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Identified Consumers: An Experiment on the Informativeness of Cross-Demand Price Effects

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Abstract

Often, firms have no information on the specification of the true demand model they are faced with. It is, however, a well established fact that trial-and-error algorithms may be used by them in order to learn how to make optimal decisions. Using experimental methods, we identify a property of the information on past actions which helps the seller of two asymmetric demand substitutes to reach the optimal prices more precisely and faster. The property concerns the possibility of disaggregating changes in each product's demand into client exit/entry and shift from one product to the other.

Keywords: purchasing technologies, experimental economics, multiproduct firms, information on cross demand price effects.

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1. Introduction

In many markets, new technologies have modified the process of purchasing a service or a product. Potential buyers are offered the comfort of «buying from home», using their network or computer cables to transmit their orders to the firms located in the other side of the line. The Internet and pay-per-view television are the most important among a number of technological advances in purchasing technologies which allow consumers to instantaneously arrive at virtual shops and choose the desired service or product. In order to initiate a purchase, the consumer must connect to the network being automatically identified by the firms. This does not necessarily require personal identification. An e-mail address or even an anonymous number is enough. The identification of the buyer, not available in the traditional buying process, can be easily processed by the firms. We will argue that this information might be relevant when designing optimal pricing strategies for multiproduct firms, in an environment with unknown demand functions for commodities which have a certain degree of substitutability.

It has already been argued that information on individual consumer actions may help the firm know the preferences of a certain group of consumers in order to apply discriminatory pricing to pay-per-view services[1]. In this paper, we set aside price discrimination effects on consumer surplus and focus on the effect of feedback from past actions on learning by multiproduct firms. We illustrate a different and more general feature of consumer identification by firms. Namely, a producer of two substitutable products who distinguishes between demand variations due to loss of consumers and due to shift of consumers from one product to the other will learn faster and more precisely the optimal prices. In fact, we find that learning from market feedback which enables the firm to distinguish between consumers lost or gained and consumers shifting from one product to the other leads to a globally optimal pricing. On the contrary, the lack of feedback which allows for the aforementioned disaggregation of demand effects tends, on average, to profits which are compatible with the hypothesis of non cooperative behavior across products. This finding is compatible

[1] Holden (1993) compares pay-per-view and network television, concluding that technological progress enables the producer to capture a larger share of the consumer surplus via price discrimination. Hansen and Kyhl (2001) analyse the consequences of a regulatory ban on pay-per-view broadcasting when the alternative is financing the events by TV commercials.

with the conjecture by García-Gallego and Georgantzís (2001), «G&G», according to which a multiproduct firm may fail to maximize profits if it applies product-specific trial-and-error algorithms.

In that paper it is shown that imposing a price-parallelism rule to multiproduct subjects is a necessary condition for the theoretical prediction of a multiproduct non cooperative equilibrium to coincide with the limit of observed actions. Here, we show that convergence to monopoly prices can be achieved by subjects spontaneously adopting optimal learning rules provided that demand feedback from past actions allows them to distinguish between direct and cross price effects.

From a theoretical point of view, Harrington (1995) studies the optimal strategies by duopolists who learn about the degree of substitutability between products. In that paper, firms are uncertain about the degree of product differentiation and learn from demand differences across products for given prices. However, it is reasonable to assume that an uninformed firm may not know any parameter (including the functional form) of the demand model. In such a case, García-Gallego (1998)[2] finds that, in a simple symmetric environment, subjects use intuitive learning rules (like trial-and-error algorithms), which make actions converge towards full information predictions.

Along the line of less optimistic results, experimental methods have often been used to illustrate limitations of learning in, from and about complex systems. Although chaotic dynamics[3], market asymmetries[4], complexity due to multiproduct activity[5], complex two-stage decisions[6] and verticalrelations[7] may also be responsible for learning failures, the informativeness of feedback from past actions is among the most important determinant factors of learning and performance by human subjects[8]. Explicit instruction[9], reasoning[10] or imposition of the optimal learning rules[11]

[2] Earlier references on simple learning rules in unknown environments are Kirman (1975), Brousseau and Kirman (1991) and Cyert and DeGroot (1973).

[3] Richards and Hays (1998).

[4] Rassenti et al. (2000) and, especially, Mason et al. (1992).

[5] Kelly (1995).

[6] Nagel and Vriend (1999a, 1999b).

[7] Durham (2000).

[8] Diehl and Sterman (1995) illustrate the effects of feedback complexity on learning. Paich and Sterman (1993), and Sterman (1994) identify failures to learn in complex systems due to misperception of feedback.

[9] As shown in Sterman (1994).

[10] Vriend (2000).

[11] As an option of price parallelism offered to subjects in Harstad et al. (1998) and an explicit imposition of perfect parallelism in García-Gallego and Georgantzís (2001).

by the experimentalist improves a subject's performance in an unknown environment. Nevertheless, little has been said on the ability of firms to spontaneously learn the optimal rule leading to a globally optimal strategy. On that direction, our aim in this paper is to illustrate how information on cross demand price effects is a strategy which can be used to facilitate learning and improve performance in an initially unknown environment.

Our experiment is based on the simplest environment possible in order to test for behavioral differences which are due to (non) availability of information on cross demand price effects. We consider a firm which produces two asymmetric, imperfectly substitutable products. Subjects have no information on the specification of the true demand model. Prices are chosen during fifty periods. In each period, production costs are fixed and relatively high. In one treatment of the experiment subjects receive information about product-specific demand price effects. In the other treatment, this information is disaggregated in direct and cross effects. Our findings indicate that in an asymmetric setting, the G&G conjecture can be rephrased to account for spontaneous convergence to a globally optimal strategy, provided that information on past performance allows for a more global consideration of the firm's problem.

The remaining part of the paper is organized in the following way. Section 2 presents benchmark theoretical predictions for the model used and discusses the experimental design. In section 3, we analyze the experimental data and in section 4, we conclude.

2. Theoretical predictions and experimental design

Consider a monopolist selling varieties 1 and 2 of a differentiated product whose demand is described by:

$$q_1 = a_1 - bp_1 + \mu p_2 \tag{1}$$
$$q_2 = a_2 - bp_2 + \mu p_2 \tag{2}$$

Parameters a_1 and a_2 are the demand intercepts denoting different variety specific market sizes. Parameter b is the common own demand slope, whereas μ ($0 \leq \mu \leq b$) corresponds to the effect of product's one price on the demand for the other product. In fact, an interpretation of our model as a special case of a model of spatial competition[12]

[12] Note that, in this case, the assumed model can be equivalent to a spatial model where demand

allows us to use as identical the following terminologies: «number of units demanded» and «number of consumers purchasing a unit of the product». In that case, identification of the consumer's «address» (ideal variety) on the line of product characteristics allows the firm to know whether a given price increase (decrease) causes the consumer to shift from one product to the other or to exit from (enter into) the market.

