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PQ Strategies in Monopolistic Competition: Some Insights from the Lab

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Abstract

We present results from 50-rounds experimental markets in which firms decide repeatedly both on price and quantity of a perishable good. The experiment is designed to study the price-quantity setting behavior of subjects acting as firms in monopolistic competition. In the implemented treatments subjects are asked to make both production and pricing decisions given different information sets. We investigate how subjects decide on prices and quantities in response to signals from the firms' internal conditions, i.e., individual profits, excess demand, and excess supply, and the market environment, i.e., aggregate price level. We find persistent heterogeneity in individual behavior, with about 46% of market followers, 28% profit-adjusters and 26% demand adjusters. Nevertheless, prices and quantities tend to converge to the monopolistically competitive equilibrium and that subjects' behavior is well described by learning heuristics.

JEL codes: TBD

Keywords: Market experiments; Price-Quantity competition.

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1 Introduction

Traditionally two main frameworks to describe firms' competition can be distinguished. Cournot competition refers to the case when firms decide the quantity of the good they produce and then prices adjust such that the markets clear. On the contrary, a framework in which the selling price represents the strategic variable for the firm and quantities clear the markets is referred to as Bertrand competition. Both Cournot and Bertrand competition have been widely studied theoretically and by means of economic experiments.

However, economic frameworks characterized by only pure strategies do not describe all possible market scenarios. In fact in practice prices are usually determined by firms and not through some market clearing mechanism and it may happen that firms are not always able to satisfy the market demand at a given price. Moreover, the production process might take some time, hence firms need to carry on production in advance and they cannot react immediately to a possible increase in the demand. Moreover, it is reasonable to think that firms, when strategically interacting with competitors are indeed facing a simultaneous price-quantity decision problem. Starting from Shubik (1955) a wide strand of economic literature on price-quantity competition has been developed. Price-quantity competition models within an oligopolistic set up can be distinguished into three main classes. The first refers to those frameworks in which firms face price competition under a capacity limitation constraint (see e.g. Levitan and Shubik (1972); Osborne and Pitchik (1986); Maskin (1986)). The second category is described by a framework in which firms set price and quantity through sequential choices. Some examples can be found in Kreps and Scheinkman (1983) and Friedman (1988). Finally, the third category, known as PQ games (Price-Quantity games), develops a set up in which a firm has to decide simultaneously on prices and quantities. In particular, firms face price competition in an economic framework with perishable goods and production in advance (see e.g. Levitan and Shubik (1978); Gertner (1986)).

The present paper develops an economic experiment within a monopolistically competitive market along the PQ games approach. Price-quantity competition has also been analyzed in economic experiments. Brandts and Guillen (2007) conduct an experiment in which groups of two or three subjects form a market of a homogeneous, perishable good. The market demand and the marginal cost of production is constant. Both with two and three firms, the typical patterns that occur are collusion after a few periods, constant fights, and collusive price after a fighting phase (possibly due to bankruptcy). The average price shows an increasing patter in both treatments. Cracau and Franz (2012) compare the subjects' actions with the unique mixed-strategy Nash equilibrium in a duopoly with a homogeneous good, linear demand and constant marginal costs. They find evidence that subjects do not play according to the mixed-strategy Nash equilibrium: prices depend on the outcome of the previous round (whether the subject had the lowest price or not), subjects produce less than the market demand at the price they charge and they make positive profits on average. The average price is more or less constant during the experiment. Both papers analyse price-quantity competition in oligopolistic markets. Davis and Korenok (2011) implement a monopolistically competitive experimental market in order to examine the capacity of price and information frictions to explain real responses to nominal price shocks. In their experiment, subjects were acting as firms setting prices in monopolistic competition with a known demand function.

Monopolistic price-quantity competition as described in Dixit and Stiglitz (1977) and Blanchard and Kiyotaki (1987) also plays an important role in modern macroeconomics, e.g. in the New Keyenesian framework (see e.g. Woodford (2003)), but also in agent-based macro models (e.g. Delli Gatti, Desiderio, Gaffeo, Cirillo, and Gallegati (2011)). In agent-based macro models one has to make assumptions about the firms' individual price-quantity decision rules in a monopolistic competition setting. An important goal of our paper is to use a macro experiments to obtain empirical evidence about price-quantity decision rules. Two main questions that we want to address are:

- Does aggregate market and individual firm behaviour in the experiment converge to the monopolistically competitive outcome in a more complicated market environment, i.e., without knowledge of the demand function and with production set in advance?

- What are the price-quantity setting strategies used by the subjects in response to signals from the firms internal conditions, i.e., individual profits, excess demand, excess supply, and the market environment, i.e., aggregate price level, as well as in the impact of different information sets on the market outcome?

The two research questions outlined above are functional to the final goal of our experiment that consists in deriving price-quantity strategies by means of experimental data on subjects acting as firms in a monopolistically competitive market.

Macro experiments to study simultaneously individual decision rules, their interactions and the emerging aggregate outcome are becoming increasingly important, see e.g. the survey in Duffy (2008). Our strategy to fit simple first-order heuristics to individual price-quantity decisions and explain aggregate market behavior as the emerging outcome is similar to the work on learning-to-forecast experiments (see Hommes (2011) for an overview).

The remainder of the paper is organized as follows. Section 2 reviews the theoretical benchmarks, describes the experimental setting and presents the results of the experimental markets. Section 3 analyses individual price-quantity setting behavior. Section 4 evaluates the impact of individual strategies on aggregate outcomes. Section 5 concludes.

2 The price-quantity setting experiment

In the following section we will describe the theoretical framework underlying the experiment (in subsection 2.1), the experimental design (in subsection 2.2) and the experimental results (in subsection 2.3).

2.1 Monopolistically competitive market

The market structure underlying our experiment is a variant of the standard monopolistically competitive market structure described by Dixit and Stiglitz (1977) and Blanchard and Kiyotaki (1987) among others. We consider a market with n firms, where each firm i offers a differentiated product at a price p_i with common constant marginal costs c. The demand for good i is linear and given by

$$q_i = \alpha - \beta p_i + \theta \overline{p} \,, \tag{2.1}$$

where $\overline{p}$ is the average market price, $\alpha > 0$ and $\beta > \theta/n > 0$.[1] We simplify standard models of monopolistic competition by specifying a linear demand function.[2] Several experimental studies on market with differentiated products use linear demand, e.g., Huck, Normann, and Oechssler (2000), Davis (2002), and Davis and Korenok (2011). Under the assumption of known demand function, the first order condition for the firms' profit maximization leads to the following best reply function:

$$p^{BR} = \alpha' + c/2 + \theta' \overline{p} \,, \tag{2.2}$$

where $\alpha' = \alpha/2\beta$ and $\theta' = \theta/2\beta$. Invoking symmetry we can solve for the monopolistically competitive equilibrium price (MC)

$$p^{MC} = \frac{1}{1-\theta'} \left(\alpha' + \frac{c}{2} \right) \,. \tag{2.3}$$

[1] The restriction on the parameters ensures that demand depends negatively on the firms' own price and positively on the average market price, as in standard treatment of monopolistically competitive markets (see, e.g., Blanchard and Kiyotaki (1987)).

[2] Consumers' demand is linear when they have quadratic utility over the differentiated products, see e.g., Vives (1999).

The standard model of monopolistic competition assumes atomistic dimensions of firms, meaning that strategic considerations do not affect optimal price choices. However, given the limited numbers of firms present in experimental markets, sellers may view their pricing decisions as having some impact on the average market price. Therefore, following Davis and Korenok (2011), we also present the Nash equilibrium price (NE) as a second benchmark market outcome, given by

$$p^{NE} = \frac{1}{1-\theta^n}\left(\alpha^n + \frac{c}{2}\right) , \tag{2.4}$$

where $\alpha^n = (\alpha n/2(n\beta - \theta))$ and $\theta^n = (\theta(n-1)/2(n\beta - \theta))$.[3] Notice however that, even in the presence of a limited amount of firms in the market, ten in our case, the monopolistically competitive and Nash equilibrium price are quite close. For the sake of completeness, we also present two alternative theoretical benchmarks, namely the Walrasian outcome (W) in which myopic undercut of other firms' prices leads to the Walrasian price (p^W) equal to the marginal costs (c), i.e. $p^W = c$, and the collusive outcome (CO) in which joint profit maximization gives the collusive price level p^{CO}, i.e.:

$$p^{CO} = \frac{c}{2} + \frac{\alpha'}{1-2\theta'} \, .$$

2.2 Experimental design

In our experiment, each market consists of 10 firms with identical cost structure choosing prices and quantities simultaneously and repeatedly for 50 periods. At the beginning of each period, firms are endowed with symmetrically differentiated *perishable* products, whose demand is identified by Eq. (2.1). The first difference with the theoretical benchmark outlined in Section 2.1 is the fact that subjects do *not* know the exact specification of the demand function (2.1). Firms in our experimental markets are only endowed with qualitative information about the

[3] See Davis and Korenok (2011) for details.

Variable	MC	NE	W	CO
p	12	12.3	8	22
q	7	6.9	8.17	4

Table 1: Benchmark equilibrium values for price and quantity in Monopolistic Competition (MC), Nash Equilibrium (NE), Walrasian equilibrium (W) and Collusive equilibrium (CO)

market structure, but they do not know neither the exact value of the structural coefficients α, β, and θ, nor the functional form of the demand for their product. The second important difference is the fact that subjects have to decide upon their production level in advance, i.e., before market demand is realized. This important feature of our experimental design, together with the assumption that goods are perishable, implies that bankruptcy might happen in the experiment. Given that production is decided in advance, firms can go bankrupt if they set a price too high so that part or all the production remain unsold and lost. The main idea behind the design is to understand whether subjects (acting as firms) in the experiment converge to the monopolistically competitive outcome in a more complicated market environment, i.e., without knowledge of the demand function and with production set in advance. Moreover, we are interested in analyzing the price-quantity setting strategies used by the subjects in response to signals from the firms' internal conditions, i.e., individual profits, excess demand, excess supply, and the market environment, i.e., aggregate price level, as well as in the impact of different information sets on the market outcome.

Treatments

The experiment consists of 8 markets, divided into two 4-markets treatments. In all sessions of the experiment we fixed parameters at $\alpha = 10.5$, $\beta = 1.75$, $\theta = 1.45833$, and $c = 8$, so that the benchmark equilibrium values are those summarized in table 1. In the first 4-markets treatment subjects are asked to decided upon the quantity to produce and the selling price. When submitting their price-quantity decisions in each period t, they observe their own price, the average market price, their quantities, their sales, their profits and their excess supply up to and including period $t-1$. Moreover, given that the expected average price might be an important variable in deciding both how much to produce and at which price to sell, we explicitly ask subjects in each period to submit a forecast of the average market price for that period. Notice that in treatment 1 firms observe their "positive" excess supply, i.e., the difference between the quantity produced and their sales. Hence subjects do not have information about "negative" excess supply, i.e., excess demand.

The second 4-markets treatment has the same decision and informational structure of treatment 1, with the only exception being that firms can now observe also the excess demand. Therefore in treatment 2 subjects also have information about the portion of demand they were not able to satisfy given their price and quantity decisions and the average market price.

Distinguishing between treatment 1 and treatment 2 allows us to assess the impact of alternative information sets and, ultimately, different market structures (one in which it is possible to observe excess demand and another in which it is only possible to observe eventual involuntary inventories) on the market outcome.

Procedures

The experiment took place at the CREED laboratory at the University of Amsterdam, March 2013. Data were collected in a series of 20- and 30-participants sessions. Subjects are randomly assigned at visually isolated computers to form the 10-firms markets.[4] At the beginning of each session subjects are given the experimental instructions. Participants are instructed about their role as firms in a market, with the task of producing and selling a certain good for 50 periods, and they are given *qualitative* information about the market structure. Firms have to choose a quantity to produce between 0 and 40, and at the same time they decide upon a price between 0 and 30. There was a constant cost of 8 ECU

[4]Notice that subjects were not informed about the size of each market

(Experimental Count Units) per unit produced. Subjects' earnings are given by realized cumulated profits at the end of the experiment. In order to accommodate possible losses, we granted subjects an initial endowment of 500 ECU. If a firm's capital balance became negative, it was considered bankrupted. The owners of bankrupted firms were forced to wait until the end of the experiment in order to preserve anonymity. Finally, in an effort to measure the expectation formation process of individual firms and measure the impact of expected average price on individual price-quantity strategies, we explicitly ask subjects to submit predictions for the average market price in each period. If a firm's forecast lies within 1 ECU of the subsequently observed market price, the firm earns a forecast prize of 0.10 €. Otherwise the forecast prize is zero. Earnings from the forecasting game supplement the market earnings paid to subjects at the end of the experiment in euros at a rate 75 ECU = 1 €. The experimental instructions together with an example of the screenshot visualized by the participants in the experiment can be found in appendix A.

2.3 Experimental results

This subsection describes the results of the experiment. Figs. 1 and 2 depict the behavior of individual prices and quantities together with the average market price and the average production respectively in treatment 1 and treatment 2. The dashed lines in the figures represent the monopolistically competitive equilibria for price and quantity.

