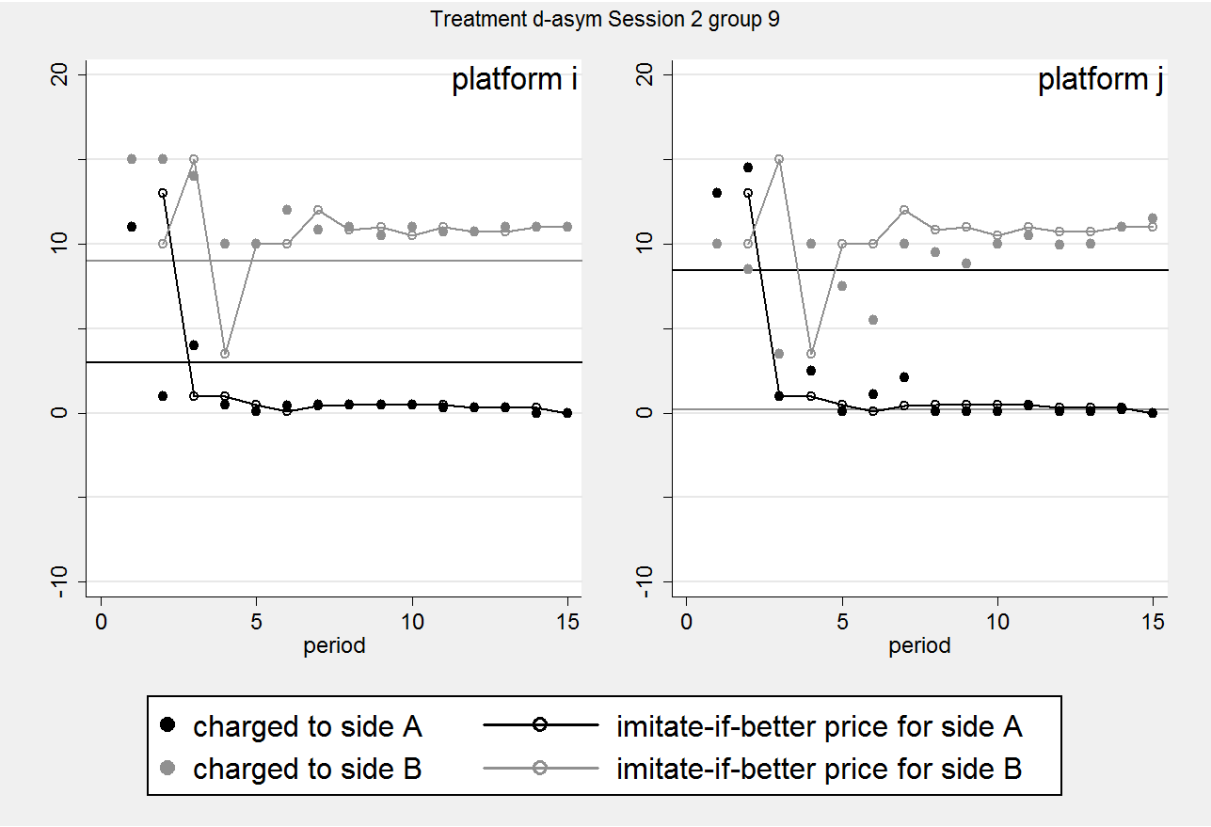

Figure 11: Actual price decisions in the experiment (dots) and prices that participants should have charged if they followed the rule "imitate-if-better" (connected circles) in treatment d-asym session 2 group 9. The solid lines show the equilibrium prices.

Figure 12 shows how many price decisions can be classified as best-responses or imitation. For this classification the actual observations and the theoretical values do not have to be exactly identical. Instead we classified a decision as best response/imitation when the absolute difference between the actual charged price and the price given by the respective explanation is ≤ 0.5 for both prices of a participant.

Not all decisions can be clearly assigned. For example, many observations in the left sides of Figures 10 and 11 can be classified as both best responses and imitation. Nonetheless, Figure 12 shows that there are many cases of imitation that cannot be simultaneously classified as best responses. The most striking part of Figure 12 is the development of the platform-j-participants in treatment *asym*. These participants seem to have imitated very often and have given almost no best responses. A result already shown in Table 7. However, in the other treatments there are also several cases of imitation. We will discuss this finding in more detail in the following chapter.

Result 3: We cannot reject Hypothesis 3. Actual many pricing decisions can be reconstructed by imitation learning.