Costs of production are fixed and equal to . Then, the monopolist's profits are:

$$\pi = p_1q_1 + p_2q_2 - F \tag{3}$$

whose maximization with respect to prices gives the following solutions:

$$p_1^m = \frac{a_1b + \theta a_2}{2(b^2 - \theta^2)} \tag{4}$$

$$p_2^m = \frac{a_2b + \theta a_1}{2(b^2 - \theta^2)} \tag{5}$$

functions of two varieties 1, 2, sold at locations 1, 2, at distance from each other on an open line with uniformly distributed consumers with unitary density, are:

$$q_1 = \frac{R_1 - p_1}{t} + \frac{x_{12}}{2} + \frac{p_2 - p_1}{2t}$$

$$q_2 = \frac{R_2 - p_2}{t} + \frac{x_{12}}{2} + \frac{p_1 - p_2}{2t}$$

where are the consumer's reservation prices for variety 1 and 2, respectively.

Therefore, monopoly prices are:

$\mathrm{p}_1^m = \frac{3R_1 + R_2 + 2tx_{12}}{8}$, $\mathrm{p}_2^m = \frac{R_1 + 3R_2 + 2tx_{12}}{8}$. Then, both models are identical, with $a_1 = \frac{2R_1 + tx_{12}}{2t}$, $a_2 = \frac{2R_1 + tx_{12}}{2t}$. In such a case, we can reinterpret product-specific market size in terms of reservation price, unit transportation cost and distance between the two locations.

Although we are interested in the case of a monopolist who jointly offers the two products, following the findings in G&G, it will, also, be interesting to have the duopoly solution in mind as a benchmark:

$$p_1^c = \frac{2a_1 b + \theta a_2}{4b^2 - \theta^2} \tag{6}$$

$$p_2^c = \frac{2a_2 b + \theta a_1}{4b^2 - \theta^2} \tag{7}$$

In the experiment, we assume $(a_1, a_2) = (1000, 750)$; $F = 100000$ and $(b, \mu) = (1.5, 0.5)$: Given the values of the parameters, monopoly optimal prices are $(p_1^m, p_2^m) = (468.75, 406.25)$: Bertrand equilibrium prices are $(p_1^c, p_2^c) = (385.71, 314.28)$. Therefore, total revenues corresponding to the aforementioned solutions are, respectively, $R_1 = 386718.75$ and $R_b = 371324.75$, from which fixed costs have to be substracted in order for net profits to be obtained ($\pi_m = 286718.75$ and $\pi_b = 271324.75$).

In each session, subjects were assigned to computers running the software of the corresponding treatment. In the organization of the sessions, Urs Fischbacher's software *z-Tree 2011* was used as the interface available to each subject selling the two products in a market whose demand was simulated by the program. Each session lasted approximately 1 hour. Before each session started, subjects received qualitative information on the relation between the two products in demand («imperfect substitutes») and on the fact that «the first product is of a higher quality than the second». Detailed written instructions[13] were distributed to the subjects before each session, containing information on their firm's cost structure[14] and the information that would be provided to them after they made their decisions for each period (depending on the treatment).

Subjects were volunteers recruited among our 1st and 2nd year students in Business Administration. All subjects were paid in cash (Spanish Pesetas) immediately after each session (and informed that this would be so before participating) accord-

13 See appendix A.1.

14 As can be seen from the parameter values chosen, a relatively high fixed cost, which was non separable with respect to the two goods, was introduced, leading to the possibility of a net loss, in order for subjects to be helped in correcting strategies which significantly deviated from the optimal ones.

ing to their performance in the experiment. Average earnings were approximately $15 (2500 Pesetas). Data on the behavior of sixty seller-subjects were collected, 30 for each treatment. In both treatments, each subject was faced with the market described above over 50 periods. The only link between successive periods was experience gained from past actions. In order to maintain our subjects' interest constant over time, each one's earnings were randomly chosen among the fifty periods of the session. Real monetary rewards were obtained applying a 1/100 exchange rate between real and experimental currency units.

The only decision variables were the prices of the two products. A price could be any integer from the interval [0; 1000]. The information each subject received on past actions is a key issue studied here. After setting prices for the two products in each period, a subject received product-specific information on the resulting demand and revenues, as well as variations (from period 2 onwards) with respect to the previous period. Total revenues from the two products were also provided on the screen. Together with all the information described so far, an additional column appears on a subject's screen in treatment 2, so that each period's demand variation is disaggregated into two parts:

a) Demand gained or lost due to entry or exit of clients caused by the variation of this period's prices with respect to those of the previous period.

b) Demand shifted from one product to the other caused by the variation in the price difference across products with respect to the previous period.

A positive sign indicates a shift from product 1 to 2, whereas a negative sign indicates a shift for product 2 to product 1.

In order to illustrate the difference between the two treatments, let us consider the following example. Suppose that, in period 1, a subject fixes the following prices: $p_1 = 400$, $p_2 = 400$. The feedback received on the two products' demands at the end of the period in both treatments is the same: $q_1 = 600$, $q_2 = 350$. Now, suppose that, in period 2, the subject sets $p_1 = 500$, $p_2 = 300$. This decision implies $q_1 = 400$, $q_2 = 550$. Demand variations with respect to past periods are automatically calculated and presented on the subject's information screen. The difference between treatments concerns the information on demand variations with respect to past periods. Specifically, in treatment 1, the subject would receive $dq_1 = -100$ and $dq_2 = 200$, whereas in treatment 2 this information would be disaggregated, specifying the variation due to exit of product 1's buyers $dq^I_1 = -150$, due to entry of product 2's buyers $dq_2 = 150$ and due to clients shifting from product 1 to product 2 ($dq^{II}_1 = 50$).

After the end of the experiment, a post-play questionnaire was given to each subject aiming at controlling for differences in subjects' beliefs across treatments concerning the degree of substitutability between goods and possible changes in demand conditions. Our aim was to test whether learning from different feedbacks on past actions affects subjects' beliefs concerning the features of the market.

3. Data analysis and results

3.1. *Nonparametric estimation of the density functions*

In both treatments, strategies have been converging towards optimal ones towards the end of each session. However, we are interested in assessing the accuracy and speed of such convergence and test for differences across treatments. In order to obtain a first picture of the data, we apply nonparametric methods to estimate the distribution function for prices and revenues. The application of this approach does not make assumptions about the distribution of the observed data and, therefore, fits perfectly our objective. In fact, the method is specially helpful to graphically represent the data when a large number of observations is available. In this case, the smooth density function estimated offers a very close approximation of the actual dispersion of the data. We smooth the data using a kernel function K which satisfies:

$$\int_{-\infty}^{\infty} K(X)\, dx = 1 \tag{8}$$

Among multiple options for the kernel selection, we have chosen the Gaussian Kernel because of computing straightforwardness. The expression of the function used is:

$$\mathrm{K(t)} = \frac{1}{\sqrt{20\pi}} e^{-\frac{1}{2} t^2} \tag{9}$$

Kernel smoothing consists of estimating the following density function[15]:

[15] This kernel estimator is a sum of bumps placed at the observations.

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left[\frac{x - X_i}{h} \right] \tag{10}$$

where h is a smoothing parameter (window width or bandwidth)[16], n is the number of observations and X_i is the ith-observation of the variable under study.

In order to observe the speed and degree of convergence to optimal monopoly prices in both treatments, we estimate the aforementioned univariate density function for the prices of the two products sold by players. We group prices chosen by subjects in five intervals composed of ten periods each (300 observations in each graph). We also consider the pool of observations from the first five periods, in order to obtain the distribution of strategies in the very beginning of the sessions. Appendix A.2 includes the graphical representations of the estimated price distribution density functions. On each graph, a vertical line indicates the optimal monopoly price, given the values of the parameters used in the experiment. Odd figure numbers between 1-12 (13-24) correspond to prices chosen in treatment 1 for product 1 (2) and even figure numbers correspond to prices chosen in treatment 2 for product 2.