In both treatments we observe a slow convergence of average prices and quantities to (a neighborhood of) the MC benchmark. A common feature to all experimental markets is an initial phase of decreasing prices and quantities. In fact, at the beginning of the experiment subjects' decisions tend to cluster around a focal point, i.e., the middle of the interval of feasible prices and quantities. In this initial learning phase several firms set prices which are too high relatively to the average price, experiencing low demand and thus making losses. Consequently, such firms

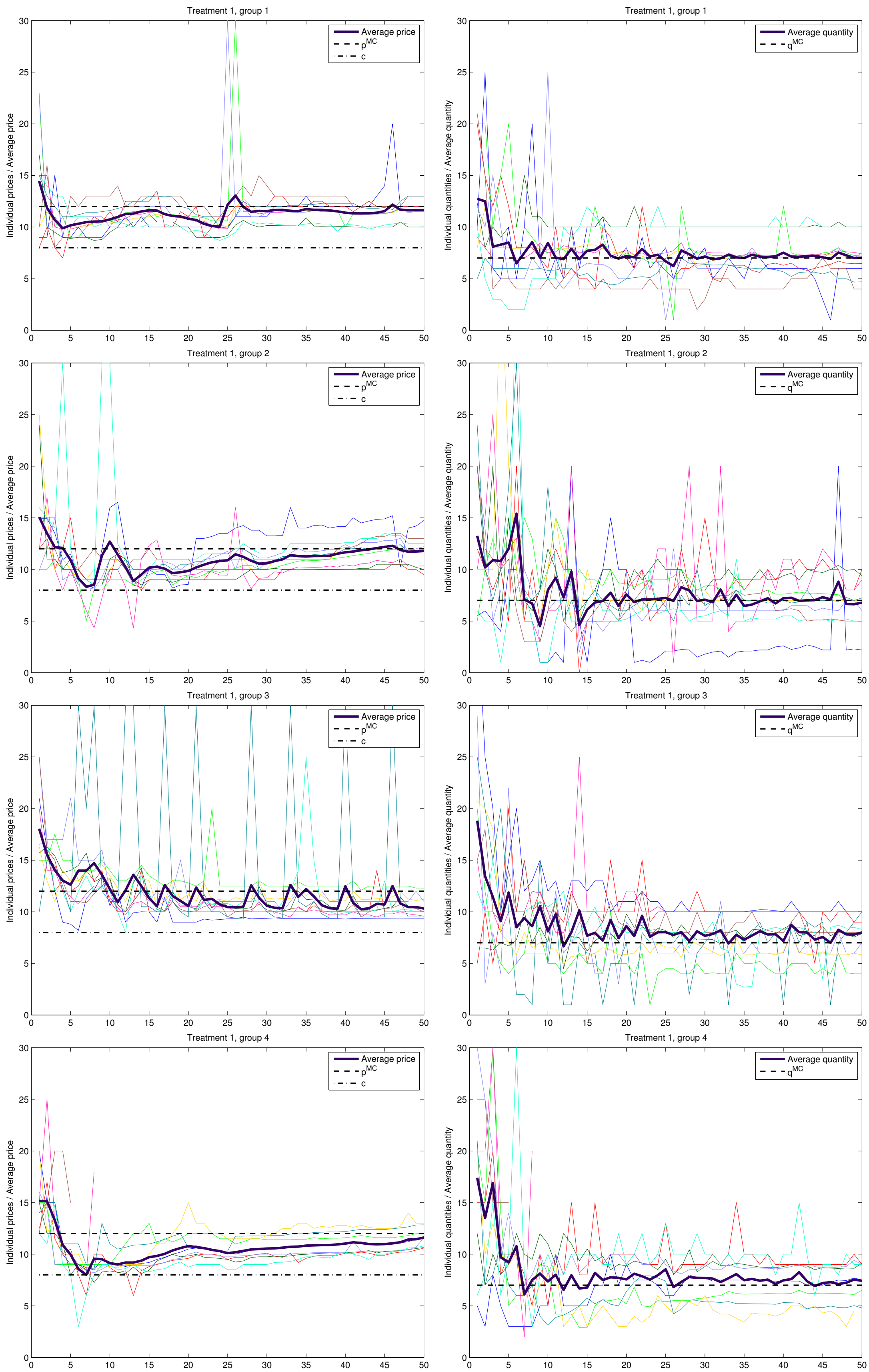


Figure 1: Treatment 1. **Left panels:** Individual prices (thin lines) and aggregate price (thick line). **Right panels:** Individual quantities (thin lines) and average quantity (thick line)

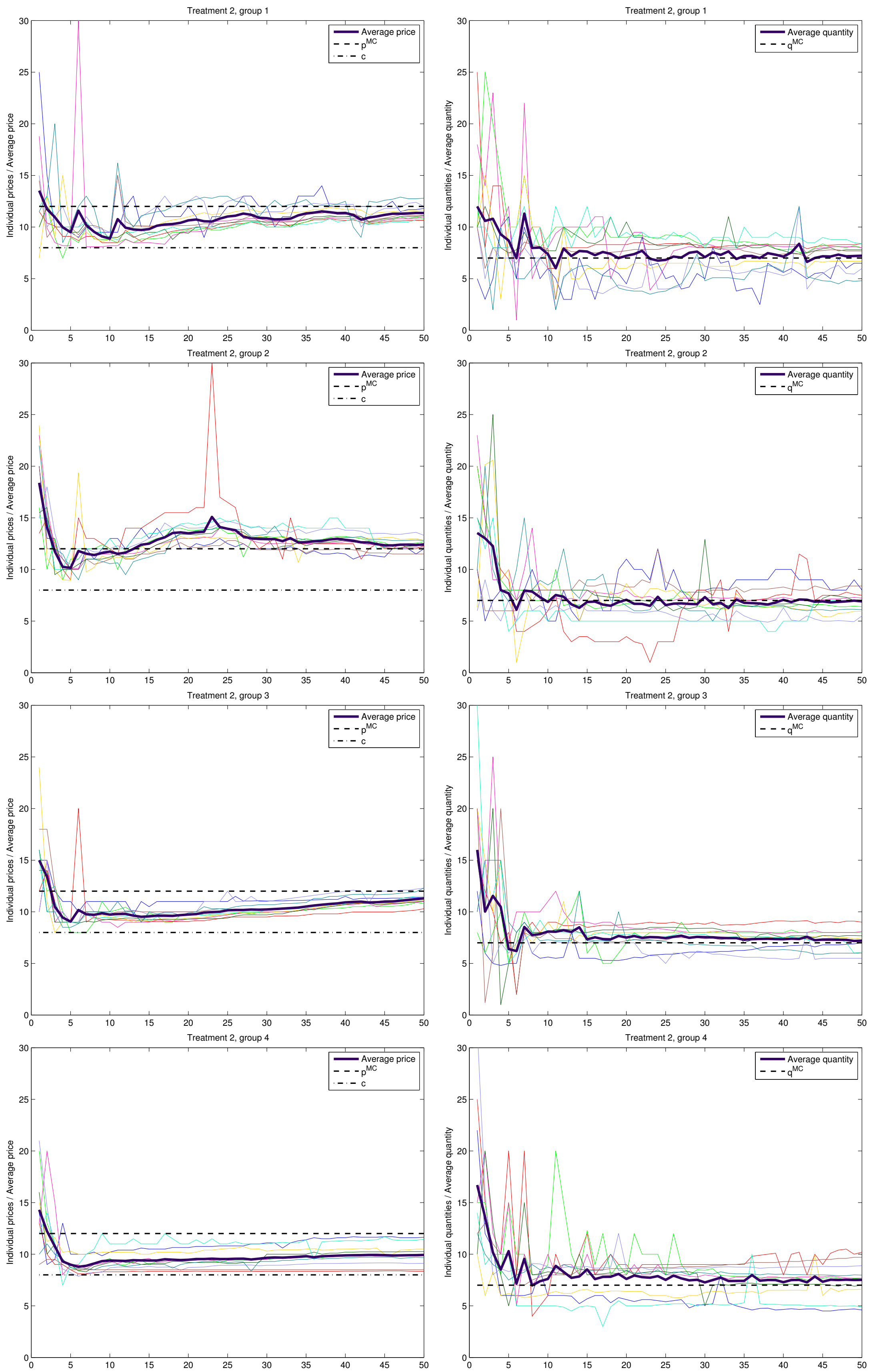


Figure 2: Treatment 2. **Left panels:** Individual prices (thin lines) and aggregate price (thick line). **Right panels:** Individual quantities (thin lines) and average quantity (thick line)

start cutting their prices causing therefore a decrease in the average market price. This behavior explains the observed negative trend in initial prices. Individual production is also adjusted to accommodate demand, on the basis of observed excess supply (and excess demand in case of treatment 2). As the experiment proceeds and subjects learn about the market, the downward trend in prices is reversed before subjects reach the Walrasian outcome and prices tend to converge slowly to the MC equilibrium from below[5]. The evolution of average profits over time in both treatment 1 and treatment 2, represented in the left panel of Fig. 3, confirms these learning dynamics.

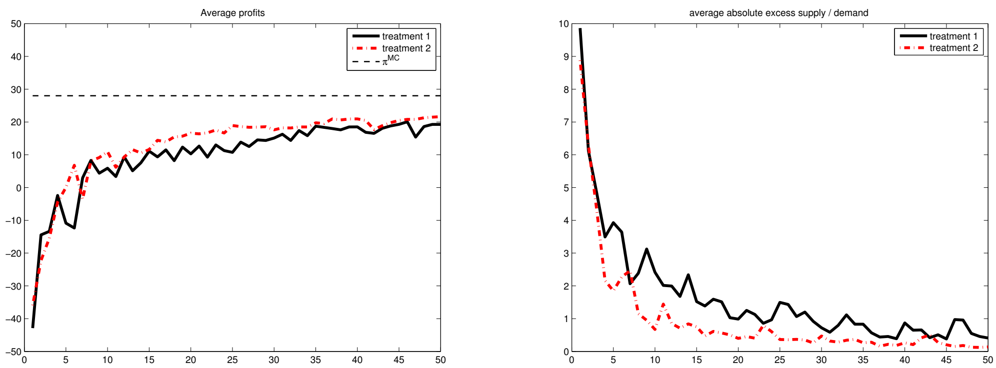


Figure 3: **Left panel:** Evolution of average profits compared to MC equilibrium profits. **Right panel:** Evolution of the absolute value of the excess supply / demand. In the case of treatment 1 we included in the plot the unobserved excess demand component.

Exceptions to these stylized dynamics are represented by group 3 in treatment 1 and group 2 in treatment 2. In the former, the price dynamics follow an oscillatory pattern due to one subject strategically setting the maximum price in several periods in the attempt to increase the market price (see Fig. 1). In the latter, after the initial learning phase, subjects coordinate on an upward trend in prices, causing the market price to increase beyond the MC equilibrium level. However, after 23 periods this trend is reversed since equilibria above the MC price are unstable due to the individual incentive to reduce the price in order to increase profits, and this causes prices to converge to the stable MC equilibrium from above.

[5] In treatment 1, groups 2 and 4, the minimum realized price is close to the Walrasian equilibrium $p^W = c = 8$.

Comparing treatment 1 and treatment 2 we observe in 3 that average profits are higher in treatment 2 than in treatment 1, and the difference is statistically significant at the 5% level (Mann-Whitney U-test, p-value equal to 0.00). This difference is due to the extra information available to subjects in treatment 2 about excess demand. Fig. 3 also plots the evolution over time of the absolute value of excess supply / demand for treatment 1 and 2.[6] We find a significant difference between the average absolute value of excess supply / demand between treatment 1 and 2 (Mann-Whitney U-test, p-value equal to 0.00), suggesting that subjects use the extra available information and increase their profits.

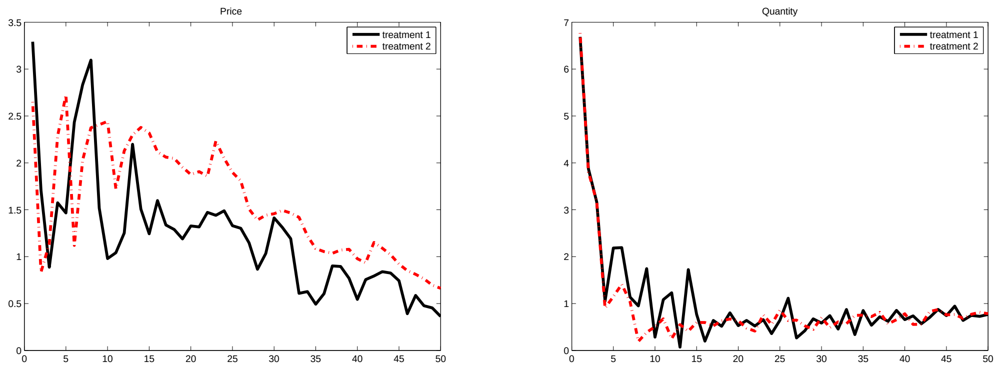


Figure 4: **Left panel:** Median of the absolute difference between the average price and the MC equilibrium price. **Right panel:** Median of the absolute difference between the average quantity and the MC equilibrium quantity.

