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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 we find that subjects' behavior is well described by learning heuristics.

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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 decide on production in advance and they cannot react immediately to possible changes 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 setup 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

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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 setup 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 are 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 pattern 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 analyze 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 Keynesian framework (see e.g. [Woodford, 2003](#)), but also in agent-based macro models (e.g. [Delli Gatti et al., 2011](#)). Agent-based macro models 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 the following:

- Does aggregate market and individual firm behavior 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](#) analyzes 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 [Section 2.1](#)), the experimental design (in [Section 2.2](#)) and the experimental results (in [Section 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

$$q_i = \alpha - \beta p_i + \theta \bar{p}, \quad (2.1)$$

where \bar{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

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 \(1999\)](#).

demand e.g. Huck et al. (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:

$$p^{BR} = \alpha' + c/2 + \theta' \bar{p}, \quad (2.2)$$

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

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

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

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

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 the 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 market structure, but they do not know either the exact value of the structural coefficients α , β , and θ or 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 remains 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.

2.2.1. 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 decide 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.

³ See Davis and Korenok (2011) for details.

Table 1

Benchmark equilibrium values for price and quantity in monopolistic competition (MC), Nash equilibrium (NE), Walrasian equilibrium (W) and Collusive equilibrium (CO).

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

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.

2.2.2. Procedures

The experiment took place at the CREED laboratory at the University of Amsterdam, March 2013, and it was programmed using the PET software.⁴ 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.⁵ 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 (Experimental Count Units) per unit produced. In order to accommodate possible losses, we granted subjects an initial endowment of 500 ECU. Subjects' earnings are given by realized cumulated profits at the end of the experiment. If a firm's capital balance became negative, it was considered bankrupted. Overall, we observed only two episodes of bankruptcy, namely subjects 4 and 8, treatment 1 group 4, which occurred in the early stage of the experiment.⁶ 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 the Online 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 relative to the average price, experiencing low demand and thus making losses. Consequently, such firms 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.⁷ 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.

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.

Comparing treatment 1 and treatment 2 we observe in Fig. 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).

⁴ PET software was developed by AITIA, Budapest, and is available at <http://pet.aitia.ai>.

⁵ Notice that subjects were not informed about the size of each market.

⁶ Subject 8 went bankrupt in period 6 while subject 4 went bankrupt in period 9.

⁷ In treatment 1, groups 2 and 4, the minimum realized price is close to the Walrasian equilibrium $p^W = c = 8$.

