Evidence about Mercosur's Business Cycle[1]

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Abstract: This paper analyzes the business cycles within each of the Mercosur members and Chile in order to investigate if they are synchronized, which is a necessary condition to harmonize the economic policies among these countries. To estimate the business cycles for each country we apply the Beveridge-Nelson-Stock-Watson trend-cycle decomposition, taking into account long-run and short-run restrictions through definitions of *cointegration* and *serial correlation common feature*, respectively. The domain frequency approach is used to analyze how synchronized the economies' business cycles are. The results suggest that, in general, these business cycles are not synchronized and thus may generate an enormous difficulty conciliating policies into Mercosur.

Key-words: Mercosur, business cycles, trend-cycle decomposition, common features, spectral analysis.

Jel Codes: C32, E32, F02, F23.

Resumo: Este artigo analisa o ciclo de negócio de cada país integrante do Mercosul e do Chile com o intuito de investigar se eles são sincronizados, pois esta uma condição necessária para a integração das políticas econômicas destes países. Para estimar o ciclo de negócios de cada país nós aplicamos a decomposição tendência-ciclo de Beveridge-Nelson-Stock-Watson, levando em conta restrições de longo prazo e curto prazo através dos conceitos de cointegração e correlação serial comum, respectivamente. A abordagem do domínio da freqüência é utilizada para se avaliar quão sincronizados os ciclos de negócios são. Os resultados sugerem que, em geral, estes ciclos não são sincronizados, o que pode gerar uma enorme dificuldade para conciliar políticas dentro do Mercosul.

Palavras-chave: Mercosul, ciclo de negócios, decomposição tendência-ciclo, característica comum, análise espectral.

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1 Introduction

The design of economic blocks, like the European Union, have the purpose to amplifying the society welfare through unification of economic policies and commercial agreements. According to Backus and Kehoe (1992) and Chistodoulakis and Dimelis (1995), the success of these politics depends on the similarities of the economic block members. In this sense, it is imperative to analyze the degree of synchronism among their business cycles. A business cycle is a periodic but irregular up-and-down movement in economic activity, measured by fluctuations in real GDP and other macroeconomic variables. However, in compliance with Lucas (1977), we will focus our analysis on GDP, that is, we define business cycles as the difference between the effective product of an economy and its long-run trend.

Presently, the Mercosur's members are Argentina, Brazil, Paraguay and Uruguay. These countries differ in their institutions, economic policies and industrial structures, creating an enormous internal asymmetry in Mercosur (Flores, 2005). However, despite these differences, we can still investigate if their business cycles have similar characteristics. The objective of this work is twofold: identify possible common structural features among Mercosur's countries and analyze the degree of synchronization among their business cycles, using a measure of comovements[3]. Mercosur was created in 1991; however, our data set ranges from 1951 to 2000. Therefore, if we find evidence in favor of synchronization we can safely assume this cannot be attributed only to Mercosur[4]. In fact, what we propose is the inverse causality: the similarities among the countries provoke their integration. Following this direction, we will also include in our sample Chile, a country of large expression in South America which recently has become an associated member of the Mercosur.

In the empirical literature there is no consensus about how to estimate the trend-cycle components of economic series and how to analyze the so-called comovements. During the past few decades a rich debate about the abilities of different statistical methods to decompose time series in long and short term fluctuations has taken (Baxter and King, 1995; Guay and St-Amant, 1996). Among the more common univariate methodologies are the Hodrick-Prescott (HP) filter and the Beveridge and Nelson (BN) decomposition. However, these methodologies do not take in account the existence of common features among the economics series. In addition, as shown by Harvey and Jaeger (1993) the HP filter can induce spurious cyclicality when applied to integrated data. Therefore, in order to obtain a measure of the business cycles, we implemented the analysis using the Beveridge-Nelson-Stock-Watson (BNSW) multivariate trend-cycle decomposition, considering long-run and short-run common features. Common features, as defined by Engle and Kozicki (1993), arise when series exhibit comovements, i.e., when they are generated from common

[3]Two countries present comovements when their real GDP expansions and downturns are simultaneous.

[4]Also because it does not have a consensus that the advent of Mercosur led to an increase in the flow of commerce among its integrated parts.

factors. A feature is a characteristic of an economic time series such as serial correlation, seasonality, trend, heteroskedasticity, etc. Cointegration is a special case of common features, arising when the series contain common stochastic trends. Engle and Kozicki (1993) and Vahid and Engle (1993) proposed the Serial Correlation Common Feature (SCCF) as a measure of common cyclical feature in short-run. The vast literature on time series has focused on long-term comovements by means of cointegration; however, more recently, the existence of short-run comovements among stationary time series has been analyzed in many empirical works. For example, Gouriéroux and Peaucelle (1993) analyzed some questions about purchase power parity; Campbell and Mankiw (1990) found a common cycle between consumption and income for most G-7 countries; Engle and Kozicki (1993) found common international cycles in GNP data for OECD countries; Engle and Issler (2001) found common cycles among sectorial output for US; and Candelon and Hecq (2000) tested the Okun's law..

It is worth noting that the existence of a common cyclical feature neither implies nor is implied by the existence of similar business cycles as observed by Quah (Engle and Kozicki, 1993-comment) and Cubadda (1999). Therefore, to investigate the degree of business cycle's comovements, first we must find the economic cycle of each country and then analyze what is the degree of synchronization of their comovements. This may be done by analyzing their linear correlations in time domain or the measures of coherence and phase in frequency domain (Wang, 2003). Additionally, it is important investigate characteristic of each economic cycle. This can be done by measures of volatility and persistence.

Our results indicate the existence of common trends and common cycles among the economies under study. Hence, the existence of such comovements provides support for some types of convergence and for sustainability of an optimal currency area (Beine et al., 2000). Thus, we confirm the necessity to use a multivariate approach, which is our first contribution. Our second contribution is in respect to business cycle analysis. The frequency domain results indicate that Brazil and Uruguay business cycles are synchronized and that the same occurs between Argentina and Chile. But, this result is not sufficient to assure a symmetry into the economic block.

