STRUCTURAL CHANGES IN THE BRAZILIAN INTERREGIONAL ECONOMIC SYSTEM, 1985-1997: HOLISTIC MATRIX INTERPRETATION

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ABSTRACT: In this paper, we focus on the changes in the interregional trade flows in the Brazilian economy. Interregional trade matrices are constructed for two years, 1985 and 1997, and a Machlup-Goodwin-type model is applied following Haddad, *et al.*, (1999). The model is used to explore changes in the trade structure among the 27 Brazilian states. Holistic matrix methods such as cluster and structural analyses are applied to the interregional system to explore the nature of the trade structure and the changes evident over the period 1985-1997.

1. INTRODUCTION

Changes in bilateral trade relations are one of the most important characteristics in modern economies. Globalization, trade agreements and the creation of free trade areas are some of the factors that can produce important changes in trade flows between countries. Similar influences may be demonstrated for changes in interregional trade flows within national economies, as factors and sectors react to changes in external trade regimes. One obvious method for studying bilateral trade is the gravity model, which offers a systematic way to measure what patterns of bilateral trade are normal around the world. Frenkel (1997) surveys and estimates a series of gravity models of bilateral trade among countries. His main goal is to examine data on bilateral trade in order to access the influence of geographical proximity versus preferential trading policies in creating regional concentration in trade.

The basic assumption in a gravity model of bilateral trade is that trade between countries depends positively on their size and inversely on distance. The application of gravity-type models to interregional trade (between states in a country, for example) is straightforward, and became very popular in the literature (see Isard, 1998). These models can also be applied to study temporal changes in bilateral trade, usually using pooled time-series and cross-sectional data. In this framework, a simple time-dummy variable can be specified to test change in the overall mean of bilateral trade (e.g. Frenkel, 1997, p.82).

Although very useful to examine the role of size and distance in bilateral trade, the gravity type model seems inadequate when applied to explore temporal changes in interregional trade systems. First, the only temporal change examined in the model is the overall mean of bilateral trade[1]. Secondly, and maybe more importantly, pooled time series in this case implies a loss of information as the structure of trade is joined in a single variable.

In this paper, we evaluate other methodologies to study changes in the system of interregional trade applying holistic matrix methods. A Machlup-Goodwin-type model is employed following Haddad, *et al.,* (1999). This model is used to explore changes in the trade structure. Thereafter, cluster and structural analyses are applied to the input-output matrices in an exploratory fashion to determine more precisely the nature of the changes.

Two interregional matrices were constructed for 1985 and 1997, based on recently published data. The selected methodologies are used to examine changes in the exchange structure among the 27 Brazilian states. First, a gravity type model is estimated to access some broad changes and tendencies in the interregional system. Some shortcomings in the gravity model are discussed, and the proposed matrix methods are introduced in Section 3. These holistic matrix methods are then used to explore structural changes in the Brazilian interregional system. The following section interprets the results, compares the findings derived from the different methods and offers some perspectives on the exploratory analyses. The paper concludes with some reflections on the findings and their implications for more general modeling exercises.

2. THE MATRIX OF INTERSTATE TRADE FLOWS AND THE BRAZILIAN CASE

Two important changes in the Brazilian economy were the trade liberalization process, which took place since late 1980s, and the stabilization plan initiated in 1994. These two policy decisions, among others, have strongly affected the Brazilian economy in many ways; however, most analysis and interpretation of these recent economic changes have focused on macroeconomic impacts and national issues. Regional and spatial effects of these changes are important issues that have been relatively neglected. For example, the impact in the exchange trade structure among regions remains an undeveloped issue. Typically, analysts resort to the development of interregional computer general equilibrium (ICGE) models to address the spatial impacts of macro policies (see,

[1] Also a panel data estimation could be carried out, and dummy interactions specified, but these specifications do not change the problem of identifying structural change.

for example, Haddad, 1999). The present paper may be seen as an *exploratory* analysis of changes in the structure of interregional trade since there is no attempt to craft explanation from an ICGE. The questions posed are relatively simple, yet important ones. For example, over the period of analysis that macro trade liberalization took place, is it possible to detect any impact on the regional patterns of trade, in terms of origin-destination flows, the magnitude of the flows and the general pattern of exchange?

A further exploration concerns the concentration of economic activity. Fujita *et al.* (1999) explored theoretical models to study the effects of reducing an external trade barrier. Their interpretation "... suggests that external trade liberalization, although it brings a spatial deconcentration of industry as a whole, may also bring spatial clustering of particular industries, as locations come to specialise" (pp. 330). One would thus expect that spatial clustering of activities would be accompanied by a similar clustering of flows, although other factors, such as transportation costs in particular and transfer costs in general, would play an important role (see Magalhães *et al.*, 2001).

The link between these theoretical findings and the interregional exchange structure depends on the spatial distribution of the activities and how the trade liberalization process has affected each industry. Moreira (2000) has explored sectoral impacts of changes in the Brazilian economy. His analysis revealed that intra-industry specialization has occurred, and that in most of the sectors, the shares of imports and exports have increased. This change, among others, has probably affected the exchange structure between regions.

The data used to construct the matrices are interstate flows (CONFAZ, 1999 and IBGE, 1996), gross regional product (GRP) and total production, by state. Table 1 summarizes the data collected for 1985 and 1997, and displays the share in total population by state to provide a sense of the uneven spatial distribution. It is worth noting that the state shares in national GDP and total population have not changed very much, whereas regional trade balance (domestic exports less domestic imports as a share of GRP) in some states have displayed large changes.

The development of the **M**atrix of **I**nterstate **T**rade **F**lows (MIST) model follows Haddad, *et al.* (1999). However, while the latter paper deals with countries in a global economy, in the present context, attention will be directed to interactions between states within a national economy. Consider the following balance identity, which is applicable for each state i in the national economy:

$$X_i + C_i + I_i + G_i \equiv M_i + Y_i \tag{1}$$

where:

$$X_i + C_i + I_i + G_i = \text{total production of the state } i \tag{2}$$

$$M_i + Y_i = \text{total domestic demand in state } i = \text{total expense of the state } i \tag{3}$$

Table 1. Brazilian Interregional Data, Summary (1985, 1997).

