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A B S T R A C T

Using data obtained from experiments reported in García-Gallego (1998) and García-Gallego and Georgantzís (2001), we estimate a simple model of adaptive behavior which could describe pricing in a market whose demand conditions are unknown to the firms. Divergence between the limit of observed prices over time and theoretical predictions concerning multiproduct firms could be partially explained as a result of learning limitations associated with multiple task-oriented problem solving. However, optimal multiproduct pricing requires that subjects use two different kinds of rules: one concerning responses to prices charged by other players and another concerning pricing of own products. Even in a simple environment like the one studied here, subjects seem to be far more successful in learning a number than learning a rule.

JEL: C72, C9, L1.

Keywords: Adaptive Learning, Experimental Oligopoly, Multiproduct Firms.

1 Introduction

Learning is a complex phenomenon. Any attempt to classify or exhaustively review the existing literature would risk being too narrowly focused on only few of a large number of phenomena underlying learning. In this paper, we focus on the role of simple adaptive rules on decision making by agents with minimal information on their market environment.

In economics, the interest that the issue of learning has gained over the past decade is mainly due to the implications it has concerning an economic agent's rationality and behavior in a market. In fact, the most common type of learning studied by economists concerns the case of a market in which firms ignore some important features of their environment and/or the type of other firms they are faced with. It is commonly assumed that, in the case of a market with these characteristics, agents use simple (or less simple) *learning strategies* or *rules* (*algorithms*) which aim at both improving performance in the future and reducing losses due to ignorance in the present.

Early studies address the issue of how to model the behavior of imperfectly informed agents who do not hold correct beliefs concerning their environment and the type of their competitors and whether such behavior converges to any limit point that could be considered as an equilibrium situation consistent with the agents' beliefs.[1] In more recent literature, learning failures are explained as the result of a large number of factors. Among such factors, we mention misperception of feedback in complex environments[2], limitations in subjects' learning when exposed to strategic complexity[3], multiproduct activity[4], market asymmetries[5], vertical relations[6], *etc.*

[1]The role of specific learning rules is studied by Cyert and DeGroot (1971, 1973), Kirman (1975), Friedman (1976), Robson (1986), *etc.*

[2]Paich and Sterman (1993) and Sterman (1994).

[3]Richards and Hays (1998) and García-Gallego *et al.* (2000a).

[4]Kelly (1995) and García-Gallego and Georgantzís (2001).

[5]García-Gallego *et al.* (2000).

[6]Durham (2000).

Despite the pessimistic view that one might get from this long list of factors limiting an agent's ability to learn in an initially unknown environment, a number of recent studies indicate that, under certain circumstances, simple try-and-error algorithms may yield convergence towards full-information equilibrium predictions. This fact has been mostly confirmed in simple settings with minimal information on past actions like, for example, the symmetric price-setting oligopoly in García-Gallego (1998).[7] Along a similar strand in the literature, we find a number of specific conditions and learning strategies which may cause an agent's performance in an unknown environment to converge towards certain points predicted as full-information equilibria. Examples include knowledge of the maximum attainable pay off[8], imitation of successful players[9] and experience gained in the past[10].

However, as the level of complexity and the degree of task multiplicity increases, pessimism about the ability of humans to successfully learn from past actions emerges from the fact that optimal behavior across a number of tasks and along a number of periods, requires the use of optimal (complex) rules which go beyond fixing a certain strategic variable to a given optimal level. As reported by Kelly (1995) on an experimental multi-product monopoly, subject behavior is more likely to converge to equilibrium predictions when strategy options are simple. Theoretical work on experimentation has addressed the issue of optimal learning on a *ceteris paribus* basis.[11] Therefore, we know how a perfect

[7]In the presence of similar information on past actions, a much weaker convergence (if any) towards static Nash equilibrium output is obtained in an experimental *asymmetric* quantity setting oligopoly studied by Rassenti *et al.* (2000).

[8]Dawid (1997).

[9]Duffy and Feltovich (1999), Offerman and Sonnemans (1998) and Bosch and Vriend (1999).

[10]Nagel and Vriend (1999a, 1999b)

[11]See Harrington (1995) and the literature cited there. As the author points out, previous work to his own focused mainly on experimentation in a single-agent setting. Furthermore, Harrington's work improves our understanding of how firms should act in the presence of an unknown degree of product differentiation. However, real-world uninformed firms of the kind described in that article are very unlikely

learning machine would learn about *one* of the factors affecting its performance in an unknown environment. However, optimal learning is such a complex task that, even in the presence of relatively low degrees of complexity, it would be easier to defend the realism of assuming perfect knowledge of market conditions than assuming knowledge and use of the optimal learning rules.

Along a different tradition[12], experimentation with complex systems has been used to assess the performance of human subjects in unknown and relatively complex environments. In that literature, learning failures and some of their causes are identified. However, the results obtained cannot be used to predict to what degree certain rules which are spontaneously used by the subjects cause strategies to converge towards a certain limit point. Therefore, despite the insightful conclusion that performance in a complex setting may be improved as the experimentalist introduces more (or better) information[13], systematic instruction with simulation tools[14] and improvement of reasoning capabilities [15], little has been said about which rules are spontaneously used by economic agents in unknown environments and whether such rules yield specific predictions concerning convergence to certain limit points. In order to assess the role of simple and realistic algorithms (which are spontaneously adopted by humans) on adaptation to full information equilibrium behavior, the distinction between *adopting a strategy* and *using an adaptive rule* becomes necessary.[16]

The analysis presented here can be seen as an extension of the experimental work

to possess perfect information on the demand intercept, own demand elasticity and the functional form of the demand function.

[12]See, for example, Paich and Sterman (1993), Diehl and Sterman (1995) and Sterman (1994).

[13]García-Gallego *et al.* (2000).

[14]Sterman (1994).

[15]Vriend (1997) and Sterman (1994).

[16]In various contexts, the distinction and the relation between strategies and rules has been proposed as an important feature of human learning in initially unknown market conditions (Slonim (1999), Kirchkamp (1999)).

reported in García-Gallego (1998), G-G hereforth, and García-Gallego and Georgantzís (2001), G-GG. In G-GG, it was shown that a multiproduct oligopolist would fail to earn as high profits as predicted by the multiproduct noncooperative equilibrium because[17] product-specific application of try-and-error algorithms favors convergence to a single-product equilibrium. In G-GG, the price parallelism rule for products of the same manufacturer is shown to be a necessary condition for convergence to a multiproduct noncooperative equilibrium to be observed. However, despite the simplicity of the rule, most human subjects fail to spontaneously learn how to use it. We use data from the experiments reported in G-G and G-GG to study whether convergence to a certain oligopolistic equilibrium depends on the use of specific adaptive rules spontaneously adopted by experimental subjects. We do not aim at presenting an exhaustive study on aggregate behavior observed from all the experimental sessions reported in the two aforementioned articles. Rather, we study individual behavior in a number of selected experimental sessions which are interesting either because of their convergence towards specific limit points, or because subjects seem to have been using specific types of adaptive rules.

The remaining part of the paper is organized in the following way: Section 2 briefly reviews the framework and results obtained in G-G and in G-GG. In section 3, a model of adaptive pricing behavior is presented and results obtained from its estimation are discussed. Section 4 contains concluding remarks.

2 Experimental oligopolies with single-product and multiproduct firms

We briefly review here the experimental framework proposed in G-G and G-GG. The reader will find a detailed description of the experimental design and the results summarized here in those articles.

In G-G, a number of experiments with different levels of product differentiation and

[17]As shown in G-G.

single-product firms, was found to systematically yield the same conclusion: in the absence of any explicit agreement on pricing strategies (like, for example, price parallelism according to a pre-game convention regarding price alignments) the single-product Bertrand equilibrium price is the attractor of price strategies by initially uninformed subjects.[18]

In the same market setup, G-GG investigate the convergence of agents' decisions in a multiproduct oligopoly. Different industry configurations are studied assuming different intensities of multiproduct activity. Three groups of experiments are analyzed. First, with single-product firms, second, with multiproduct firms acting in the absence of any exogenously imposed pricing rule and, third, with multiproduct firms to which a specific pricing rule is imposed: equal prices for products of the same firm. An important question is raised. That is, whether multiproduct firms facilitate convergence to any price level closer to the collusive than to the Bertrand-Nash outcome. Or, in any case, whether the existence of multiproduct firms alone is a sufficient condition for the multiproduct Bertrand-Nash to be observed.

Among a relatively small number of similar experimental studies on oligopoly behavior, G-G and G-GG use a plausible scenario of a market with five varieties which may be served by single-product firms or, alternatively, by combinations of multiproduct and single-product firms. By varying the number of products per firm, the experimentalist varies the complexity of the task faced by the subjects. The data obtained from different treatments are totally comparable, although by increasing the number of products per firm the number of players in each session decreases. This implies a lower degree of strategic complexity and, at the same time, an increase in the importance of each subject's actions on the market outcome. Furthermore, the initially symmetric situation (five firms offering five symmetrically differentiated varieties) contrasts with the asymmetric oligopoly in which a more multiproduct firm competes with a less single-product one. In other words, despite the effort to fulfil the ceteris paribus requirement, an inevitable mix of factors

[18] An an experimental test of conscious parallelism is reported in Harstad *et al.* (1998), where the option of price-matching behavior is explicitly offered to subjects, leading to higher than Bertrand equilibrium price levels.

should be accounted for when assessing the effects of complexity on learning by our experimental subjects.

In the multiproduct setting, systematic divergence between theoretical predictions and experimental results is observed. However, it is shown that, if multiproduct firms are restricted to apply a price parallelism rule, the observed outcome is closer to the theoretically predicted behavior for fully informed multiproduct subjects. In very few cases, subjects learn the optimal rule during the experiment. This is what we call *learning* a rule as opposed to *learning* a number. The former requires an explicit understanding by the subjects of the optimal strategy to follow. Such an understanding implies learning a more complicated mechanism than a simple adjustment of prices near certain numbers which, from a certain moment in each experiment, are recognized by almost everybody as the *correct* ones. When subjects are interviewed at the end of each session, it is not surprising that subjects whose performance has been closer to what could be seen as an optimal behavior rule report perceptions which are closer to the true specification of the model, although it is rather exceptional that their reply correctly reflects the symmetry of cross-product demand substitutability.

2.1 Framework

There are 5 varieties of a differentiated product offered by $N \leq 5$ firms (depending on the number of multiproduct firms in the industry) during 35 periods. Price is the only decision variable of each firm at each period. Market structure is denoted by $S = (m_1, \ldots, m_i, \ldots, m_N)$, where m_i is the number of products sold by firm i.

The market response is computer simulated. Players know own demands and profits as well as the strategies of their rivals in the past.