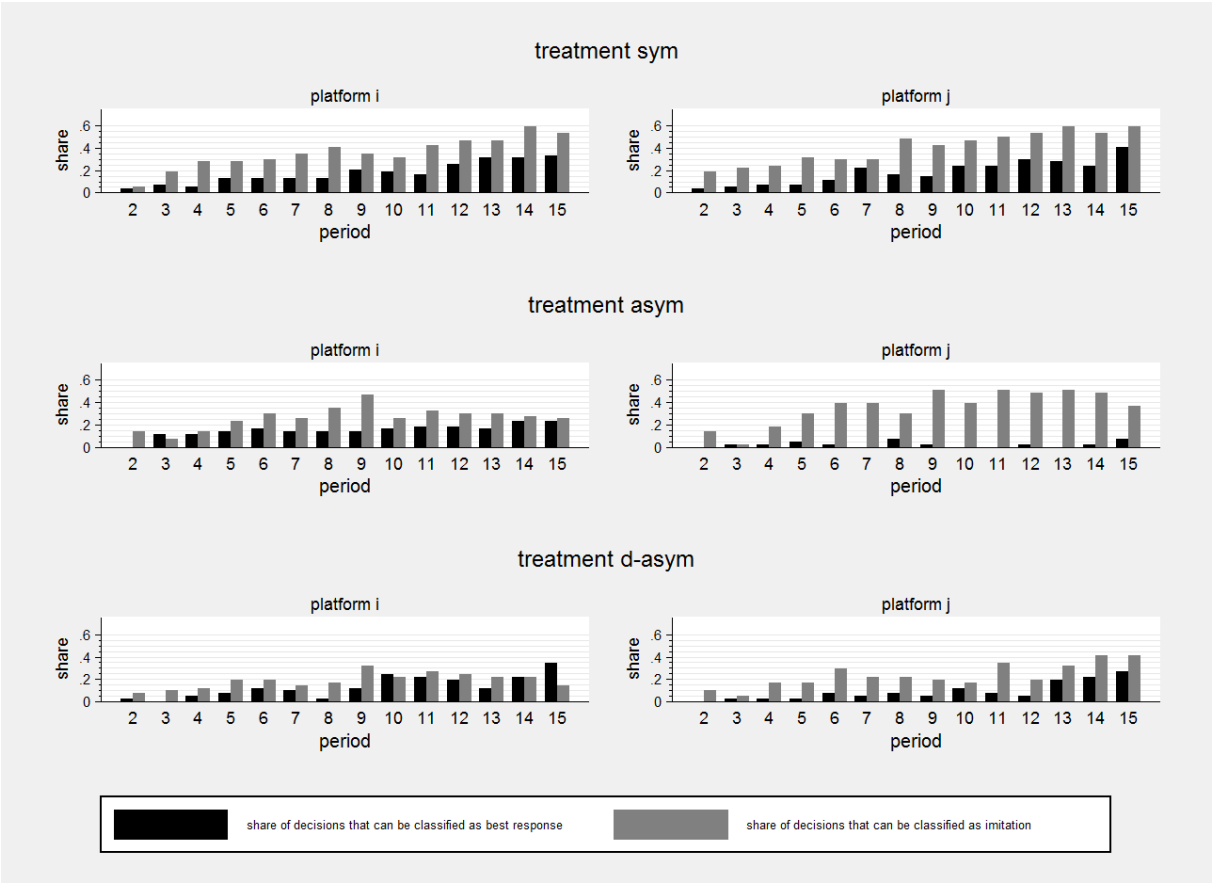

Figure 12: Proportion of all decisions (without period 1) that can be classified as best responses or imitation.

5. Discussion

In our treatments there are, if at all, only weak trends to the respective equilibria. However, in favor of theory we observe that the number of extensive violations in terms of theory (e.g. inverse price structure, uniform prices) decrease. In this context, the finding that many observations can be classified as imitation is noTable. According to

Gigerenzer (2002), Gigerenzer and Selten (2002) and Gigerenzer and Brighton (2016) human decision-makers rather use heuristics instead of optimization when they face constrains in time and/or cognitive performance. Imitation, respectively, the decision rule "imitate-if-better" is such a simple heuristic that was apparently used – even though the calculator in the experimental setting facilitated giving best responses to prices in prior periods.

5.1 Is imitation useful heuristic in our experiment?

Duersch, Oechssler, and Schipper (2012) demonstrate conditions under which imitation is "unbeaTable". They highlight that the only class of symmetric two-player games in that "imitate-if-better" can be exploited are any generalizations of the rock-paper-scissor game. However, our symmetric treatment falls under the conditions under which an exploitation of this heuristic is impossible. That means, even a fully rational, forward-looking participant, without any constrains in time and computational capacities who is aware that he is playing against an imitator cannot achieve a significantly higher[15] profit (see Feldman, Kalai, and Tennenholtz 2010; Duersch, Oechssler, and Schipper 2012). In our symmetric treatment prices converge to the Nash equilibrium if an imitator and a best-response-player is matched. Moreover, if two imitators are matched prices also converge to the equilibrium if there is a minimum of exploration and if players want to become better off in absolute terms.[16]
Consequently, in the symmetric treatment "imitate-if-better" was a suiTable heuristic if participants wanted to maximize their individual profits. Therefore, there is a match between this (obviously popular) decision rule and the experimental environment in the symmetric treatment. Consequently, imitators act ecologically rational in the sense of Gigerenzer (2002) and Gigerenzer and Brighton (2016). Of course, under this definition using the calculator giving best responses on prior period prices is also evolutionary viable. Accordingly, best-response-players are ecologically rational, too.

In the asymmetric and double-asymmetric treatment the heuristic "imitate-if-better" is not suiTable to increase individual profits. When a best-response-player and an imitator are matched the best-response-player obtains a considerably higher profit (measured in percent of the equilibrium profit). If two imitators are matched, the outcome is not a priori clear. However, it is not possible that both imitators reach their respective profit maximum. Nevertheless, a number of price-settings can be reconstructed by our definition of imitation.

