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# Implicit Collusion Models of Export Pricing: An Econometric Application to the Japanese Case

**Eiichi Tomiura**

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## ABSTRACT

This paper tries to provide a framework to analyze the export price competition from a new perspective, by interpreting observed export price variation over time as a result of dynamic changes in the relative sustainability of implicit collusion among exporters.

Two alternative supergame models are adapted from industrial organization literature.

The first model, which originates in Green and Porter(1984), considers the case where decisions by other firms are unobservable. Given the imperfect information, rational firms cut their prices even if all the firms keep the implicit collusion because firms cannot distinguish negative shocks to industry demand from a rival's deviation. This model helps explain how unpredictable negative demand shocks affect export prices.

The second model, which was originally developed by Rotemberg and Saloner(1986), emphasizes the cyclical aspect of export demand movements. If the level of export demand is currently higher than that expected in the future, the present time offers a good opportunity for deviation because the current gain from cheating dominates the future loss from being punished. This theory predicts that implicit collusion among exporters tends to destabilize during exchange rate depreciation.

To test the relevancy of these two alternative models in the case of Japanese exports, I estimate the export pricing equation by the switching regression with the regime classification dummy which is allowed to follow a Markov transition process and is determined endogenously by the Bayes' rule based on maximum-likelihood estimates. The behavior of textile export price provides evidence supporting the model which predicts that an unanticipated demand decrease triggers a breakdown of collusion. In other industries, although implied price changes are too moderate, dynamic changes in the sustainability of collusion are consistent with reasonable industrial characteristics. Although the industries examined here are broadly defined, the econometric study in this paper will be a first-step preliminary experiment on the applicability of dynamic oligopoly models to export pricing.

**Implicit Collusion Models of Export Pricing:**
**An Econometric Application to the Japanese Case**

**Eiichi Tomiura**

*Faculty of Economics, Shinshu University*
*and*
*Special Research Fellow, MITI Research Institute*

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## 1. Introduction

This paper tries to provide a framework to analyze the export price competition from a new perspective, by interpreting observed export price variation over time as a result of dynamic changes in the relative sustainability of implicit collusion among exporters. The motivation of this approach is twofold: the increasing importance of oligopoly in world trade and the development of supergame analyses in theoretical and empirical industrial organization.

Two alternative models will be introduced, by applying the supergame theory, to formalize the individual firm's incentive to deviate from the collusive equilibrium.

The first model, or the "demand uncertainty model," which originates in Green and Porter(1984), considers the case where decisions by other firms are unobservable. Given the imperfect information, a rational firm gets suspicious of rivals' secret price cuts when the export demand for own product decreases unexpectedly. Firms sometimes shift to a punishment phase by cutting their prices even if all the firms keep the implicit collusion because firms cannot distinguish negative shocks to industry demand from a rival's deviation. Since the demand in foreign countries is often affected by so many factors that individual firms cannot correctly take account of, this model helps explain how unpredictable negative demand shocks affect export price changes in the real world.

The second model, or the "fluctuation model," which was originally developed by Rotemberg and Saloner (1986), emphasizes the cyclical aspect of export demand movements. If the level of export demand is currently higher than that expected in the future, the present time offers a good opportunity for deviation because the current gain from cheating during booms dominates the future loss from being punished in unfavorable market conditions[1]. Hence, this theory predicts that implicit collusion among exporters tends to destabilize during exchange rate depreciation.

To test the relevancy of these two alternative models, I estimate the export pricing equation by the econometric technique which has already been established in the empirical industrial organization literature as follows: The regime classification dummy, which is allowed to follow a Markov transition process, will be determined endogenously by the Bayes' rule based on maximum-likelihood estimates. Thus estimated regime probability could be interpret as a measure of the "relative sustainability" of implicit collusion. The Japanese export behavior is a good case to test implicit collusion models both because of their low pass-through in export prices and of the (mis-)perception of collusive behavior among Japanese corporations. This paper estimates export pricing equations for four Japanese industries. Although the industries are broadly defined, my econometric estimation will hopefully serve as a first-step preliminary experiment.

This paper is structured as follows: Section 2 introduces the two models which theoretically formalize export pricing. Section 3 constructs the econometric model and introduces approaches to test the theoretical predictions. Section 4 reports the estimation results from Japanese industries. Section 5 concludes.

## 2. Theory

As oligopoly industries generally increase their importance in world trade, the gains from applying the supergame theory to export pricing behaviors must be greater. This section introduces two alternative supergame models, adapted from theoretical industrial organization literature, to draw the predictions on export prices.

### 2.1. Demand uncertainty model

Suppose that firms compete in prices and that each firm cannot directly observe the prices chosen by competitors. Facing such uncertainty, a rational firm may infer others' price from the level of demand for his own product and detect a rival's secret price cut by a unanticipated decrease in his export demand. Any slight deviation from the collusive price is thus perfectly detected and drives firms into the competitive phase to punish the deviating firm. As the repeated game models show, given the discount rate of the firms, there exist the price level and the minimal punishment length that sustain the collusion without inducing a deviation.

In the real world, however, it is sometimes hard to detect a rival's deviation by indirect inference from changes in demand for each firm. If uncertain factors which cannot be known by the individual firm at the time of pricing decisions play a crucial role in export demand determination, the enforcement mechanism described above sometimes breaks down even if no firm deviates from the collusive pricing because each firm cannot distinguish a rival's secret price cut from an exogenous negative shock to the export market. The demand uncertainty model formalizes this intuition.

Before introducing formal models, we should clarify the information structure surrounding the export pricing because the timing issue is critical in dynamic games. This paper considers the following timing:

1. The exchange rate becomes known.[2]
2. Each firm chooses its export price.[3]
3. Aggregate export demand is revealed to the individual firm.

Consider an industry where domestic firms supply products to a foreign market in a simple two-country framework. Let me call the exporters the Japanese firms and the export market the U.S., just to make things concrete.