Players are not aware of the demand function, which is symmetric with respect to all varieties and, for variety $i \epsilon \{1, 2, 3, 4, 5\}$ in period t, is given by:

$$q_{it} = \alpha - \beta p_{it} + \theta \sum_{j \neq i} p_{jt} \tag{1}$$

where parameters α and β represent, respectively, the intercept and the slope of the demand function. Both are fixed and constant. The parameter θ corresponds to the effect of the other varieties' prices on the firm's demand with respect to variety i. Discussion of the properties, implications and justification for the use of this model are provided in G-G and, especially, G-GG.

Unit costs are equal for all varieties. Unit (marginal) costs $c_i = c$, are constant and there are no fixed production costs. Firms are assumed to produce exactly what they can sell.

As benchmark theoretical predictions, we use the following one-shot perfect information equilibrium concepts:

1) SBNE (Single Bertrand-Nash Equilibrium), corresponding to $S = (1, 1, 1, 1, 1)$, satisfying the first order conditions: $\frac{\partial \Pi_i}{\partial p_i} = 0$.

2) MBNE (Multiproduct Bertrand-Nash Equilibrium), corresponding to $S = (m_1, \ldots, m_i, \ldots, m_N)$, satisfying that: $\frac{\partial \Pi_i}{\partial p_{ik}} = 0$ where k is one of the m_i varieties sold by firm $i \in \{1, \ldots, N\}$.

3) Collusive equilibrium or industry-wide cartel optimum, corresponding to $S = (5)$, satisfying the first order conditions: $\frac{\partial \Pi}{\partial p_i} = 0$, where $\Pi = \sum_{i=1}^{5} \Pi_i$.

Table 1 presents the resulting theoretical values of equilibrium prices and profits for the parameter values used in the experiments: $\alpha = 500$, $\beta = 3$, $c = 40$, and two values of parameter θ ($\theta = 0.14$ and $\theta = 0.4$).

Equilibrium prices reflect some of the characteristics of the theoretical model. Prices are higher the higher the number of multiproduct firms - given a number of products per firm - and the higher the number of products per firm -, given a number of multiproduct firms in the industry. Equilibrium prices set by a multiproduct firm are higher than those set by another firm, if the former produces more products than the latter. Obviously, the same relations hold with respect to the corresponding equilibrium profits. Finally, a higher value of θ ($\theta = 0.4$) leads to higher strategic complementarity and, therefore, higher prices (and profits), as compared with the case in which $\theta = 0.14$. The difference between prices corresponding to any pair of equilibria is larger the higher the value of θ.

prices	p_1		p_2		p_3		p_4		p_5		p_i	
$S \downarrow \theta \rightarrow$	0.14	0.4	0.14	0.4	0.14	0.4	0.14	0.4	0.14	0.4	*Single/less multipr.*	*Multiproduct*
$(1,1,1,1,1)$	113.9	140.9	113.9	140.9	113.9	140.9	113.9	140.9	113.9	140.9	$\frac{\alpha+\beta c}{2(\beta-2\theta)}$	-
$(3,2)$	117.9	161.5	117.9	161.5	117.9	161.5	116.0	153.4	116.0	153.4	$\frac{2\alpha\beta+2\beta^2 c-\alpha\theta-3\beta\theta c-2\theta^2 c}{2(2\beta^2-6\beta\theta+\theta^2)}$	$\frac{2\alpha\beta+2\beta^2 c-4\beta\theta c-2\theta^2 c}{2(2\beta^2-6\beta\theta+\theta^2)}$
profits	Π_1		Π_2		Π_3		Π_4		Π_5		Π_i	
$(1,1,1,1,1)$	16415	30547	16415	30547	16415	30415	16415	30547	16415	30547	$\frac{\beta[\alpha-c(\beta-4\theta)]^2}{4(\beta-2\theta)^2}$	-
$(3,2)$	16500	32494	16500	32494	16500	32494	16549	33453	16549	33453	$\frac{(\beta-\theta)(2\beta-\theta)^2(\alpha-\beta c+4\theta c)^2}{4(2\beta^2-6\beta\theta+\theta^2)^2}$	$\frac{\beta^2(\beta-2\theta)(\alpha-\beta c+4\theta c)^2}{(2\beta^2-6\beta\theta+\theta^2)^2}$

Table 1: Theoretical Values of Equilibrium Prices and Profits

3 Adaptive behavior by single-product and multi-product subjects

In G-GG we tested the whole range of possible industry configurations, as far as intensity of multiproduct activity is concerned. In the present work, from the overall set of experimental data obtained in G-G and G-GG, we will consider just 12 individual sessions from three treatments[19]: One with 5 single-product firms (sessions 1-4), one with two multiproduct firms selling three and two varieties each (experiment 11), and one with the same multiproduct structure, but in the presence of the rule of *equal prices for products of the same firm* (experiment 12).

From the first treatment, we have chosen experiments 1-4. Each pair of those experiments consists of two replications of the same situation. The difference between experiments 1, 2 and experiments 3, 4 is that they are run assuming different product differentiation parameters ($\theta = 0.14$ and $\theta = 0.4$, respectively). The second treatment corresponds to experiment 11 and includes the case of two multiproduct firms, suplying three and two varieties each. In the present study, we analyze two replications of the basic structure for each value of θ (labeled as "11" and "11($r2$)" in G-GG for $\theta = 0.14$, and "11($R1$)" and "11($R3$)" for $\theta = 0.4$, following their original numbering). Finally, in the third treatment which corresponds to experiment 12, two multiproduct firms supply three and two varieties each faced with the exogenously imposed restriction of applying a rule of pricing equally products sold by the same firm. Again, two replications for each value of the parameter $\theta = 0.14$ are studied (labels are "12($r1$)", "12($r2$)" for $\theta = 0.14$ and "12($R2$)", "12($R3$)" for $\theta = 0.14$).

Prices collected from the sessions studied here are presented in figures 1-12. Note that the joint monopoly ('m') and Bertrand-Nash ('B') prices are provided to make convergence to a certain theoretical equilibrium easier to observe. Note, also, that, in the case of

[19]For comparability and ease of cross-reference, we will maintain, throughout the text, the numbering of individual experiments' introduced in G-GG.

multiproduct Bertrand-Nash equilibria, there is a different equilibrium price for each type of firm ('B3' for multiproduct firms with three products and 'B2' for firms selling two products).

It is a general feature of the evolution of prices over time that price dispersion decreases and that in the last 5 periods all prices are between slightly below the Bertrand-Nash equilibrium and the joint monopoly price. This is a rough but reliable evidence of the fact that learning takes place during each session.

Table 2 presents price averages and variances, for the first 20 and the last 15 periods, calculated for each experiment, considering the sample obtained from collecting prices charged by the same type of firm.

Ex./S	Rule	Type	Av_{1-20}	NV_{1-20}	Av_{21-35}	NV_{21-35}	$\%\Pi^{1-20}$	$\%\Pi^{21-35}$
1 ($\theta = 0.14$)		multi.	–	–	–	–	–	–
$S = (1,1,1,1,1)$	No	single.	109.77	2.56	115.50	0.015	91.35	99.82
2 ($\theta = 0.14$)		multi.	–	–	–	–	–	–
$S = (1,1,1,1,1)$	No	single.	96.39	3.83	112.52	0.027	76.64	99.23
3 ($\theta = 0.4$)		multi.	–	–	–	–	–	–
$S = (1,1,1,1,1)$	No	single.	143.01	15.28	138.24	1.331	87.86	94.23
4 ($\theta = 0.4$)		multi.	–	–	–	–	–	–
$S = (1,1,1,1,1)$	No	single.	103.47	5.68	139.77	2.130	62.43	96.48
11 ($\theta = 0.14$)		multi3.	116.15	0.17	117.62	0.02	94.05	100.03
$S = (3,2)$	No	multi2.	120.90	0.13	117.23	0.01	95.52	99.87
11($r2$) ($\theta = 0.14$)		multi3.	132.01	0.54	112.77	0.02	89.49	98.84
$S = (3,2)$	No	multi2.	207.07	1.04	111.16	0.02	76.65	98.55
11($R1$) ($\theta = 0.4$)		multi3.	146.76	0.34	159.20	0.14	86.04	96.38
$S = (3,2)$	No	multi2.	148.67	0.32	149.33	0.15	84.69	96.71
11($R3$) ($\theta = 0.4$)		multi3.	128.31	0.27	135.31	0.06	75.64	89.94
$S = (3,2)$	No	multi2.	121.80	0.29	132.86	0.05	72.32	87.66
12($r1$) ($\theta = 0.14$)		multi3.	113.20	0.20	115.13	0.02	90.25	99.37
$S = (3,2)$	Yes	multi2.	108.80	0.08	113	0.02	96.95	99.26
12($r2$) ($\theta = 0.14$)		multi3.	108.80	0.35	118.66	0.01	74.69	100.15
$S = (3,2)$	Yes	multi2.	113.60	0.14	117.46	0.01	94.03	100.07
12($R2$) ($\theta = 0.4$)		multi3.	144.80	0.17	166.13	0.01	90.90	103.78
$S = (3,2)$	Yes	multi2.	139.60	0.14	166.13	0.01	90.65	100.79
12($R3$) ($\theta = 0.4$)		multi3.	172.90	0.23	178.33	0.01	91.80	103.17
$S = (3,2)$	Yes	multi2.	162.05	0.15	168.40	0.02	101.22	105.90

Table 2: Observed price averages (Av), normalized variances (NV) and percentage of theoretical (Bertrand-Nash) profits achieved by intervals of time (periods 1 to 20 and 21 to 35 respectively). The *'rule'* column refers to the enforcement (or not) of equal prices for products sold by the same firm. The 'Type' column refers to the type of firm whose prices over the corresponding interval have been used to calculate average and variance.

It can be seen that an intense multiproduct activity alone (in the absence of the *equal prices for products of the same firm* rule) is not sufficient a condition for higher than the single-product non-cooperative equilibrium price levels to be observed. More detailed analysis indicates that, in experiment 11, intense multiproduct activity ($S = (2, 2, 1)$) did not yield prices close to the corresponding *multiproduct Bertrand-Nash* (MBNE) equilibrium price, nor did it yield significant price differences with respect to the Bertrand-Nash equilibrium of the single-product set-up (SBNE). In fact, in session 11($R3$), convergence of the average price (139.13 for multiproduct firms and 138.44 for single-product ones) closer to the SBNE (140.9) is obtained, not only in comparison with the corresponding MBNE or any other theoretical candidate, but, also, as compared to convergence of prices in experiments 3 and 4 to the SBNE.

In experiment 12, a rule according to which a multiproduct firm prices equally all the varieties it sells, was enforced. As shown for all the results presented in G-GG, in the absence of the aforementioned rule, it seems that *some*, but not intense, multiproduct activity does not lead to any higher than the SBNE price. The application of the rule in configurations with intense multiproduct activity, like is experiment 12, yields significantly higher than SBNE prices. Also, the prediction of the theoretical model that, in equilibrium, multiproduct firms charge higher prices than do single-product firms is not given any support in the absence of the rule of equal prices for products sold by the same firm.

