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Expansions and contractions in some Latin American countries: a view through non-linear models

Luis E. Arango and Luis F. Melo^{*,+}

Abstract

The study of the asymmetric behavior of macroeconomic variables over the business cycles phases has had a long tradition in economics. In this work we find evidence in favor of the hypothesis of having a STAR-type nonlinear asymmetric behavior of the economic activity, over the last two decades, in four Latin American countries: Brazil, Chile, Colombia and Mexico. For Venezuela the null hypothesis of a linear process could not be rejected under the method placed by Granger and Teräsvirta (1993). Economic activity is proxied by monthly based industrial production indexes. Except for the case of Mexico we arrive to asymmetric representations of the processes. However, evidence of asymmetric behavior is found according to the impulse response function analysis for all the countries.

JEL classification: C22, C52.

Key words: real industrial production index, nonlinearities, STAR models, impulse responses.

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⁺ E-mail addresses: larangth@banrep.gov.co and lmelove@banrep.gov.co.

I. Introduction

The behavior of variables associated to the business cycle has long been of interest to researchers. It also has been of interest the linearity or nonlinearity of the macroeconomic variables movements over phases of the business cycle. The discussion has also considered the symmetric or asymmetric fashion in which such movements take place. Symmetric cycles occur when all types of shocks are *i.i.d.* and zero mean and when the dynamic propagation mechanisms that convert these shocks into fluctuations of economic activity do not depend on whether the shocks are positive or negative.

References on asymmetries of the macroeconomic variables over the cycles are dated as early as Mitchell (1927, pp. 330-34) and Keynes (1936, p. 314). We can think of asymmetries as cycles that have different distance from peak to trough than from trough to peak. That is, contractions become much shorter and steeper than expansions. This clearly suggests that the motion of economic activity is different for booming and for slow down phases (Teräsvirta and Anderson, 1992; Zarnowitz, 1992; Granger, Teräsvirta, and Anderson, 1993; Peel and Speight, 2000). Sichel (1993) distinguished two different properties associated to the concept of asymmetry. These properties are *deepness* and *steepness*. The former identifies situations in which troughs are much below trend than peaks are above it or situations where peaks are above the trend much above than troughs are below it. The latter refers to situations in which contractions are steeper than expansions or the other way around.

Asymmetric phases of the business cycle might appear under some circumstances both economic and dynamic. Following the motivation of Kontolemis (1997), based on industrial organization literature, it could be the case that exit from an industry is less costly than entry and as a result production could fall rapidly and expand slowly. In addition, the asymmetric property might also be associated to the relative easy with which a firm may reduce production below full capacity when orders decline, compared with the difficulty of increasing production when capacity constraints are present. From the point of view of dynamics, cyclical asymmetries might raise for a number of reasons¹. Firstly, for the type of shock that affects the economy, e.g. adverse supply shocks might correspond to recessions while beneficial demand shocks might correspond to expansions or the other way around. Secondly, for the time-variance property of

the propagation mechanism. And, thirdly there may be an asymmetry in the way the economy responds to a positive shock compared to a negative one (Acemoglu and Scott, 1994).

Given the evidence (Boldin, 1999) suggesting that most econometric models cannot capture empirically important asymmetries and that linear models are incapable of capturing business cycles asymmetries (Simpson et al., 1999), we use the method proposed by Granger and Teräsvirta (1993) to study the nonlinear business cycle properties of the industrial production index of five economies²: Brazil, Chile, Colombia, Mexico, and Venezuela over the last two decades. Regardless that our reduced form approach do not allow us to distinguish the first two dynamics reasons mentioned above, we address the third possibility by using the impulse response functions on our preferred smooth transition specification.

The aim of this work is to obtain some evidence about such a regularity associated to asymmetric business cycles. We characterize the movements of the industrial production by using smooth transition regression models. Armed with a description of the dynamics of each index we estimate next impulse response functions for the extreme regimes of the cycle to observe the importance of positive and negative shocks both in expansion and recessions. At the end, we obtain evidence of nonlinear behavior for all countries but Venezuela. Except for the case of Mexico, we arrive to asymmetric representations of the data generation processes (DGP). Most tellingly, through the impulse response functions we show asymmetric responses of the variables depending on the regime the variables are shocked.

Other goals have been previously reached by focusing on the total output. These are the cases of Fernández and Gonzalez (2000) and Torres (1999). The first work showed that the cycles of Colombia, Brazil and Costa Rica are highly correlated through coffee. In addition, this work emphasizes on the role of the terms of trade for generating the cycle comovements of the output of some Latin American economies. Torres (1999), found a similarity in the characteristics of the cycles of a set of Latin American countries³. This coherence of the movements over the phases of the cycle is explained by external factors such the capital inflow occurred between 1991 and 1994 (see also Banco de la República, 2001). However, as we have

¹ Boldin (1999) has showed how the effects of monetary policy are stronger during turning points and outright recessions than in expansions.

² Other nonlinear methods used to capture the business cycle features are threshold models (Tsay, 1989; Tiao and Tsay, 1944) and Markov-switching regime models (Hamilton, 1989).

³ Argentina, Brazil, Chile, Colombia, Peru and Venezuela.

said above, our paper is aimed to check the hypothesis of having asymmetric cycles in some Latin American countries.

The paper is organized as follows. Section two shows the behavior of the industrial production index for each country included in the sample. Section three describes aspects related to the nonlinear approach we follow. Section four presents some results and discusses the dynamics we find. Finally, section five draws some conclusions.