Beyond this introduction, the article is organized in the following form. Section 2 presents the econometric methodology. Section 3 reports the results. Finally, the conclusions are summarized in the last section.

2 Identification of Business Cycles

To implement the BNSW decomposition we need to estimate a VAR model in order to identify the long-run and short-run comovements. The existence of common cycles is synonymous of the existence of SCCF while cointegration implies that series have common stochastic trends.

2.1 Econometric Model with short and long run constrains

Consider a Gaussian Vector Autoregression of finite order p, VAR(p), such that:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + \varepsilon_t \tag{1}$$

where y_t is a vector of n first order integrated series, $I(1)$, and ϕ_i, $i = 1, \ldots, p$ are matrices of dimension $n \times n$ and $\varepsilon_t \sim Normal\,(0, \Omega)$.[5] Consider still $y_0, y_{-1}, ..., y_{1-p}$ known initial values. The model (1) could be written equivalently as:

$$\Pi\,(L)\; y_t = \varepsilon_t \tag{2}$$

where $\Pi\,(L) = I_n - \sum_{i=1}^{p} \phi_i L^i$ and L represents the lag operator. Notice that, the polynomial matrix $\Pi\,(L)$ is $\Pi\,(1) = I_n - \sum_{i=1}^{p} \phi_i$ when $L = 1$.

2.1.1 Long run restrictions (Cointegration)

The following assumption are assumed:

Assumption 1 *: The* $(n \times n)$ *matrix* $\Pi\,(\cdot)$ *satisfies:*

1. Rank $(\Pi\,(1)) = r$, $0 < r < n$, *such that* $\Pi\,(1)$ *can be expressed as* $\Pi\,(1) = -\alpha\beta'$, where α *and* β *are* $(n \times r)$ *matrices with full column rank* r.

2. The characteristic equation $|\Pi\,(L)| = 0$ *has* $n - r$ *roots equal to* 1 *and all other are outside the unit circle.*

The assumption 1 implies that y_t is cointegrated of order $(1, 1)$. The elements of α are the adjustment coefficients and the column of β span the cointegration space. Decompound the polynomial matrix $\Pi\,(L) = \Pi\,(1)\,L + \Pi^{*}\,(L)\,\Delta$, where $\Delta \equiv (1 - L)$ is the difference operator, a Vetorial Error Correction Model (VECM) is obtained:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \varepsilon_t \tag{3}$$

where $\alpha\beta' = -\Pi\,(1), \Gamma_j = -\sum_{k=j+1}^{p} \phi_k$ $(j = 1, ..., p-1)$ and $\Gamma_0 = I_n$.

[5] Futhermore, ε_t satisfies $E\,(\varepsilon_t) = 0$; $E\,(\varepsilon_t \varepsilon_\tau) = \begin{cases} \Omega, & se\ t = \tau \\ 0_{n \times n}, & se\ t \neq \tau \end{cases}$, where Ω is no singular.

2.1.2 Common Cycles restrictions (SCCF)

The VAR(p) model can present additional restriction of short time as showed by Vahid and Engel (1993).

Definition 1 *Serial Correlation Common Feature-SCCF hold in (3) if exist a* $(n \times s)$ *matrix* $\tilde{\beta}$ *of rank* s*, whose column span the cofeature space, such as* $\tilde{\beta}'(\Delta y_t) = \tilde{\beta}'\varepsilon_t$*, where* $\tilde{\beta}'\varepsilon_t$ *is a s-dimensional vector that constitute an innovation process with respect to information prior to period* t*, given by* $\{y_{t-1},\ y_{t-2}, ..., y_1\}$.

Consequently SCCF exist if the matrix $\tilde{\beta}$, called the matrix of cofeature vectors, satisfy the following assumptions:

Assumption 2 $\tilde{\beta}'\ \Gamma_j = 0_{s\times n} \qquad j = 1, ..., p-1$

Assumption 3 $\tilde{\beta}'\ \alpha\beta' = 0_{s\times n}$

The existence of short and long run restrictions implies that representations of VECM in (3) can be written such as two subsystem, the first doesn't aggregate information for Δy_t due to the existence of $\tilde{\beta}$ and the second subsystem that add all the information to Δy_t. From a statistical point of view, these restrictions reduce the space of parameter to be estimated.

2.1.3 Trend - Cycle Decomposition

The BNSW trend-cycle decomposition can be introduced by means of the Wold representation of the stationary vector Δy_t given by:

$$\Delta y_t = C(L)\varepsilon_t \tag{4}$$

where $C(L) = \sum_{i=0}^{\infty} C_i L^i$ is matrix polynomial in the lag operator, $C_0 = I_n$ and $\sum_{i=1}^{\infty} j\ |C_j| < \infty$. Using the following polynomial factorization $C(L) = C(1) + \Delta C^*(L)$, it is possible to decompose Δy_t such that:

$$\Delta y_t = C(1)\,\varepsilon_t + \Delta C^*(L)\,\varepsilon_t \tag{5}$$

where $C_i^* = \sum_{j>i}^{\infty}(-C_j)$, $i \geq 0$, and $C_0^* = I_n - C(1)$. Ignoring the initial value y_0, and integrating both sides of (5), we obtain:

$$y_t = C(1)\sum_{j=1}^{T}\varepsilon_t + C^*(L)\varepsilon_t\ = \tau_t + c_t \tag{6}$$

Equation (6) represents BNSW decomposition where n variables that compound y_t are decomposed in n random walk process called "stochastic trend" and n stationary process named "cycles". Thus, $\tau_t = C(1)\sum_{j=1}^{T}\varepsilon_t$ and $c_t = C^*(L)\varepsilon_t$ represent the trend and cycle components, respectively.

