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The Identification of Market Structure: An Econometric Approach

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1. Introduction

The identification of market structure and the measurement of the degree of competitiveness are the subject of numerous studies in the industrial organization literature.[1] Industrial organization studies use such measures as concentration ratios, barriers to entry and a variety of monopoly power indexes, as means for the identification of market structure. Usually, however, they do not provide direct econometric estimations or statistical tests of alternative hypotheses about market structure.

In this paper we extend the use of econometric production theory techniques to a general class of oligopolistic markets.[2] We consider an oligopolistic market with general conjectural variations and provide a framework which enables us to analyze this market empirically, estimate the conjectural variation and test various hypotheses about non-competitive behavior. Furthermore, we provide a measure of the degree of oligopolistic power of a firm that measures the deviation from purely monopolistic and competitive behavioral modes. Using the firm measure we define a degree of oligopoly power index for the whole industry that can be used to test for the underlying structure of the industry. The measure of the degree of oligopolistic power we derive is a generalization of both the classical Lerner measure and the Herfindahl index.

We carry out an analysis using recently developed flexible functional forms to represent technology, thus not placing any *a priori* restrictions on substitution possibilities or on economies of scale.

In an empirical application we use our approach to estimate the degree of oligopoly power in four U.S. manufacturing industries. The industries chosen are: food, textile, machinery, and electrical machinery. On the basis of previous studies,[3] our prior notion is that the first two are competitive, whereas the last two are non-competitive. Our findings do in fact confirm these prior notions. We find that the textile industry is insignificantly non-competitive, whereas the other three are significantly oligopolistic. Of the three oligopolistic industries, the food industry is found to be the most competitive.

In Section 2 we develop the theoretical framework, in Section 3 we provide the econometric specification of our empirical application, and in Section 4 we discuss the empirical results.

2. Theoretical Framework

Consider an industry which consists of S oligopolistic firms producing a homogeneous output. Let the production function of the j^{th} firm be given by $y^j = F^j(x^j)$ where y^j, x^j are the output produced and the n dimensional vector of inputs used by the j^{th} firm. We assume that the production functions F^j are continuous, non-decreasing and quasi-concave. Let the market demand function facing the industry be given by $y = D(p,q)$ where $y = \sum_j y^j$ is total industry output, p is output price, q is a vector of exogenous variables (e.g., prices or quantities of other inputs or outputs) and $\partial D/\partial p < 0$.

The problem of the j^{th} oligopolistic firm can be written as:

$$(1) \quad \max_{p,y^j,x^j} \; [py^j - wx^j \; : \; y^j = F^j(x^j),\; y = D(p,q),\; y = \Sigma y^j,\; x^j, y^j \geq 0]$$

where w is the vector of input prices. Breaking the maximization problem into two stages we can write it as the following equivalent problem

$$\max_{p,y^j}[py^j - C^j(w,y^j) : y = D(p,q),\ y = \Sigma y^j\ \ y^j \geq 0]$$

where $C(w,y^j) \equiv \min_{x^j}[wx^j : y^j = F^j(x^j),\ x^j \geq 0]$ is the cost function which is dual to F.[4]

If the cost function is differentiable with respect to input prices w, then Shephard's [1970] Lemma implies that the oligopolist's demand for inputs conditional on output y^j may be found by differentiating the cost function with respect to input prices

(3) $$x^j = \nabla_w C^j(w,y^j)$$

where ∇_w is the vector of partial derivatives of C^j with respect to w. The oligopolist's optimality condition with respect to output is obtained from (2) as

(4) $$p(1 - \frac{\theta^j}{\eta}) = \partial C^j(w,y^j)/\partial y^j$$

where η and θ^j are defined by

(5) $$\eta = - \frac{\partial D(p,q)}{\partial p} \frac{p}{y}$$

(6) $$\theta^j = \frac{\partial y}{\partial y^j} \frac{y^j}{y}$$

i.e., η is the market demand elasticity, and θ^j is the conjectural elasticity of total industry output with respect to the output of the j^{th} firm.