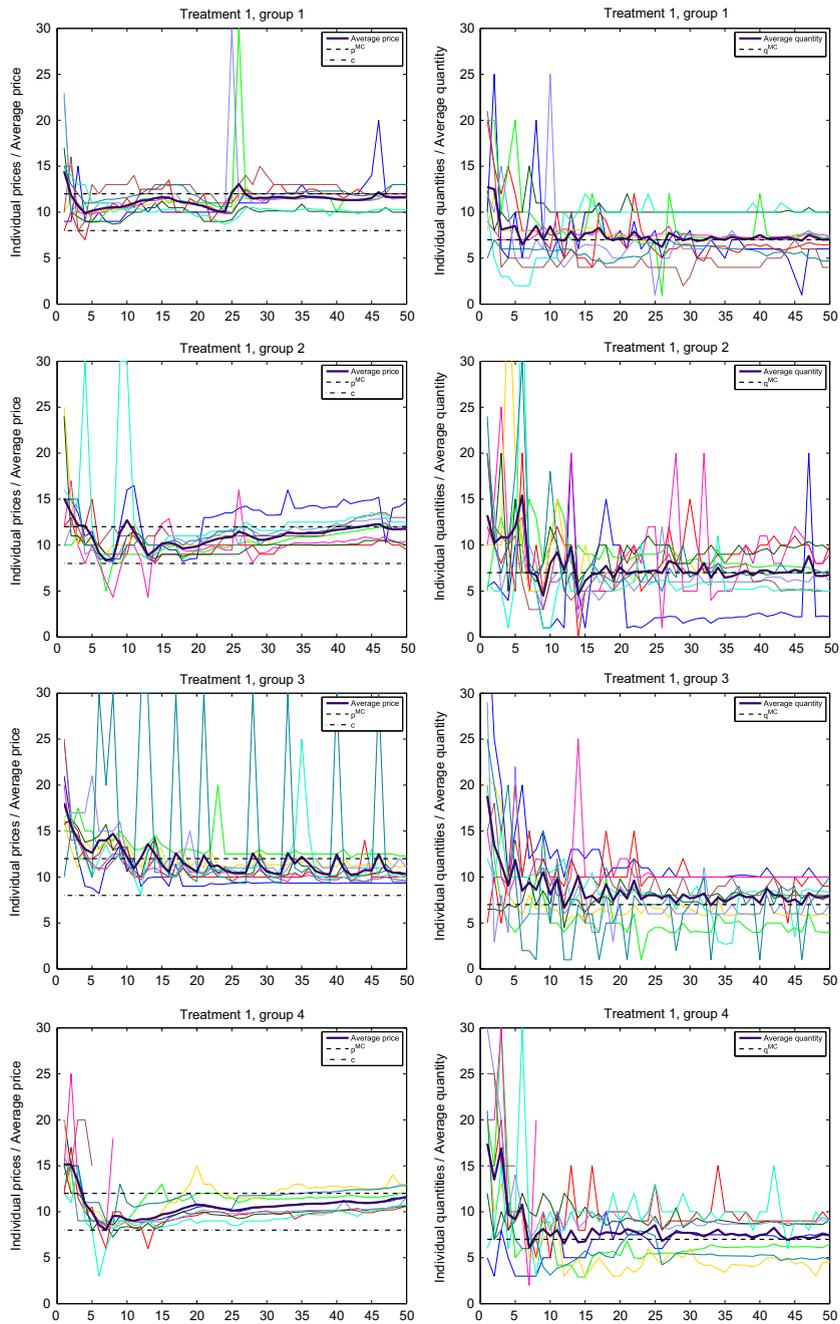


Fig. 1. Treatment 1. Left panels: individual prices (thin lines) and aggregate price (thick line). Right panels: individual quantities (thin lines) and average quantity (thick line).

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 treatments 1 and 2.⁸ We find a significant difference between the average absolute value of excess supply/demand between treatments 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.

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

⁸ In the case of treatment 1 we included in the plot the unobserved excess demand component.