State	% GRP in GDP		% Total Population		Interregional Trade Balance (% GRP)	
	1985	**1997**	**1985**	**1997**	**1985**	**1997**
Acre (AC)	0.13	0.15	0.27	0.31	-32.31	-15.80
Alagoas (AL)	0.86	0.66	1.69	1.67	-22.90	-26.85
Amapá (AP)	0.12	0.18	0.17	0.25	-34.25	-20.43
Amazonas (AM)	1.52	1.66	1.32	1.54	16.28	36.93
Bahia (BA)	5.35	4.25	8.01	7.96	-1.67	-8.87
Ceará (CE)	1.72	2.02	4.39	4.34	-19.42	-19.61
Distrito Federal (DF)	1.37	2.28	1.04	1.18	-37.90	-31.94
Espírito Santo (ES)	1.72	1.86	1.74	1.79	-14.59	21.17
Goiás (GO)	1.80	2.04	3.30	3.58	-23.60	-34.60
Maranhão (MA)	0.74	0.85	3.36	3.32	-42.43	-35.71
Mato Grosso (MS)	0.69	1.05	1.17	1.43	-43.98	-2.55
Mato Grosso do Sul (MT)	0.95	1.07	1.18	1.23	-14.29	-18.73
Minas Gerais (MG)	9.61	10.01	10.98	10.59	4.23	3.01
Pará (PA)	1.52	1.69	3.12	3.54	-24.58	-22.80
Paraíba (PB)	0.72	0.80	2.25	2.09	-28.22	-27.54
Paraná (PR)	5.92	6.07	6.08	5.73	4.25	0.29
Pernambuco (PE)	2.62	2.69	5.01	4.68	-9.47	-22.76
Piauí (PI)	0.39	0.49	1.78	1.69	-32.51	-38.45
Rio Grande do Norte (RN)	0.78	0.77	1.62	1.63	-12.19	-31.21
Rio Grande do Sul (RS)	7.88	7.95	6.38	6.12	-0.26	-2.07
Rio de Janeiro (RJ)	12.70	11.22	9.10	8.49	6.67	-13.52
Rondônia (RO)	0.48	0.48	0.59	0.79	-28.25	-25.70
Roraima (RR)	0.07	0.07	0.11	0.16	-87.35	-33.75
Santa Catarina (SC)	3.30	3.66	3.07	3.11	2.95	-5.62
São Paulo (SP)	36.12	35.48	21.28	21.77	5.99	15.38
Sergipe (SE)	0.92	0.56	0.99	1.04	-10.65	-22.46

and, I, G, X *and* M are private consumption, investment, government expenditures, exports and imports in state i respectively.

X and M are comprised of both domestic and external flows, that is, they incorporate interregional flows and foreign trade. The final demand components are consumption, C, investment, I, and government spending, G.

The trade flows X and M for each state can be decomposed in two parts, domestic and foreign:

$$X_i = \sum_{j=1}^{n} x_{ij} + \overline{X}_i \tag{4}$$

$$M_i = \sum_{j=1}^{n} m_{ij} + \overline{M}_i \tag{5}$$

The x_{ij} s are the sales of the state i to the state j and $\overline{X}_i$ are the foreign exports of the state i. In a similar way, the m_{ij} s are purchases (imports) of the state i from the state j and $\overline{M}_i$ are foreign imports by the state i. The interregional flows matrices $[x_{ij}]$ and $[m_{ij}]$ are the same. The diagonal elements are zero, as we are treating each state as an individual firm. Therefore, all intra-state intermediate consumption and final demand is in the 'final demand' vector.

Substituting (4) and (5) in (1):

$$\sum_{j=1}^{n} x_{ij} + \overline{X}_i + C_i + I_i + G_i = \sum_{j=1}^{n} m_{ij} + \overline{M}_i + Y_i = E_j \text{ for } i = 1,\ldots, n. \tag{6}$$

where E_j is the total final demand in the state i.

The result will be an input-output-type table in which the rows describe the distribution of a state's domestic production throughout the national economy plus foreign exports ($\sum_{j=1}^{n} x_{ij} + \overline{X}_i + C_i + I_i + G_i$), while the columns reveal the composition of a state domestic expenditure plus foreign imports ($\sum_{j=1}^{n} m_{ij} + \overline{M}_i + Y_i$). Table 2 shows the layout of the MIST. The mathematical structure of the system consists of a set of n linear equations with n unknowns. In similar fashion to input-output systems, the solutions are straightforward mathematically, but there are differences in the economic interpretations of some of the results.

The system of n equations can be written in matrix notation as:

$$\text{TZ} + \text{F} = \text{Z} \tag{7}$$

where:

T is the interregional import coefficients matrix $(n \times n)$, Z is the total final demand vector $(n \times 1)$ and F is the exogenous final demand vector $(n \times 1)$.

Table 2: Matrix of Interstate Trade Flows.

		STATES								Final Demand (C+I+G+X)
		1	2	.	.	.	.	n-1	n	
STATES	1		*E*	*X*	*P*	*O*	*R*	*T*	*S*	
	2	*I*								
	.	*M*								
	.	*P*								
	.	*O*								
	.	*R*								
	n-1	*T*								
	N	*S*								
Foreign Imports										
GRP										

Solving (7) yields:

$$Z = (I - T)^{-1} F \tag{8}$$

In the next section, some methodology that focuses on aggregate analysis of structure is reviewed and applied to the interregional systems for both years. The objective here is to probe for structural changes and similarities that gravity models and more casual inspection of the matrices might overlook.

3. EMPIRICAL ANALYSIS

First of all, a gravity type model is estimated using the information derived from the two interregional trade matrices introduced in the previous section. Cluster analysis and derivatives of bi-proportional adjustment mechanisms have proven to be popular, and valued, methods for uncovering changes in the structure of economic systems. These will be reviewed in turn and then applied to the Brazilian interregional system.

3.1 Gravity Type Model

A gravity model for interstate trade flows (1985 and 1997) is estimated using the data outlined in the previous section together with some geographic characteristics. The database for the estimation is constructed pooling the two cross sectional matrices. The dependent variable is the trade flow from state i to state j. The explanatory variables are the gross regional products of state i and j. These represent supply and demand effects; the expected result is that the larger the GRP the larger the trade flows between the states. Spatial characteristics are introduced through three variables. The simple distance between the states captures the overall effect of transport costs. Two dummies are introduced to indicate a common border between states and the location in the same macro region. A time dummy is introduced to identify the year (it equals 1 in 1997 and

0 in 1985). The effect of this dummy is the interaction with the constant term. If this dummy is not significant, then the mean bilateral trade in both years has not changed.

All the variables are used in (natural) logarithmic form. The proposed model is:

$$\log(TRADE_{ij}) = \alpha + \beta_1 \log(GRP_i) + \beta_2 \log(GRP_j) + \beta_3 \log(DIST_{ij}) + \beta_4(ADJACENCY_{ij}) + \beta_5(D97) + \beta_6(DREG) + u_{ij} \quad (9)$$

where:

$TRADE_{ij}$ is the flow of trade from state i to state j

GRP_i is the GRP of state i (supply effect)

GRP_j is the GRP of state j (demand effect)

$DIST_{ij}$ is the distance between states i and j

$ADJACENCY_{ij}$ indicates when two states share a common land border

D97 is a time dummy (1997 = 1)

DREG indicates when two trading partners are located in the same macro region

Table 2a shows the gravity model results. The variables have the expected sign and are highly significant, except for the dummy variable. This result implies that there is no change in the overall mean of the bilateral trade flows between 1985 and 1997. It is worth noting that the estimated distance coefficient (-0.656) is in the usual range for these models (see Fujita *et.al.* 1999 p.98; and Frenkel, 1997, p.72).