The condition given by (4) simply says that the oligopolistic firm equates its marginal cost with its <u>perceived</u> marginal revenue. This decision is clearly different than the decision rules of either a competitive firm, or a purely monopolistic one. Furthermore, the perfectly competitive and purely monopolistic rules can be obtained as special cases when $\theta^j = 0$

and $\theta^j = 1$, respectively. In the first case (4) becomes the competitive price equals marginal cost rule and in the second, it becomes the (actual) marginal revenue equals marginal cost rule. These restrictions provide us with a basis for statistical tests about the underlying market structure.

Let us now define the degree of oligopoly power of the j^{th} firm as

(7) $$\lambda_j = \frac{p - \partial c^j/\partial y^j}{p} = \frac{\theta^j}{\eta}$$

Given that $\partial c^j/\partial y^j \geq 0$ and that profits are non-negative it follows that

(8) $$0 \leq \lambda_j \leq 1$$

If the firm is perfectly competitive λ_j reaches its lower bound and if the firm is a pure monopolist then $\lambda_j = 1/\eta$, i.e., our measure becomes the same as the classical Lerner[5] degree of monopoly power measure.

Given the degree of oligopoly power of the individual firms we can define the degree of oligopoly power, or of non-competitive power, of the industry as

(9) $$\lambda = \Sigma(\frac{p - \partial c^j/\partial y^j}{p})S_j = \Sigma \frac{\theta^j}{\eta}S_j = \Sigma\lambda_j S_j$$

where S_j is the output share of the j^{th} firm. This measure is the weighted sum of the λ_j, the weights being the corresponding market shares. It is, therefore, a measure of the ratio of total pure economic profit in the industry and total industry revenues.

It is interesting to note that the oligopoly power measure given by (9) is a generalization of the classical Lerner monopoly power measure (which is given by $1/\eta$) and the Herfindahl index[6] (which takes the sum of squared shares). To see this, substitute (6) into (9) to obtain

$$(10) \qquad \lambda = \sum_j \frac{\partial y}{\partial y^j} s_j^2 \frac{1}{\eta}$$

which involves both the Lerner and Herfindahl indexes as special cases. The terms $\partial y/\partial y_j$ are the conjectural variations of the firms in the industry. If, for example, the firms behave as Cournot oligopolists then $\partial y/\partial y_j = 1$ for all j and out index becomes $\lambda = \frac{1}{\eta} \sum_j s_j^2$ which is proportional to Herfindahl index. If the firms do not behave as Cournot oligopolists, λ may still be proportional to the Herfindahl index, if all firms have the same conjectural variations.

For empirical implementation we have to specify functional forms for the cost functions C^j and the market demand function D(p,q), from which we can then derive the optimality conditions (3) and (4) for the different firms. In addition, we have to make some assumptions about the θ^j terms, the simplest one being, of course, that the θ^j's are constant. Alternatively, we could consider the θ^j's as some (say linear) functions of the exogenous variables which are to be determined and estimated as part of the full model.

To estimate such a model we require detailed firm specific time series, i.e., input and output data for the individual firms. If such data are available, then, in principle, there should be no problem in estimating a full industry model consisting of the systems (3) and (4) for the different firms. Given the estimated parameters of such a model we could carry out various tests about the θ^j's, calculate the degree of oligopoly power of the industry and test various hypotheses about the market structure of the industry.

Our aim in this paper is, however, more modest. We wish to introduce this as a possible approach for the estimation of the degree of oligopoly power and undertake a simple initial empirical application of this approach. Thus, we simplify the model so that we can consider it on an aggregate rather than firm level, or more specifically, so that we can consider the conditions (3) and (4) as industry, rather than firm conditions.