Convergence of prices and quantities is illustrated in more detail in Fig. 4. The graphs show the median of the absolute difference between the market and the MC equilibrium prices and quantities over the four markets for both treatment 1 and treatment 2. Both variables show convergence to the MC equilibrium. In the case of prices, we observe a higher degree of convergence in treatment 1 when compared to treatment 2, statistically significant at the 5% level (Mann-Whitney U-test, p-value equal to 0.00). In the case of quantities, there is no statistically significant difference in the degree of convergence between treatments (Mann-Whitney U-test, p-value equal to 0.26). Although average prices and quantities show a tendency

[6] In the case of treatment 1 we included in the plot the unobserved excess demand component.

towards equilibrium, there is substantial heterogeneity among the individual price and quantity decisions.

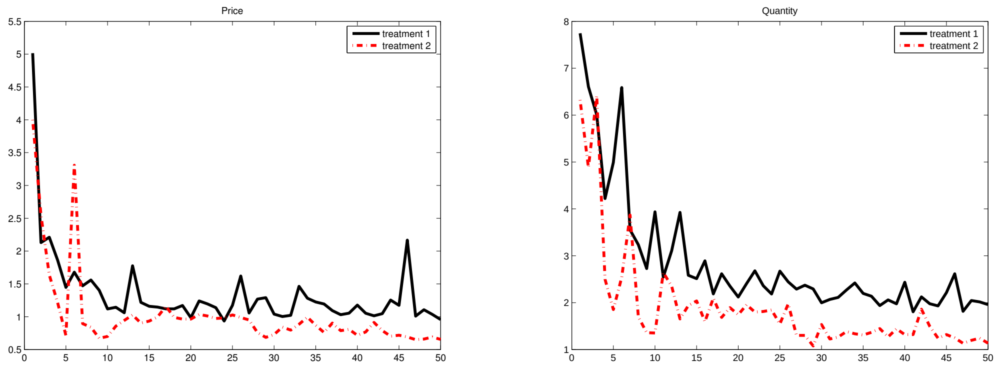


Figure 5: **Left panel:** Median of the standard deviations of individual prices. **Right panel:** Median of the standard deviations of individual quantities.

Fig. 5 shows the median of the standard deviations of individual decisions for each period over the four markets of each treatment. A low standard deviation implies a high level of coordination among the subjects. For both price and quantity, we observe a higher degree of coordination among individual decisions in treatment 2 than in treatment 1 (Mann-Whitney U-test, p-value equal to 0.00 for both price and quantity). Due to additional information subjects are apparently better able to coordinate their price-quantity decisions.

3 Individual PQ strategies

In this section we investigate the price and quantity setting strategies of individual firms as well as their forecasting rules for the market price. We are interested in understanding how subjects decide on prices and quantities in response to signals from the firms' internal conditions, i.e., individual profits, excess supply, excess demand and the market environment, i.e., aggregate price level.

3.1 First-Order Heuristics (FOH)

We started by estimating for each participant general linear behavioral rules including lagged observations of variables in the information set. What emerged from the estimation of these general behavioral rules is that there are some clear regularities across groups and treatments regarding the variables used by the rules and the sign of the coefficients. More specifically, the most popular significant regressor in the estimation of individual forecast of the market price is the last available value of the forecasting objective. This is followed in most groups by either the most recent own prediction or the second last available forecasting objective. In the case of pricing and production strategies, the most popular strategic variables were the expected market price and the most recent decisions on prices and quantities. In the light of the observed stylized facts, we restricted the general behavioral rules along the empirical regularities in order to increase efficiency of the estimates and to make the estimated rules easier to interpret from a behavioral point of view. We fitted First-Order Heuristics (FOH)[7] of the form

$$\overline{p}^{e}_{i,t} = c + \alpha_1 \overline{p}_{t-1} + \alpha_2 \overline{p}^{e}_{i,t-1} + \alpha_3 \overline{p}_{t-2} + \varepsilon_t \tag{3.1}$$

$$p_{i,t} = c + \beta_1 p_{i,t-1} + \beta_2 \overline{p}^{e}_{i,t} + \beta_3 \Pi_{i,t-1} + \beta_4 S_{i,t-1} + u_t \tag{3.2}$$

$$q_{i,t} = c + \gamma_1 q_{i,t-1} + \gamma_2 p_{i,t} + \gamma_3 \overline{p}^{e}_{i,t} + \gamma_4 S_{i,t-1} + \eta_t \tag{3.3}$$

to our experimental data. In eq. (3.1) the variable $\overline{p}$ refers to realisations of the aggregate price, while the variable $\overline{p}^{e}_{i}$ refers to individual forecasts of the aggregate price. In eq. (3.2) the variable p_i refers to individual prices, the variable Π_i is defined as $\Pi_i = \Delta p_i \cdot \mathrm{sgn}(\Delta \pi_i)$, where π_i are individual profits and the Δ is the first order difference operator,[8] while the variable S_i refers to individual excess supply/demand. In eq.(3.3) the variable q_i refers to individual quantity. Eq. (3.1)

[7]For other applications of the FOH in modelling experimental data such as data on expectation formation see e.g., Heemeijer, Hommes, Sonnemans, and Tuinstra (2009) and Assenza, Heemeijer, Hommes, and Massaro (2011).

[8]We also estimated eq. (3.2) using $\Pi_i = \Delta p_i \Delta \pi_i$ as profit feedback measure and estimation results did not change significantly.

can be rewritten as

$$\overline{p}^e_{i,t} = c' + \alpha'_1 \overline{p}_{t-1} + \alpha'_2 \overline{p}^e_{i,t-1} + \alpha'_3 (\overline{p}_{t-1} - \overline{p}_{t-2}) + \varepsilon_t \tag{3.4}$$

and it can be interpreted as an anchoring-and-adjustment heuristic (see Tversky and Kahneman (1974)). The first three terms are a weighted average of the forecasting objective's sample mean, the latest realization of the forecasting objective, and the latest own prediction. This weighted average is the (time varying) "anchor" of the prediction, which is a zeroth order extrapolation from the available data at period t. The fourth term is a simple linear, i.e. first order, extrapolation using the two most recent realizations of the forecasting objective; this term is the "adjustment" or trend extrapolation part of the heuristic. An advantage of the FOH rule is that it simplifies to well-known rules-of-thumb for different boundary values of the parameter space. For example, the price prediction rule reduces to Naive Expectations if $\alpha'_1 = 1$, $c' = \alpha'_2 = \alpha'_3 = 0$, to Adaptive Expectations if $\alpha'_1 + \alpha'_2 = 1$, $c' = \alpha'_3 = 0$, or to Trend Following Expectations if $\alpha_1 = 1$, $c' = \alpha_2 = 0$, $\alpha_3 > 0$. The first three terms in eq. (3.2) represent a simple anchor for the individual pricing decisions. The term Π_i captures individual price adjustments in the direction that led to an increase in profits in the last period. A significant and positive coefficient in eq. (3.2) represents evidence for some sort of gradient learning behavior, as Π_i could be considered as a rough approximation of the (sign of the) slope of the profit function. The last term in the price setting strategy captures price movements in response to the observed past excess supply/demand. The rule in eq. (3.3) includes the past quantity and the expected market price as reference for quantity setting. Moreover, the individual price set in period t included in eq. (3.3) represents an important decisional variable for quantity setting, as it directly influences the demand for the firm's product, while the presence of the last term S_i captures quantity adjustments due to observed past excess supply/demand. Some comments on the explanatory variables included in model (3.1) – (3.3) are in order. The FOH in eq. (3.1) assumes no dependence of individual forecasts of market price on the contemporaneous individual price. This restriction stems from the theoretical setting of monopolistically competitive markets, in which firms are assumed to take the aggregate price as parametric in their decision process, i.e., the firm is assumed not to believe that its price might have a significant influence on the aggregate price.[9] Moreover, the monopolistically competitive market structure reproduced in the experimental markets postulates that prices have an impact on quantities demanded and not viceversa. Therefore, eq. (3.2) assumes no dependence of individual prices on individual quantities. Finally, both contemporaneous individual prices and (expected) average market price are included in eq. (3.3), as this specification nests the real (expected) demand function.

3.2 Estimation results

The econometric procedure adopted to estimate system (3.1) – (3.3) is explained in Appendix B. Tables 4 – 11 in Appendix C report the results of the estimation of the FOH model to individual time series of market price forecasts, pricing and production decisions.

Market price forecasting rules

Overall, 58% of the subjects use the time-varying anchor composed by the first three terms in (3.4), while the remaining 42% augments the anchor with the adjustment term related to the latest observed trend in market prices. Among the subjects using only the anchor component in their forecasting strategy, 29% can be classified as Naive, while 36% can be classified as Adaptive. Among the subjects using both the anchor and the adjustment term, 24% can be classified as Trend Followers.

[9] One might argue that, given the limited number of firms present in the experimental markets, sellers may view their pricing decisions as having some impact on the average market price. However, Huck, Normann, and Oechssler (2004) show, in the context of oligopolistic markets, that a number of firms $n \geq 4$ is enough to eliminate this sort of strategic reasoning and ensure convergence to either Cournot or Walrasian equilibrium.

Price setting rules

The estimation results show that subjects anchor their pricing decision in their past price and in their expected average market price. Deviations from this anchor are related to either past realized profits or past observed excess supply / demand. Only four subjects reacted to both the profit feedback variable Π_i and the excess supply / demand variable S_i. These results suggest clear behavioral strategies that can be classified into *market followers*, i.e., subjects for which $\beta_3 = \beta_4 = 0$, *profit-adjusters*, i.e., subjects for which $\beta_3 > 0$ and $\beta_4 = 0$, and *demand-adjusters*, i.e., subjects for which $\beta_3 = 0$ and $\beta_4 > 0$. Overall, 46% of the subjects are market followers, 28% are profit-adjusters and 26% are demand-adjusters.

Quantity setting rules

The quantity setting strategies clearly depend negatively on individual pricing decisions and positively on the expected market price, and they are adjusted adaptively to eliminate past observed excess supply / demand. The significant coefficients for individual prices are negative for all but five subjects (i.e. 93%)), while the coefficients for the expected market price are positive for all but seven subjects (i.e. 91%). Moreover, 15% of the subjects use quantity setting rules that replicate the actual demand function, i.e. $c, \gamma_3 > 0$, $\gamma_2 < 0$, and $\gamma_1 = \gamma_4 = 0$. Estimation results show that 38% of the subjects adjust quantity adaptively, trying to eliminate excess supply / demand.

Overall, the FOH model describe individual behavior quite nicely. The advantage of such simple model is that it has only a few coefficients to estimate and it has a simple behavioral interpretation. As an example, consider subject 9 from group 4 in treatment 1. The estimated model for this subject is

$$\begin{aligned}
\overline{p}^e_{i,t} &= 0.817\overline{p}_{t-1} + 0.238\overline{p}^e_{i,t-1} + \varepsilon_t \\
p_{i,t} &= 0.832p_{i,t-1} + 0.199\overline{p}^e_{i,t} - 0.127S_{i,t} + u_t \\
q_{i,t} &= 11.812 - 1.412p_{i,t} + 1.058\overline{p}^e_{i,t} + \eta_t,
\end{aligned}$$

which can be interpreted as follows. The subject use an anchoring or adaptive expectations rule to forecast the market price, where the anchor is represented by the weighted average of her own past forecast and the last available observation of the market price. The price setting rule can be described as an anchor and adjustment strategy, in which the price set in the current period is a weighted average of the price set in the previous period and the expected market price. Moreover, the subject decreases her price when she observes excess supply. The quantity-setting strategy is very similar to the actual demand function. The subject decides the quantity to produce by using the decision on the individual price (with a negative coefficient) and the forecast of the average price (with a positive coefficient).

4 Explaining observed aggregate behavior

In section 4.1 we perform 40-periods ahead simulations to assess whether the estimated model (3.1) - (3.3) is able to replicate the qualitative aggregate behavior observed in the experimental markets. In section 4.2 we link the observed experimental outcomes to the heterogeneity in the price-quantity strategies.

4.1 40-periods ahead simulations

For each group of both treatments we simulate 40-periods artificial markets consisting of 10 firms using the strategies estimated from the respective experimental data. The simulations are initialized using experimental observations for the initial 10 periods, corresponding to the learning phase discarded in the estimation procedure. After the learning phase the evolution of the artificial markets is completely endogenous and the market behavior of the artificial agents is determined by the estimated strategies perturbed with a white noise term. Figs. 6 and 7 report average simulated data over 500 Monte Carlo replications respectively for treatment 1 group 1 and treatment 2 group 1. Results for the other experimental groups reported in Appendix D.