Suppose that firms are risk neutral and maximize the expected present value of future export profits :

$$W = E_t[\sum_t \delta^t \Pi_t] \tag{1}$$

,where $\delta$ is the discount factor ($0< \delta <1$, assumed to be constant), $\Pi$ is the export profit per period and $E_t$ is the expectation operator conditional on the all information available at the time t. The export profit per period for a firm i (i = 1,...,n) at period t , $\pi_{it}$, is given by

$$\pi_{it} = (p_{it} - c)D\left(\frac{p_{it}}{e_t}, \frac{p_{-it}}{e_t}, P_t, Y_t\right) + u_t \tag{2}$$

,where $p_{it}$ denotes the export price charged by firm i at time t and $p_{-it}$ is the price chosen by other firms. Marginal cost (c) is assumed to be constant. Both p and c are expressed in terms of yen, and "e" is the exchange rate (yen per dollar). The export demand D also depends on the price offered by competing foreign firms and the income level of the importer country (P, Y, both expressed in dollars). As usual, $D_1 < 0$ , $D_i > 0$ ( i = 2,3,4 ) (where $D_i$ is the partial derivative of D with respect to the i-th argument). And "u" denotes the disturbance term which cannot be known at the time of pricing decision and assume $E(u_t) = 0$ for all t.

Without collusion, no firm can earn positive profit because the noncooperative Bertrand price competition is repeated every period.

Consider the following trigger strategy; keep choosing the collusive price as long as the collusion is sustained and charge the competitive price during the punishment phase once the collusion breaks down.

Now, suppose that export demand becomes lower than anticipated in spite of collusive pricing kept by all firms. Then, since the realized u in this case is negative,

$$\pi = (p^c - c)\ \{D(p^c/e,\ p^c/e,\ P,Y) + u\}$$

$$< (p^c - c)\ E[D(p^c/e,\ p^c/e,\ P,Y)]$$

,where $p^c$ denotes the collusive price.

Since each firm cannot know the exact price charged by competitors, no firm can distinguish a rival's secret price cut from exogenous negative export demand shocks, even if all the firms know the export demand function correctly. Thus, an unanticipated export demand fall triggers a breakdown of collusion. Let me call this "uncertainty effect."

2.2. Exchange rate fluctuation model

The first theory, explained in the previous section, focuses on the uncertainty in export demand. On the other hand, we can sometimes safely assume that export demand is determined by observable factors such as current exchange rate. Then, there is no issue of uncertainty in export pricing and the issue left is the timing of deviation from collusive pricing. The second theory introduced below examines this side of export price competition.

Let the export demand for firm i now be a function of prices charged by firms:

$$D_{it} = D\left(\frac{p_{it}}{e_t}, \frac{p_{-i,t}}{e_t}\right) \qquad (2')$$

As was discussed in Section 2.1, there is no uncertainty in export demand determination in this model, since the current exchange rate is observable before the pricing decision.

Following Rotemberg and Woodford (1991), consider the case where the incentive compatibility constraint is binding:

$$\pi^m = \pi^c + x \tag{3}$$

where $\pi^m$ ($\pi^c$) denotes the per-period profit of the deviating firm (the per-period profit of a firm under collusion, respectively), and x is the future profit from the next period on ($x_t = W_t - \pi_t$ in (1)).

(3) can be rewritten as,

$$\left(p^m - c\right)D\left(\frac{p^m}{e}, \frac{p^c}{e}\right) = \left(p^c - c\right)D\left(\frac{p^c}{e}, \frac{p^c}{e}\right) + x \tag{4}$$

where $p^c$ is the collusive price which depends on the exchange rate and future profit and $p^m$ is the price chosen by the deviating firm:

$$p^c = p^c(e, x)$$

$$p^m = \arg\max_p (p - c)D\left(\frac{p}{e}, \frac{p^c}{e}\right)$$

The effect of current exchange rate change on the export price can be examined by differentiating both sides of (4) with respect to e as follows:

$$\left(p^m - c\right)\left[D_1^m\left(-\frac{p^m}{e^2} + \frac{1}{e}\frac{\partial p^m}{\partial e}\right) + D_2^m\left(-\frac{p^c}{e^2} + \frac{1}{e}\frac{\partial p^c}{\partial e}\right)\right] + D^m\frac{\partial p^m}{\partial e}$$

$$= \left(p^c - c\right)\left(D_1^c + D_2^c\right)\left(-\frac{p^c}{e^2} + \frac{1}{e}\frac{\partial p^c}{\partial e}\right) + D^c\frac{\partial p^c}{\partial e} \tag{5}$$

where $D^m$ and $D^c$ represent the export demand level when this firm deviates to the monopoly pricing and when all the firms keep collusive pricing, respectively, as follows:

$$D^m = D(p^m/e, p^c/e)$$

$$D^c = D(p^c/e, p^c/e)$$

and $D_i$ denotes the partial derivative of the export demand function with respect to the i-th argument (i=1,2).

Let the own- and cross-elasticity of export demand be $\varepsilon_1$ and $\varepsilon_2$ ($\varepsilon_2 > 0 > \varepsilon_1$). Then, (5) can be rearranged to

$$\partial p^c / \partial e = (A-B) / (C-D) \tag{6}$$

,where

$$A = (\varepsilon_1 + \varepsilon_2)(\pi^m - \pi^c) / e$$

$$B = \left( D^m + \frac{\varepsilon_1 \pi^m}{p^m} \right) \frac{\partial p^m}{\partial e}$$

$$C = \varepsilon_2 (\pi^m - \pi^c) / p^c$$

$$D = D^c + \frac{\varepsilon_1 \pi^c}{p^c}$$

Here, the following points help us determine the sign of each argument on the right-hand side of this equality. First, the deviating firm's profit is higher than collusive profit ($\pi^m > \pi^c$). Second, since the own price effect is normally stronger than the cross-price effect, we can safely assume $\varepsilon_1+\varepsilon_2<0$.[4] The combination of these two points require that A must be negative and that C must be positive. Third, as the deviating firm chooses monopoly pricing, the price chosen by the deviating firm must satisfy the Lerner equality ($1- c/p^m = -1/\varepsilon_1$). This relation means that B equals to zero and that D must be negative.

Therefore, we obtain

$$\partial p^c / \partial e < 0 \tag{7}$$

which indicates low export price under exchange rate depreciation.

