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Technological Regimes in the Brazilian Manufacturing Industry: An Empirical Investigation

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Abstract

The paper aims at assessing technological regimes in the context of the Brazilian manufacturing industry along the 2000-2005 period. The industries were classified in terms of SM-I and SM-II technological regimes by means of multivariate statistical methods based on variable approximating technological opportunity, appropriability, cumulativeness and knowledge base. The evidence indicated some salient classification contrasts with respect to previous evidence for developed countries. In particular, the pharmaceuticals and paper and cellulose sectors in the Brazilian case have some expected specificities. When one consider contrasts between SM-I and SM-II for the totality of firms, one observes discernible differences in the case of two hypotheses: the share of small firms is higher in SM-I industries than in SM-II industries and in SM-I industries, profit rates are lower than in SM-II industries.

JEL-Code: L600, O300.

Keywords: technological regimes, manufacturing industry, Brazil.

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1. Introduction

The role of innovation in stimulating economic growth was increasingly recognized with the endogenous growth literature [see e.g. Romer (1990)]. In fact, abrupt changes following innovation have been recognized since Schumpeter (1912, 1942); the author contended that innovation would be responsible for incessantly destroying the old and creating the new. The notion of *creative destruction* innovation encompasses two major categories: the radical innovations that follow the precepts of creative destruction so as to dramatically alter existing structures, and incremental innovations that follow an incremental process of *creative accumulation*.

Following that lead, Nelson and Winter (1982) and Kamien and Schwartz (1982) highlighted two salient innovative patterns: the first is characterized in term of a *creative destruction*, with an easy entry of new innovator, whose entry in the market introduces new ideas, processes and products that have disruptive effects in the competitive environment. This pattern was labeled as Schumpeter Mark I (SM-I), which can also be associated to a widening pattern, since this pattern allows an expansion of the knowledge base.

A second pattern is related to the notion of *creative accumulation*. In this pattern the innovation process is conducted by the large established firms, which have institutionalized the innovation process allowing the creation of relevant barriers to entry for new innovators. This pattern was named Schumpeter Mark II (SM-II), which is also known as a "deepening" pattern, since the innovation is dominated by a few firms that are continuously innovative through the accumulation over time of technological and innovative capabilities

The concept of technological regimes articulates technological opportunity, appropriability, cumulativeness and knowledge base conditions to define de SM-I and SM-II[1]. Thus the use of this concepts allow advances in empirical frameworks, enabling that a growing number of studies arise in the literature, like Malerba and Orsenigo (1995, 1997), Mesa and Gayo (1999), Breschi et al. (2000) and Van Dijk (2000, 2002) for different European countries [France, Germany, Italy, Netherlands, Spain and United Kingdom].

The majority of the studies focused on advancing statistical approaches for classifying the industries in terms of these two patterns by considering the aforementioned conditions as relevant underlying factors. Therefore, the emphasis is on inter-sectorial heterogeneities in the populations of innovative firms as associated to structural and dynamic features. It is important to stress that the studies by Van Dijk (2000, 2002) further explore contrasts between SM-I and SM-II industries in terms of statistical tests of specific hypotheses but in the context of firms in general.

The present paper aims at considering a similar analysis in the case of the Brazilian manufacturing industry taking as reference rich survey data that are increasingly becoming available. The study can be motivated in different grounds:

a) The existing literature concentrated on developed countries and it would be relevant to investigate a large emerging economy like Brazil where one observes the coexistence of traditional sectors and more dynamic and innovative sectors. Nevertheless, it appears that the typical level of technological effort is yet low as

[1] See Malerba & Orsenigo (1995) for an overview.

suggested by Gonçalves and Simões (2005) and Kannebley Jr, et al. (2005) and Zucoloto and Toneto Jr. (2005);

b) The underlying structural factors that define the two regimes warrant further investigation. In fact, previous studies by Van Dijk (2000, 2002) had relied on the prevailing classification used in Malerba and Orsenigo (1995) that referred to different countries. The consideration of tests comparing SM-I and SM-II industries that do not rely on classifications for other countries is warranted, and the consideration of an emerging economy can address a gap in the literature.

The remainder of the paper is organized as follows. The second section discusses the empirical characterization of technological regimes. The third section discusses data sources, construction of variables and the regimes´ classification. The fourth section considers contrasting patterns in the two types of regimes in terms of different statistical tests. The fifth section brings some final comments.

2. Technological Regimes: Empirical Characterization

A salient contrast can be made in terms of the SM-I (“widening”) and SM-II (“deepening”) regimes that would respectively be related to industrial dynamics. Breschi et al (2000) characterize the SM-I as a sector with a high technological opportunity associated with a low appropriability and cumulativeness conditions and an applied knowledge base conditions. The articulation of these conditions reflects in intense industry dynamics, high entry of new innovators, low concentration and great instability in the innovators hierarchy. The SM-II, on the other hand, is characterized as a sector with a high technological opportunity, with high appropriability and cumulativeness condition and a knowledge base closer to basic science. The combination of these conditions reflects sectors with reduced entry of new innovators, high concentration in innovative activities and an established hierarchy in the group of innovators.