Comparing treatments, we take pairs of graphs corresponding to the same subperiod of the experiment. We observe how in comparison to treatment 1, in treatment 2 subjects converge to the monopoly prices faster and more precisely with respect to both products. Therefore, the main conclusion of our analysis is straightforward: Additional information on cross-demand price effects improves both the accuracy and the speed of convergence to optimal strategies.

We apply the same method to estimate density functions for total revenues reached by subjects in both treatments, grouped in the aforementioned intervals (odd figures among figures 25-36 correspond to revenues in treatment 1 while even figures correspond to treatment 2). As a consequence of the result obtained with respect to prices, in any interval of periods considered, more subjects in the second treatment earn a given level of profits.

Alternatively, it has taken less periods for a certain number of subjects in the second treatment to earn a certain amount of money than it has taken for the same to happen in the first treatment.

[16] The kernel function determines the shape of the bumps while the window width h determines their width. Bandwidth selection is much more important than kernel's. If h is chosen too small, then an excessive number of bumps is generated and spurious fine structure becomes visible. If h is chosen to large, then some features presented in the data are hidden. In order to offer a reasonable balance between these two extremes, we choose the h proposed by Sheather and Jones (1991) from the study by Park and Marron (1990) due to its proved superior performance.

3.2. *Testing for homogeneity*

We study whether the samples of prices obtained from the two treatments of the experiment come from different populations. A Mann-Whitney test is used to test for homogeneity of price samples across treatments[17]. Each test is performed for prices corresponding to five intervals of time of ten periods as well as the total of periods played. The results are summarized in table 1. Throughout the paper, a common level of significance, has been used.

Table 1. z values corresponding to a Mann-Whitney test comparing prices across treatments. Entries in bold characters indicate statistical significance of differences (critical value: 1.96)

Periods	1–10	11–20	21–30	31–40	41–50	1–50
p_1	–2.18	–1.14	–4.50	–3.22	–3.42	–5.93
p_2	–1.75	–0.70	–0.88	–0.13	–0.43	–1.29

We find significant differences between treatments only in the prices of product 1 (the one with a larger market size). In almost all intervals and for the total number of periods (except for the interval of periods 11-20), we observe that the median price of product 1 in treatment 1 is significantly lower than the median price of the same product in treatment 2. However, no significant differences between treatments are found for the price median of product 2 (that of a smaller market size). Hence, we can say that subjects choose higher prices for product 1 in treatment 2 than in treatment 1. Having in mind figures 1-12, we observe that these higher prices for product 1 are closer to the monopoly price than prices chosen by subjects in treatment 1. Therefore, subjects who are provided with information on cross demand price effects seem to discern which is the product whose market size is larger (potentially more profitable) and set significantly higher prices for it.

[17] Assuming that we have two samples whose sizes are n_1 and n_2, and the respective ranks are R_1 and R_2, we calculate the statistics U_1 and U_1, where $U_1 = n_1n_2 + n_1 \frac{n_1 + 1}{2} - R_1$ and $U_2 = n_1n_2 + n_2 \frac{n_2 + 1}{2} - R_2$, and compare $U_m = \min \{U_1, U_2\}$, with the corresponding critical values provided in the tables. If the statistic obtained is higher than that in the tables, we reject the hypothesis of homogeneity, which would imply that the two samples belong to two different populations.

3.3. *Price dispersion*

In this section, we compare observed prices with optimal ones. In order to do this, we express price observations as normalized differences from the corresponding optimal value. Then, normalized observations which are closer to zero imply prices which are closer to the optimal ones. In table 2 we include the percentage of normalized price observations which fall within four different intervals, which are defined to express four different levels of accuracy.

Table 2. Percentage of normalized price observations falling within a confidence interval around the optimal prices. Entries in bold characters indicate statistical significance of differences across treatments

		Treatment 1		Treatment 2	
Period	Interval	p1	p2	p1	p2
1-10	0-0.1	7.66 %	3.33 %	19.66 %	25.33 %
	0-0.3	29.33 %	30.66 %	66.00 %	63.00 %
	0-0.5	56.33 %	57.66 %	76.33 %	79.67 %
	0-1	94.00 %	96.66 %	91.33 %	95.00 %
11-20	0-0.1	31.66 %	24.00 %	34.66 %	39.33 %
	0-0.3	62.66 %	61.00 %	78.66 %	79.00 %
	0-0.5	70.00 %	72.00 %	88.00 %	89.66 %
	0-1	93.66 %	98.33 %	93.66 %	94.33 %
21-30	0-0.1	36.66 %	24.33 %	60.33 %	60.33 %
	0-0.3	68.00 %	65.33 %	89.33 %	88.00 %
	0-0.5	76.00 %	73.66 %	95.00 %	95.00 %
	0-1	99.33 %	98.33 %	96.00 %	96.33 %
31-40	0-0.1	33.00 %	26.66 %	75.00 %	74.66 %
	0-0.3	74.33 %	62.33 %	93.33 %	94.66 %
	0-0.5	77.00 %	80.00 %	96.33 %	96.00 %
	0-1	96.00 %	100.00 %	98.33 %	98.66 %
41-50	0-0.1	41.33 %	37.00 %	80.33 %	86.00 %
	0-0.3	75.33 %	73.66 %	98.33 %	96.66 %
	0-0.5	80.66 %	84.33 %	99.33 %	98.00 %
	0-1	98.33 %	99.66 %	100.00 %	100.00 %

As we would have expected, due to learning, the percentage of normalized prices falling within any of the intervals considered increases over time in almost[18] all cases. Comparison across treatments indicates that in any sub-period of the session, the percentage of normalized prices falling within any range of values is significantly[19] higher for treatment 2 than for treatment 1, except in the case of the broadest range of values (0-1) considered. That is, unless an excessively permissive test of accuracy is performed, significant differences are found with respect to the percentage of prices lying sufficiently close to the optimal ones, supporting the argument that the additional information provided to the subjects increases the speed and accuracy of the convergence process. This finding can be interpreted as an extension of the result obtained from comparison of median differences with respect to the price of product 1 over to the prices of both products.

3.4. *Testing for alternative predictors of observed behavior*

In this section, we test whether differences across treatments are compatible with the G&G conjecture. That is, whether deviations from optimal behavior in treatment 1 can be explained as the result of locally (product-specific) optimal but globally suboptimal pricing. According to this hypothesis, learning from product-specific application of simple trial-and-error algorithms would lead closer to the predictions based on the assumption of non-cooperative behavior across products (Single-Product Bertrand Nash Equilibrium, SBNE). Otherwise, globally optimal learning rules would yield convergence closer to the Multiproduct Monopoly Equilibrium (MME).If the conjecture is confirmed, we can interpret the role of the additional information in treatment 2 as a factor favoring a globally optimal behavior.

