CICLOS DE NEGÓCIOS E COMPORTAMENTO COLUSIVO : ALGUMAS EVIDÊNCIAS EMPÍRICAS DE SETORES INDUSTRIAIS BRASILEIROS

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RESUMO

Há um grande interesse recente, tanto a nível teórico quanto a nível empírico, na aplicação de superjogos para tentar entender o comportamento dos oligopólios. Uma razão é a importância das estratégias de precificação como reposta às mudanças na demanda agregada, o que é de particular relevância para considerações de políticas públicas. Neste trabalho, contrastamos as predições para movimentos de preços ao longo dos ciclos de negócios de dois modelos, e comparamos as evidencias empíricas obtidas ara o Brasil com aquelas obtidas para os setores da industria americana da transformação.

Para os setores industriais brasileiros utilizamos análise de dados em painel para tentar inferir em que medida os ciclos econômicos afetam o comportamento colusivo. O estudo usa dados das firmas líderes da industria brasileira da transformação obtidos da Pesquisa Industrial Anual produzida pelo Instituto Brasileiro de Geografia e Estatística (PIA/IBGE), e dados do Instituto de Pesquisa Econômica Aplicada (IPEA) para construir um painel de dados de variáveis para 22 setores industriais brasileiros, tais como margem preço custo (PCM), medidas de concentração industrial (CR4) e utilização de capacidade instalada da industria da transformação (CU).

Os modelos estimados verificam a robustez e como estes indicadores afetam o comportamento colusivo das firmas líderes brasileiras da industria da transformação durante as oscilações dos ciclos de negócios no período 1986-1995. O trabalho também foca na capacidade das firmas de agirem cooperativamente para construírem e manterem um cartel em um ambiente econômico particular.

Os parâmetros das equações foram estimados por Mínimos Quadrados Ordinários e Máxima Verossimilhança. O primeiro foi utilizado em pool cross section e em especificações com efeitos fixos no intecepto, e o segundo nas especificações com efeitos fixos no intercepto e efeitos aleatórios setoriais nos parâmetros.

Nossos principais resultados são :
1) Não há uma relação homogênea entre concentração e margem preço custo nos setores industriais brasileiros. De fato, em alguns casos, altos níveis de concentração estão associados a baixos níveis de margem preço custo.
2) O sinal dos parâmetros da industria como um todo não é o mesmo para cada setor. Para a industria como um todo, CR4 é positivo, o que significa que altos níveis de concentração ajudam a aumentar as margens preço custo. Entretanto, os efeitos aleatórios setoriais nos dizem que este fato não se verifica em alguns casos quando analisamos cada setor. As punições por não participar do cartel não são eficientes em todos os casos.
3) Considerando que a utilização de capacidade instalada nos diz se as margens preço custo são pró ou contra cíclicas, para a industria como um todo e para os setores, PCM é procíclica.
4) Aumento do estoque de capital não ajuda a aumentar PCM. Pelo contrário, reduz PCM.
5) Os efeitos macroeconômicos de 1992,1993 e 1994 ajudaram a aumentar PCM
6) O comportamento colusivo nos subperíodos 1986-1990 e 1992-1995 são diferentes do comportamento colusivo detectado para o período como um todo.

PALAVRAS CHAVES : Análise de Dados em Painel. Comportamento Colusivo de Oligopólios. Ciclos de Negócios.

Códigos JEL : L13, L16, C33, C72 Classificação ANPEC : area 04

ABSTRACT

Recently there has been new interest in the focus of theoretical and empirical research level in the application of supergames to oligopoly behavior. One reason is the importance of pricing behavior in trigger-strategy models in response to aggregate demand, which are of particular relevance for public policy considerations. In this paper, we contrast the predictions for price movements over the business cycles of two such models; and the empirical evidence in Brazil compared with that of American manufacturing industries.

For Brazilian manufacturing industries, the work applies a panel data framework to analyze how business cycles affect collusive behavior. The study uses data from Brazilian leading firms within each manufacturing sector from the Brazilian annual industrial research (PIA) produced by the Brazilian Census Bureau (IBGE); and data from Brazilian

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Applied Economic Research Institute (IPEA) to build a panel data of variables for 22 Brazilian manufacturing sectors, which includes price-cost margin(PCM), measures of industry concentration (CR4) and capacity utilization (CU).

The estimated models check the robustness and the way these indicators affect collusive behavior of Brazilian leading firms during the swings of the business cycles over the period 1986-1995. The work also focuses on the strength of the cooperative attitude of firms in building up and maintaining a cartel in a particular macroeconomic environment.

To estimate the parameters of the equations, we use Ordinary Least Squares and Maximum Likelihood methods. We use the first in pool cross sections and time fixed effects in intercept specifications, and the second in time fixed effects in intercepts and sectorial random effects in parameters.

Our main results are :

1) There is no homogeneous relationship between concentration and price-cost margin in Brazilian industrial manufacturing sectors. In fact, in some cases, higher concentration levels means low price-cost margin levels.
2) The sign of the parameters for the industry as a whole is not the same for each sector. For the industry as a whole, CR4 is positive, which means that high concentration levels help improve price-cost margins. However, sectorial random effects tell us that this fact does not hold in some cases when we analyze each sector. Punishments for not participating in the cartel is not efficient in all cases.
3) Considering that capacity utilization tells us whether the price-cost margins are pro or countercyclical, for the industry as a whole and all sectors, PCM is procyclical. This means that the behavior of leading firms are like the Green and Porter (1984) model predicts.
4) Improvement of capital stock does not help improve PCM. On the contrary, it reduces PCM.
5) The macroeconomic effects in 1992, 1993 and 1994 helped improve PCM.
6) Collusive behavior in sub-periods 1986-1990 and 1992-1995 is not the same for the period as a whole.

KEYWORDS : Panel Data Analysis. Oligopoly Collusive Behavior. Business Cycles.

1. INTRODUCTION

Recent game theoretic developments, like the supergame models developed by Green and Porter (1984) and Rotemberg and Saloner (1986) offer excellent approaches to explain collusion during business cycles. The first model predicts that margins should exhibit procyclical behaviour, while the second suggests anticyclical margins.

Although classical empirical approaches usually apply cross section analysis, as shown in Schmalensee (1989), recent empirical works have used panel data analysis, whose results are much stronger than cross-section outcomes. An example is the results to United States detected by Domowitz, Hubbard and Peterson (1986A and B).

In this paper, we contrast the predictions for price movements over the business cycles of two such models; and the empirical evidence in Brazilian, compared to American, manufacturing industries.

