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Determinants of Industrial Structure: A Brazilian Case Study

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Summary. — Concentration ratios for 119 Brazilian industries are expressed as a combination of scale effects, the size of the suboptimal sector, and the rate of entry of new firms into the industry. Variables found to be significant determinants of suboptimal capacity and entry, hence of industrial concentration, include foreign ownership, state ownership, exports, tariff protection, minimum efficient scale, capital intensity, advertising, and geographic concentration.

1. INTRODUCTION

The large literature on the determinants of industrial concentration, much of which has been surveyed by Curry and George (1983), is notable for its neglect of developing countries. With two exceptions — Lall's study of Malaysia (1979) and Blomström's study of Mexico (1986) — all of the studies published to date refer to developed economies, typically Canada, the United States or the United Kingdom. The present paper adds to the meager literature on this topic in the developing countries by analyzing industry data assembled from the tax returns of nearly 50 thousand Brazilian firms for fiscal year 1980. It is hoped that the findings of this exploratory study will be of interest to researchers and will stimulate further work in this area in Brazil and other semi-industrial countries.

The standard model employed to analyze the determinants of industrial structure consists of the regression of concentration ratios on a number of explanatory variables. This paper reports the results of the application of such a model to Brazilian data, including as regressors foreign ownership, state ownership, exports, tariff protection, minimum efficient scale, capital intensity, advertising, the geographic concentration of production and industry growth.

Davies and Lyons (1982), in an important study, draw upon a growth model developed by Simon and Bonini (1958) to construct "synthetic" concentration ratios from estimates of minimum efficient scale, the size of the suboptimal sector, and the rate of entry into the efficiently scaled sector of an industry. In this study, I construct synthetic concentration ratios for 119 Brazilian industries with results that are quite similar to those obtained by Davies and Lyons for 100 UK industries. I then specify and estimate regression equations for two components of industrial structure: suboptimal capacity and the rate of entry. Separate analyses of these two components are useful, for decreases in the extent of suboptimal capacity and decreases in the rate of entry both result in increased concentration, but a decrease in the extent of suboptimal capacity brings efficiency gains along with the increased concentration, whereas a decrease in the rate of entry does not.

2. THE CONVENTIONAL APPROACH APPLIED TO BRAZILIAN DATA

Researchers interested in the determinants of industrial structure typically regress the simple concentration ratio on a number of industry variables in order to infer the independent influence of scale economies (positive), market size (negative), geographic concentration (positive) and, less often, tariff protection (negative) and the presence of transnational firms (posi-

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tive). This section reports the results of the application of this type of regression model to Brazilian data.

The data base used in this study contains information for nearly 50 thousand firms which operated in Brazil's manufacturing sector in 1980. These firms own only 25% of the manufacturing establishments covered by the 1980 manufacturing census, but they account for well over 95% of the total output of the sector. The data were assembled for fiscal 1980 income tax returns and are described in greater detail in another paper (Willmore, 1987). The income tax returns were crossed with industrial product tax (IPI) information on employment for the first semester of 1979 and, for many of the larger firms, with published balance-sheet data for 1980. IPI returns for 1980 provided information on the number of plants operated by each firm.

The variables used in the regression equation are described in Table 1. With three exceptions (PROTECT, GEOG and GROWTH), all variables were constructed from data for individual firms; firms were assigned to a four-digit industry on the basis of their main product line. This list of variables covers nearly all that have been included in empirical studies of the determinants of interindustry differences in concentration. In addition, two explanatory variables — state ownership and export intensity — are included in this type of regression model for the first time.

(a) *Estimates of minimum efficient scale (MES)*

Almost all studies of interindustry differences in concentration include the ratio of minimum efficient scale to market size (MES/Q) as an explanatory variable, and all find large, positive and significant coefficients for this variable. Two arguments are usually advanced as an explanation of this result. First, in industries with a high MES/Q, technology leads to high concentration because the market will support only a limited number of plants of minimum efficient scale. Second, when an MES plant represents a large proportion of the market, this is supposed to impede entry, for existing firms are likely to retaliate if they lose a large share of their market. A potential entrant can avoid the threat of retaliation by building a plant of less than minimum efficient scale, but will then face the disadvantage of production costs that are higher than those of existing rivals.

Minimum efficient or "optimal" scale is an important, possibly the most important, determinant of industrial structure. It is also the most difficult to measure. Three main techniques of measurement have been proposed, namely the engineering, statistical cost and survivor techniques. Engineering estimates are generally considered to be the most reliable, but they are costly to obtain, so are available for very few industries and then only for advanced industrial countries. Statistical cost analysis using cross-section data is a less costly alternative. This technique requires "cost and output data from a sample of plants that produce uniform outputs, use uniform accounting systems, pay identical factor prices, and have similar technological circumstances" (Klein, 1962, p. 119). Ideally, one should control for differences in capacity utilization as well. Needless to say, our data refer to firms rather than plants, and in any case fall far short of meeting these requirements. The "survivor test" developed by Stigler (1958) requires data on changes in the share of various size groups of firms in total industry output over time. Plan sizes that account for an increasing proportion of an industry's output are assumed to be efficient, so the resulting estimates reflect much more than scale economies in production. Census data for such a study are available for Brazil, but published figures are much too aggregate to be of value, so the survivor technique has not yet been applied to Brazil.

Lacking data to measure minimum efficient scale, most researchers in industrial countries and virtually all researchers in developing countries have turned to proxy measures drawn from the observed size distribution of plants in each industry. Weiss (1963) considered a reasonable proxy for MES to be the "midpoint plant size," i.e. the hypothetical plant of a size such that half of the industry output is accounted for by larger plants. In other words, one-half of the output of each industry is assumed to originate in plants of less than minimum efficient scale. Comanor and Wilson (1967) proposed a variant that is quite similar: the average size of all plants larger than Weiss' midpoint plant. Both MES proxies are typically expressed as a percentage of industry output in interindustry studies. The Comanor-Wilson proxy has come to dominate empirical work on the determinants of concentration in the United States, and has also been used in studies of Malaysia (Lall, 1979), Japan (Caves and Uekusa, 1976), and Canada (Caves *et al.*, 1980). Braga (1983) used the Comanor-Wilson proxy in a study of Brazil that focuses on the determinants of profitability rather than the determinants of market structure.

Ornstein *et al.* (1973) and Davies (1980) have argued that MES proxies drawn from the size distribution of plants, when expressed as a share of total industry output, are best interpreted as

Table 1. *Description of the data (sample size = 119 four-digit industries)*

Variable	Description*	Mean (std. dev.)
CR4	Four-firm concentration ratio, defined as the proportion of industry output accounted for by the four largest firms	0.511 (0.250)
FOR	Proportion of industry output accounted for by foreign-owned firms. A firm is classified as foreign if nonresidents hold 10% or more of the equity, provided that state ownership does not exceed the foreign share	0.259 (0.263)
STATE	Proportion of industry output accounted for by state enterprises. Firms with minority state participation were not classified as state enterprises	0.024 (0.117)
EXPORT	Exports as proportion of total industry sales	0.007 (0.080)
PROTECT	Rate of effective protection in Brazil, 1980–81, measured by observed prices rather than legal tariffs. This variable is available at a somewhat higher level of aggregation than that used for other variables, so the same statistic serves for several industries in some instances	0.611 (0.795)
MES	Natural logarithm of the output (value-added in 1980 cruzeiros) of a plant of minimum efficient scale	19.049 (1.041)
Q	Natural logarithm of industry output (value-added in 1980 cruzeiros)	23.157 (1.226)
K/L	Natural logarithm of the capital-labor ratio, measured as the ratio of the book value (in end-1980 cruzeiros) of assets to employment	13.053 (0.783)
NWVA/L	A proxy for capital intensity, measured as the natural logarithm of the ratio of nonwage value-added (in 1980 cruzeiros) to employment	13.050 (0.703)
ADV	Advertising expenditures expressed as a proportion of domestic sales	0.011 (0.017)
C	A dummy variable equal to one if the industry produces consumer goods and zero otherwise	0.429
GEOG	Geographic concentration of production, measured as the sum (over 26 Brazilian states and territories) of the absolute value of the proportion of adult population in the state minus the proportion of industry shipments originating in the state. This index takes values between zero and two.	0.984 (0.253)
GROWTH	1980 index of industrial production (1975 = 1.0) at the two-digit level of aggregation	1.468 (0.155)