This result sounds contradictory to that from the previous model because this asserts that the competitive phases emerge more often under higher level of export demand. Explicit contrast of basic assumptions, however, is important. The difference derives from the following: the previous model focuses on the comparison of anticipated current export demand with realized one, while this model compares the current export demand with the future one. The difference in the assumption about the timing is crucial. Export price is chosen before total export demand becomes known in the first model. In the second model, however, the decision to undercut the price is made after knowing the actual exchange rate.[5] Let me call this driving force in the second model the "fluctuation effect."

Next, we can study the effect of *future* changes on the current export price within the same model. Differentiating (4) with respect to x yields

$$\left(p^m - c\right)D_2^m \frac{1}{e}\frac{\partial p^c}{\partial x} = D^c \frac{\partial p^c}{\partial x} + \left(p^c - c\right)\left(D_1^c + D_2^c\right)\frac{1}{e}\frac{\partial p^c}{\partial x} + 1 \tag{8}$$

By rearranging, as in the previous differentiation,

$$\partial p^c / \partial x = 1/(C-D) \quad > 0. \tag{9}$$

Therefore, export price is high, for example, when the exchange rate depreciation is expected in the future. In other words, the collusion is more easily sustained at the same current exchange rate level when expected future export demand is on the expanding trend than on the declining trend because current gain from deviation is smaller than future loss from being punished. Let me call it "expected fluctuation effect" in contrast to the previously discussed "current fluctuation effect."

## 3. Econometric procedures

This section explains the econometric approaches to test the theoretical predictions from the previous two supergame models.

### 3.1. Econometric model

To test the predictions provided by the two models, we need an econometric model which flexibly allows various behavioral assumptions. First, consider the following pricing equation:

$$\ln p_t = \beta_0 + \beta_1 \ln q_t + \beta_2 \ln w_t + \beta_3 I_t + \Sigma_i \gamma_i DUM_{it} + v_t \tag{10}$$

Here, "I" is the key indicator variable, of which the definition will be explained in detail later, taking zero in the collusive phase and one in the competitive phase for negative $\beta_3$, and "w" denotes the input cost, $DUM_i$ (i = 2,..., 12) are seasonal dummies for monthly data, and v is the i.i.d. error term with mean zero[6]. When export quantity and seasonal dummies are not significant, the pricing equation will be simplified to

$$\ln p_t = \beta_1 + \beta_2 \ln w_t + \beta_3 I_t + v_t. \tag{11}$$

Next, as in Section 2.2., consider the corresponding export demand function:

$$\ln q_t = \alpha_0 + \alpha_1 \ln p_t + \alpha_2 \ln e_t + \alpha_3 \ln P_t + \alpha_4 \ln Y_t + \Sigma_i \delta_i DUM_{it} + u_t \tag{12}$$

Thus, a system of export market consists of (10) (or (11)) and (12).

Since the goal of this paper is to check the significance of the switching dummy, we have to find a series of $\{I_t \mid t = 1,..., T\}$. Exploiting the results in empirical industrial organization literature, I will take the following two approaches:

(A) Define $\{I_t\}$ exogenously from the economic theory (as in Baker(1989)).

(B) Detect $\{I_t\}$ endogenously from data (as in Porter(1983), Lee and Porter(1984), and Porter(1985)) .

### 3.2. Estimation

#### 3.2.1. Estimation with exogenous dummy

The approach (A) in the previous section is suitable to test the "uncertainty effect." The economic reasoning underlying this approach is straightforward: the demand uncertainty model suggests the definition of the switching dummy based on the unanticipated change in export demand by

$$I_t = 1, \quad \text{if} \quad u_t < 0 \qquad (13)$$
$$= 0 \quad , \text{otherwise}$$

where $u_t$ is the estimation error of the export demand function.

Suppose that a firm forms its estimate about the export demand by the function (12). Then, it is rational for a firm to switch its pricing strategy depending on the sign of the estimated residual (u) of this export demand function; i.e., negative "u" implies the possibility of some firms' defection and drives firms into a competitive period. This leads us to the definition of the switching dummy given above.[7]

After estimating the export demand function (12), the pricing equation (10) or (11) is estimated with a thus defined dummy. Under this definition, the essence of the uncertainty effect is boiled down to the one-tailed test of the null hypothesis $H_0 : \beta_3 < 0$.

3.2.2. Estimation with endogenous dummy

One of the most serious problem of the previous approach derives from the unobservability of the "true" sequence of the $\{I_t\}$. In other words, the sequence of dummies exogenously defined by the unanticipated demand changes does not necessarily coincide with the true switches even if the theoretical model is valid because each firm may have a different estimate of demand from ours and/or because some factors other than demand changes may have an impact on pricing. The exogenous dummy is a measure of the true switching factor with some errors. As in the usual cases of errors-in-variables models in econometrics, least squares estimation yields biased estimators.

Instead of using the imperfect sample separation information derived from the export demand function, we can estimate the probability of being in the "competitive" period ($\lambda$) by maximum likelihood and can classify each period into either "collusive" or "competitive" phase based on the estimation result[8]. This consists of the essence of Approach (B) which I will explain in what follows.

Suppose that the i.i.d. sequence of $\{I_t \mid t = 1,\ldots,T\}$ follows the Bernouilli distribution[9]

$$\begin{aligned} I_t &= 1 \quad \text{with probability} \quad \lambda \\ &= 0 \quad \text{with probability} \quad (1-\lambda). \end{aligned} \tag{14}$$

Then, the log likelihood function is given by

$$L = \Pi_t \ln f(p_t)$$

with the probability density function

$$f(p_t) = \lambda\, g(p_t \mid I_t = 1) + (1-\lambda)\, g(p_t \mid I_t = 0)$$

where g is the conditional density given $I_t$.