Interestingly, the proportion of imitators in the double-asymmetric treatment is smaller than in the asymmetric treatment. This is striking since we consider the task in the

[15] In a Cournot oligopoly setting Schipper (2009) shows that imitators can even outperform best-response-players.
[16] Vega-Redondo (1997), Schipper (2003) and Apesteguia, Huck, and Oechssler (2007) show for several games that imitation can lead to competitive outcomes and not to Nash equilibria if small mistakes are allowed. Crucial for this finding are the assumptions that players are interested in relative payoffs and that spiteful behavior is possible. That means, a player who suffers less from an adjustment towards the competitive outcome than the opponent(s) would do this adjustment due to the relative better result. As the spiteful player is considered as new benchmark, imitators are expected to follow this player towards the competitive outcome level. Using the same line of argumentation, Apesteguia, Huck, and Oechssler (2007) suggest for a simple 3-player Cournot game that competitive outcomes become more likely if players can imitate their immediate competitors. However, we do not assume (and did not find evidence) that players are only interested in relative outcomes.

double-asymmetric treatment as the most complicated one. Hence, it would be reasonable to expect that participants use the simple "imitate-if-better"-heuristic more frequently under double-asymmetry. However, Smith (2003), Haltiwanger and Waldman (1985) and Fehr and Tyran (2008) stress the importance of market institutions and the strategic environment. While under some institutions/environments convergence towards the equilibrium is encouraged, other institutions and environments are less helpful. In our context imitation causes bigger financial losses in the double-asymmetric treatment than in the asymmetric treatment. These bigger losses can be considered as hints for participants in the double-asymmetric treatment that imitation is not expedient. That means participants can exploit the structures of information in the environment (Gigerenzer 2002; Gigerenzer and Brighton 2016) of the double-asymmetric treatment. These stronger incentives for best-responses against imitation can potentially explain some of our results. However, as we have shown in the previous chapter, the majority of the participants in the double-asymmetric treatment was not able to charge optimal prices and several participants have even worsened in the course of the periods. Nevertheless, we expect that with more periods the suboptimal "imitate-if-better"-heuristic would disappear in the asymmetric and in the double-asymmetric treatment. Furthermore, as the higher complexity in the double-asymmetric treatment comes along with stronger incentives we would expect that imitation should decline faster in the double-asymmetric treatment than in the asymmetric treatment. This does not necessarily imply that the speed of convergence towards equilibrium is higher in the double-asymmetric treatment (Hypothesis 2). It is also possible that participants switch from "imitate-if-better" to another suboptimal heuristic. However, participants who abandon imitation should have recognized that the optimal price structures differ between platforms

5.2 External validity

Finally, we want to discuss the implications of our empirical findings for real world two-sided markets and for competition policy. First, we have to assert that our experiment provides – at best – very limited support for the standard equilibrium theory of two-sided markets. On the whole, the strategic interdependencies in two-sided markets are much more complicated than those in markets for standard consumption goods. Simple but effective learning strategies such as imitation may not work in platform markets so that it is uncertain whether Nash equilibria are reached at all. With respect to the concept of ecological rationality Vernon Smith (2003) emphasizes that rationality is often embodied in the institutions of social interaction. Our data suggest that the standard rules of market interaction which work so well in one-sided markets may not work as well in two-sided markets. At the least, learning processes take more time than in standard markets.

Second, however, we have to take into account that firms may invest much more time and resources into price setting in real world two-sided markets than the participants in our experiment. Yet even if they hire excellent experts, those researchers may lack a reliable knowledge basis regarding the structure of the market. In addition, many two-sided markets are highly innovative and provide numerous innovations in small intervals of time (Evans and Gawer 2016). In this case relying on data from the past may lead to serious mistakes in actual business policy.

Taken together, our conclusion is that it remains quite unclear whether the equilibrium theory of two-sided markets covers the most important features of market behavior.

Acknowledging our limited understanding of two-sided markets further implications for competition policy may arise. First, there is uncertainty whether current market prices represent strategic behavior, competitive equilibrium behavior, or price setting in disequilibrium (Hayek 1989). Second, socially optimal prices have only been derived for restrictive assumptions (Rochet and Tirole 2003; Armstrong 2006; Weyl 2009, 2010) so that we do not have reliable characteristics of socially optimal states. Given this lack of knowledge, our experiment advises competitive authorities to behave very cautiously. In particular, they should avoid extreme punishments of ways of behavior that we only partially understand.

6. Conclusion

Participants in our laboratory experiment struggled to find the equilibrium prices for the two sides of the market. This is certainly due the high complexity of the task. It is not only a matter of setting a second price, but also that interdependencies must be taken into account when choosing the two prices. For example, if the price for market side A is too high, the platform will obviously lose customers from market side A. Since both market sides are connected through indirect network effects, the platform will also lose demand on market side B. This in turn reduces the attractiveness of the platform for market side A, so that it can be expected that the platform under consideration will lose more customers on market side A (and so on). If there is a competitor, suboptimal pricing is even more detrimental since each costumer that switches to the competitor leads to a higher attractiveness of the competitor for the second market side. All in all, participants were not able to charge optimal prices within the 15 periods of the experiment.

From a behavioral point of view the pricing decisions of many participants are well comprehensible. Since the complexity of the task was high, the participants used simple heuristics instead of optimization. The more sophisticated participants tend to use the calculator and give best responses to the prior-period prices of the competitor. However, our investigation shows that imitating a more successful competitor was even more popular. Although this imitation heuristic is quite naive it works very well in symmetric structures like those given in our treatment *sym*. Under asymmetric structures imitation leads to poor results and a more sophisticated competitor might exploit imitation. As one might expect, the imitation heuristic was given up the faster, the more negative the consequences were. Most negative were the consequences in treatment *d-asym*, which we consider to be the most complicated of our three treatments. From this we conclude, that the complexity of the task has two effects. On the one hand, it makes finding the optimal pricing more difficult so that, on average, we find prices that are further away from optimal prices. On the other hand, higher complexity leads to stronger signals of the dysfunctionality of imitating behavior so that, on an individual level, the equilibrium is reached in more markets.

Altogether, the suboptimal pricing in our experiment is mainly driven by the complexity of the strategic environment. A central question is how well the popular heuristics fit to the incentives given by the strategic environment.