Assuming that long-run restrictions exist, then r cointegration vectors exist $(r < n)$. These vectors eliminate the trend component which implies that $\beta' C(1) = 0$. Thus, $C(1)$ has dimension $n - r$ which means that exist $n - r$ common trends. Analogously, assuming short-run restrictions, there are s cofeature vectors that eliminate the cycles, $\tilde{\beta}' C^*(L) = 0$, which implies that $C^*(L)$ has dimension $n - s$, which is the number of common cycles. It is worth noting that $r + s \leq n$ and the cointegration and cofeatures vector are linearly independent.[6] To find the common trends it is necessary (and sufficient) to multiply equation (6) by $\tilde{\beta}'$, such that

$$\tilde{\beta}' y_t = \tilde{\beta}' C(1) \sum_{j=1}^{T} \varepsilon_t \ = \tilde{\beta}' \tau_c$$

This linear combination doesn't contain cycles since cofeatures vectors eliminate all cycles. In the same way, to get the common cycles it is enough multiply equation (6) by β', and so

$$\beta' y_t = \beta' C^*(L) \varepsilon_t \ = \beta' c_t$$

This linear combination doesn't contain the stochastic trend, because the cointegration vectors eliminate the trend component.

Special case A special case emerges when $r + s = n$. In this case the estimate of trend and cycle components of y_t becomes extremely easy. Once $\tilde{\beta}'$ and β' are linearly independent matrices, it is possible to build a matrix A, such as $A_{n\times n} = \left[\tilde{\beta}', \beta'\right]'$ has full rank and therefore is invertible. Partition the columns of its inverse according as $A^{-1} = \left[\tilde{\beta}^- \ \ \beta^-\right]$ and recover the trend and cycle components by pre-multiplying y_t by A^{-1} :

$$\begin{aligned} y_t = A^{-1} A y_t &= \tilde{\beta}^- \left(\tilde{\beta}' y_t\right) + \beta^- \left(\beta' y_t\right) \\ &= \tau_t + c_t \end{aligned} \tag{7}$$

This implies that $\tau_t = \tilde{\beta}^- \tilde{\beta}' y_t$ and $c_t = \beta^- \beta' y_t$. Therefore, trend and cycles are linear combinations of y_t. Note that τ_t is generated by a linear combination of the cofeature vectors and contain only trends (because $\tilde{\beta}' y_t$ is a random walk component) while c_t is generated by a linear combination of cointegration vectors and contain only cycles (because $\beta' y_t$ is $I(0)$ and serially correlated).

Another special case emerges when the VAR model has order one $(p = 1)$ and cointegration is present. In this case is straightforward to determine the existence of common cycle (the number of cofeatures vectors

[6] See Vahid and Engle (1993).

is found trivially). Note that since VAR(1) model has r cointegration vectors, its error correction model becomes:

$$\Delta y_t = \alpha\beta' y_{t-1} + \varepsilon_t$$

Therefore, by definition of SCCF, $\tilde{\beta}$ is such that $\tilde{\beta}'\alpha\beta' = 0$. In other words $\tilde{\beta}$ lies in the null space of $\beta\acute{\alpha}$. Once the rank of $\beta\acute{\alpha}$ is r, its null space has rank $n - r$. In summary, if we have a VAR(1) with r cointegration vectors, we known a priori that exist $n - r$ cofeatures vectors and consequently, we could recovered the cyclical and tendency compounds through equation (7).

2.2 Estimation

To implement the methodology above, we need to estimate the VAR order (p), the number of cointegration vectors (r) and the number of cofeature vectors (s). We follow the hyerarquical procedure due to Vahid and Engle (1993) to estimate these parameters. To estimate p we apply the following informational criteria: Schwarz (SC) and Hannan-Quinn (HQ) (Lütkepohl, 1993). To identify r, it is used Johansen cointegration test. As these procedures are usual, we only report in detail the common cycles test, that is, the SCCF test, used to obtain the cofeatures vectors.

The SCCF test is based on canonical correlations. In the equation (3) we observe that all serial correlation of Δy_t are captured by $\alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Delta\Gamma_j y_{t-j}$ once ε_t is an innovation. Simplifying, we called Q_t a conditional set given by $Q_t = \{\beta' y_{t-1}, \Delta y_{t-1}, \ldots, \Delta y_{t-p+1}\}$. The idea is simple: the canonical correlation find the linear combination of the elements Δy_t that will be orthogonal to set Q_t. Therefore, this linear combination is such that doesn't exist any structure between Δy_t and Q_t beyond an innovation. An expression $CanonCorr\left(X_t, Z_t \mid W_t\right)$ denote a canonical correlation between X_t and Z_t conditional on W_t, such that W_t can contain deterministic terms as constants, deterministic trend, seasonal dummies etc. Therefore, $CanonCorr\left[\Delta y_t, \left(y'_{t-1}\beta, \Delta y'_{t-1}, \ldots, \Delta y'_{t-p+1}\right)' \mid W_t\right]$ allow to obtain canonical correlations, called eigenvalues, that are used to test the presence of a reduced rank model. Based on Tiao and Tsay (1985), Vahid and Engle (1993) propose a sequential test for SCCF, assuming that the rank of β is known. The sequence of hypotheses to be tested are: $H_0 : rank\left(\tilde{\beta}\right) \geq s$ against $H_a : rank\left(\tilde{\beta}\right) < s$, starting with $s = 1$ against the alternative model with $s = 0$ (doesn't exist common cycle). If the null hypotheses is not rejected we implement the test for $s = 2$, and so on.