Among the sessions chosen, the first four exhibit typical characteristics of experiments with single-product firms. Strong convergence towards perfect information noncooperative equilibrium is achieved by the end of almost all sessions. Evidence of a less clear convergence result is provided only by experiment 2. It can be foreseen that, with a longer time horizon, prices would have converged closer to Bertrand-Nash equilibrium in this experiment too. Nevertheless, it is interesting to observe that convergence in this session would have taken much more time than has taken in the rest of the sessions of its type. Analysis of adaptive behavior in this and comparison with the other single-product sessions will help us see some of the features of individual behavior which may affect the accuracy and speed of convergence towards a certain equilibrium prediction.

Among the rest of the sessions on which our study of adaptive behavior is based, two replications of experiment 11, namely $11(R1)$ and $11(r2)$, offer us in an exceptionally clear way evidence in favour of the following claim: *'Some subjects, throughout the experiment, go beyond learning a number -such as the equilibrium price- and adopt the optimal pricing rule.'* By exogenously inposing this rule in one of the treatments, the design in G-GG allows us to formally account for the role of price parallelism across products sold by the same firm on the compatibility between observed limit behavior and the full-information MBNE predictions.

Table 3 summarizes tests performed for all individual sessions in experiments 11 and 12. As in the majority of the experiments, in which no specific pricing rules were imposed to multiproduct players, varieties sold by the same firm were priced differently. Most multiproduct players had no doubt on the gains from such a strategy in terms of their possibilities of *learning*. However, the imposition of the *rule* to multiproduct firms has been clearly shown to help them *escape* from the attraction of the single-product noncooperative equilibrium.

Equilibrium	No Rule				Rule			
	$\theta = 0.14$		$\theta = 0.4$		$\theta = 0.14$		$\theta = 0.4$	
	p_1, p_2, p_3	p_4, p_5	p_1, p_2, p_3	p_4, p_5	$p_1 = p_2 = p_3$	$p_4 = p_5$	$p_1 = p_2 = p_3$	$p_4 = p_5$
SBNE	55 %	83 %	88 %	83 %	33 %	33 %	0 %	0 %
MBNE(2-P Firm)	44 %	83 %	77 %	33 %	66 %	66 %	0 %	33 %
MBNE (3-P Firm)	33 %	50 %	66 %	33 %	100 %	66 %	0 %	100 %
Between MBNE(3P)-Coll.	0 %	0 %	0 %	0 %	0 %	0 %	100 %	0 %
Collusive	11 %	16 %	33 %	0 %	0 %	0 %	0 %	0 %

Table 3: Configuration S=(3,2), Experiments 11, 12 and replications. Percentage of average prices compatible with the corresponding equilibrium or range between equilibria. Notation: SBNE= Bertrand-Nash equilibrium for the single-product oligopoly, MBNE(2-P Firm)=Multiproduct Bertrand-Nash equilibrium for the firm that produces 2 products, MBNE (3-P Firm)=Multiproduct Bertrand-Nash for the firm that produces 3 products, Between MBNE(3P)-Coll.=Between the multiproduct Bertrand-Nash equilibrium of the 3-products firm and the collusive solution.

3.1 A model of adaptive behavior

As pointed out by Rassenti *et al.*(2000), best response dynamics may be unstable. Stability of the convergence process is guaranteed if not too heterogenously adaptive players exhibit some inertia with respect to their past own strategies. A broad family of adaptive models which involve such inertia will be referred to as *partial adjustment best-response models.* Having this in mind, we propose an adaptive model for multiproduct firms (already presented for the case of single-product firms in G-G) which allows for different degrees of responsiveness to rival strategies in the past.

Suppose that at period t, firm i's price for product k is a linear function of the firm's expectation at t for the prices charged by firm i's rival, j, and the prices chosen by i for its other products ($r \neq k$) so that

$$p_{kt} = A_k + B_k E_{it} + \sum_{r \neq k} G_{kr} p_{rt} \tag{2}$$

where

$$E_{it} = w \cdot E_{it-1} + (1 - w) \cdot \Sigma p_{jt-1} \tag{3}$$

is the way in which i forms its expectations on the sum of its rivals' prices as a linear combination of the already existing expectation from the previous period and the sum of the prices set by the firm's rivals in the period before.

This implies a broad range of adaptive models, according to the value of w. That is, if w is high, the subject is reluctant to adapt his/her expectations to what has been observed in the last period. If, on the contrary, w is low, then the subject forms its expectations in a straightforward way by assuming that this period's prices will be similar to what was observed in the last period. Obviously, in the case of single-product firms, a reduced form of the model will be used in which the *other own products* term is dropped[20].

[20]A similar model is estimated for the asymmetric quantity-setting oligopoly in Rassenti *et al.* (2000), who observe that such models of behavior can be seen as special cases of the general adaptive learning formulation in Milgrom and Roberts (1991).

Estimation results are presented in tables 4-9. For each session, pricing of each product (or, in experiment 12, group of products) is explained with the corresponding adaptive model estimated for 5 different values of the parameter w ($w \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$). This results in a discrete but reliable representation of the behavior of each model over the continuum of values for $w \in (0, 1)$. In each case, the model which performs best is discussed.

With respect to the single-product experimental oligopolies studied, it is worth observing that the models which best explain individual behavior in experiment 2 are the ones involving the highest w parameters ($w = 0.9$ for varieties 1-4 and $w = 0.5$ for variety 5). This contrasts with what we obtain studying data from sessions 1, 3 and 4, where best-performing models are compatible with smaller w parameters ($w = 0.1$ for 12 of the remaining 15 regressions, $w = 0.3$ for two of them, whereas only pricing of the fifth variety in experiment 4 is best explained by a model with an $w = 0.9$ parameter). Another difference between experiment 2 and the other three single-product experiments studied concerns responses to prices charged by rival firms in the past. In experiment 2, a small in absolute value, but statistically significant negative coefficient of the variable term, indicates that in each period, firms have mostly *price-cut* the prices set by their rivals in the last period. This contrasts with intuition and theory which both suggest that the best response to a price increase by a rival is a price increase. In fact, strong statistical significance is obtained in all regressions for all coefficients of the term accounting for responses to prices charged by the rivals in the previous period. A surprisingly consistent pattern indicates that such coefficients obtained from experiment 1 have an average of 0.164, whereas slightly higher averages (0.208 and 0.21, respectively) correspond to coefficients obtained from experiments 3 and 4. The behavior of firms reflected on the coefficients of the variable terms also indicate a relatively homogeneous type of responses to rival prices in the past. Considering that the requirement of homogeneity in the type of individually adopted rules is a requirement for convergence, some clearer convergence towards Nash behavior in experiment 3 as compared to experiment 4 might be explained through the fact that, in experiment 3, the dispersion of the coefficient estimates around their mean is much lower than is the same magnitude in experiment 4 (the average deviation of the *price response* term coefficient for the former is 0.024 and for the latter is 0.048). However, we should also note that the coefficient estimates obtained for these terms are significantly higher than the response coefficients of the corresponding static best reply functions (0.02 for experiments 1 and 2, 0.06 for experiments 3 and 4). Even if we take into account the partially adaptive nature of the model ($w > 0$), the adaptive models estimated here cannot be seen as some stochastic and lagged version of static best response functions. Nevertheless, the fact that response coefficients in experiment 1 are significantly lower than those in experiments 3 and 4 correctly reflects the different degrees of strategic complementarity among varieties ($\theta = 0.14$ in experiment 1 and $\theta = 0.4$ in experiments 3 and 4). Finally, the lack of any systematic statistical significance, sign or size of the constant term estimates of the regressions, indicates their scarce importance for the convergence process.

In the following claim, we summarize our observations concerning the relation between individual adaptive rules adopted spontaneously by uninformed economic agents and convergence to a perfect-information static equilibrium:

Claim 1: *Given the specification in G-G, the adoption of a partially adaptive price-response behavior model by initially uninformed single-product firms, makes convergence to non cooperative full information equilibrium more accurate (faster) if w is low, price responses fulfil the requirement of positively sloped reaction functions and individual responses to rival prices in the past come from a homogeneous population of subjects.*

We move now to the results obtained from experimental oligopolies with multiproduct firms. As static results reported in G-GG indicate, behavior is not as homogeneous as in the single-product case. This has produced a much larger variety in the dynamics observed and the subsequent convergence to a certain limit point. A first look at figures 5-8, containing price information collected from experiments 11, 11($r2$), 11($R1$) and 11($R3$), leads us to the following observation: session 11($R1$) converges to a significantly higher price than the Bertrand-Nash equilibrium would predict. On the contrary, the other three experiments converge to prices which would fail to confirm the static equilibrium prediction that the presence of multiproduct firms is associated with higher prices. As we have already said, this result was obtained from applying rigorous statistical tests for all replications of experiment 11. Session $11(R1)$ is a clear exception to this rule. Let us compare the estimates obtained from the adaptive model for this session with the estimates obtained from the other three sessions. We should first note that, overall, the adaptive models estimated for the replications of experiment 11 perform better than the models estimated for experiments 1-4. Especially in the case of session $11(R1)$, all values of the parameter w give similarly good results. In the case of the other three sessions, most models reach their best performance for medium values of w ($w = 0.3, 0.5, 0.7$) except for the model estimated for firm 2 in experiment 11 which performs best for $w = 0.9$. However, higher w values correspond to the firms with less products which implies that they are more adaptive to prices set by their rivals in the past. In other words, firms with less products give their rivals the role of price leaders. Another general feature has been that price responses to rival prices in the past have been much weaker than what have been in the single-product case. Significance of the corresponding response term coefficients is not systematic either. Therefore, contrary to the case of single-product oligopolists, in the case of experiments with multiproduct firms, we would like to stress the importance of rules concerning pricing of own products by multiproduct firms.

We will be interested in a special type of rule which we call price parallelism of products sold by the same firm. As we have defined and used this rule in G-GG, it requires that products sold by the same firm are priced equally. However, in this treatment, multiproduct firms were free to choose any price for each one of their products. Therefore, we will check whether a firm has spontaneously use this rule by comparing its own cross-product coefficients with unity. If this is the case, we will call it a case of *perfect price parallelism*. If a rather large coefficient but significantly less than 1 is obtained, we will call it a case of *partial price parallelism*. It is easy to see that, in session $11(R1)$ the firm selling 3 products has adopted perfect price parallelism when pricing its first and third products and partial parallelism when pricing its second product. The firm's rival has also exhibited a strong tendency to set equal prices for its own products. In the rest of the replications of experiment 11 parallelism in the prices of own varieties has been less and not as systematic as in the case of session $11(R1)$. Specifically, firm 1 in experiment 11 has exhibited a strong tendency to adopt price parallelism, but the firm's rival responded adopting only partial price parallelism. A stronger divergence between the two rivals is observed in sessions $11(R3)$ and $11(r2)$ in which perfect parallelism by one firm (firm 1 in the former and firm 2 in the latter) is responded by no parallelism at all by the other firm. A final remark concerns the lack of systematic responses to prices charged by rivals in the past. In fact, negative price responses (against the expected positive ones) are surprisingly many (almost half of the corresponding significant coefficients).