The related empirical literature can be schematically summarized in two strands:

(a) Empirical classification of industries in SM-I and SM-II types

Taking as reference structural and dynamic factors characterizing the industries, Breschi et al. (2000) propose to obtain a synthetic characterization of the different industries by means of the multivariate statistical method of principal components (PC). The method attempts to describe the variation in observed data by considering linear combinations (the PCs) of the representative variables such that one considers successively orthogonal PCs that explain a decreasing portion of the data variance[2]. Thus, once one has selected a number of PCs that accounts for a significant portion of the data variation, the idea is to interpret the signs of the coefficients of that synthetic indicator with respect to different variables (by inspecting the *factor loadings*) so as to classify each industry in one of the two categories of technological regimes. In previous applications, one was able to focus on the first (dominant) PC as it accounted for significant portion of the data variance ranging from 49% to 81% in the different cases addressed by the aforementioned authors. The empirical strategy advanced by those works essentially focused on the interpretation of the first PC (called SCHUMP) that was obtained upon the consideration of 3 variables:

[2] See Manly (1994) for an overview.

(i) ENTRY: percentage share of patent applications by firms applying for the first time in a given technological class;

(ii) STABILITY: is measured by the Spearman rank correlation coefficient between the hierarchies of firms patenting in two different periods;

(iii) C4: represents the concentration ratio of the top four patenting firms in a given technological class

The analysis relied on patent data from the EPO-CESPRI database and an industry was classified as SM-I in the case of a negative and lower value of SCHUMP**,** whereas positive and higher value would favor the SM-II classification. In order to gain further confidence on the classification, Breschi et al. (2000) conducted econometric analysis to explain the synthetic indicator SCHUMP against variables that would proxy technological opportunity, appropriability and cumulativeness and the knowledge base. The evidence thus obtained provided additional motivation for the adopted classification approach. Nevertheless, it is important to stress that even innovation criterion based on patents cannot be totally exempt from some caution as those often have a strategic role and not necessatily reflect a relevant innovative results

<u>Contrasts between regimes for the full population of firms</u>

The research line mentioned in (a) relates to the population of innovating firms. Van Dijk (2000, 2002) suggest to explore contrasts between SM-I and SM-II regimes taking as reference structural and dynamic aspects in the context of the full population of firms as the next natural step in the research of technological regimes, For that purpose, he considered tests for diferences in means for a set of hypotheses summarized in table 1 for the industry in Netherlands with the already mentioned caveat that the classification of industries relied in results for other country.

Table 1

Technological regimes: general contrasts

HYPOTHESES	**1**	The share of small firms is higher in SM-I industries than in SM-II industries
	2	Concentration levels are lower SM-I industries than in SM-II industries
	3	Entry barriers are lower in SM-I industries than in SM-II industries
	4	Capital intensity is lower in SM-I industries than in SM-II industries
	5	In SM-I industries, profit rates are lower than in SM-II industries
	6	In SM-I industries, entrants are more productive than incumbents, whereas in SM-II industries incumbents are more productive than entrants
	7	In SM-I industries, the amount of turnover due to entry and exit is higher than in SM-II industries
	8	The turbulence within the group of incumbent firms is higher in SM-I industries than in SM-II industries
	9	The contribution of the entry and exit process to productivity growth is higher in SM-I industries than in SM-II industries, and vice versa for incumbents' contributions

Source: Van Dijik (2002)

In the present paper, we intend to consider both lines of research in the case of the Brazilian manufacturing industry by exploring multiple data sources that were previously not explored on that context. Therefore, one intends to implement a data intensive study that can provide a first attempt to fill the gap in the related literature for developing countries but of course does not rule out less coarser characterizations of technological regimes. For example, Leiponen and Drejer (2007) suggest further intra-regimes heterogeneities that might deserve further investigations.

3. Technological Regimes in Brazil: Empirical Analysis

3.1 - Data construction

The main data source of the present study is provided by a comprehensive survey on technological innovation in the context of the Brazilian industry [Pesquisa de Inovação Tecnológica-PINTEC, Instituto Brasileiro de Geografia e Estatística-IBGE], which is a bi-annual basis, that considers active firms with main revenues associated with extractive or manufacturing industry and with 10 or more employees. The database was built from microdata, for the years of 2000, 2003 and 2005[3]. It is worth mentioning that the questionnaire closely follows the one from the Community Innovation Survey (CIS 1) that focus on European countries. However, in the Brazilian database one does not face a micro-aggregation limitation. A complementary source was the annual industrial survey [Pesquisa Industrial Anual-PIA, Instituto Brasileiro de Geografia e Estatística-IBGE] that was matched with the previous database to construct some indicators. The data description will consider two steps of the analysis.

a) The classification of industries in terms of technological regimes: in this case, we considered a principal components procedure inspired in Breschi et al. (2000). However, it is important to highlight differences pertaining the definition of innovating firms and the level of aggregation. In the former aspect there is a contrast with previous studies by not be exclusively relying on patent data, what reflects data availability in the present application. Accordingly, we do not work with technological classes and were able to consider industrial sectors

[3] The authors are grateful to the IBGE for the access to the microdata of PINTEC, that are subject confidentiality and are provided solely for the purpose of academic research.