By assuming normal distribution $N(0, \sigma^2)$ for the error term v, we can estimate the probability $\lambda$ and coefficients $\beta$ of the pricing equation by maximum likelihood. These estimates, in turn, determine the probability of $\{I_t = 1\}$ for each period by the following Bayes' rule:

$$\Pr\{I_t = 1\} = \frac{\lambda g(p_t | I_t = 1)}{\lambda g(p_t | I_t = 1) + (1-\lambda) g(p_t | I_t = 0)} \tag{15}$$

This probability classifies the whole sample period into the "competitive" phase and the "collusive" phase by

$$I_t = 1 \quad \text{if} \quad \text{Prob}\{I_t = 1\} > 0.5$$
$$= 0 \quad \text{otherwise.}$$

Thus, the switching dummy $I_t$ is endogenously determined from the data.

Another interpretation can be given to this probability, though it deviates from the original econometric procedure. Rather than focusing on the rigid threshold level of 0.5, we can interpret this probability as a continuous measure of "relative vulnerability / sustainability" of implicit collusion; i.e., lower probability of I = 1 means that the collusion is more sustainable.

The original implication of implicit collusion models, however, may not be captured by thus simple i.i.d. assumption about the switching dummy which I have just introduced. The competitive and collusive phases may persist more than one period because the underlying theory predicts the long enough punishment period after a deviation to sustain the implicit collusion. Hence, the $\text{Prob}\{I_t = 1\}$ may be serially correlated rather than i.i.d. Consider the estimation including the dummy variable whose process is a Markov chain with the following transition probability:

$$\lambda_{ij} = \text{Prob}\{I_t = j \mid I_{t-1} = i\} \tag{16}$$

,where i and j takes zero or one. After obtaining estimates of $\lambda_{ij}$, we can calculate the regime probability of the competitive or collusive phase by

$$\lambda_i = \lambda_{ij} / (\lambda_{ij} + \lambda_{ji}) \tag{17}$$

assuming stationarity. Further, the estimated mean duration of the phase i will be given by $1/\lambda_{ij}$.[10]

### 3.2.3. Comparison of two approaches

The performances of these two approaches should be compared to reach the final conclusion. The specification test of Hausman(1978) is applicable to the cases like ours, as Hajivassiliou(1986) pointed out. The estimator with endogenous dummy does not depend on the information derived from export demand function, while the estimator with exogenous dummy fully makes use of it. Then, if the switching dummy is really determined by the unanticipated export demand changes, the former is inefficient. The consistency of the latter depends on the correctness of the information from export demand function, while the former is always consistent. Therefore, under the null hypothesis that the export pricing regime is actually classified by the unanticipated export demand changes, the test statistics defined below follows the $\chi^2$ distribution

$$H = (\beta_1 - \beta_2)' (V(\beta_1) - V(\beta_2))^{-1} (\beta_1 - \beta_2) \tag{18}$$

where $\beta$ and V are the coefficient vector and variance-covariance matrix of the maximum-likelihood estimates of the export pricing equation and the subscript 1 and 2 means that the dummy is determined without (with, respectively) employing export demand residuals.

## 4. The case of Japanese exports

### 4.1. Data description

The data employed in estimation are briefly described in this section. The appendix will provide additional explanations of them in detail.

Out of the export price indices (p), reported monthly in yen terms by the Bank of Japan, I use the following four classifications: machinery, metals, chemicals and textiles. Though the main reason for my choice of this industrial classification is first-hand data availability, we must note here that there remains a problem in assuming collusion at this level of disaggregation. As will be reiterated in the concluding remarks, the results from this paper must be supplemented in the future by other studies on industries defined narrowly enough to safely assume collusion/punishment mechanism.

To avoid troubles caused by the conventionally used unit-value index, I define export "quantity" (q) as the export value which is reported in trade statistics divided by the corresponding export price "p."

Included as explanatory variables in the regressions are (a) the input cost of each industry, (b) the exchange rate, (c) the producers price indices as a proxy for the price offered by foreign competitors, (d) the industrial production as a proxy for importers' income, since GNP data are not available on a monthly basis, and (e) monthly dummies for seasonal adjustment. Both (c) and (d) are for U.S. and OECD European countries.

The sample period is from January 1976 to December 1988, with 156 monthly observations available. This choice enables us to test the theoretical predictions because drastic exchange rate fluctuations and substantial demand uncertainty during this period provide us with rich information about pricing behaviors.

### 4.2. Estimation results

#### 4.2.1. Estimates with exogenous dummy

Table 1 reports the results of the approach employing the exogenous dummy based on the unanticipated changes in export demand. Estimated standard errors are in parentheses below the estimated coefficients.[11] The export demand function of which the estimated residuals form the dummy is estimated by the two-stage least-squares (2SLS). Since export quantity and seasonal dummies are not significant in the export pricing equation, they are omitted from the final estimates. As a result, pricing equations can be estimated by the ordinary least squares method (OLS) because export demand and pricing equations, (11) and (12), form a recursive system.

All the four regressions of the export demand function record high fit and each estimated coefficient has the correct sign as predicted by the theory ($\alpha_1 < 0$, $\alpha_i > 0$ ($i$=2,3,4) in (12)) (not shown in the table to save space).

As Table 1 shows, the coefficient of the switching dummy ($\beta_3$) is negative in three industries. In the chemical industry, the sign of the coefficient is positive but statistically insignificant, as its t-value is the lowest of the four. This seems to be consistent with the demand uncertainty model. The regime dummy coefficient, however, is significantly different from zero only for the textile industry only if we choose a generous 20% significance level. Hence, the relative weakness of the statistical results from the exogenous dummy approach makes us wait for the results of endogenous-dummy estimates to draw the conclusions.

4.2.2. Estimates with endogenous dummy

The estimation results of the maximum-likelihood without employing information from export demand residuals are shown in Table 2. The iterative calculations converged for all four equations. The initial value of $\lambda$ has been set at 0.5, which implies the uniform prior probability about switches. Naturally, the coefficients of the input cost are reasonably positive and significant in all industries. The estimated coefficient of the dummy is significantly different from zero in the textile industry at any conventional significance level and also in the machinery industry at the 10% significance level. This suggests that there exist switches in export pricing in these two industries. The estimates imply that the export price level in the competitive phase is lower than that in the collusive phase by five percent in the textiles, and by two percent in the machinery. The quantitative magnitude of price changes across competition phases in this case is roughly comparable with that in Baker(1989) in the case of steel prices, although quite moderate compared with that by Porter(1983) which reports price variation of more than 60%.[12]

The probability of being in the "competitive" phase ($\lambda_1$) varies from industry to industry: lowest in the machinery industry ($\lambda_1$=0.29) and highest in the textile industry ($\lambda_1$=0.92), which may imply the industrial difference in the difficulty of coordinating price decisions.