We summarize these observations in the following claim:

Claim 2: *Adaptive behavior by multiproduct firms who are not informed on the demand model can be described using the model presented here. Convergence to higher than SBNE prices is not observed unless subjects adopt industry-wide price parallelism. In fact, in most cases parallelism will not be adopted at a sufficient level, and convergence to single-product Bertrand-Nash will be observed. However, following Claim 1, convergence will be poor mostly because responses to rival prices do not systematically fulfil the requirement of positively sloped best response functions.*

As we can see from table 3, convergence towards higher than SBNE prices is obtained once price parallelism is imposed to multiproduct subjects as a compulsory rule of behavior. In fact, the prediction that firms with more products will set higher prices than firms with less products is also fulfiled.

Let us check whether these elements relate with the subjects' adaptive behavior. The model to estimate becomes again similar to the one for single-product firms, given that own products are equally priced by definition. However, in each session firm 1 produces three products, whereas firm 2 produces only two.[21] In each pair of sessions, we have one session with differing and another with similar w values for which the model performs

[21]As suggested in G-GG, the framework is also appropriate for addressing the issue of market power.

best.[22] Despite these differences, all of the sessions converge towards limit points which are compatible with both MBNE predictions: (1) prices will be higher than would be in a SBNE and (2) prices charged by firms selling more products will be higher than prices charged by firms selling less products. Therefore, convergence (which is much less accurate than that obtained with single-product firms) towards limit points compatible with full-information equilibrium predictions, does not depend on behavior features captured by parameter w. Finally, response term coefficients also exhibit a less systematic pattern than that obtained for the single-product sessions (1-4). As suggested in Claim 1, homogeneity of adaptive behavior across subjects would facilitate convergence towards the SBNE. The asymmetric power structure in the configuration studied here induces asymmetries in the attitude of firms towards the variety-specific symmetric demand they are faced with. Subsequently, convergence towards any limit point is achieved with less accuracy and slower than that observed in the case of oligopolies with single-product firms.

We summarize the conclusions from the estimation of the model for this third treatment in the following claim:

Claim 3: *The imposition of the perfect parallelism rule to multiproduct subjects confirms theoretical predictions concerning higher than SBNE prices and higher prices for firms with more products. However, convergence to any limit point is less accurate than that obtained from oligopolies with single-product firms, because (see Claim 1), adaptive behavior is not sufficiently homogenous across subjects.*

4 Concluding remarks

We have used some of the experimental data obtained from a large number of experimental markets with single product and multiproduct firms to study the relation between indi-

[22] $w = 0.1$ for firm 1 in sessions 12($r1$) and 12($R2$). In the same sessions, firm 2 behaves according to a higher w value ($w = 0.5$ in session 12($r1$) and $w = 0.9$ in session 12($R2$)). In each one of the other two sessions of experiment 12, firm behavior is best described by the same w value ($w = 0.7$ and $w = 0.5$ for sessions 12($r2$) and 12($R3$), respectively).

vidual adaptive behavior and convergence. The sessions chosen correspond to the most representative and most interesting cases observed as far as convergence and adaptive behavior are concerned.

Generally speaking, most markets with single-product firms sharply converge towards the corresponding full-information static equilibrium. This is not necessarily true for the equivalent equilibrium concept in the case of markets with multiproduct firms.

As suggested in G-GG, in the presence of single-product firms alone, the algorithm according to which a profitable price increase is followed by a further increase in the next period, leads to the corresponding non-cooperative equilibrium level. Contrary to that, multiproduct configurations fail to converge to the corresponding *multiproduct* Bertrand-Nash equilibria, if multiproduct activity is not intense (many multiproduct firms producing large part of the products in the market), or if multiproduct firms apply the aforementioned algorithm with respect to *each* one of their products separately. Both a pricing rule for multiproduct firms (or cartels), according to which they price all their products equally and intense multiproduct activity, are necessary conditions for convergence to the theoretical *multiproduct* Bertrand-Nash equilibrium price levels.

We introduce an adaptive model for multiproduct firms allowing us to study each firm's way of responding to prices charged by rivals in the past and rules according to which multiproduct firms price their own products in each period. The results obtained from the estimation of the adaptive model show that, in general, agents use simple mechanical rules to decide their strategies. They choose their strategies learning that their performance in the past has depended on their rivals' actions.

Estimation results indicate that adaptive behavior is more homogeneous across subjects in the experiments with single-product firms. In fact, when this is not confirmed and responses to rival prices in the past do not fulfil the requirement of a positively sloped response function, convergence is slower (or less accurate).

Responses to rival prices become less significant in predicting whether behavior in a market with multiproduct firms will converge towards prices which are higher than those predicted for oligopolies with single-product firms. Instead, the rule according to which a multiproduct firm's own varieties are equally priced, becomes crucial. Adoption of industry-wide parallelism will push prices above single-product non cooperative levels. On the contrary, partial price parallelism was found insufficient to guarantee convergence to higher than single-product non-cooperative levels. The explicit (non spontaneous) adoption of price parallelism guarantees convergence of prices towards levels predicted by static full-information equilibrium for markets with multiproduct firms. However, an intrinsic asymmetry in the design of the corresponding configuration raises a further question. That is, whether convergence of such a multiproduct market can ever become as clear as that observed in the case of symmetric oligopolies with single-product firms. For the moment, the answer is *no*.

An interesting insight gained from the illustration of the specific cases studied here concerns symmetric adjustment procedures adopted by not too heterogenously adaptive subjects. The resulting dynamics guarantee, then, sharp convergence to the corresponding full-information static equilibrium. Subsequently, asymmetric market configurations like the multiproduct oligopolies studied here, lead the subjects to the formation of asymmetric theories and expectations concerning rival strategies and market conditions. The resulting dynamics are responsible for a rather poor convergence towards the same limit point as that to which an industry with single-product firms would tend over time. Learning the optimal rule for multiproduct pricing has been rather unusual. If the rule is exogenously imposed, firms escape from the single-product equilibrium, but in no case convergence is as strong as is in experimental oligopolies with single product firms.

Multiproduct subjects, who were interviewed at the end of each session, seemed to reject the hypothesis of *similarity* between their products and that of *symmetric variety-specific demand conditions*. On the contrary, by pricing equally its products, a multiproduct firm would realize that variety-specific demand conditions are symmetric. However, multiproduct players who start pricing differently their products (which has been the case in the vast majority of experiments with multiproduct firms in the absence of any imposed pricing rule) cannot appreciate this fact, nor can they *learn*, in most cases, the *equal prices for products of the same firm* rule, once they have created different histories for different products.

Future research should aim at investigating not only the limitations of human learning in complex environments, but also, the efficiency of simple learning rules which are usually adopted in the presence of smaller obstacles due to market asymmetries and task multiplicity. Having in mind the behavior reported here, consider the following three levels of learning: First, learning a number, like in this case the equilibrium (or the *right*) price, means a basic implicit learning which is reached by following mechanical steps in order to correct bad performance in the past. Second, learning a rule is like a meta-learning with respect to the aforementioned first level of learning. In this case, a multiproduct player may come to the conclusion that "...this is what I have to do with respect to my two products..." or "...this is the best strategy to follow if my rival undercuts price too much...". Third, to really learn about this environment requires knowing details like "These three products are substitutes in a symmetric way". It has been straightforward to establish that, while the first level of learning is reached in one way or another in all the experiments, the third type of learning has not been achieved by anyone of our subjects. Some non-systematic evidence for second-level learning and its implications for convergence to certain limit points has been put forward.

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5 Appendix: Tables and Figures

Single		*Experiment 1* ($\theta = 0.14$)					*Experiment 2* ($\theta = 0.14$)				
ω	*Est.*	p_1	p_2	p_3	p_4	p_5	p_1	p_2	p_3	p_4	p_5
$\omega = 0.1$	$\hat{A}_k$	81.55	68.88	2.50	30.73	16.38	113.52	112.17	113.06	109.32	120.27
	(t)	(8.88)	(3.79)	(0.33)	(7.05)	(2.15)	(6.83)	(11.14)	(8.61)	(17.85)	(10.27)
	$\hat{B}_k$	0.07	0.12	0.24	0.18	0.21	0.02	0.01	0.01	0.02	-0.02
	(t)	(3.50)	(2.78)	(13.27)	(18)	(11.66)	(0.28)	(0.23)	(0.20)	(1.30)	(0.73)
	R^2	0.275	0.186	0.84	0.90	0.80	0.0025	0.001	0.0015	0.049	0.016
$\omega = 0.3$	$\hat{A}_k$	84.14	71.85	3.87	34.37	23.43	142.31	115.93	116.50	113.27	123.11
	(t)	(9)	(3.94)	(0.60)	(7.34)	(2.73)	(8.67)	(11.49)	(8.87)	(18.23)	(10.56)
	$\hat{B}_k$	0.07	0.11	0.24	0.17	0.19	-0.05	0	0	0.02	-0.03
	(t)	(3.30)	(2.68)	(16.92)	(17.30)	(9.89)	(0.92)	(0.02)	(0.03)	(0.82)	(0.94)
	R^2	0.249	0.18	0.884	0.89	0.748	0.0258	0	0	0.02	0.025
$\omega = 0.5$	$\hat{A}_k$	88.50	75.28	8.94	40.90	34.05	172.76	123.58	125.72	121.95	124.48
	(t)	(9.17)	(4.12)	(1.53)	(7.24)	(3.42)	(11.36)	(12.32)	(9.60)	(19.42)	(10.70)
	$\hat{B}_k$	0.06	0.10	0.23	0.16	0.17	-0.12	-0.02	-0.02	0	-0.03
	(t)	(3)	(2.56)	(17.80)	(13.30)	(8.23)	(2.54)	(0.59)	(0.48)	(0.19)	(1.03)
	R^2	0.20	0.17	0.90	0.84	0.66	0.163	0.01	0.0071	0.001	0.0316
$\omega = 0.7$	$\hat{A}_k$	95.28	78.81	22.75	52.88	50.37	191.82	136.01	138.24	136.40	121.11
	(t)	(9.47)	(4.33)	(2.98)	(7)	(4.22)	(14.88)	(14)	(10.82)	(23.31)	(10.37)
	$\hat{B}_k$	0.04	0.09	0.20	0.14	0.14	-0.16	-0.04	-0.05	-0.04	-0.03
	(t)	(2.25)	(2.72)	(13.30)	(9.71)	(6.04)	(4.57)	(1.73)	(1.37)	(2.25)	(0.87)
	R^2	0.13	0.18	0.838	0.715	0.512	0.398	0.084	0.053	0.131	0.023
$\omega = 0.9$	$\hat{A}_k$	104.44	87.58	56.32	74.51	75.49	171.07	136.83	140.88	145.27	109.05
	(t)	(9.92)	(4.77)	(4.17)	(6.98)	(5.16)	(13.37)	(15.05)	(11.55)	(39.30)	(9.20)
	$\hat{B}_k$	0.02	0.09	0.14	0.09	0.09	-0.13	-0.05	-0.06	-0.06	0
	(t)	(1.33)	(2.60)	(5.91)	(5.11)	(3.53)	(4.92)	(2.75)	(2.28)	(7.83)	(0.03)
	R^2	0.046	0.168	0.495	0.43	0.267	0.40	0.187	0.137	0.653	0