II. Behavior of the industrial production indexes

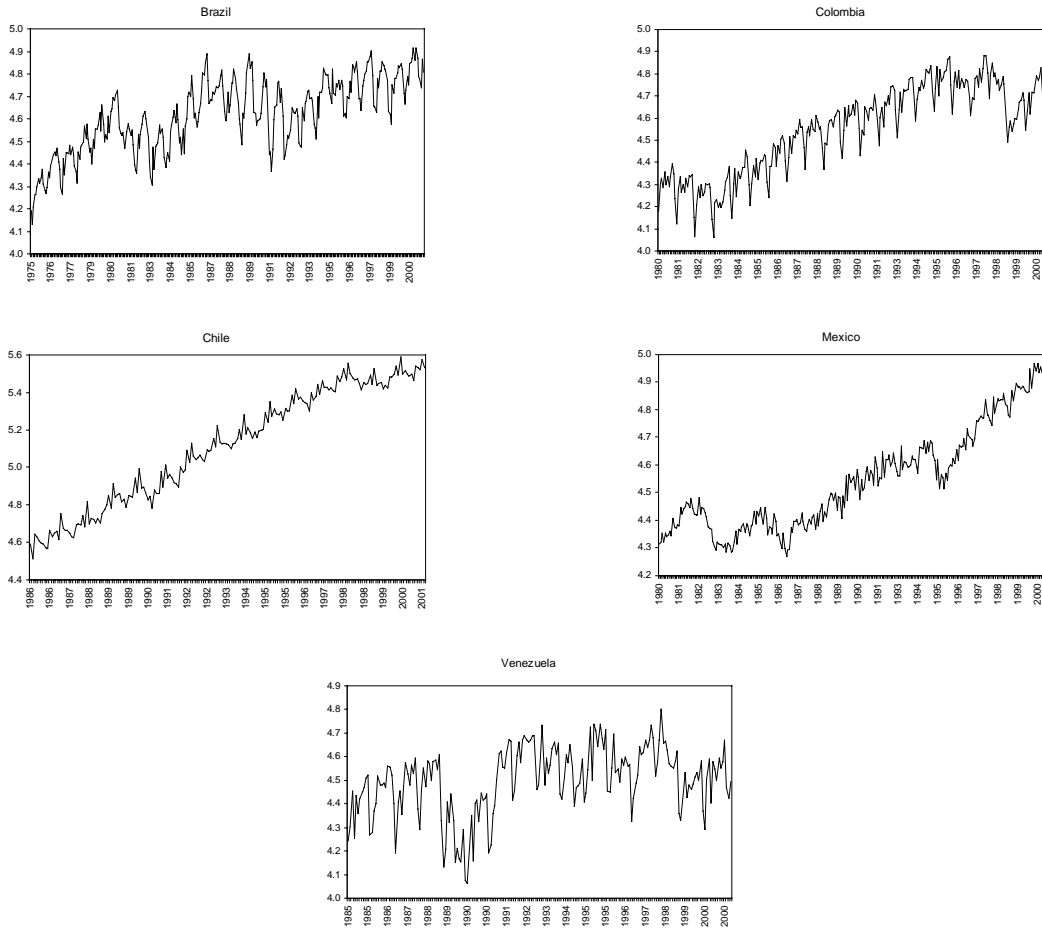
The countries included in the study are Brazil, Chile, Colombia, Mexico and Venezuela. The variable (industrial production index) as well as the countries were chosen on the basis of the availability and frequency (monthly) which is more plausible to behave in a nonlinear fashion (Figure 1). Appendix 1 to this work includes details about the sample period, the variables and the sources.

The evolution of the industrial activity matches some aggregate behavior of the economies at hand. For example, the slow growth rate of Brazil over the last four years; the almost steady growth of Chile within the sample period; the recessions of Colombia at the beginning of the eighties and the end of the nineties; the down turns suffered by Mexican economy about 1983, 1985 and 1995; and, finally, the irregular behavior of the industrial activity in Venezuela with sharp contraction at the end of the eighties. It is important to notice that no common pattern, among the variables, arises.

III. Modeling approach

The nonlinear approach we follow, belongs to the smooth transition autoregressive models put forth by Granger and Teräsvirta (1993), Teräsvirta (1994, 1998), and surveyed by van Dijk, *et al.* (2000). In brief, these type of models assume that a (stationary and ergodic) process moves smoothly between the two extreme regimes instead of abruptly from one regime to the other as it is assumed in the threshold autoregressive (TAR) models (Tong, 1990; Priestly, 1988; Tsay, 1989)⁴.

Figure 1. Real industrial production index of selected Latin American countries



According to this approach, it could be the case that the DGP of a variable can be represented by a smooth transition autoregressive model of order p [STAR(p)], which can be written as:

$$y_t = \beta_0 + \sum_{j=1}^p \beta_j y_{t-j} + (\beta_0^* + \sum_{j=1}^p \beta_j^* y_{t-j}) F(y_{t-d}) + \varepsilon_t \quad (1)$$

where y_t is the variable of which we are interested in the dynamics, F is a heaviside transition function bounded by zero and one and ε_t is an *i.i.d.* process with zero mean and finite variance.

Following Teräsvirta (1994), the testing strategy is carried out on two transition functions: the *logistic* function:

⁴ For the case of Colombia Arango (1998) applied the same approach on the PIB dated annually between 1925 and 1992.

$$F(y_{t-d}) = (1 + \exp\{-\gamma(y_{t-d} - c)\})^{-1}, \quad \gamma > 0 \quad (2)$$

which replaced in (1) yields the logistic STAR(p) model [LSTAR(p)], and the *U-shaped exponential* transition function:

$$F(y_{t-d}) = 1 - \exp(-\gamma(y_{t-d} - c)^2), \quad \gamma > 0 \quad (3)$$

which replaced in (1) gives the exponential STAR(p) model [ESTAR(p)]. The parameter γ represents the speed of the transition process. As we shall see below, the selection between LSTAR and ESTAR models is done by using the data, even in those cases where the economic theory makes some predictions for that.