classified at the 3-digits level (CNAE3). The criterion adopted for defining an innovating firm was the implementation of either some process or product innovation or yet if they use some intellectual property instrument (like patent, secrecy, license, trademarks, etc.) during the survey period[4]. Upon the sample of selected innovating firms, 3 indicators were considered for implementing the principal components analysis (PCA):

.**ENT**: approximates the entry of new innovators, by comparing PINTEC surveys for 2000, 2003 and 2005, one identified the firms that first appeared as innovators in 2005 for each 3-digits sector. The indicator is then defined as the proportion of those relative to the total number of firms in the particular sector in 2005;

. **CONC**: is the indicator that measures the concentration of innovating firms and is measured in terms of revenues accruing from innovation activities (process or product). This indicator was built upon firm-level data for the PINTEC in 2005 from which we obtain the share of revenues attributed to innovative activities and that information was matched with data on total revenues for the same firms available from the PIA for 2005. The combination of these two variables allows the creation of what we call "innovation revenue" for each of the 3-digits sector. Thus proceeding, we were able to generate firm-level data on innovation revenues s. The related shares (s_i) can then be readily used to calculate the Herfindahl concentration index defined as $H = \Sigma_i s_i^2$;

[4] It is important to note that even though in PINTEC one does not have any information about the number or the classification of the firm´s patent, there is only a question on whether they have used a intellectual property, like patents.

.**STAB**: indicator for hierarchical stability of innovators that aims at approximating the degree of technological dynamism of the sector. To construct this indicator, first we identified the innovating firms in 2000 based on the PINTEC and then we generate the innovation revenues with the procedure described in the previous item for 2000 and 2005, important to say that in cases where we have a non-innovating firms we assigned a zero revenue. The stability indicator then compares the ranking of innovation revenues in each 3-digits sector between the two years in terms of the Spearman correlation coefficients. Given the small number of firms in some sectors, we considered only those where a significant correlation coefficient was obtained. Thus, starting from an initial sample of 112 sectors at the 3-digits level (comprising extractive and manufacturing industries) one ends with a final sample composed of 69 sectors. The corresponding summary statistics for those indicators are presented in table 2.

Table 2

Summary statistics – indicators for regime classification

Variable	Obs.	Mean	Std. Dev.	Min	Max
stab	69	0,225	0,143	0,016	0,775
entry	69	0,278	0,077	0,091	0,435
conc	69	0,337	0,250	0,062	1,000
schmp	69	0,042	0,189	0,168	0,933

Source: Author´s calculations from PINTEC and PIA database

Following the classification of industries in accordance to technological regimes, Breschi et al. (2000) further investigated the adherence to factors which are supposed to portray the SM-I and SM-II regimes. In the present paper, we will consider such complementary analysis in terms of discriminant analysis as will be discussed later. The following variables constructed upon the PINTEC are considered:

.**TECOP**: indicator for technological opportunity tries to assess how easy the innovations are likely to emerge in a given sector. The indicator was built adding the responses provided by the firms with respect to the importance of available external sources of innovation. A larger value would indicate greater technological opportunities;

. **APROP**: the indicator of appropriability aims at identifying the degree of protection derived from intellectual property. It is obtained by adding the responses provided by innovating firms in questions related to the importance of patents and the different intellectual property mechanisms to protect the innovation activity. This indicator is an inverse proxy, such that a smaller value is expected to reflect a greater appropiability;

.**CUMUL**: intends to identify the degree of dependence between innovation and past technological knowledge. The indicator is constructed by adding responses provided by the firms with respect to the prevailing constancy that they undertake research and development. A larger value would denote a higher cumulativeness;

. **KBASE**: this indicator refers to the knowledge base and attempts to identify to what extent the technological knowledge have a more generic or more applied dimension. One considers for the innovating firms, the share of employees that possess educational background related to generic and applied knowledge. For this category, we constructed two indicators. First, the indicator **BASIC** highlights how generic is the knowledge base and was obtained by adding the shares of employees related to basic/generic sciences (Chemistry, Physics, Biology, and Mathematics). Second indicator **APPL** considered an analogous procedure but in terms of employees´ shares related to applied sciences (engineers, physicians, architects among others), The interpretation of the indicators is direct: the larger the value of the basic science (applied science) indicator more generic (applied) will be the technological knowledge

b) Inter-industry contrasts

Following Van Dijk (2000, 2002) it is possible to conceive tests that highlight the contrasts between SM-I and SM-II. The tests allow us to infer if, statistically, is relevant to classify industries according to this methodology and to implement those tests we consider sample comprising the totality of firms and not only the innovating firms. To construct the variables used to test the differences between the SM-I and SM-II, we work with the universe of all firms aggregated in 4-digits sectors (CNAE4)[5] and instead of use the PINTEC database, we use the Relação Anual de Informações Sociais (RAIS, Ministry of Labor and Employment, Brazil), that is an annual survey with a census character, for the period of 10 years (1995-2005).The variables will be used in tests in section 3 and are described next. The tests were implemented for the sectorial mean values across the years in the aforementioned period span.