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Appendix

Calculation of theoretical solutions

Our four initial demand functions

$$
\begin{aligned}
n_A^i &= A^i - c_A^i \cdot p_A^i + cR_A \cdot \left(p_A^j - p_A^i\right) + a_A^i \cdot n_B^i + b_A^i \cdot n_A^i \\
n_A^j &= A^j - c_A^j \cdot p_A^j + cR_A \cdot \left(p_A^i - p_A^j\right) + a_A^j \cdot n_B^j + b_A^j \cdot n_A^j \\
n_B^i &= B^i - c_B^i \cdot p_B^i + cR_B \cdot \left(p_B^j - p_B^i\right) + a_B^i \cdot n_A^i - b_B^i \cdot n_B^i \\
n_B^j &= B^j - c_B^j \cdot p_B^j + cR_B \cdot \left(p_B^i - p_B^j\right) + a_B^j \cdot n_A^j - b_B^j \cdot n_B^j
\end{aligned}
$$

can be rearranged simultaneously to get the demand functions that only depend on the prices:

$$
n_A^i = \frac{\left(cR_A \cdot \left(p_A^i - p_A^j\right) - A^i + c_A^i \cdot p_A^i\right) \cdot b_B^i + \left(cR_B \cdot \left(p_B^i - p_B^j\right) - B^i + c_B^i \cdot p_B^i\right) \cdot a_A^i + cR_A \cdot \left(p_A^i - p_A^j\right) - A^i + c_A^i \cdot p_A^i}{\left(-1 + b_A^i\right) \cdot b_B^i + a_A^i \cdot a_B^i - 1 + b_A^i}
$$

$$
n_A^j = \frac{\left(cR_A \cdot \left(p_A^j - p_A^i\right) - A^j + c_A^j \cdot p_A^j\right) \cdot b_B^j + \left(cR_B \cdot \left(p_B^j - p_B^i\right) - B^j + c_B^j \cdot p_B^j\right) \cdot a_A^j + cR_A \cdot \left(p_A^j - p_A^i\right) - A^j + c_A^j \cdot p_A^j}{\left(-1 + b_A^j\right) \cdot b_B^j + a_A^j \cdot a_B^j - 1 + b_A^j}
$$

$$
n_B^i = \frac{\left(c_R^B \cdot \left(p_B^j - p_B^i\right) + B^i - c_B^i \cdot p_B^i\right) \cdot b_A^i + \left(cR_A \cdot \left(p_A^i - p_A^j\right) - A^i + c_A^i \cdot p_A^i\right) \cdot a_B^i + cR_B \cdot \left(p_B^i - p_B^j\right) - B^i + c_B^i \cdot p_B^i}{\left(1 + b_B^i\right) \cdot b_A^i + a_A^i \cdot a_B^i - 1 - b_B^i}
$$

$$
n_B^j = \frac{\left(cR_B \cdot \left(p_B^i - p_B^j\right) + B^j - c_B^j \cdot p_B^j\right) \cdot b_A^j + \left(cR_A \cdot \left(p_A^j - p_A^i\right) - A^j + c_A^j \cdot p_A^j\right) \cdot a_B^j + cR_B \cdot \left(p_B^j - p_B^i\right) - B^j + c_B^j \cdot p_B^j}{\left(1 + b_B^j\right) \cdot b_A^j + a_A^j \cdot a_B^j - 1 - b_B^j}
$$

In the sake of ease we waive any costs. Therefore the profit of platform i is given by $n_A^i \cdot p_A^i + n_A^i \cdot p_A^i$:

$$
\begin{aligned}
\Pi^i &= -p_A^i \cdot \frac{a_A^i \cdot B^i - a_A^i \cdot c_B^i \cdot p_B^i + a_A^i \cdot c_R^B \cdot p_B^j - a_A^i \cdot cR_B \cdot p_B^i + A^i - c_A^i \cdot p_A^i + cR_A \cdot p_A^j - cR_A \cdot p_A^i + b_B^i \cdot cR_A \cdot p_A^j - b_B^i \cdot cR_A \cdot p_A^i + b_B^i \cdot A^i - b_B^i \cdot c_A^i \cdot p_A^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i} - p_B^i \\
&\cdot \frac{A^i \cdot a_B^i - c_B^i \cdot p_B^i + cR_B \cdot p_B^j - cR_B \cdot p_B^i - b_A^i \cdot B^i + b_A^i \cdot c_B^i \cdot p_B^i - b_A^i \cdot cR_B \cdot p_B^j + b_A^i \cdot cR_B \cdot p_B^i - cR_A \cdot p_A^i \cdot a_B^i - c_A^i \cdot p_A^i \cdot a_B^i + cR_A \cdot p_A^j \cdot a_B^i + B^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i}
\end{aligned}
$$

Analogously the profit of platform j is given by $n_A^j \cdot p_A^j + n_A^j \cdot p_A^j$:

$$
\begin{aligned}
\Pi^j &= -p_A^j \cdot \frac{a_A^j \cdot B^j - a_A^j \cdot c_B^j \cdot p_B^j + a_A^j \cdot cR_B \cdot p_B^i - a_A^j \cdot cR_B \cdot p_B^j + A^j - c_A^j \cdot p_A^j + cR_A \cdot p_A^i - cR_A \cdot p_A^j + b_B^j \cdot cR_A \cdot p_A^i - b_B^j \cdot cR_A \cdot p_A^j + b_B^j \cdot A^j - b_B^j \cdot c_A^j \cdot p_A^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j} \\
&- p_B^j \cdot \frac{-c_B^j \cdot p_B^j + cR_B \cdot p_B^i - cR_B \cdot p_B^j - b_A^j \cdot B_j + A_j \cdot a_B^j + B_j + b_A^j \cdot c_B^j \cdot p_B^j - b_A^j \cdot cR_B \cdot p_B^i + b_A^j \cdot cR_B \cdot p_B^j - cR_A \cdot p_A^j \cdot a_B^j - c_A^j \cdot p_A^j \cdot a_B^j + cR_A \cdot p_A^i \cdot a_B^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j}
\end{aligned}
$$