*Output is measured as value added by the firm. The basic data are available from the author on request. *Source*: PROTECT: Tyler (1985); GEOG: IBGE, 1980 industrial census: GROWTH: UN Economic Survey of Latin America 1983; all other variables: Secretaria da Receita Federal, tax returns for 1980.

measures of plant-level concentration rather than measures of the minimum size of an efficiently scaled plant. This is most evident in the Comanor-Wilson proxy, which is a reciprocal indicator of the number of plants that account for half the output of an industry. Such proxies perform well in regressions of concentration on MES because the size distribution of plants automatically related to the size distribution of firms, hence to measures of firm concentration. In fact, they often perform too well, with the high correlation between concentration and MES suppressing the efficiency of other explanatory variables.

In order to avoid estimating a model that is dangerously close to an identity, I have developed new estimates of minimum efficient scale that are inspired by the work of Lyons (1980) and are based on the decision of firms to operate a second plant. A key assumption is that a firm will exhaust economies of scale in its first plant before opening a second or third plant.

Suppose the average cost curve for a plant is L-shaped as in Figure 1 such that unit costs are constant beyond minimum efficient scale (MES). A single-product firm producing less than MES and minimizing production cost will operate only one plant. Single plant operation is thus a

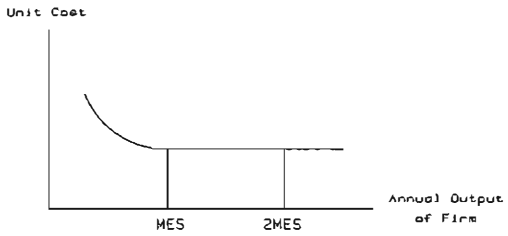

Figure 1. *Hypothetical average cost curve.*

certainty for firms smaller than MES. As the size of a firm increases, the probability that it operates a single plant decreases. At an output twice that of minimum efficient scale (2MES), unit costs are equal for a single plant or two plants, so the firm will be indifferent between the two alternatives and the probability of operating a single plant is 0.5. When more than two plants are possible, Lyons shows that the probability that a firm operates a single plant decreases steadily for size greater than 2MES. Only at 2MES is the probability of operating a single plant precisely equal to 0.5.[1]

With only aggregate census data available to him, Lyons found it necessary to estimate 2MES on the basis of the average number of plants operated by various size classes of firms. The Brazilian data permit direct estimates employing observations on the number of plants operated by individual firms; unfortunately there is no way of knowing whether all the plants of a particular firms are located in the same industry. The following nonlinear model was estimated for each industry:

$$Y_i = P_i + u_i$$
where $$P_i = 1/(1 + e^{-b0 - b1 \log S_i})$$

and the disturbance term (u_i) is an independently distributed random variable with zero mean. Y_i is a dichotomous variable which takes the value of one if a firm operates a single plant and zero if it operates two or more plants. The variable $\log S$ is the natural logarithm of the size of the firm, measured as cruzeiros of value added.

This type of binary choice model restricts the estimated probabilities (the P_is) to the zero-to-one interval and is referred to as logit analysis. (See Pindyck and Rubinfeld, 1981, ch. 10.) The error term is heteroskedastic because the variance of u is larger the closer the P_i is to one-half. Therefore it is necessary to iteratively reweight the least squares results, the weights being the reciprocal of P_i $(1-P_i)$ from the previous iteration, in order to produce asymptotically efficient and unbiased estimates of the parameters (Kmenta, 1971, pp. 425–427 and 461–462). Once the parameters of the model are estimated, it is possible to calculate the value of S that corresponds to a probability of 0.5 for a single-plant operation; one-half of this value becomes our estimate of minimum efficient scale.

From an initial list of 192 industries, I eliminated five "miscellaneous" categories, five covering repair rather than manufacture, six with very localized markets, and one with low coverage in the data base, leaving a total of 175 industries. Of these industries, it was possible to obtain 119 usable estimates for minimum efficient scale. The observations for an industry were deleted if the logit regression failed to converge in 200 iterations or if the estimate of 2MES lay outside the range of firm sizes in the industry. The fit of the remaining 119 equations was typically not very good, for the asymptotic standard errors were often larger than the estimated coefficients. These MES estimates, as a percentage of total industry output, average 2.7%, ranging from a low of 0.1% (concentrated flavors and aromas) to highs of 12.5% (photographic material) and 13.9% (grease). The estimates are biased downwards, for if a multiplant firm has plants in two or more industries, the firm with all its plants is assigned to a single industry in our data base. Nonetheless, while it is difficult to place much confidence in specific estimates of MES, the figures may correlate well with true MES. At the very least, these estimates are not correlated with concentration by definition as in the case of the widely used Comanor-Wilson proxy and similar measures drawn from the size distribution of plants.

(b) *Empirical findings*

The results of the regression of four-firm concentration ratios on a variety of explanatory variables are reported in Table 2. In general, they compare quite favorably to those reported by researchers for industrial countries. All significance levels are conservatively reported with two-tailed tests even though one-tailed tests are appropriate for some coefficients. The ratio MES/Q does not enter the equations directly, but market size (Q) is controlled in inferring the independent effect of MES on concentration.

A White (1980) test shows that it is highly probable that the error term of equation (2) in Table 2 is heteroskedastic. As is well known, estimation by ordinary least squares (OLS) in the presence of heteroskedasticity produces inefficient, albeit unbiased, parameter estimates and biased, inconsistent estimates of their variance.

Table 2. *Determinants of concentration (CR4) (OLS regression results across 119 Brazilian industries, 1980)*

Variable*	Equation (1)	Equation (2)
Constant	2.068	1.657
	(3.92†)	(3.30†)
	[4.21†]	[2.99†]
Ownership		
FOR	0.373	0.376
	(4.93†)	(5.39†)
	[4.76†]	[5.30†]
STATE	0.760	0.743
	(4.32†)	(4.84†)
	[5.80†]	[6.36†]
Trade		
EXPORT	0.564	0.462
	(2.56‡)	(2.17‡)
	[2.94†]	[2.58†]
PROTECT	−0.014	−0.037
	(−0.66)	(−1.78§)
	[−0.74]	[−1.90§]
Technology		
MES	0.012	0.003
	(0.61)	(0.135)
	[0.70]	[0.146]
Q	−0.125	−0.118
	(−7.29†)	(−7.169†)
	[−19.82†]	[−7.086†]
K/L	0.058	
	(2.13‡)	
	[2.42‡]	
NWVA/L		0.100
		(3.79†)
		[3.97†]
Other		
ADV*C	2.244	2.360
	(1.86§)	(2.03‡)
	[1.95§]	[2.37†]
ADV*(1−C)	0.343	−0.311
	(0.22)	(−0.21)
	[0.52]	[−0.47]
GEOG	0.118	0.108
	(1.72§)	(1.66§)
	[1.85§]	[1.65§]
GROWTH	0.038	−0.008
	(0.33)	(−0.08)
	[0.38]	[−0.09]
R^2	0.557	0.593

*The dependent variable is the four-firm concentration ratio (CR4). Statistics in parentheses are OLS t ratios; those in square brackets are heteroskedastic-consistent t ratios.
†Significant at the 1% level in a two-tailed test.
‡Significant at the 5% level in a two-tailed test.
§Significant at the 10% level in a two-tailed test.