We specify an aggregate cost function $C = C(w,y)$ and get the industry input demand functions from this aggregate cost function as

(11) $$x = \nabla_w C(w,y)$$

We also write (4) on the aggregate level as

(12) $$p(1 - \frac{\theta}{\eta}) = \partial C(w,y)/\partial y$$

where θ is the industry conjectural elasticity, which is some weighted average of the θ^j's. Condition (12) can be interpreted as saying that the weighted average perceived marginal revenue is equal to the weighted average industry marginal cost. Like any other aggregation problem, for this type of aggregation to be strictly valid, certain aggregation conditions have to be satisfied. We could, therefore, assume that the required conditions for aggregation are satisfied, or alternatively, consider the condition as holding or average. We prefer the latter, since the conditions for aggregation usually require constant returns to scale technologies which we do not want to impose. Furthermore, from (4) it is clear that if all firms are perfectly competitive, it must be the case that the industry as a whole is competitive as well. In other words, if $\theta^j = 0$ for all j, then the weighted average of the θ^j, which we denoted as θ, must also be zero. Furthermore, since $\theta^j \geq 0$ for all j, it is also clear that θ will not be zero unless all $\theta^j = 0$. Thus, θ is zero if and only if all $\theta^j = 0$. Since we are primarily interested in estimating θ and testing whether the industry is perfectly competitive or not, the aggregate model is actually less harmful than it may initially seem.

Thus, as an initial application of our approach, we proceed by considering the aggregate model, being fully aware that, as is usually the case with aggregate models, it may involve some aggregation problems.

We could, for example define $\theta = \Sigma\, \theta^j S^j$ and $\partial C(w,y)/\partial y = \Sigma S^j \partial C^j(w^j y^j)/\partial y^j$ and then condition (12) is obtained by simply multiplying both sides of (4) by the corresponding shares and then taking the sum over all firms. In this case θ and $\partial C/\partial y$ are in fact a weighted average of the firm's conjectural elasticities and marginal costs. Furthermore, in condition (12), average marginal costs are equated with average perceived marginal revenues.

Given (9) we get the degree of oligopoly power of the industry as

(13) $$\lambda = \frac{\theta}{\eta}$$

where θ is the average conjectural elasticity. The degree of oligopoly power which is the average deviation of price from firms marginal costs is, therefore, also the deviation of price from average marginal costs. Clearly, if all firms are perfectly competitive and equate price with marginal costs, then the degree of oligopoly power of the industry is zero. Furthermore, λ cannot be zero unless all firms are perfectly competitive. The condition $\lambda = 0$ is, therefore, a necessary and sufficient condition for the industry to be perfectly competitive.

Given functional forms for C and D, and given aggregate industry input and output data we could estimate the industry model given by (11) and (12) and the underlying market demand function if we assume that θ is a parameter to be estimated in the model. In general, however, θ will not be a parameter, but some function of the exogenous variables of the model. Thus, we take $\theta = \theta(w)$ which allows for θ to vary over time reflecting variations in the economic environment characterized by the exogenous variables. For the sake of simplicity we approximate θ as a linear function of the exogenous variables.

3. Econometric Specification

Having outlined the theoretical framework we now apply to two U.S. manufacturing industries. The industries chosen are: (1) food and kindred products, (2) textile, (3) machinery, and (4) electrical machinery which correspond to the manufacturing industry classification of the Survey of Current Business (SCB). According to previous studies[7] and prior notions the first two industries are believed to be competitive whereas the last two are believed to be non-competitive.

We assume that there are two competitively price "variable inputs" in each of the industries; labour x_L and intermediate inputs x_M, whose prices are w_L, w_M respectively.[8] In addition to labour and intermediate inputs the industry uses a capital input K. In our study we treat the capital input as a "fixed input", in the sense that we do not explicitly consider the capital choice decision. It should be noted, however, that this does not mean that capital is actually held fixed, but that the firm's decision is conditional on the level of capital which changes over time. The reason for this treatment of capital is that by doing so we avoid the need to obtain price of capital data, which is usually quite difficult to construct.

The price and quantity series for labour, intermediate inputs and output are obtained from various issues of the Survey of Current Business.