In the VECM (3) of order $p - 1$ the significance of the s smallest eigenvalues is determinated through the following statistical:

$$\xi_s^{SCCF} = -T\sum_{i=1}^{s} Ln\left(1 - \hat{\lambda}_i^2\right) \sim \chi^2_{(v_1)}, \quad s = 1, ..., n - r \tag{8}$$

$\hat{\lambda}_1 > \hat{\lambda}_2 ..... > \hat{\lambda}_s$, with $v_1 = s\left[n\left(p - 2\right) + r + s\right)]$ where n is the dimension of the system and p the lag

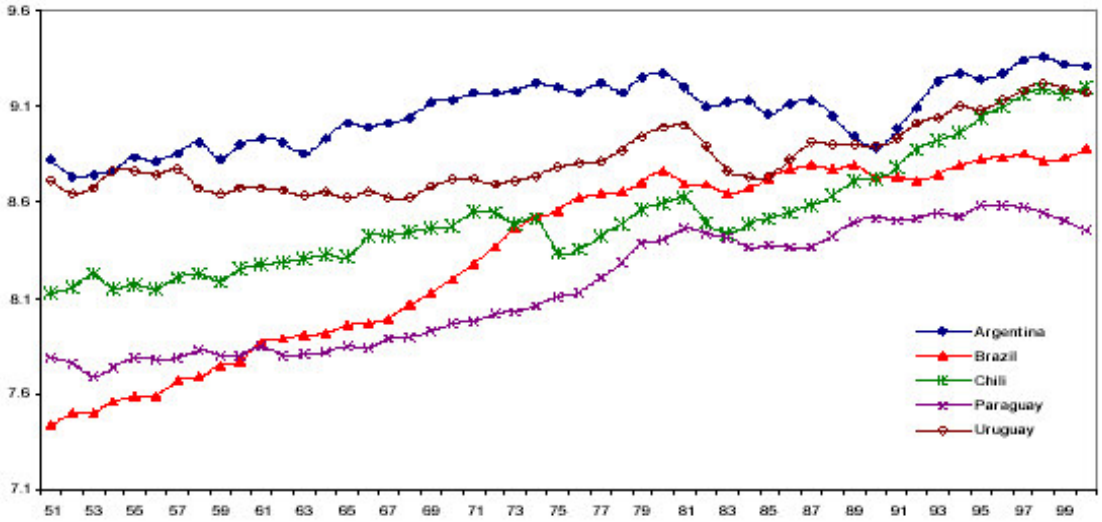
order of the VAR model. Suppose that the statistical test (8) has found s independent linear combinations of the elements of Δy_t orthogonal to Q_t, this implies that exist a $n \times s$ matrix $\tilde{\beta}$ of full rank s with s eigenvectors associate with the s smallest eigenvalues. Notice as mencioned, $\tilde{\beta}$ is the matrix of cofeature.

3 Results

3.1 Database

The database used was extracted from *Penn World Table*[7], corresponding to Real GDP *per capita* series of Mercosur countries and Chile. The frequency is annual, ranging from 1951 to 2000. The Figure 1 report the GDP in log terms.

$Figure\,1-$ Real GDP (in log) *per capita* series of Mercosur countries and Chile (1951-2000)



3.2 Common Features analysis

Since BNSW decomposition assumes that the series are I(1), we begin our analysis applying the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. The null hypothesis of both is the presence of unit root. The results for all countries are reported in Table 1 which shows that the tests do not reject the unit root null hypothesis, at 5% level of significance[8].

[7]Heston, Robert Summers and Bettina Aten, Penn World Table Version 6.1, Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002. Real GDP per capita (Constant Prices: Chain series) $http$: $//pwt.econ.upenn.edu/php\_site/pwt\_index.php$

[8]In the case of ADF test, the choice of lags of the dependent variable in the right side of the test equation is based on the Schwarz criterion. In PP test we use the nucleus of Bartlett and the window of Newey-West. In both tests we include constant and linear

$Table\,1-$ Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests

	ADF			PP		
Country	Statistic	Critic value (5%)	p-value	Statistic	Critic value (5%)	p-value
Argentina	-2.4169	-3.5064	0.3666	-2.0519	-3.5043	0.5589
Brazil	-0.6553	-3.5064	0.9707	-0.6646	-3.5043	0.9701
Chile	-1.1101	-3.5043	0.9168	-1.2620	-3.5043	0.8856
Paraguay	-1.0891	-3.5085	0.9201	-1.7570	-3.5043	0.7101
Uruguay	-2.5112	-3.5064	0.3217	-2.0536	-3.5043	0.5580

To estimate the VAR model, the first step it is to choose its order adequately. We choose two criteria of information to be minimized: Hannan-Quinn (HQ) and Shwarzs (SC). Table 2 shows the results for $p \in \{1, 2, 3, 4, 5\}$. As the data are annual we consider that an upper bound of 5 lags is sufficient. We observe that the two criteria suggest $p = 1$, that is, a VAR(1) model.

$Table\,2-$ VAR order

	Lag				
Criteria	1	2	3	4	5
SC	-16.1869*	-15.1793	-13.9064	-12.4350	-13.2744
HQ	-16.9424*	-16.5643	-15.9209	-15.0790	-16.5480
Note: * indicate lag suggested by information criteria					

Hence, we implement diasgnostic tests in order to verify if the specification used is satisfactory. The LM test of serial autocorrelation does not indicate the presence of autocorrelation in the residuals, at 5% level of significance[9]. Moreover, we do not find evidence of heteroskedasticity, at 5% level of significance, and we do not reject the null hypothesis that residuals have normal distribution, at 5% level of significance[10].

In addition, we use the procedure of Johansen (1988) to test if the series are cointegrated. We consider two cases. In the first case, we introduce a constant in the cointegration vector. In the second case, besides the constant, we consider a linear trend. The results based on the trace statistics are presented in Table 3 and Table 4. When we only consider the constant - Table 3 -, it is not possible to reject the null hypothesis

trend. In any case, the results are robust to exclusion of the deterministic components.

[9]The null hypothesis of the LM test is the absence of serial correlation until the lag h. We consider h from 1 to 5.