The point to be made is that the gravity model is often used as a measure of structural change but it does not "tell us the story". In order to explore the structural changes in the inter-regional trade system, holistic matrix methods are explored in the next sections.

3.2 Cluster Analysis

Regional and industrial cluster identification has proven to be very popular in local and regional development research and practice.[2] This paper will apply some of these concepts in the study of the changes in the estimated Brazilian interstate trade matrix. The purpose will be to identify possible changes in the interregional linkages between states over this time period (1985-1997).

The first approach employs an interindustry linkage measure proposed by Czamanski and Ablas (1979). The following four coefficients based on input-output flows, i.e. the interregional trade matrix, describe the relative importance of the links, either for the supplying or for the purchasing state:

[2] A survey of the concepts and applications of cluster analysis can be found in Bergman and Feser (1999).

Table 2a. Gravity Model.

Dependent Variable is $TRADE_{ij}$		
	Parameter	***t*-statistic**
Constant	-22.795	-22.542
GRP_i	1.375	51.519
GRP_j	0.964	36.155
$DIST_{ij}$	-0.656	-9.418
$ADJACENCY_{ij}$	0.835	6.744
D97	-0.126	-1.757*
DREG	0.349	2.841
Number of observations	1247	
R-squared	0.805	
Adjusted R-squared	0.804	
F-statistic	852.126	
Prob(F-statistic)	0.000	

*Not significant at 5% level
All variables taken in natural log terms

$$a_{ij} = \frac{x_{ij}}{\sum_j x_{ij}}; \; a_{ji} = \frac{x_{ji}}{\sum_i x_{ji}};$$
$$b_{ij} = \frac{x_{ij}}{\sum_i x_{ij}}; \; b_{ji} = \frac{x_{ji}}{\sum_j x_{ji}}; \qquad (10)$$

where x_{ij} is the yearly flow in R$ millions of goods and services traded from state *i* to state *j*. Each coefficient is an indicator of dependence between states *i* and *j*, in terms of relative purchasing and sales linkages:

a_{ij}, a_{ji}: good purchases by *j* (*i*) from *i* (*j*) as a proportion of *j*'s (*i*'s) total good purchases. A large value for a_{ij} suggests that state *j* depends on state *i* as a source for a large proportion of its total purchases.

b_{ij}, b_{ji}: good sales from *i* (*j*) to *j* (*i*) as a proportion of *i*'s (*j*'s) total good sales.

A large value for b_{ij}, for example, suggests that state *i* depends on state *j* as a market for a large proportion of its total sales.

The largest of the four coefficients is selected for each pair of states. This yields a symmetric data matrix, L_{U}, that, when subjected to hierarchical cluster analysis, generates clusters that at least partially capture indirect linkages between states.

This approach investigates the isolated functional linkage between pairs of states. Another criterion used for grouping industries (i.e. states) in a cluster was similarity between their total profiles of suppliers and buyers, including those outside the cluster (Czamanski and Ablas, 1979). This second approach indicates whether or not states have comparable purchase or selling patterns, since two states may be members of a cluster in the absence of direct linkages. It employs four correlations to describe the similarity between the exchange structure of two states, *k* and *l*:

$r(a_{ik}, a_{il})$: degree to which purchasing patterns are similar.

$r(b_{ki}, b_{li})$: degree to which output selling patterns are similar.

$r(a_{ik}, b_{li})$: degree to which the buying pattern of state *k* is similar to the selling pattern of state *l*.

$r(b_{ki}, a_{il})$: degree to which the buying pattern of state *l* is similar to the selling pattern of state *k*.

From these sets of correlations covering all possible pairs of states, an *n* x *n* intercorrelation matrix, L_V, was produced by selecting the highest of the four correlations for each pair of states.

A high $r(a_{ik}, a_{il})$ coefficient indicates that the two states, *k* and *l*, have similar purchase structures. A high $r(b_{ki}, b_{li})$ coefficient signifies that the two states, *k* and *l*, trade their products to a similar set of states. A high $r(a_{ik}, b_{li})$ coefficient implies that state *k* selling profile is related to state *l* purchase pattern. The reason for picking the highest of these four correlations is to identify the stronger linkages between each pair of states.[3]

Each column of this symmetric matrix describes the pattern of linkage between each state and all other states in the set. Hierarchical cluster analysis can be used to identify groups of related states. The matrices L_U and L_V will be calculated for the two years, 1985 and 1997. Hierarchical cluster analysis will be used to identify clusters in each case, and the results will be compared. The focus will be the change between the clusters identified in 1985 and 1997, for each matrix.

Hierarchical cluster methods are clustering algorithms that try to find reasonable clusters without having to look at all possible configurations. In the case of agglomerative hierarchical methods, they proceed by a series of successive mergers. Starting with the individual elements, the most similar are first grouped, and these initial groups are merged according to their similarities. *Linkage methods* are some of these agglomerative hierarchical methods. This

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[3] We are not, at this time, trying to identify which linkages (selling or purchasing) are the most important. Other methodologies are necessary to make this analysis, they will be implemented in section 3.3 and 3.4.