We specify the demand function facing the industry as a Cobb-Douglas function

$$(14) \quad \ell g y = a + \eta \, \ell g(p/S) + \rho \, \ell g(q/S)$$

where S is the implicit GNP price deflator and q is GNP in current dollars. The demand elasticity is therefore constant and given by the parameter η.

We also assume that the industry cost function is given by a translog function

$$\ln C = \alpha_o + \sum_i \alpha_i \ln w_i + \frac{1}{2} \Sigma\Sigma\alpha_{ij} \ln w_i \ln w_j + \sum_i \beta_{iy} \ln w_i \ln y$$
$$+ \sum_i \beta_{iK} \ln w_i \ln K + \gamma_y \ln y + \frac{1}{2} \gamma_{yy} (\ln y)^2 + \gamma_{yK} \ln y \ln K + \delta_K \ln K$$
$$+ \delta_{KK} (\ln K)^2 \qquad i,j = L, M \tag{15}$$

where the parameters are assumed to satisfy the linear homogeneity in prices and symmetry restrictions

$$\Sigma \alpha_i = 1, \sum_i \alpha_{ij} = 0 \quad \forall j, \sum_j \alpha_{ij} = 0 \quad \forall i, \sum_i \beta_{iy} = 0, \quad \sum_i \beta_{iK} = 0,$$
$$\alpha_{ij} = \alpha_{ji}. \tag{16}$$

Applying Shephard's Lemma to the cost function (15), we get the input cost share equations as

$$S_L = \alpha_L + \alpha_{LL} \ln w_L + \alpha_{Ln} \ln w_M + \beta_{Ly} \ln y + \beta_{LK} \ln K \tag{17}$$

$$S_M = \alpha_M + \alpha_{LM} \ln w_L + \alpha_{MM} \ln w_M + \beta_{My} \ln y + \beta_{MK} \ln K \tag{18}$$

where S_L, S_M are the cost shares of labour and materials respectively.

Given the specified cost function we get the output optimality condition (4) as

$$p = (\gamma_y + \beta_{Ly} \ln w_L + \beta_{My} \ln w_M + \gamma_{yy} \ln y + \gamma_{yK} \ln K) \frac{c}{y} / (1 - \frac{\theta}{\eta}) \tag{19}$$

where θ is given by a linear function

$$\theta = A_o + A_L w_L + A_M w_M + A_K K \ . \tag{20}$$

Since cost shares sum to one, only one of the input share equations in (17), (18) is independent. In the estimation we therefore drop one of the input share equations (the material share equation) and identify its parameters using the adding up (or homogeneity) restrictions.

The full model for each of the four industries is therefore given by the cost function (15), the demand function (14), the labour cost share equation (17) and the price equation (19) with θ being defined by (20).

For empirical implementation these models have to be imbedded within a stochastic framework. To do this, we assume that equations (14), (15), (17) and (20) are stochastic due to either errors in optimization or technical errors and define the additive disturbance term in the i^{th} equation at time t as $e_i(t)$, $t=1...T$. We also define the column vector of disturbances at time t as e_t. We assume that the vector of disturbances is joint normally distributed with mean vector zero and non-singular covariance matrix Ω

$$(21) \quad E[e^j(s)\, e'^j(t)] = \begin{cases} \Omega & t=s \\ 0 & t\neq s \end{cases}$$

Since we have a simultaneous system in which both the supply and demand equations appear, it is necessary to use a simultaneous estimation technique that will take account of this simultaneity. To do this we use the full information maximum likelihood method, treating y, p, s_L and C as endogenous variables and all the others as exogenous. It can be verified that the conditions for identification are satisfied.