By deriving the profit functions according to the prices one obtains the first order conditions.

$$
\begin{aligned}
\frac{\partial \Pi^i}{\partial p_A^i} &= -\frac{a_A^i \cdot B^i - a_A^i \cdot c_B^i \cdot p_B^i + a_A^i \cdot cR_B \cdot p_B^j - a_A^i \cdot cR_B \cdot p_B^i + A^i - c_A^i \cdot p_A^i + cR_A \cdot p_A^j - cR_A \cdot p_A^i + b_B^i \cdot cR_A \cdot p_A^j - b_B^i \cdot cR_A \cdot p_A^i + b_B^i \cdot A^i - b_B^i \cdot c_A^i \cdot p_A^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i} \\
&- p_A^i \cdot \frac{-c_A^i - cR_A - b_B^i \cdot cR_A - b_B^i \cdot c_A^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i} - p_B^i \cdot \frac{-cR_A \cdot a_B^i - c_A^i \cdot a_B^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i} = 0
\end{aligned}
$$

$$\frac{\partial \Pi^i}{\partial p_B^i}$$
$$= -p_A^i \cdot \frac{-a_A^i \cdot c_B^i - a_A^i \cdot cR_B}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i}$$
$$- \frac{b_A^i \cdot c_B^i \cdot p_B^i - b_A^i \cdot cR_B \cdot p_B^j + b_A^i \cdot c_R^B \cdot p_B^i - cR_A \cdot p_A^i \cdot a_B^i - c_A^i \cdot p_A^i \cdot a_B^i + cR_A \cdot p_A^j \cdot a_B^i + B^i - c_B^i \cdot p_B^i + cR_B \cdot p_B^j - cR_B \cdot p_B^i - b_A^i \cdot B^i + A^i \cdot a_B^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i}$$
$$- p_B^i \cdot \frac{b_A^i \cdot c_B^i + b_A^i \cdot cR_B - c_B^i - cR_B}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i} = 0$$

$$\frac{\partial \Pi^j}{\partial p_A^j}$$
$$= -\frac{a_A^j \cdot B^j - a_A^j \cdot c_B^j \cdot p_B^j + a_A^j \cdot cR_B \cdot p_B^i - a_A^j \cdot cR_B \cdot p_B^j + A^j - c_A^j \cdot p_A^j + cR_A \cdot p_A^i - cR_A \cdot p_A^j + b_B^j \cdot cR_A \cdot p_A^i - b_B^j \cdot cR_A \cdot p_A^j + b_B^j \cdot A_j - b_B^j \cdot c_A^j \cdot p_A^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j}$$
$$- p_A^j \cdot \frac{-c_A^j - cR_A - b_B^j \cdot cR_A - b_B^j \cdot c_A^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j} - p_B^j \cdot \frac{-cR_A \cdot a_B^j - c_A^j \cdot a_B^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j} = 0$$

$$\frac{\partial \Pi^j}{\partial p_B^j}:$$
$$= -p_A^j \cdot \frac{-a_A^j \cdot c_B^j - a_A^j \cdot cR_B}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j}$$
$$- \frac{b_A^j \cdot c_B^j \cdot p_B^j - b_A^j \cdot cR_B \cdot p_B^i + b_A^j \cdot cR_B \cdot p_B^j - cR_A \cdot p_A^j \cdot a_B^j - c_A^j \cdot p_A^j \cdot a_B^j + cR_A \cdot p_A^i \cdot a_B^j + B^j - c_B^j \cdot p_B^j + cR_B \cdot p_B^i - cR_B \cdot p_B^j - b_A^j \cdot B^j + A^j \cdot a_B^j}{aAj \backslash cdot\ aBj - 1 + bAj - bBj + bBj \backslash cdot\ bAj}$$
$$- p_B^j \cdot \frac{b_A^j \cdot c_B^j + b_A^j \cdot cR_B - c_B^j - cR_B}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j} = 0$$

Rearranging these equations to the respective price leads to the best response functions of the platforms. However, the expressions become even more complicated (especially the resulting equilibrium prices). Therefore we give the best response functions for the specific parameterization that is provided in the following Table.

Treatment	A	B	a_A^i	a_A^j	a_B^i	a_B^j	$b_A = b_B$	c_A	c_B	$cR_A = cR_B$
symmetric (*sym*)	10	2	0.6		0.8		0.1	0.5	0.3	0.5
asymmetric (*asym*)	10	2	0.6	0.4	0.7	0.984	0.1	0.5	0.3	0.5
double asymmetric (*d-asym*)	10	2	0.01	0.92	0.99	0.2	0.1	0.5	0.3	0.5

With these values the best response functions of Treatment *sym* are:

$$p_A^i = \frac{785}{239} + \frac{175}{956} \cdot p_A^j - \frac{45}{478} \cdot p_B^j$$
$$p_B^i = \frac{3715}{956} + \frac{55}{478} \cdot p_A^j + \frac{1515}{3824} \cdot p_B^j$$
$$p_A^j = \frac{785}{239} + \frac{175}{956} \cdot p_A^i - \frac{45}{478} \cdot p_B^i$$
$$p_B^j = \frac{3715}{956} + \frac{55}{478} \cdot p_A^i + \frac{1515}{3824} \cdot p_B^i$$

Thus the equilibrium prices (rounded to one decimal place) of Treatment *sym* are $p_A^i = p_A^j = 3.2$ and $p_B^i = p_B^j = 7.0$.

