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Price Taking or Price Making Behavior: An Alternative to Full Cost Price Functions

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PRICE TAKING OR PRICE MAKING BEHAVIOR:

AN ALTERNATIVE TO FULL COST PRICE FUNCTIONS

Victor Ginsburgh and Isra'el Zang

September 3, 1975

PRICE TAKING OR PRICE MAKING BEHAVIOR:
AN ALTERNATIVE TO FULL COST PRICE FUNCTIONS*

by

Victor Ginsburgh⁺ and Israël Zang⁺⁺

1. Introduction

In almost all econometric investigations on price behavior, prices are deduced from full cost equations. In this paper, we propose an alternative formulation in which the firm bases its price behavior not only on cost considerations, but also on prices charged by competitors: more precisely, a producer may choose to adjust his price either to variations in costs or to variations of his competitor's prices. In Section 2, we develop the theoretical framework on which the model is grounded. Section 3 is concerned with the estimation method and its sampling properties. Numerical results for the Common Market countries are given in Section 4.

*An earlier version of this paper was given at the Third World Congress of the Econometric Society, August 20-26, 1975, Toronto. The authors are grateful to A. P. Barten for very useful comments; all errors and misinterpretations remain with the authors.

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2. The Theory of Price Determination

There are essentially two theories which explain how prices are formed [5], [6]: first, the classical theory which relates price changes \dot{p} to a disequilibrium between supply S and demand D

$$\dot{p} = \alpha(D-S) .$$

The second approach is target return pricing formulated as:

$$p = \pi \frac{K}{Q} + w \frac{L}{Q} + p_m \frac{M}{Q}$$

where π is the target rate of return, K the capital stock, w the wage rate, p_m material prices and L and M total man hours and material inputs at the standard rate of output Q . In some cases a variant is considered, which is the full cost equation

$$p = (1+\lambda) \left(w \frac{L}{Q} + p_m \frac{M}{Q} \right)$$

where λ is a markup constant.

The first approach adapts to a competitive economy, the second fits better to an oligopolistic market and is clearly based on long term considerations of the firm.

In most empirical studies, both schemes are combined and two types of variables contribute to the explanation of prices: (a) variables measuring a disequilibrium in the market, such as new and unfilled orders, inventory levels, rate of capacity utilization and (b) variables measuring changes in costs of labor and material inputs. For instance, Lipsey and Parkin [13] consider the following price equation

$$\dot{p} = \alpha_1 \dot{w} + \alpha_2 \dot{m} + \alpha_3 \dot{q}$$

where \dot{m} and \dot{q} are the rates of change of import prices and per capita output ($q = Q/L$); \dot{q} is supposed to measure the tensions on the market.

In the sequel, we shall mainly be concerned with the second formulation, which is more frequently used.

It is striking that in the target return pricing and the derived approaches, the situation of competing producers is only taken into account as far as the commodities they produce constitute inputs of the firm, and hence, are part of the cost.

On the aggregate level, the same holds for trade partners of the country. For instance, Amano [1] and Barten and d'Alcantara [4] find that, in most cases, world prices contribute, in a very significant way, to the formation of export prices: if producers want to keep their share on foreign markets, they have to adjust export prices on the prices of their competitors.

Similar arguments can be thought to apply to domestic prices. However, we draw a distinction between two types of situations, which may lead to two different behaviors of the firm as far as the pricing of its output is concerned: price taking or price making. The type of behavior will depend in general on the competitiveness of the firm (or the country) and on characteristics such as market share, specialization, aggressivity, etc. But clearly, in both cases, the firm (country) has to take into account the competitors' prices: more specifically, the price p will be based on a comparison between cost considerations and the price p^* charged by competitors (or importers).

In the presence of fairly competitive markets, this mechanism will

result in the equalization of prices: $\dot{p} = \dot{c} = \dot{p}^*$ where

$c = \pi \frac{K}{Q} + w \frac{L}{Q} + p_m \frac{M}{Q}$. In less competitive markets and if information is not perfect, one can expect the following scheme to apply in the short run:

$$(2.1) \quad \dot{p} = \min\{\dot{c}, \dot{p}^*\} .$$

Prices adjust to whatever the smallest change: manufacturing cost or competing (import's) prices.