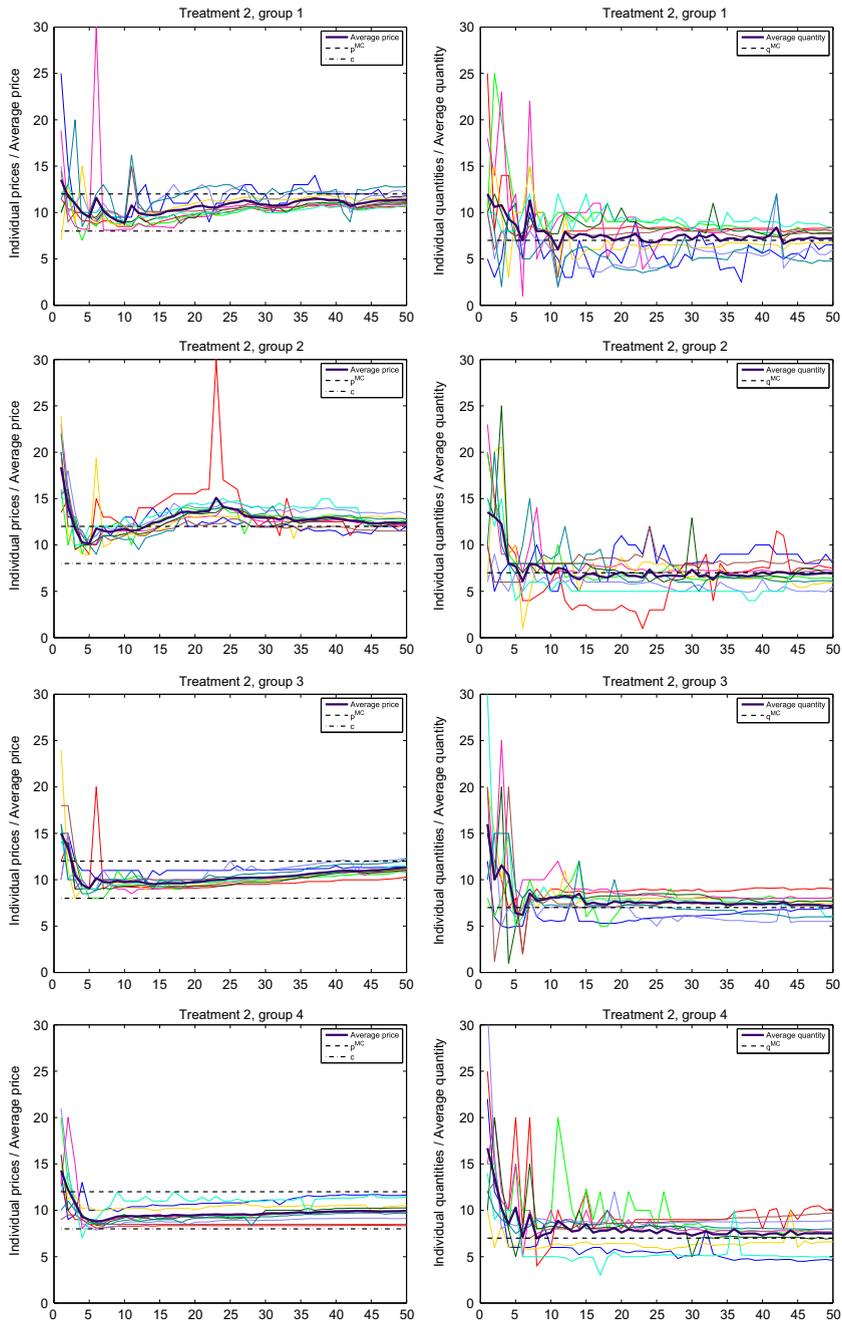


Fig. 2. Treatment 2. Left panels: individual prices (thin lines) and aggregate price (thick line). Right panels: individual quantities (thin lines) and average quantity (thick line).

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

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. Although firms display a higher level of coordination in treatment 2, Fig. 4

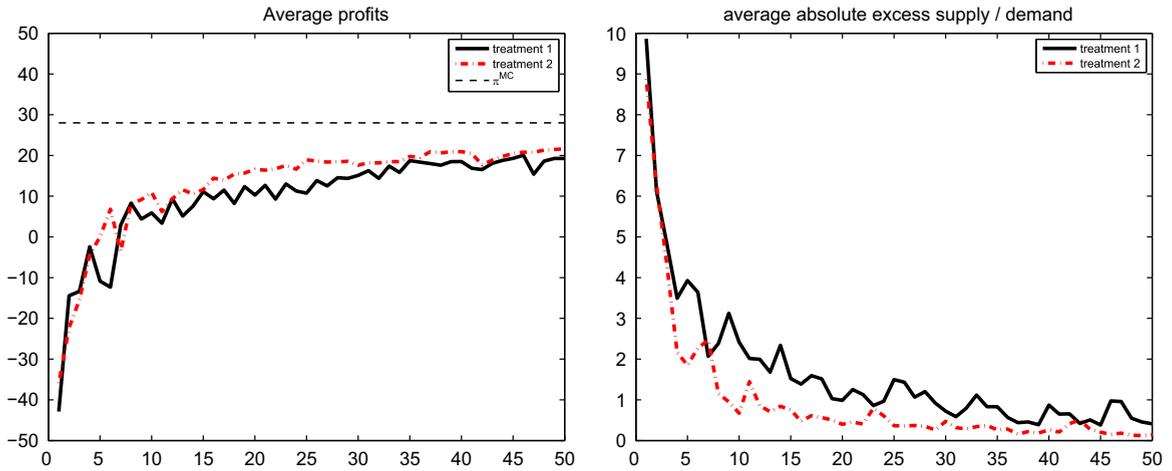


Fig. 3. Left panel: evolution of average profits compared to MC equilibrium profits. Right panel: evolution of the absolute value of the excess supply/demand. In the case of treatment 1 we included in the plot the unobserved excess demand component.