[10]In the normality test we consider the orthogonalization of Cholesky.

because the trace statistics is lower than the critical value. Then, we observe that the data support the existence of one cointegration relation. However, when adding the linear trend in the cointegration vector we get a distinct result - Table 4. In this case, it is not possible to reject the null hypothesis, what suggests the existence of two cointegration relations.

$Table$ 3– Johansen's cointegration test (constant)

Trace Test			
Null hypothesis	Statistic	Critical value 5%	p-value
$r = 0$*	67.72698	69.81889	0.0726
$r \leq 1$	39.16940	47.85613	0.2536
$r \leq 2$	12.09077	29.79707	0.9287
$r \leq 3$	4.302681	15.49471	0.8776
$r \leq 4$	0.091914	3.841466	0.7617

Note: *indicating rejection of null hypothesis, at 5% level of significance

Cointegration Vector					
Argentina	Brazil	Chile	Paraguay	Uruguay	Constant
1.0000	-0.803808	0.318184	0.853932	-1.114491	-2.202155

$Table$ 4– Johansen's cointegration test (constant and trend)

Trace Test			
Null hypothesis	Statistic	Critical value 5%	p-value
$r = 0$*	85.35115	88.8038	0.0865
$r \leq 1$*	51.83557	63.8761	0.3360
$r \leq 2$	24.58712	42.9152	0.8099
$r \leq 3$	10.74544	25.8721	0.8893
$r \leq 4$	4.209521	12.5179	0.7116

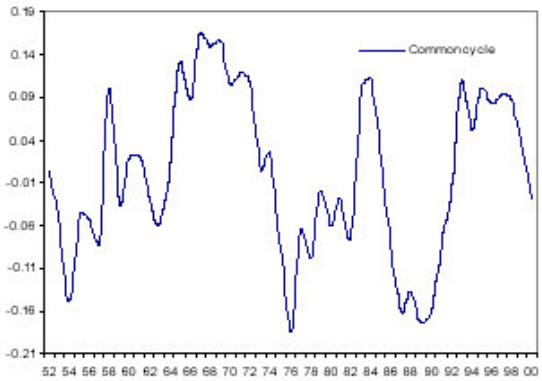
Note: *indicating rejection of null hypothesis, at 5% level of significance

Cointegration vectors						
Argentina	Brazil	Chile	Paraguay	Uruguay	Constant	Trend
1.0000	0.0000	-0.305191	-0.772830	-0.126393	0.735536	0.008703
0.0000	1.0000	0.045125	-1.207428	0.532186	-3.196465	-0.015736

Regarding the common cycles test, since we estimate a VAR model with $p = 1$ we are in the second special case in which $s = n - r$. As a result, once $r = 1$ there are four common trends and $s = 4$, existing only one common cycle. On the other side, if $r = 2$ there are three common trends and $s = 3$, with two common cycles. Figure 2 illustrates the common cycles for both cases.

$Figura\,2-$ Common Cycles.

Constant in the cointegration vector



Constant and trend in the cointegration vector

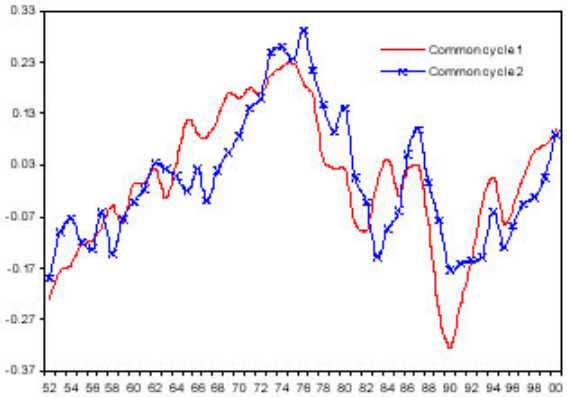


Figure 3 shows the cyclical components of each country for the case with constant in the cointegration vector. Notice that the cyclical components of all countries present a harmonic movement, because there is only one common cycle among all the series. It means that each cyclical component is spanned by the same base (the unique common cycle). This result is very strong since it suggests a perfect collinearity among the business cycles. Therefore, we consider the specification with the linear trend in the cointegration vector as the preferred one, disrespecting the other case in the subsequent analysis. Figure 4 shows the cyclical components of each country for the case with constant and linear trend in the cointegration vector. We note an enormous contraction in Argentina in 90's, as expected. Moreover, in the case of Brazil the period of the economic miracle is apparent.

Figure 3– Ciclical components for $s = 4$ and constant.