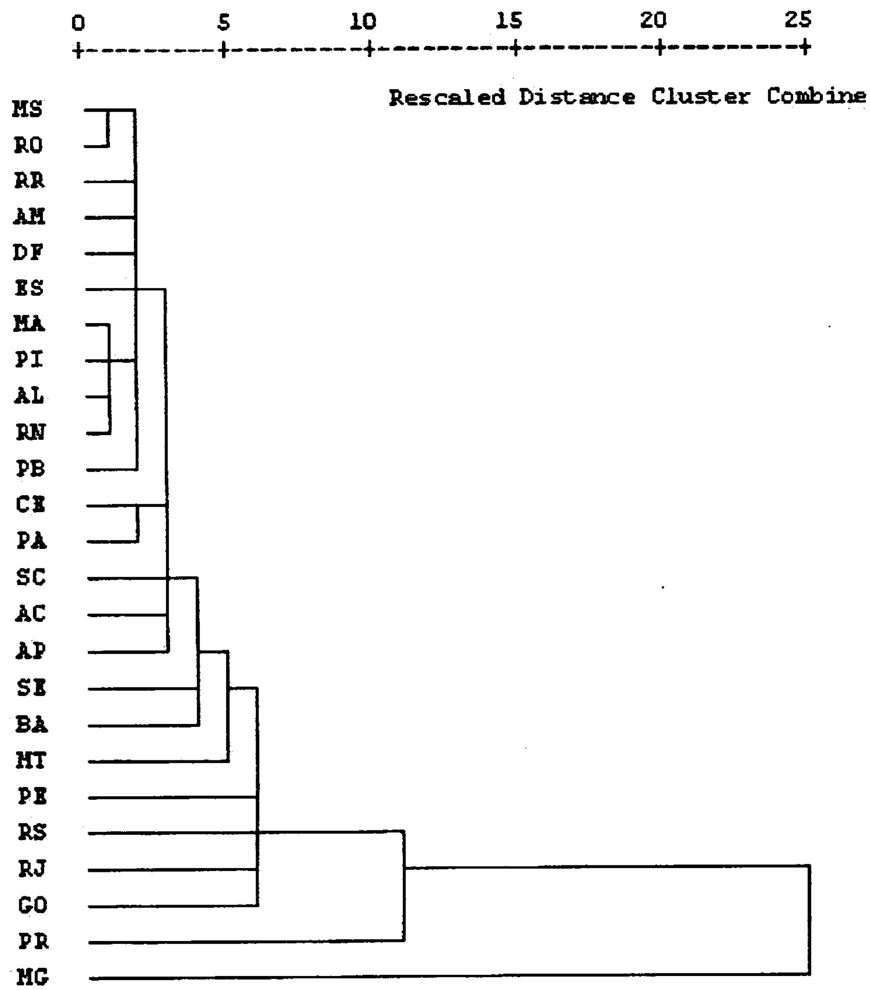

Figure 1a. Hierarchical Cluster Analysis – Matrices. Dendrogram Using Single Linkage. L_U Matrix 1985.

paper employs the *single linkage* procedure to identify the hierarchical clusters in the matrices L_U and L_V.[4]

In the single linkage procedure, groups are formed from the individual elements by merging nearest neighbors, where the term nearest neighbor connotes the smallest distance or large similarity. A description of this method

[4] This procedure and others for hierarchical cluster analysis are available in the release 10.1.0 of the SPSS package.

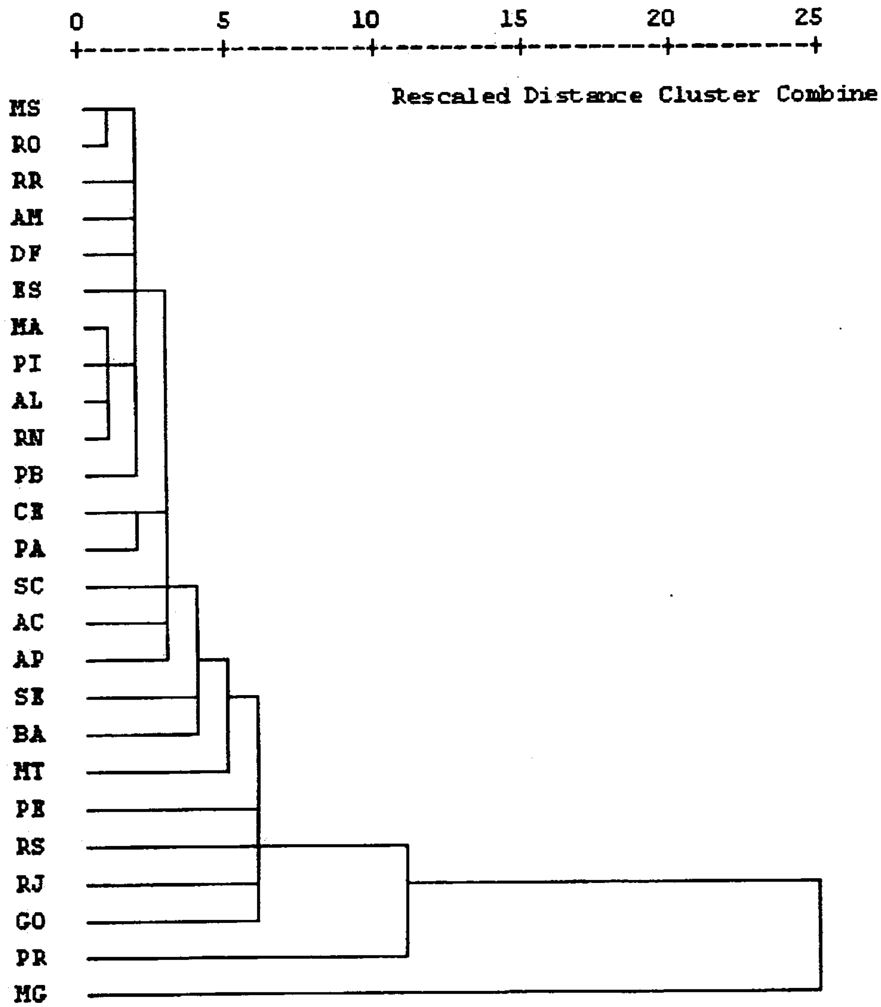

Figure 1b. Dendrogram using Single Linkage
L_U Matrix 1997.

can be found in Johnson and Wichern, 1998.[5] The results of the method can be displayed in the form of a two-dimensional diagram known as *dendrogram*, or tree diagram. The *dendrogram* illustrates the mergers that have been made at successive levels; each level (branch in the tree) implies a specific cluster and the distance between levels show the similarity between clusters (minimum distance means maximum similarity).

[5] Different methods applied to the L_U and L_V matrices (*complete linkage, average linkage, ward's hierarchical clustering method, between groups*) have generated similar results. The single linkage was adopted because it can delineate non elipsoidal clusters (Johnson and Winchern (1998), pp. 742-744).