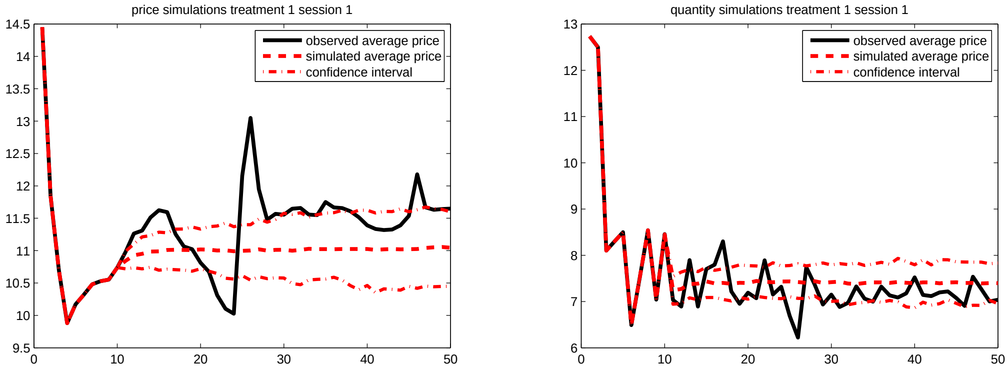


Figure 6: **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of 500 Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of 500 Monte Carlo simulations.

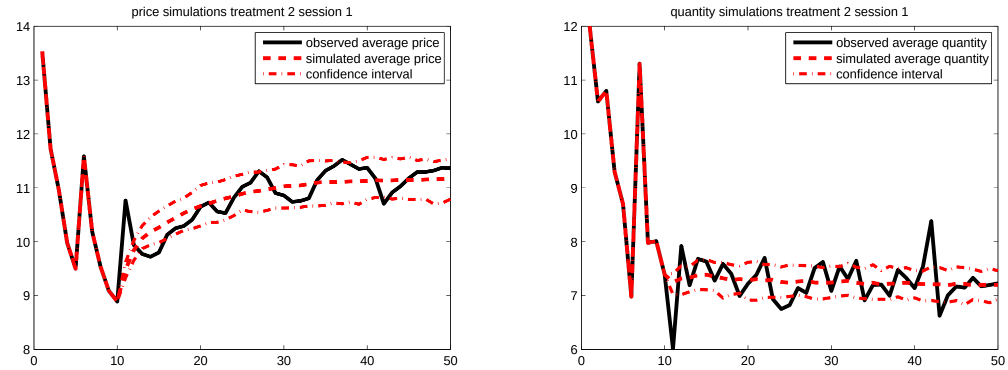


Figure 7: **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of 500 Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of 500 Monte Carlo simulations.

Overall, the simulated markets are able to reproduce the qualitative behavior observed in the experimental economies. The interaction between the estimated strategies produce on average an aggregate behavior which resembles the experimental outcome. In the next section we will use the artificial markets with the estimated strategies to understand the impact of different strategies on the experimental outcomes.

4.2 Heterogeneous strategies and aggregate dynamics

In order to gain some insights about how the estimated FOH affect the observed market outcome we focus on the estimated price-setting strategy. This allows us to simplify the analysis and it is justified on the grounds that, in the theoretical framework of monopolistic competition, the individual price is the main strategic variable.

As a first step, we consider the impact on aggregate price dynamics of the anchor term in the price-setting rule, given by the first three terms in eq. (3.2). In particular, we analyze the case in which all subjects use a price-setting strategy of the form

$$p_{i,t} = c_i + \beta_{i,1} p_{i,t-1} + \beta_{i,2} \overline{p}^e_{i,t} + u_{i,t} \, ,$$

and we start with the simplest possible case in which agents hold naive expectations concerning the average market price, i.e., $\bar{p}^e_{it} = \bar{p}_{t-1}$. In this simple scenario we can abstract from considerations about the quantity-setting strategy, as the individual price does not depend on realized profits nor realized excess supply. Aggregating across subjects we can write the dynamic equation governing the evolution of market price as

$$\bar{p}_t = \bar{c} + \bar{\beta}_1 \bar{p}_{t-1} + \bar{\beta}_2 \bar{p}_{t-1} + u_t \, ,$$

where $\bar{c}$, $\bar{\beta}_1$ and $\bar{\beta}_2$ denote the average coefficients across subjects. The system has a deterministic steady state given by $\bar{p} = \bar{c}/(1 - \bar{\beta}_1 - \bar{\beta}_2)$, which is stable if $\bar{\beta}_1 + \bar{\beta}_2 < 1$.[10] We consider, for illustration purposes, treatment 1 group 1, for which the average estimated coefficients of market followers are $\bar{c} = 1.2392$, $\bar{\beta}_1 = 0.4262$ and $\bar{\beta}_2 = 0.4649$, leading to an equilibrium price $\bar{p} = 11.3792$. We then turn to the model in which both subjects' forecasting and price-setting strategies are given by the actual rules estimated from experimental data. We simulate the model for 10000 periods to allow the system to reach a steady state, perform 500 Monte Carlo replications, and compute the average equilibrium price which is given by $\bar{p^*} = 11.2737$. The "theoretical" equilibrium value and the simulated value are quite similar. Moreover, we remark that these values are rather close to the average of the actual market price in treatment 1 group 1, which is $\bar{p'} = 11.3336$.

The simple example considered above shows the importance of the anchor used by subjects in determining the equilibrium price and its stability. The intuition is that in an uncertain environment characterized by limited information about the market structure and about other firms' actions, subjects anchor their price strategies in the observed market price. In order to understand how such long-run aggregate behavior emerges we need to consider the adjustment terms in the price strategy (3.2).

The impact of profit-driven adjustment

The introduction of the profit adjustment term makes the dynamic system too complicated to tackle analytically, therefore we resort to numerical simulations. To isolate the effect of the profit adjustment term we set up an artificial market where all the agents have the same forecast, price decision and quantity decision

[10] We remark that in a deterministic steady the profit feedback variable $\Pi = 0$. Moreover, subjects learn to eliminate excess supply / demand over time, as shown in Fig. 3.

strategies up to an idiosyncratic noise term

$$\overline{p}^e_{i,t} = \overline{p}_{t-1} + \varepsilon_{i,t} \tag{4.1a}$$

$$p_{i,t} = p_{i,t-1} + \beta_3 \Pi_{i,t-1} + u_{i,t} \tag{4.1b}$$

$$q_{i,t} = 10.5 - 1.75 p_{i,t} + 1.4583 \overline{p}^e_{i,t} + \eta_{i,t}\,. \tag{4.1c}$$

The agents use naive expectations to forecast the average price and, in order to avoid complex interactions between price and quantity decisions, we suppose that subjects know the structural parameters describing the demand functions, but they ignore the pricing decisions of other agents. Therefore quantity is set according to the expected demand. The individual pricing rule instead uses an anchor given by past individual price and the adjustment term is given by the profit feedback variable. We set the coefficient β_3 equal for all agents. As stated above, the only source of heterogeneity are the idiosyncratic shocks. In Fig. 8, left panel, we show how, for a value of $\beta_3 = 0.5$, the average price over 500 Monte Carlo replications converges to a neighborhood of the Nash equilibrium.[11] It is interesting to note that the simulated markets do not reach the collusive equilibrium due to the heterogeneity introduced by the idiosyncratic noise.[12] In fact, the asynchronous movements in individual prices might lead some agents to "overshoot" and set a price too high compared to the average price, resulting in lower profits and therefore to a downward revision of the price in the next period. If we shut down the idiosyncratic noise terms, or equivalently we consider a market with a representative agent, the market price reaches the collusive outcome as shown in the right panel of Fig. 8.

The analysis performed above shows that including a profit adjustment term in the pricing strategies has the effect of pushing the market price towards the Nash

[11] By varying β_3 we can evaluate the impact of the profit adjustment term on individual and the market behavior. When $\beta_3 = 0$ individual prices, and consequently the aggregate market price, are clearly non stationary. As β_3 increases, the system becomes stationary and converges to a neighborhood of the Nash equilibrium. As β_3 increases further, the system starts to oscillate.

[12] We remark that simulating a system with heterogeneous coefficients $\beta_{i,3}$ would lead to the same conclusions.

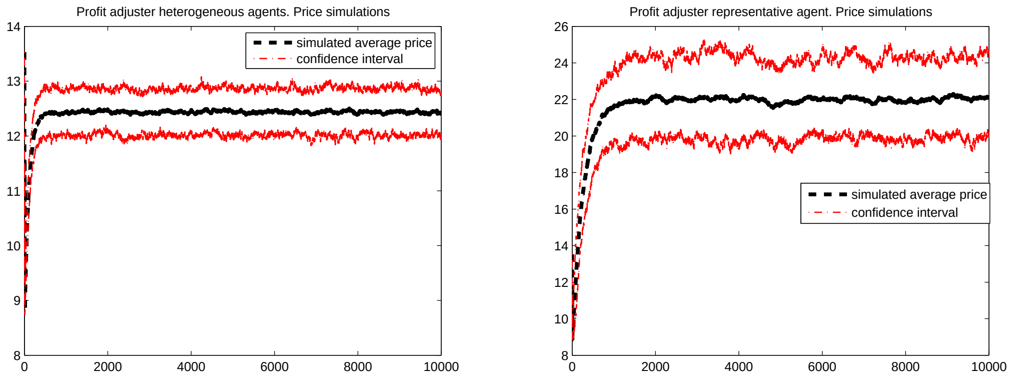


Figure 8: **Left panel** Simulated average price with profit adjusters heterogeneous agents and 95% confidence interval with $\beta_3 = 0.5$. **Right panel:** Simulated average price with profit adjuster representative agent and 95% confidence interval.

equilibrium, and this seems to explain the convergence to the average price levels observed in the experimental markets. However, it is difficult to isolate the impact of the price adjustment term in the observed data because of the interaction between price strategies, price forecast and quantity setting rules in the determination of individual profits. Nevertheless, we try to find evidence for the impact of profit-seeking price setting strategies in our experimental data in the following way.

In each period, the best response function for price setting is given by eq. (2.2). Since subjects do not know the realized market price in the current period, we compute the *expected best response* by substituting the realized average price with the expected average price in order to get

$$p_{i,t}^{BR} = \alpha' + c/2 + \theta' \overline{p}_{i,t}^{e} \,. \tag{4.2}$$

The distance between the expected best response and the individual price gives information about the tendency of the subjects to move the price in the direction of a profit increase. The absolute distance is computed for each subject on the last

40 periods of the experiment, i.e. leaving out the learning phase, as

$$d_{i,t} = \left| \frac{p_{i,t} - p_{i,t}^{BR}}{p_{i,t}^{BR}} \right| . \tag{4.3}$$

The absolute distance from the expected best response is not affected by the quantity strategy and it is conditioned on the price forecast, giving a reliable information about the price setting behavior of the subjects. We expect the profits adjusters to set the price in the direction of the expected best response. This would imply the average distance of the profit-adjusters to be low relatively to the other strategy categories, namely demand-adjusters and market followers. To test this assumption we compute the average absolute distance for each subject in all sessions, $\bar{d}_i$, and perform the following regression

$$\bar{d}_i = \phi_1 \delta_i^{\pi} + \phi_2 \delta_i^{d} + \phi_3 \delta_i^{m} , \tag{4.4}$$

where δ_i^{π}, δ_i^{d}, and δ_i^{m} are indicator variables taking value 1 if subject i is respectively a profit-adjuster, demand-adjusters and market followers. The results of the regression analysis are shown in table 2. The average distance of the profit adjusters from the expected best response is the lowest among the strategy categories. The difference is significant at 90% confidence level with respect to the average distance of the market adjusters. It is not possible to reject the hypothesis that the demand adjusters have a higher average distance, but they are at the upper extreme of the confidence interval. The profit adjusters tend to move towards their expected best response. Put differently, we can say that profit-adjusters tend to move up-hill on the profit function, confirming the results obtained by simulations in the previous sections.

The impact of demand adjustment

The demand-adjusters use realized excess supply to adjust prices. In order to study the effect of the demand adjustment strategy we need to slightly modify the setting

Strategy category	Absolute average distance	90% confidence interval
profit adjusters	0.0757	0.0528, 0.0986
demand adjusters	0.0927	0.0703, 0.1151
market adjusters	0.1047	0.0870, 0.1225

Table 2: Absolute average distance from expected best response.

described in system (4.1). Using the expected demand function with the true values of the structural coefficients as a quantity-setting strategy would imply an almost zero excess supply by construction, eliminating any feedback to the price strategy. Therefore we use a very simple adaptive strategy as quantity-setting rule. The equations describing the artificial system set up to study the impact of the demand adjustment term reads as follows:

$$\overline{p}^e_{i,t} = \overline{p}_{t-1} + \varepsilon_{i,t} \tag{4.5a}$$

$$p_{i,t} = p_{i,t-1} + \beta_4 S_{i,t-1} + u_{i,t} \tag{4.5b}$$

$$q_{i,t} = q_{i,t-1} + \gamma_4 S_{i,t-1} + \eta_{i,t}\,. \tag{4.5c}$$

The price forecast strategy, reported only for completeness, has no influence on the price-quantity decisions. Demand adjusters move prices in the direction determined by the excess supply, aiming at minimising it. The result of such behavior is that system (4.5) has infinite deterministic equilibria on the locus of points described by the demand function. In any price-quantity point on the demand function, the quantity adjuster is in equilibrium since $S_{i,t-1} = 0$. When performing simulations of system (4.5) we observe individual time series that are not settling around any stationary value and the simulated outcomes of price and quantity decisions lie around the demand function.[13] The effect of quantity adjusters on average price is ambiguous. In fact, demand adjusters set the price to reduce excess supply without paying attention to the direction that would maximize profits. From a behavioral perspective, the demand-adjustment strategy can be read as a loss-minimization

[13]Estimating the individual simulated quantity as a function of individual simulated price and average price for each agent, we obtain coefficients almost equal to the true coefficient in the demand function.

heuristic. By avoiding any over production and by setting the price above the constant production cost, the demand adjusters may not maximize profits but they are able to minimize the losses.