First, in the Appendix, we present the evolution of average prices for the two treatments in Figures 37 (product 1) and 38 (product 2). It is observed that average

[18] Exceptions are observed only in three cases: (1) treatment 1, p_1, interval 0-0.1, moving from periods 21-30 to periods 31-40 percentage falls from 36.66% to 33%, (2) treatment 1, p_2, interval 0-0.3, moving from periods 21-30 to periods 31-40 percentage falls from 65.33% to 62.33%, (3) treatment 2, , interval 0-1, moving from periods 1-10 to periods 11-20 percentage falls from 95% to 94.33%.

[19] A χ^2 test has been performed in order to compare the corresponding percentages of prices falling within a given range in a given sub-period of the experiment.

prices obtained from treatment 2 converge faster and more precisely towards the MME prediction than do average prices obtained from treatment 1. In fact, the average price of product 1 in treatment 2 tends to the corresponding MME prediction with more precision than any other price does. Furthermore, the price of product 2 in the same treatment tends to significantly higher levels than predicted in the MME but remains closer to it (from above) than does the same average in treatment 1 (from below). In any case, average prices are closer to the MME prediction than to the SBNE.

In assessing the difference between optimal and observed prices, we would like to know whether deviations are best explained as individual mistakes reflected on wrong price differences across products and/or as misjudgment of the right level of prices. In order to this, we treat period price differences across products (the evolution of averages is presented in Figure 39) and period average individual price (the evolution of averages is presented in Figure 40) as individual observations. Significant differences are obtained with respect price levels only. Specifically, in treatment 1, price levels converge precisely to the average price level predicted in the MME. Contrary to price levels, price differences do not significantly vary across treatments and are very close to the MME prediction. Summarizing, we could assert that any significant differences in the behavior of subjects across treatments are best explained as result of differences in the average level of individual period prices for the two products.

A more rigorous analysis, has been used to support the results discussed above. We compare the average price obtained from any of the aforementioned sub-periods of the experiment (as well as the total of periods played) with the SBNE and the MME[20]. The results are summarized in table 3.

Testing for equality between theoretical and observed prices, we obtain that the MME prediction is not confirmed in treatment 1 for any sub-period. The SBNE is a good predictor only for p1 in the ten first periods. However, the MME is an accurate predictor for subjects' behavior in treatment 2 for both products after the first twenty periods (in the case of product 2 after the first ten periods).

[20] With a z-test where $z_b = \frac{(\bar{p} - p^B)\sqrt{N}}{\sigma}$ and $z_m = \frac{(\bar{p} - p^M)\sqrt{N}}{\sigma}$ in which $\bar{p}$ is the average price and N is the number of observations corresponding to any of the sub-periods considered, p^B is the price predicted by the SBNE, p^M is the MME price and σ is the standard deviation of the population. The null hypothesis corresponding to z_b (z_m) is $H_0 : \bar{p} = p^B$ ($H_0 : \bar{p} = p^M$).

Table 3. values corresponding to a z-test comparing prices in both treatments with SBNE and MME. Entries in bold characters indicate statistical significance of differences across treatments (critical value: 1.96)

Period	Statistics	T1–p1	T1–p2	T2–p1	T2–p2
1-10	$\bar{p}$	374.55	354.02	412.26	382.73
	σ	182.68	174.98	155.37	141.14
	z_b	–1.04	3.81	2.94	8.31
	z_m	–8.83	–5.02	–6.23	–2.77
11-20	$\bar{p}$	429.64	387.39	436.21	394.11
	σ	151.36	135.67	119.87	108.56
	z_b	5.02	9.17	7.27	12.64
	z_m	–4.33	–2.25	–4.67	–1.90
21-30	p	422.49	388.58	459.77	398.60
	σ	127.43	125.74	93.98	83.51
	z_b	4.84	10.22	13.51	17.32
	z_m	–6.23	–2.42	–1.56	–1.56
31-40	$\bar{p}$	436.99	380.57	461.59	401.37
	σ	116.02	114.67	65.39	61.37
	z_b	7.62	9.87	20.10	24.42
	z_m	–4.68	–3.81	–1.73	–1.21
41-50	$\bar{p}$	444.01	386.49	468.96	406.97
	σ	111.07	104.24	30.05	37.58
	z_b	9.01	11.95	47.98	42.61
	z_m	–3.81	–3.12	0.12	0.33
1-50	$\bar{p}$	421.53	379.41	447.76	396.75
	σ	142.36	133.93	104.59	94.01
	z_b	9.68	18.59	22.85	33.69
	z_m	–12.78	–7.74	–7.74	–3.87

The analysis is completed with the study of total revenues. We compare average total revenues in both treatments with total revenues corresponding to MME (R_m) and total revenues corresponding to SBNE (R_b). In Figure 41, we present the average total revenues per period for the two treatments. It is easy to observe how average total revenues of treatment 2's subjects converge with high precision to R_m and, in the contrary, average total revenues of treatment 1's subjects converge with the same precision to R_b.

Table 4. Mean and Standard Deviation corresponding to total revenues in each sub-period of the experiment

	Periods	1-10	11-20	21-30	31-40	41-50
$\bar{R}$	T1	307345	340086	351630	359946	365290
	T2	340462	360452	367621	377419	383641
σ_R	T1	88688	71576	62299	46580	43702
	T2	84086	68414	63440	35646	10141

In table 4, we present simple statistics (mean and standard deviation) for total revenues confirming this affirmation.

Therefore, the G&G conjecture is confirmed by average profits. In other words, subjects receiving feedback on past actions which allows them to distinguish between direct and cross demand effects earn on average monopoly profits, whereas subjects in the basic treatment tend to earn, on average, profits corresponding to the Bertrand-Nash prediction.

3.5. *Testing for differences in performance improvement indices*

It would be reasonable to ask whether not only static performance but also performance improvements (dynamic performance) in treatment 2 have dominated improvements in treatment 1. We are interested in two issues. First, in the number of periods in which prices chosen by subjects are closer to monopoly prices than have been prices in the previous period[21]. Second, we study how large each approximation to the MME has been by accounting for the reduction of the difference between monopoly price and the price chosen.

We define an improvement index $I = nd$ where n is the percentage of periods in which subjects are closer to the monopoly prices as compared to the previous period and d is the ratio of the reduction to monopoly price. Thirty such indices are computed (one for each subject) in each treatment[22].

[21] We assume that this condition is also (weakly) satisfied if at least one price is closer to the corresponding MME than has been the price of the same product in the previous period, while the other price does not vary with respect to the aforementioned period.

[22] Indices are available upon request from the authors.

A Mann-Whitney test is used to test for homogeneity in the population of indices across treatments. Statistically significant differences are obtained. Specifically, we find that *I* is significantly higher in treatment 2 than in treatment 1 (z = –2.35). Therefore, dynamic performance is also enhanced by feedback on cross demand effects.

3.6. *Testing for correlation of prices across products*

Following the analysis in G&G, it is interesting to look for correlation of prices across products. In that work, multiproduct subjects were faced with a symmetric problem. Then, the optimal pricing rule was perfect price parallelism (equal prices for products of the same firm). Even in that simple framework, subjects did not seem to spontaneously learn the optimal rule unless the design was such that the rule was exogenously imposed by instruction. In the asymmetric framework studied here the optimal rule is far more complicated and, thus, less likely to be spontaneously learned by subjects. However, parallel pricing of the two products seems to be an important issue to have in mind when learning by multiproduct subjects is addressed.