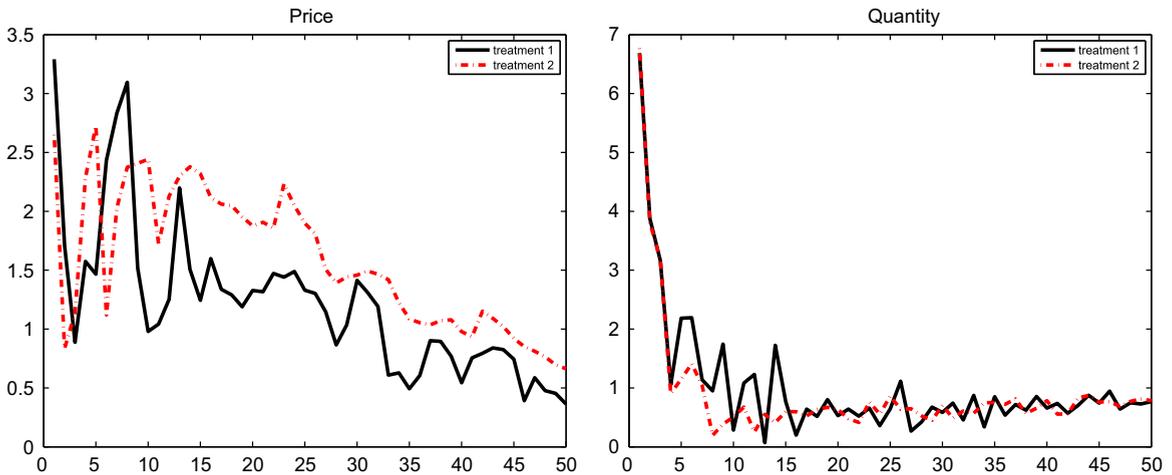


Fig. 4. Left panel: median of the absolute difference between the average price and the MC equilibrium price. Right panel: median of the absolute difference between the average quantity and the MC equilibrium quantity.

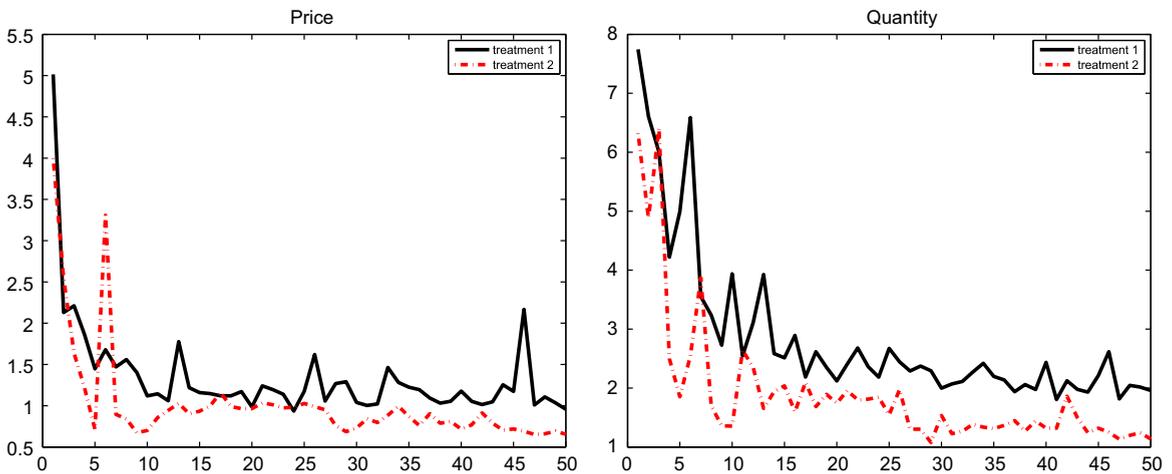


Fig. 5. Left panel: median of the standard deviations of individual prices. Right panel: median of the standard deviations of individual quantities.

shows that, in the same treatment, the difference between market price and the MC equilibrium is higher. The different market behaviors in the two treatments are due to the different information sets available to firms. In particular, the higher informational content provides a lower incentive for firms to explore the price–quantity space. The intuition behind this result is further developed in [Section 4.3](#).

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)⁹ of the form

$$\bar{p}_{i,t}^e = c + \alpha_1 \bar{p}_{t-1} + \alpha_2 \bar{p}_{i,t-1}^e + \alpha_3 \bar{p}_{t-2} + \varepsilon_t \quad (3.1)$$

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

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

to our experimental data. In Eq. (3.1) the variable \bar{p} refers to realizations of the aggregate price, while the variable \bar{p}_i^e 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 $\Pi_i = \Delta p_i \cdot \text{sgn}(\Delta \pi_i)$, where π_i are the individual profits and the Δ is the first order difference operator,¹⁰ and it captures individual price adjustments in the direction that led to an increase in profits in the last period, 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) can be rewritten as

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

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 the profit feedback on individual pricing decisions. 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

⁹ For other applications of the FOH in modelling experimental data such as data on expectation formation see e.g. [Heemeijer et al. \(2009\)](#) and [Assenza et al. \(2011\)](#).

¹⁰ 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.

assumed not to believe that its price might have a significant influence on the aggregate price.¹¹ Moreover, the monopolistically competitive market structure reproduced in the experimental markets postulates that prices have an impact on quantities demanded and not vice versa. 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 the Online Appendix B. Tables 4–11 in the Online Appendix C report the results of the estimation of the FOH model to individual time series of market price forecasts, pricing and production decisions.