.**share of small firms**: measured in terms of the share of small firms in total sector firms. It is important to emphasize two points in the construction of this variable, first that we consider small firms those which have more than 5 and less than 100 employees, and second when we calculate de share of small firms in a sector, we made this calculations using the number of employees instead the number of firms;

[5] We assume that the classification of the 4-digits industry in SM-I or SM-II follows the broader related 3-digits classifications

.Industrial concentration: Herfindahl index at the 4-digits level obtained upon especially requested tabulation from the PIA-IBGE;

.Suboptimal scale: proportion of the employment that occurs in firms below the minimum efficient scale (MES). This reference was approximated in terms of the median size of firms as motivated, for example, by Sutton (1997). It is an inverse measure of barriers to entry and the necessary data was obtained

. Capital intensity: capital stock divided by revenues. The capital stock was obtained with the perpetual inventory method relying in different issues of the PIA survey whereas the sectorial data for revenues were readily available from that source.[6] Note that, for this variable it was possible to construct the variable at the 3-digits level;

.Profit rate: is the profit rate calculated by dividing the gross value of production (minus operating expenses) by the total revenues of the sector at the 4-digits level;

.Labor productivity: gross production value divided by the total number of employees as obtained from the PIA at the 4-digits level;

.Entry rate: number of new firms relative to the previously prevailing stock. Calculated at the 4-digits level upon data from the RAIS;[7]

. Exit rate: analogous calculation for exiting firms;

.Turbulence: This variable was calculated as the average of the annual changes in the proportion of employees (relative to total employment in the sector) of the firms

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[6] Additional details on the construction of the capital stock are discussed in appendix 2.
[7] The identification of entering and exiting firms requires identification codes for comparison across successive years and once more we had special access to the restricted microdata.

that were active throughout the sample period. throughout the sample period (1995 - 2005);

3.2 – Classification of technological regimes: empirical results

Initially, we focus on principal components analysis (PCA) based on the ENT, CONC and STAB indicators. As indicated by table 3, one can motivate the sole retention of the first principal component (henceforth named SCHUMP) that accounts for 53,3% of the data variance. The relevant factor loadings are presented in table 4.

Table 3

Principal components - communalities

Components	Eigenvalue	Proportion of variance	Cumulative proportion of variance
1	1.597	0.533	0.533
2	0.707	0.236	0.768
3	0.695	0.232	1.000

No. of observations: 69

Source: Author´s calculations from PINTEC and PIA database

Table 4

Principal components - factor loadings

Variable	Comp1	Comp2	Comp3
ENT	-0.576	0.683	0.450
CONC	0.575	0.729	-0.371
STAB	0.581	-0.045	0.813

No. of observations: 69

Source: Author´s calculations from PINTEC and PIA database

The factor loadings for the first principal component appear to be consistent with the theoretical foundations as one observes a negative sign for ENT whereas the loadings for CONC and STAB are positive. The inspection of the signs of the factor scores coefficients of SCHUMP with respect to each particular sector allows to classify those according to technological regimes. A negative sign would indicate a SM-I regime and positive sign a SM-II regime. Thus proceeding, we were able to classify 69 3-digits sectors in terms of SM-I and SM-II regimes as listed in appendix

It is important, however, to gain additional confidence on the classification by considering the role of variables related to technological opportunity (**TECOP),** appropriability (**APROP),** cumulativeness **(CUMUL),** knowledge base (either BASIC or APPL) as previously discussed. Breschi et al. (2000) undertake a regression analysis with analogous explanatory variables. In the present paper, we consider the multivariate statistical technique of linear discriminant analysis (LDA). Given a sample segmented in groups (SM-I and SM-II in the present application), one is willing to obtain discriminant functions in accordance to the criterion of maximizing the discrimination between groups and minimizing the heterogeneity within the groups. [See Manly (1994) for an overview]. Discriminant functions are sensitive to the scale of the considered variables. Thus, we consider standardized variables in terms of the subtraction by the mean and division by the standard deviation.

In the present application, the LDA approach can be useful as a kind of validation to the adopted classification, with 2 groups and 3 indicators one will face a single discriminant function. The discriminating effects of the aforementioned indicators on the innovation patterns (as summarized by the technological regimes) will be considered in terms of the procedures outlined by Morrison (1969). In that sense, if $|b_{j;SM-I}| > |b_{j;SM-II}|$, (where $b_{j\,;i}$ is the coefficient of the discriminant function associated to indicator *j* and to the innovation pattern i) the indicator would favor a

SM-I regime. Conversely, if $|b_{j;SM-I}| < |b_{j;SM-II}|$, the indicator would discriminate in favor of a SM-II regime. Next, table 5 present the relevant related results.

The inspection of the table reveal some inconsistencies with the theory as the discriminant coefficient associated with CUMUL in SM-I sectors indicate that the higher the value of that indicator the larger would be the probability of classification as SM-I when one would expect the opposite. Therefore, there is some evidence of classification errors. To further assess such errors, we calculate discriminating scores for each 3-digits sector and upon a criterion motivated by Morrison (1969), adopt the classification rule that $Z_{SM-I} > Z_{SM-II}$, would suggest the classification as SM-I.