For Brazilian manufacturing industries, the work applies a panel data framework to analyze how business cycles affect collusive behavior. The study uses data from Brazilian leading firms within each manufacturing sector from the Brazilian annual industrial research (PIA) produced by the Brazilian Census Bureau (IBGE); and data from Brazilian Applied Economic Research Institute (IPEA) to build a panel data for 22 Brazilian manufacturing sectors which includes price-cost margin (PCM), measures of industry concentration (CR4) and capacity utilization (CU).

The estimated models check the robustness and the way these indicators affect collusive behavior of Brazilian firms during the swings of the business cycles over the period 1986-1995. The work also focuses on the strength of the cooperative attitude of firms in building up and maintaining a cartel in a particular macroeconomic environment.

To estimate the parameters of the equations, we use Ordinary Least Squares and Maximum Likelihood methods. The first one in pool cross sections and time fixed effects in intercept specifications, and the second in time fixed effects in intercepts and sectorial random effects in parameters.

Our main results are :

1) An homogeneous relationship between concentration and price-cost margin does not exist in many leading firms in each Brazilian industrial manufacturing sectors. In fact, in some cases, higher concentration levels means low price-cost margin levels.
2) The sign of the parameters for the industry as a whole is not the same for each sector. For the industry as a whole, CR4 is positive, which means that high concentration levels help improve price-cost margins. However, sectorial random effects tell us that this fact does not hold in some cases when we analyze each sector. Punishments for not participating in the cartel is not efficient in all cases.
3) Considering that capacity utilization tells us whether the price-cost margins are pro or countercyclical, for the industry as a whole and all sectors PCM is procyclical. This means that the behavior of leading firms are like the Green and Porter (1984) model predicts.
4) Improvement of capital stock does not help improve PCM. On the contrary, it reduces PCM.
5) The macroeconomic effects in 1992, 1993 and 1994 helped improve PCM.
6) Collusive behavior in each sub-period is not the same for the period as a whole. Firms in 1986-1995 worked according to Green and Porter model, but had not a definite strategy in 1986-1990 and worked according to Rotemberg and Saloner(1986) model in 1992-1995.

The theory that we use to interpret the results is presented in section 2; in section 3 we discuss the data base and the variables; in section 4 we discuss the econometric models; in section 5 we present the results of our estimated models and interpretations; in section 6 we offer some conclusions; and in section 7 we summarize the references that we used.

2. THEORY

According to Schmalensee (1989) inter industry studies of the relations among market structure, conduct and performance began with Bain (1951,1956) involving detailed case studies of particular industries. During the 1960s, research interest shifted from industry studies to inter-industry work.

Nevertheless, a number of critics have been testing the data and methods used in inter-industry research and the interpretation of their findings. According to Schmalensee (1989) an important shift has happened in the theory of imperfectly competitive markets and in the econometric industry studies employing formal models of conduct. However, this has not been shown to be enough to explain collusive behavior over business cycles. Recent game theoretic developments, like the supergame models proposed by Green and Porter (1984) and Rotemberg and Saloner (1986) offer an excellent approach to explain collusion during business cycles .

Shapiro (1989) calls attention to the fact that in infinitely repeated oligopoly games (supergames) the requirement that threats be credible turns out to be much less restrictive than it was in finite horizon games.

Formally, a supergame consists of an infinite number of repetitions of some stage game. The repetitions take place at dates t=0, 1, ... , with player i's action at date t denoted by x_{it} , i=1 , ..., n . $\pi_{it} = \pi_i(x_t)$ is player i's period-t payoff if the vector of actions $x_t=(x_{1t}, x_{2t}, ..., x_{nt})$ is played at date t. Considering $0<\delta<1$ the per- period discount factor, player i's overall payoff in the game is given by

$$\pi_{it} = \sum_{t=0}^{\infty} \delta^t \pi_{it}$$

The game beginning at date t looks the same for all t's, in the sense that the feasible strategies and the prospective payoff that they induce are always the same. History matters only because the firms remember what has happened in the past and condition their current actions on previous behavior .

Supergames are well suited for the exploration of the efficacy of tacit collusion. In this way, the following question appears : Can the oligopolists, without any explicit collusion, support the profit-maximization outcome purely with credible threats to punish any defector who failed to cooperate with the proposed collusive arrangement ?

In Green and Porter's (1984) model , they examine the nature of a cartel self-enforcement in the presence of demand uncertainty using a noncooperative game. They are considering that other game theories have shown that , in principle, it may be possible for firms in an industry to form a self-policing cartel to maximize their joint profits .

They are studying a situation in which demand fluctuation is *not directly observed* by firms which lead to unstable industry performance . They make four hypotheses : first, the industry is presumed to be stable over time; second, output quantity is assumed to be the only decision variable which firms can manipulate; third, information about the industry and its environment is public; and fourth, the information which firms use to monitor whether the cartel is in a collusive or reversionary state must be imperfectly correlated with the firm's conduct (it means that reversion would never occur) .

The intuition behind this model is that firms will act monopolistically while prices remain high, but they will revert to a Cournot behaviour when prices fall. It means that firms agree with a trigger price to which they compare the market price when they set their production. Whenever the market price dips below the trigger price while the firm-set has been acting monopolistically, they will revert to a Cournot behaviour for some fixed amount of time before resuming monopolistic conduct. If, at a given time, firms are supposed to be colluding, and a firm produces more than its share of the monopoly output, then its net return at that time will increase. Anyhow, by increasing the probability that the market price will fall below the trigger price, the firm incurs a greater risk that the industry will enter a reversionary episode during which profits will be low for everyone. If the firms are producing their monopolistic share to be the firms noncooperatively optimal action, the marginal expected loss in future profits from possibly triggering a Cournot reversion must exactly balance the marginal gain from over-producing . [3]

Green and Porter (1984) show that the industry might produce at a monopolistic level most of the time in a Nash equilibrium in trigger price strategies. Firms will initially produce their respective shares of this restricted industry output, and will continue to do so until the market price falls below the trigger price (p*) . Then they will produce Cournot outputs for the duration of the reversionary episode, regardless of what happens to prices during this time . At the conclusion of the episode, t periods after the price drop, they will resume the monopolistic production . This will continue until the next time that $p_t<p^*$ and so on .

Note that the marginal return to a firm from increasing its production in normal periods must be offset exactly by the marginal increase in risk of suffering a loss in returns by triggering a reversionary episode . Finally, there are two more observations : no firm ever defects from a cartel ; and it is rational for them to participate in reversionary episodes .

Rotember and Saloner (1986) explore the response of oligopoly to fluctuations in the demands for their products, considering *observable* shifts in industry demand.