As noted above, it is hard to disentangle the effect of each price-setting strategy on aggregate dynamics by looking at experimental data because these effects depends on the interactions between price-setting, forecasting and quantity-setting rules. Therefore, in order to find empirical evidence for the effect of the demand-adjustment strategy, we adopt an empirical strategy similar to the case of profit adjustment.

The particular feature of the demand-adjusters is that they tend to move the price in response to the excess supply in the previous period. Ideally they tend to move toward a zero excess supply:

$$S_{i,t-1} \equiv q_{i,t-1} - \alpha + \beta p_{i,t-1} - \theta \bar{p}_{t-1} = 0\,. \tag{4.6}$$

However, as observed in the estimation of the FOH (see section 3), when setting their price in period t, subjects take into account their expected market price for the current period. By substituting the average price with the market price forecast and rearranging equation 4.6, we can compute the demand-adjusters' target price:

$$p^S_{i,t} = \frac{1}{\beta}\big(\alpha + \theta \bar{p}^e_t - q_{i,t-1}\big)\,. \tag{4.7}$$

The idea is that the demand-adjusters are moving the price in the direction that reduces the excess supply of last period, taking into account the change in average price, i.e. using the market price forecast. We define the absolute distance from the target price as

$$d_{i,t} = \left| \frac{p_{i,t} - p^S_{i,t}}{p^S_{i,t}} \right|, \tag{4.8}$$

Strategy category	Absolute average distance	90% confidence interval
profit adjusters	0.0610	0.0309, 0.0911
demand adjusters	0.0361	0.0066, 0.0655
market adjusters	0.0673	0.0439, 0.0906

Table 3: Absolute average distance from zero excess supply.

compute the average for each subject, $\bar{d}_i^S$, and perform the following regression

$$\bar{d}_i^S = \varphi_1 \delta_i^\pi + \varphi_2 \delta_i^d + \varphi_3 \delta_i^m \,, \tag{4.9}$$

where the indicators δ_i^π, δ_i^d, and δ_i^m have the same interpretation as above. The results of the regression analysis are shown in table 3. As expected, the average absolute distance is lowest for the demand-adjusters. The difference with the market followers is significant at 90% confidence level, while it is not possible to reject the hypothesis that profit-adjusters have a higher average distance. The adjustment terms, even if they are working on different signals have some common effects on the price decision. From the empirical analysis it seems that the price direction for a profit improvement is often in the same direction that reduces the excess supply and vice-versa.

5 Conclusions

We conducted an experiment aimed at investigating market dynamics in a monopolistically competitive framework with limited information. Overall, we find that the price-quantity dynamics converge to (a neighborhood of) the monopolistically competitive outcome, even with limited information about the demand function, in both treatment 1 and treatment 2. Although aggregate variables converge to the MC equilibrium, we find evidence for substantial and persistent heterogeneity in individual prices and quantities. We investigate the individual price-quantity setting behavior and evaluate the impact of different price-setting strategies on aggregate dynamics. We find that simple behavioral rules described by First-Order-Heuristics

(FOH) describe individual strategies quite nicely. Simulation results confirm that the FOH model is able to reproduce qualitative features of the observed experimental outcomes. As for the impact of individual strategies on aggregate dynamics, our results suggest that heterogeneity in individual strategies explains experimental outcomes. In particular, we conclude that profit-adjustment strategies have the effect of leading the market in a neighborhood of the MC equilibrium. The presence of market followers and demand-adjusters prevents markets from converging exactly to the MC outcome, but also prevents coordination on the collusive outcome. Persistent behavioral heterogeneity therefore affects aggregate market outcomes.

Appendix

A Experimental Instructions

A.1 Overview

This is an experiment about economic decision making. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money that will be paid to you in cash at the end of the experiment.

The whole experiment is computerized, therefore you do not have to submit the paper on your desk. Instead, you can use it to make notes. There is a calculator on your desk. If necessary, you can use it during the experiment.

Please do not talk with others for the duration of the experiment. If you have a question please raise your hand and one of the experimenters will answer your question in private.

A.2 General description

- In this experiment each of you will be a firm in a market producing and selling a certain perishable product (more on this below). All firms in this market produce *similar* but not identical products.
- The consumers in this economy are simulated by a computer program.
- The currency used in the economy is ECU (Experimental Count Units).
- The market consists of *50 periods* in total.

Your tasks (a firm)

A. At the beginning of each period you (a firm) have to decide which quantity to produce and at which price to sell. To make your decisions you should take into account that:

- The production costs are 8 ECU per unit, whether you sell it or not. All firms produce at the same unit cost.

- The units produced are perishable, meaning that the production decided upon at the beginning of each period is available for sale only in that period.

- You can produce *decimal* quantities up to two decimal places. For example, if you want to produce 13.75 units, type "13.75". Due to technological restrictions it is not possible to produce more than 40 units.

- You can set any price between 0 and 30 ECU. For example, if you want to set a price of 21.34 ECU, type "21.34".

- You will earn profits by selling units that you produced. Your profit *per unit sold* is the difference between the price received from selling that unit and the cost of producing that unit. Note however that if you decide to produce a certain quantity of units, you have to pay the cost of production for those units whether you sell them or not. Thus, your total profit in each period is

  Profit = Price per unit Number of units sold - Cost per unit × Number of units produced

- Setting a higher price will increase your earnings *per unit sold.* However, as your price increases, the consumers can afford to buy fewer units. Moreover, as your price increases relative to the other firms, some consumers will substitute away from you and buy more from other firms. In fact, your price and the average market price (the average of all firms prices) determine your sales: The higher your price, the fewer units you sell. Given your price, the higher the average market price, the more units you sell.

B. In addition to deciding which quantity to produce and at which price to sell, at the beginning of each period you will also forecast the average market price.

- You earn a forecast prize of 0.10 Euro in each period if your prediction is within 1 ECU of the realized average market price in that period.

The consumers

In today's experiment the consumers are simulated by a computer program. After all firms have decided the quantities to produce and their prices, the automated consumers will be "shopping". Observe that:

- The consumers will make all advantageous purchases possible. Importantly, in today's experiment the products offered by each firm are distinguishable to the consumers, and the product offered by one firm is not a perfect substitute of the product offered by another firm. For this reason, the consumers may buy some units of the product offered by a firm setting a price higher than the other firms.
- The consumers'decisions are dictated by a pre-specified relationship that determines the rate of substitutability between products. This relationship is affected only by firms' prices in a period. As described above, the higher your price, the fewer units you sell. Given your price, the higher the average market price, the more units you sell.

A.3 Your earnings

A. Market earnings

Each firm starts with an initial capital balance of 500 ECU. In each period, your profit in ECU will be given by

Profit = Price per unit Number of units sold - Cost per unit $\times$ Number of units produced

This profit will be added to your capital balance. If in some periods you make negative profits, they will be subtracted from your capital balance.

Your market earnings will be given by your capital balance at the end of the experiment.

A firm can go bankrupt if its capital balance is negative. The owners of a bankrupt firm must stay in their place until the experiment ends. The owners of a bankrupt firm will then only receive a *show up fee* of 5 Euros as final reward.

B. Forecast prize

In addition to the money that you can earn from participating in the market, you can earn a forecast prize of 0.10 Euro per period if your forecast of the average market price is within 1 ECU of the realized average market price.

C. Total earnings

Your total earnings for participating in today experiment will equal the market earnings plus the forecast prize. If your firm goes bankrupt, you will only receive a show up fee of 5 Euros. The cash payment to you at the end of the experiment will be in Euros. The conversion rate is 75 ECU to 1 Euro.

A.4 The computer screen

Below is a sample screen for a firm C03 at the start of period 10. All numbers in this screenshot are provided only to give an EXAMPLE of the screen display; they SUGGEST NOTHING about how you should make your quantity and pricing decisions.

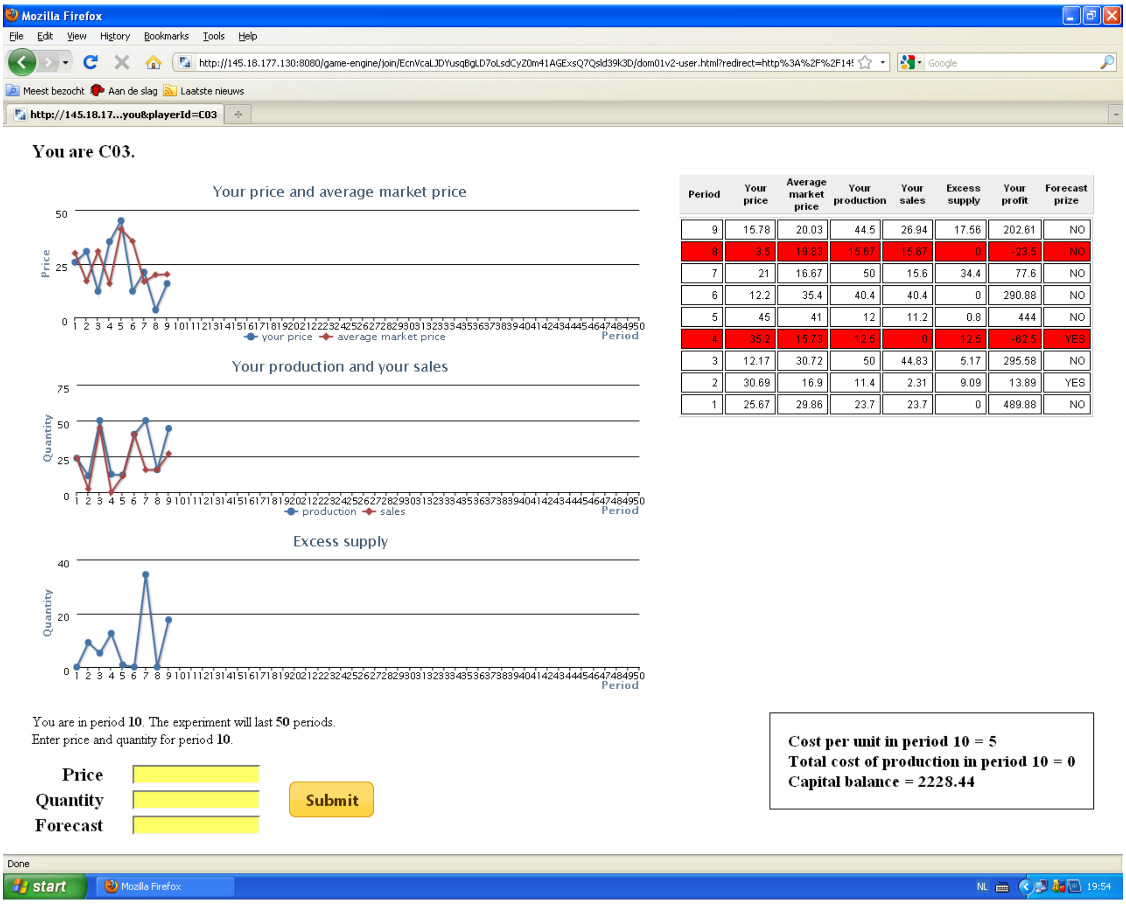
In period 10, firm C03 must enter a price in the "Price" box, a quantity in the "Quantity" box and a forecast of the average market price in the "Forecast" box located in the *bottom-left* corner of the screen. After making its choices, firm C03 has to submit its decisions by clicking the "Submit" button.

The box in the *bottom-right* corner reports the following information:

- The cost to produce one unit in ECU for period 10.
- The total cost of production in period 10, given by the unit cost of production times the quantity that firm C03 is willing to produce. In each period you can check the total cost of production before submitting your choice.
- The capital balance of firm C03 up to period 10.

The rest of the screen allows you to track results from preceding periods.

The graphs on the upper-left corner of the screen report respectively:



- **Top graph:** a graphical representation of your price (blue series) and the average market price (red series).

- **Middle graph:** a graphical representation of your production (blue series) and your sales (red series).

- **Bottom graph:** a graphical representation of the excess supply, which is the difference between the quantity that you produced minus the quantity that you sold given your price and the average market price. Note that this series cannot be negative since you cannot sell more than what you produce.

The table on the *upper-right* corner contains information about the results in the experiment and it is supplemental to the graphs in the left part of the screen. The *first column* of the table shows the time period. The last period, in this case period 10, is always at the top. The *second* and *third columns* of the table show respectively your prices and the average market prices. The *fourth* and *fifth columns* of the table show respectively the quantities that you produced and the quantities that you sold. The *sixth* *column* of the table shows the excess supplies, which are the differences between the quantities that you produced minus the quantities that you sold. The *seventh column* of the table shows the profits realized in each period. If in a period you realize negative profits, the row corresponding to that period will be marked in red. Finally the *eighth column* of the table shows whether in each period you earned the forecast prize or not.