By introducing the Markov process into the switching dummy series, richer results become available.[13]

For example, the probability of collusion breakdown in the machinery industry ($\lambda_{01}$ =0.37) is approximate to that in the chemical industry (0.31) but the regime probability of a competitive period ($\lambda_1$) is much lower in the machinery industry (0.29 < 0.67), because price wars in the chemical industry are more persistent ($\lambda_{11}$ =0.84 >

0.11). In other words, estimated mean duration of price war ($1/\lambda_{10}$) is much longer in the chemical industry than in the machinery industry (6.39 months > 1.12 months ), although the collusive phase also persists longer ($1/\lambda_{01}$ =3.19 months > 2.71 months ).

In the metal industry, the probability of continuing a price war ($\lambda_{11} = 0.83$) is almost the same as that in the chemical industry (0.84), but the collusion is much more volatile ($\lambda_{01} = 0.76 > 0.31$). As a result, the expected duration of the collusive phase is quite short ($1/\lambda_{01}$ = 1.32 months), and price wars persist long ($1/\lambda_{10}$ = 5.79 months).

The probability computed by (15), or the "relative vulnerability" of implicit collusion is drawn in Figure 1 for four industries. A glimpse of the figures gives us some clear features as follows: First, the collusion in the machinery industry becomes significantly vulnerable after the drastic yen appreciation process since 1985, although the probability of $I_t = 1$ is always smaller than 0.5, which means no all-out price wars in the sample period. Second, in the textiles industry, firms charge competitive prices almost all the time in the sample period with some exceptional periods of short-lived collusion. Third, the sustainability of collusion in the metal industry decreases almost monotonically over time rather than being characterized by periodical switches. Lastly, the variation of collusion vulnerability in the chemical industry over time is quite small, prob{I=1} moving from 0.310 to 0.317, with a relatively big rise around 1978.

These industrial features summarized above may find intuitive interpretations in the following way: First, industries with substantial market power in export markets such as the Japanese machinery industry and oligopolistic industries such as the chemicals tend to have a lower probability of I = 1. Second, industries with less market power and with larger numbers of firms are likely to be in the competitive phase for a longer time as in the case of the textiles industry. Third, the sustainability of collusion may decline over time as the market power of the member firms diminishes in the global market, as in the case of the Japanese metal industry. Lastly, the sustainability of collusion in industries where cost changes dominate the pricing tends to be strongly affected by such episodes as the "oil shock" (e.g. , the chemicals in 1978).

Thus, although none of them should be exaggerated without industrial case studies which investigate background information including historical and institutional factors surrounding export pricing decisions[14], we have obtained the estimated sustainability of implicit collusion which is consistent with reasonable industrial features.[15]

4.2.3. Specification test

Combining the results of both approaches suggests that unanticipated export demand changes affect sustainability of collusion in the textiles industry. Therefore, it is useful to conduct the specification test discussed in Section 3.4. for the textiles industry to determine whether the unanticipated export demand change is *the* determinant of pricing regime switches.

The test statistics H defined in (18) is calculated as H=6.1811. Under the 2.5% significance level, the null hypothesis that unanticipated export demand change is the correct regime classification information cannot be rejected.[16]Therefore, beyond other factors, the demand uncertainty effect well characterizes the dynamic export price competition in the textile industry[17]. However, this result should be interpreted with caution because we observe only three significant episodes of regime shift in the sample period.

## 5. Concluding remarks

The econometric study in this paper suggests, at least as a first approximation to some of the industries examined, the relevance of dynamic oligopoly model in export pricing. Switches between collusion and punishment periods are observed in the textile export price, supporting the model which predicts that unanticipated negative shocks to industry demand triggers a breakdown of collusion. In other industries, although implied price changes are too moderate for us to characterize export pricing as switches between states, dynamic changes in the relative sustainability of collusion are consistent with reasonable industrial characteristics.

Divergence of the results across industries is not embarrassing but rather reasonable because the game theory from which we draw predictions on export pricing behaviors heavily depends on the industry-specific factors. This, however, implies the needs to further excavate the detailed information surrounding the pricing decisions in each industry. In this sense, my choice of disaggregation level of industries, which are larger than the minimum necessary to achieve collusion, might have clouded the results in this paper. Since the theory of implicit collusion assumes that exporting firms have high market power in the world market of narrowly defined products, we need to check the plausibility of this assumption. Actually, the success of researches triggered by Porter(1983) in empirical industrial organization critically depends on the database which is sufficiently information-rich to investigate of the regional railroad cartel. Therefore, based on my preliminary experiment on the applicability of the implicit collusion models to export price competition, what must be required next is econometric studies employing more disaggregated data and/or case studies of narrowly-defined industries.

## Appendix

[ Export price ] (p)

FOB price in terms of yen ( Laspeyres index )

Source: Bank of Japan, *Economic Statistics Annual*, various issues

Classifications : (1) textiles ,

(2) metals and related products ,

(3) chemicals

(4) machinery ( including transport equipment )

[ Export quantity ] (q)

Export "quantity" is defined as export value ( custom clearance basis ) divided by export price (p).

Source : Ministry of Finance , Government of Japan "Custom clearance statistics"

Classifications ; same as those of export price

[ Input cost ] (W)

Input price based on Input-Output table ( wholesale price for domestic input and import CIF price for imported input.)

Source : Bank of Japan *Economic statistics annual*, various issues

Classifications : (1) textiles ,

(2) basic metal products and metal products ,

(3) chemicals

(4) machinery and equipment

[ Exchange rate ] (e)

The yen-US dollar rate is the monthly closing rate (yen per dollar).