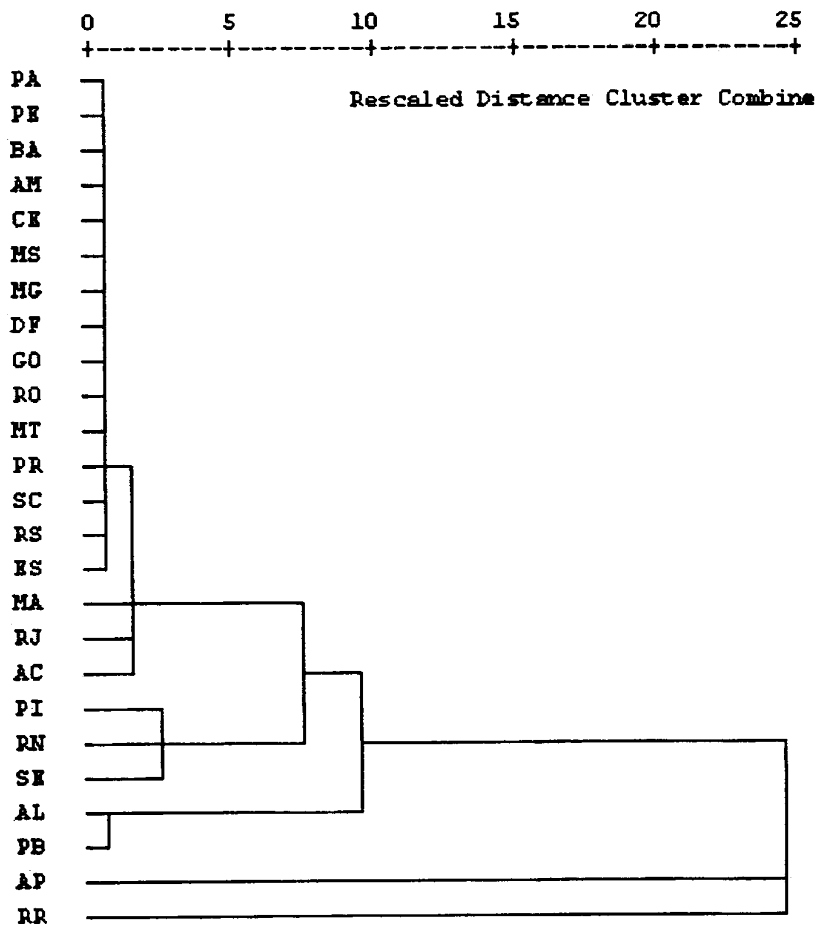

Figure.2a. Hierarchical Cluster Analysis - Matrices $\mathbf{L_V}$
Dendrogram using Single Linkage
$\mathbf{L_V}$ Matrix 1985.

The matrices subject to the hierarchical cluster method are symmetric distance matrices produced from the original data (matrix). In the case of the L_U and L_V matrices the distance matrix produced for the algorithm are simple transformations of the values (high correlation implies low distance).

Figure 1 reveals the *dendrograms* for the matrices L_U in 1985 and 1997. The state of São Paulo was dropped from the analysis because its very different (and dominant) pattern tended to hide the differences among other states. For 1985, various groups of states can be seen to cluster at intermediate levels. Recall that the L_U matrix captures the interdependence between states. Therefore the 1985 *dendrogram* indicates a highly different pattern in the interregional linkages. This characteristic is less evident if we observe the *dendrogram* for the L_U matrix in 1997. Here, a large group of states that cluster at lowers levels (great similarity) is observed. In the following levels, only two states come together,

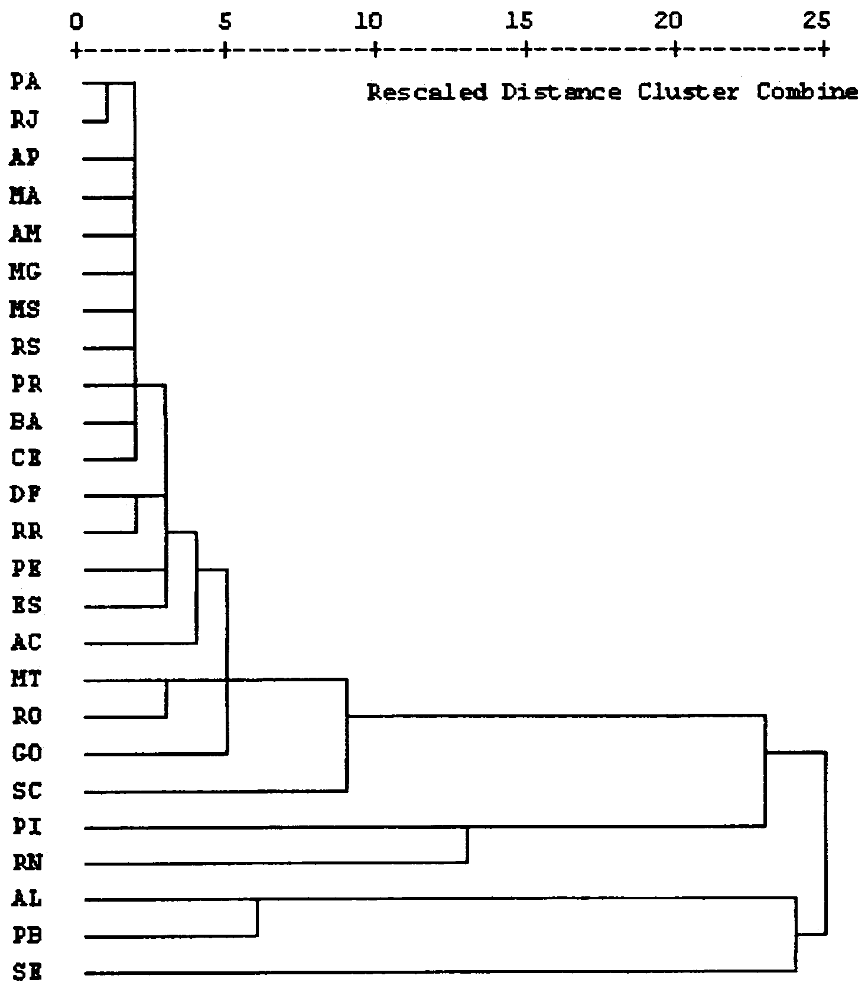

Figure 2b. Dendrogram using Single Linkage
L_V Matrix 1997.

Minas Gerais (MG) and Parana (PR). We should note that, in 1997, these two large states in the Brazilian economy and as well Rio Grande do Sul (RS) and Rio de Janeiro have clustered together. Sao Paulo (not shown) remains a dissimilar component in the interregional pattern of linkages.

The two *dendograms* in Figure 1 illustrate a homogeneity tendency at intermediate and lower levels. Some states that have dissimilar interregional linkage structures in 1985 become more similar in 1997. Only two states, Minas Gerais and Parana, become more dissimilar in this period.

In Figure 2, the *dendograms* for the L_V matrices show a pattern similar to those revealed in Figure 1. The movement in the hierarchical clusters maintains the same trend as in the L_U matrices, but seems to be stronger. Recall that the L_V matrix captures the similarity in the exchange structure between states. Some clusters at higher levels have vanished; only Sao Paulo remains in its position as a very different structure in 1997.

3.3 Causative Matrix

Since the exploration focuses on modeling structural economic change, defined as changes in interactions among states, an input-output type model has been chosen since it provides a rich representation of economic structure. The causative matrix approach focuses on these inter-states interrelationships. The causative matrix method has been applied to input-output tables by Jackson, *et al.*, (1990); this methodology will be implemented in the Machlup-Goodwin-type model established here.