Table 5

Discriminant coefficients - initial analysis

Indicators	$b_{j;SM-I}$	$b_{j;SM-II}$	$b_{j;SM-I} - b_{j;SM-II}$
TECOP	4.140	1.999	2.141
APROP	-1.153	-0.418	-0.735
CUMUL	2.316	2.279	0.037
BASIC	-0.148	-0.496	0.348
APPL	0.760	-0.034	0.794
CONSTANT	-5.857	-2.543	-3.314

Source: Author´s calculations from PINTEC and PIA database

In fact, misclassification appeared as non-negligible. It was possible to identify 3 out of 14 SM-I sectors that were misclassified. Similarly, 7 out of the 55 SM-II sectors appear to involve misclassifications. After adjusting the classifications as outlined before, we obtain the discriminant function and the related results are presented in table 6:

Table 6

Discriminant coefficients – adjusted sectors

Indicators	$b_{j:SM-I}$	$b_{j:SM-II}$	$b_{j:SM-I} - b_{j:SM-II}$
TECOP	9.618	3.092	6.526
APROP	-2.036	-0.623	-1.413
CUMUL	0.984	2.055	-1.070
BASIC	3.109	0.085	3.024
APPL	2.756	0.366	2.390
CONSTANT	-13.788	-2.804	-10.983

Source: Author´s calculations from PINTEC and PIA database

The results display consistency with the expected economic fundamentals discussed by Breschi et al. (2000). In particular, one can guarantee that sectors with greater technological opportunities are classified as SM-I whereas those with greater appropriability and cumulativeness would be classified as SM-II. A final verification of the separation power associate to the discriminant function is warranted, to do this we calculate de eigenvalue and canonical correlation, which is a synthetic measure of association between groups of variables considering linear combinations of indicators in each group so as to maximize the related correlation. The evidence is summarized next in table 7.

Table 7

Canonical correlation and eigenvalues associated to the discriminant function

Canonical correlation	Eigenvalue	Likelihood ratio	F (5,63) statistic	p-value
0.847	2.541	0.282	32.02	0.000

Note: the null hypothesis assumes that the canonical correlation is zero

Source: Author´s calculations from PINTEC and PIA database

The results show that the SM-I and SM-II patterns are well discriminated by the corresponding function given the observed high values for the eigenvalue and canonical correlation and the high significance indicated by the obtained p-value.

Moreover, the Mahalanobis distance had a value of 12.238 with a corresponding statistic F(5,63) = 30.620 [p-value: 0.000] and thus provided evidence of a significant distance (difference) between the mean vectors of the SM-I and SM-II patterns.

Finally, to further confirm such differences in means, we calculate de Wilks' lambda test, which report a statistic of 0.2824, with a p-value of 0.000. This result shows that the previous evidence based on the different tests favor the rejection of the null hypothesis and thus delineates significant mean discrepancies between SM-I and SM-II sectors.

It is worth considering an initial comparison with the classifications obtained by Breschi et al. (2000) for Italy, Germany and United Kingdom and by Mesa & Gayo (1999) for Spain[8]. For example, it is possible to observe that sectors associated to textiles, electrical equipment, machines and equipment's in general appear to follow a SM-I pattern, and in the other hand, sectors related to chemicals, pharmaceuticals, oil and gas, and vehicle manufacturing appear to conform to a SM-II pattern. In the Brazilian case, similar patterns emerge in those sectors, however, a salient contrast is provided in the case of pharmaceuticals that were classified as SM-I. That result might reflect the dominance of subsidiaries of multinational firms as the important R&D efforts are likely to take place in their headquarters facilities abroad. The importance of Brazilian firms in that industry only stared increasing in the 2000s with the dissemination of generic drugs but in any case it refers to established active principles and therefore do not involve important innovative efforts.

[8] The mentioned authors focused on patent indicators for defining innovating firms and thus worked with technological classes. Therefore, a straightforward comparison with the Brazilian case is not readily available but some salient results can be mentioned.

Additionally, one can note that sectors that involve products derived from pulp and paper that were classified as SM-I in previous studies are classified as SM-II in the Brazilian case. A distinguishing characteristic in the case of pulp and paper is that Brazil has a significant competitive advantage, since it presents soil conditions, climate and insolation level that favor the growth of natural and planted forests.

The Brazilian pulp and paper companies are characterized by being integrated from the beginning of the chain, as they have both planted forests that the supply of pulp for the paper production, and produce paper to be sold. More specifically, the pulp sector is, like presented by Dores et al. (2007, p.122), highly intensive in capital, with high efficiency and minimal scales displaying a cyclical behavior of prices. Another relevant characteristic of this sector it is highly concentrated, with the 7 largest companies, in 2005, accounting for over 90% of production, according to data from the aforementioned authors. Thus, we can summarize the characteristics of this sector as intensive in capital, with high minimal scale, and with production concentrated in few big companies which is much more a SM-II characteristic than a SM-I, so the changing proposed by the LDA seems to be appropriate.

Following the classifications of sectors according to technological regimes, the next natural step is to explore structural contrasts between the sectors operating under the SM-I and SM-II regimes. For that purpose, the next section considers the test of different hypotheses that were advanced by Van Dijk (2000, 2002) for the totality of firms and not only the innovating ones.