Consider N symmetric firms producing a homogeneous good in an infinite-horizon setting; and an inverse demand function as $P(Q_t, \varepsilon_t)$. Let Q_t be the industry output in period t and ε_t is the realization at t of ε^*, the random variable denoting the observable demand shock . They assume that P is increasing in ε_t, that ε^* has the domain $[\varepsilon^*, \varepsilon_*]$ and a distribution function $F(\varepsilon)$, and that these are the same across periods . They denote firm i's output in period t by q_{it} so that

$$Q_t = \sum_{i=1}^{N} q_{it}$$

At the beginning of each period, all firms learn the realization of ε^*. Firms then simultaneously choose the level of their choice variable (price or quantity). These choices then determine the outcome for that period in a way that depends on the choice variable. In the case of quantities, the price clears the market given Q_t; in the case of prices, the firm with the lowest price sells as much as it wants at its quoted prices. The firm with the second lowest price then supplies as much of the remaining demand at its quoted price as it wants, and so forth. The strategic choices of all firms then become common knowledge and this one-period game is repeated.

[3] For appropriated distributions of demand disturbance, reversionary episodes can occur without any firm defecting, only because of low demand . In this way, over a long period, Cournot and collusive behavior will be observed at various times as well .

The observation of ε_t causes the following effect : the punishments that firms face depend on the future realization of ε^* . The expected value of such punishments therefore depends on the expected value of ε^* . However, the benefit for cheating in any periods depends on the observable ε^*. The consequence is that, if punishments are larger enough to outweigh the gain from cheating, then the collusive outcome is sustainable. Implicitly colluding oligopolies are likely to behave more competitively in periods of high demand. During those periods, many oligopolistic industries tend to have relatively low prices. *Implicit collusion is more difficult when their demand is relatively high.*

When demand is relatively high and price is the strategic variable, the benefit to a single firm from undercutting the price that maximizes joint profits is larger . A firm that (modestly) lowers its price gets to capture a larger market until the others are able to change their prices . The punishment from deviating is less affected by the state of demand if punishments are meted out in the future, and demand tends to return to its normal level . Thus, when demand is high, firm can expect the benefit from deviating from the output that maximizes joint profits may exceed the punishment for deviating .

Those results confront the traditional industrial organization theory, which is that price wars occur in recessions . In fact, if collusion is stronger in booms than in busts, it is an empirical question .

Empirical evidences

Domowitz, Hubbard and Petersen (1986B) found some empirical evidences from 57 American manufacturing industrial sectors using panel data analyses and information on four-digit-SIC level manufacturing industries over the period 1958 to 1981. For each category of industries they model the PCM as a function of industry measures of concentration (C4), capital-output-ratio (K/Q), advertising-sales ratio (A/S) and capacity utilization in manufacturing (CU) , this last one as a measure of aggregate demand. They estimated poll cross section and fixed effects via Ordinary Least Squares (OLS) the following equation:

$$PCM_{it} = \beta_0 + \beta_1 C4_{it} + \beta_2 (K/Q)_{it} + \beta_3 (A/S)_{it} + \beta_4 CU_t + \varepsilon_{it} ,$$

where i and t denote the industry and time period, respectively .

The principal results are :

1) the levels of price-cost margins of concentrated, homogeneous-good industries, while higher than those of unconcentrated counterparts, appear to be close to those predicted by a single-period Cournot-Nash equilibrium than monopoly.
2) There is little evidence to support the idea that price cost margins of these industries have different cyclical patterns from other industries apart from effects by level of industry concentration.
3) Maximum price declines for concentrated industries give little support for the occurrence of price wars during either recessions or booms.
4) Finally, consistent with the predictions of the Rotemberg-Saloner model, the industries with high price-cost margins have more countercyclical price movements than those exhibited by other industries. That gradual price adjustment is quantitatively important for those industries, suggests, however, that other factors may lie behind the apparent rigidity of prices.

3. ECONOMETRIC MODELS

According to Hsiao (1986), a panel data set is one that follows a given sample of individuals over time, providing multiple observations on each individual in the sample. The use of panel data provides a means of resolving or reducing the magnitude of a key econometric problem that often arises in empirical studies, namely, the real reason of one finds (or does not find) certain effects is because of omitted (mismeasured, not observed) variables that are correlated with explanatory variables. The oft-touted power of panel data derives from their theoretical ability to isolate the effects of specific actions, treatments or more general policies.

When only a few observations are available for different individuals over time, it is exceptionally important to make the most efficient use of the data across individuals to estimate that part of the behavioral relationship containing variables that differ substantially from one individual to another, in order that the lesser amount of information over time can be used to best advantage for estimation of the common part of the relationship studied.

Aggregated time-series data are not particularly useful for discriminating between hypotheses that depend on microeconomic attributes. Nor will a single individual time series data set provide information on the impact of different socio-demographic factors. Cross-sectional data, while containing variations in microeconomic variables cannot be used to model dynamics. The estimated coefficients from a single cross section are more likely to reflect interindividual or interfirm behavior. In fact, it is impossible to make inference about dynamics of change from cross-sectional evidence.

Among the advantages that panel data has over conventional cross-sectional or time-series data sets, we can list :

- A larger number of data points, increasing the degrees of freedom and reducing the collinearity among explanatory variables – hence improving the efficiency of econometric estimates.
- Allow analyze a number of important economic questions that can not be addressed using cross-sectional or time-series data sets. Whereas dynamic effects typically cannot be estimated using a cross-sectional data set, a single time-series data set cannot usually provide precise estimates of dynamic coefficients either.

Panel data models are classified according to the intercept and slopes. It is possible (1) homogeneous intercepts and slope, it means the intercept and parameters are the same for all units of analyze and over time (pool cross section); (2) heterogeneous intercepts and homogeneous slopes, it means the intercepts can vary through time or among the units of analyzes, being fixed or random, and the parameters can be the same for all units of analyze and over time; (3) or Heterogeneous intercepts and slopes, it means the intercept and slopes can vary through time or among the units of analyze, being fixed or random.

The fixed-effects model is viewed as one in which investigators make conditional inferences on the effects that are in the sample. The random-effects model is viewed as one in which investigators make unconditional or marginal inferences with respect to the population of all effects.