To allow for the presence of heteroskedasticity, I estimated for each equation White's heteroskedasticity-consistent covariance matrix of the parameters and report the corresponding t ratios in square brackets below the OLS t ratios. The advantage of White's method over others (Goldfeld and Quandt, 1972, ch. 3) is that it does not require any assumption as to the pattern of heteroskedasticity; rather it provides a general test for heteroskedasticity and a variance-covariance matrix for the parameters that is a consistent estimator of the true variance-covariance matrix.[2]

A two-tailed test of significance is clearly appropriate for the coefficient of foreign ownership (FOR). The *indirect* effects of foreign investment on concentration are unambiguously positive, and operate through the effect of the presence of transnational firms on other variables such as exports, scale economies, capital intensity and advertising. (See Willmore, 1985 and 1986.) The *direct* effects, however, can be positive or negative depending on the conduct of transnational firms in Brazil.

The coefficient of FOR will be negative, or at least not positive, if investment takes place as a defensive reaction in oligopolistic industries (Knickerbocker, 1973). Students of the Canadian economy (Eastman and Stykolt, 1960; English, 1964) have hypothesized that such a process turned protected Canadian industries into "miniature replicas" of the corresponding US industry: the same firms are present with similar market shares, but with plant sizes well below minimum efficient scale. This hypothesis received support from Rosenbluth (1970) who found that the positive correlation between foreign control and concentration was due solely to the tendency of foreign-owned firms to rank among the largest in each industry.[3] More recently, Caves *et al.* (1980, pp. 53–54 and 270–274) found direct evidence of the "miniature replica effect" of foreign direct investment of Canada's industrial structure. Evans (1977) argues that a similar effect operates in Brazil's pharmaceutical industry.

Conversely, one can expect the independent effect of FOR on concentration to be positive if transnational firms produce with lower costs either because they are efficient or because they obtain better terms than local competitors in financial and input markets, and drive competitors out of business by cutting prices and improving quality (Newfarmer, 1979). both Lall (1979) using Malaysian data and Blomström (1986) using Mexican data found support for this hypothesis, in contrast to findings reported for Canada and other industrial countries (Caves, 1982, pp. 100–103).

The results for Brazil confirm those reported by Lall and Blomström: the presence of transnational firms has an independent, positive effect on concentration in developing countries. The coefficient for FOR is statistically significant at the 1% level, and each increase of three percentage points in foreign control is associated with an increase of more than one percentage point in the four-firm concentration ratio.[4] Partial correlation does not, of course, prove causality, but it is more likely that the results are due to transnationals causing higher concentration than to high concentration attracting transnationals. The thesis that concentration is a cause of foreign investment (Knickerbocker, 1973; Caves, 1982, pp. 97–100) refers to industrial concentration in the country of origin, not to concentration in a host country like Brazil.

Nevertheless, some questions remain. The positive coefficient on foreign ownership in these regressions does not explain how transnational enterprises increase concentration. Is it through greater efficiency, which leads to the disappearance of small, high-cost producers? If so, there are efficiency gains that offset the increased monopoly power. Is it through predatory conduct or the ability to obtain special concessions from governments? If so, the increased concentration results in an unambiguous welfare loss (see Lall, 1979, p. 337).

The coefficient of STATE ownership is also positive, highly significant and even larger than that of foreign ownership. This conforms to *a priori* expectations: the presence of state enterprises, which have access to government funding of their deficits, can be expected to discourage entry into an industry, especially entrants of suboptimal scale with high unit production costs. There is also a possibility that the causation runs the other way, i.e. from concentration to state ownership rather than the reverse. The state may invest heavily in industries that would be highly concentrated in any event in order to socialize what would otherwise amount to private and foreign monopoly positions. This explanation is more relevant for simple than for partial correlation. The fact that STATE has an independent effect on concentration after accounting for the effect of other explanatory variables suggests strongly that the direction of causation is from state ownership to industrial concentration.

Of the two trade variables, only export intensity has a coefficient that is significantly different from zero. The expected sign of the coefficient of EXPORT is ambiguous: the possibility of exporting allows firms to reach minimum efficient scale without facing a demand constraint, but it is difficult for small firms with high unit production costs to survive in such a competitive environment. Since the sign of the coefficient is positive, it appears that exporting increases concentration, on average, in Brazilian industries. Protective tariffs can be expected to lower concentration as it is customarily measured, i.e., ignoring sellers of imported goods, because with fewer imports there is room for a larger number of domestic producers (Caves *et al.*, 1980, p. 52). The coefficient of PROTECT is negative as expected, but it is not statistically significant.

The coefficient of minimum efficient scale (MES) is positive as expected, but is not statistically significant. In contrast, the negative coefficient of market size (Q) is highly significant, implying the existence of a positive relationship between the ratio of MES to Q and seller concentration. The capital intensity variables, assets per employee (K/L) and nonwage value added per employee (NWVA/L), represent an attempt to measure both barriers to entry and the cost disadvantage of plants smaller than minimum efficient scale. In addition, capital intensity is known to be correlated with economies of scale, such that Ornstein *et al.* (1973) actually use K/L as a proxy for scale economies. Both of the capital intensity variables, when entered separately into the equation, have the expected positive coefficient and both are statistically significant, especially NWVA/L.

The regression results provide evidence that in Brazil, as in most industrial countries, high levels of advertising are associated with high levels of seller concentration.[5] In accord with *a priori* expectations, the effect of advertising on concentration is significant only for consumer goods. If advertising represents a barrier to entry, one would expect its effect to be greater in industries which produce final consumer goods than in industries that produce capital and intermediate goods for other industries.

The coefficient of the index of geographic concentration (GEOG) is positive and significant, which indicates that geographically dispersed industries tends to record lower levels of concentration at the national level once one accounts for the effect of other independent variables. This variable can be regarded as a correction for the improper geographic definition of industries with high transport costs. Finally, the coefficient of industry GROWTH is not significantly different from zero, which may indicate that market growth has not been captured to any disproportionate extent by the leading four firms in each industry.

3. THE SIMON-BONINI GROWTH MODEL

The regression model of the previous section is widely used and provides useful insights, but it lacks a theoretical foundation. To remedy this defect, I draw upon a growth model developed by Simon and Bonini (1958) and refined by Davies and Lyons (1982). The model is quite similar to that applied by Simon (1955) to the distribution of words, scientific papers, city sizes, personal income and biological species. It rests on three crucial assumptions:

(1) Technology: L-shaped cost curves. Technological considerations determine minimum efficient scale (MES) in each industry and unit costs are assumed to be constant for all rates of output above MES.