B Estimation procedure

Model (3.1) - (3.3) constitutes a linear simultaneous equations model. Simultaneity might result in correlation between error terms and some of the regressors, causing OLS estimates to be inconsistent. Thus we proceed as follows.

1. We estimate eq. (3.1) by OLS, eliminating iteratively insignificant regressors, highest p-value first.

2. We estimate eq. (3.2) by 2SLS using the significant regressors from the estimation in the previous step as instruments for $\overline{p}^e_{i,t}$, and test the null hypothesis that the error terms are uncorrelated with the regressor $\overline{p}^e_{i,t}$ using the Hausman test for regressors' endogeneity.

   (a) If the null is rejected then we estimate eq. (3.2) by 2SLS eliminating iteratively insignificant regressors, highest p-value first.

   (b) If the null is not rejected, we estimate eq. (3.2) by OLS eliminating iteratively insignificant regressors, highest p-value first.

3. We estimate eq. (3.3) by 2SLS using the significant regressors from the estimation in the previous step as instruments for $p_{i,t}$, and test the null hypothesis that the error terms are uncorrelated with the regressor $p_{i,t}$ using the Hausman test for regressors' endogeneity.

   (a) If the null is rejected then we estimate eq. (3.3) by 2SLS eliminating iteratively insignificant regressors, highest p-value first.

   (b) If the null is not rejected, we estimate eq. (3.3) by OLS eliminating iteratively insignificant regressors, highest p-value first.

Eq. (3.2) contains the interaction term $\Pi_i = \Delta p_i \cdot \mathrm{sgn}(\Delta \pi_i)$, therefore when estimating the pricing rule we also include the regressors Δp_i and $\mathrm{sgn}(\Delta \pi_i)$. However, since these terms have no clear behavioural interpretation, we eliminate them from our specification whenever the profit feedback variable Π_i is not significant.

We excluded from the estimation sample an initial learning phase of 10 periods and we include period dummies for outliers, i.e., observations which deviate more than three standard deviations from the sample mean. In order to deal with potentially heteroskedastic or autocorrelated errors when testing for endogeneity, we use the method proposed by Kiefer, Vogelsang, and Bunzel (2000),[14] and we test for both instruments exogeneity and weak instruments.

C Estimation results

The following tables 4 – 11 report the results of the estimation of the FOH model (3.1) – (3.3) for all groups in Treatment 1 and 2.

[14]In principle we could have used HAC standard errors when calculating the test statistic, which should be asymptotically equivalent to the Hausman test statistic (see Davidson and MacKinnon (1993), p. 239). However, in small samples this approach can lead to large size distortions (see, e.g., Andrews (1991) and Andrews and Monahan (1992)).

Treatment 1, group 1

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	**2.084**	**0.570**	0.000	**0.216**	0.824	0.242	0.528	0.865
2	-0.074	**0.707**	**0.426**	**0.298**	0.981	0.369	0.217	0.021
3	**0.673**	**1.071**	**-0.128**	**-0.133**	0.987	0.007	0.026	0.984
4	0.058	**0.794**	0.000	**0.195**	0.981	0.029	0.025	0.006
5	0.521	**0.947**	0.000	0.000	0.940	0.021	0.067	0.775
6	0.216	**0.905**	**0.502**	**0.083**	0.986	0.059	0.170	0.656
7	4.980	**0.565**	0.000	0.000	0.286	0.042	0.069	0.001
8	-0.578	**1.075**	0.000	0.000	0.646	0.010	0.034	0.781
9	-0.109	**1.009**	0.000	0.000	0.989	0.925	0.963	0.863
10	-0.165	**1.015**	0.000	0.000	0.976	0.016	0.012	0.959

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	-0.470	**0.833**	**0.225**	-0.061	**-0.529**	**0.490**	0.000	0.874	0.023	0.046	0.624	OLS
2	**4.577**	0.000	**0.640**	0.000	0.000	0.000	0.000	0.439	0.213	0.182	0.876	OLS
3	**5.078**	0.000	**0.551**	0.000	0.000	0.000	0.000	0.990	0.441	0.742	0.986	IV
4	-0.476	**0.250**	**0.790**	0.000	0.000	0.000	**-0.183**	0.978	0.129	0.048	0.989	OLS
5	-0.524	**0.167**	**0.876**	0.000	0.000	0.000	0.000	0.966	0.006	0.025	0.355	OLS
6	**2.589**	**0.479**	**0.236**	0.000	0.000	0.000	0.000	0.626	0.447	0.612	0.000	IV
7	2.760	**0.749**	0.000	0.149	**-0.371**	**0.328**	0.000	0.989	0.012	0.040	0.042	OLS
8	2.519	**0.446**	**0.387**	0.000	0.000	0.000	0.000	0.455	0.316	0.288	0.918	OLS
9	0.147	**0.554**	**0.381**	0.000	0.000	0.000	0.000	0.760	0.119	0.050	0.650	OLS
10	**-3.808**	**0.785**	**0.562**	0.033	-0.053	**0.233**	0.000	0.897	0.415	0.381	0.044	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**18.848**	0.000	**-1.064**	0.000	**-0.744**	0.642	0.293	0.354	0.026	OLS
2	**24.141**	0.000	**-1.488**	0.000	**-0.591**	0.878	0.000	0.000	0.160	OLS
3	**13.666**	0.000	**-3.993**	**3.463**	0.000	0.869	0.137	0.331	0.382	OLS
4	2.140	**0.605**	**-0.987**	**1.064**	**-0.664**	0.573	0.233	0.163	0.188	OLS
5	2.683	**0.432**	**-3.620**	**3.733**	0.000	0.853	0.125	0.146	0.068	IV
6	**10.044**	0.000	0.000	0.000	0.000	0.754	0.688	0.836	0.832	OLS
7	**9.160**	**0.482**	**-0.488**	0.000	**-0.657**	0.393	0.144	0.276	0.000	IV
8	**8.912**	0.000	**-0.955**	**0.656**	0.000	0.747	0.016	0.068	0.636	OLS
9	**10.167**	0.000	0.000	0.000	0.000	0.700	0.437	0.113	0.708	OLS
10	**3.869**	**0.887**	**-0.265**	0.000	**-0.533**	0.887	0.335	0.625	0.021	OLS

Table 4: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 1, group 1. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 1, group 2

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	0.671	**0.951**	**0.280**	0.000	0.913	0.774	0.942	0.870
2	0.385	**0.954**	**0.521**	0.000	0.732	0.690	0.060	0.555
3	0.110	**0.542**	0.000	**0.439**	0.842	0.120	0.152	0.764
4	**2.878**	0.000	**0.814**	**0.724**	0.791	0.217	0.247	0.001
5	0.473	**0.363**	0.000	**0.588**	0.833	0.654	0.761	0.766
6	**1.222**	**0.882**	0.000	0.000	0.895	0.055	0.020	0.678
7	0.822	**0.923**	**0.514**	0.000	0.910	0.546	0.692	0.000
8	**1.219**	**0.884**	**0.485**	0.000	0.920	0.115	0.152	0.138
9	-2.041	**1.159**	**0.720**	0.000	0.738	0.193	0.380	0.891
10	0.696	**0.939**	0.000	0.000	0.852	0.028	0.047	0.766

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	-5.296	**0.376**	**1.199**	0.000	0.000	0.000	0.000	0.639	0.422	0.306	0.927	OLS
2	**2.823**	**0.258**	**0.404**	0.000	0.000	0.000	**-0.106**	0.865	0.676	0.861	0.976	IV
3	1.041	**0.912**	0.000	0.000	0.000	0.000	**-0.154**	0.911	0.314	0.266	0.407	OLS
4	**4.711**	**0.536**	0.000	-0.068	-0.197	**0.426**	0.000	0.834	0.731	0.490	0.466	OLS
5	1.165	**0.566**	**0.340**	0.000	0.000	0.000	**-0.160**	0.851	0.138	0.333	0.602	OLS
6	0.135	**0.455**	**0.473**	0.000	0.000	0.000	0.000	0.880	0.356	0.277	0.017	OLS
7	2.218	**0.807**	0.000	0.000	0.000	0.000	0.000	0.641	0.136	0.216	0.560	OLS
8	0.968	**0.929**	0.000	0.000	0.000	0.000	**-0.425**	0.849	0.313	0.475	0.133	OLS
9	2.735	**-0.148**	**1.043**	0.000	0.000	0.000	0.000	0.858	0.414	0.685	0.000	IV
10	**1.424**	**0.248**	**0.646**	-0.075	-0.084	**0.325**	**-0.165**	0.896	0.182	0.346	0.654	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**3.155**	0.000	0.000	0.000	0.000	0.605	0.000	0.000	0.871	OLS
2	**4.702**	**0.479**	0.000	0.000	0.000	0.508	0.447	0.618	0.895	OLS
3	-0.205	**1.052**	0.000	0.000	**-1.118**	0.797	0.003	0.016	0.120	OLS
4	8.181	**0.312**	**-1.860**	**1.668**	**-0.790**	0.498	0.005	0.001	0.442	OLS
5	**7.179**	0.000	0.000	0.000	0.000	0.653	0.350	0.027	0.679	OLS
6	0.490	**0.329**	**0.612**	0.000	**-0.990**	0.428	0.160	0.288	0.104	IV
7	**5.996**	0.000	0.000	0.000	0.000	0.463	0.696	0.849	0.716	OLS
8	**11.546**	0.000	**-1.556**	**1.192**	**-1.023**	0.800	0.007	0.008	0.025	OLS
9	**8.016**	**0.309**	**-0.807**	**0.517**	**-0.397**	0.849	0.293	0.004	0.843	OLS
10	**6.948**	0.000	**-1.197**	**1.214**	0.000	0.589	0.309	0.790	0.650	OLS

Table 5: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 1, group 2. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 1, group 3

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	**5.561**	**0.548**	0.000	0.000	0.492	0.515	0.007	0.001
2	**11.295**	0.000	**0.429**	0.000	0.620	0.218	0.324	0.000
3	**5.790**	**0.506**	0.000	0.000	0.617	0.915	0.660	0.049
4	**6.202**	**0.485**	**0.186**	0.000	0.807	0.327	0.378	0.004
5	**7.037**	**0.400**	**0.188**	0.000	0.791	0.047	0.268	0.042
6	0.906	**0.897**	0.000	0.000	0.852	0.007	0.014	0.496
7	**11.846**	0.000	0.000	0.000	0.487	0.410	0.211	0.663
8	**8.578**	**0.463**	0.000	**-0.226**	0.553	0.439	0.717	0.026
9	**1.961**	**0.821**	**0.112**	0.000	0.908	0.029	0.091	0.476
10	**3.628**	**0.656**	0.000	0.000	0.362	0.326	0.215	0.027

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**9.382**	0.000	0.000	0.000	0.000	0.000	**-0.056**	0.865	0.000	0.000	0.972	OLS
2	**10.079**	0.000	0.000	0.000	0.000	0.000	0.000	0.914	0.632	0.735	0.903	OLS
3	3.329	**0.363**	**0.415**	0.015	**-0.195**	**0.215**	0.000	0.972	0.260	0.209	0.024	OLS
4	2.167	**0.268**	**0.449**	0.000	0.000	0.000	0.000	0.728	0.297	0.119	0.000	OLS
5	-1.113	0.000	**1.102**	0.000	0.000	0.000	0.000	0.765	0.121	0.300	0.179	IV
6	**3.392**	**-0.246**	**0.908**	0.000	0.000	0.000	**0.118**	0.885	0.944	0.772	0.186	IV
7	**9.307**	0.000	**0.157**	0.130	0.095	**0.158**	0.000	0.675	0.327	0.176	0.911	OLS
8	2.472	0.000	**0.697**	0.000	0.000	0.000	0.000	0.486	0.601	0.850	0.469	IV
9	0.930	**0.282**	**0.637**	0.000	0.000	0.000	**-0.445**	0.874	0.785	0.865	0.520	IV
10	**14.030**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.678	0.274	0.000	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**-6.052**	**0.596**	**1.125**	0.000	**-0.309**	0.667	0.812	0.256	0.798	IV
2	**8.747**	0.000	**-1.112**	**1.109**	0.000	0.923	0.102	0.289	0.231	OLS
3	**-8.195**	0.000	0.000	**1.109**	0.000	0.694	0.074	0.198	0.711	IV
4	**10.013**	0.000	0.000	0.000	0.000	0.931	0.000	0.005	0.732	OLS
5	1.642	**0.358**	**-0.728**	**0.940**	**-0.235**	0.494	0.583	0.523	0.423	OLS
6	**5.642**	**0.319**	0.000	0.000	**-0.365**	0.731	0.622	0.873	0.880	OLS
7	**16.115**	0.000	**-0.844**	0.000	0.000	0.429	0.725	0.444	0.719	OLS
8	-0.419	0.000	0.000	**0.805**	0.000	0.227	0.857	0.244	0.991	OLS
9	**3.588**	**0.538**	0.000	0.000	0.000	0.303	0.753	0.439	0.014	OLS
10	**6.337**	0.000	0.000	0.000	0.000	0.000	0.656	0.996	0.000	OLS

Table 6: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 1, group 3. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 1, group 4