Table 4: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it}$

Single		*Experiment 3* ($\theta = 0.4$)					*Experiment 4* ($\theta = 0.4$)				
ω	*Est.*	p_1	p_2	p_3	p_4	p_5	p_1	p_2	p_3	p_4	p_5
$\omega = 0.1$	$\hat{A}_k$	50.72	8.03	31.75	-2.04	41.43	22.36	7.78	84.59	-2.09	8.90
	(t)	(2.22)	(0.45)	(1.67)	(0.15)	(1.02)	(1.10)	(0.97)	(2.99)	(0.07)	(0.33)
	$\hat{B}_k$	0.18	0.23	0.20	0.25	0.18	0.22	0.23	0.10	0.27	0.19
	(t)	(7.78)	(12.36)	(10.15)	(16.73)	(4.34)	(8.20)	(22.80)	(2.86)	(7.10)	(5.40)
	R^2	0.647	0.822	0.758	0.894	0.367	0.659	0.93	0.199	0.60	0.46
$\omega = 0.3$	$\hat{A}_k$	54.20	10.26	34.66	0.23	41.44	24.06	9.48	85.83	-0.07	8.74
	(t)	(2.28)	(0.57)	(1.76)	(0.01)	(1.03)	(1.19)	(1.20)	(3.03)	(0)	(0.33)
	$\hat{B}_k$	0.18	0.23	0.19	0.24	0.18	0.22	0.23	0.10	0.27	0.19
	(t)	(7.28)	(12.17)	(9.80)	(16.53)	(4.55)	(8.14)	(22.60)	(2.78)	(7.07)	(5.49)
	R^2	0.618	0.817	0.739	0.892	0.38	0.658	0.932	0.194	0.60	0.478
$\omega = 0.5$	$\hat{A}_k$	61.59	16.51	40.95	6.22	42.19	28.33	13.13	88.13	3.18	8.85
	(t)	(2.39)	(0.84)	(1.90)	(0.39)	(1.06)	(1.35)	(1.51)	(3.08)	(0.12)	(0.34)
	$\hat{B}_k$	0.16	0.22	0.18	0.23	0.18	0.21	0.22	0.09	0.27	0.19
	(t)	(6.40)	(10.90)	(8.62)	(14.68)	(4.60)	(7.64)	(20.18)	(2.72)	(7.10)	(5.88)
	R^2	0.553	0.779	0.691	0.86	0.394	0.634	0.918	0.182	0.60	0.50
$\omega = 0.7$	$\hat{A}_k$	77.46	32.07	55.26	21.08	44.85	37.93	20.98	91.64	9.19	8.74
	(t)	(2.61)	(1.29)	(2.15)	(0.97)	(1.13)	(1.65)	(1.83)	(3.17)	(0.34)	(0.36)
	$\hat{B}_k$	0.15	0.19	0.16	0.21	0.18	0.20	0.21	0.09	0.27	0.20
	(t)	(5.05)	(7.80)	(6.15)	(10.19)	(4.69)	(6.66)	(14.13)	(2.58)	(6.96)	(6.35)
	R^2	0.40	0.65	0.56	0.74	0.40	0.56	0.857	0.164	0.595	0.552
$\omega = 0.9$	$\hat{A}_k$	116.22	77.14	95.98	67.35	61.35	56.75	37.43	92.56	27.42	4.03
	(t)	(3.19)	(2.13)	(2.75)	(1.90)	(1.44)	(2.12)	(2.24)	(3.22)	(0.91)	(0.22)
	$\hat{B}_k$	0.07	0.13	0.10	0.15	0.17	0.18	0.20	0.11	0.27	0.25
	(t)	(1.95)	(3.33)	(2.70)	(3.92)	(3.87)	(4.77)	(8.30)	(2.65)	(5.85)	(9.80)
	R^2	0.10	0.25	0.185	0.316	0.31	0.40	0.696	0.175	0.50	0.744

Table 5: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it}$

Multi		*Experiment 11* ($\theta = 0.14$)					*Experiment 11(r2)* ($\theta = 0.14$)				
$S(3,2)$		*Firm 1*			*Firm 2*		*Firm 1*			*Firm 2*	
ω	*Est.*	p_1	p_2	p_3	p_4	p_5	p_1	p_2	p_3	p_4	p_5
	$\hat{A}_k$	14.59	10.36	-5.38	28.08	45.69	-137.17	76.69	87.16	11.95	-13.16
	(t)	(3.34)	(2.2)	(-1.56)	(1.70)	(3.47)	(3.46)	(5.93)	(3.18)	(1.08)	(1.19)
	$\hat{B}_k$	0.14	0.16	0.01	0.05	0.05	0.08	-0.02	0.04	-0.03	0.03
	(t)	(2.18)	(2.68)	(0.20)	(1.62)	(1.85)	(3.90)	(2.71)	(2.50)	(1.08)	(1.39)
$\omega = 0.1$	$\hat{G}_{kr}$	-0.41	-0.4	0.5	0.6	0.48	2.60	0.28	-0.24	0.99	0.99
	(t)	(-2.49)	(-2.49)	(5.69)	(3.64)	(3.64)	(9.04)	(9.26)	(8.62)	(76.62)	(76.15)
	$\hat{G}_{kl}$	1.02	1.01	0.50	-	-	-0.45	0.07	0.34	-	-
	(t)	(5.69)	(5.67)	(5.67)	-	-	(2.04)	(0.89)	(0.89)	-	-
	R^2	0.95	0.96	0.98	0.51	0.52	0.794	0.746	0.25	0.996	0.996
	$\hat{A}_k$	17.81	14.52	-7.16	28.22	46.14	-156.77	80.11	93.19	17.32	-18.2
	(t)	(4.42)	(3.14)	(-1.87)	(1.70)	(3.48)	(3.92)	(6.25)	(3.23)	(1.62)	(1.69)
	$\hat{B}_k$	0.23	0.23	-0.04	0.05	0.05	0.08	-0.02	0.04	-0.04	0.05
	(t)	(3.77)	(3.72)	(-0.70)	(1.62)	(1.74)	(3.70)	(2.63)	(2.22)	(1.66)	(1.92)
$\omega = 0.3$	$\hat{G}_{kr}$	-0.50	-0.53	0.56	0.61	0.49	2.67	0.27	-0.20	0.99	0.99
	(t)	(-3.36)	(-3.36)	(5.60)	(3.72)	(3.72)	(9.24)	(9.44)	(1.60)	(82.50)	(83.08)
	$\hat{G}_{kl}$	0.91	0.97	0.56	-	-	-0.39	0.05	0.27	-	-
	(t)	(5.67)	(6.09)	(6.09)	-	-	(1.66)	(0.67)	(0.67)	-	-
	R^2	0.96	0.96	0.98	0.51	0.52	0.79	0.75	0.176	0.996	0.996
	$\hat{A}_k$	17.38	13.83	-8.26	27.24	46.56	-181.17	84.32	100.50	23.54	-23.87
	(t)	(4.32)	(2.80)	(-2.30)	(1.66)	(3.44)	(4.54)	(6.74)	(3.37)	(2.26)	(2.28)
	$\hat{B}_k$	0.15	0.14	-0.05	0.05	0.03	-0.09	-0.02	0.03	-0.06	0.06
	(t)	(3.70)	(2.99)	(-1.44)	(1.75)	(1.27)	(3.46)	(2.50)	(1.22)	(2.30)	(2.36)
$\omega = 0.5$	$\hat{G}_{kr}$	-0.44	-0.52	0.58	0.62	0.53	2.76	0.27	-0.17	0.99	1.00
	(t)	(-3.05)	(-3.05)	(6.73)	(3.98)	(3.98)	(9.62)	(9.64)	(1.30)	(99)	(100.20)
	$\hat{G}_{kl}$	1.01	1.15	0.57	-	-	-0.30	0.03	0.18	-	-
	(t)	(6.73)	(7.70)	(7.69)	-	-	(1.28)	(0.40)	(0.42)	-	-
	R^2	0.96	0.96	0.98	0.52	0.49	0.79	0.76	0.11	0.996	0.996
	$\hat{A}_k$	14.86	10.84	-7.53	23.37	46.86	-224.89	92.42	114.87	32.82	-31.85
	(t)	(3.66)	(2.19)	(-2.38)	(1.44)	(3.38)	(5.73)	(7.84)	(3.77)	(3.16)	(3.02)
	$\hat{B}_k$	0.07	0.06	-0.03	0.05	0	0.14	-0.04	0.01	-0.08	0.08
	(t)	(3.16)	(2.23)	(-1.94)	(2.06)	(0.19)	(3.97)	(4.00)	(0.31)	(2.35)	(2.23)
$\omega = 0.7$	$\hat{G_{kr}}$	-0.38	-0.46	0.57	0.66	0.61	2.93	0.26	-0.11	0.98	1.01
	(t)	(-2.60)	(-2.60)	(7.57)	(4.63)	(4.63)	(10.24)	(10.40)	(0.82)	(98)	(101.40)
	$\hat{G}_{kl}$	1.13	1.28	0.54	-	-	-0.19	0.01	0.04	-	-
	(t)	(7.57)	(8.39)	(8.39)	-	-	(0.83)	(0.07)	(0.08)	-	-
	R^2	0.96	0.96	0.98	0.53	0.47	0.797	0.789	0.078	0.996	0.996
	$\hat{A}_k$	12.06	7.53	-5.55	13.59	50.12	-308.94	128	201.23	-25.55	42.25
	(t)	(2.78)	(1.57)	(-1.84)	(0.79)	(3.72)	(6.87)	(11.14)	(6.83)	(2.32)	(3.89)
	$\hat{B}_k$	0.03	0.03	-0.01	0.05	-0.03	0.26	-0.11	-0.13	0.09	-0.13
	(t)	(1.99)	(1.99)	(-1.97)	(2.25)	(-1.56)	(2.08)	(4.07)	(1.55)	(1.06)	(1.65)
$\omega = 0.9$	$\hat{G}_{kr}$	-0.37	-0.38	0.53	0.76	0.67	3.23	0.21	-0.02	1.01	0.98
	(t)	(-2.27)	(-2.27)	(7.63)	(5.76)	(5.76)	(8.18)	(8.07)	(0.15)	(45.73)	(46.62)
	$\hat{G}_{kl}$	1.23	1.30	0.53	-	-	-0.04	-0.07	-0.46	-	-
	(t)	(7.63)	(8.35)	(8.35)	-	-	(0.15)	(1.00)	(1.02)	-	-
	R^2	0.95	0.96	0.98	0.54	0.51	0.734	0.799	0.138	0.996	0.996