In case the firm is not faced with strong competition, the producer will feel free to adjust his price on long term considerations of cost elements; however, the firm may find it more profitable in the short run to compare its price with the competitor's and adjust to whatever the largest change

$$(2.2) \quad \dot{p} = \max\{\dot{c}, \dot{p}^*\} .$$

It is perhaps rather extreme to assume that the producer will assign the same weight to two criteria, one of which is really "hard data" (costs) and the other has a more subjective content (competitor's prices). In other words, it does not seem realistic to consider that a one percent change in costs will have the same effect as a one percent change in the competitors' prices; (2.1) and (2.2) should thus be specified more generally as

$$(2.3) \quad \dot{p} = \begin{matrix} \max \\ \text{or} \\ \min \end{matrix} \{ \dot{c}, \gamma \dot{p}^* \}$$

where γ represents a nonnegative constant. If, as is usually the case, one retains full cost pricing instead of target return pricing, (2.3)

can be written

$$(2.4) \quad \dot{p} = \begin{matrix} \max \\ \text{or} \\ \min \end{matrix} \{ (1+\lambda)\dot{d}, \gamma\dot{p}^* \}, \quad \text{with} \quad d = w \frac{L}{Q} + p_m \frac{M}{Q}$$

Very often, in estimating price equations, one combines elements of the classical supply demand theory and of the target return pricing theory.¹ If this approach is followed, one has:

$$(2.5) \quad \dot{p} = \begin{matrix} \max \\ \text{or} \\ \min \end{matrix} \{ (1+\lambda)\dot{d}, \gamma\dot{p}^* \} + \sum_{i=1}^s \eta_i T_i$$

where the T_i 's ($i = 1, 2, \dots, s$) are variables representing pressure of demand and other influences and the η_i 's are parameters.

3. Estimation Methods

Equation (2.4) can be considered to belong to the family of "two-regime" models introduced some years ago and revived by Fair and Jaffee in [8]. Indeed adding disturbance terms u and v , (2.4) can be written²

$$(3.1) \quad \dot{p} = \max\{ (1+\lambda)\dot{d} + u, \gamma\dot{p}^* + v \}$$

or alternatively $\dot{p} = (1+\lambda)\dot{d} + u$ if $(1+\lambda)\dot{d} + u \geq \gamma\dot{p}^* + v$ and $\dot{p} = \gamma\dot{p}^* + v$ otherwise.³

¹See e.g. [3], [5], [6], [7], [11].

²In the remaining part of the paper we deal with the model $\dot{p} = \max\{\cdot\}$. The alternative formulation $\dot{p} = \min\{\cdot\}$ can be easily deduced from the first.

³Equation (2.5) leads to the following more difficult model
 $\dot{p} = (1+\lambda)\dot{d} + \sum_i \eta_{i1} T_i + u$ if $(1+\lambda)\dot{d} + \sum_i \eta_{i1} T_i + u \geq \gamma\dot{p}^* + \sum_i \eta_{i2} T_i + v$ and

Let us write this model more generally as

$$(3.2) \quad y = \max\{X_1\beta_1 + u_1; X_2\beta_2 + u_2\}$$

where X_i is a matrix of n_i observations on p_i variables; β_i is a vector of p_i parameters; u_i is a vector of n_i random disturbances $NID(0, \sigma_i^2)$ and y is a vector of $n = n_1 + n_2$ observations.