The “heaviside” properties of the transition function F can be seen as follows. In (2) we note that when $\gamma \rightarrow \infty$ and $y_{t-d} > c$ then $F = 1$, but when $c \geq y_{t-d}$, $F = 0$, so that (1) becomes a TAR(p) model. When $\gamma \rightarrow 0$, (1) becomes an AR(p) model. In (3) we observe that the ESTAR model becomes linear [AR(p)] both when $\gamma \rightarrow 0$ and when $\gamma \rightarrow \infty$. In either transition function, the variable y_{t-d} can generate monotonic changes in the parameters of (1) rather than discrete movements between regimes⁵.

The LSTAR model can describe asymmetric realizations. That is, in our particular case, this model can generate one type of dynamics for increasing growth rate of the industrial index and another for reductions of such a variable. Hence, with the transition function (2) either in the upper ($F = 1$) or the lower regime ($F = 0$), expression (1) becomes a different linear AR(p) model.

The ESTAR model implies that increases and reductions of the transition variable have similar dynamics. For this model, the outer regime ($F = 1$) corresponds to $y_{t-d} = \pm\infty$ and (3) is replaced in (1) to obtain a linear AR(p) model; the middle regime ($F = 0$) results when $y_{t-d} = c$, and (3) replaced into (1) yields a linear AR(p) model.

The strategy for building a STAR model requires the estimation the artificial regression [see Teräsvirta (1994, 1998) for details]:

⁵ Acemoglu and Scott (1994, p. 1305) view this particular transition function, based on past values of the variable at hand, as a potential weakness of this specification.

$$y_t = \pi_{00} + \sum_{j=1}^p (\pi_{0j}y_{t-j} + \pi_{1j}y_{t-j}y_{t-d} + \pi_{2j}y_{t-j}y_{t-d}^2 + \pi_{3j}y_{t-j}y_{t-d}^3) + \varepsilon_t \quad (4)$$

and test the null $H_0: \pi_{1j} = \pi_{2j} = \pi_{3j} = 0, (j=1, \dots, p)$, against a two-tails alternative. In practice, the Lagrange multiplier-type test of linearity is replaced by an F -test in order to improve the size and power of the test. Third, consider the value of d as given and use a sequence of tests specified in (5)-(7) to choose between ESTAR and LSTAR models. Such a sequence is:

$$H_{03} : \pi_{3j} = 0, \quad j=1, \dots, p. \quad (5)$$

$$H_{02} : \pi_{2j} = 0 \mid \pi_{3j} = 0, \quad j=1, \dots, p. \quad (6)$$

$$H_{01} : \pi_{1j} = 0 \mid \pi_{2j} = \pi_{3j} = 0, j=1, \dots, p. \quad (7)$$

and it is based on the relationship between the parameters in (4) and (1) with either (2) or (3). For the ESTAR model $\pi_{3j} = 0, j = 1, \dots, p$, but $\pi_{2j} \neq 0$ for at least one j if $\beta_j^* \neq 0$. For the LSTAR model $\pi_{1j} \neq 0$ for at least one j if $\beta_j^* \neq 0$. If H_{03} is rejected, a LSTAR model is selected. If H_{03} is not rejected and H_{02} is rejected then an ESTAR model is selected. If H_{03} and H_{02} are not rejected but H_{01} is, then a LSTAR model is selected. No clear-cut conclusion is obtained when H_{02} and H_{01} are rejected. In this case we test:

$$H'_{02} : \pi_{2j} = 0 \mid \pi_{1j} = \pi_{3j} = 0, \quad j=1, \dots, p \quad (8)$$

however, if H_{02} is rejected, then H'_{02} should be rejected even more strongly. In any case, the decision is based on whether H_{03} , H_{02} or H_{01} is rejected more strongly.

IV. Empirical issues

To arrive to an appropriate form of the variables, we first take logs of the five industrial production indexes and eliminate seasonal effects, when necessary, by running a regression on a constant and seasonal dummies for monthly data. Finally, first differences of the resulting

variables were used to undertake the estimation process given the evidence of non stationarity of the series.

In all the cases, but Venezuela, evidence of non-linearity, in the sense considered here, were found according to the results⁶. The models fitted appear in Table 1.

Table 1A. LSTAR model for Brazil

	Coefficient	S. D.	t-value	p-value
Linear part				
Constant	0.001	0.002	0.620	0.536
y_{t-1}	-0.308	0.050	-6.210	0.000
y_{t-3}	0.114	0.048	2.366	0.019
y_{t-9}	0.138	0.047	2.929	0.004
y_{t-12}	0.156	0.050	3.133	0.002
y_{t-13}	0.110	0.051	2.149	0.032
Dummy 914	0.149	0.037	4.007	0.000
Non linear part (Transition variable: y_{t-4})				
Constant	-0.009	0.005	-1.768	0.078
$\hat{\gamma}$	27.583	47.736	0.578	0.564
\hat{c}	0.025	0.005	4.606	0.000
y_{t-5}	-0.400	0.115	-3.470	0.001

With respect to the results, we can pay attention on the values of gamma's ($\hat{\gamma}$) and the thresholds (\hat{c}) of each model. As we said before, gamma represents the speed of the transition process while the threshold represents the value that triggers the change of one regime to the other (see Figure 2). In the case of Brazil we observe a sudden, rather than smooth, movement from one regime to the other. It is the consequence of the high value of gamma (27.583). A

⁶ Not shown here for space reasons as well as the results of the tests for stationarity of the series. However, all the results are available from the authors upon request.

rather different situation is observed in Chile (1.417), Colombia (4.130) and Mexico (0.606)⁷. The thresholds are statistically equal to zero for Chile and Colombia.