Table 6: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it} + \Sigma G_{kr} p_{rt},\ _{r \neq k},\ _{l > k}$

Multi		*Experiment 11(R1)* ($\theta = 0.4$)					*Experiment 11(R3)* ($\theta = 0.4$)				
$S(3,2)$		*Firm 1*			*Firm 2*		*Firm 1*			*Firm 2*	
ω	*Est.*	p_1	p_2	p_3	p_4	p_5	p_1	p_2	p_3	p_4	p_5
	$\hat{A}_k$	-2.52	1.20	2.03	24.94	-10.35	-6.47	162.09	37.30	204.32	156.62
	(t)	(-1.03)	(0.65)	(0.67)	(3.39)	(-1.56)	(-0.30)	(4.16)	(1.97)	(5.34)	(4.06)
	$\hat{B}_k$	-0.01	0.02	-0.01	-0.08	0.13	0.04	-0.04	-0.06	-0.13	-0.03
	(t)	(-0.27)	(1.23)	(-0.42)	(-2.23)	(6.48)	(0.89)	(-0.42)	(-1.49)	(-1.76)	(-0.45)
$\omega = 0.1$	$\hat{G}_{kr}$	1.05	0.58	-0.04	1.06	0.68	0.05	0.25	0.88	-0.19	-0.16
	(t)	(7.00)	(7.00)	(-0.16)	(9.31)	(9.31)	(0.61)	(0.61)	(13.25)	(-1.01)	(-1.02)
	$\hat{G}_{kl}$	-0.02	0.38	1.03	-	-	0.96	-0.47	-0.08	-	-
	(t)	(-0.16)	(4.48)	(4.48)	-	-	(13.25)	(-1.10)	(-1.10)	-	-
	R^2	0.99	0.99	0.988	0.90	0.95	0.86	0.069	0.87	0.11	0.032
	$\hat{A}_k$	-2.50	1.15	2.08	26.02	-12.90	-14.31	192.35	44.51	222.34	190.29
	(t)	(-1.02)	(0.62)	(0.69)	(3.54)	(-1.83)	(-0.63)	(4.87)	(2.18)	(5.01)	(4.72)
	$\hat{B}_k$	0	0.01	-0.01	-0.07	0.11	0.06	-0.16	-0.08	-0.16	-0.10
	(t)	(-0.27)	(1.22)	(-0.52)	(-2.30)	(5.79)	(1.20)	(-1.33)	(-1.75)	(-1.87)	(-1.38)
$\omega = 0.3$	$\hat{G}_{kr}$	1.05	0.58	-0.04	1.03	0.75	0.06	0.33	0.88	-0.25	-0.19
	(t)	(7.00)	(7.00)	(-0.16)	(10.54)	(10.54)	(0.80)	(0.80)	(13.53)	(-1.29)	(-1.29)
	$\hat{G}_{kl}$	-0.03	0.38	1.03	-	-	0.96	-0.57	-0.10	-	-
	(t)	(-0.16)	(4.52)	(4.52)	-	-	(13.53)	(-1.36)	(-1.36)	-	-
	R^2	0.99	0.99	0.98	0.90	0.947	0.86	0.11	0.87	0.122	0.08
	$\hat{A}_k$	-2.50	1.04	2.25	27.59	-16.22	-24.14	220.31	53.60	241.09	220.21
	(t)	(-1.01)	(0.56)	(0.74)	(3.72)	(-2.11)	(-0.98)	(5.66)	(2.47)	(4.86)	(5.46)
	$\hat{B}_k$	0	0.01	-0.01	-0.06	0.09	0.09	-0.27	-0.11	-0.19	-0.18
	(t)	(-0.20)	(1.18)	(-0.72)	(-2.33)	(4.94)	(1.55)	(-2.17)	(-2.08)	(-2.04)	(-2.20)
$\omega = 0.5$	$\hat{G}_{kr}$	1.05	0.58	-0.04	0.98	0.84	0.08	0.42	0.88	-0.30	-0.23
	(t)	(6.98)	(6.98)	(-0.17)	(12.28)	(12.28)	(1.06)	(1.06)	(13.82)	(-1.54)	(-1.54)
	$\hat{G}_{kl}$	-0.03	0.39	1.03	-	-	0.97	-0.67	-0.12	-	-
	(t)	(-0.17)	(4.58)	(4.57)	-	-	(13.81)	(-1.66)	(-1.66)	-	-
	R^2	0.99	0.99	0.988	0.91	0.94	0.87	0.188	0.88	0.137	0.153
	$\hat{A}_k$	-2.44	0.82	2.63	30.17	-20.68	-24.29	220.06	54.60	242.45	215.58
	(t)	(-0.96)	(0.43)	(0.86)	(3.98)	(-2.42)	(-0.99)	(5.68)	(2.55)	(5.16)	(5.35)
	$\hat{B}_k$	0	0.01	-0.01	-0.05	0.07	-0.09	-0.27	-0.12	-0.20	-0.17
	(t)	(-0.19)	(1.15)	(-0.95)	(-2.45)	(4.11)	(1.57)	(-2.18)	(-2.18)	(-2.22)	(-2.07)
$\omega = 0.7$	$\hat{G}_{kr}$	1.05	0.58	-0.04	0.93	0.94	0.08	0.42	0.87	-0.30	-0.23
	(t)	(6.99)	(6.99)	(-0.17)	(14.90)	(14.90)	(1.07)	(1.06)	(13.73)	(-1.56)	(-1.56)
	$\hat{G}_{kl}$	-0.03	0.39	1.03	-	-	0.97	-0.68	-0.12	-	-
	(t)	(-0.17)	(4.63)	(4.63)	-	-	(13.74)	(-1.68)	(-1.68)	-	-
	R^2	0.99	0.995	0.989	0.934	0.93	0.87	0.188	0.879	0.156	0.141
	$\hat{A}_k$	-2.33	0.87	2.53	34.30	-25.92	-8.51	152.88	34.63	180.40	137.15
	(t)	(-0.88)	(0.43)	(0.78)	(4.33)	(-2.66)	(-0.46)	(4.51)	(2.09)	(5.39)	(4.16)
	$\hat{B}_k$	0	0.01	-0.01	-0.05	0.06	0.06	-0.02	-0.07	-0.09	0.01
	(t)	(-0.28)	(0.69)	(-0.48)	(-2.75)	(3.42)	(1.36)	(-0.17)	(-1.77)	(-1.25)	(0.17)
$\omega = 0.9$	$\hat{G}_{kr}$	1.05	0.59	-0.04	0.88	1.03	0.04	0.25	0.89	-0.17	-0.13
	(t)	(7.18)	(7.18)	(-0.16)	(17.84)	(17.84)	(0.58)	(0.58)	(13.77)	(-0.86)	(-0.86)
	$\hat{G}_{kl}$	-0.02	-0.39	1.02	-	-	0.96	-0.45	-0.07	-	-
	(t)	(-0.16)	(4.52)	(4.52)	-	-	(13.77)	(-1.02)	(-1.03)	-	-
	R^2	0.99	0.995	0.988	0.912	0.92	0.866	0.065	0.87	0.071	0.026

Table 7: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it} + \Sigma G_{kr} p_{rt},\ _{r \neq k},\ _{l>k}$

Multi (rule)		*Experiment 12(r1)* ($\theta = 0.14$)		*Experiment 12(r2)* ($\theta = 0.14$)	
$S(3,2)$		*Firm 1*	*Firm 2*	*Firm 1*	*Firm 2*
ω	*Est.*	$p_i,\ i = 1,2,3$	$p_i,\ i = 4,5$	$p_i,\ i = 1,2,3$	$p_i,\ i = 4,5$
$\omega = 0.1$	$\hat{A}_k$	65.53	86.84	10.06	97.84
	(t)	(2.85)	(15.62)	(0.34)	(13.01)
	$\hat{B}_k$	0.22	0.07	0.45	0.05
	(t)	(2.13)	(4.34)	(3.56)	(2.40)
	R^2	0.12	0.36	0.28	0.15
$\omega = 0.3$	$\hat{A}_k$	75.53	81.17	-9.79	96.47
	(t)	(3.38)	(14.02)	(-0.33)	(12.5)
	$\hat{B}_k$	0.18	0.09	0.55	0.05
	(t)	(1.74)	(5.14)	(4.23)	(2.52)
	R^2	0.083	0.45	0.35	0.16
$\omega = 0.5$	$\hat{A}_k$	87.61	78.93	-16.19	95.12
	(t)	(4.13)	(13.21)	(-0.59)	(12.16)
	$\hat{B}_k$	0.12	0.96	0.58	0.06
	(t)	(1.26)	(5.36)	(4.82)	(2.66)
	R^2	0.046	0.46	0.41	0.17
$\omega = 0.7$	$\hat{A}_k$	99.96	83.81	2.38	94.34
	(t)	(5.29)	(13.76)	(0.10)	(12.27)
	$\hat{B}_k$	0.07	0.08	0.51	0.07
	(t)	(0.75)	(4.45)	(4.84)	(2.81)
	R^2	0.017	0.375	0.42	0.19
$\omega = 0.9$	$\hat{A}_k$	109.19	95.33	50.84	97.94
	(t)	(7.57)	(18.32)	(2.64)	(13.56)
	$\hat{B}_k$	0.03	0.05	0.33	0.06
	(t)	(0.34)	(3.00)	(3.32)	(2.50)
	R^2	0.003	0.214	0.25	0.16