(2) Stochastic process: Gibrat's law of proportionate effect. For firms larger than MES, percentage rates of growth are stochastic and independent of past growth and firm size. Growth rates do, of course, vary because of differences in efficiency, investment strategies, mergers, "animal spirits" and numerous other factors exogenous to the model, but growth prospects are not related to past growth or size. A small firm is, by assumption, just as likely to experience a 10% increase (or a decline) in output as is a large firm.

(3) Economic behavior: "Relatively constant" entry of new firms into the efficiently scaled portion of the industry. In particular, Simon and Bonini assume that "industry" growth is positive, and a constant portion is accounted for by new entrants. Industry growth, however, refers to the growth of output of firms larger than minimum efficient scale, and an "entrant" can be a small firm that grows to a size larger than MES. The rate of entry, defined as the proportional contribution of entrants to total change of output, is an important parameter of the model; following the notation of Davies and Lyons, I refer to it with the Greek letter θ (theta).

These three assumptions yield the prediction that observed firm sizes will fit a Yule distribution, which the Pareto curve approximates in the upper tail.[6] Most conveniently, Simon and Bonini show that the inequality parameter α of the Pareto and Yule distributions is a simple function of the rate of entry, *viz.*:

(3) $\alpha = 1/(1 - \theta)$

α takes values between unity and infinity, whereas values for θ must lie between zero (no new entrants) and unity (all industry growth is accounted for by new entrants). Since α is an inverse measure of size inequalities, "in this particular model, the concentration in an industry is not independently determined, but is a function of the rate of new entry" (Simon and Bonini, 1958, p. 615). The parameter θ is assumed to be a constant, but "a slow change in θ can be expected to modify the steady-state distribution (of firms) only slightly" (Simon and Bonini, 1958, p. 611).

Davies and Lyons (1982) have examined the implications of the Simon-Bonini model for simple concentration ratios. They point out that a feature of the Pareto distribution for $\alpha > 1$ (implying $\theta > 0$) is

(4) $\bar{S} = [\alpha/ (\alpha-1)]$ MES

where $\bar{S}$ is the average size of all firms in excess of MES and MES lies within the Pareto range. If the condition of $\alpha > 1$ is not met, then no finite mean exists for the Pareto distribution. Equation (4) is applicable only to growing industries with a positive rate of entry. It is not applicable to a mature or declining industry characterized by exit rather than entry. Nor is it applicable to an industry with a very small MES that lies outside the Pareto range.

Combining equations (3) and (4), θ can be shown to equal the ratio of minimum efficient scale to the average size of "efficient" firms:

(5) $\theta = \text{MES}/\bar{S}$.

The rate of entry into an industry (θ) is simply minimum efficient scale divided by the average size of firms larger than MES. If, for example, MES is 10% of the average size of firms larger than MES, the rate of entry will also be 10%. This result has important implications for empirical research: it opens the possibility of extracting, from cross-section data, inferences concerning industry dynamics. Given an independent estimate of MES, and information on the size distribution of firms within an industry, it is possible to calculate θ. θ can also be calculated from data on new entrants into an industry over time. Such data are not available for Brazil, so estimates of θ reported in this paper are derived from a single cross-section of firms.

Defining the share of suboptimal firms as y and total industry size as Q, synthetic concentration ratios can be derived as follows (see the appendix):

(6) $\text{CR4}' = (1-y)^{1-\theta} [(4/\theta) (\text{MES/Q})]^{\theta}$.

Taking partial derivatives of this expression, it is possible to show that concentration varies positively with MES/Q and inversely with θ and y. Concentration ratios will be higher when minimum scale is large relative to industry size, rate of entry is low and suboptimal capacity is small. The positive relationship between concentration ratios and minimum efficient scale does not depend on the argument that minimum scale requirements act as "barriers to entry." On the contrary, the relationship between concentration and MES is positive when the rate of entry is held constant. If high MES discourages entry, this would be an additional, indirect effect of minimum scale on concentration.

Davies and Lyons suggest that equation (6) permits a decomposition of concentration into stochastic (economic?) factors, represented by θ or α, and technological factors, represented by MES/Q and y. The model is somewhat more complex, however, for the variables on the right-hand side of the equation are jointly determined. The rate of entry (θ) surely depends on y, for firms in the suboptimal sector represent an important pool of potential entrants. In addition, both θ and y may be affected by variations in minimum efficient scale. The *partial* derivative of concentration with respect to MES/Q is unambiguously positive; the *total* derivative can conceivably be negative if the indirect effects through y and θ are strong enough and of an offsetting sign. Since minimum efficient scale is exogenous, the total derivatives of y and θ, like their partial derivatives, are unambiguously negative irrespective of the fact that θ may be a positive function of y.

As θ approaches its upper limit (unity) where all "industry" growth is accounted for by new entrants, the four-firm ratio tends to

$$(7)\ CR4' = 4\ MES/Q.$$

By implication, the suboptimal sector does not exist ($y = 0$) and all firms are precisely the size of a plant of minimum efficient scale. This special case is, however, of little interest since "even without impediments to entry, there is no reason why *all* new capacity should be provided by new firms" (Davies and Lyons, 1982, p. 908). At the other extreme, when entry into the efficient sector of an industry is almost completely impeded (θ tends to zero), the concentration ratio approaches the ratio of the efficient sector to total industry output ($1-y$). In other words, as new entry diminishes, the concentration ratio approaches unity unless the industry contains firms of suboptimal size.

Derivation of equation (6) requires the assumption that at least five firms in each industry are larger than minimum efficient scale, i.e., that the five largest firms lie outside the suboptimal sector. (See the appendix.) Not all the 119 Brazilian industries satisfy this assumption. Four highly concentrated industries — petroleum fuels (dominated by state-owned PETROBRAS), ice cream (dominated by a transnational enterprise), yeast, and photographic equipment — contain only one firm that is larger than MES. An additional seven industries have only two firms larger than MES, eight have only three firms larger than MES, and 12 have only four firms larger than MES. The remaining 88 industries of the sample contain five or more firms larger than MES.

Following Davies and Lyons, I have performed a simple test of the fit of this model by regressing actual four-firm concentration ratios against those predicted by equation (6):

$$(8)\ CR4 = \underset{(0.011)}{-0.025} + \underset{(0.019)}{0.969}\ CR4'$$

$$R^2 = .959 \qquad n = 119$$

The standard errors of the intercept and slope are shown in parentheses. The result is quite similar to that found by Davies and Lyons with data for 100 industries in the United Kingdom. In particular, the slope is close to unity, indicating that the model is equally applicable to low and high concentration industries, and the intercept is negative, indicating a general tendency to overpredict actual concentration. Nonetheless, three differences are discernible in comparing the Brazilian results to theirs. First, the overall fit is somewhat better, with a coefficient of determination of 0.959, compared to 0.900 in the UK sample. Second, the residual plot shows a slight tendency for the regression to *overpredict* central values of CR4. This finding is opposite that of Davies and Lyons, who report (1982, p. 909, fn. 2) a tendency to *underpredict* central values of concentration ratios, but it confirms their results in the sense that the fit is better for large and small values of the concentration ratio. Third, and most important, the negative intercept is only one-third the size of that found with UK data, and it is less significant, achieving statistical significance only at the 3% level ($t = -2.21$).

Davies and Lyons provide an appealing explanation for the negative intercept in the regression of actual on synthetic concentration ratios. Their estimates of MES, like mine, refer strictly to minimum efficient *plant* size whereas the model is based on minimum efficient *firm* size. If multiplant economies are important, then minimum efficient scale for a firm will exceed that of a single plant and estimated MES will systematically underestimate true MES. Since θ is calculated from equation (5), an underestimate of MES can lead to an underestimate of θ, hence the overestimate of the concentration ratio.[7] In support of this hypothesis, Davies and

Lyons cite a correlation of -0.55 between the extent of overestimation of concentration ($Cr' - CR$) and their estimates of MES, which suggests that overprediction of concentration is smallest in industries with high MES for plants; these are precisely the industries in which differences between plant and firm scale economies are likely to be the smallest.