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	-0.000	**0.682**	**0.902**	**0.318**	0.963	0.073	0.042	0.102
2	**-0.844**	**1.076**	0.000	0.000	0.985	0.087	0.215	0.017
3	-0.423	**0.345**	**0.449**	**0.692**	0.978	0.361	0.204	0.077
5	-0.595	**1.054**	0.000	0.000	0.945	0.094	0.255	0.163
6	0.402	**0.967**	0.000	0.000	0.928	0.740	0.600	0.453
7	0.015	**1.002**	0.000	0.000	0.873	0.057	0.099	0.021
9	-0.584	**0.817**	0.000	**0.238**	0.975	0.600	0.859	0.167
10	-0.416	**1.038**	**0.450**	0.000	0.983	0.522	0.357	0.242

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	-0.245	**0.514**	**0.510**	0.000	0.000	0.000	**-0.066**	0.991	0.106	0.156	0.518	IV
2	**1.738**	**0.161**	**0.614**	0.000	0.000	0.000	0.000	0.946	0.185	0.266	0.511	OLS
3	**11.584**	0.000	0.000	0.000	0.000	0.000	0.000	0.597	0.004	0.010	0.547	OLS
5	1.178	**0.923**	0.000	0.000	0.000	0.000	**-0.632**	0.849	0.456	0.622	0.324	OLS
6	-0.058	0.000	**0.929**	0.000	0.000	0.000	0.000	0.872	0.173	0.317	0.021	OLS
7	0.915	0.000	**0.858**	0.000	0.000	0.000	0.000	0.857	0.377	0.665	0.423	IV
9	-0.382	**0.832**	**0.199**	0.000	0.000	0.000	**-0.127**	0.913	0.819	0.007	0.918	IV
10	1.095	**0.910**	0.000	0.000	0.000	0.000	0.000	0.792	0.666	0.837	0.395	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**7.247**	0.000	0.000	0.000	0.000	0.000	0.067	0.004	0.000	OLS
2	**9.447**	0.000	0.000	0.000	0.000	0.497	0.037	0.081	0.915	OLS
3	0.616	**-0.088**	**-0.365**	**0.954**	**-0.361**	0.911	0.059	0.032	0.141	OLS
5	**4.315**	0.000	0.000	0.000	0.000	0.480	0.024	0.064	0.449	OLS
6	**10.511**	**0.593**	0.000	**-0.620**	**-0.847**	0.685	0.018	0.062	0.002	OLS
7	**8.945**	0.000	0.000	0.000	0.000	0.000	0.731	0.039	0.000	OLS
9	**11.812**	0.000	**-1.412**	**1.058**	0.000	0.445	0.324	0.137	0.974	OLS
10	**9.243**	0.000	**-1.762**	**1.596**	0.000	0.871	0.002	0.004	0.002	OLS

Table 7: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 1, group 4. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 2, group 1

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	1.412	**0.465**	**0.346**	**0.397**	0.929	0.798	0.162	0.001
2	**0.557**	0.000	**0.792**	**0.950**	0.980	0.063	0.000	0.025
3	0.403	**0.486**	**0.336**	**0.447**	0.891	0.062	0.008	0.109
4	-0.523	**0.328**	**0.325**	**0.718**	0.988	0.043	0.054	0.681
5	**1.129**	**0.757**	0.000	**0.139**	0.963	0.415	0.527	0.195
6	-0.254	**0.241**	**0.346**	**0.778**	0.940	0.164	0.388	0.823
7	-0.172	**1.010**	**-0.266**	0.000	0.920	0.767	0.021	0.704
8	**0.939**	**0.456**	**0.518**	**0.450**	0.950	0.237	0.073	0.045
9	**3.427**	**0.669**	0.000	0.000	0.893	0.068	0.189	0.048
10	0.540	**0.953**	**-0.287**	0.000	0.938	0.739	0.001	0.027

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**4.192**	**0.626**	0.000	0.000	0.000	0.000	**-0.475**	0.303	0.648	0.352	0.918	OLS
2	0.231	**0.283**	**0.656**	0.000	0.000	0.000	**-0.102**	0.977	0.682	0.776	0.425	IV
3	**-1.323**	**0.628**	**0.500**	0.000	0.000	0.000	0.000	0.960	0.267	0.236	0.013	OLS
4	-1.202	**0.587**	**0.513**	0.000	0.000	0.000	0.000	0.956	0.061	0.240	0.020	OLS
5	0.435	**0.502**	**0.481**	0.000	0.000	0.000	**0.053**	0.977	0.070	0.004	0.111	OLS
6	0.716	**0.932**	0.000	**0.089**	**-0.526**	**0.395**	0.000	0.892	0.092	0.320	0.457	OLS
7	**7.031**	**0.405**	0.000	0.108	-0.085	**0.354**	0.000	0.566	0.375	0.239	0.651	OLS
8	-0.097	**0.395**	**0.612**	0.049	**-0.138**	**0.171**	0.000	0.977	0.676	0.328	0.132	OLS
9	-0.206	**0.337**	**0.652**	0.000	0.000	0.000	0.000	0.935	0.076	0.261	0.470	OLS
10	**12.066**	0.000	0.000	0.000	0.000	0.000	0.000	0.355	0.001	0.002	0.644	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**3.696**	0.000	**-0.907**	**1.175**	**0.410**	0.248	0.013	0.039	0.000	IV
2	**2.167**	**0.593**	**0.111**	0.000	**-0.218**	0.941	0.935	0.097	0.007	OLS
3	**14.150**	0.000	**-1.199**	**0.654**	**-0.315**	0.797	0.001	0.000	0.253	OLS
4	**16.340**	0.000	0.000	**-0.770**	0.000	0.130	0.016	0.015	0.035	OLS
5	**-2.249**	0.000	**0.759**	0.000	**-0.208**	0.930	0.592	0.843	0.057	OLS
6	**15.217**	0.000	**-1.908**	**1.230**	**-0.190**	0.659	0.003	0.004	0.001	OLS
7	6.069	0.000	**-1.065**	**1.096**	0.000	0.812	0.381	0.444	0.011	IV
8	**7.140**	**0.165**	**-1.977**	**1.909**	0.000	0.948	0.271	0.503	0.184	IV
9	**21.678**	0.000	0.000	**-1.171**	0.000	0.364	0.231	0.079	0.018	OLS
10	**10.383**	0.000	**-0.926**	**0.558**	0.000	0.850	0.000	0.000	0.000	OLS

Table 8: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 2, group 1. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 2, group 2

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	0.885	**0.941**	0.000	0.000	0.829	0.157	0.254	0.415
2	-0.323	**0.424**	**0.471**	**0.603**	0.905	0.875	0.236	0.824
3	0.557	**0.955**	0.000	0.000	0.896	0.047	0.005	0.212
4	0.632	**0.688**	0.000	**0.256**	0.973	0.059	0.076	0.061
5	1.117	**0.233**	0.000	**0.680**	0.944	0.738	0.897	0.002
6	0.151	**0.914**	0.000	**0.072**	0.989	0.007	0.010	0.000
7	1.130	**0.573**	0.000	**0.343**	0.932	0.946	0.396	0.000
8	0.147	**0.986**	0.000	0.000	0.966	0.000	0.000	0.000
9	0.150	**0.553**	**0.344**	**0.440**	0.919	0.166	0.365	0.953
10	-0.561	**0.414**	**0.656**	**0.628**	0.964	0.775	0.316	0.278

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**4.093**	**0.662**	0.000	0.000	0.000	0.000	0.000	0.452	0.014	0.027	0.011	OLS
2	**3.888**	**0.716**	0.000	-0.182	**-0.328**	**0.260**	0.000	0.899	0.784	0.433	0.672	OLS
3	**6.245**	**0.522**	0.000	0.000	0.000	0.000	0.000	0.643	0.888	0.314	0.854	OLS
4	1.052	**0.195**	**0.711**	0.000	0.000	0.000	0.000	0.963	0.000	0.000	0.526	IV
5	2.094	**0.619**	**0.222**	0.005	**-0.222**	**0.232**	0.000	0.895	0.550	0.176	0.043	OLS
6	**1.291**	**0.898**	0.000	0.000	0.000	0.000	**-0.164**	0.922	0.001	0.001	0.751	OLS
7	1.402	**0.581**	**0.339**	0.000	0.000	0.000	**-0.181**	0.851	0.772	0.813	0.553	IV
8	**5.250**	0.000	**0.515**	0.010	0.169	**0.381**	**0.134**	0.901	0.598	0.212	0.005	OLS
9	0.738	**0.947**	0.000	0.000	0.000	0.000	**-0.399**	0.777	0.470	0.614	0.589	OLS
10	-0.239	**0.675**	**0.351**	0.012	**-0.273**	**0.343**	0.000	0.938	0.469	0.772	0.663	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	4.840	0.000	**-1.063**	**1.273**	0.000	0.662	0.311	0.428	0.039	OLS
2	**7.626**	**0.541**	**-0.353**	0.000	0.000	0.731	0.937	0.933	0.403	OLS
3	**5.943**	0.000	**-0.741**	**0.795**	0.000	0.926	0.009	0.015	0.633	OLS
4	**2.862**	**0.606**	0.000	0.000	0.000	0.376	0.383	0.747	0.691	OLS
5	**4.710**	**0.357**	**-1.131**	**1.099**	0.000	0.628	0.599	0.498	0.070	OLS
6	**13.603**	0.000	**-0.529**	0.000	0.000	0.847	0.000	0.000	0.585	OLS
7	**1.749**	**0.692**	0.000	0.000	**-0.278**	0.513	0.491	0.172	0.599	OLS
8	**4.228**	**0.740**	0.000	**-0.175**	**-0.635**	0.909	0.584	0.011	0.009	OLS
9	**11.940**	0.000	**-1.953**	**1.557**	**0.276**	0.738	0.768	0.909	0.000	IV
10	**11.748**	0.000	**-2.075**	**1.687**	0.000	0.875	0.859	0.939	0.002	IV

Table 9: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 2, group 2. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 2, group 3

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	0.044	**0.699**	**0.488**	**0.298**	0.999	0.190	0.491	0.002
2	-0.025	0.000	**1.108**	**1.002**	0.995	0.001	0.009	0.000
3	-0.385	**0.082**	0.000	**0.958**	0.978	0.219	0.207	0.005
4	0.367	0.000	0.000	**0.967**	0.879	0.984	0.999	0.833
5	**1.581**	**0.443**	0.000	**0.408**	0.806	0.122	0.119	0.543
6	-0.080	**0.468**	0.000	**0.540**	0.985	0.264	0.013	0.074
7	**1.633**	**0.849**	0.000	0.000	0.943	0.017	0.031	0.000
8	**0.498**	**0.656**	0.000	**0.299**	0.982	0.253	0.227	0.051
9	**-1.593**	**1.148**	0.000	0.000	0.955	0.062	0.023	0.092
10	-0.288	**1.039**	**-1.058**	0.000	0.953	0.434	0.750	0.137

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**8.198**	0.000	**0.284**	0.000	0.000	0.000	0.000	0.861	0.201	0.370	0.603	OLS
2	0.459	**0.738**	**0.201**	0.000	0.000	0.000	**-0.110**	0.987	0.008	0.021	0.916	OLS
3	1.189	0.000	**0.865**	**0.100**	**0.245**	**-0.409**	**0.081**	0.807	0.218	0.021	0.003	OLS
4	-0.039	**1.015**	0.000	0.005	**-0.798**	**0.769**	**-0.218**	0.984	0.000	0.000	0.438	OLS
5	-0.306	**1.034**	0.000	0.000	0.000	0.000	**-0.121**	0.989	0.928	0.722	0.774	OLS
6	**-0.325**	**1.033**	0.000	**0.034**	**-0.347**	**0.572**	**-0.159**	0.993	0.128	0.058	0.380	OLS
7	0.343	**0.975**	0.000	-0.039	**-0.445**	**0.504**	0.000	0.863	0.712	0.850	0.992	OLS
8	-0.071	**0.857**	**0.155**	0.008	**-0.415**	**0.350**	0.000	0.992	0.510	0.282	0.207	OLS
9	-0.269	**1.030**	0.000	0.000	0.000	0.000	**-0.217**	0.969	0.690	0.411	0.124	OLS
10	**-3.565**	0.000	**1.386**	0.000	0.000	0.000	0.000	0.895	0.210	0.448	0.779	IV

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**9.977**	**0.149**	**-1.636**	**1.304**	**-0.394**	0.947	0.105	0.042	0.000	OLS
2	**1.629**	**0.820**	0.000	0.000	**-0.482**	0.663	0.019	0.019	0.000	OLS
3	1.303	0.000	**4.590**	**-3.878**	0.000	0.700	0.259	0.087	0.017	IV
4	**6.283**	**0.387**	**-0.368**	**0.238**	0.000	0.972	0.268	0.516	0.018	IV
5	**26.064**	**-0.887**	0.000	**-1.085**	**0.668**	0.919	0.991	0.808	0.013	IV
6	0.358	**0.946**	0.000	0.000	**-0.556**	0.807	0.052	0.047	0.803	OLS
7	**8.772**	0.000	**-1.197**	**1.023**	**-0.189**	0.598	0.512	0.321	0.010	IV
8	**4.306**	**0.501**	**-0.479**	**0.426**	**-0.647**	0.829	0.855	0.204	0.886	IV
9	-0.385	**1.044**	0.000	0.000	**-0.431**	0.932	0.287	0.630	0.023	OLS
10	**15.281**	0.000	**-0.782**	0.000	0.000	0.854	0.329	0.417	0.028	OLS