Table 8: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it}$

Multi (rule)		*Experiment 12(R2)* ($\theta = 0.4$)		*Experiment 12(R3)* ($\theta = 0.4$)	
$S(3,2)$		*Firm 1*	*Firm 2*	*Firm 1*	*Firm 2*
ω	*Est.*	$p_i,\ i = 1,2,3$	$p_i,\ i = 4,5$	$p_i,\ i = 1,2,3$	$p_i,\ i = 4,5$
$\omega = 0.1$	$\hat{A}_k$	73.49	69.72	62.24	102.82
	(t)	(4.78)	(6.14)	(2.59)	(11.33)
	$\hat{B}_k$	0.27	0.18	0.35	0.12
	(t)	(5.32)	(7.28)	(4.78)	(7.06)
	R^2	0.46	0.62	0.40	0.60
$\omega = 0.3$	$\hat{A}_k$	81.70	63.24	63.96	99.38
	(t)	(5.29)	(6.40)	(2.85)	(12.17)
	$\hat{B}_k$	0.25	0.19	0.32	0.13
	(t)	(4.77)	(9.14)	(5.03)	(8.27)
	R^2	0.41	0.72	0.43	0.67
$\omega = 0.5$	$\hat{A}_k$	89.48	61.17	73.59	98.25
	(t)	(6.08)	(7.98)	(3.54)	(14.04)
	$\hat{B}_k$	0.22	0.20	0.32	0.13
	(t)	(4.47)	(11.95)	(4.98)	(9.84)
	R^2	0.377	0.812	0.43	0.745
$\omega = 0.7$	$\hat{A}_k$	96.39	67.99	93.98	103.89
	(t)	(7.56)	(12.93)	(4.92)	(16.09)
	$\hat{B}_k$	0.21	0.19	0.26	0.13
	(t)	(4.64)	(16.16)	(4.37)	(9.81)
	R^2	0.395	0.887	0.37	0.744
$\omega = 0.9$	$\hat{A}_k$	106.67	88.31	131.54	128.18
	(t)	(11.22)	(23.96)	(7.88)	(16.50)
	$\hat{B}_i$	0.20	0.18	0.17	0.09
	(t)	(5.20)	(17.74)	(2.74)	(5.02)
	R^2	0.451	0.90	0.184	0.43

Table 9: Estimation of the Adaptive Model: $p_{kt} = A_k + B_k E_{it}$

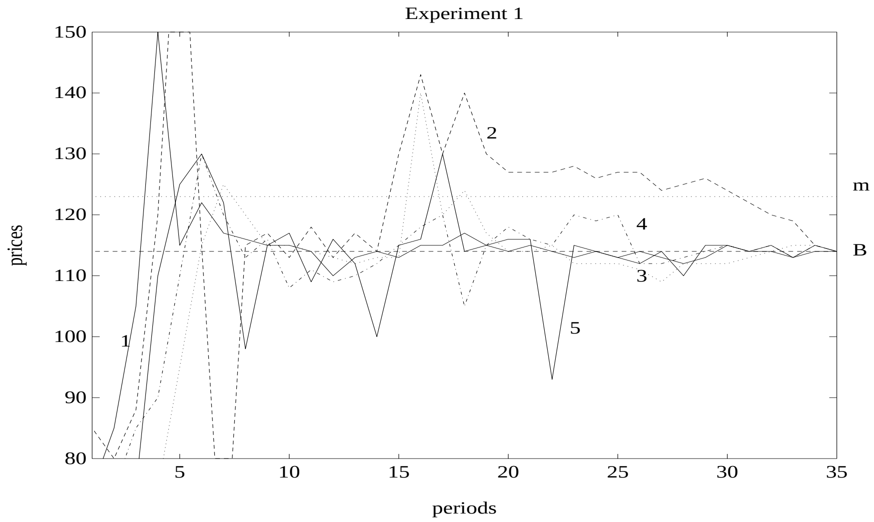

Figure 1: $S = (1,1,1,1,1)$ $(\theta = 0.14)$ experimental prices and theoretical equilibrium values.

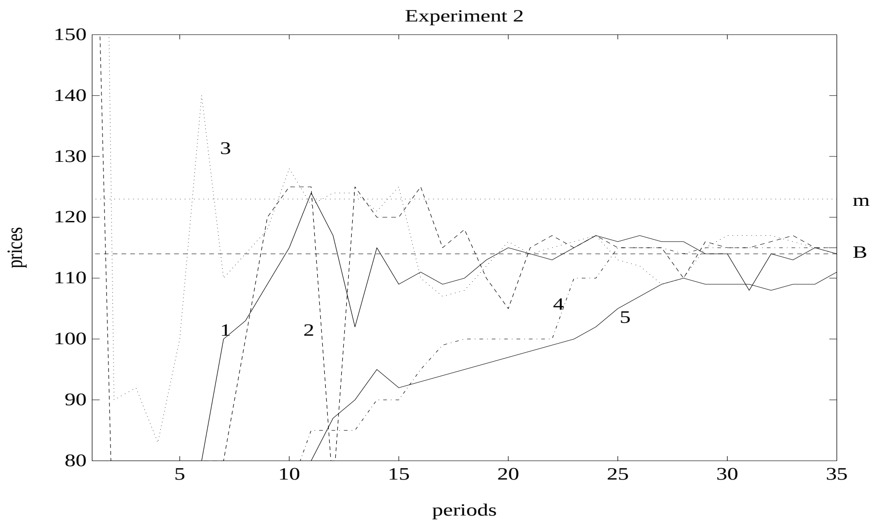

Figure 2: $S = (1,1,1,1,1)$ $(\theta = 0.14)$ experimental prices and theoretical equilibrium values.

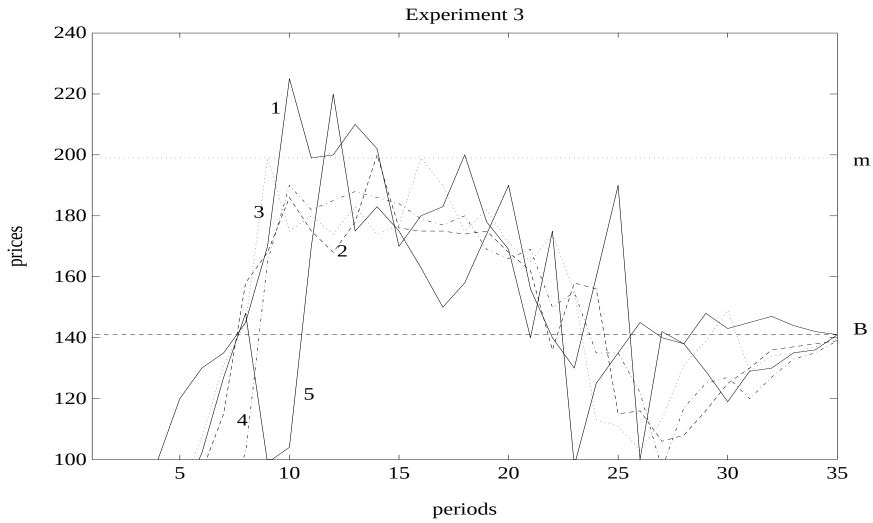

Figure 3: $S = (1, 1, 1, 1, 1)$ $(\theta = 0.4)$ experimental prices and theoretical equilibrium values.

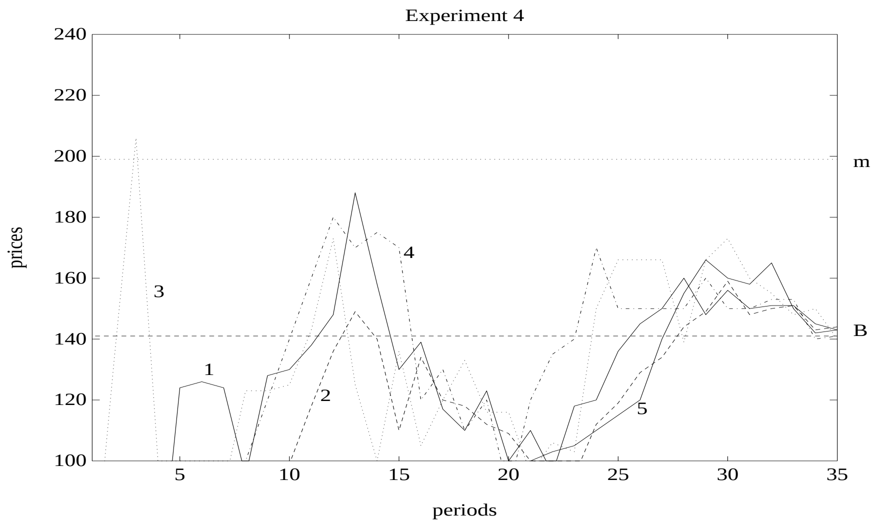

Figure 4: $S = (1, 1, 1, 1, 1)$ $(\theta = 0.4)$ experimental prices and theoretical equilibrium values.

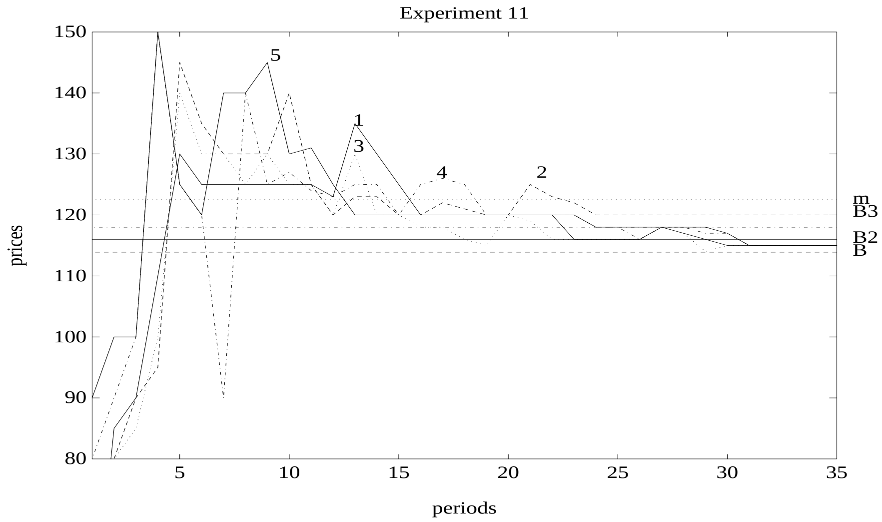

Figure 5: $S = (3, 2)$ (no rule) ($\theta = 0.14$) experimental prices and theoretical equilibrium values.