4. Empirical Results

We estimate each of the four models with the symmetry and linear homogeneity (in prices) restrictions imposed. In all cases there are 17 free parameters to be estimated. The maximum likelihood estimates and standard errors are given in Table 1. Given the parameter estimates we calculate the conjectural elasticities and the degree of oligopoly power measures for the four industries

Table 1

Parameter Estimates
(Standard Errors in Parentheses)

Parameter	Food	Textile	Machinery	Electrical Machinery
			Industry	
α_o	11.3058 (.0431)	9.0599 (.0124)	9.8804 (.0110)	9.7619 (.0119)
α_L	.5008 (.0030)	.5337 (.0057)	.5088 (.0057)	.4954 (.0067)
α_{LL}	.2402 (.0188)	.2595 (.0138)	.2675 (.0394)	-.1119 (.0437)
α_{LK}	-.0290 (.0333)	-.0707 (.0250)	.0069 (.0177)	.1173 (.0252)
β_{Ly}	-.1805 (.0330)	-.2649 (.0217)	-.1143 (.0203)	-.0285 (.0231)
γ_y	.7374 (.0519)	.5535 (.0435)	.7034 (.0379)	.4954 (.0314)
γ_{yy}	.0519 (.0206)	.0362 (.0209)	.0906 (.0154)	.0461 (.0111)
γ_{yK}	.5004 (.1089)	.0837 (.0209)	.0324 (.0366)	-.0378 (.0228)
δ_K	-.1072 (.0645)	-.1508 (.0627)	.0221 (.0323)	.1726 (.0297)
δ_{KK}	-.9712 (.1713)	-.2520 (.0953)	-.1674 (.0323)	.0042 (.0189)
a	-.0283 (.0034)	.0897 (.0153)	.0564 (.0217)	.0512 (.0140)
η	-.6754 (.0874)	-.4990 (.1001)	-1.457 (.2288)	-.8293 (.0920)
ρ	.5606 (.0278)	.9953 (.0910)	1.1500 (.0533)	1.4363 (.0517)
A_o	.5505 (.1080)	.0721 (.0544)	.5777 (.1151)	.3943 (.0565)
A_L	.1397 (.0278)	.0381 (.0284)	.0757 (.0689)	-.0669 (.0303)
A_M	-.1235 (.0245)	-.0239 (.0176)	-.0936 (.0902)	.0511 (.0358)
A_K	-.3881 (.0943)	-.0300 (.0238)	-.1286 (.0558)	.0312 (.0160)

and report the figures in Tables 2 and 3.

To identify the underlying market structure we first test whether θ is zero or not. A sufficient condition for θ to be zero is $A_o = A_L = A_M = A_K = 0$. Therefore, we first test for this condition against the alternative that not all the A's are zero. The χ^2 statistics which are given in Table 4 indicate that the null hypothesis is rejected for all four industries. Since θ is not a constant[9] but a function of the exogenous variables and given the signs of the estimated parameters (A_o, A_K, A_L, A_M) it is clear that the rejection of the above null hypothesis does not necessarily imply the rejection of $\theta = 0$. The restrictions $A_o = A_L = A_M = A_K = 0$ are sufficient but not necessary for θ to be zero. Therefore, to test whether θ itself is equal to zero we calculate the estimated θ values and their standard errors all evaluated at the sample means and test for their significance locally. The t values which are given in Table 4 indicate that the conjectural elasticity is insignificant in the textile industry, but significant in all the other three industries. Thus, we conclude that the degree of non-competitiveness is insignificant in the textile industry, but significant in the other three industries. It should be noted, however, that θ, at the mean, is much lower in the food industry than in the machinery or electrical machinery industries.

We next test whether θ is equal to one or not. A sufficient condition for θ to be one is $A_o = 1$, $A_L = A_M = A_K = 0$. Thus, we first test for these restrictions against the alternative that the parameters are unrestricted. The χ^2 values which are given in Table 4 indicate that this hypothesis is rejected for all four industries.