Several methods have been proposed to estimate the parameters of such a two-regime model (we exclude, of course, the trivial case in which one is able to classify the observations a priori):

- (a) Maximization of the likelihood function; this requires the evaluation of 2^n equations, which is prohibitive for n even as small as 10.
- (b) Maddala and Nelson [14], devise a computationally complicated method for maximizing directly the likelihood function.
- (c) Fair and Jaffee [8], followed by Fair and Kelejian [9], Amemiya [2], Maddala and Nelson [14], assume the existence of a variable z which can be used to provide information to classify the observations between the two regimes; more specifically, they add to (3.1) an equation

$$z = \emptyset[(X_1\beta_1 + u_1) - (X_2\beta_2 + u_2)] + u_3$$

where $\emptyset > 0$ is a parameter and u_3 a random disturbance (in some variants of the method, u_3 is neglected; note that z is usually a variable belonging to X_1 and/or X_2).

$\bar{p} = \gamma\bar{p}^* + \sum_i \eta_{i2}T_i + v$ otherwise. In this case $\eta_{i1} = \eta_{i2}$ ($i = 1, 2, \dots, s$). Of course, $\eta_{i1} \neq \eta_{i2}$ is also plausible, but not consistent with the way (2.5) is written.

- (d) Goldfeld and Quandt [10] consider the special case, also studied by Fair and Jaffee [8], in which y is generated by either regime according to whether $z \leq z_0$ or $z > z_0$; they imagine a procedure in which the cutoff value z_0 is estimated along with the other parameters, whereas Fair and Jaffee assume z_0 to be known.
- (e) Quandt [15] finally⁴ assumes that either regime is chosen by nature with an unknown probability π , which is then estimated together with the remaining coefficients.

The case we deal with cannot be solved by using methods (c) and (d), since there hardly exists a variable z which will provide exogenous information to classify the observations. Method (a) does not apply either for reasons already mentioned. Finally (b) and (e) are the only approaches which would work; however, the complexity of the methods (mainly of (b)) and their relatively poor computational behavior⁵ lead us to look for other possibilities.

We describe two methods, based on a simplifying assumption, namely that the variance of the disturbances in both regimes is the same; it can, we think, hardly be argued that this assumption is really less realistic than the usual one of two different distributions.

⁴We only concentrate on the procedures in which the switching from one regime to the other can happen for any observation in the sample and an unknown number of times. An extensive bibliography for other cases (one single switch or known number of switches) can be found in [15].

⁵This is the case in almost all empirical studies trying to maximize a likelihood function with one of the known algorithms described in [10]; often the method does not converge (which can be the sign of a flat likelihood function) or it converges to different values if different starting points are chosen. See e.g. [14], [15].

The model can now be written as

$$(3.3) \quad y = \max\{X_1\beta_1, X_2\beta_2\} + u$$

and the estimation problem formulated as follows: find vectors β_1 and β_2 solution of the following mixed integer non-linear program

$$(3.4) \quad \min[y - \Delta X_1\beta_1 - (I-\Delta)X_2\beta_2]'[y - \Delta X_1\beta_1 - (I-\Delta)X_2\beta_2]$$

subject to

$$(3.5) \quad \Delta(X_1\beta_1 - X_2\beta_2) \geq 0$$

$$(3.6) \quad (I-\Delta)(-X_1\beta_1 + X_2\beta_2) \geq 0$$

where Δ is a diagonal matrix of order n of which the diagonal elements δ_i are zero or one; the variance covariance matrix of the disturbances is

$$\Omega = \Delta\sigma^2 + (I-\Delta)\sigma^2 = \sigma^2 I .$$

Clearly, as such, the problem is intractable.

Let us thus first consider the case of only one explanatory variable per regime, appearing under the max operator

$$y = \max\{\alpha_1 x_1, \alpha_2 x_2\} + u^6$$

which can alternatively be written

⁶The more general model $y = \max\{\alpha_1 x_1, \alpha_2 x_2\} + \sum_{j=3}^P \alpha_j x_j + u$ does not introduce any new difficulty, except that the notation becomes more cumbersome.