Table 10: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 2, group 3. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

Treatment 2, group 4

Dependent variable: $\bar{p}^e_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$\bar{p}_{t-1}$	$\Delta\bar{p}$	$\bar{p}^e_{i,t-1}$	R^2	AC(-1)	AC(-2)	W
1	0.305	**0.582**	0.000	**0.389**	0.867	0.085	0.026	0.289
2	0.345	0.000	0.000	**0.966**	0.885	0.982	0.999	0.811
3	0.383	**0.408**	**0.455**	**0.554**	0.958	0.188	0.076	0.145
4	0.559	**0.942**	0.000	0.000	0.966	0.519	0.016	0.009
5	-0.015	**0.993**	0.000	**0.009**	1.000	0.390	0.600	0.259
6	-1.043	**1.119**	**0.280**	0.000	0.904	0.188	0.017	0.675
7	**1.077**	**0.889**	0.000	0.000	0.953	0.313	0.335	0.059
8	-0.263	**0.725**	0.000	**0.290**	0.966	0.342	0.337	0.430
9	**-0.775**	**0.571**	0.000	**0.509**	0.953	0.022	0.043	0.002
10	0.034	0.000	**0.563**	**0.998**	0.975	0.362	0.114	0.392

Dependent variable: $p_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$p_{i,t-1}$	$\bar{p}^e_{i,t}$	$\pm(\Delta\pi_i)$	Δp_i	$\pm(\Delta\pi_i)\Delta p_i$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	0.400	**0.967**	0.000	-0.010	-0.222	**0.532**	0.000	0.947	0.828	0.376	0.877	OLS
2	**2.814**	**0.663**	0.000	0.001	**-0.590**	**-0.341**	0.000	0.675	0.008	0.007	0.000	OLS
3	-2.315	0.000	**1.232**	0.000	0.000	0.000	**-0.025**	0.844	0.284	0.396	0.097	IV
4	1.296	0.000	**0.864**	-0.010	**-0.596**	**0.689**	0.000	0.926	0.610	0.877	0.000	IV
5	1.132	**0.891**	0.000	0.000	0.000	0.000	**-0.152**	0.698	0.268	0.373	0.001	OLS
6	**-6.482**	**0.397**	**1.264**	0.000	0.000	0.000	0.000	0.931	0.249	0.375	0.390	IV
7	-0.767	**1.083**	0.000	0.025	**-0.467**	**0.679**	0.000	0.879	0.402	0.725	0.505	OLS
8	**8.500**	0.000	0.000	0.000	0.000	0.000	0.000	NA	NA	NA	NA	OLS
9	**7.388**	0.000	**0.400**	0.000	0.000	0.000	0.000	0.660	0.737	0.667	0.501	OLS
10	0.901	**0.538**	**0.362**	0.001	-0.227	**0.402**	0.000	0.768	0.770	0.759	0.714	OLS

Dependent variable: $q_{i,t}$

Estimated coefficients (5% significance, learning phase = 10 periods)

Subject	c	$q_{i,t-1}$	$p_{i,t}$	$\bar{p}^e_{i,t}$	$S_{i,t-1}$	R^2	AC(-1)	AC(-2)	W	Method
1	**16.254**	0.000	**-0.999**	0.000	0.000	0.920	0.894	0.143	0.210	IV
2	-4.614	**1.375**	0.000	0.000	**-1.597**	0.483	0.530	0.674	0.050	OLS
3	**76.618**	**-2.456**	**-5.097**	0.000	**2.696**	0.820	0.009	0.071	0.142	OLS
4	**18.545**	0.000	0.000	**-1.096**	0.000	0.652	0.761	0.684	0.164	OLS
5	**7.102**	0.000	**-0.818**	**0.798**	**-0.191**	0.953	0.000	0.000	0.000	OLS
6	**10.491**	**0.420**	**-0.629**	0.000	**-0.404**	0.975	0.075	0.225	0.010	OLS
7	**6.289**	0.000	0.000	**0.252**	0.000	0.981	0.004	0.002	0.005	OLS
8	0.307	**0.970**	0.000	0.000	0.000	0.964	0.172	0.268	0.012	OLS
9	**11.795**	0.000	**-1.312**	**0.826**	0.000	0.936	0.222	0.513	0.000	OLS
10	**14.679**	0.000	**-0.693**	0.000	0.000	0.833	0.879	0.719	0.000	IV

Table 11: Estimated coefficients of First-Order Heuristics (FOH) rules for the participants of Treatment 2, group 4. Coefficients in bold are significant at the 5% level. Insignificant coefficients have been deleted iteratively. The R^2 measure in case of IV estimation has been constructed as in Pesaran and Smith (1994). Columns AC(1), AC(2) and W report respectively the p-values for the Breusch-Godfrey test (in case of OLS estimation) or the Sargan test (in case of IV estimation) with 1 or 2 lags, and the White test for heteroskedasticity. The Method column indicates the final estimation method.

D Simulated markets

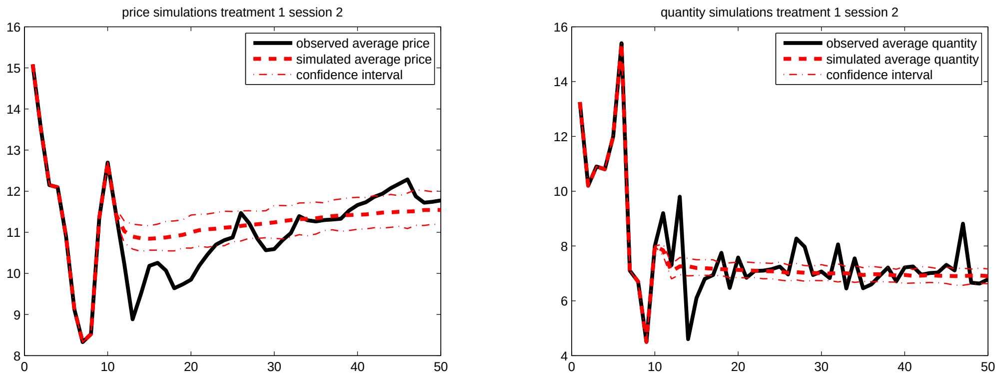


Figure 9: Treatment 1, group 2. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

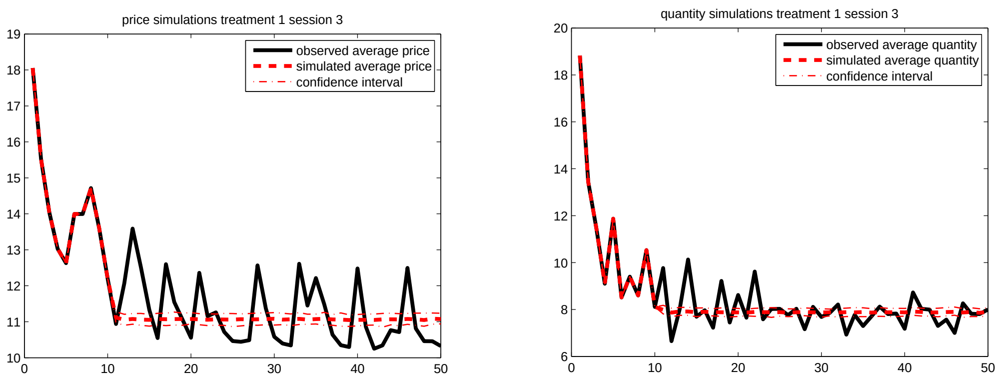


Figure 10: Treatment 1, group 3. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

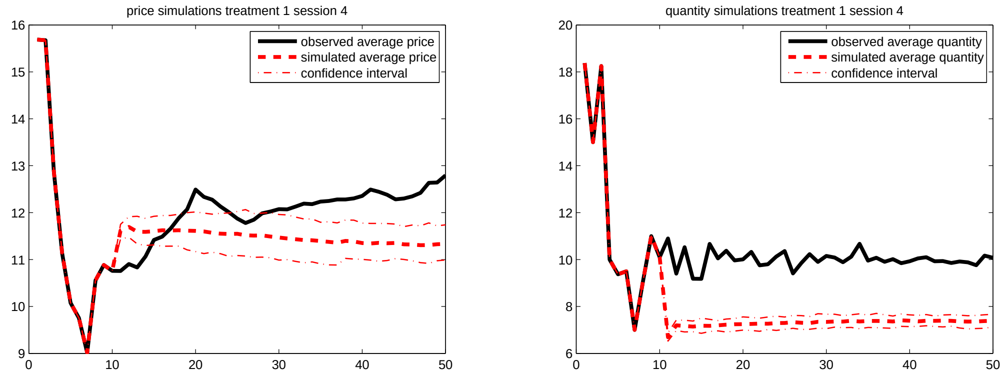


Figure 11: Treatment 1, group 4. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

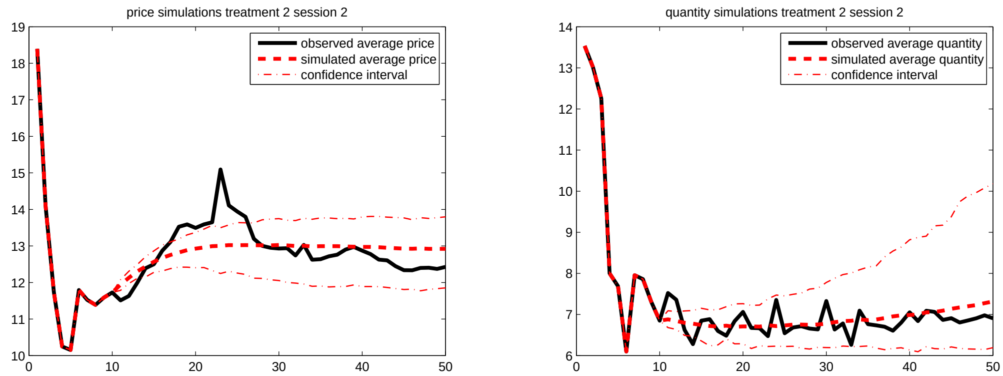


Figure 12: Treatment 2, group 2. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

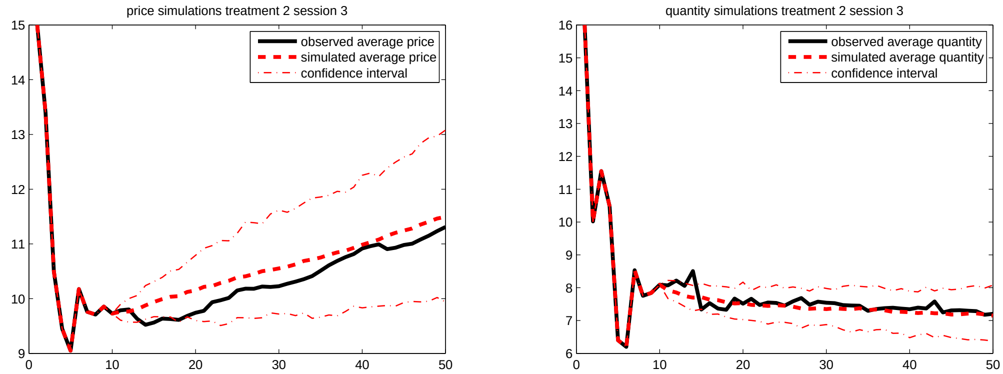


Figure 13: Treatment 2, group 3. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

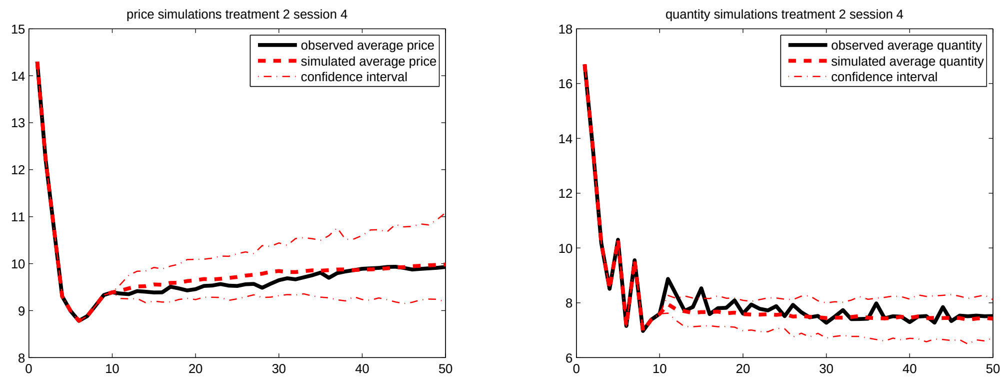


Figure 14: Treatment 2, group 4. **Left panel:** Simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of Monte Carlo simulations. **Right panel:** Simulated and observed average quantity. The simulated average quantity is created with a set of Monte Carlo simulations.

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