4. Technological Regimes and Inter-Industry Heterogeneity

4.1 – Relevant statistical tests: a brief digression

Van Dijk (2000, 2002) explored inter-industry contrasts for industrial sectors classified in terms of technological regimes. The analysis considers the totality of the population as reference and not only a sample of innovating firms. The related hypotheses had been summarized in table 1 and will be considered in the next sub-section as data availability allows.

The referred empirical approach makes use of tests for difference in means of the form[9]:

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{(n_x - 1)s_x^2 + (n_y - 1)s_y^2}{n_x + n_y - 2}}\sqrt{\frac{1}{n_x} + \frac{1}{n_y}}} \qquad (1)$$

The null hypothesis of the test is the equality of means across the different groups and the statistic is distributed as a Student t with (n_x+n_y – 2) degrees of freedom. However, this version for unequal sample sizes assumes equal variances. If such requirement is not tenable, one needs to rely on expression (2) for the test, known as Welch´s t test:

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \sim t(v) \qquad (2)$$

Under the null hypothesis the relevant degrees of freedom are obtained in accordance to the Satterthwaite formula[10]. Therefore, it is important to assess the constancy of the variances prior to the application of the test for difference in means so as to decide the appropriate version. For that purpose, we consider Lavene´s test

[9] See Dixon and Massey (1983) for an introduction to those tests.

[10] Where v = $[\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}]^2/[(\frac{s_x^2}{n_x})^2/(n_x-1) + (\frac{s_y^2}{n_y})^2/(n_y-1)]$

as properly outlined by Forsythe (1974). All the tests were implemented with Stata 11.0.

4.2 – Empirical results

The one-tailed tests for difference in means related to the different hypotheses listed in table 1 are presented in table 8. Due to data availability restrictions we were not able to test the previously mentioned hypotheses 6 and 9.

Table 8

One-tailed tests for difference in means

	Hypotheses	Test statistic	Mean (std. error) SM-I	Mean (std. error) SM-II	p-value (diff. > 0)	p-value (diff. < 0)
1	The share of small firms is higher in SM-I industries than in SM-II industries	3,235	0.576 (0.015)	0.502 -0,017	0.001	-
2	Concentration levels are lower SM-I industries than in SM-II industries	-1.493 (*)	0.169 (0.181)	0.208 (0.174)	-	0.069
3	Entry barriers are lower in SM-I industries than in SM-II industries	-1.125 (*)	0.086 (0.004)	0.094 (0.006)	0.869	-
4	Capital intensity is lower in SM-I industries than in SM-II industries	-1.078 (*)	0.156 (0.035)	0,218 (0.178)	-	0.144
5	In SM-I industries, profit rates are lower than in SM-II industries	-2.776	0.352 (0.012)	0.423 (0.250)	-	0.003
7	Entry rate is larger in SM-I industries than in SM-II industries	0.232 (*)	0.051 (0;002)	0.050 (0.002)	0.408	-
	Exit rate is larger in SM-I industries than in SM-II industries	-1.102	0.054 (0.002)	0.571 (0.003)	0.864	-
8	The turbulence within the group of incumbent firms is higher in SM-I industries than in SM-II industries	0.258 (*)	0.147 (0.007)	0.145 (0.006)	0.398	-

(*) indicates acceptance of the equality of variances in accordance to Lavene´s test considered at the 5 % significance level. In those cases one considered the t test for differences in means in the version indicated in expression (1) whereas in other cases in the version from expression (2).

Source: Author´s calculations from PINTEC and PIA database

Previous analogous tests, implemented by Van Dijk (2000, 2002) for the Netherlands, provided a strong support for the various hypotheses. However, one has to be cautions given that the classification used in those studies were based in evidence obtained by Malerba et al. (1995) for a different country. Thus, the tests presented in this sub-section attempt to partially fill a gap in the literature in the context of an emerging economy, and to advance on the works of Van Dijik *op. cit.*, by trying to implement a proper methodology for classification of industrial sectors, and respect the characteristics of the Brazilian industry.

The test results show that in the present application, the contrasts between SM-I and SM-II are not overly sharp. In fact, one can observe significant differences only for two hypotheses. The share of small firms is higher in SM-I industries than in SM-II industries (hip. 1) and in SM-I industries, profit rates are lower than in SM-II industries.

The somewhat weak results pertaining differences between sectors SM-I and SM-II can be analyzed from two aspects. In the empirical front, beyond improving the measurement of some variables it would be worth exploring the relationship between technological classes and industrial sectors. On the other hand, one cannot rule out important specificities of the Brazilian industry that would lead to sectorial patterns of innovation that do not reflect the same standards of developed countries.

Guidolin (2007) sought to classify the Brazilian industry in technological regimes as proposed by Marsali (2002). In this study the author can show that the technological regimes observed in the Brazilian industry differ from those observed for developed countries mainly due to the characteristics of Brazilian innovative process, which are different from process of developed countries.

These results demonstrate significant differences between the types of analysis developed for the Brazilian industry and those developed to developed countries, mainly due to the characteristics of the industry and more specifically to the Brazilian industrialization process. Viotti (2002) highlights that for typical Brazilian industries there have been a strategic focus on the acquisition of technology via foreign direct investment, which may have inhibited the development of technology internally. These specific characteristics of Brazilian industry would make most attempts to classify the Brazilian industry according to a pre-established standard for developed countries a questionable approach.