There are some of the likely biases when parameter heterogeneities among cross-sectional units are ignored. Similar patterns of bias will also arise if the intercepts and slopes vary through time, even though for a given time period they are identical for all individuals. When data do not support the hypothesis of coefficients being the same, yet the specification of the relationships among variables appears proper, then it would seem reasonable to allow variations in parameters across cross-sectional units and/ or over time as a means to take account of the interindividual and/or interperiod heterogeneity. With panel data, we can use a different transformation of the data to induce different and deductible changes in the biases in the estimated parameters that can the be used to identify the importance of measurement errors and recover the "true" parameters, changing economic structures that imply that the response parameters may be varying over time and/ or may be different for cross-sectional units.

Intimately related to the problem of efficient use of the data is the issue of fixed-effects or random-effects inference. To decided what model is better, it is useful to use Akaike Information Criteria (AIC) and Residual Standard Error (RSE).

4. DATA AND VARIABLES

The study uses data from Brazilian leading firms within each manufacturing sector from the Brazilian annual industrial research (PIA) produced by the Brazilian Census Bureau (IBGE); and data from Brazilian Applied Economic Research Institute (IPEA) to build a panel data of variables for 22 Brazilian manufacturing sectors for the period 1986-1995 which includes price cost margin, measures of industry concentration, capital output ratio and capacity utilization. Some data for 1991 are not available.

The sample data was used for define 4 variables: PCM, or price-cost-margin, that is (value of sales – payroll – cost of materials) / value of sales; CR4, or concentration ratio for the 4 biggest leading firms in each manufacturing sector; K/Q or capital/output ratio, that is fixed capital stock/ value of sales; and CU, or capacity utilization, that is the percentage of production capacity used in each year for the industry as a whole. PCM, CR4 and K/Q have time and unit dimension and we get from IBGE. CU has only time dimension and we get from IPEA. As Domowitz, Hubbard and Peterson (1986B) proposed, CU is used as a measure of aggregate demand.

First we estimate the parameters as a pool cross section. However, there is possible specification problems. [4] So, we include time and sector effects (fixed and random) in intercept and in slopes. In the next section we show the main results.

5. RESULTS

5.1 DESCRIPTIVE STATISTICS

The variables summary statistics and the correlations among variables give us a first idea of how the variables are related. As we can see in Table 1A, almost all variables has strong variability in the panel. The exception is aggregated industry capacity utilization. Considering Table 1B, price-cost margin (PCM) is positively correlated with concentration ratio (CR4) , and negatively with the natural logarithm of capital-output ratio (Ln(K/Q))[5] and capacity utilization (CU). Table 1C (appendix) reports price-cost margins and concentration ratio for each sector in each year, and gives us some interesting information [6]. Not always high concentrated industries have high PCM. Sectors [7] 0,14,15,16,18,19 and 20 show high concentration ratios and low PCM. The other sectors show the expected pattern: high concentration and high PCM (21,22,23,27,28,29,30) or low concentration ratio and low PCM (10,11,12,13,17,24,25,26) .

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[4] By specification problem we mean the selection of variables to be included in a behavioral relationship as well as the manner in which these variables are related to the variables that affect the outcome but appear in the equation only through the error term. If the effects of the omitted variables are correlated with the included explanatory variables, and if these correlations are not explicitly allowed for, the resulting estimates will be biased.

[5] Box-Cox method recommended logarithmic transformation for K/Q.

[6] See table 5 for a qualitative summary (appendix).

[7] Sectors codes and names are in table 5 (appendix) .

TABLE 1A : Summary statistics

	CR4	PCM	Ln(K/Q)	CU %
Min	0,19	0,10	-4,92	72,00
1st Qu	0,33	0,39	-2,82	77,00
Mean	0,57	0,47	-1,58	79,00
Median	0,58	0,46	-1,65	80,00
3rd Qu	0,77	0,47	-0,36	81,00
Max	1,00	0,86	1,74	83,00
Std Dev	0,23	0,13	1,47	3,66

TABLE 1B : Correlations among variables

	CR4	PCM	Ln(K/Q)	CU %
CR4	1,00	0,22	-0,08	-0,02
PCM	0,22	1,00	-0,36	-0,21
Ln(K/Q)	-0,08	-0,36	1,00	-0,18
CU %	-0,02	-0,21	-0,18	1,00

In spite of the fact that summary statistics and correlations give us an overview of the variables performance, it is not enough to make inference and get conclusions. Partial correlations for example are omitted. So, some more sophisticated analysis are necessary.

5.2 REGRESSIONS

We tested the following specification

$$PCM_{it} = \beta_0 + \beta_1 CR4_{it} + \beta_2 \ln(K/Q)_{it} + \beta_3 CU_t + \varepsilon_{it},$$

considering (1) homogeneous intercepts and slope (pool cross section) via Ordinary Least Square (OLS); (2) heterogeneous intercepts and homogeneous parameters via OLS; and (3) heterogeneous intercepts and slopes via Maximum Likelihood (ML).

REGRESSIONS RESULTS

Table 2 shows the pool cross section results. Intercept and all parameters are statistically significant, but only CR4 is positively correlated with PCM. All variables are statistically significant together, as F-statistic shows. Although this regression shows good statistical performance, it has some problems. The correlation between intercept and CU slope estimate is almost minus one. According to section 4 above, information may have been omitted and parameters estimates can be biased. Considering time or sectorial, fixed or random effects, in intercept or other parameters is a way to get the omitted information and reduce or eliminate the possible bias.

We first try to get time effects. Table 3 gives us the results of time fixed effects in intercept estimation via OLS. We use dummy variable for each year and for 1992,1993 and 1994 they are positive and statistically significant correlated with PCM; but for 1987, 1988, 1989 and 1995 they were not significant statistically, so we take them out [8]. The results here are almost the same in pool cross section regression: all variables are statistically significant alone and together, CR4 is positively correlated with PCM and ln(K/Q) has negative correlation. But CU coefficient is positive, the correlations between CU parameter and intercepts are no more perfectly negative, and the RES in this equation is smaller than in pool cross section estimation. It is possible that some information has been omitted and the equation in Table 2 gives us the wrong sign of CU parameter.

[8] We haven't data for 1991, so we didn't use dummy for this year.

Considering that CU is a very important variable in this model, we try to get more information estimating sectorial random effects in the parameters.