In order to study the correlation of prices across products, we obtain the Spearman correlation coeffcient[23]. First, results are aggregated by calculating the percentage of experiments in each treatment for which a significant correlation between prices exists. Second, we obtain the average Spearman correlation coefficient corresponding to the aforementioned experiments. These results (classified according to whether a negative or positive correlation exists) are reported in Table 5.

It is easy to observe that a higher corresponds to prices selected by treatment 1's subjects. This implies that subjects without disaggregated information tend to link their strategies across products in a stronger way than subjects with information on cross demand effects. However, the difference in the percentages of experiments in which a positive correlation of prices exists is not statistically significant.

[23] The coefficient is r_s, where d_i is the difference between a subject's ranks according to the corresponding values of the two characteristics under study (which are supposed to exhibit some correlation) for a given sample size and rs = $1 - \dfrac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$.

Table 5. Percentage of significant correlations and average Spearman coeffcients r_s across prices

	Significant correlations		Spearman	
Treatment	P C	N C	P C	N C
1	70.00 %	10.00 %	0.73	0.61
2	66.66 %	16.66 %	0.64	0.52

3.7. *Explicit knowledge*

In a post-play questionnaire, subjects were asked two questions to which three possible answers were provided. First, subjects were asked to give their perception of the degree of product substitutability. The three possible answers were: «Close substitutes», «Weak substitutes» and «Unknown». Second, subjects were asked whether they had felt that demand conditions had been changing from one period to the other, to which one among three possible answers could be chosen: «Changing», «Not Changing», «Unknown». While the first question refers to a subjective and qualitative judgement on product substitutability, the second refers to an objective feature of the system with which subjects were faced. Table 1 summarizes the results obtained from the questionnaire.

We cannot establish statistically significant[24] differences across treatments. Therefore, at the end of their session, subjects in different treatments have similar beliefs concerning product substitutability. Specifically, almost half of them think of it as being high and half of them consider it low. Furthermore, a large majority of them realize that they have been exposed to an invariant demand system. Not less interesting is the fact that a constant (across treatments) percentage of the population wrongly think that the contrary is true.

[24] A χ^2 test can be used to reject the hypothesis that responses are uniformly distributed along the three answers to both questions by subjects participating in both treatments.

Table 6. Percentage of answers to post-play questionnaire

		Substitutes			Demand Conditions	
Treatment	Close	Weak	Unknown	Change	No Change	Unknown
1	43.3 %	43.3 %	13.3 %	23.3 %	73.3 %	3.3 %
2	46.6 %	53.3 %	0.0 %	16.6 %	73.3 %	10 %

4. Conclusions

We have reported the results obtained from a simple experiment on monopoly learning. The intuition behind the argument presented here is the following. In the traditional buying process, disaggregated information on direct and cross demand price effects is obtained by firms only when one product price is modified while remaining product prices are constant. Given that firms face menu costs in price setting, if a price change in several products is required, a simultaneous change is more profitable. This synchronization of price changes by multiproduct firms is also reported by Fisher and Konieczny (2000) in the case of Canadian newspaper prices. These authors observe that, when changing nominal prices is costly, multiproduct press firms synchronize price changes, while price changes across firms are staggered (although no information about direct and cross demand price effects is obtained in this case). If feedback is such that individual purchasing decisions can be identified, firms take advantage of synchronizing price changes without loss of information about direct and cross demand price effects.

We have used experimental methods to test the value of information on cross demand price effects in an asymmetric differentiated multiproduct monopoly. Our design is based on two treatments in which all other things are kept constant except for feedback received by the subjects from past actions. When firms can identify product-specific demand variations which are due to consumers shifting from one product to the other, their actions converge faster and more precisely to the optimal ones. In the treatment in which subjects can distinguish between direct and cross-demand price effects average earnings tend to maximal levels towards the end of the experiment.

In the absence of information which allows for such a disaggregation of direct and cross-demand effects average earnings tend to the level predicted under the assumption of non cooperative behavior across products. Dynamic performance (measured by an index of performance improvement with respect to past actions) is also enhanced by feedback which allows the firm to identify demand lost or gained and demand shifting from one product to the other. Finally, differences in the behavior of subjects across treatments seem to be related to a misjudgment of the right price level rather than to wrong price differences across products.

Our results suggest that a multiproduct firm whose product specific feedback from its past actions does not permit identification of consumers shifting from one product to the other and consumers gained or lost, may earn on average non cooperative profits because it is likely to set (on average) lower prices. A straightforward conclusion from this observation is that consumer identification yields convergence towards privately (socially) superior (inferior) outcomes. Of course, this implication of our results may be less strong if we take into account dynamic inefficiencies which may be reflected on a longer time to convergence and, thus, the need for more price adjustments before equilibrium is reached. However, when assessing the desirability of consumer identification in the purchasing process, it is important to take into account its role in the feedback firms receive from past actions. Our findings indicate that not only the speed of convergence but also the limit towards which actions tend over time will be determined by identification of individual purchasing decisions, having non trivial implications for the resulting static and dynamic efficiency of the market.

A final remark concerns explicit knowledge of the underlying conditions. Our post-play questionnaire indicates that subjects have not gained sufficient knowledge to unanimously answer to the question concerning the degree of product substitutability. In fact, our setting is such that an objective evaluation of product substitutability cannot be obtained by simply playing our pricing game for 50 periods[25]. However, our results indicate that an explicit knowledge of a parameter is not a necessary condition in order for convergence towards optimal strategies to be obtained.

[25] Real world businessmen might have used econometric methods to estimate the corresponding parameter of our model. In fact, Clemen et al. (2000) reports on the consistence and use of manager's estimates for the relation between variables which are crucial for decision making in real world markets.

A. Appendix

A.1. *Instructions*

A.1.1. Treatment 1

The purpose of this experiment is to study how subjects take decisions in specific economic contexts. The instructions are simple. Follow them carefully and depending on your performance, you will receive a quantity of money in cash at the end of the experiment. The quantity of money that you will obtain is going to depend proportionally on your benefits in one period, which will be randomly chosen among the 50 periods of the experiment.

In any moment you can ask any question about the experiment. Out of these doubts any communication among you and the rest of participants is forbidden and implies your exclusion from the experiment.

You have to use the following information:

1. You are the only firm in the industry and you sell two imperfectly substitutable products. In each period, your costs are independent of your production level and therefore, fixed and equal to $F = 100000$ (corresponding to both products in a non-separate way).

2. Your decision variable is price. Each period you have to decide the prices of your two products and wait for the demand and benefits that correspond to those prices. A price must be an integer among 0 and 1000. This process will be repeated 50 periods without limitation in the time in which you will make your decision.

3. In each period, your revenues from each product are the result of multiplying demand with price. Your net product is equal to the sum of your revenues from each product minus F.

4. The reward you will receive for your participation in this experiment consists of a quantity equal to your profits in one of the 50 periods (randomly chosen) multiplied by an equivalence factor $E = 1/100$: experimental current units.

5. At the end of each period, a screen will inform you on:

a) The demands corresponding to the prices chosen for each product (q_1 and q_2).

b) Your corresponding revenues for each product (R_1 and R_2) and the total revenue ($R_1 + R_2$).

6. After the first two periods, you will also receive information about the variations in demand and partial and total revenue with respect to those obtained in the previous period (dq_1, dq_2 and dR_1, dR_2, $d(R_1 + R_2)$ respectively).