5. Final Comments

The paper aimed at assessing technological regimes in the context of the Brazilian manufacturing industry. The classification procedure for identifying SM-I and SM-II technological regimes followed the lead of Brescia et al. (2000) though with a different criterion for defining innovating firms. The obtained results are somewhat intuitive in the majority of cases and some salient classification discrepancies with developed countries emerged in the cases of pharmaceuticals and paper and cellulose sectors. However, specificities of those sectors in the Brazilian case make those contrasts as not surprising. The validation of the classification by means of discriminant analysis provided additional confidence in the obtained results.

Finally, a set of hypotheses advanced by Van Dijk (2000, 2002) were made to contrast SM-I and SM-II sectors for the totality of firms. The evidence thus obtained were weaker than those obtained for the Netherlands. Specifically, the share of small firms is higher in SM-I industries than in SM-II industries and in SM-I industries, profit rates are lower than in SM-II industries. Altogether, the evidence seems to indicate less clear cut contrasts between sectors under the two technological regimes that can in part reflect the low technological effort prevailing in a large number of industrial sectors in Brazil.

Possible avenues do future research could involve a finer tuning within technological regimes along the lines of Leiponen and Drejer (2007) and consider should the necessary data be available. improved measurement for some variables, as for example in the case of productivity.

Appendix 1: Perpetual Inventory Method

The stock of capital variable, used as a component of the capital intensity variable, was built using the perpetual inventory method. This method allows us to estimate the capital stock, starting from an initial capital stock depreciated and then summing the acquisitions (investments) in machinery and equipment and deducing the losses of fixed assets. This method can be summarized in terms of the following expression:

where K_{jt+1} and K_{jt}, respectively denote, the capital stock of sector *j* in the *t+1* and *t* periods; I_{jt} is the investment of sector *j* in period *t*; $S_{j,t}$ stands for the scrapping of capital stock, δ is the average rate of depreciation, which we assumed, based on studies of Alves and Silva (2008) and Ferreira & Guillién (2004), equal to 9%.

As showed by the above equation it is necessary to define an initial stock of capital enabling us to estimate the remaining periods of the sample. The 1995`s stock of capital was set as the initial point because this year is the last that the IBGE disclosed an estimative for stock of capital as measured by total fixed assets Consequently, after 1995 the capital stock data is obtained recursively adding to the previous year´s deflated capital stock, the net investments made in the current year (investments in machinery and equipment less scrapping of fixed assets). The application of this method allows to estimate the stock of capital to the period of 1995 to 2005, enabling us to build the capital intensity variable.

Appendix 2

Industrial sectors classified according to their technological regimes

CNAE	Sector	SCHUMP
	Schumpeter Mark I	
152	PROCESSING, PRESERVATION AND PRODUCTION OF CANNED FRUITS, VEGETABLES AND OTHER VEGETABLES	-0,113
154	DAIRY*	-0,114
155	GRIND, MANUFACTURING OF STRACH PRODUCTS AND BALANCED DIETS FOR ANIMALS	-0,123
158	MANUFACTURE OF OTHER FOOD PRODUCTS*	-0,047
176	MANUFACTURE OF ARTIFACTS FROM TEXTILE FABRIC - EXCEPT APPAREL - AND OTHER TEXTILE ITEMS	-0,043
212	MANUFACTURE OF PAPER, PLAIN CARDBOARD, CARDBOARD	-0,031
222	PRINTING AND RELATED SERVICES FOR THIRD PARTY	-0,066
242	MANUFACTURING OF ORGANIC CHEMICALS*	-0,018
245	MANUFACTURE OF PHARMACEUTICAL PRODUCTS	-0,16
246	MANUFACTURE OF AGRICULTURAL DEFENSIVE	-0,007
247	MANUFACTURE OF SOAPS, DETERGENT, CLEANING PRODUCTS AND ARTICLES OF PERFUME*	-0,042
248	MANUFACTURE OF PAINTS, VARNISH, ENAMELS, LACQUERS AND RELATED PRODUCTS	-0,072
249	MANUFACTURE AND PREPARATIONS OF CHEMICALS MISCELLANEOUS	-0,166
251	MANUFACTURE OF RUBBER PRODUCTS	-0,042
264	MANUFACTURE OF CERAMIC PRODUCTS*	-0,015
271	PRODUCTION OF PIG IRON AND FERROALLOY*	-0,056
275	FOUNDRY	-0,118
282	FABRICATION OF TANKS, BOILERS AND METAL RESERVOIRS	-0,143
283	FORGING, STAMPING, POWDER METALLURGY AND METAL PROCESSING SERVICES*	-0,105
289	MANUFACTURE OF MISCELLANEOUS METAL	-0,096
291	MANUFACTURE OF ENGINES, PUMPS, COMPRESSORS AND TRANSMISSION EQUIPMENT	-0,103
292	MANUFACTURE OF MACHINERY AND EQUIPMENT FOR GENERAL USE	-0,147
293	MANUFACTURE OF TRACTORS AND MACHINERY AND EQUIPMENT FOR AGRICULTURE, POULTRY, AND ANIMALS PRODUCTS*	-0,128
296	MANUFACTURE OF MACHINERY AND EQUIPMENT FOR OTHER SPECIFIC USE	-0,086
302	MANUFACTURE OF MACHINERY AND EQUIPMENT FOR ELECTRONIC SYSTEMS DATA PROCESSING	-0,062
313	MANUFACTURE OF WIRES, CABLES AND ELECTRIC LEADS ISOLATED	-0,08
315	MANUFACTURE OF LAMPS AND LIGHTING EQUIPMENT	-0,092
316	MANUFACTURE OF ELECTRICAL EQUIPMENT FOR VEHICLES - EXCEPT BATTERIES	-0,036
321	MANUFACTURE OF BASIC ELECTRONIC MATERIAL*	-0,005
323	MANUFACTURE OF RADIO AND TELEVISION RECEIVERS AND PLAYBACK, RECORDING OR AMPLIFICATION OF SOUND AND VIDEO *	-0,095
331	MANUFACTURING EQUIPMENT AND TOOLS FOR MEDICAL USES-HOSPITAL, AND DENTAL LABORATORIES AND APPARATUS ORTHOPEDIC	-0,131
332	MANUFACTURING EQUIPMENT AND MEASURING INSTRUMENTS, AND CONTROL TEST - CONTROL EQUIPMENT EXCEPT INDUSTRIAL PROCESSES	-0,109
333	MANUFACTURE OF MACHINERY AND EQUIPMENT ELECTRONIC SYSTEMS INDUSTRIAL AUTOMATION AND DEDICATED TO CONTROL THE PRODUCTION PROCESS	-0,117
334	MANUFACTURING EQUIPMENT, MATERIALS AND OPTICAL INSTRUMENTS, FOR PHOTOGRAPHIC AND CINEMATOGRAPHIC INDUSTRY	-0,054
343	MANUFACTURE OF CABINS, CARTS AND TRAILERS	-0,060
344	MANUFACTURE OF PARTS AND ACCESSORIES FOR AUTOMOTIVE VEHICLES	-0,111