3.2.1. Market price forecasting rules

Overall, 58% of the subjects use the time-varying anchor composed of the first three terms in (3.4), while the remaining 42% augment 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, i.e., $\alpha'_1 = 1$, $c' = \alpha'_2 = \alpha'_3 = 0$ in the estimated Eq. (3.4), while 36% can be classified as Adaptive, i.e., $\alpha'_1 + \alpha'_2 = 1$, $c' = \alpha'_3 = 0$ in the estimated Eq. (3.4). The remaining 35% use a combination of the first three terms in (3.4) as their anchor. Among the subjects using both the anchor and the adjustment term, 24% can be classified as Trend Followers, while the remaining 76% extrapolate the last change in observed prices starting from an anchor given by the combination of the first three terms in (3.4).

3.2.2. 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 five 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.

3.2.3. 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 describes 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

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

which can be interpreted as follows. The subject uses an anchoring or an 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.

¹¹ 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 et al. (2004) show, in the context of oligopolistic markets, that a number of firms $n \geq 4$ are enough to eliminate this sort of strategic reasoning and ensure convergence to either Cournot or Walrasian equilibrium.

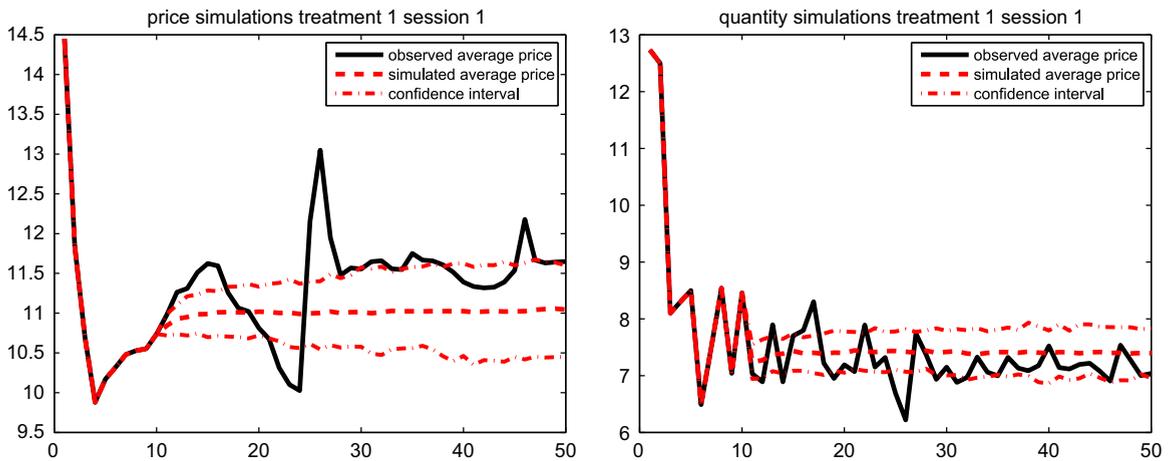


Fig. 6. Left panel: simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of 500 Monte Carlo simulations. Right panel: simulated and observed average quantity. The simulated average quantity is created with a set of 500 Monte Carlo simulations.

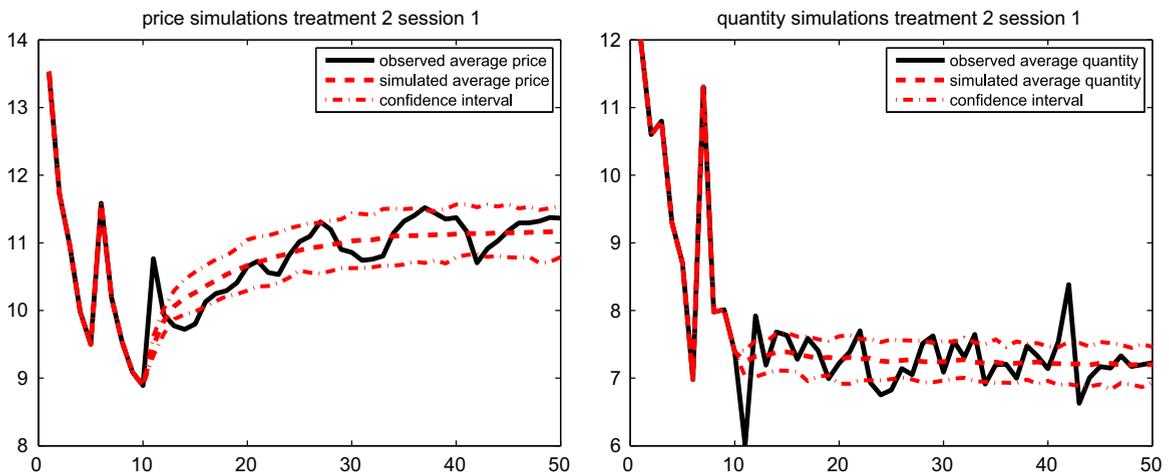


Fig. 7. Left panel: simulated and observed average price and 95% confidence interval. The simulated average price is created with a set of 500 Monte Carlo simulations. Right panel: simulated and observed average quantity. The simulated average quantity is created with a set of 500 Monte Carlo simulations.