A.1.2. Treatment 2

The instructions to subjects participating in the treatment 2 included an additional seventh point:

7. Each period's demand variation is disaggregated into two parts:

a) Demand gained or lost due to entry or exit of clients caused by the variation of this period's prices with respect to those of the previous period ($dq^I{}_1$ and $dq^{II}{}_2$). A positive sign indicates entry and a negative one corresponds to loss of consumers who had previously bought the product.

b) Demand shifted from one product to the other ($dq^{II}{}_1$) caused by the variation in the price difference across products with respect to the previous period. A positive sign indicates a shift from product 1 to 2, whereas a negative sign indicates a shift on the contrary direction.

A.2. *Density functions*

A.2.1. Product 1 Prices (Treatments 1, 2)

A vertical line indicates the theoretical prediction for an optimal.

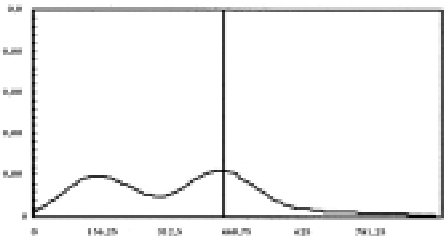

Figure 1: T1 , periods 1-5 (p_1).

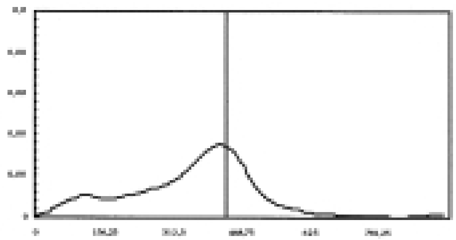

Figure 2: T2, periods 1-5 (p_1).

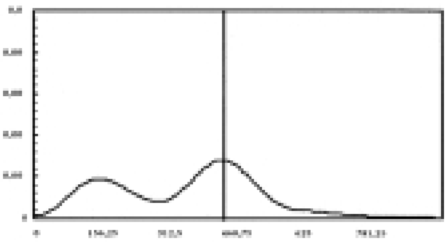

Figure 3: T1 , periods 1-10 (p_1).

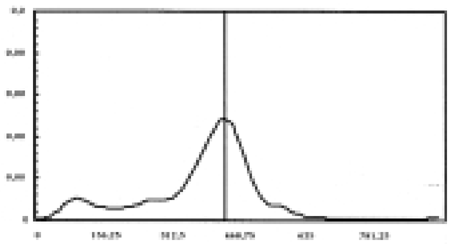

Figure 4: T2, periods 1-10 (p_1).

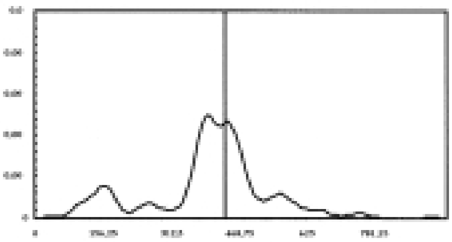

Figure 5: T1, periods 11-20 (p_1).

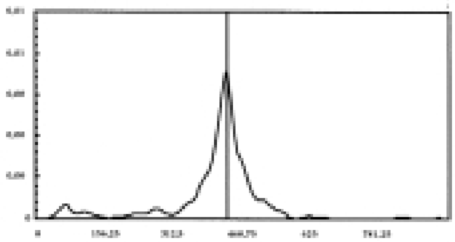

Figure 6: T2, periods 11-20 (p_1).

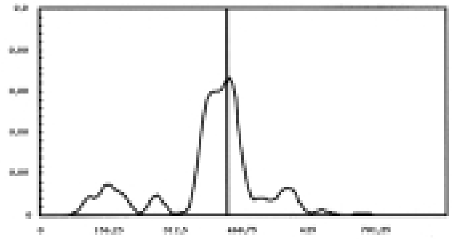

Figure 7: T1, periods 21-30 (p_1).

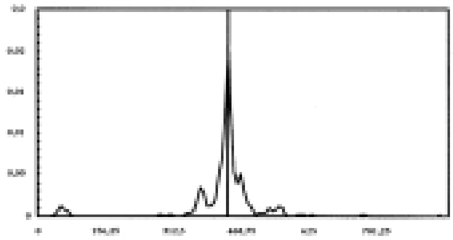

Figure 8: T2, periods 21-30 (p_1).

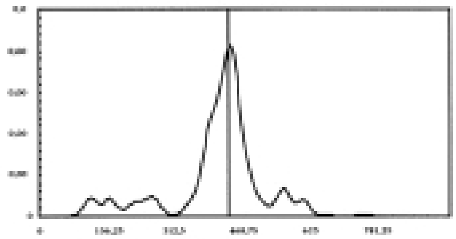

Figure 9: T1, periods 31-40 (p_1).

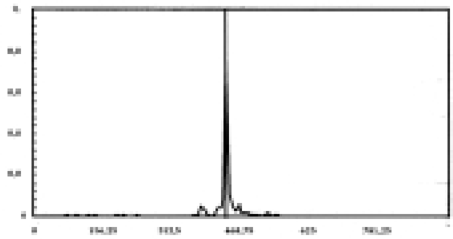

Figure 10: T2, periods 31-40 (p_1).

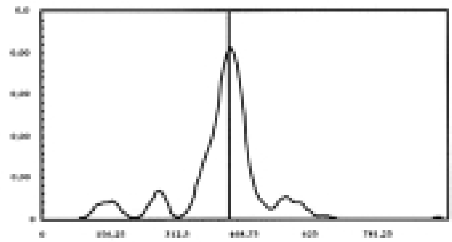

Figure 11: T1 , periods 41-50 (p_1).

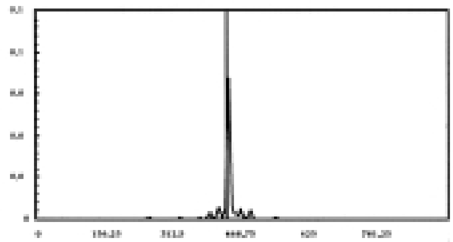

Figure 12: T2, periods 41-50 (p_1).

A.2.2. Product 2 Prices (Treatments 1, 2)

A vertical line indicates the theoretical prediction for an optimal.

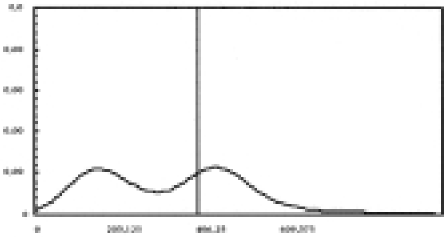

Figure 13: T1 , periods 1-5 (p_2).

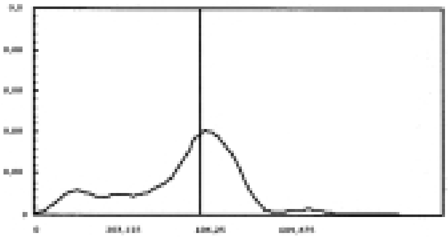

Figure 14: T2, periods 1-5 (p_2).