The T matrix is observed in two periods, t and $t+k$. Hence, two Leontief inverses are calculated as in (8). Starting from the inverse matrix $B=(I-T)^{-1}$, two transition matrices are computed, B_M^t and B_M^{t+k}. These matrices are the normalized Leontief matrices in each period, t and $t+k$. The transition matrices are the Leontief inverse normalized by their respective column sums:

$$B_M^t = B^t (M^t)^{-1} \tag{11}$$

$$B_M^{t+k} = B^{t+k} (M^{t+k})^{-1} \tag{12}$$

where M^t and M^{t+k} are diagonal matrices whose elements m_{jj} equal the sums of the jth column of the respective B matrix.

Matrix B_M^{t+k} is assumed to be linked to the matrix B_M^t as follows:

$$B_M^{t+k} = CB_M^t \tag{13}$$

The C matrix maps the change between B_M^t and B_M^{t+k}. This *left causative matrix* is obtained by inverting B_M^t :

$$C = B_M^{t+k} (B_M^t)^{-1} \tag{14}$$

Jackson, *et al.* (1990) show that the causative matrix goes beyond examining direct changes in the elements of B_M by including the relative effects from other states. The resulting matrix C should be compared to the identity matrix. Elements of C different from those of an identity matrix indicate changing structure in the network of exchange interactions linking states.

The C matrix has n^2 elements that may be analyzed. Two sets of elements can be used to summarize this information. As pointed out by Jackson, *et al.* (1990), the row sums of the C matrix are also interpretable: off-diagonal row sums greater than 0 mean generally greater contributions to output multipliers, hence these states experience greater impacts when final demand in other states changes. The diagonal elements show the relative endogenization in the states of their own final demand output impacts.[6]

A typology of the nature of structural changes for each of the 26 states is presented by combining these elements of the causative matrix. Given S_i, the off-diagonal row sum for state i, and d_i, the diagonal element for state i, the following classification is established, related to changes in each state own final demand and demand from other states[7]:

Type I: $d_i > 1, S_i > 0$

In this case, the state became relatively more dependent on its own final demand impacts and more dependent on other states demand.

Type II: $d_i < 1, S_i > 0$

State i became relatively less dependent on its own final demand impacts and more dependent on other states demand. Therefore, trade became relatively more important to stimulate production in state i.

Type III: $d_i < 1, S_i < 0$

As in type II, state i became relatively less dependent on its own final demand impacts, but less dependent on other states demand.

Type IV: $d_i > 1, S_i < 0$

In this case, state i became relatively more dependent on its own final demand impacts and less dependent on other states demand. Therefore, trade became relatively less important to stimulate output in state i.

Table 3 displays the results obtained with the causative matrix. None of the states has a type III classification, and most of them have a type IV typology. This type IV group clusters the bigger states in the Brazilian economy including Sao Paulo, Minas Gerais, Parana and Rio Grande do Sul. Therefore, an important feature in the changing structure points to greater endogenization in the states of own final demand impacts and decreased output impacts created from other states. In such a way, trade became relatively less important to these states.

The type I group shows states that became relatively more dependent on its own final demand impacts and more dependent on other states demand. The distinctive feature here is the increased output impacts created from other states. Therefore, trade became relatively more important to these states. This last movement in particularly significant in Amazonas and Rio de Janeiro, two important states in the North and Southeast regions, respectively.

3.4 Biproportional Filters

The left causative matrix model applied earlier is appropriate for the study of changes in backward linkages because attention has been directed to changes in column coefficients. As pointed out by Jackson *et al.* (1990), a right causative

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[6] Sonis, *et al.*, (1996) employing an alternative decomposition have referred to this as self and non-self changes in demand.

[7] Jackson *et al.* (1990) applied the same typology for US industrial sectors .

Table 3. Structural Change in the Inter-state Exchange Relationships, Based on the Methodology of Left Causative Matrix.

State	Type	Off-diagonal Sum	Diagonal
Amazonas	I	0.3296	1.0025
Rio de Janeiro		0.1664	1.1676
Pernambuco		0.1484	1.0286
Piauí		0.0230	1.0096
Rio Grande do Norte		0.0210	1.0725
Rondônia		0.0096	1.0136
Para	II	0.1283	0.9940
Mato Grosso do Sul		0.0657	0.9766
Maranhão		0.0537	0.9471
Distrito Federal		0.0262	0.9885
Amapá		0.0023	0.9121
Roraima		0.0014	0.8699
Acre		0.0002	0.9914
São Paulo	IV	-0.7763	1.0748
Minas Gerais		-0.4130	1.1615
Paraná		-0.2198	1.0772
Mato Grosso		-0.1437	1.0130
Goiás		-0.1339	1.1271
Ceara		-0.0765	1.0425
Espírito Santo		-0.0635	1.0812
Bahia		-0.0454	1.0603
Paraíba		-0.0335	1.0320
Sergipe		-0.0254	1.1986
Santa Catarina		-0.0234	1.0321
Alagoas		-0.0164	1.0947
Rio Grande do Sul		-0.0135	1.0394

matrix model would be appropriately defined for sales (rows) coefficients, where interest is in the forward linkages. Conceptually, a left causative matrix is associated with demand-driven (Leontief) models, and right causative matrix with supply-driven (Ghosh) models[8].

The bi-proportional filter methods proposed by Mesnard (2000a) are appropriate tools to analyze structural change but avoiding reliance on one of these hypotheses. Although the results from the biproportional filters cannot be

[8] There is a large volume of literature about what model can be considered as the more attractive (for example Oosterhaven, 1988, Mesnard, 1997 and 2000b). In general the demand driven model is considered more plausible and much more used.

directly compared with those from the left causative matrix[9], they do provide additional information to analyze structural changes in input-output-type systems.

The idea is to generalize the comparison of technical and allocation coefficients. In this method, the two flow matrices are compared directly, without using technical coefficients or normalized Leontief matrices. Therefore, "...*ex ante* stability of technical and allocation coefficients will not be posed and their stability will be measured eventually *ex post*, that could help to dismiss one of the alternative hypothesis or both eventually." (Mesnard, 2000b, p. 6)

The basic principle in this method is to project an initial flow matrix T using the margins (columns and row sums) of a final matrix T^*. We should compute a matrix $\hat{T}$ as close as possible to T, with the margins of T^*. This is a similar undertaking to the normalization of both columns and rows. After that, the differences between $\hat{T}$ and T^* can be analyzed using an indicator of changes like the Frobenius norm of the columns and rows.