$$(3.7) \quad \min \sum_{i=1}^n [y_i - \alpha_1 \delta_i x_{1i} - \alpha_2 (1 - \delta_i) x_{2i}]^2$$

subject to

$$(3.8) \quad \delta_i (\alpha_1 x_{1i} - \alpha_2 x_{2i}) \geq 0$$

$$(3.9) \quad (1 - \delta_i) (-\alpha_1 x_{1i} + \alpha_2 x_{2i}) \geq 0$$

$$(3.10) \quad \delta_i = \{0, 1\} .$$

If we fix the δ_i 's, we end up with n linear constraints; every constraint is a ray dividing the (α_1, α_2) -space into two half spaces; if we make a very weak nondegeneracy assumption, namely $x_{1i}/x_{2i} \neq x_{1j}/x_{2j}$, all $i \neq j$, two possibilities show up: either the only feasible point is $(0,0)$ because the constraints point in contradictory directions, or the feasible set is a cone defined and bounded by only two constraints, all other constraints pointing in the feasible direction. The two situations are illustrated in Figures 1 and 2 respectively.

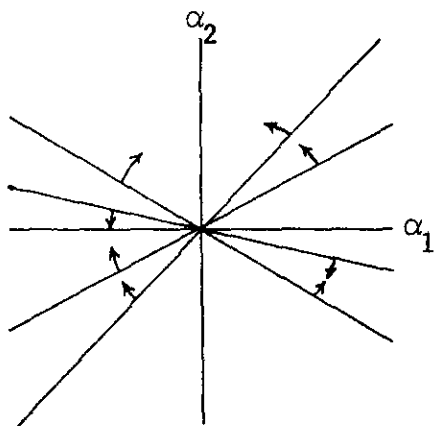


FIGURE 1

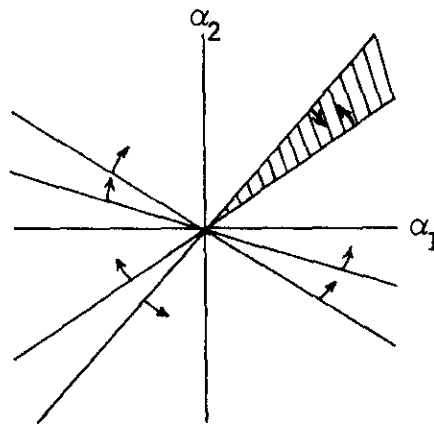


FIGURE 2

This remark leads to the following simple algorithm:

1) Step 0.

$$\text{Set } S^* = \sum_{i=1}^n y_i^2, \alpha_1^* = \alpha_2^* = 0 .$$

Reorder the observations by decreasing order of the ratio x_{1i}/x_{2i} .

If $x_{2i} = 0$, take any large number for the ratio. Since we assume non-degeneracy, each ratio determines a different ray in the (α_1, α_2) -plane.

2) Step j . ($j = 1, \dots, n$) .

j1. Take (newly reordered) observations j and $j+1$ (if $j = n$ take the first observation as the $j+1^{\text{th}}$) as binding constraints; fix all the δ_i 's in a way that all constraints will point in the right direction (like in Figure 2).

j2. Compute

$$(3.11) \quad S = \min \sum_{i=1}^n [y_i - \alpha_1 \delta_i x_{1i} - \alpha_2 (1 - \delta_i) x_{2i}]^2$$

with the above fixed δ_i 's , subject to the two binding constraints generated in step j1. Since this minimization problem is two dimensional convex quadratic with two linear constraints, the solution is carried out very simply by solving a Kuhn-Tucker system.⁷

Check whether $S < S^*$; if the answer is positive, put $S^* = S$ and store the new values of α_1^* and α_2^* solution of (3.11).

j3. Fix $\delta_i = 1 - \delta_i$ ($i = 1, 2, \dots, n$) ; this will reverse all the constraints and do the same as in Step j2 with the new δ_i 's .

⁷Since there are only two constraints, we have two Kuhn-Tucker multipliers and four possibilities of which only two need to be checked.

3) Termination.

If $j = n+1$ stop; the solution is S^* , α_1^* and α_2^* .