Table 1B. LSTAR model for Chile

	Coefficient	S. D.	<i>t</i>-value	<i>p</i>-value
Linear part				
Constant	0.026	0.018	1.442	0.151
y_{t-7}	-0.181	0.057	-3.173	0.002
y_{t-10}	0.347	0.232	1.496	0.137
y_{t-12}	0.525	0.052	10.021	0.000
Non linear part (Transition variable: y_{t-10})				
Constant	-0.037	0.031	-1.191	0.236
$\hat{\gamma}$	1.417	0.804	1.761	0.080
\hat{c}	-0.004	0.010	-0.365	0.716
y_{t-1}	-0.561	0.127	-4.428	0.000
y_{t-6}	-0.187	0.107	-1.745	0.083

The transition functions presented in figure 2 show a different variety of forms. In the case of Brazil we have a sharp transition between the two regimes which is compatible with the dynamic of the series (figure 1) that show very clear the cycles of the economy without a mark transition between the regimes. For Colombia and Chile a smoothed transition is shown, but in the case of Chile there is almost no lower regime corresponding to contractions. This result may be related with the fact than the Real Industrial Production Index for Chile (Figure 1) do not present clear periods of deceleration compared with other Latin American countries.

The transition function over time presented in Figure 3 can help us to identify the biggest contractions for these countries. This is the case of the 1981-83 recession of Brazil and the 1998-99 recession of Colombia when the transition function shows several values close to

⁷ Even though in Table 1 we show the *p*-value's associated with null hypothesis that $\gamma=0$, this is not useful for this parameter since the distribution for the estimator of γ under this null hypothesis does not follow either a normal nor

zero. As noted before, the Chilean case is more difficult to interpret since there is almost no lower regime strictly speaking and for Mexico the interpretation is different since we have an ESTAR instead of a LSTAR model.

Table 1C. LSTAR model for Colombia

	Coefficient	S. D.	<i>t</i>-value	<i>p</i>-value
Linear part				
Constant	-0.007	0.006	-1.223	0.223
y_{t-1}	-0.686	0.125	-5.493	0.000
y_{t-3}	0.303	0.091	3.328	0.001
y_{t-10}	-0.129	0.052	-2.501	0.013
y_{t-13}	-0.105	0.051	-2.069	0.040
Dummy 914	0.129	0.032	3.993	0.000
Non linear part (Transition variable: y_{t-1})				
Constant	0.022	0.013	1.656	0.099
$\hat{\rho}$	4.130	1.884	2.192	0.029
\hat{c}	0.010	0.007	1.314	0.190
y_{t-2}	-0.339	0.123	-2.764	0.006
y_{t-3}	-0.802	0.183	-4.372	0.000
y_{t-4}	-0.318	0.115	-2.750	0.006
y_{t-6}	0.252	0.102	2.476	0.014
y_{t-8}	-0.182	0.102	-1.772	0.078

Finally, we have to mention that no evidence of misspecification of the models is found on the basis of the Ljung-Box, MacLeod-Li, LM-ARCH, and Jarque-Bera tests. Furthermore, non-remaining nonlinearity, and parameter constancy (Teräsvirta, 1998), are highly satisfactory⁸.

a *t*-distribution (see Teräsvirta, 1994).

⁸ Also available from the authors on request.

Table 1D. ESTAR model for Mexico

	Coefficient	S. D.	t-value	p-value
Linear part				
Constant	-0.001	0.003	-0.536	0.592
y_{t-1}	-0.495	0.059	-8.358	0.000
y_{t-3}	0.248	0.054	4.547	0.000
y_{t-5}	0.042	0.058	0.728	0.467
y_{t-6}	0.118	0.055	2.135	0.034
y_{t-12}	0.373	0.091	4.078	0.000
Dummy 954	-0.071	0.025	-2.884	0.004
Dummy 974	0.075	0.024	3.196	0.002
Non linear part (Transition variable: y_{t-1})				
Constant	0.009	0.006	1.678	0.095
$\hat{\rho}$	0.606	0.473	1.281	0.202
\hat{c}	-0.008	0.005	-1.557	0.121
y_{t-4}	0.254	0.175	1.449	0.149
y_{t-12}	-0.616	0.182	-3.394	0.001