There are many methods to carry out the projection of a matrix from the margins of another, with the biproportional filter being just one of them. The result of a biproportion that gives to T the same margins of T^*, $\hat{T} = K(T,T^*)$, is given by $\hat{T} = PTQ$, where P and Q are diagonal matrices. These matrices respectively allow $\hat{T}$ to respect the margin (14) and closeness (15) conditions:

$$\sum_i \hat{t}_{ij} = \sum_i t^*_{ij} \text{ for all } i \tag{15}$$

$$\sum_j \hat{t}_{ij} = \sum_j t^*_{ij} \text{ for all } j \min \sum_i \sum_j \hat{t}_{ij} \log \frac{\hat{t}_{ij}}{t_{ij}} \tag{16}$$

The RAS algorithm is one of the biproportional filters that obey these two conditions. Moreover, the RAS has a unique solution, as demonstrated by Bacharach (1970), and all algorithms respecting these two conditions give the same results (Mesnard, 1994). All the projections calculated in this paper utilize the RAS algorithm.[10]

The *biproportional ordinary filter* (Mesnard, 1998) is the projection of matrix T in the margins of T^*: $\hat{T} = K(T,T^*)$. The resultant $\hat{T}$ matrix is compared to T^* through the difference matrix: $T^* - \hat{T}$. Then, relative variations for columns and rows are computed:

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[9] The results from the left causative method cannot be compared with those from the right causative matrix as well.

[10] The applied computation procedure for RAS utilized in this paper is included in the DAGG program, available at Monash University (www.monash.edu.au/policy/gpmark.htm).

$$\sigma_j^C = \frac{\sqrt{\sum_i [t_{ij}^* - K(T,T^*)_{ij}]^2}}{\sum_i t_{ij}^*}, \text{ for column } j \qquad (17)$$

$$\sigma_i^R = \frac{\sqrt{\sum_j [t_{ij}^* - K(T,T^*)_{ij}]^2}}{\sum_j t_{ij}^*}, \text{ for row } i \qquad (18)$$

The biproportional ordinary filter can also be computed in the reverse order. In this case, the projection of matrix T^* is in the margins of T: $T' = K(T^*,T)$. The resultant T' matrix is compared to T through the difference matrix. As in (16) and (17), relative variations for columns and rows can be computed:

$$\sigma_j^C = \frac{\sqrt{\sum_i [t_{ij} - K(T^*,T)_{ij}]^2}}{\sum_i t_{ij}}, \text{ for column } j \qquad (19)$$

$$\sigma_i^R = \frac{\sqrt{\sum_j [t_{ij} - K(T^*,T)_{ij}]^2}}{\sum_j t_{ij}}, \text{ for row } i \qquad (20)$$

Therefore, there are two possible sets of different results, the direct (17 and 18) and reverse (19 and 20) biproportional filters. There is no criterion to indicate which of them is better or more adequate.

To avoid the double projection, the biproportional mean filter (Mesnard, 1998) can be used. In this case, each matrix T and T^* is projected in the margins of the mean of these matrices. Then we have two projected matrices, $K(T,\overline{T})$ and $K(T^*,\overline{T})$, where $\overline{T} = 1/2\ (T+T^*)$. These two matrices are compared calculating relative variations for columns and sums:

$$\sigma_j^C = \frac{\sqrt{\sum_i [K(T^*,\overline{T})_{ij} - K(T,\overline{T})_{ij}]^2}}{\sum_i \bar{t}_{ij}}, \text{ for column } j \qquad (21)$$

$$\sigma_i^R = \frac{\sqrt{\sum_j [K(T^*,\bar{T})_{ij} - K(T,\bar{T})_{ij}]^2}}{\sum_j \bar{t}_{ij}}, \text{ for row } i \tag{22}$$

In this case, only one set of calculations is made. This result removes the effects of the differential growth of states, but not the effect of differences in the size of states.

A third biproportional filter offers the option of eliminating the difference in the sizes of states. The idea is to normalize both columns and sums simultaneously in each matrix. This *biproportional bimarkovian filter* (Mesnard, 2000b) employs bimarkovian or binormalized matrices in which both margins (column and rows sums) are equal to 1. Then, the resulting projections are compared as in previous filters:

$$\sigma_j^C = \sqrt{\sum_i [K(T^*,1^M)_{ij} - K(T,1^M)_{ij}]^2}, \text{ for column } j \tag{23}$$

$$\sigma_i^R = \sqrt{\sum_j [K(T^*,1^M)_{ij} - K(T,1^M)_{ij}]^2}, \text{ for row } i \tag{24}$$

where 1^M represents column and row margins equal to 1.

Table 4 summarizes the results for row vectors. The first column shows the normalized allocation coefficients, the simple relative variation in row coefficients between the two matrices. The second and third columns are the results from the ordinary biproportional filter, direct (18) and reverse (20). The following columns display the results for the biproportional mean (22) and bimarkovian (24) filters.

The results for column vectors are in Table 5. The first column shows the normalized purchasing coefficients, the simple relative variation in column coefficients between the two matrices. The results from the ordinary biproportional filter, direct (17) and reverse (19) are in the second and third column. Results for the biproportional mean (21) and bimarkovian (23) filters are in the last two columns.

4. INTERPRETATION

The empirical analysis carried out has highlighted different aspects of structural changes in the Brazilian interregional system. Although the results cannot be directly compared, some findings were closely related.

The gravity model was able to identify the role and importance of larger states (in terms of GRP) in bilateral trade, as they have greater trade flows, as buyers and/or suppliers. It was also possible to assess the importance of spatial

Table 4. Structural Change in the Interstate Exchange Relationships Biproportional Filters, Brazil 1985-1997.

Row Vectors (%)

State	Norm. Alloc. Coeff.	Biprop. Direct	Biprop. Reverse	Biprop. Mean	Bimark.
Acre (AC)	25.49	55.09	44.82	52.12	45.37
Alagoas (AL)	17.54	8.72	9.87	9.44	14.52
Amapá (AP)	45.53	46.52	39.50	53.15	64.51
Amazonas (AM)	13.50	6.52	8.20	7.51	73.67
Bahia (BA)	5.63	17.23	17.76	17.40	15.36
Ceará (CE)	6.28	13.06	10.79	11.64	14.61
Distrito Federal (DF)	13.85	28.39	20.72	28.16	18.33
Espírito Santo (ES)	19.50	28.19	33.84	27.35	29.44
Goiás (GO)	15.27	19.90	20.23	20.27	21.67
Maranhão (MA)	11.53	19.86	23.17	18.59	35.50
Mato Grosso (MS)	20.72	34.29	35.26	33.82	31.30
Mato Grosso do Sul (MT)	9.31	16.97	16.12	17.94	47.93
Minas Gerais (MG)	19.82	7.76	6.37	7.12	16.49
Pará (PA)	8.97	12.29	12.44	12.30	58.05
Paraíba (PB)	9.94	19.98	13.95	17.12	19.52
Paraná (PR)	14.98	8.63	7.00	7.80	21.61
Pernambuco (PE)	6.55	12.31	16.11	10.86	12.74
Piauí (PI)	16.24	33.24	20.95	39.58	59.20
Rio Grande do Norte (RN)	11.42	21.67	18.89	24.97	15.78
Rio Grande do Sul (RS)	18.91	10.79	9.45	9.90	19.39
Rio de Janeiro (RJ)	35.08	14.79	16.83	15.83	16.52
Rondônia (RO)	15.58	27.06	21.59	26.64	46.29
Roraima (RR)	75.39	42.30	22.74	45.48	59.64
Santa Catarina (SC)	4.65	14.28	14.57	13.97	20.75
São Paulo (SP)	13.07	8.36	11.02	8.24	19.12
Sergipe (SE)	11.16	31.16	13.76	29.88	19.23