TABLE 2 : Pool cross section (OLS)

	Value	Std. Error	t value	Pr(>|t|)
Intercept	1,15	0,18	6,40	0,00
CR4	0,10	0,04	2,85	0,00
Ln(K/Q)	-0,04	0,01	-6,27	0,00
CU	-0,01	0,00	-4,43	0,00

Residual standard error: 0.1149 on 194 degrees of freedom
F-statistic: 20.91 on 3 and 194 degrees of freedom, the p-value is 8.867e-012
Number of observations : 198

Correlation of Coefficients:

	Intercept	CR4	Ln(K/Q)
CR4	-0,14		
Ln(K/Q)	-0,14	0,09	
CU	-0,99	0,03	0,18

TABLE 3 : Time fixed effects in intercept (OLS)

	Value	Std Error	t value	Pr(>|t|)
CR4	0,053	0,031	1,694	0,092
Ln(K/Q)	-0,081	0,007	-11,769	0,000
CU	0,003	0,000	10,791	0,000
D92	0,244	0,028	8,857	0,000
D93	0,257	0,029	9,019	0,000
D94	0,135	0,026	5,183	0,000

Residual standard error: 0.1007 on 192 degrees of freedom
F-statistic: 742.7 on 6 and 192 degrees of freedom
The p-value is 0
Number of observations : 198

Correlation of Coefficients

	CR4	Ln(K/Q)	CU	D92
Ln(K/Q)	0,212			
CU	-0,628	0,528		
D92	-0,205	-0,552	-0,333	
D93	-0,186	-0,586	-0,375	0,413
D94	-0,135	-0,448	-0,335	0,347

We consider heterogeneous intercepts and slopes via Maximum Likelihood (ML) and estimate time fixed effects in intercepts and sectorial random effects in parameters. Table 4 give us the results. Again, CR4, CU and D92, D93 and D94 have positive signs, and lnK/Q has negative sign.

TABLE 4 : Time fixed effects in intercept and sectorial random effects in parameters (ML)

	Value	Std,Error	z ratio(C)
CR4	0,06731	0,06832	0,985208
Ln(K/Q)	-0,07343	0,00518	-14,1747
CU	0,00311	0,00039	7,856754
D92	0,22763	0,01451	15,68342
D93	0,24153	0,01488	16,2256
D94	0,12447	0,01274	9,764696

Conditional Correlations of Coefficients

	CR4	Ln(K/Q)	CU	D92	D93
Ln(K/Q)	0,42252				
CU	-0,80144	-0,01143			
D92	-0,26888	-0,52414	0,080999		
D93	-0,21155	-0,55363	0,001011	0,55889	
D94	-0,15408	-0,4441	-0,0294	0,46887	0,48569

Sectorial Random Effects

SECTOR	CR4	Ln(K/Q)	CU
0	-0,00924	0,00431	-0,00059
10	0,07641	0,00388	0,000948
11	-0,06415	-0,00586	0,000731
12	-0,09922	-0,00477	-0,00061
13	0,08703	0,00645	-0,00016
14	-0,28017	-0,01564	-0,00013
15	-0,08968	-0,00468	0,000213
16	-0,17877	-0,0105	0,000186
17	-0,10217	-0,01025	0,001415
18	-0,08978	-0,00516	-0,00011
19	-0,09582	-0,00735	-6E-05
20	0,08493	0,00815	-0,00035
21	0,45951	0,0346	-0,00087
22	0,05482	0,00893	-0,00042
23	-0,00388	-0,00127	0,000146
24	-0,16468	-0,0129	0,000633
25	-0,22553	-0,01545	0,000102
26	0,08626	0,00582	-0,00071
27	0,31737	0,02169	-0,00124
28	0,25915	0,01200	9,45E-05
29	-0,02279	-0,00526	0,000169
30	0,00038	-0,00678	0,000616

Number of Observations: 198

AIC: -540,2167

Correlation of Random Effects

	CR4	Ln(K/Q)
Ln(K/Q)	0,87675	
CU	-0,59939	–0,52467

The sign of sector random effect is an information that should be stressed. As we can see, the sign is not the same for each sector, sometimes in the opposite sign of the homogenous parameters.

We could say that we get a robust result when considering time and sectorial effects. Tables 3 and 4 show CR4 and CU positively correlated with PCM, and lnK/Q negatively correlated. So, we can believe that pool cross section (Table 2) gives us the wrong sign to CU.

Considering that we have any data for 1991 and that period 1986-90 doesn't have the same characteristics of the period 1992-95, we tested if Brazilian leading firms had or not the same behavior in each sub-period before and after 1991. Graphics in appendix show us a different standard to each variable under analysis, specially CU and LNKP, whose values show a U shape.

We followed the same methodology used to estimate the parameters considering the period as a whole. The best model is in table 6 below. It shows us that the collusive behavior was not the same in each sub-period. PCM is not correlated with concentration ratio in the period 1992-1995 (CR49295) and with capacity utilization in the period 1986-1990 (CU8690). Capital output ratio, however, keeps the result. PCM has negative correlation with LNKP8690 and with LNKP9295.

TABLE 6 : sub-periods 1986-90 and 1992-95 (ML)

	Value	Std.Error	z ratio(C)
(Intercept)	0.3954	0.02228	17.7445796
CR48690	-0.001627	0.000480	-3.3901740
CR49295	0.000381	0.000382	0.9977335
LNKP8690	-0.066557	0.010583	-6.2889282
LNKP9295	-0.0531443	0.022940	-2.3165947
CU8690	0.001763	0.0026103	0.6756889
CU9295	-0.014357	0.002085	-6.8826097

Conditional Correlations of Coefficients

	(Intercept)	CR48690	CR49295	LNKP8690	LNKP9295	CU8690
CR48690	-0.534073					
CR49295	-0.8863112	0.45127916				
LNKP8690	0.27469280	0.50041649	-0.2718257			
LNKP9295	0.06744109	-0.05810740	0.05700273	0.32847507		
CU8690	-0.18935509	-0.29010265	0.18352558	-0.55071129	-0.06460	
CU9295	0.12347622	-0.08743201	0.06884791	0.01016002	0.28074	-0.00896

Sectorial Random Effects

Sector	LNKP8690	LNKP9295	CU8690
0	0.00561870	-0.0280102	-0.0026619
10	-0.0061074	0.0277914	0.0027757
11	0.0017608	0.0123845	0.00010402
12	0.03943981	0.1076407	-0.0051958
13	0.01435707	0.0082410	-0.0032632
14	0.04179433	0.1550845	-0.0036874
15	-0.0062160	-0.0427484	-0.0003242
16	0.01104745	0.0789998	0.0007103
17	-0.0128322	0.0094283	0.00366125
18	0.0030819	0.0824762	0.0028776
19	0.0002608	-0.046032	-0.0021068
20	0.0099978	0.048753	-0.000365
21	-0.021371	-0.182927	-0.002708
22	-0.0041691	-0.040946	-0.0007616
23	-0.0181807	-0.021121	0.0036586
24	0.0097024	0.0607103	0.0002393
25	0.01928840	0.0588745	-0.0022647
26	0.0381293	0.0699967	-0.0065335
27	-0.0238685	-0.0934014	0.0018916
28	-0.0695576	-0.177632	0.0097047
29	-0.003553	-0.054935	-0.0015375
30	-0.0286228	-0.032626	0.0057877

AIC: -407.099

Correlation of Random Effects

	LNKP8690	LNKP9295
LNKP9295	0.7519917	
CU 8690	-0.8064862	-0.2167347

INTERPRETATIONS

The parameters of the regressions above show us that, for the industry as a whole, higher concentration ratio (CR4) and high capacity utilization (CU) means high price-cost margin (PCM); and that improved stock of capital (lnK/Q) reduces PCM. Also, the dummy variables tell us that the macroeconomic performance of the Brazilian economy in 1992,1993 and 1994 helped the industry as a whole to improve PCM levels (in other years it was not statistically significant).