The minimization problem (3.7)-(3.10) is clearly non-convex and non-differentiable. Hence it may have--and in practice it shows to have--nonglobal local solutions. The main feature of the outlined algorithm besides its simplicity, is that it terminates after n steps, finding the global solution to (3.7)-(3.10).

When we come to the general model (3.4)-(3.6), things get much more difficult. At this stage, it has proved difficult to extend our algorithm to models containing more than one variable per regime under the max operator. Therefore, we had to use a general optimization routine⁸ combining the Newton-Raphson steepest descent and Marquardt methods; of course, we are no longer sure to find the global optimum. Tests have however been made with the model

$$y = \max\{\alpha_1 x_1 + \beta_1; \alpha_2 x_2 + \beta_2\} + u$$

and the results are satisfactory, as will be seen in Section 4.

It does not appear possible to conceive a sampling theory for the methods we propose. There are two reasons for this: first, the likelihood function--in the absence of inequality constraints--contains continuous (the β 's) and discrete (the δ 's) variables, and is thus neither continuous nor differentiable; second as noted by Zellner [16], even for disturbances satisfying the usual assumptions, the presence of inequality restrictions on the coefficients influences the distributions of the

⁸Harwell Subroutine Library: subroutine VA05A.

estimators which are no longer normal.

The first problem--non-continuity of the likelihood function--can be disposed of by following Fair and Jaffee's suggestion [8] to consider standard errors of the estimates, conditional on the δ 's . But, as is shown by Judge and Takayama [12], there is no known way out of the difficulty introduced by the inequality constraints.

We had thus to rely upon sampling experiments; only the simple model

$$y = \max\{\alpha_1 x_1, \alpha_2 x_2\} + u$$

has been examined. The true values of the coefficients are $\alpha_1 = 0.50$; $\alpha_2 = 0.25$ in one series of runs and $\alpha_1 = 0.25$, $\alpha_2 = 0.50$ in a second. The number of observations varies from 20 to 60; the u_i 's are $NID(0, \sigma^2)$ and the number of replications in each experiment is 20. For x_1 and x_2 we choose actual series relative to the problem discussed in the next section: Since only 20 observations are available for each series, we joined end to end 2 or 3 series to generate 40 and 60 observations.

The results are given in Tables 1, 2 and 3 for cases 1 and 2 corresponding respectively to $\alpha_1 = 0.50$, $\alpha_2 = 0.25$ and $\alpha_1 = 0.25$, $\alpha_2 = 0.50$. Table 1 contains the mean biases $\frac{1}{20} \sum_{i=1}^{20} (\hat{\alpha}_{ij} - \alpha_j)$, where $\hat{\alpha}_{ij}$ is the estimate for α_j ($j = 1, 2$) in replication i ($i = 1, \dots, 20$) and α_j is the true value. Table 2 contains the mean square errors $\frac{1}{20} \sum_{i=1}^{20} (\hat{\alpha}_{ij} - \alpha_j)^2$ and finally, in Table 3 we give the values $\frac{\sum_{i=1}^{20} \hat{\sigma}_{ij}^2}{\sum_{i=1}^{20} (\hat{\alpha}_{ij} - \alpha_j)^2}$ where $\hat{\sigma}_{ij}^2$ ($j = 1, 2$) is the "variance" of $\hat{\alpha}_j$ in replication i ; in computing the $\hat{\sigma}_{ij}^2$ values we do as if the δ 's were given instead of computed along with the α 's . The ratios are meant

Table 1 : Monte Carlo experiments : Mean biases.

	Number of observations	$\sigma = 0.005$		$\sigma = 0.010$		$\sigma = 0.020$		$\sigma = 0.040$	
		α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
Case 1	20	0.0042	0.0060	0.0047	-0.0641	-0.0052	-0.1941	-0.0417	-0.1179
	40	-0.0005	-0.0273	-0.0001	-0.2121	-0.0008	-0.0244	-0.0007	-0.1936
	60	0.0002	-0.0255	-0.0009	-0.0275	-0.0001	0.0256	0.0014	-0.2485
Case 2	20	0.0044	0.0089	0.0009	0.0097	-0.038	-0.062	-0.0440	-0.1585
	40	-0.0004	-0.0019	-0.0001	-0.0089	-0.0006	-0.0760	-0.0006	-0.2754
	60	0.0002	-0.0005	-0.0009	0.0031	0.0001	-0.0447	0.0016	-0.1325

Table 2 : Monte Carlo experiments : Mean square errors.