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 the Online Appendix D.

Overall, the simulated markets are able to reproduce the qualitative behavior observed in the experimental economies. The interaction between the estimated strategies produces 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

$$p_{i,t} = c_i + \beta_{i,1} p_{i,t-1} + \beta_{i,2} \bar{p}_{i,t}^e + u_{i,t},$$

and we start with the simplest possible case in which agents hold naive expectations concerning the average market price, i.e., $\bar{p}_{i,t}^e = \bar{p}_{t-1}$. 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 $\bar{\beta}_1 + \bar{\beta}_2 < 1$.¹² 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 10,000 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).

4.2.1. 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 strategies up to an idiosyncratic noise term:

$$\bar{p}_{i,t}^e = \bar{p}_{t-1} + \varepsilon_{i,t} \quad (4.1a)$$

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

$$q_{i,t} = 10.5 - 1.75 p_{i,t} + 1.4583 \bar{p}_{i,t}^e + \eta_{i,t}. \quad (4.1c)$$

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 is 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.¹³ It is interesting to note that the simulated markets do not reach the collusive equilibrium due to the heterogeneity introduced by the idiosyncratic noise.¹⁴ 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 equilibrium,¹⁵ 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 among price strategies, price forecast and quantity setting rules in the

¹² 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.

¹³ 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 nonstationary. 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.

¹⁴ We remark that simulating a system with heterogeneous coefficients $\beta_{i,3}$ would lead to the same conclusions.

¹⁵ In a market populated by profit-adjusters only we observe convergence to the Nash rather than the MC equilibrium. This is due to the fact that the number of firms is finite. In such an environment, when firms increase their price they have a sensible impact on the average price. The profit-adjusters strategy tends to move the price in the direction leading to an increase of profits. Suppose that all firms are at the MC equilibrium and that one firm by chance slightly increases the price. Given that the number of firms in the simulation is limited, this price change has a non-negligible effect on the average price. This leads to a positive value of the profit feedback variable inducing a further increase of the individual price. The profit feedback mechanism provides an individual incentive to deviate from the MC equilibrium moving the market in the direction of the Nash equilibrium.

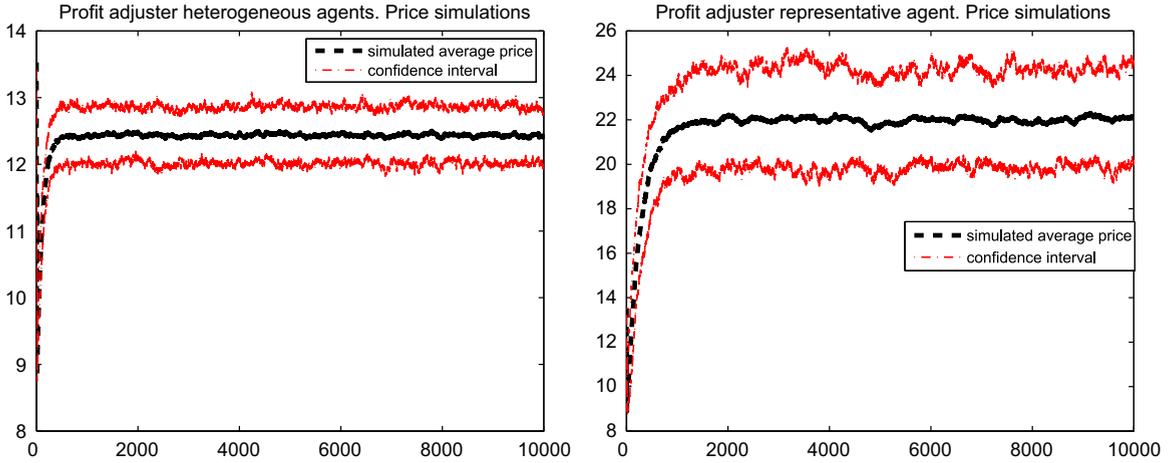


Fig. 8. Left panel: simulated average price with profit adjusters heterogeneous agents and 95% confidence interval with $\beta_3 = 0.5$. Right panel: simulated average price with profit adjuster representative agent and 95% confidence interval.