The best response functions of Treatment *asym* are:

$$p_A^i = \frac{17960}{4439} + \frac{1895}{8878} \cdot p_A^j - \frac{495}{8878} \cdot p_B^j$$
$$p_B^i = \frac{12410}{4439} + \frac{605}{8878} \cdot p_A^j + \frac{1590}{4439} \cdot p_B^j$$
$$p_A^j = \frac{28335}{22931} + \frac{4701}{45862} \cdot p_A^i - \frac{18675}{91724} \cdot p_B^i$$
$$p_B^j = \frac{159700}{22931} + \frac{22825}{91724} \cdot p_A^i + \frac{45575}{91724} \cdot p_B^i$$

Equilibrium prices (rounded to one decimal place) in Treatment *asym* are $p_A^i = 3.5$, $p_A^j = 0.2$, $p_B^i = 6.8$ and $p_B^j = 11.2$.

The best response functions of Treatment *d-asym* are:

$$p_A^i = \frac{1048050}{542999} + \frac{148995}{1085998} \cdot p_A^j - \frac{110475}{542999} \cdot p_B^j$$
$$p_B^i = \frac{3685510}{542999} + \frac{135025}{542999} \cdot p_A^j + \frac{492505}{1085998} \cdot p_B^j$$
$$p_A^j = \frac{25925}{3979} + \frac{2425}{7958} \cdot p_A^i + \frac{1675}{15916} \cdot p_B^i$$
$$p_B^j = -\frac{57160}{35811} - \frac{18425}{143244} \cdot p_A^i + \frac{3885}{15916} \cdot p_B^i$$

Equilibrium prices (rounded to one decimal place) in Treatment *d-asym* are $p_A^i = 3.0$, $p_A^j = 8.4$, $p_B^i = 9.0$ and $p_B^j = 0.2$.

For calculating the collusion prices the profit function of platform i and the profit function of platform j must be summed up. The joint profit function is given by:

$$\Pi^{ij} = -p_A^i \cdot \frac{a_A^i \cdot B^i - a_A^i \cdot c_B^i \cdot p_B^i + a_A^i \cdot cR_B \cdot p_B^j - a_A^i \cdot cR_B \cdot p_B^i + A^i - c_A^i \cdot p_A^i + cR_A \cdot p_A^j - cR_A \cdot p_A^i + b_B^i \cdot cR_A \cdot p_A^j - b_B^i \cdot cR_A \cdot p_A^i + b_B^i \cdot A^i - b_B^i \cdot c_A^i \cdot p_A^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i}$$
$$- p_B^i \cdot \frac{b_A^i \cdot c_B^i \cdot p_B^i - b_A^i \cdot cR_B \cdot p_B^j + b_A^i \cdot cR_B \cdot p_B^i - cR_A \cdot p_A^i \cdot a_B^i - c_A^i \cdot p_A^i \cdot a_B^i + cR_A \cdot p_A^j \cdot a_B^i + B^i - b_A^i \cdot B^i - c_B^i \cdot p_B^i + cR_B \cdot p_B^j - cR_B \cdot p_B^i + A^i \cdot a_B^i}{a_A^i \cdot a_B^i - 1 + b_A^i - b_B^i + b_B^i \cdot b_A^i}$$
$$- p_A^j \cdot \frac{a_A^j \cdot Bj - a_A^j \cdot c_B^j \cdot p_B^j + a_A^j \cdot cR_B \cdot p_B^i - aAj \cdot cR_B \cdot p_B^j + A^j - c_A^j \cdot p_A^j + cR_A \cdot p_A^i - cR_A \cdot p_A^j + b_B^j \cdot cR_A \cdot p_A^i - b_B^j \cdot cR_A \cdot p_A^j + b_B^j \cdot A^j - b_B^j \cdot c_A^j \cdot p_A^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j}$$
$$- p_B^j \cdot \frac{B^j + b_A^j \cdot c_B^j \cdot p_B^j - b_A^j \cdot cR_B \cdot p_B^i + b_A^j \cdot cR_B \cdot p_B^j - cR_A \cdot p_A^j \cdot a_B^j - c_A^j \cdot p_A^j \cdot a_B^j + cR_A \cdot p_A^i \cdot a_B^j - b_A^j \cdot B^j - c_B^j \cdot p_B^j + cR_B \cdot p_B^i - cR_B \cdot p_B^j + A^j \cdot a_B^j}{a_A^j \cdot a_B^j - 1 + b_A^j - b_B^j + b_B^j \cdot b_A^j}$$

With this function the collusive prices that maximize the total profit can be determined. Since we only allowed prices greater than or equal to 0 in the experiment, the maximization for Treatment *asym* must be done under the constraint that all four prizes must be greater than or equal to 0. Without this constraint, one collusive price in Treatment *asym* would be negative. The result of the maximization can be seen in Table 2. We abstain from presenting further calculation steps.