The present study lends considerable support to Davies and Lyons' explanation of the synthetic concentration ratio's tendency to overpredict actual concentration. The finding of a smaller and less significant intercept in the regression for Brazil compared to that for the United Kingdom is fully consistent with *a priori* expectations: multiple plant operations are not very common in Brazil, so differences between minimum efficient plant scale and minimum efficient firm scale are presumably smaller in Brazil than in the United Kingdom. Another finding consistent with these expectations is the weak correlation between overestimation of concentration in Brazil ($CR4' - Cr4$) and our estimates of MES: the correlation coefficient is only -0.14, which is not statistically significant.

4. DETERMINANTS OF SUBOPTIMAL CAPACITY AND THE RATE OF ENTRY

The "synthetic" concentration ratio expresses industrial concentration as a function of scale effects (MES/Q), the size of the suboptimal (Y) and the rate of entry (θ). Scale economies are determined by the state of technology and by relative factor prices. The question that remains is what determines suboptimal capacity and the rate of entry into an industry? This section addresses this question using standard regression techniques, but first a logistic transformation is applied to the dependent variables y and θ using the formulae $\log\,[y/(1-y)]$ and $\log\,[\theta/(1-\theta)]$. Log refers to the natural logarithm of the expression in brackets. These transformations convert variables that are bounded by zero and unity into variables more appropriate for ordinary least squares regression. The transformations also improve the fit of the equations, but the main conclusions are not affected when the equations are estimated with untransformed dependent variables.

(a) *Suboptimal capacity*

For the 119 industries of our sample, output from suboptimal plants as a proportion of total industry output averages 33% and ranges from a low of zero (safety matches) to a high of 83% (textile fibers). The logit of y is not defined for $y = 0$, so the safety match industry was deleted. For the remaining 118 industries, the following model was estimated:

$$y = f\,(\text{FOR ?, STATE } -, \text{ EXPORT } -, \text{ PROTECT } +, \text{ MES } +, \text{ Q } -, \text{ K/L or NWVA/L } -, \text{ ADV ?, GEOG } -, \text{ GROWTH ?}).$$

The expected signs of the coefficients are listed after each variable. The explanatory variables are identical to those used in the concentration regressions of Section 2, and the dependent variable is described in Table 3.

This model of the determinants of suboptimal capacity is similar to those estimated for the United States (Duetsch, 1973; Cory 1981) and Canada (Gupta, 1979; Dickson, 1979; Baldwin and Gorecki, 1985). The main difference is that the North American studies include the concentration ratio as an independent variable along with most of the remaining explanatory variables. Although all of the researchers find a strong inverse relationship between concentration and the extent of suboptimal capacity, it is difficult to explain this result in terms of concentration "causing" a decrease in suboptimal capacity. Indeed, a positive causal relationship is more likely, for "if oligopolistic leaders follow a limit-pricing policy this may permit smaller firms on the fringe of the industry . . . to continue to operate plants of less than MES and survive" (Duetsch, 1973, p. 218). Equation (6) above predicts an inverse relationship, but the causation is the reverse: concentration is high by definition where suboptimal capacity is low once one accounts for the effects of scale (MES/Q) and entry (θ) on concentration. There is no theoretical justification for the inclusion of concentration with a negative coefficient in a model in which suboptimal capacity is the dependent variable. Nonetheless, such regressions are included to show that in Brazil, as in North America, the coefficient of the concentration ratio (CR4) is negative and highly significant in a statistical sense.

Table 4 reports the regression results for four specifications of the equation. A White test indicates significant heteroskedasticity at the 10% level in each equation. While this is not a high level of significance for a single equation, it is very unlikely that this level would be obtained in all four equations by chance, so the heteroskedastic-consistent t ratios are reported in brackets below the OLS results. In most cases the two t ratios differ but little.

Both ownership variables prove to be highly significant additions to the regression model.

Table 3. *Description of the data: addendum (sample size = 119 four-digit industries)*

Variable	Description	Mean (std. dev.)
y	Output from suboptimal firms as a proportion of industry output	0.330 (0.220)
θ	Rate of entry, conceptually the proportional contribution of new entrants to industry growth, estimated from cross-section data as the ratio of MES to the average size of efficiently scaled firms	0.296 (0.150)
$\log\frac{y}{1-y}$	Logit of y, defined for 118 industries	−1.012 (1.464)
$\log\frac{\theta}{1-\theta}$	Logit of θ	−1.049 (0.973)

Foreign ownership has a negative effect on the amount of suboptimal capacity in an industry. This finding provides no support for a "miniature replica effect" of foreign investment in Brazil.[8] It is consistent with the hypothesis that foreign-owned firms exert competitive pressures on local firms, increasing their efficiency (Blomström and Persson, 1983) or driving them out of business (Newfarmer, 1979). The coefficient of STATE ownership is also negative and nearly twice as large as the coefficient for FOR. This is strong evidence that the presence of state enterprises discourages the existence of small firms in an industry, i.e., that it is state ownership that increases concentration rather than concentration that attracts state ownership. The size and significance of both FOR and STATE fall in equations (11) and (12) due to collinearity with the concentration ratio (CR4).

The size of the FOR and STATE coefficients in the logit regressions are somewhat difficult to interpret, so an example may be useful. In equation (9), each additional percent of industry output that originates in foreign-owned plants results in a decrease of 0.02303 in the logit of y, i.e., the logarithm of $[y/(1-y)]$. The effect of FOR varies with the level of y; at the mean of y (0.33) a percentage increase in foreign control (FOR) decreases suboptimal capacity by one-half a percentage point to 0.325. Similarly, for $y = 0.33$ a percentage increase in state ownership decreases the size of the suboptimal sector by one percentage point to 0.32.

Export opportunities and tariff protection can also affect the extent of suboptimal capacity in an industry. The existence of export markets provides an opportunity for firms to escape the constraints of the domestic market and expand their plants to minimum efficient scale. A negative coefficient is thus predicted for EXPORT. Protection from competing imports allows suboptimal, high-cost plants to survive, so a positive coefficient is expected for PROTECT. Both coefficients have the expected sign and tend to be significant at customary levels of confidence, confirming the results reported in three Canadian studies.

Scale economies combined with limited markets are believed to result in barriers to the entry of firms of minimum efficient scale (MES). Suboptimal capacity can be high in industries with large MES relative to industry size (Q) because of the price-depressing effects of suboptimal plants or the entry of new firms with MES plants. There is another, less noble, reason to expect a positive coefficient for MES: MES is measured with considerable error, and estimates of y are derived from estimates of MES. If MES is underestimated, so is y. There is reason then to expect a spurious correlation between y and MES simply because the measurement errors of the two variables are correlated. Since the coefficient of MES is highly significant, whereas that of Q is not, measurement errors seem to dominate the estimates of the coefficient of MES.[9] MES is best regarded as a control variable that purges the dependent variable of measurement error.

The coefficient of the capital-intensity variable is negative, and significant in each of the first two equations. The negative coefficient is expected, for capital-intensity is supposed to proxy the cost disadvantages of small-scale plants: the more capital-intensive an industry, the greater the indivisibilities and the greater the penalties of operating at less than minimum efficient scale.