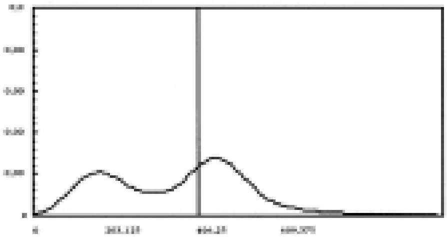

Figure 15: T1 , periods 1-10 (p_2).

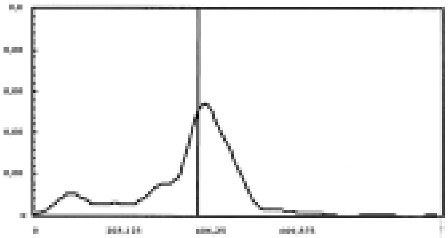

Figure 16: T2, periods 1-10 (p_2).

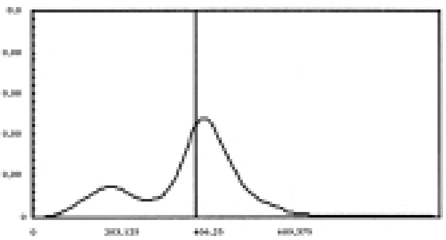

Figure 17: T1 , periods 11-20 (p_2).

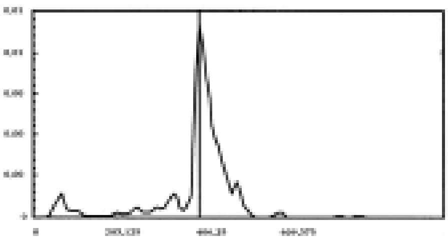

Figure 18: T2, periods 11-20 (p_2).

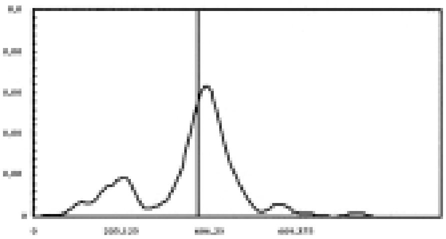

Figure 19: T1, periods 21-30 (p_2).

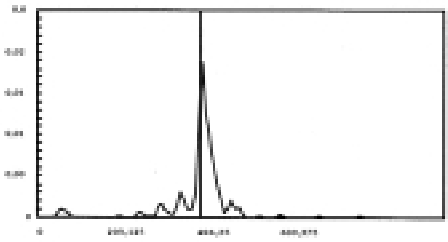

Figure 20: T2, periods 21-30 (p_2).

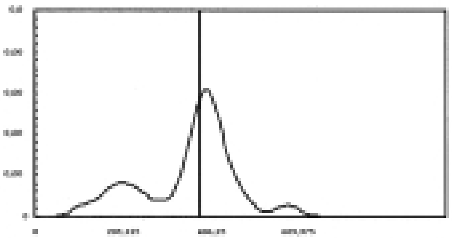

Figure 21: T1, periods 31-40 (p_2).

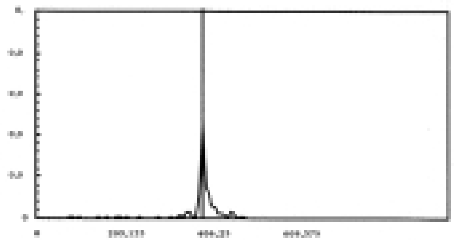

Figure 22: T2, periods 31-40 (p_2).

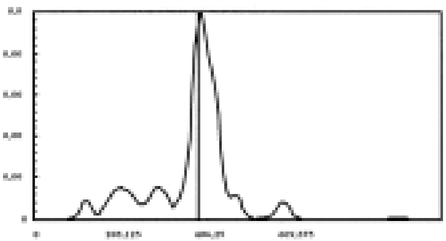

Figure 23: T1 , periods 41-50 (p_2).

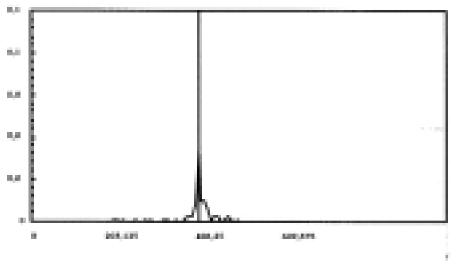

Figure 24: T2, periods 41-50 (p_2).

A.2.1. Total revenues (Treatments 1, 2)

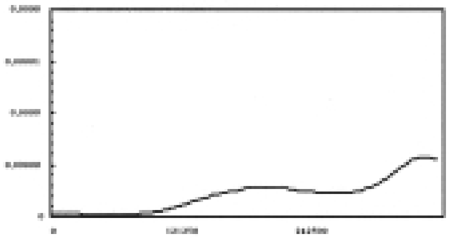

Figure 25: T1, periods 1-5.

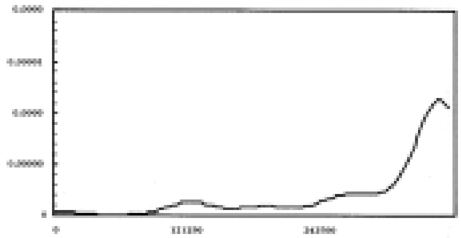

Figure 26: T2 , periods 1-5.

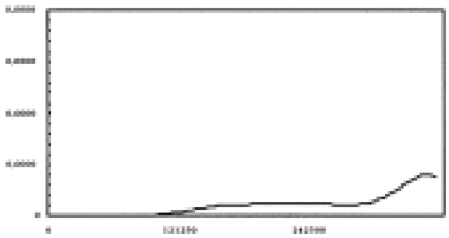

Figure 27: T1, periods 1-10.

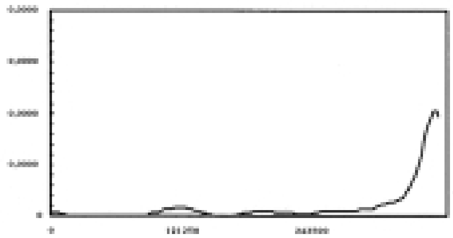

Figure 28: T2, periods 1-10.

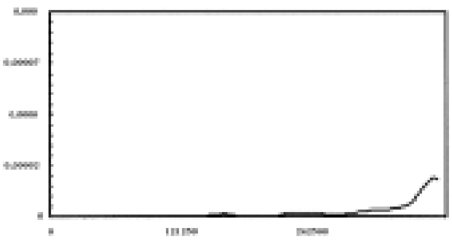

Figure 29: T1 , periods 11-20.

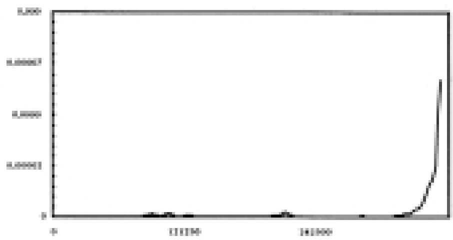

Figure 30: T2, periods 11-20.

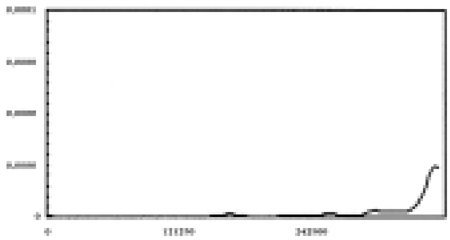

Figure 31: T1 , periods 21-30.