	Number of observations	$\sigma = 0.005$		$\sigma = 0.010$		$\sigma = 0.020$		$\sigma = 0.040$	
		α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
Case 1	20	0.0003	0.0134	0.0013	0.0521	0.0027	0.1756	0.0218	0.3908
	40	0.0000	0.0143	0.0000	0.0945	0.0000	0.1397	0.0000	0.3166
	60	0.0000	0.0052	0.0000	0.0184	0.0000	0.0374	.0001	.2128
Case 2	20	0.0004	0.0009	0.0013	0.0064	0.0160	0.0032	0.0176	0.3281
	40	0.0000	0.0008	0.0000	0.0031	0.0000	0.0750	0.0000	0.2954
	60	0.0000	0.0005	0.0000	0.0055	0.0000	0.0174	0.0001	0.1303

Table 3 : Monte Carlo experiments : $\sum_i \hat{\sigma}_{ij}^2 / \sum_i (\hat{\alpha}_{ij} - \alpha_j)^2$

	Number of observations	$\sigma = 0.005$		$\sigma = 0.010$		$\sigma = 0.020$		$\sigma = 0.040$	
		α_1	α_2	α_1	α_2	α_1	α_2	α_1	α_2
Case 1	20	.79	.85	.62	.75	1.74	.47	.88	1.02
	40	.89	.75	1.60	.50	1.34	.85	1.38	.61
	60	1.22	.63	1.54	.68	1.50	1.10	1.22	.56
Case 2	20	.70	1.64	.81	.83	.96	.15	1.73	.56
	40	.91	.98	1.69	1.20	1.33	.40	1.35	.40
	60	1.27	1.31	1.52	.55	1.42	.73	1.25	.43

to show whether the usual notion of standard deviation of a coefficient (once the δ 's are fixed) gives some meaningful informations in this specific model.

The results are very satisfactory as far as mean biases and mean square errors are concerned, especially if one has in mind that, with actual data, the standard deviation of the error is 0.010. Table 3 shows that the usual computation of the standard deviations of the estimates is worthwhile: the $\frac{\sum_i \hat{\sigma}_{ij}^2}{\sum_i (\hat{\alpha}_{ij} - \alpha_j)^2}$ ratios are not too far from one; it is however not really clear whether they converge to one when the sample size increases.

4. Price Formation in the EEC Countries

The model proposed in Section 2 has been applied to the formation of aggregate consumer prices in the EEC countries, with the exception of Luxemburg omitted for lack of statistical data.

The equations were specified as

$$(4.1) \quad \dot{p} = \underset{\min}{\text{or}} \left\{ \underset{\max}{\xi_1 \dot{d}}, \gamma_1 \dot{p}^* \right\} + u$$

and

$$(4.2) \quad \dot{p} = \underset{\min}{\text{or}} \left\{ \underset{\max}{\xi_1 \dot{d} + \xi_0}, \gamma_1 \dot{p}^* + \gamma_0 \right\} + u .$$

For each country k a synthetic series of competitive prices p_k^* has been computed in the following way:

$$(4.3) \quad \dot{p}_k^* = \sum_{i=1}^m a_{ik} \dot{p}_i .$$

In (4.3) a_{ik} represents the share of country's i exports in country's k total imports, with the condition $\sum_{i=1}^m a_{ik} = 1$ (imports of k from non EEC countries are neglected); p_k is the aggregate index of consumer prices in country k ; m is the number of EEC countries ($m = 8$: Belgium, Denmark, France, Germany, Italy, Ireland, Netherlands and the United Kingdom). We chose to represent competition by a weighted average of consumer prices rather than export prices for two reasons: first, the former are measured with much more accuracy than unit values of exports and second, at the aggregate level, we think that they give a better measure of what happens in neighboring countries than the rather artificial concept of export prices: the information that reaches the firm is either the import price of a competitive commodity--and this is barely measured by the average foreign trade prices--or the general price level (especially during these last years in which every newspaper is happy to write how fortunate "we" are in comparison to country C where prices have increased with p percent).