factors determining the trade flows. Neighboring states trade more, as happens with states in the same macro region. Distance was also a relevant variable explaining bilateral trade. However, the gravity model was not useful for interpreting or undercovering structural changes, as the time dummy failed to recognize the character of structural change. The holistic matrix methods revealed different aspects of the structural changes in the interregional trade. Cluster analysis showed that the larger states became more similar in their exchange pattern. Besides, the less developed states tended to group together and São Paulo exhibited a very distinctive pattern. The role of São Paulo as a central point in the exchange structure can explain its increased surplus in the interregional trade balance.

Table 5 Structural Change in the Interstate Exchange Relationships Biproportional Filters, Brazil 1985-1997.

Column Vectors (%)

State	Norm. Purch. Coeff.	Biprop. Direct	Biprop. Reverse	Biprop. Mean	Bimark.
Acre (AC)	55.59	20.86	14.75	22.01	42.40
Alagoas (AL)	55.41	16.75	20.80	15.40	16.79
Amapá (AP)	16.16	43.04	17.75	42.01	59.10
Amazonas (AM)	10.56	4.73	8.71	5.94	60.15
Bahia (BA)	12.20	11.50	14.02	11.41	21.14
Ceará (CE)	7.43	15.44	10.84	15.37	16.57
Distrito Federal (DF)	32.70	5.95	5.75	6.92	10.61
Espírito Santo (ES)	26.20	20.83	14.20	17.87	12.08
Goiás (GO)	16.13	18.84	10.29	15.70	16.74
Maranhão (MA)	21.05	9.25	17.57	9.92	51.91
Mato Grosso (MS)	32.35	22.62	7.23	21.94	51.10
Mato Grosso do Sul (MT)	21.98	11.71	24.37	11.06	22.46
Minas Gerais (MG)	9.72	8.77	31.71	9.26	27.87
Pará (PA)	16.73	12.02	13.69	11.35	62.06
Paraíba (PB)	14.89	13.48	21.78	11.87	13.99
Paraná (PR)	5.47	5.19	9.20	5.79	26.86
Pernambuco (PE)	7.13	14.98	15.72	15.42	23.20
Piauí (PI)	44.13	11.69	13.63	12.25	38.15
Rio Grande do Norte (RN)	32.84	16.28	12.66	14.28	7.80
Rio Grande do Sul (RS)	10.71	9.40	13.01	11.30	42.32
Rio de Janeiro (RJ)	20.73	27.15	29.22	28.30	31.28
Rondônia (RO)	23.11	17.71	14.80	15.98	39.98
Roraima (RR)	49.67	73.30	72.16	72.86	71.13
Santa Catarina (SC)	7.46	14.40	12.33	13.28	20.50
São Paulo (SP)	14.94	6.27	7.66	6.82	24.93
Sergipe (SE)	33.01	18.99	16.61	18.01	10.33

It is worth comparing the movement in the interregional trade balance between 1985 and 1997 (Table 1) and the empirical results. The left causative matrix results for type II are always related with states that have deficits in both years. Three big states (Sao Paulo, Minas Gerais and Paraná) have surplus in both years and the same type IV classification. We could say that for these big states the greater endogenization of their own final demand impacts offsets the decreasing impact from other states' final demand.

As pointed out earlier, the left causative matrix methodology is a demand-driven approach. The biproportional filter is an appropriate method to analyze the data without imposing this hypothesis. A general finding from tables 4 and 5 is that we cannot argue in support of either a demand (or supply) hypothesis. The row and column vectors have similar magnitudes (the means for each filter are very similar), therefore demand and supply effects are both relevant in the analysis. This result is not surprising since row and column coefficients are roughly equal in view of the definitional relationship between input and output coefficients (e.g. Oosterhaven, 1988).

The bimarkovian filter seems to be the most appropriate because it takes into account the size of the states. As can be seen in table 1, the Brazilian states are very different, and this can generate misleading results. Probably this is the reason why the results from biproportional filters are, in some cases, very different. However, a more formal and theoretical comparison among the biproportional filters should be done to establish their differences.

From the bimarkovian filter, an interesting result is that states with higher changes in row vectors are the same ones that have higher changes in column vectors. The rankings of the first ten states with larger changes in row and column vectors contain almost the same states and, excluding Rio Grande do Sul, all the states are from the less developed regions, the North and Northeast.[11] These results indicate that among the less developed states, the structural change was in both allocation and supply coefficients. On the other hand, the more developed states (São Paulo, Rio de Janeiro, Minas Gerais and Paraná) have more important changes in their selling patterns.[12]

5. CONCLUSION

The motivation of this paper was to explore the changes in the structure of interregional trade in the Brazilian economy. Such exploratory analysis was carried out by means of a gravity type model and some additional matrix methods. The gravity model and the holistic methods may be seen as complementary approaches to the understanding of interregional trade patterns. The first approach helps to understand the various factors that may contribute to the spatial distribution of trade (e.g. neighboring states, large states, regional characteristics, etc.)

The holistic approaches using MIST helped to uncover structural changes in more detail. In the cluster analysis, it was possible to identify the changing pattern of trade relations. The causative matrix methods highlighted the changing composition of intraregional and interregional demand. The bi-proportional filter showed that supply and purchases state profiles have both changed, and these changes were more important in a specific group of states.

The analysis carried out in this paper presented a way of generalization about the type of trade involved in an interregional system and its changing composition over time. As the economy evolves, there are important implications for these structural differences in the articulation and implementation of development policies. Policies designed to reduce disparities across regions need

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[11] These states are Amapá, Maranhão, Mato Grosso, Acre, Rio Grande do Sul, Rondônia, Piauí, Amazonas, Para e Roraima and Mato Grosso do Sul.

[12] These states are between the 11th and 14th position in the ranking for changes in the column coefficient (bimarkovian filter).

to be assessed in the context of the structure of both the targeted regional economies and the structure of their interaction with the rest of the country. Interregional trade can both enhance and undermine regional policies, in the former case by spreading the benefits from demand growth in other regions while, in the latter case, significant leakages may end up concentrating development benefits in a small number of regions (see Hulu *et al.*, 1992). The tension between spread and backwash effects provides one of the major challenges for spatial development strategy and findings described in this paper speak to the important role that knowledge of interregional trade can play in contributing to a more complete understanding of the structure of a multiregional economy.

NOTE

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