The expected sign for ADV is ambiguous. Gupta (1979) found a positive coefficient, which he interpreted as evidence that advertising is a barrier to entry into the efficiently scaled sector

Table 4. *Determinants of suboptimal capacity (y)* (OLS regression results across 118 Brazilian industries, 1980)

Variable*	Equations (9)	(10)	(11)	(12)
Constant	−4.919 (−1.59) [−1.57]	−2.493 (−0.84) [−0.79]	4.899 (2.83†) [3.07†]	4.928 (2.91†) [3.09†]
Ownership				
FOR	−2.303 (−5.20†) [−4.42†]	−2.320 (−5.68†) [−5.04†]	−0.514 (−2.00‡) [−1.77§]	−0.562 (−2.25‡) [−1.99‡]
STATE	−4.279 (−4.18†) [−5.28†]	−4.222 (−4.72†) [−6.20†]	−0.628 (−1.08) [−1.44]	−0.746 (−1.39) [−2.01‡]
Trade				
EXPORT	−3.009 (−2.36‡) [−2.42‡]	−2.428 (−1.98‡) [−2.06‡]	−0.200 (−0.29) [−0.23]	−0.140 (−0.20) [−0.16]
PROTECT	0.188 (1.50) [1.57]	0.332 (2.74†) [2.78†]	0.117 (1.77§) [1.73§]	0.145 (2.14‡) [2.34‡]
Technology				
MES	0.719 (5.83†) [5.70†]	0.760 (6.39†) [6.06†]	0.809 (12.32†) [12.01†]	0.806 (12.36†) [12.04†]
Q	−0.130 (−1.31) [−1.36]	−0.167 (−1.76§) [−1.62*]	−0.747 (−11.68†) [−11.29†]	−0.745 (−11.67†) [−11.10†]
K/L	−0.377 (−2.37‡) [−2.68†]		−0.081 (−0.95) [−1.00]	
NWVA/L		−0.609 (−3.94†) [−3.97†]		−0.101 (−1.12) [−1.09]
Other				
ADV*C	−14.780 (−2.12‡) [−1.88§]	−15.489 (−2.32‡) [−2.34‡]	−3.740 (−1.00) [−0.95]	−3.977 (−1.06) [−1.06]
ADV*(1−C)	−2.515 (−0.28) [−0.50]	0.801 (0.09) [0.17]	0.176 (0.04) [0.06]	0.770 (0.16) [0.25]
GEOG	−0.919 (−2.28‡) [−2.27‡]	−0.811 (−2.13‡) [−1.93§]	−0.381 (−1.78§) [−1.63]	−0.361 (−1.71§) [−1.50]
GROWTH	−0.031 (−0.05) [−0.05]	0.265 (0.41) [0.45]	0.098 (0.28) [0.27]	0.125 (0.35) [0.35]
CR4			−4.899 (−16.68†) [−16.22†]	−4.834 (−15.74†) [−14.90†]
R^2	0.572	0.607	0.883	0.883

*The dependent variable is log $[y/(1\text{-}y)]$. Equations (9) and (10) are theoretically preferred. Statistics in parentheses are OLS t ratios; those in square brackets are heteroskedastic-consistent t ratios.
†Significant at the 1% level in a two-tailed test.
‡Significant at the 5% level in a two-tailed test.
§Significant at the 10% level in a two-tailed test.

of an industry, causing a larger proportion of firms to remain smaller than minimum efficient scale. His finding might also be interpreted as evidence of monopolistic competition, i.e., small firms that survive by differentiating their products through advertising. In our regressions, the coefficient of ADV is negative, but significantly so only for industries producing consumer goods. Brazilian industries thus reveal an inverse relationship between advertising and the size of the suboptimal sector. This result may reflect the existence of economies of scale in advertising, such that the cost disadvantage of a suboptimal firm is greater in industries with heavy advertising expenditures. It may also reflect technological dualism in Brazilian industries, with firms in the suboptimal sector producing simple products with no advertising and firms in the efficiently scaled sector producing branded and advertised products.

The index of geographic concentration (GEOG) is an inverse measure of regional segmentation of markets due to transportation costs. A negative coefficient is expected for this variable because high transportation costs allow suboptimal firms to survive in areas distant from the main centers of population. The findings reported in Table 4 conform to those expected for this variable.

The effect of growth on suboptimal capacity is an empirical issue, depending upon whether additional output tends to be produced in plants smaller than or larger than minimum efficient scale. Duetsch (1973) found for the United States an inverse relationship between growth of industry output and the extent of suboptimal capacity. The results reported in Table 4 suggest that in Brazil there is no systematic relationship between growth and suboptimal capacity. Gupta (1979) and Dickson (1979) report the same finding in their studies of Canada.

(b) *Rate of entry*

The rate of entry (θ) is defined as the proportional contribution of new entrants to total change in "industry" output, where "industry" excludes those firms that are smaller than minimum efficient scale (MES). Our data refer to a single year, so it was necessary to estimate θ as MES divided by the average size of efficiently scaled firms. These estimates average 0.30 and range from 0.01 (automobiles) to 0.64 (iron alloys). Those who are hesitant to read dynamic implications into cross-sectional data can regard θ as an inverse measure of the size of efficiently scaled firms, size being measured in units of MES plants. With either interpretation, increases in θ are desirable in that they represent possible gains in allocative efficiency through increased competition with no loss in technical efficiency. The same is not true for decreases in industrial concentration, for this might occur at the cost of inefficiencies resulting from an increase in the size of the suboptimal sector.

There is virtually no empirical work and, with the notable exception of Davies and Lyons (1982, pp. 911–918), very little empirically relevant theory concerning the determinants of inter-industry differences in the rate of entry. The size of the suboptimal sector, y, is an obvious candidate for an explanatory variable, for suboptimal firms need only grow to minimum efficient scale in order to "enter" the industry. The simple regression of θ on y is $\theta = 0.125 + 0.52\,y$ with a correlation coefficient of 0.77. On average, a percentage point increase in y is associated with an increase of one-half a percentage point in the rate of entry. Other variables suggested by Davies and Lyons are entry barriers, industry growth, the discount rate, demand elasticity and the expected behavior of new entrants.

Given the primitive state of existing theory and the limitations of our data, it seems reasonable to regress the logit of θ on y and on all of the explanatory variables used in the model of the determinants of y. This exploratory regression does not include all of the possibilities mentioned by Davies and Lyons, and it does include additional variables not mentioned by them, namely ownership, trade and geographic concentration. This admittedly *ad hoc* model has one serious defect: the main explanatory variable, y, is known to be a function of the remaining explanatory variables, which can result in severe problems of multicollinearity. Fortunately, in the present case multicollinearity was not a problem, but regression results are also presented excluding the variable y.

Table 5 reports the results of this exercise. The coefficient of suboptimal capacity (y) is positive as expected and highly significant in the presence of other explanatory variables. Correction for heteroskedasticity does not affect this conclusion. At the mean of θ (0.30), an increase of one percentage point in suboptimal capacity is associated with an increase of one-half a percentage point in the rate of entry, which is the same result obtained in the simple regression of θ on y.