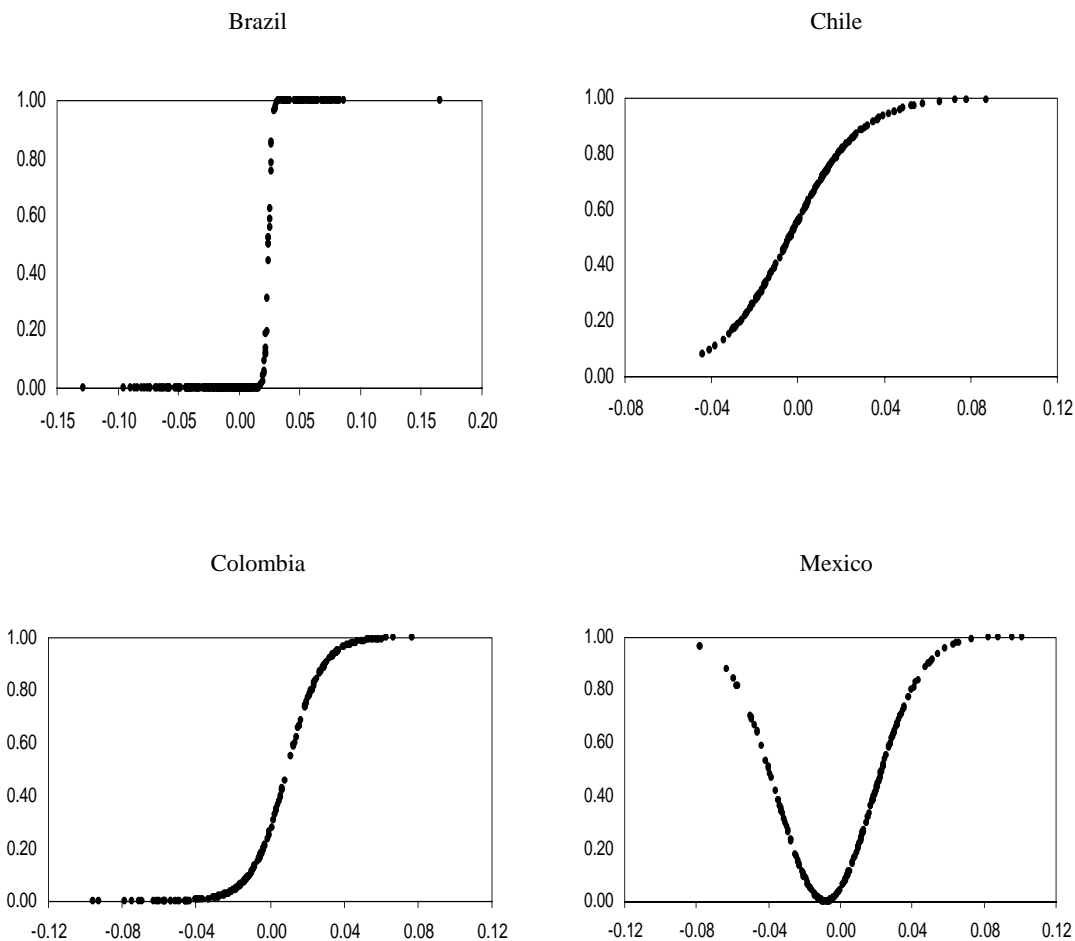
The difficulty to interpret the some of the estimates of a STAR-type model can be overcome by analyzing the limit values that describe the local dynamics and the impulse response functions. For LSTAR models, the lowest and highest growth rates of industrial production index are associated to $F = 1$ and $F = 0$, respectively. For ESTAR models, however, this is not the case since the outer regime can be associated to both expansions and contractions as in the case of Mexico (Figure 2).

For describing the local dynamics, we use the roots of the models that can be obtained from:

$$z^p - \sum_{j=1}^p (\hat{\beta}_j + \hat{\beta}_j^* F) z^{p-j} = 0 \quad (9)$$

for $F = 0, 1$ (Table 2).

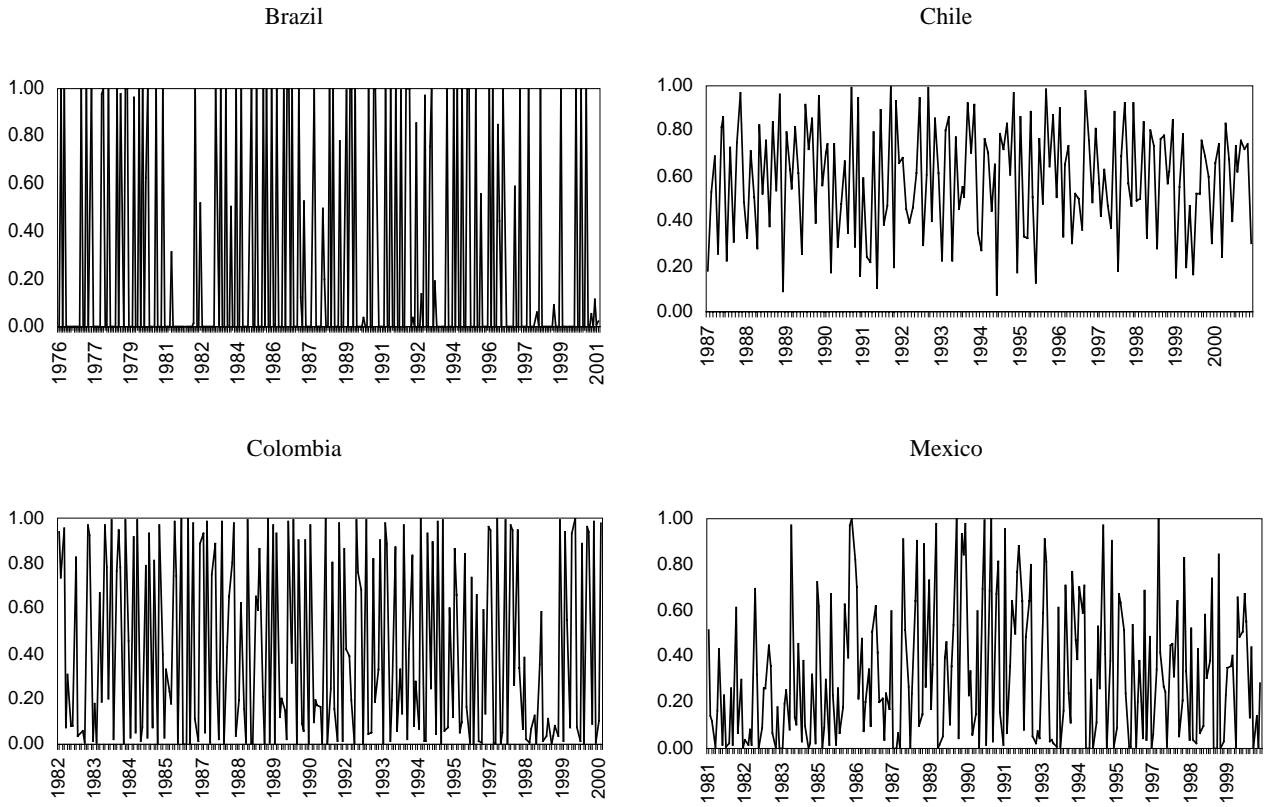
Figure 2. Transition function



The dominant roots of the regimes of both recession and expansion are locally stable. This is the case for all countries except for the upper regime of Chile. For this country the number of points in the upper regime of transition function is not high: Such a situation could be interpreted in the following sense: once the industrial activity is in the (extreme) upper regime, any exogenous force arises to reduce the performance of the economy with the aim of moving it down.