Random effects give us the deviations of the value of each parameter in each sector around the average parameter. The final result is the sum of the value of the average parameter with each sectorial random effect. Sometimes the sectorial sign can change. Observing sectorial random effects, we can see that, on one hand, high concentration improve PCM in the industry as a whole and in sectors 0,10,11,13,20,21,22, 23 and 26 to 30. However, for the sectors 12,14 to 19,24,25 high concentration does not help improve PCM. [9] On the other hand, improve capital stock reduce PCM level for the industry as a whole and all sectors.

The sign of capacity utilization variable (CU) helps us identify whether the behavior of the leading firms within each Brazilian industrial manufacturing sector is like the Green and Porter (1984) or the Rotemberg and Saloner (1986) models predict.

According to Green and Porter (1984) model, PCM should be procyclical. This is what we find for each sector and the industry as a whole. The overall sign of CU is positive in all sectors [10] . According to this model, it means that the leading firms in each of those sectors act monopolistically while prices remain high, but they revert to a Cournot behavior when prices fall. In other words, the leading firms in those sectors agree with a trigger price to which they compare the market price when they set their production. Whenever the market price dips below the trigger price while the firm-set has been acting monopolistically, they will revert to a Cournot behavior for some fixed amount of time before resuming monopolistic conduct.

As Shapiro (1989) notes, in infinitely repeated oligopoly games (supergames) the requirement that threats be credible turns out to be much less restrictive than it was in finite horizon games. This is what those results in tables 4 and 5 show. In sectors 0,14,15,16,18,19 we have high concentration levels and low price cost margins levels; and negative sign for sectorial random effects for CR4. In sectors 21,22,23,27,28,29,30 we have high concentration levels and high PCM levels, and positive sign for sectorial random effects for CR4. It means that, for the first group of sectors, punishments to drop out the cartel are not enough to keep firms acting as a monopoly. For the second group of sectors, however, punishments to drop out are high enough to keep firms acting as a monopoly.

Nevertheless, analyzing sub-periods the result is different. Considering that the sign of capacity utilization variable (CU) helps us identify whether the behavior of the leading firms, they weren’t following a definite strategy in 1986-1990 period because PCM is not correlated with CU8690; and was playing according to Rotemberg and Saloner (1986) models predictions in 1992-1995 period because PCM is negatively correlated with CU9295. It means that the benefit to a single firm from undercutting the price that maximizes joint profits is larger in 1992-1995 years. Firms in this period had any reason to build up or maintain a cartel. We could say that, in this context, the best strategy for a relatively long period is not the best strategy for short periods.

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[9] Sectors 0,11,23,29 have negative random effects for CR4, but they are smaller than the value of the CR4 average parameter. See table 4.

[10] The value of the random effect for CU is almost zero in each sector. See table 5.

In fact, during 1986-1995 Brazilian economy was a laboratory, where many macroeconomics experiments were done, whose main results are high volatility levels of the main macroeconomic aggregate indicators in the period analyzed, as summarized in table 7 below. The results found for the sub-periods show us that firms worked with a different strategy in each situation.

TABLE 7 : Brazilian aggregate macroeconomic indicators

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
ARIR %	-0,4	-8,8	7,3	43,4	-29,2	-12,4	30,2	7,1	24,8	35,7
GDPGR %	7,5	3,5	-0,1	3,2	-4,3	1	-0,5	4,9	5,9	4,2
MPGR %	11,7	1	-2,6	2,9	-8,2	0,3	-4,2	7	6,7	1,9
CPI %	65,2	415,9	1037,7	1783,0	1476,7	480,2	1157,8	2708,4	909,7	14,8

ARIR = ANNUAL REAL INTEREST RATE; GDPGR = GROSS DOMESTIC PRODUCT GROWTH RATE; MPGR = MANUFACTURING PRODUCT GROWTH RATE; CPI = CONSUMER PRICE INDEX. SOURCE: Brazilian Central Bank

According to Domowitz, Hubbard and Petersen (1986B), in American manufacturing industries, collusion improved profits and PCM had a prociclycal behavior for the industry as a whole during the period 1958-1981, and improvements in capital stock also helped improve PCM levels. American manufacturing industry behavior was according to that predicted by the Rotemberg and Saloner (1986) model. But their study did not consider specific information about each manufacturing firm. Here, due to the sectorial random effects, we could get the specific behavior in each manufacturing sector.

6. CONCLUSIONS

In this paper we analyzed the impacts of concentration, capital stock and aggregated demand level over sectorial price-cost margin for 22 Brazilian industrial sectors within leading firms in the period 1986-1995. We found that:

1) There is no homogeneous relationship between concentration and price-cost margin in Brazilian industrial manufacturing sectors. In fact, in some cases, higher concentration levels means low price-cost margin levels.
2) The sign of the parameters for the industry as a whole is not the same for each sector. For the industry as a whole, CR4 is positive, which means that high concentration levels help improve price-cost margins. However, sectorial random effects tell us that this fact does not hold in some cases when we analyze each sector. Punishments for not participating in the cartel is not efficient in all cases
3) Considering that capacity utilization tells us whether the price-cost margins are pro or countercyclical, for the industry as a whole and all sectors, PCM is procyclical. This means that the behavior of leading firms are like the Green and Porter (1984) model predicts.
4) Improvement of capital stock does not help improve PCM. On the contrary, it reduces PCM.
5) The macroeconomic effects in 1992, 1993 and 1994 helped improve PCM.
6) Collusive behavior in each sub-period is not the same for the period as a whole. Firms in 1986-1995 worked according to Green and Porter model, but had not a definite strategy in 1986-1990 and worked according to Rotemberg and Saloner(1986) model in 1992-1995.