The series on costs \dot{d} was also obtained synthetically as a linear combination of wages and import prices:

$$(4.4) \quad \dot{d} = \theta \dot{w} + (1-\theta) \dot{p}^M$$

where w represents the wage rate, p^M the unit value index of imports and θ is a parameter such that $0 \leq \theta \leq 1$. For both models (4.1) and (4.2) the best a priori chosen value for θ proved to be 1. This is not too surprising since, in general, the values for β_2 in the usual linear model $\dot{p} = \beta_1 \dot{w} + \beta_2 \dot{p}^M$ are very small compared to β_1 .

Both the $\min\{\cdot\}$ and the $\max\{\cdot\}$ formulations were tried, but

only the $\max\{\cdot\}$ formulation gave valuable results. Whether this means that each country can be considered as a "price maker" instead of a "price taker" is questionable; in general we would not suggest that the method is able to test whether a country, as a whole, behaves as price taker or maker.

The results appear in Tables 4 and 5 for both models (4.1) and (4.2). The data used are annual and cover the period 1953 to 1972.⁹ Both tables give the values of the parameters, the correlation coefficients (in Table 4, we also give the correlation coefficient for the usual linear model $\dot{p} = \beta_1 \dot{w} + \beta_2 \dot{p}^M + u$) and the value of $N(\delta)$ which is the number of times consumer prices adjust to domestic considerations of costs.

In general, as far as fit is considered, our approach gives slightly better results than the usual linear model. With the exception of Ireland in Table 4, the coefficients make sense and are consistent with a priori economic reasoning: for the model without intercepts, the parameters corresponding to the p^* variable (competition) are much higher for small countries (Belgium, Denmark, Netherlands) than for the larger (France, Italy, the United Kingdom). In the other model, the intercepts can be considered as trends, since all the variables are expressed in percentage changes; the negative intercept in the "cost regime" is thus consistent with the assumption of increasing productivity; the positive intercept in the other regime allows for the effects of economic integration, and increasing influence of international trade and competition.

⁹We are indebted to A. P. Barten and G. d'Alcantara for having allowed us to use their data on the Common Market economics.

TABLE 4: Price Formation in the EEC

$$\hat{p} = \max\{\xi_1 \hat{d}, \gamma_1 \hat{p}^*\} + u$$

	Parameters		Goodness of Fit (R^2)		N(δ) max = 19
	ξ_1	γ_1	Our Model	Linear Model	
Belgium	.369	.900	.85	.84	14
Denmark	.434	.869	.83	.83	16
France	.484	.513	.91	.93	17
Germany	.316	.000	.89	.89	19
Ireland	.465	-.864	.87	.85	18
Italy	.369	.408	.93	.94	18
Netherlands	.436	.818	.94	.94	18
United Kingdom	.520	.499	.95	.95	18

TABLE 5: Price Formation in the EEC

$$\hat{p} = \max\{\xi_1 \hat{d} + \xi_0, \gamma_1 \hat{p}^* + \gamma_0\} + u$$

	Parameters				Goodness of Fit R^2	N(δ) max = 19
	ξ_1	ξ_0	γ_1	γ_0		
Belgium	.690	-.031	.227	.017	.85	11
Denmark	.394	.001	.301	.035	.89	10
France	1.744	-.140	.343	.023	.96	17
Germany	.421	-.010	.179	.020	.89	13
Ireland	.720	-.032	.015	.026	.85	8
Italy	.477	-.013	.242	.023	.93	15
Netherlands	.693	-.028	.133	.022	.95	16
United Kingdom	.574	-.004	.220	.018	.95	16

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