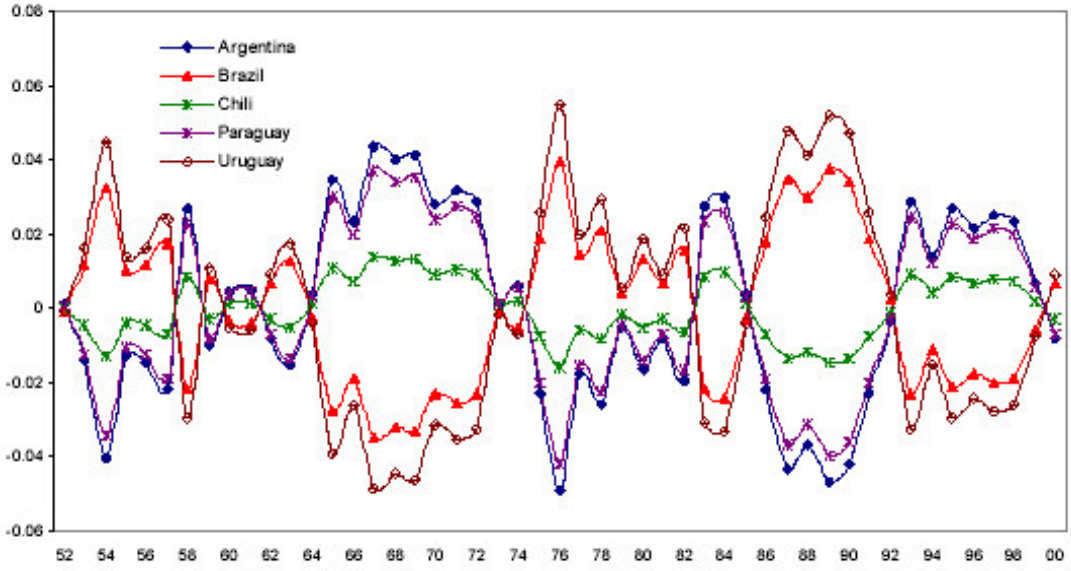
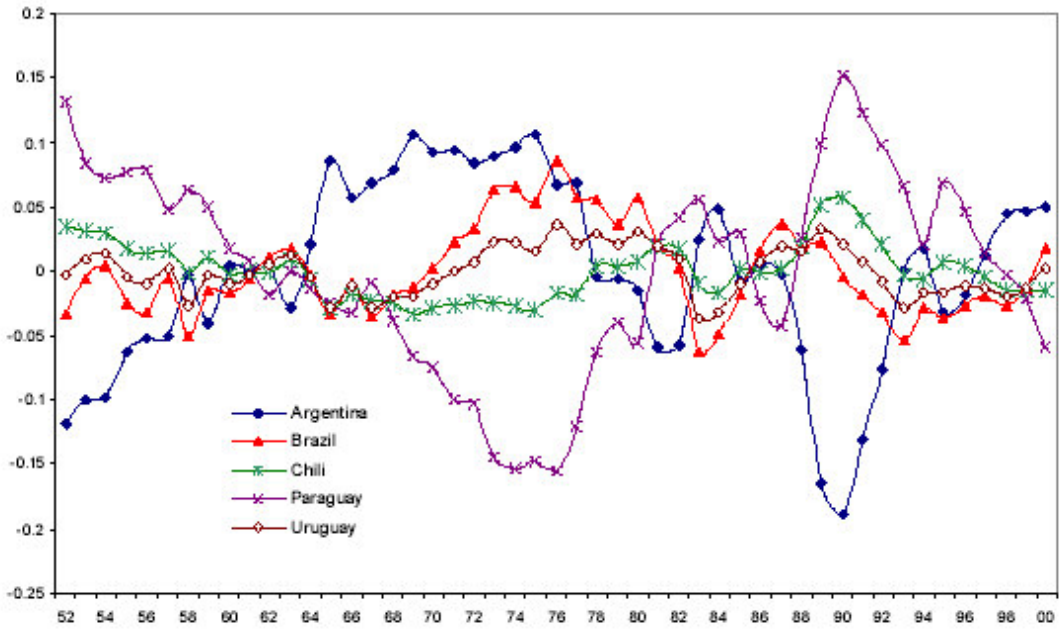


Figure 4– Ciclical components for $s = 3$ with constant and trend.



Therefore, a multivariate approach allow us to identify the interaction among the economic cycles being possible to analyze the degree of influences of the common characteristics in its economics cycles. In the

next section we analyze the economic cycles obtained from the BNSW decomposition, considering the common cycles and the common trend restrictions.

3.3 Business Cycles' Analysis

In order to get information on the business cycles we analyze the cyclical components of the countries, estimating their volatility, persistence and comovements. The measure of volatility is the standard deviation and the measure of persistence is the cycle correlation with its first lag (Campbell and Mankiw, 1989). Table 5 reports the results for volatility and persistence. We observe that Chile and Paraguay present the greater measure of volatility and persistence. For example, the volatility of Brazil and Uruguay is only about 30% of the volatility of Chile. Considering the persistence, there is a minor disparity between the countries.

$Table\,5-$ Economic Cycles

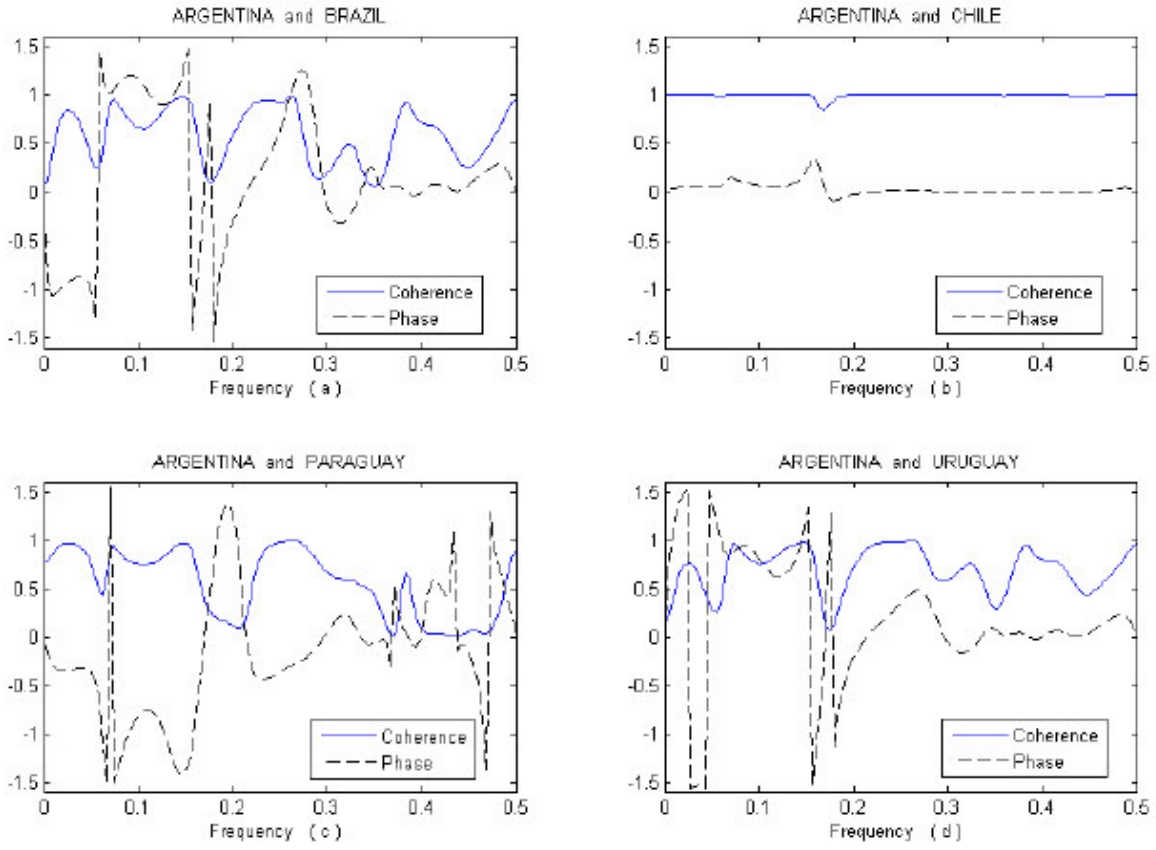
Countries	Argentina	Brazil	Chile	Paraguay	Uruguay
Volatility	0.1013	0.0441	0.1426	0.1413	0.0391
Persistence	0.8615	0.7236	0.8868	0.8910	0.8520