The dynamics of the variables can also be analyzed by using the impulse response function (IRF). This function shows the effect of a shock on a series over time. It can be calculated as the difference between the conditional expected value of the series with and without the shock:

Figure 3. Transition function over time



$$\begin{aligned}
 IRF(\delta, t)_k &= E(y_{t+k} | \varepsilon_t = \delta, \varepsilon_{t+1} = 0, \dots, \varepsilon_{t+n} = 0, y_{t-1}, y_{t-2}, \dots) \\
 &\quad - E(y_{t+k} | \varepsilon_t = 0, \varepsilon_{t+1} = 0, \dots, \varepsilon_{t+n} = 0, y_{t-1}, y_{t-2}, \dots)
 \end{aligned} \tag{10}$$

for $k = 1, 2, \dots$. In equation (10) the *IRF* indicates the dynamic effect of a shock of magnitude δ on the series y_t , k periods ago. The evaluation of the conditional expected values used in (10) for the STR models is complicated since the expected value is not invariant. In this case, Lundbergh and Teräsvirta (2000) use Monte Carlo or bootstrapping methods to approximate the expected value of the non linear function.

In the case of linear models, the *IRF* is symmetric and time independent. The first property implies that a shock of magnitude $-\delta$ has the same effect of a shock of magnitude $+\delta$, while the second one implies that the response of a shock does not depend on the time period when this is given.

Table 2. Characterization of extreme regimes polynomials and dominant roots**A. Brazil**

F=0			F=1		
Root	Modulus	Period	Root	Modulus	Period
0.91	0.91	.	-0.44± 0.86i	0.96	3.1
-0.45± 0.79i	0.91	3.0	0.77± 0.49i	0.91	11.2
0.04± 0.88i	0.88	4.1	0.87	0.87	.
0.75± 0.44i	0.88	11.8	± 0.86i	0.86	4.0

B. Chile

F=0			F=1		
Root	Modulus	Period	Root	Modulus	Period
-0.99	0.99	.	-1.05	1.05	.
-0.84± 0.51i	0.99	11.5	-0.89± 0.52i	1.03	2.4
0.97	0.97	.	0.82± 0.52i	0.97	11.1
-0.81± 0.52i	0.96	2.44	-0.48± 0.80i	0.93	3.0

C. Colombia

F=0			F=1		
Root	Modulus	Period	Root	Modulus	Period
-0.61± 0.72i	0.94	2.8	0.36± 0.89i	0.96	5.3
-0.82± 0.38i	0.91	2.3	-0.55± 0.75i	0.93	2.9
0.82± 0.22i	0.85	24.2	-0.85± 0.29i	0.90	2.2
-0.14± 0.83i	0.85	3.6	-0.81	0.81	.

D. Mexico

F=0			F=1		
Root	Modulus	Period	Root	Modulus	Period
-0.54± 0.81i	0.98	2.9	-0.91± 0.20i	0.93	2.2
-0.82± 0.48i	0.95	2.4	-0.30± 0.87i	0.92	3.3
-0.95	0.95	.	-0.65± 0.65i	0.92	2.7
0.92	0.92	.	0.86± 0.18i	0.88	30.8

In the case of nonlinear models the situation is rather different since the *IRF* does not have restrictions about symmetry of a shock effects and they are time dependent (see Koop, Pesaran and Potter, 1996). Potter (1995) defined the following measure of asymmetry:

$$ASYM(\delta, t)_k = IRF(\delta, t)_k + IRF(-\delta, t)_k \quad (11)$$

for $k = 1, 2, \dots$. In contrast to linear specification, in the non linear models this measure is not necessarily equal to zero and depends upon the date when the shock is given.

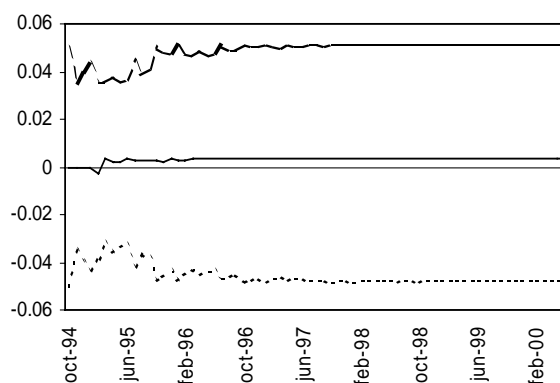
In words, the impulse responses showed in Figure 4 are obtained by shocking the variables at different (selected) dates each corresponding to a each regime (as close to the extreme as possible)⁹. Each picture contains three lines, the superior one and the inferior one represent the IRF given a positive and a negative shock, respectively. The one in the middle represents the *ASYM* coefficient, i.e. equation (11).

As we can see from the Figure 4, the variables exhibit asymmetric responses¹⁰. However, this result is not clear for Chile in the lower regime, where the impact of positive and negative shocks almost compensates. This result reinforces the evidence of the asymmetry of the business cycles in the selected Latin American countries.

As expected we have a positive asymmetry when the shocks are given in the upper regime and negative asymmetry when the shocks are given in the lower regime. The only exceptions is the Chilean case in lower regime; as noted earlier, this result may be related with the form of the transition function for this country (Figure 2).

In all the cases, except for Brazil, we can see that the asymmetry coefficient is bigger when the shock is given in the upper regime instead of the lower regime which indicates than the positive shocks are more persistent than the negative ones.