Schumpeter Mark II		
132	MINERAL EXTRACTION OF NON-FERROUS METALS	0,937
141	EXTRACTION OF STONE, SAND AND CLAY	0,063
142	EXTRACTION OF OTHER NON-METALLIC MINERALS	0,224
153	PRODUCTION OF VEGETABLE, OILS AND ANIMALS FATS	0,115
159	MANUFACTURE OF BEVERAGES	0,026
160	MANUFACTURE OF TOBACCO PRODUCTS	0,499
174	MANUFACTURE OF TEXTILES ARTIFACTS INCLUDING WEAVING.	0,161
177	MANUFACTURING OF FABRICS AND KNITWEAR	0,034
182	MANUFACTURE OF CLOTHING ACCESSORIES AND PERSONAL PROTECTIVE EQUIPMENT	0,001
211	MANUFACTURE OF PULP, AND OTHER SUPPLIES FOR PRODUCTION OF PAPER	0,205
213	MANUFACTURE OF PAPER OR CARDBOARD PACKAGING	0,293
232	PRODUCTION OF OIL DERIVATIVES	0,458
234	PRODUCTION OF ETHANOL	0,014
243	MANUFACTURING AND RESINS ELASTOMERS	0,003
261	MANUFACTURE OF GLASS AND GLASS PRODUCTS	0,347
263	MANUFACTURE OF ARTIFACTS OF CONCRETE, CEMENT, FIBERCEMENT, PLASTER AND STUCCO	0,096
269	APPLIANCES STONES AND MANUFACTURE OF LIME AND OTHER PRODUCTS OF NON-METALLIC MINERALS	0,049
272	STEEL	0,027
274	METALLURGY OF NON-FERROUS METALS	0,016
281	MANUFACTURE OF METAL STRUCTURES AND ARTICLES OF HEAVY BOILERS	0,06
284	MANUFACTURE OF CUTLERY, HAND TOOLS AND BLACKSMITHING	0,106
294	MANUFACTURE OF MACHINE TOOLS	0,202
295	MANUFACTURE OF MACHINERY AND EQUIPMENT FOR USE IN MINERAL EXTRACTION AND CONSTRUCTION	0,312
297	MANUFACTURE OF ARMS, AMMUNITION AND MILITARY EQUIPMENT	0,163
298	MANUFACTURE OF APPLIANCES	0,045
314	MANUFACTURE OF BATTERIES, BATTERIES AND ELECTRIC ACCUMULATORS	0,069
319	MANUFACTURE OF OTHER EQUIPMENT AND ELECTRIC APPLIANCES	0,223
322	MANUFACTURE OF EQUIPMENT FOR TELEPHONY AND RADIOTELEPHONY AND TELEVISION AND RADIO TRANSMITTERS	0,021
335	MANUFACTURE OF WATCHES AND TIMERS	0,137
342	MANUFACTURE OF TRUCKS AND BUSES	0,065
351	CONSTRUCTION AND REPAIR OF CRAFT	0,136
352	CONSTRUCTION, INSTALLATION AND REPAIR OF RAILWAY VEHICLES	0,475
359	MANUFACTURE OF OTHER TANSPORT EQUIPMENT	0,211

* Sectors whose classification was changed based on the analysis of discriminant functions.

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