Table 2
Absolute average distance from expected best response.

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

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

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

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 relative 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.

Table 3
Absolute average distance from zero excess supply.

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

4.2.2. 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 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 setup to study the impact of the demand adjustment term read as follows:

$$\bar{p}_{i,t}^e = \bar{p}_{t-1} + \varepsilon_{i,t} \quad (4.5a)$$

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

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

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 minimizing 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 path dependence in aggregate behavior with simulated outcomes of price and quantity being conditional to the set of initial conditions. 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 heuristic. By avoiding any overproduction and by setting the price above the constant production cost, the demand adjusters may not maximize profits but they are able to avoid large 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 depend on the interactions among 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:

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

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 Eq. (4.6), we can compute the demand-adjusters' target price

$$p_{i,t}^S = \frac{1}{\beta} (\alpha + \theta \bar{p}_t^e - q_{i,t-1}). \quad (4.7)$$

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

$$d_{i,t} = \left| \frac{p_{i,t} - p_{i,t}^S}{p_{i,t}^S} \right|, \quad (4.8)$$

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

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

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.

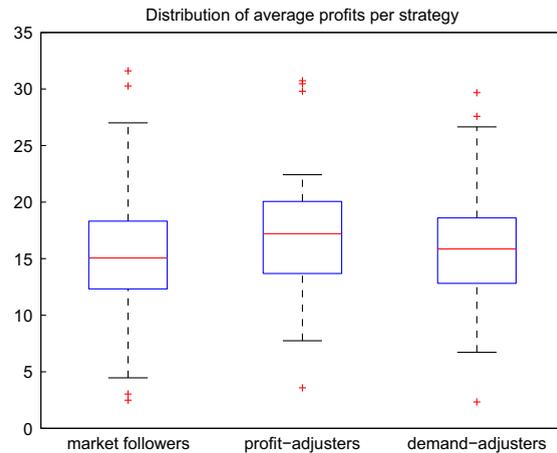


Fig. 9. Distribution of average individual profits per strategy (pooled data). On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually.

4.2.3. Interaction among behavioral strategies

In order to help develop the intuition behind the impact of each strategy type on aggregate dynamics, the simulations presented so far take into account extreme scenarios, i.e., environments featuring only one behavioral type of firm. To gain further insights on the impact of heterogeneity on aggregate dynamics, we perform additional simulations in which we allow the different strategies to interact in the same market and we vary their proportions along a grid. The simulation outcomes show that the proportions of strategies present in the market have an effect on the equilibrium reached by the system and on the speed of convergence. Increasing the share of each behavioral type in the composition of market strategies leads to the outcomes described in the previous section. In particular, a higher share of profit-adjusters favors market convergence towards the Nash equilibrium, the impact of market followers depends on the estimated coefficients, while demand-adjusters do not represent a market force pushing towards the Nash equilibrium and realized dynamics depend on the initial conditions. To investigate the speed of convergence as a function of the strategy composition we define the price interval $[11,13]$, which includes both the Nash and the MC equilibrium, and compute the speed of convergence as the number of periods needed by the system to reach it. A stylized fact emerging from the simulations is that a higher share of profit-adjusters increases the speed of convergence of the system to the $[11,13]$ price interval, while a higher fraction of demand-adjusters slows down convergence. The intuition for the latter result is that demand-adjusters set their price in order to reduce excess supply, which does not necessarily coincide with a price movement in the direction of the Nash/MC neighborhood. Table 2 shows that the average distance of demand-adjusters' prices from the best response price is higher when compared to profit-adjusters' prices. In this sense, demand-adjusters do not represent a market force pushing towards equilibrium. Market followers seem to have a limited impact on convergence speed depending on the estimated coefficients.¹⁶

The experimental outcomes show persistent heterogeneity in firms' behavior. In fact, less sophisticated strategies survive market competition. Fig. 9 shows the distribution of average individual profits divided by firms' category pooled over treatments. Although the median profit is higher for profit-adjusters, differences among groups are not statistically significant (Mann–Whitney U -test, 0.05 level), i.e., profit-adjusters do not necessarily make more profits than other categories of firms. The intuition for this result is the following. Profit-adjusters set their price following the direction that led to an increase in profits in the previous period. However, realized individual profits depend crucially on the decisions of other subjects. If profit-adjusters set their price too far from the average price, even if in the right direction (i.e., in the direction corresponding to a positive slope along the profit function), individual demand will be relatively small and this may result in lower profits. With other subjects following the market, profit-adjusters play therefore a crucial role in pushing the economy towards equilibrium. Fig. 10 displays the distribution of average individual profits in different treatments. The difference between profit levels of profit-adjusters and demand-adjusters is more pronounced in treatment 1. In fact, the mass of demand-adjusters is skewed towards higher profit levels in treatment 2 when compared to treatment 1. Demand-adjusters in treatment 2 have access to additional information, i.e., excess demand, and this results in higher profits.