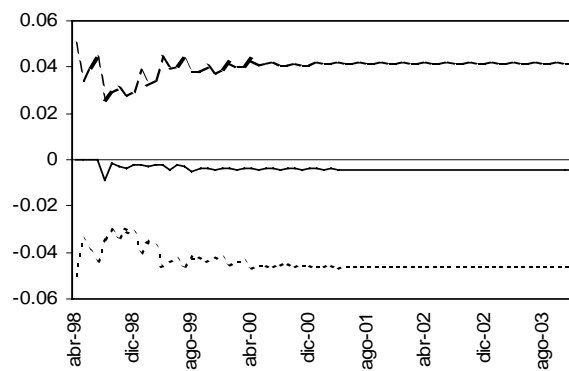
Figure 4. Impulse response functions
A. Brazil. Effect of a shock in the upper regime (September 1994)



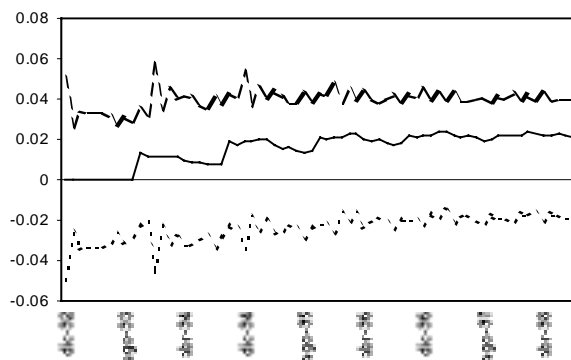
⁹ The results are obtained from 1,000 bootstrapping replications.

¹⁰ That is, the *ASYM* coefficient is not zero.

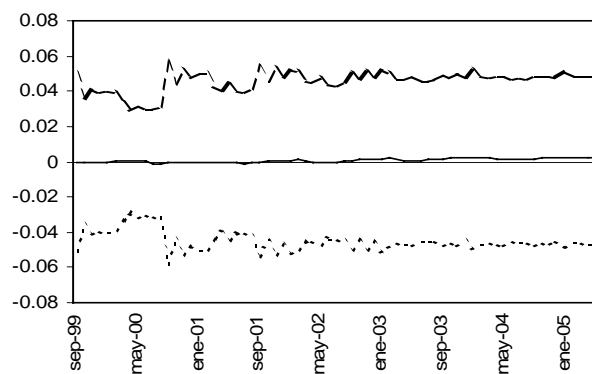
B. Brazil. Effect of a shock in the lower regime (March 1998)



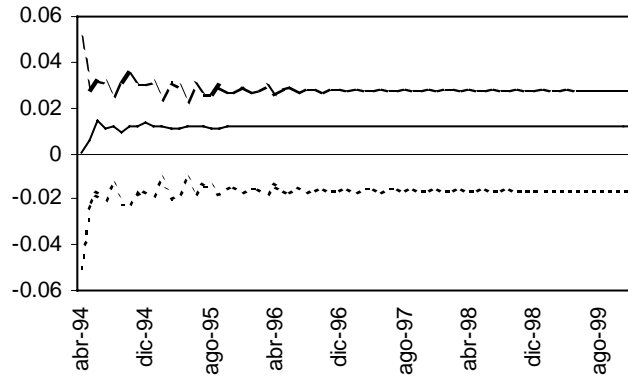
C. Chile. Effect of a shock in the upper regime (November 1992)



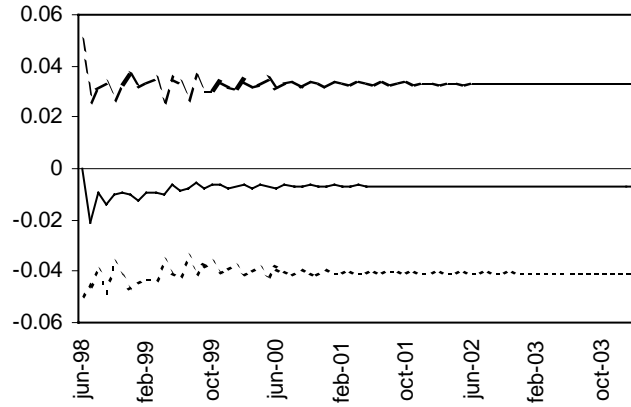
D. Chile. Effect of a shock in the lower regime (August 1999)



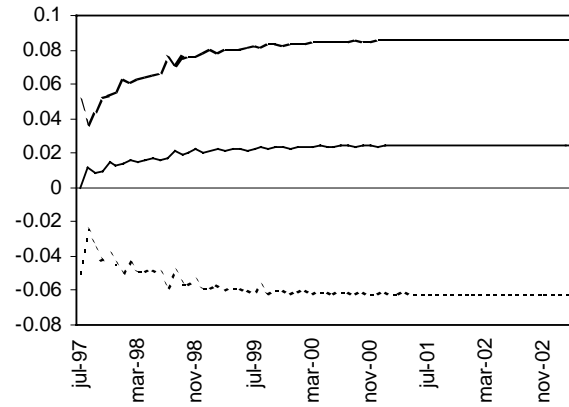
E. Colombia. Effect of a shock in the upper regime (March1994)



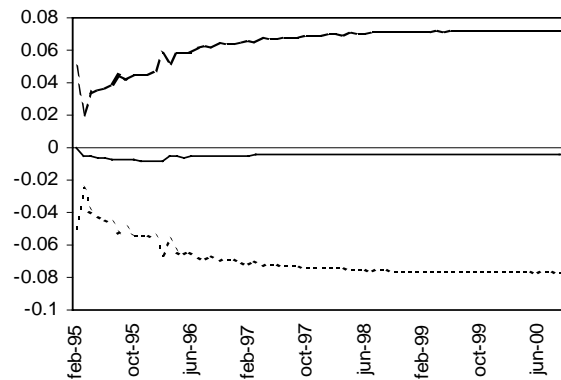
F. Colombia. Effect of a shock in the lower regime (May 1998)



G. Mexico. Effect of a shock in the upper regime (March1994)



H. Mexico. Effect of a shock in the lower regime (January 1995)



V. Conclusions

In this paper we employ the real industrial production index as the proxy for economic activity and present evidence of having nonlinear business cycles in most of the selected Latin American countries: Brazil, Chile, Colombia and Mexico. For Venezuela, the hypothesis of linearity could not be rejected. The evidence of nonlinearity is supported by the smooth transition autorregressive model adjusted for each country and the asymmetries found in the analysis of the impulse response functions.