Source : Bank of Japan "Economic statistics annual," various issues

The nominal effective exchange rate of the yen is calculated by the weighted average of destination countries' currency per yen with weight based on trade in manufactured goods between 17 industrial countries.

Source : International Monetary Fund, *International Financial Statistics*

[ Foreign producer price and industrial production ] (PUS, PEU ; IUS, IEU)

Producer price and total industrial production in the US (PUS, IUS) and in OECD European countries (PEU, IEU).

Source : OECD (1990) *Main Economic Indicators : Historical Statistics 1969–1988*

## Notes

This paper is based on the results from research projects in which the author participated as Special Research Fellow at MITI Research Institute during the fiscal year 1996 and on a substantially revised version of the first chapter in my Ph.D. dissertation at M.I.T. I acknowledge Paul R. Krugman, Julio Rotemberg and Rudiger Dornbusch for their insightful suggestions to the original thesis. Ryutaro Komiya and Masao Hisatake provided valuable comments in revising the draft. All remaining errors are mine.

1. Recently, Bagwell and Staiger(1997) theoretically generalizes the Rotemberg-Saloner model by considering the two-state Markov process for growth rates. The countercyclical pricing emerges in their model when the intertemporal correlation of business cycle is negative.
2. Since I assume no menu costs or no adjustment process for changing prices, there exists no uncertainty issue in the *current* exchange rate in this framework. Different assumptions on the timing are found, for example, in Marston(1990).
3. Here, I assume that the firm's decision variable is the yen price, even if export contracts are concluded in terms of the dollar in many cases of exports by Japanese firms. One of the supports for this assumption can be found in that many Japanese firms adopt the "in-house" exchange rate to evaluate each contract in terms of the yen.
4. I also assume that the elasticity is constant for all levels of export demand. This assumption of constant-elasticity demand function is consistent with the log-linear econometric model which will be introduced in the next section.
5. Another important difference is that the uncertainty model predicts periodic switches between collusion and competition even if no firm deviates, while no switch is observed in equilibrium in the fluctuation model.
6. The pricing equation in the collusive phase is assumed to have the identical functional form to that in the competitive phase, except only for the constant term.
7. A slightly different definition is given in Baker(1989). He considers the case where the threshold level does not necessarily coincide with zero.
8. Here, I follow the procedure taken by Porter(1983).

9. As Porter (1983) pointed out, if the enforcement mechanism analyzed in the previous section actually works, then, the switches are not independent over time but rather serially correlated. I will soon relax the i.i.d. assumption and allow the correlation by introducing a Markov transition process.

10. I employ the simple estimation procedure by Goldfeld and Quandt(1973) which yields consistent estimators. A more efficient estimator is proposed by Cosslett and Lee(1985). Recently, Ellison(1995) simultaneously estimates pricing/demand parameters and regime shift dynamics.

11. All the variables employed in estimation are in the logarithm of the original data. Export demand functions are estimated after taking the first-difference to deal with serial correlation. Export pricing equation is not estimated in the first-difference form. Ellison(1995) refers to some reasons for this, while Cosslett and Lee(1985) considers the case of serial correlation of order one for both equations.

12. I have to note that the significance in the machinery industry is relatively marginal in that the likelihood ratio test rejects the null hypothesis of no switches only in the textiles industry. This results in a moderate price change across competition phases. The export price in the competitive period is lower than that in the collusive period by 0.94 % (machinery), 5.24 % (textiles), 1.84 % (metals), and 0.08 % (chemicals).

13. As for the textile industry, only the result of i.i.d. Bernouilli case is reported in Table 2 because iterative calculation allowing Markov transition did not converge.

14. Since a substantial share of Japanese exports has been subject to trade-protection-related measures (for example, automobiles, steels and textiles), the results obtained in this section might be distorted.

15. To study determinants of the phase of competition ($I_t$), I conduct probit regressions with $I_t$ as the dependent variable. Main results are as following: (a) The negative residuals in export demand raise the probability of collusion breakdown significantly in the textile industry. (b) In all industries, current yen appreciation significantly triggers the emergence of competitive pricing. (c) The results from regressions on current or future expected export size vary across industries and are not decisive. The analysis of expected exchange rates is worth independent work.

16. The maximum-likelihood estimates with the exogenous dummy which is used in calculating H are not shown in the tables, but are quite similar to those by two-stage least squares in Table 1.

17. One of the possible reasons for this industrial difference could be found in the role of trading companies. The export of Japanese textiles has been often handled by trading companies, while manufacturers are directly involved in foreign trade of their own products in other industries. Hence, even if the number of manufactures is larger, more oligopolistic export pricing can be observed in the textile industry if a small number of trading companies are the price setters. This interpretation is suggested by Masao Hisatake.

**TABLE 1 ESTIMATION WITH EXOGENOUS DUMMY**

$$\ln P_t = \beta_0 + \beta_1 \ln W_t + \beta_2 I_t + v_t$$

$$I_t = 1 \quad \text{if} \quad u_t < 0 \qquad , u_t = Q_t - D(P_t)$$

| | MACHINERY | TEXTILES | METALS | CHEMICALS |
|---|---|---|---|---|
| constant | 2.59946***<br>(0.42098) | −0.95564<br>(0.15949) | −0.87655***<br>(0.27686) | 0.84381***<br>(0.24091) |
| W | 0.43051***<br>(0.092696) | 1.01541***<br>(0.35361) | 1.19367***<br>(0.061829) | 0.80968***<br>(0.054869) |
| I | −0.0078977<br>(0.012541) | −0.0062169*<br>(0.0062882) | −0.0086163<br>(0.012975) | 0.0026064<br>(0.021103) |
| $R^2$ | 0.11703 | 0.84331 | 0.70788 | 0.58515 |

**(NOTES)**

1. The significance of coefficient estimate is denoted by asterisks as follows ;
   *** ; significantly different from zero at 1% level
   ** ; significantly different from zero at 10% level
   * ; significantly different from zero at 20% level
2. $R^2$ is the coefficient of determination after degree of freedom adjustment.
3. Regressors in the export demand function are constant term, export price, exchange rate, total industrial production in U.S. and OECD European countries, producers price index in U.S. and OECD European countries, and monthly dummies. Instruments for two-stage least squares are input cost, and all the regressors excluding the export price.