The highly significant coefficients of FOR and STATE indicate that both foreign and stae ownership have direct, negative effects on entry into the efficiently scaled sector of an industry. This is in addition to the negative effect these

Table 5. *Determinants of entry at efficient scale (θ) (OLS regression results across 119 Brazilian industries, 1980)*

Variable*	Equations (13)	(14)	(15)	(16)
Constant	−4.946	−3.765	−4.101	−2.634
	(−2.89†)	(−2.22‡)	(−2.05‡)	(−1.37)
	[−2.91†]	[−1.77§]	[−2.19‡]	[−1.03]
Ownership				
FOR	−0.752	−0.745	−1.314	−1.314
	(−2.89†)	(−2.94†)	(−4.57†)	(−4.91†)
	[−2.32†]	[−2.29†]	[−4.04†]	[−4.06†]
STATE	−2.485	−2.332	−3.379	−3.282
	(−4.24†)	(−4.32†)	(−5.06†)	(−5.57†)
	[−4.37†]	[−4.61†]	[−5.35†]	[−6.35†]
Trade				
EXPORT	−1.215	−1.159	−2.165	−1.835
	(−1.67§)	(−1.60)	(−2.59‡)	(−2.25‡)
	[−1.53]	[−1.47]	[−2.53‡]	[−2.31‡]
PROTECT	0.031	0.054	0.060	0.134
	(0.43)	(0.75)	(0.73)	(1.66§)
	[0.43]	[0.75]	[0.91]	[1.94§]
Technology				
MES	0.339	0.369	0.521	0.553
	(4.76†)	(5.06†)	(6.80†)	(7.36†)
	[3.84†]	[4.51†]	[6.33†]	[6.98†]
Q	−0.145	−0.154	−0.159	−0.181
	(−2.62†)	(−2.78†)	(−2.45‡)	(−2.86†)
	[−2.63†]	[−2.71†]	[−2.50‡]	[−2.59†]
K/L	−0.000		−0.178	
	(−0.01)		(−1.71§)	
	[−0.00]		[−1.75§]	
NWVA/L		−0.123		−0.326
		(−1.29)		(−3.22†)
		[−1.12]		[−2.70†]
Other				
ADV*C	−6.658	−7.228	−11.518	−11.909
	(−1.67§)	(−1.82§)	(−2.51‡)	(−2.68†)
	[−2.04‡]	[−2.09‡]	[−2.65†]	[−3.01†]
ADV*(1−C)	−4.312	−3.441	−1.736	0.366
	(−0.86)	(−0.68)	(−0.30)	(0.06)
	[−1.29]	[−1.05]	[−0.56]	[0.12]
GEOG	−0.186	0.143	−0.201	−0.172
	(0.81)	(0.64)	(−0.77)	(−0.69)
	[0.87]	[0.64]	[−0.85]	[−0.70]
GROWTH	0.211	0.300	−0.009	0.151
	(0.57)	(0.81)	(−0.02)	(0.36)
	[0.55]	[0.82]	[−0.02]	[0.41]
y	2.136	1.976		
	(6.42†)	(5.83†)		
	[6.32†]	[6.82†]		
R^2	0.697	0.702	0.579	0.606

*The dependent variable is log [θ/(1-θ)]. Equations (13) and (14) are theoretically preferred. Statistics in parentheses are OLS *t* ratios; those in square brackets are heteroskedastic-consistent *t* ratios.
†Significant at the 1% level in a two-tailed test.
‡Significant at the 5% level in a two-tailed test.
§Significant at the 10% level in a two-tailed test.

variables have on entry because of their effect on y, the size of the suboptimal sector. The point estimates of the coefficients suggest that at the mean rate of entry ($\theta = 0.30$) an increase of seven percentage points in foreign control results in a reduction in θ to 0.29 whereas an increase of only two percentage points in state ownership produces the same reduction in the rate of entry. It is, of course, conceivable that causation runs from low rates of entry to foreign and state ownership rather than the reverse. If entry is easier for foreign than for domestic firms, industries with low rates of entry may "attract" a disproportionate number of transnational subsidiaries. Similarly, low rates of entry may attract state enterprises that attempt to socialize the monopoly profits. Cross-section data with a univariate model are not appropriate for tests of causality; a definitive study must await time-series data or a more complex, multivariate regression model. Nonetheless, the fact that the coefficients of both ownership variables are highly significant when they enter regression equations along with other variables lends support to the thesis that the causation runs from foreign and state ownership to low rates of entry.

The trade variables add very little to the regression, so it appears that any effect they have on the rate of entry comes mainly through their effect on y, the size of the suboptimal sector. Nonetheless, it is interesting to note that the rate of entry is somewhat higher in industries with low exports and high protection. This reinforces, through not significantly, the effects that occur through y. The negative sign for the coefficient of EXPORT is opposite that which might have been predicted, for one would expect a higher rate of entry into industries where firms can easily overcome the demand constraint through exports.

The coefficients of the scale variables, MES and Q, are both significant, but the signs are opposite that expected if economies of scale act as a barrier to entry. This probably results from the fact that the dependent variable is estimated indirectly as MES divided by the average size of efficiently scaled firms. The positive coefficient of MES could result from spurious correlation with θ and the negative coefficient for industry size means nothing more than the larger the industry the larger the average size of the efficiently scaled firms.

The coefficient of capital intensity is not significant, an indication that capital intensity in itself does not constitute a barrier to entry in Brazilian industries. This result contrasts sharply with the inverse relationship found between y and capital intensity, and supports the use of capital intensity as a proxy for the cost disadvantage of a suboptimal plant. The absolute capital requirements of a plant of minimum efficient scale is a better measure of capital intensity as an entry barrier, but the coefficient of this variable was similarly not significantly different from zero in an experimental regression not reported here.

None of the remaining variables perform very well, but there is evidence that, at least for industries producing consumer goods, high advertising expenditures directly restrict entry into the efficiently scaled sector. This is in addition to the negative, indirect effects of advertising on entry through the reduction in the size of the suboptimal sector.

5. CONCLUSIONS

The statistical analysis of this paper demonstrates that factors that influence industrial structure in other parts of the world are also determinants of industrial structure in Brazil. By far the most interesting finding is that the presence of transnational enterprises has an independent and positive effect on industrial concentration. This finding is opposite that found for developed countries, where foreign ownership of plants tends to increase competition and reduce concentration in industries of the host country. (See Caves, 1982, ch. 4 and the references cited therein). It coincides with findings of the two existing studies of developing countries: Malaysia (Lall, 1979) and Mexico (Blomström, 1986). It is thus very probable that the effect of foreign ownership on industrial structure differs depending on whether the host economy is developed or underdeveloped.

Foreign ownership increases concentration in Brazilian industries both by reducing suboptimal capacity and by reducing the rate of entry of firms at efficient scale, so it is not possible to conclude, with the evidence at hand, whether the net effect of the increased concentration is beneficial or harmful to the host country. Foreign ownership also has positive, indirect effects on concentration through its effect on other determinants of industrial structure such as exports, capital intensity and advertising (Willmore, 1985 and 1986).

Other findings of interest can be summarized as follows:

(1) State ownership has a positive effect on concentration due to a negative effect on suboptimal capacity and a negative effect on entry of new firms into an industry. These effects are similar, but much stronger, than those observed for foreign ownership. It appears that large state

enterprises inhibit, to a much greater extent than transnational enterprises, the entry of privately owned firms of any size.

(2) High export ratios and low effective protection are both associated with less suboptimal capacity. Exports allow small firms to reduce costs by growing to minimum efficient scale. Tariff barriers allow suboptimal firms to survive by supplying domestic consumers at high cost.