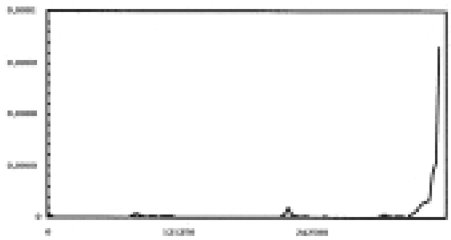

Figure 32: T2, periods 21-30.

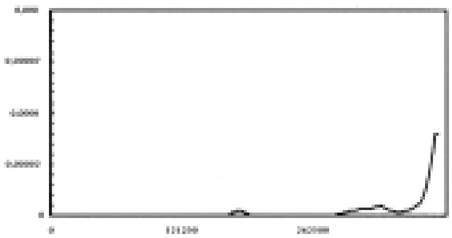

Figure 33: T1 , periods 31-40.

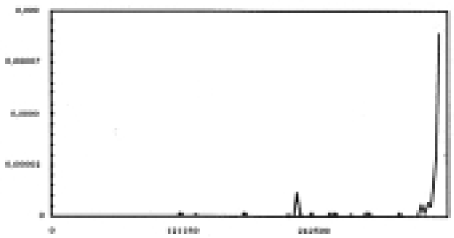

Figure 34: T2, periods 31-40.

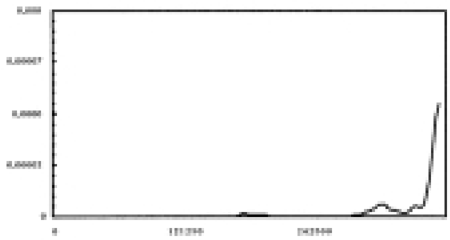

Figure 35: T1 , periods 41-50.

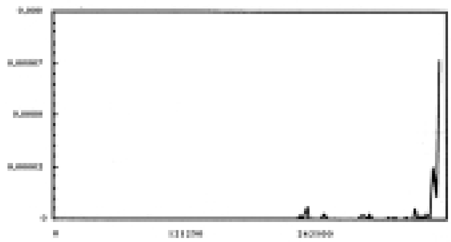

Figure 36: T2, periods 41-50.

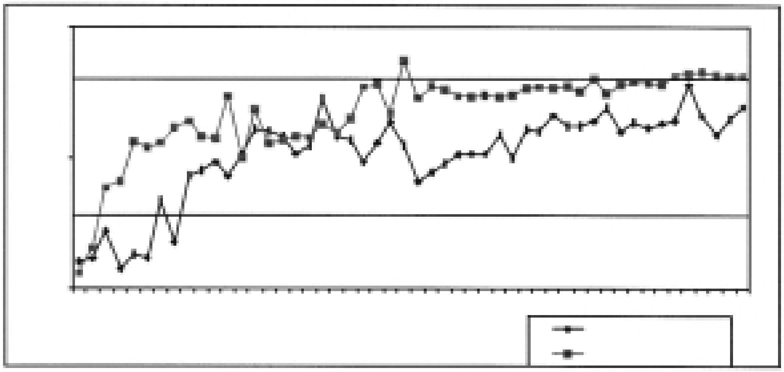

Figure 37: Evolution of average price for product 1.

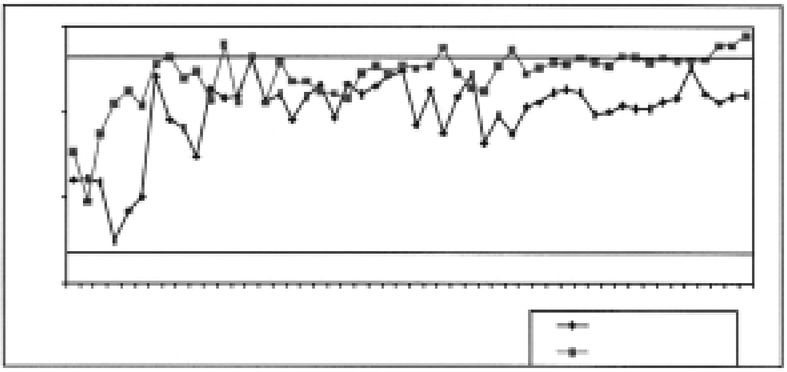

Figure 38: Evolution of average price for product 2.

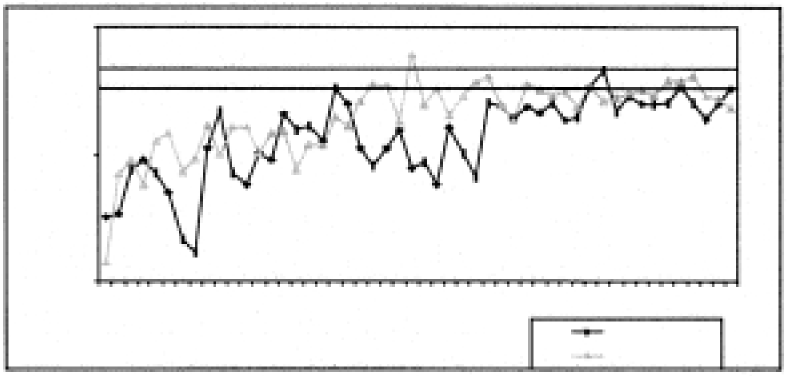

Figure 39: Evolution of average price differences (across products).

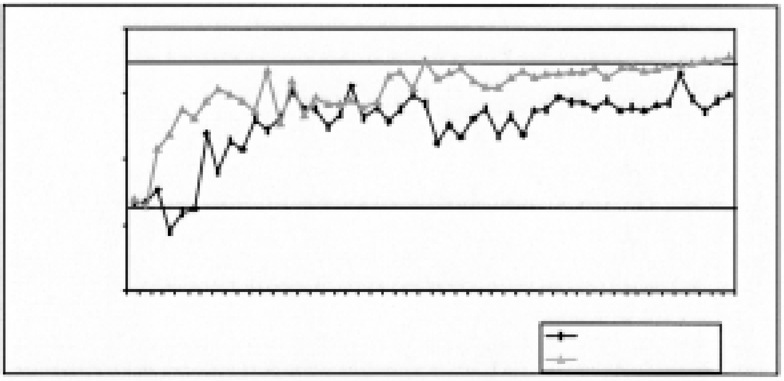

Figure 40: Evolution of average price levels (both products).

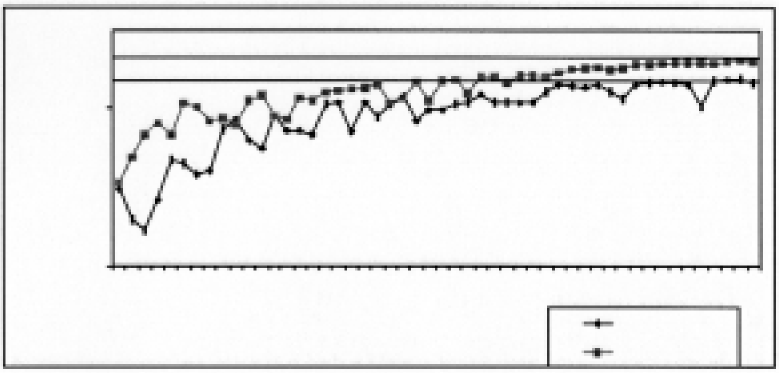

Figure 41: Evolution of average total revenues.

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