7. REFERENCES

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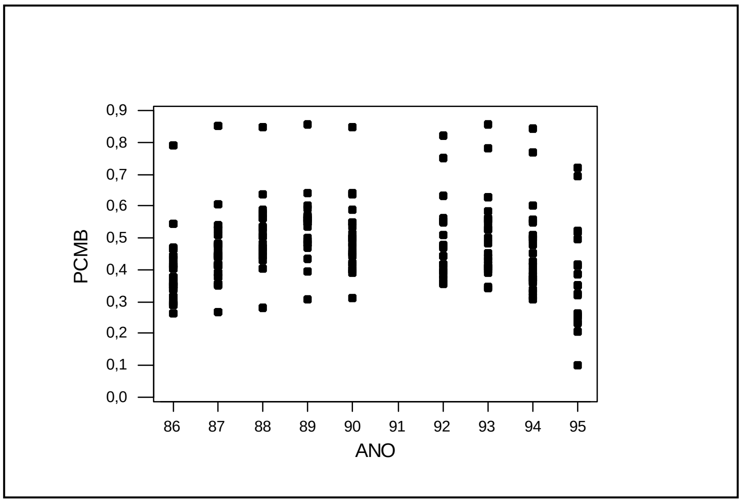
TABLE 1C : PCM AND CR4 FOR EACH SECTOR AND YEAR

YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM
86	0	0.743519	0.343295	10	0.322395	0.465922	11	0.285786	0.295582	12	0.238700	0.316924
87	0	0.735475	0.269856	10	0.299498	0.510464	11	0.283091	0.392051	12	0.273717	0.410926
88	0	0.724059	0.279258	10	0.298790	0.563725	11	0.301481	0.469221	12	0.274449	0.443178
89	0	0.736509	0.308697	10	0.286630	0.564907	11	0.330883	0.481629	12	0.285546	0.434223
90	0	0.725722	0.312141	10	0.289532	0.536672	11	0.304443	0.397811	12	0.286254	0.388686
92	0	0.755162	0.416022	10	0.301873	0.559838	11	0.325732	0.418884	12	0.276906	0.393678
93	0	0.760340	0.343839	10	0.299748	0.560876	11	0.325727	0.438308	12	0.403939	0.408816
94	0	0.761859	0.339946	10	0.304460	0.507649	11	0.336105	0.359515	12	0.379166	0.373327
95	0	0.764315	0.100082	10	0.303621	0.418436	11	0.341159	0.258698	12	0.412171	0.263601
YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM
86	13	0.316447	0.358836	14	0.557482	0.263846	15	0.742184	0.375959	16	0.713421	0.338624
87	13	0.324661	0.458527	14	0.520254	0.35438	15	0.751600	0.445547	16	0.783921	0.415457
88	13	0.334166	0.578222	14	0.555214	0.403788	15	0.771516	0.505477	16	0.912600	0.456737
89	13	0.342090	0.557213	14	0.524829	0.394239	15	0.774361	0.499357	16	0.866372	0.560285
90	13	0.333453	0.500662	14	0.533253	0.398512	15	0.778216	0.41629	16	0.873528	0.420359
92	13	0.270502	0.551107	14	0.643903	0.356676	15	0.835069	0.400877	16	0.903560	0.360005
93	13	0.251819	0.583021	14	0.665324	0.347041	15	0.781460	0.398116	16	0.920357	0.450901
94	13	0.257986	0.476486	14	0.674663	0.316159	15	0.781170	0.330622	16	0.978330	0.374981
95	13	0.271003	0.35173	14	0.654459	0.205304	15	0.809593	0.237967	16	0.968878	0.321222
YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM			
86	17	0.348705	0.358863	18	0.932282	0.349699	19	0.721161	0.287763			
87	17	0.331935	0.44581	18	0.927100	0.480244	19	0.726757	0.418287			
88	17	0.360054	0.534382	18	0.846864	0.481337	19	0.753808	0.443046			
89	17	0.335882	0.550134	18	0.822249	0.49337	19	0.765517	0.549885			
90	17	0.368029	0.48406	18	0.826489	0.450948	19	0.741215	0.45781			
92	17	0.414432	0.443888	18	0.829634	0.472932	19	0.780065	0.382389			
93	17	0.389534	0.390536	18	0.818902	0.525366	19	0.798387	0.406659			
94	17	0.437968	0.363641	18	0.827837	0.383779	19	0.809008	0.307842			
95	17	0.384167	0.414426	18	0.835670	0.254828	19	0.924843	0.233289			
YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM			
86	20	0.603547	0.375976	21	0.520163	0.443803	22	0.743081	0.433042			
87	20	0.589183	0.414249	21	0.587129	0.528354	22	0.769547	0.436883			
88	20	0.535801	0.428836	21	0.605531	0.58868	22	0.758777	0.519293			
89	20	0.485089	0.470255	21	0.628816	0.5942	22	0.780348	0.568355			
90	20	0.531147	0.475147	21	0.541869	0.638019	22	0.875708	0.547831			
92	20	0.539080	0.477795	21	0.692938	0.7527	22	0.839394	0.55519			
93	20	0.558384	0.545731	21	0.605486	0.779321	22	0.893655	0.626042			
94	20	0.547747	0.453562	21	0.577852	0.767761	22	0.832925	0.558184			
95	20	0.559957	0.352314	21	0.587830	0.691742	22	0.779835	0.518378			
YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM
86	23	0.802047	0.418485	24	0.236754	0.413164	25	0.287829	0.350899	29	0.507434	0.471837
87	23	0.775983	0.541477	24	0.255263	0.483199	25	0.281185	0.476107	29	0.485306	0.443516
88	23	0.833639	0.563502	24	0.247909	0.531488	25	0.286498	0.5042	29	0.514594	0.46844
89	23	0.766320	0.601341	24	0.251777	0.536428	25	0.341595	0.569716	29	0.508868	0.547396
90	23	0.772617	0.499626	24	0.272627	0.514686	25	0.276827	0.49716	29	0.517175	0.549637
92	23	0.834342	0.508396	24	0.276661	0.469947	25	0.394341	0.372559	29	0.525019	0.396423
93	23	0.873040	0.527274	24	0.290411	0.500551	25	0.466382	0.430952	29	0.568683	0.418082
94	23	0.833408	0.496172	24	0.273967	0.411729	25	0.350616	0.425475	29	0.636018	0.548887
95	23	0.769796	0.388136	24	0.303054	0.255066	25	0.308319	0.326297	29	0.627150	0.496984
YEAR	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM	SEC	CR4	PCM
86	26	0.189327	0.300201	27	0.645838	0.4044	28	0.954898	0.790726	30	0.646166	0.545629
87	26	0.190799	0.377251	27	0.610117	0.353302	28	0.963167	0.850911	30	0.616990	0.606263
88	26	0.190319	0.46288	27	0.741877	0.573865	28	0.974257	0.84823	30	0.582066	0.634474
89	26	0.235136	0.484209	27	0.683894	0.556973	28	0.978580	0.856777	30	0.605164	0.642525
90	26	0.230986	0.444452	27	0.711949	0.642083	28	0.975297	0.846936	30	0.566006	0.59006
92	26	0.243617	0.442942	27	0.682355	0.632325	28	0.972462	0.822452	30	0.541755	0.549511
93	26	0.274145	0.483147	27	0.703744	0.627618	28	0.991008	0.854256	30	0.521982	0.557289
94	26	0.261179	0.393082	27	0.703367	0.599709	28	1.000000	0.844839	30	0.538988	0.499028
95	26	0.278807	0.352426	27	0.684492	0.521299	28	1.000000	0.721759	30	0.589231	0.387023