(3) As expected, there is a strong, positive relationship between minimum efficient scale (MES) and the size of the suboptimal sector. Nonetheless, the regression equations show increased MES to have a positive effect on the rate of entry into an industry. This surprising result stems from spurious correlation: MES is measured with considerable error, and estimates of the rate of entry are derived from estimates of MES. This illustrates the need for improved MES estimates if work on the determinants of industrial structure in Brazil is to advance.

(4) Capital intensity has a positive effect on industrial concentration. There is little evidence that capital intensity acts as a barrier to the entry of efficiently scaled firms, for its direct effects are limited to the size of the suboptimal sector. Capital intensity seems to perform as a proxy for the cost disadvantage of small-scale plants: the more capital-intensive an industry, the greater the indivisibilities and the greater the penalties of operating at less than minimum efficient scale.

(5) Advertising expenditures have an independent, positive effect of industrial concentration, at least in industries producting goods for final consumption. This is due both to the association of advertising with low rates of entry and to the association of advertising with low amounts of suboptimal capacity. This implies that potential entrants and firms of suboptimal size face greater cost disadvantages in industries with high levels of advertising. It may also reflect technological dualism, with advertising expenditures concentrated in the efficiently scaled sector of each industry.

NOTES

1. In long-run equilibrium any firm smaller than 2MES would operate only one plant. "When looking at any one point in time, however, we cannot hope to observe long-run equilibrium. We therefore take a probabilistic approach to the firm's decision to set up a second plant . . ." (Lyons, 1980, p.22).

2. The White test consists of regressing the squared residuals on the products and cross-products of all explanatory variables from the original regression. The coefficient of determination of this artificial regression, when multiplied times the number of observations is asymptotically distributed as a Chi-square statistic with $k(k+1)/2$ degrees of freedom, k being the number of regressors in the original equation. White's variance-covariance matrix is

$$(X'X)^{-1}V(X'X)^{-1}$$

where X is the k by n matrix of explanatory variables and

$$V = n^{-1} \sum_i \hat{u}^2 (X_i'X_i), \quad i = 1, 2, \ldots, n.$$

3. It is interesting to note that the positive correlation between concentration and foreign control in Guatemala (Willmore, 1976) and Brazil (Willmore, 1987) is not attributable solely to the size distribution of foreign-owned firms.

4. As Evans (1977) might predict, the pharmaceutical industry is an outlier in equations (1) and (2). The actual four-firm concentration ratio is .31; the estimated ratio is .57 in equation (1) and .56 in equation (2).

5. Lall (1979) also found in Malaysia a positive association between advertising outlays and concentration, but Blomström (1986) found a *negative* and highly significant coefficient for advertising in his Mexican study.

6. The density function of the Yule distribution is given by $f(s) = KB\ (S, \alpha + 1)$ where S is firm size, K and α are parameters, and $B\ (S, \alpha + 1)$ is the Beta function of S and $(\alpha + 1)$. As S tends to infinity, $f(s)$ tends to $AS^{-(\alpha+1)}$ which is the well-known Pareto distribution, with parameters A and α.

7. Note, however, that estimates of $\bar{S}$ will be biased downwards if MES is underestimated, and this can offset the downward bias in estimates of θ.

8. Gupta (1979) also found a significantly negative coefficient for foreign ownership in Canada, the home of the "miniature replica effect," but Baldwin and Gorecki (1985) were not able to replicate his result.

9. The coefficient of industry size (Q) becomes highly significant when the concentration ratio (CR4) is included as an explanatory variable, but there is no theoretical justification for the inclusion of CR4 with a negative coefficient.

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APPENDIX: DERIVATION OF THE FOUR-FIRM CONCENTRATION RATIO FROM THE SIMON-BONINI GROWTH MODEL

Since the inequality parameter of the Pareto distribution is a function of the rate of entry (θ), *viz.*,

$$(3.0)\quad \alpha = 1/(1-\theta),\quad 0 \leqslant \theta < 1$$

it follows that θ can also be expressed in terms of α:

$$(3.1)\quad \theta = 1 - (1/\alpha)\quad \text{for } \alpha \geqslant 1.$$

Note that α is an inverse measure of size inequalities, so θ is equal to zero (blockaded entry) when α is equal to unity and approaches unity as α approaches infinity.

The cumulative function of the Pareto distribution can be written as

$$(3.2)\quad F(S) = (MES/S)^{\alpha}\ \text{for } S > MES.$$

(See Klein, 1962, p. 151) $F(S)$ is the proportion of firms larger than size S and MES is minimum efficient scale, i.e., the smallest size of firm that minimizes unit costs of production. MES must be equal to or larger than the smallest firm in the Pareto distribution. Equation (3.2) can be rewritten replacing α with $1/(1-\theta)$:

$$(3.3)\quad F(S) = (MES/S)^{1/(1-\theta)}.$$

Let $S5$ be the size of the fifth largest firm and N be the number of firms equal to or larger than MES. If $S5 \geqslant$ MES, then $4/N$ is the proportion of firms larger than $S5$ and it follows from equation (3.3) that

$$(3.4)\quad 4/N = (MES/S5)^{1/(1-\theta)}.$$

Solving equation (3.4) for $S5$,

$$(3.5)\quad S5 = MES\ (4/N)^{\theta-1}.$$

The aggregate size of firms larger than MES may be defined as N times the average size of firms larger than MES:

$$(3.6)\quad \Sigma S \equiv N\bar{S}.$$

This definition allows us to rewrite equation (3.5) as:

$$(3.7)\quad S5 = MES(4\bar{S}/\Sigma S)^{\theta-1}.$$

If $\alpha > 1$, which implies a value for θ greater than zero, then the mean size of all firms exceeding a given value in the Pareto distribution is equal to $\alpha/(\alpha-1)$ times that value. It follows that the mean size of firms larger than MES is

$$(4.0)\quad \bar{S} = (\alpha/\alpha-1)MES.$$

Since θ is equal to $(\alpha-1)/\alpha$, this implies that

$$(5.0)\quad \theta = MES/\bar{S}$$

and, from equation (3.7),

$$(5.1)\quad S5 = MES[(4/\Sigma S)(MES/\theta)]^{\theta-1}.$$

If $\bar{S}4$ is the average size of the four largest firms in an industry, then

$$(5.2)\quad \bar{S}4 = (\alpha/\alpha-1)S5 = S5/\theta$$

from the characteristic of the Pareto distribution that the mean size of all firms exceeding a given value is equal to $\alpha/(\alpha-1)$ times that value.

Combining equations (5.1) and (5.2),

$$(5.3)\quad \bar{S}4 = (MES/\theta)^{\theta}\ (4/\Sigma S)^{\theta-1}.$$

Let Q equal total industry output. The four-firm concentration ratio can then be defined as

$$(5.4)\quad CR4 \equiv 4\ \bar{S}4/Q.$$

Substituting the expression from equation (5.3) for $\bar{S}4$, the "synthetic" concentration ratio can be expressed as

$$(5.5)\quad CR4' = (4/Q)(MES/\theta)^{\theta}\ (4/\Sigma S)^{\theta-1}.$$

Let y be the share of firms smaller than MES, such that

$$(5.6)\quad \Sigma\ S \equiv (1-y)Q.$$

Substituting this expression for ΣS in equation (5.5) produces

$$(5.7)\quad CR4' = (4/Q)\ (MES/\theta)^{\theta}\ [(1-y)Q]^{1-\theta}4^{\theta-1}.$$

Simplifying, equation (5.7) becomes

$$(6.0)\quad CR4' = (1-y)^{1-\theta}\ [(4/\theta)(MES/Q)]^{\theta}$$

which is the synthetic concentration ratio given in the text.