The degree of association among the contemporaneous movements can be obtained through the pairwise linear correlation, as reported in Table 6. We can observe that Brazil and Uruguay have high positive correlation, and in the same way Chile and Paraguay. With respect to the common cycles we see that the economic cycle of Argentina influences more common cycle 1, whereas the Paraguay influences more negatively common cycle 2.

$Table\,6-$ Linear correlations of economical cycles of countries $-$ BNSW

Countries	Argentina	Brazil	Chile	Paraguay	Uruguay	Common cycle 1	Common cycle 2
Argentina	1.0000					0.9758	0.6604
Brazil	0.2163	1.0000				0.4245	0.876
Chile	-0.9975	-0.1467	1.0000			-0.9579	-0.6056
Paraguay	-0.8445	-0.7055	0.8046	1.0000		-0.9412	-0.9598
Uruguay	-0.2709	0.8812	0.3384	-0.2866	1.0000	-0.0539	0.5439

Figure 5– Coherence and Phase

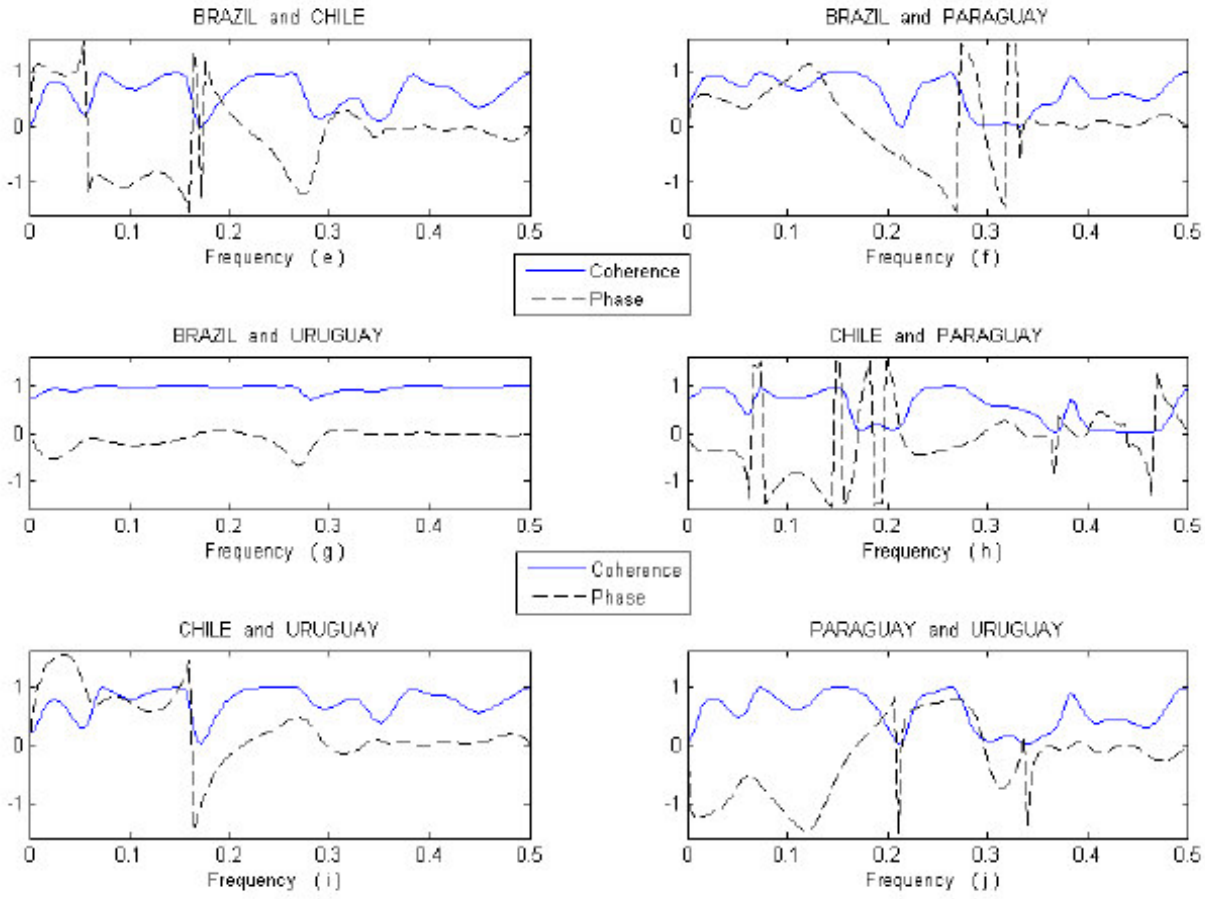


3.3.1 Analysis of business cycles' comovements

The analysis through linear correlation coefficient gives a static measure of the comovements (Engle and Kozick, 1993) since it is not a simultaneous analysis of the persistence of comovement. Another way to measure the comovement is based on the frequency domain. Analysis in the frequency domain does not bring additional information, but it is an alternative method to analyze the data. Frequency domain technique is a natural way to represent economic cycles. A measure that corresponds to correlations in the time domain is the coherence in the frequency domain[11].