Again, these restrictions are sufficient for $\theta = 1$ but not necessary, so that we carry out a local test at the sample mean. Given the estimated values of θ at the mean, and given the standard errors, it is clear that θ is significantly different than one in all four models. For example, Table 4 provides 99%

Table 2

Estimated Conjectural Elasticities

Industry

Year	Food	Textile	Machinery	Electrical Machinery
1947	.2101	.05320	.4989	.4051
1948	.1894	.05303	.4887	.4058
1949	.1860	.05175	.4841	.4029
1950	.1773	.05055	.4893	.4028
1951	.1480	.04612	.4808	.4069
1952	.1447	.04633	.4646	.4092
1953	.1557	.04869	.4577	.4118
1954	.1717	.05158	.4571	.4084
1955	.1820	.05251	.4580	.4081
1956	.1762	.05344	.4491	.4107
1957	.1741	.05431	.4360	.4135
1958	.1786	.05621	.4312	.4103
1959	.1815	.05948	.4372	.4072
1960	.1711	.05839	.4306	.4083
1961	.1797	.05933	.4328	.4076
1962	.1687	.06208	.4348	.4074
1963	.1589	.06116	.4301	.4087
1964	.1597	.06403	.4276	.4055
1965	.1336	.06578	.4160	.4061
1966	.1303	.06669	.4055	.4071
1967	.1217	.06564	.3862	.4120
1968	.1159	.06660	.3747	.4127
1969	.1054	.06901	.3712	.4132
1970	.1041	.07039	.3601	.4089
1971	.0914	.07315	.3531	.4082

Table 3

Estimated Degree of Oligopoly Power

Industry

Year	Food	Textile	Machinery	Electrical Machinery
1947	.3110	.1085	.3423	.4885
1948	.2804	.1082	.3353	.4893
1949	.2754	.1056	.3322	.4858
1950	.2626	.1031	.3357	.4857
1951	.2191	.0941	.3299	.4906
1952	.2143	.0945	.3188	.4934
1953	.2305	.0993	.3140	.4965
1954	.2542	.1052	.3136	.4924
1955	.2695	.1071	.3142	.4921
1956	.2609	.1090	.3082	.4952
1957	.2577	.1108	.2991	.4985
1958	.2644	.1147	.2958	.4946
1959	.2687	.1215	.3000	.4910
1960	.2534	.1191	.2954	.4923
1961	.2661	.1211	.2969	.4915
1962	.2498	.1267	.2983	.4912
1963	.2353	.1248	.2951	.4928
1964	.2364	.1306	.2934	.4889
1965	.1978	.1341	.2854	.4896
1966	.1929	.1361	.2782	.4908
1967	.1802	.1339	.2650	.4968
1968	.1717	.1359	.2571	.4976
1969	.1561	.1408	.2547	.4982
1970	.1541	.1436	.2471	.4930
1971	.1353	.1492	.2422	.4922

Table 4

Restrictions	χ^2 Statistics*			
	Food	Textile	Machinery	Electrical Machinery
$A_o = A_L = A_M = A_K = 0$	22.29	190.43	42.36	51.65
$A_o = 1 \quad A_L = A_M = A_K = 0$	152.91	229.784	56.198	268.068
Estimates at Sample Mean				
$\hat{\bar{\theta}}$	.1567 (.0378)	.0583 (.0433)	.4342 (.0721)	.4083 (.0435)
$\hat{\bar{\lambda}}$	.2319 (.0519)	.118 (.0438)	.2979 (.0368)	.4924 (.0305)
99% (One Side) Confidence Interval for $\hat{\bar{\theta}}$	$\hat{\bar{\theta}} < .2446$	$\hat{\bar{\theta}} < .1590$	$\hat{\bar{\theta}} < .6019$	$\hat{\bar{\theta}} < .5935$

* $\chi^2_{(4).01} = 13.3$

confidence intervals for θ (at the sample means) and clearly the hypothesis that θ is locally equal to one is rejected for all four industries.

We therefore, conclude that all four industries are significantly different than purely monopolistic industries. The rejection of pure monopolistic behaviour is, however, stronger in the textile (which was already shown to be insignificantly non-competitive) and food industries, than in the machinery and electrical machinery industries.