## TABLE 2 ESTIMATION WITH ENDOGENOUS DUMMY (SWITCHING REGRESSION)

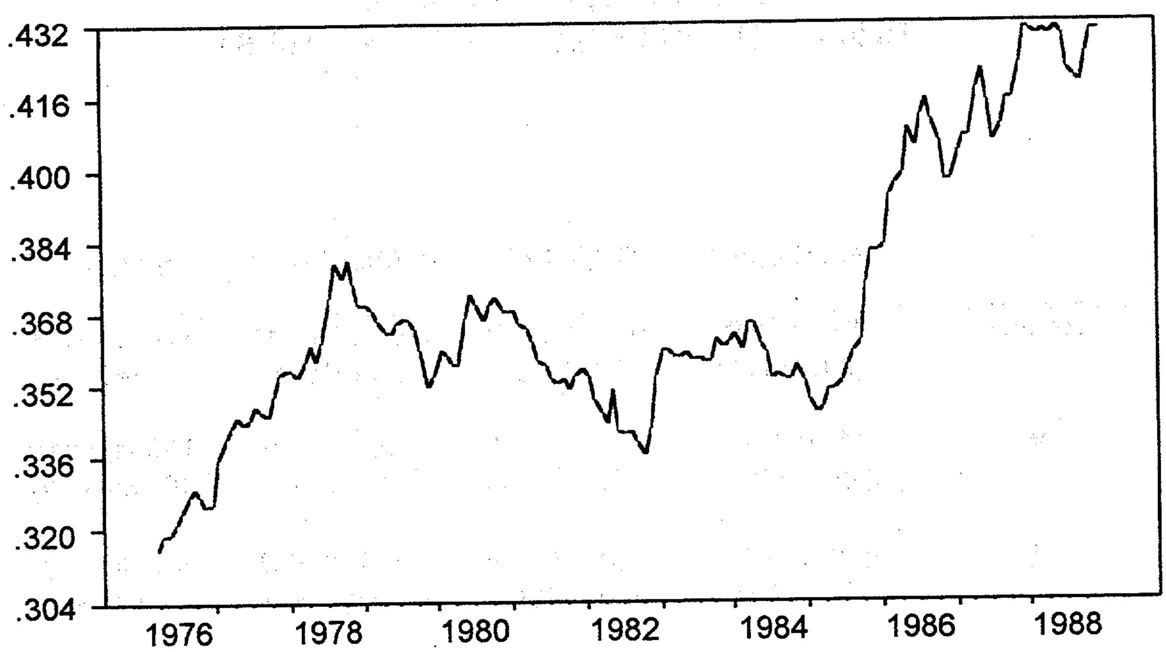
$$\ln P_t = \beta_0 + \beta_1 \ln W_t + \beta_2 I_t + v_t$$

$$\mathrm{Prob}\{ I_t = j \mid I_{t-1} = i \} = \lambda_{ij} \ (i,j = 0,1), \qquad v_t \sim N(0,\sigma^2)$$

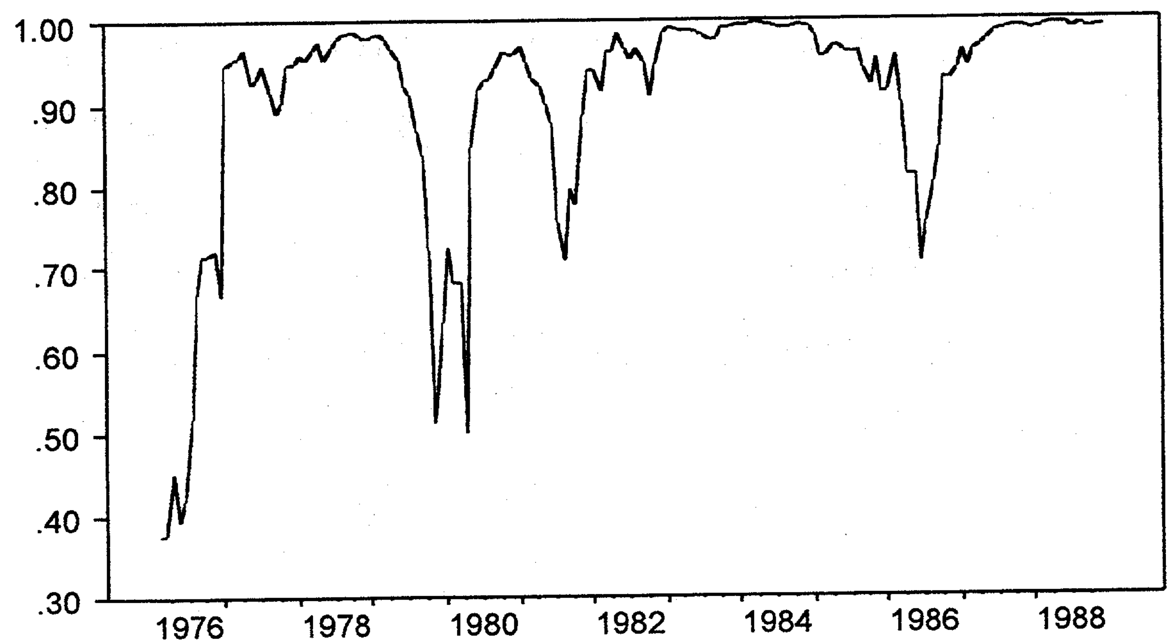
| | MACHINERY | TEXTILES | METALS | CHEMICALS |
|---|---|---|---|---|
| constant | 2.598769***<br>(0.00618140) | −0.074221***<br>(0.00917224) | −0.868501***<br>(0.1804444) | 0.8448950***<br>(0.142161) |
| W | 0.4303779***<br>(0.00137024) | 1.019955***<br>(0.00196137) | 1.194218***<br>(0.01129105) | 0.8098548***<br>(0.2697919) |
| I | −0.0093799**<br>(0.00619785) | −0.051063***<br>(0.01948610) | −0.01825822<br>(0.2922540) | −0.00079605<br>(0.08827423) |
| $\sigma$ | 0.0770346***<br>(0.00411548) | 0.0364567***<br>(0.00211646) | 0.0794543***<br>(0.00387195) | 0.1296814***<br>(0.03372322) |
| $\lambda_1$ | 0.293206 | 0.9152139 | 0.8145814 | 0.6672086 |
| $\lambda_0$ | 0.706794 | 0.0847861 | 0.1854186 | 0.3327914 |
| $\lambda_{01}$ | 0.3691916 | ---- | 0.7588793 | 0.3138129 |
| $\lambda_{11}$ | 0.1100373 | ---- | 0.8272606 | 0.8434759 |
| $\lambda_{10}$ | 0.8899627 | ---- | 0.1727394 | 0.1565241 |
| $\lambda_{00}$ | 0.6308084 | ---- | 0.2411207 | 0.6861871 |