[11] See appendix.

Figure 6– Coherence and Phase



The coherence between two variables is a measure of the degree to which these variables are jointly influenced by cycles of specific frequency. The phase of the cross spectrum indicates if cycles in specific frequency are synchronized or not. When a phase is null, it means that exist synchronized cycles in that frequency. Figures 5 and 6 show the coherence and phase of countries which are comparated pairwise[12]. These pictures show values of coherence varying between zero and one (vertical axis). Values of phase are calculated to each value of frequency and it varies between $-\pi/2$ to $\pi/2$ on the vertical axis. At the final point of the horizontal axis, the frequency 0.5 correspond to period of two year, the point 0.25 to four years, frequency 0.1 corresponds ten years, and so on.

[12]To estimate coherence it is used a MSCOHERE function of Matlab 7.0 which considers smoothed with Hamming window of 30 with 50% overlap.

Most of the Figures show that exists some frequencies where coherence is near to one. Nevertheless, there are two groups of countries that present high values of coherence for almost all values of frequency: the first is Argentina and Chile while the second is Brazil and Uruguay. These two groups present phases close to zero in almost all frequencies where the coherence is close to one. This result indicates that probably exist synchronization inside each group[13]. On the other side, couples of countries formed by other combinations present low values of coherence and their phase are generally different from zero. Therefore, these results evidence that Mercosur's business cycles are not synchronized. Additionally, Table 7 reports the highest values of coherence and their respective period. The results suggest that all the economies have a similar cycle with period of 3.82 years.

$Table\ 7-$ Highest value of coherence and their respective period (in years)

	Argentina	Brazil	Chile	Paraguay	Uruguay
Argentina	1.000	0.978 (3.82)	1.000 (3.82)	0.997 (3.82)	0.994 (3.82)
Brazil		1.000	0.978 (3.82)	0.995 (6.56)	0.999 (2.00)
Chile			1.000	0.997 (3.82)	0.994 (3.82)
Paraguay				1.000	0.991 (6.56)
Uruguay					1.000

4 Conclusion

The design of economic blocks is based on the harmonization of economic and commercial policies. However, as argued by Backus and Kehoe (1992) and Chistodoulakis and Dimelis (1995), this harmonization is well succeeded when the block members are minimally similar. In this direction, it is indispensable to analyze the dynamic of block members and the degree of synchronization of their business cycles. Regarding the Mercosur, it is common to see in the media quarrels on the intensification of this economic block, however it is not common to argue which are the necessary daily pay-conditions for this intensification and if they verify themselves. Considering the members of Mercosur (Argentina, Brazil, Paraguay and Uruguay) along with Chile, we can study the basic characteristic of their business cycles, which are, persistence, volatility and comovements. To implement this analysis we estimated a VAR model and tested the presence of common trends and common cycles. To find the countries' economic cycles we applied the BNSW trend-cycle decomposition using the restrictions of cointegration and serial correlation common features. To analyze their business cycles' comovements we used the frequency domain approach through the measures of coherence and phase, and in the time domain approach through calculation of linear correlation.

[13]Notice that linear correlation analysis in time domain also evidence existence of comovements between Brazil and Uruguay.

The results suggest that there are three common trends and two common cycles among the countries. Thus, we confirm the necessity to use a multivariate approach, which is our first contribution. The analysis of each bussines cycle suggests that: Chile and Paraguay presents the greater measure of volatility and persistence. When the business cycles' comovements are analyzed, synchronization is identified in two groups of countries: Brazil and Uruguay and between Argentina and Chile. On the other hand, an enormous asymmetry among all other combinations of the countries is evidenced. Therefore, the lack of symmetry in the Mercosur's business cycle makes difficult an advanced integration of these countries.

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Appendix

Consider a vector of two stationary variables $y_t = (X_t, Y_t)$. Let $S_{YY}(w)$ represent the *population spectrum* of Y and $S_{YX}(w)$ the *population cross spectrum* between X, Y. The *population cross spectrum* can be written in term of its real and imaginary components as $S_{YX}(w) = C_{YX}(w) + i\, Q_{YX}(w)$, where $C_{YX}(w)$ and $Q_{YX}(w)$ are labeled the *population cospectrum* and *population quadrature spectrum* between X, Y respectively.

The *population coherence* between X and Y is a measure of the degree to which X and Y are jointly influenced by cycles of frequency w.

$$h_{YX}(w) = \frac{[C_{YX}(w)]^2 + [Q_{YX}(w)]^2}{S_{YY}(w)\; S_{XX}(w)}$$

Coherence takes values in $0 \leq h_{YX}(w) \leq 1$. A value of one for coherence at a particular point means the two series are altogether in common at that frequency or cycle; if coherence is one over the whole spectrum then the two series are common at all frequencies or cycles.

The *cross spectrum* is in general complex, and may express in its polar form as:

$$S_{YX}(w) = C_{YX}(w) + i\, Q_{YX}(w) = R(w) \exp(i\, \theta(w))$$

where $R(w) = \left\{ [C_{YX}(w)]^2 + [Q_{YX}(w)]^2 \right\}^{\frac{1}{2}}$ and $\theta(w)$ represent the gain and the angle in radians at the frequency w. The angle satisfies $tang(\theta(w)) = \frac{Q_{YX}(w)}{C_{YX}(w)}$. More details in Hamilton (1994).