An examination of Table 2 confirms the tests' results. The estimated conjectural elasticities are very low for the textile industry over the whole sample period, indicating a low degree of non-competitiveness. It can also be seen that the estimated elasticities have been increasing slightly over time, in particular in the more recent years.

The estimates of θ for the food industry are also fairly low during the sample period and furthermore, they have been continuously declining over time, indicating increasing competitiveness.

The estimated elasticities for the machinery industry are similar to those of the electrical machinery industry, both with estimates substantially higher than in the textile and food industries, indicating a lower degree of competitiveness. It should also be noted that while the conjectural elasticities in the electrical machinery industry are quite stable, those in the machinery industry have been decreasing over time suggesting increasing competitiveness in the industry.

Given the estimated conjectural elasticities and the test results we, therefore, conclude that the textile industry is characterized by competitive behaviour, whereas the other three industries are characterized by significant non-competitive behaviour. The three non-competitive industries are characterized by oligopolistic behaviour, which is significantly different than pure monopoly. Furthermore, the degree of non-competitiveness in the machinery and electrical machinery industries is much higher than in the food industry.

Finally, let us examine the estimated measures of the degree of oligopoly power, given in Table 3. As we have shown above these measures are given by $\lambda = \theta/\eta$, thus they are directly related to the degree of competitiveness in the industry and inversely related to the elasticity of the market demand curve. In view of this, it is clear that different demand conditions will lead to different oligopoly power measures, even if the degree of competition remains unchanged. For example, a low demand elasticity will tend to yield a high λ and vice versa. Information on λ is, therefore, not sufficient in order to determine the degree of competition, unless we also know the demand elasticity (which enables us then to calculate θ). Thus if we want to use λ to measure the degree of competition we have to know η and to remember that with pure monopoly $\lambda = 1/\eta$, i.e., it is the deviation from $1/\eta$ that is important. On the other hand, if we are interested in the degree of oligopoly power itself, which combines the degree of competition and demand conditions, and provides a index of total non-competitive rents; λ itself provides the necessary information.

An examination of Table 3 shows that the textile industry has the lowest oligopoly power measure and that the measure increases slightly over time. It is also interesting to note that while the estimates are fairly low, they are much higher than the estimates of θ , which is due to the fact that the demand elasticity is quite low ($\hat{\eta} = .490$).

The oligopoly power measures for the food industry are higher than in the textile industry, but they are steadily declining over the sample period (and become even lower in the last sample point). Again the λ measures are higher than θ due to low demand elasticity.

The machinery industry has an oligopoly power measure which is only slightly higher than that in the food industry. The reason is, of course, that the electrical machinery industry has a much higher demand elasticity, thus reducing its oligopoly power, even though the industry is less competitive.

Finally, the electric machinery industry has the highest oligopoly power index, which is also quite stable over the sample period.

5. Conclusion

In this paper we provide a framework within which an oligopolistic industry can be empirically investigated and its degree of competitiveness estimated. We also define a degree of oligopoly power index which generalizes the classical Lerner and Herfindahl indexes.

In an empirical application we estimate the degree of competitiveness in the U.S. food, textile, machinery and electrical machinery industries and find all but the textile industry to be significantly non-competitive.

FOOTNOTES

[1]See Scherer [1970], Bain [1965], Shepherd [1970].

[2]A similar model, but without explicit consideration of conjectural variations is considered in Appelbaum [1979].

[3]See references in footnote 1 and Palmer [1973].

[4]See Diewert [1971] for its regularity properties.

[5]See Lerner [1934].

[6]See Scherer [1970].

[7]See for example Palmer [1973].

[8]For the sake of notational convenience we do not introduce an industry index. Strictly speaking, however, all variables and parameters should be indexed according to industry.

[9]We carried out a test for the hypothesis that θ is globally constant and rejected the hypothesis (at .01 significance level) in all by the electrical machinery industry. These conclusions are also confirmed by the figures given in Tables 2 and 3.

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