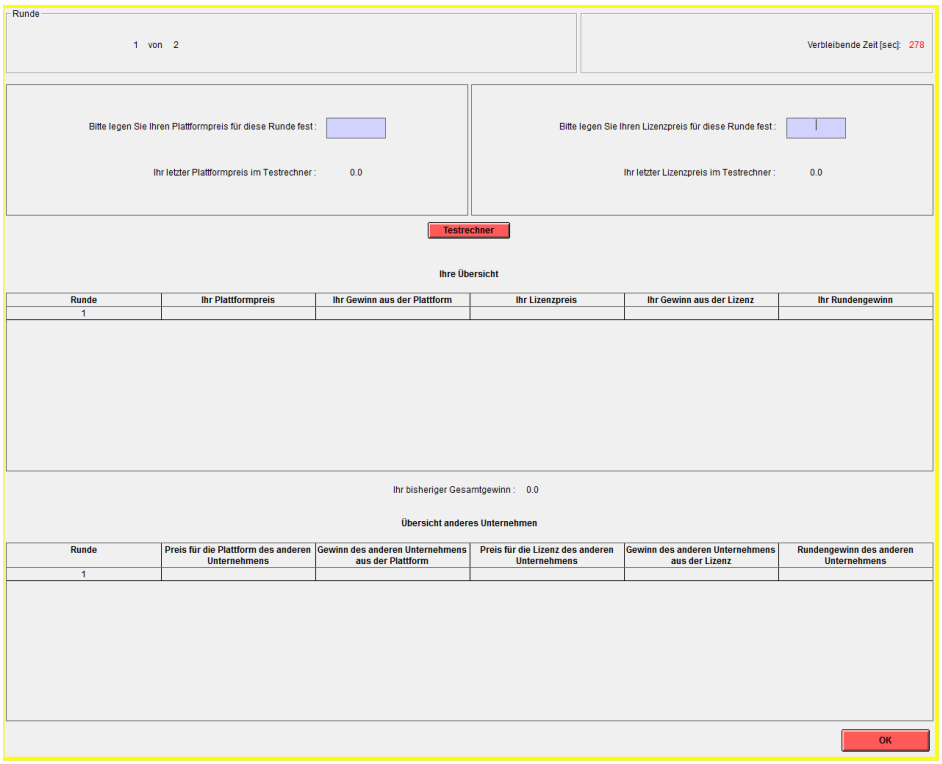

Figure 13: Example screen of the pricing stage

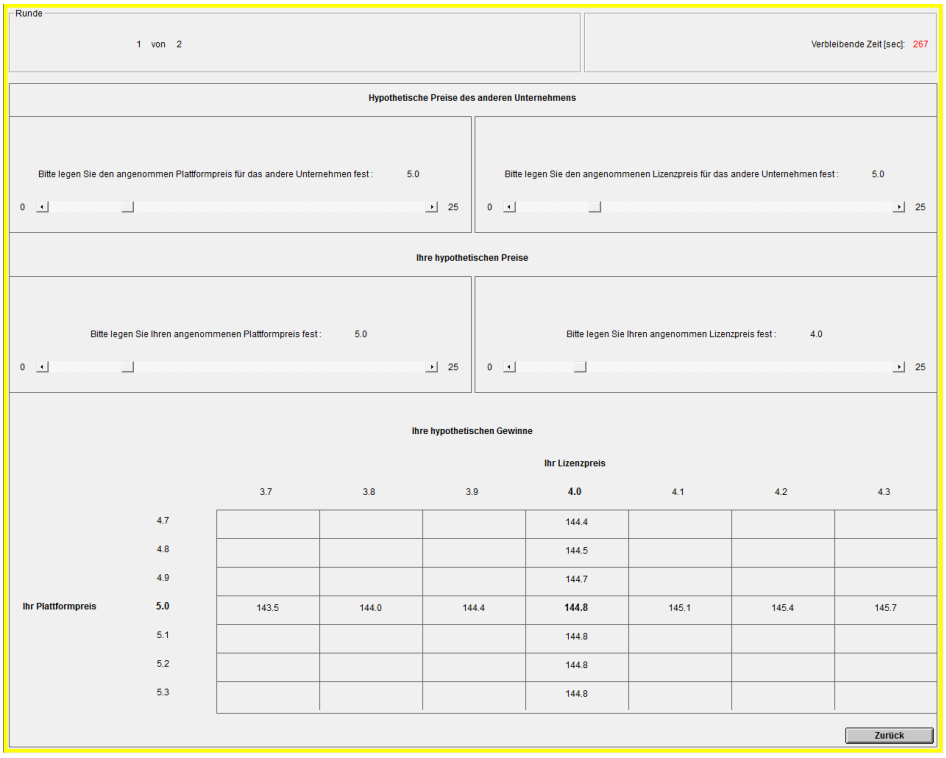

Figure 14: Example screen of calculator

Experiment-Anleitung

Sie nehmen an einem wirtschaftswissenschaftlichen Entscheidungsexperiment teil. In diesem Experiment können Sie bares Geld verdienen. Wie viel Sie verdienen, hängt von Ihren Entscheidungen und den Entscheidungen einer anderen Person im Experiment ab. Alle Teilnehmer*innen treffen ihre Entscheidungen individuell und isoliert von den anderen am Computer. Wir bitten Sie von nun an nicht mehr mit anderen Teilnehmer*innen zu sprechen.

Das Experiment läuft über **15** Runden. Zu Beginn des Experiments werden Sie zufällig **einer** anderen Person zugeordnet, mit der Sie während des gesamten Experiments interagieren. Die Identität dieser Person wird Ihnen dabei zu keinem Zeitpunkt bekannt.

Die Entscheidungen

Sie und die andere Person repräsentieren zwei unabhängige Unternehmen, die jeweils eine Spielekonsole herstellen, auf der zwei Kundengruppen, Spieler und Entwickler, zusammengebracht werden. Spieler kaufen Ihre Spielekonsole als Plattform zur Wiedergabe von Spielesoftware, die von Entwicklern angeboten wird. Letztere benötigen eine Lizenz, um entsprechende Software für Ihre Spielekonsole entwickeln zu dürfen. **In jeder Runde setzen Sie für jede der beiden Kundengruppen Ihrer Spielekonsole jeweils einen Preis, d.h. einen *Plattformpreis* (Spieler) und einen *Lizenzpreis* (Entwickler).** Die Preissetzung beider Unternehmen erfolgt in jeder Runde gleichzeitig.