**FIGURE 1 RELATIVE VULNERABILITY OF COLLUSION (Prob{$I_t$ =1})**

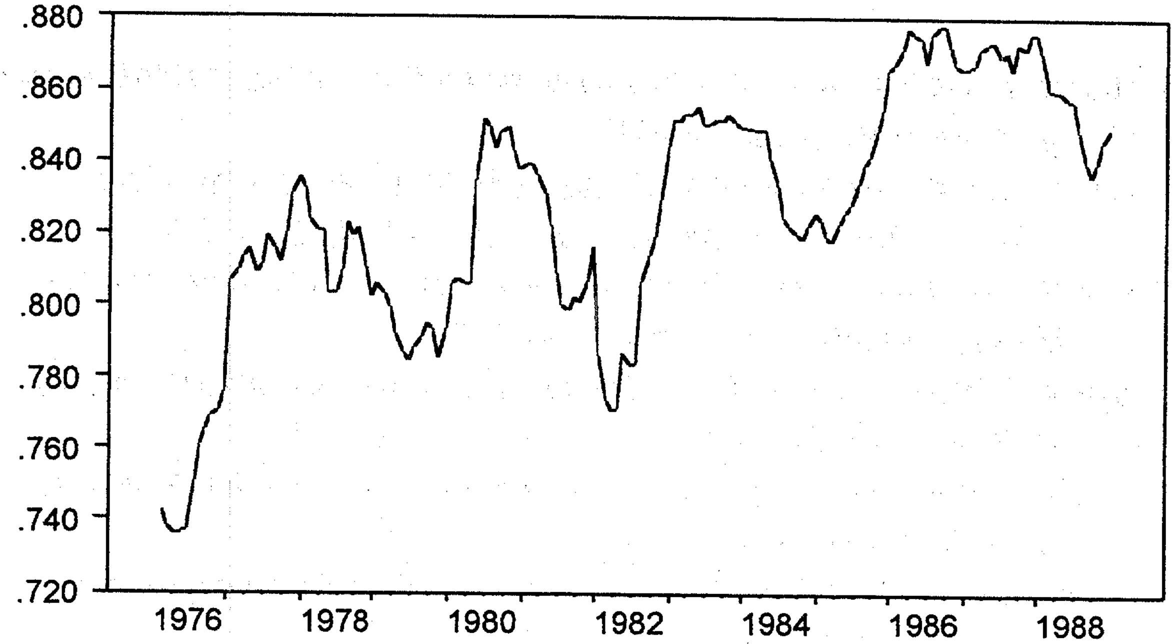
[ MACHINERY ]



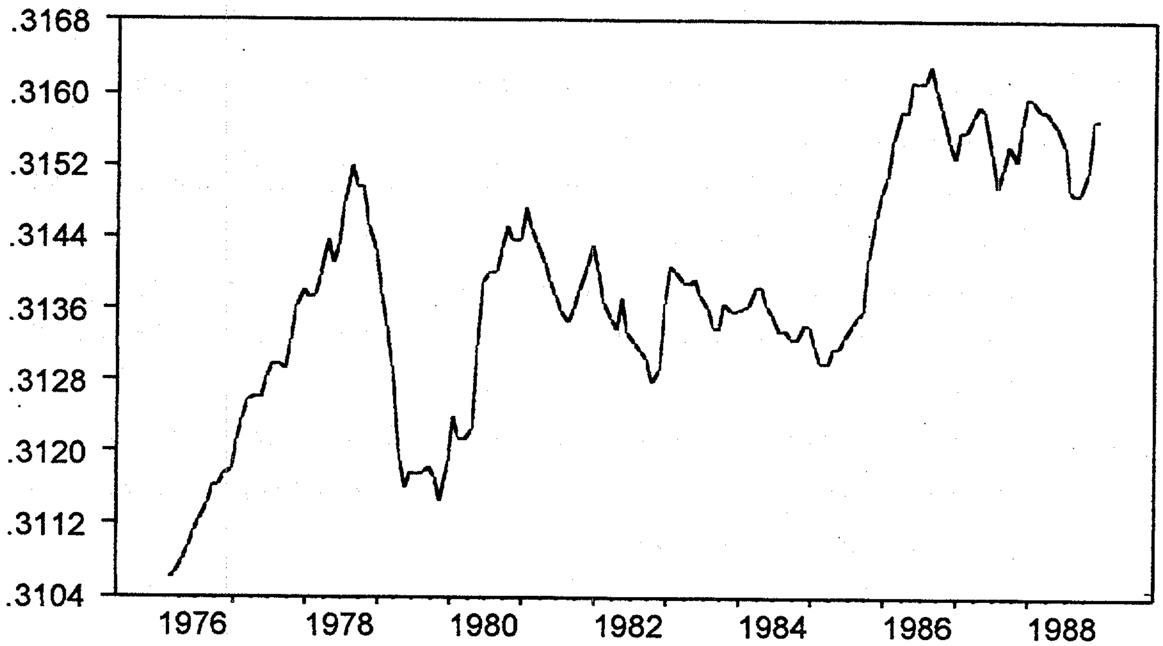

[ TEXTILES ]



[ METALS ]




[ CHEMICALS ]



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