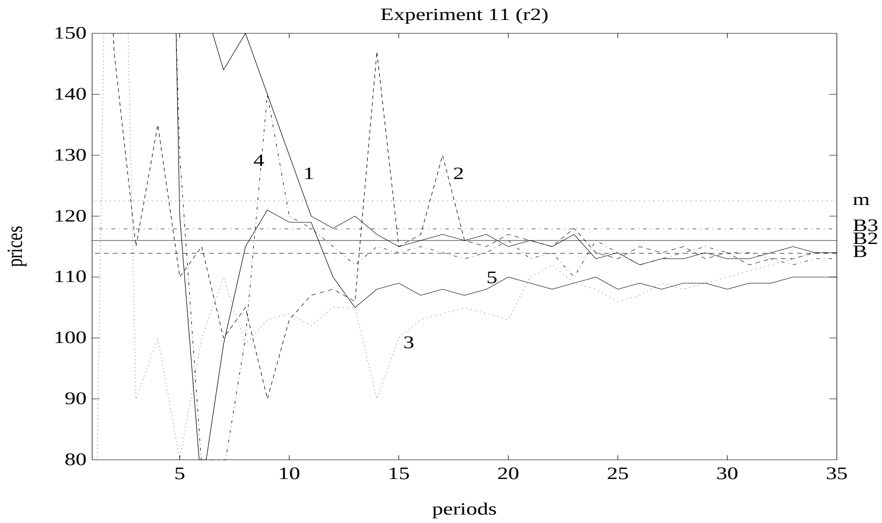

Figure 6: $S = (3, 2)$ (no rule) ($\theta = 0.14$) experimental prices and theoretical equilibrium values.

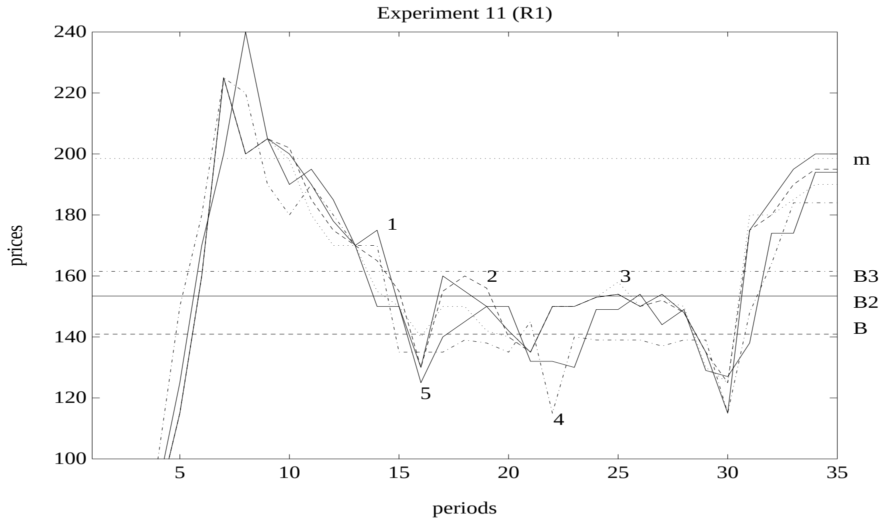

Figure 7: $S = (3, 2)$ (no rule) $(\theta = 0.4)$ experimental prices and theoretical equilibrium values.

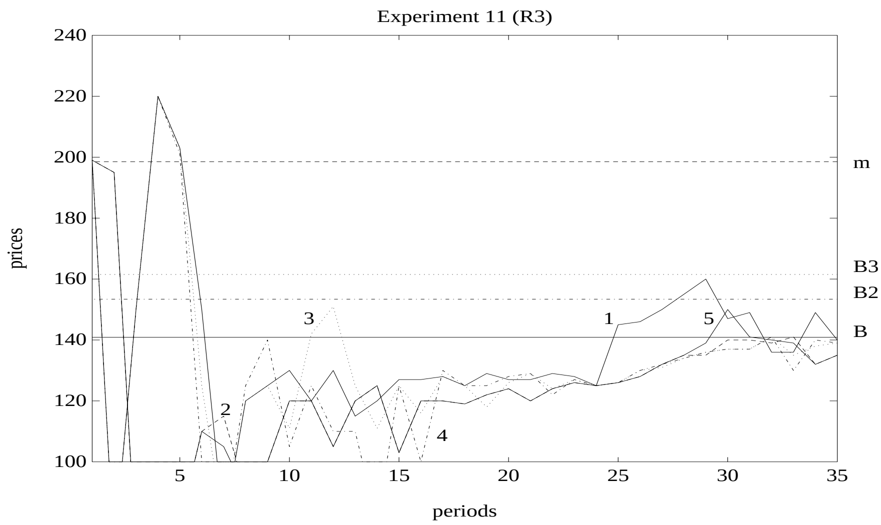

Figure 8: $S = (3, 2)$ (no rule) $(\theta = 0.4)$ experimental prices and theoretical equilibrium values.

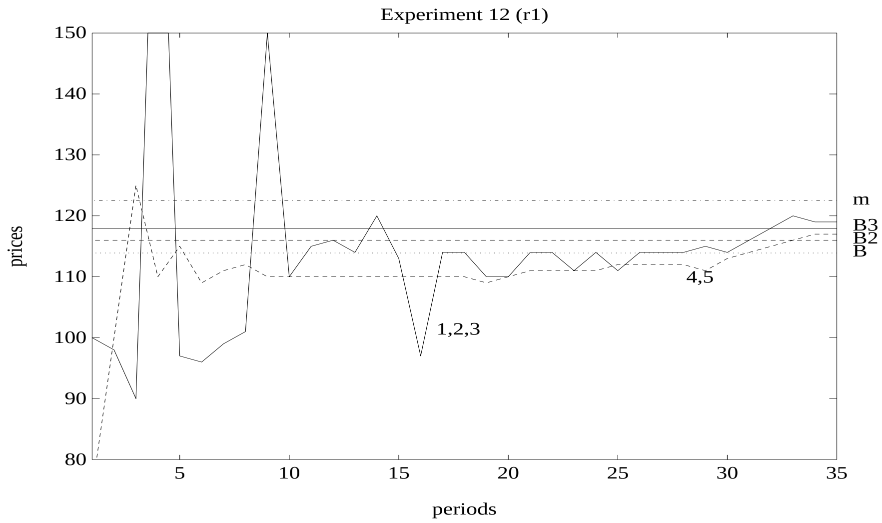

Figure 9: $S = (3, 2)$ (rule) ($\theta = 0.14$) experimental prices and theoretical equilibrium values.

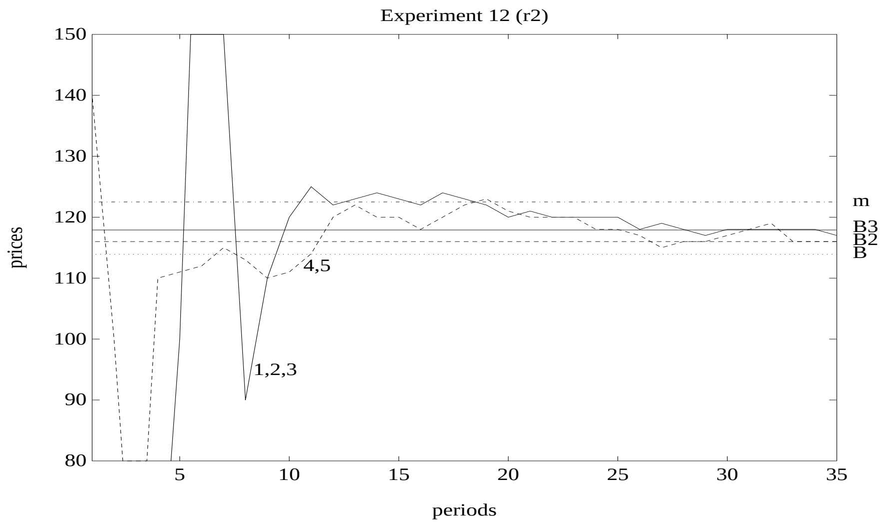

Figure 10: $S = (3, 2)$ (rule) ($\theta = 0.14$) experimental prices and theoretical equilibrium values.

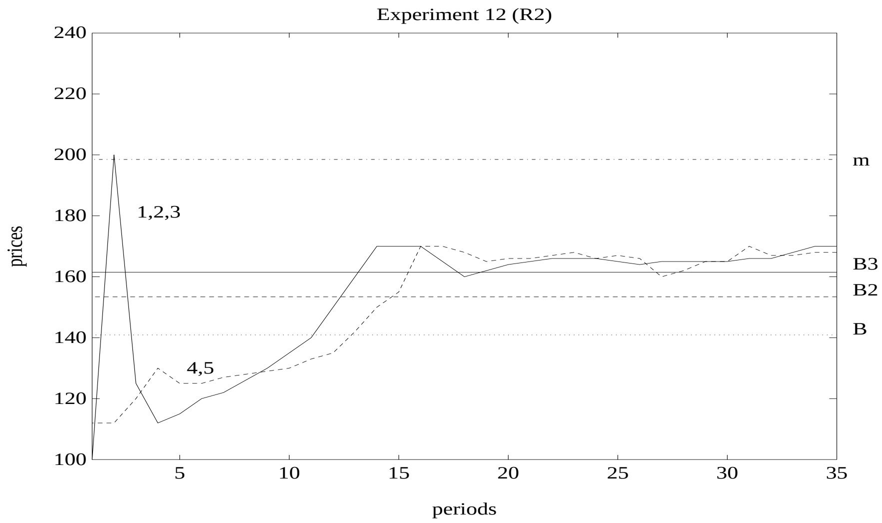

Figure 11: $S = (3, 2)$ (rule) ($\theta = 0.4$) experimental prices and theoretical equilibrium values.

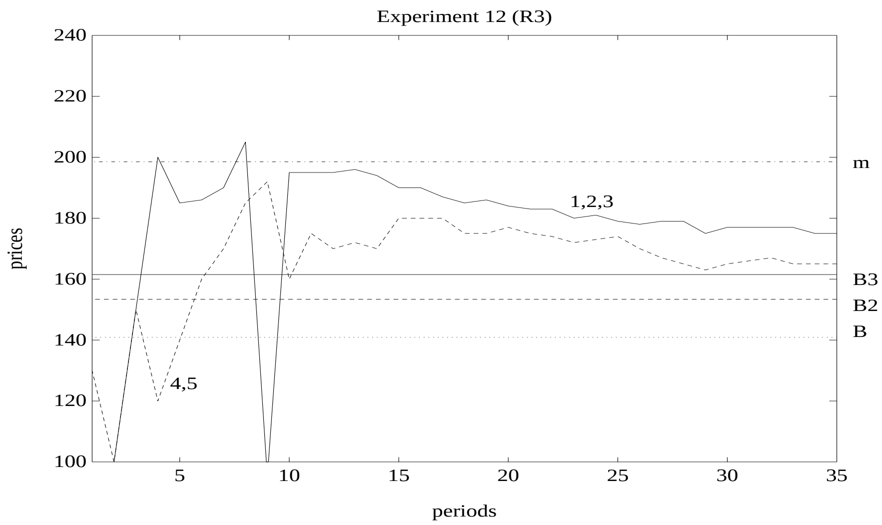

Figure 12: $S = (3, 2)$ (rule) ($\theta = 0.4$) experimental prices and theoretical equilibrium values.