Die Nachfrage einer Kundengruppe nach Ihrer Spielekonsole hängt jeweils von Ihrem Preis und dem Preis des anderen Unternehmens für diese Kundengruppe sowie von der Nachfrage der anderen Kundengruppe nach Ihrer Spielekonsole ab.

Grundsätzlich gilt, dass die **Nachfrage der Spieler nach Ihrer Plattform** umso **höher** ist,

- je niedriger *Ihr Plattformpreis*
- je niedriger *Ihr Plattformpreis* relativ zum Preis der anderen Plattform
- je höher die Nachfrage der Entwickler nach Ihrer Lizenz

Darüber hinaus gilt, dass man Spieler umso **mehr** an Ihre Plattform binden kann, je mehr andere Spieler Ihre Plattform ebenfalls nachfragen.

Diese Zusammenhänge gelten auch für das andere Unternehmen und dessen Plattform.

Für die **Nachfrage der Entwickler nach Ihrer Lizenz** gilt, dass sie umso **höher** ist,

- je niedriger *Ihr Lizenzpreis*
- je niedriger *Ihr Lizenzpreis* relativ zum Preis der Lizenz des anderen Unternehmens
- je höher die Nachfrage der Spieler nach Ihrer Plattform

Darüber hinaus gilt, dass man Entwickler umso **weniger** vom Kauf der Lizenz für Ihre Plattform überzeugen kann, je mehr andere Entwickler die Lizenz nachfragen.

Diese Zusammenhänge gelten auch für das andere Unternehmen und dessen Plattform.

Beachten Sie, dass Spieler und Entwickler sofort auf die Preise reagieren, so dass deren Nachfragen nicht von Preisen in den Vorrunden abhängen. Falls in einer Runde für ein Unternehmen die Nachfrage einer Kundengruppe negativ werden sollte, wird die Nachfrage beider Kundengruppen dieses Unternehmens auf null gesetzt und das betroffene Unternehmen nimmt in dieser Runde nicht am Markt teil.

Ihre **Gewinne** berechnen sich in jeder Runde wie folgt:

Rundengewinn = Plattformgewinn + Lizenzgewinn

= Plattformpreis x Plattformnachfrage + Lizenzpreis x Lizenznachfrage

Testrechner: Sie haben die Möglichkeit Ihre Gewinne für hypothetische Preise zu berechnen (*Plattform*- und *Lizenzpreis des anderen Unternehmens, Ihr Plattformpreis*, *Ihr Lizenzpreis*). Dafür stellen wir Ihnen einen *Testrechner* zur Verfügung. Zum Aufrufen betätigen Sie bitte die <Testrechner>-Taste. Auf dem nun eingeblendeten Bildschirm nutzen Sie die Schieberegler in der oberen Hälfte des Bildschirms, um alle hypothetischen Preise für beide Unternehmen festzulegen. In der unteren Hälfte des Bildschirms wird in einer Tabelle Ihr Rundengewinn für die von Ihnen gesetzte Preiskombination angezeigt. Zu Ihrer Übersicht werden in der Tabelle die Rundengewinne angrenzender Preiskombinationen mit ausgewiesen (jeweils Abweichungen von $\pm$ 0.1, 0.2 und 0.3 in einem der beiden Preise). Um auf den Entscheidungsbildschirm zurückzukehren, betätigen Sie die <Zurück>-Taste.

In den ersten zwei Runden haben Sie maximal fünf und danach in jeder Runde maximal drei Minuten Zeit für die Nutzung des Testrechners. Danach schaltet er sich automatisch ab. Sobald Sie Ihre Preisentscheidungen getroffen haben, klicken Sie bitte auf die <OK>-Taste. Danach werden Sie zu einer Bestätigung Ihrer Eingabe angehalten.

Auszahlung

Die Gewinne werden über alle **15** Runden aufaddiert. Dieser Gesamtgewinn wird mit einem Wechselkurs von 0.007 (in Treatment *sym und asym*) / von 0.01 (in Treatment d-asym) in Euro umgerechnet und zuzüglich einer Teilnahmevergütung von 3 Euro ausbezahlt. Die Auszahlung erfolgt **am Ende des Experiments** individuell und anonym.

Verfügbare Informationen

In jeder Runde verfügen Sie auf Ihrem Bildschirm über eine Übersichtstabelle mit den Ergebnissen aller bisher abgeschlossenen Runden. Die Ergebnisse umfassen jeweils folgende Information:

Ihr Plattformpreis, Ihr Plattformgewinn, Ihr Lizenzpreis, Ihr Lizenzgewinn, Ihr Rundengewinn sowie Preise und Gewinne des anderen Unternehmens.

Falls Sie sich das Ergebnis länger zurück liegender Runden betrachten wollen, können Sie die Scroll-Funktion auf der rechten Seite der Übersichtstabelle benutzen.

Wenn Sie nun auf die <Weiter>-Taste klicken, werden Ihnen auf dem Bildschirm einige Fragen zum Verständnis dieser Anleitung gestellt. Erst wenn alle Teilnehmer alle Fragen korrekt beantwortet haben, kann das Experiment beginnen. Bei Verständnisfragen bezüglich der Anleitungen machen Sie sich bitte per Handzeichen bemerkbar. Ihre Fragen werden dann am Platz beantwortet.