TABLE 5 : SECTOR CODES AND NAMES

SECTOR	NAME	CR4 (*)	PCM (*)
0	mineral extractive industry	H	L
10	mineral manufacturing industry	L	H/L
11	metallurgy industry	L	L
12	industrial machine and equipment manufacturing industry	L	L
13	electric material industry	L	H/L
14	cars, buses, trucks and vehicles in general industry	H	L
15	wood commodity industry	H	L
16	furniture industry	H	L
17	paper and cellulose industry	L	L
18	rubber industry	H	L
19	leather and travel articles industry	H	L
20	non petrol chemistry industry	H	L
21	pharmaceutical industry	H	H
22	perfumery, soap and candle industry	H	H
23	plastic materials industry	H	H/L
24	spinning and textile industry	L	H/L
25	cloths and shoes industry	L	L
26	vegetal manufacturing industry (like coffee, rise, fruits, etc)	L	L
27	drink industry (alcoholic and non alcoholic drinks)	H	H
28	smoke industry	H	H
29	graphic industry	H	H/L
30	Other industries	H	H/L

(*)
H= high level over the period 1986-1995, it means, bigger than 0,5 .
L = low level, it means equal or smaller than 0,5.
($0<CR4, PCM<1$).



PCMB
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0,4
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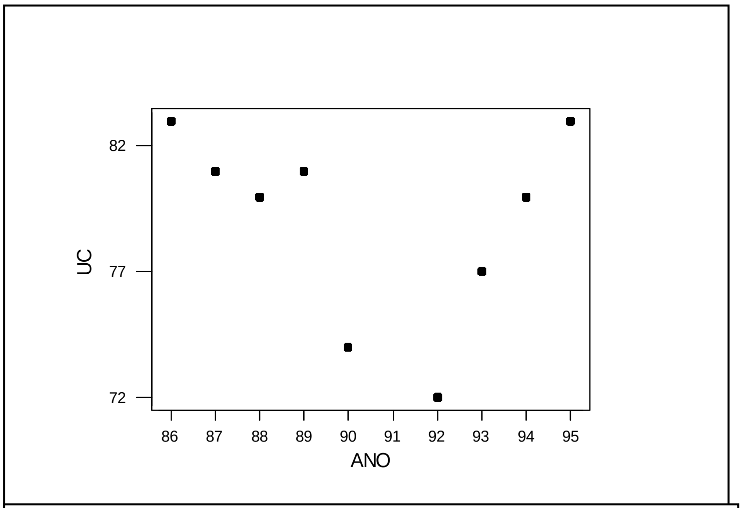
0,6
0,7
0,8
0,9
86 87 88 89 90 91 92 93 94 95
ANO



UC
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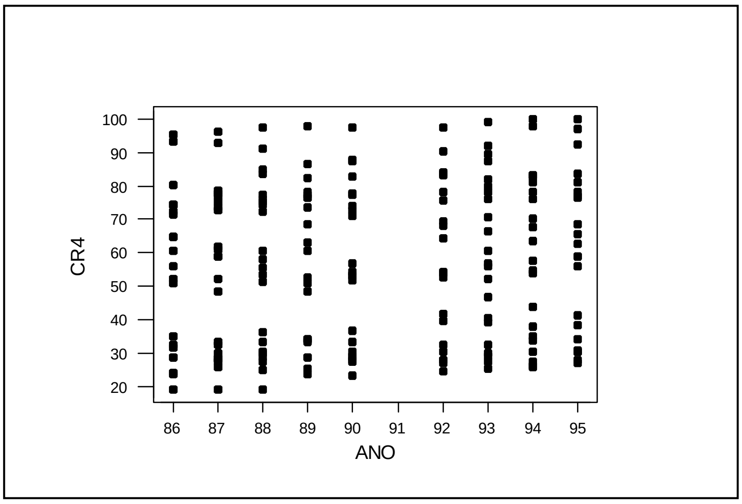
77
82
86 87 88 89 90 91 92 93 94 95
ANO



CR4
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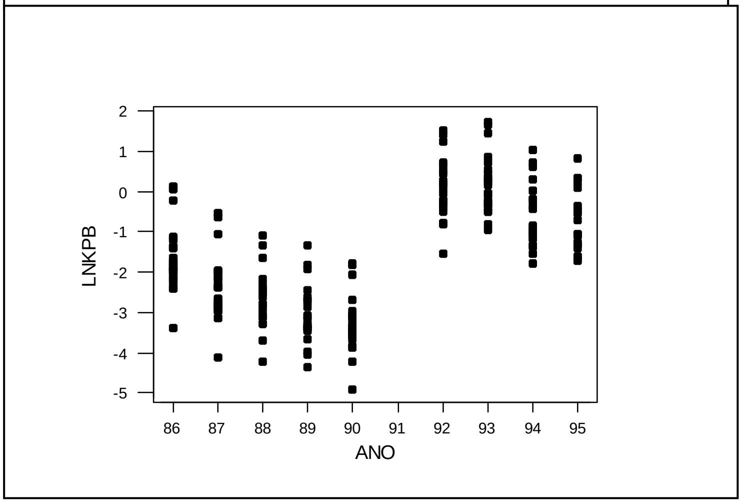
30
40
50
60
70
80
90
100
86 87 88 89 90 91 92 93 94 95
ANO



LNKPB
-5
-4
-3
-2
-1
0
1
2
86 87 88 89 90 91 92 93 94 95
ANO