4.3. The impact of different information sets

The results presented in Section 2.3 show that in treatment 2 there is lower convergence to the MC equilibrium price and a higher level of coordination in individual prices (see Figs. 4–5). This is due to the different information sets available to

¹⁶ We do not report the simulation results for the sake of brevity. Results are available from the authors upon request.

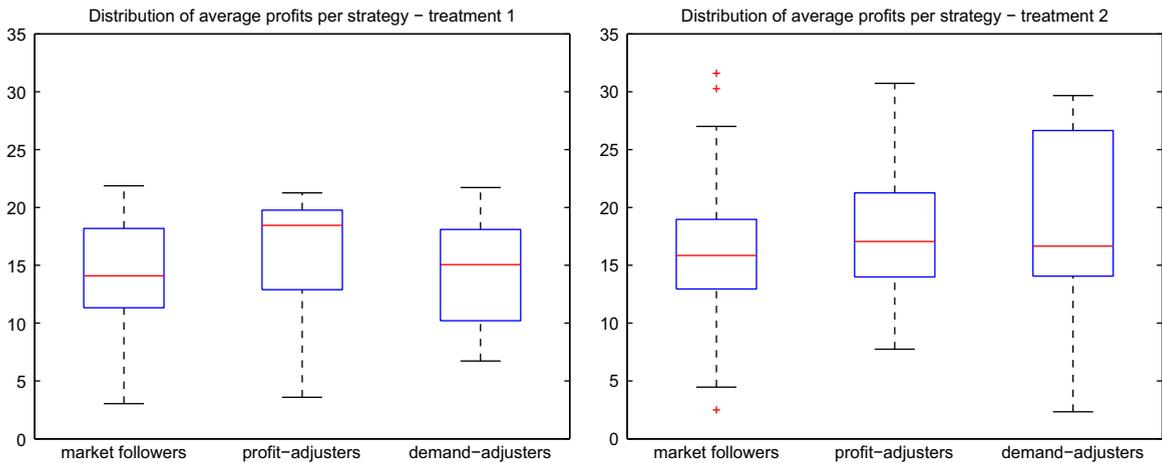


Fig. 10. Left panel: distribution of average individual profits per strategy in treatment 1. Right panel: distribution of average individual profits per strategy in treatment 2.

firms in each treatment. In particular, the limited information in treatment 1 provides subjects with an incentive to “explore” the demand function by experimenting with different prices. In order to support this hypothesis, we constructed a proxy for individual exploration via price experimentation given by the standard deviation of individual price series. A higher standard deviation implies a higher level of price experimentation. The comparison between the two proxies confirms our conjecture. The median standard deviation in treatment 1 is 1.49, while in treatment 2 is 1.18 and the difference is statistically significant (Mann–Whitney U -test, p -value 0.00).¹⁷ The lower level of exploration in treatment 2 leads firms to rely on the information conveyed by market prices in their price setting decisions. This results in a higher level of coordination among firms, and at the same time it slows down convergence to the MC equilibrium. In fact, inertia in price-setting behavior of a significant share of firms (i.e., demand-adjusters with less incentive to explore and market followers) prevents profit-adjusters from pushing the market towards the MC equilibrium. In fact in this scenario profit-adjusters may realize low profits if they deviate too much from the average price, even if they move in a direction corresponding to a positive slope in the profit function, causing the market to lock in sub-optimal regions. This explains the stylized fact of lower convergence to equilibrium in treatment 2.

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 not only prevents markets from converging exactly to the MC outcome, but also prevents coordination on the collusive outcome. Persistent behavioral heterogeneity therefore affects aggregate dynamics in our experimental markets.

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¹⁷ We also constructed an alternative proxy for individual price experimentation given by the average (absolute value of) price change between periods. The median value of this proxy in treatment 1 is 0.64, while in treatment 2 is 0.39 and the difference is statistically significant (Mann–Whitney U -test, p -value 0.00).

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Appendix A. Supplementary data

Supplementary data associated with this paper can be found in the online version at <http://dx.doi.org/10.1016/j.jedc.2014.08.017>.

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