The STAR models we have fitted shed some light on the features of the series we have considered. Thus, the nonlinearity characterized for the transition function suggest that the cycles of the four economies are asymmetric. However, this is not the case for Mexico where the best alternative happen to be a symmetric representation. Nonetheless, the dynamics suggested by the impulse response analysis is clear: for all the countries we find asymmetric responses. That is, we find that the positive shocks given in the upper regime have positive effects and negative shocks given in the lower regimes have negative effects. We also find that, in these cases, positive shocks are more persistent than the negative ones.

The shape of the estimated transition function of the non linear model seems to meet the dynamics of the data. Its sharp form in the case of Brazil may be an indication of no clear evidence of transition periods between the extreme regimes while the (almost) no existence of the lower regime of Chile could be related with the fact than its Real Production Index do not

present clear periods of deceleration compared to other Latin American countries. Also, when plotted over time, the transition function can help us to identify the biggest contractions for these countries. This is the case of the 1981-83 recession of Brazil and the 1998-99 recession of Colombia.

References

Acemoglu D. and A. Scott, (1994), Asymmetries in the cyclical behaviour of UK labour markets, *The Economic Journal*, 104, 1303-1323.

Arango, L.E., (1998), Some univariate properties of output. *Lecturas de Economía* No. 49. Universidad de Antioquia, July-December.

Banco de República, (2001), Informe de la Junta Directiva al Congreso de la República, Banco de la República.

Boldin, M. D., (1999), Should policy makers worry about asymmetries in the business cycle?, *Studies in nonlinear dynamics and econometrics*, 3 (4) 203-20.

Davies, R.B., (1977). Hypothesis Testing when a Nuisance Parameter is Present Only under the Alternative Hypothesis. *Biometrika*, 64, 247-254.

Franses P.H. and D. van Dijk (1999). *Nonlinear time series models in empirical finance*, Manuscript prepared for Cambridge University Press.

Fernández C. and A. Gonzalez, (2000), Integración y vulnerabilidad externa en Colombia, Borradores de Economía, No. 156, Banco de la República.

Granger, C.W.J. and T. Teräsvirta, (1993). *Modelling Nonlinear Relationships*. Oxford University Press. New York.

Granger, C.W.J, T. Teräsvirta. and H.M. Anderson, (1993). Modelling Nonlinearity over the Business Cycle, in J.H. Stock and M.W. Watson (eds.) *Business Cycles, Indicators and Forecasting. Studies in Business Cycles*. Volume 28. National Bureau of Economic Research. The Chicago Press. Chicago.

Hamilton J.D., (1989), A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica*, 57, 357-384.

Keynes J.M., (1936). *The General Theory of Employment, Interest and Money*. MacMillan. London.

Kontolemis Z.G., (1997), Does growth vary over the business cycle? Some evidence from the G7 countries, *Economica*, 64, 441-460.

Koop, G., M. Pesaran and S. Potter (1996), Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74, 119-147.

Lundbergh, S and T. Teräsvirta, (2000). Forecasting with Smooth transition Autoregressive Models. SSE/EFI Working Paper Series in Economics and Finance, No. 390.

Luukonen, R., P Saikkonen, and T. Teräsvirta, (1988). Testing Linearity against Smooth Transition Autoregressive Models. *Biometrika*, 75, 491-499.

Mitchell, W.C., (1927). *Business Cycles. The Problem and its Setting*. NBER, New York.

Peel, D.A. and A.E.H. Speight, (1998). Threshold Nonlinearities in output: Some International Evidence. *Applied Economics*, volume 30, Number 3, 323-333.

Priestley, M.B., (1988), *Nonlinear and Nonstationary Time Series Analysis*. Academic Press. London.

Potter, S., (1995), A nonlinear approach to US GNP, *Journal of Applied Econometrics* 10, 109-125.

Sichel, D E. (1993), Business cycle asymmetry: a deeper look, *Economic Inquiry*, Vol. XXXI, 224-236.

Simpson P.W, D.O. Osborn, and M. Sensier, (2001), Modelling business cycle movements in the UK economy, *Economica*, 68, 243-267.

Teräsvirta, T. and H.M. Anderson, (1992). Characterizing Nonlinearities in Business Cycles using Smooth Transition Autoregressive Models. *Journal of Applied Econometrics*, Vol. 7, S119-S136.

Teräsvirta, T., (1994), Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models. *Journal of the American Statistical Association*. Vol. 89, 425, 208-218.

Teräsvirta, T. (1998) Modelling economic relationships with smooth transition regressions, in *Handbook of Applied Economic Statistics*, A. Ullah and D.E.A. Giles (Eds.), Marcel Dekker, New York.

Tiao, G.C. and R.S. Tsay, (1994), Some advances in nonlinear and adaptive modelling in time series, *Journal of Forecasting*, 13, 109-131.

Tong, H., (1990), *Non-linear Time Series: A Dynamical System Approach*. University Press. Oxford.

Tsay, R.S., (1989). Testing and Modelling Threshold Autoregressive Processes. *Journal of the American Statistical Association*, Vol. 84, No. 405, 231- 240.

Torres, A., (1999), El ciclo económico de México y su relación con el ciclo económico en otros países, Banco de México, CEMLA, IV Meeting of the Network of America Central bank Researchers, Santiago de Chile.

van Dijk, D., T. Teräsvirta, and P.H. Franses, (2000), Smooth transition autoregressive models. A survey of recent developments, SSE/EFI Working Papers Series in Economics and Finance, No. 30.

Zarnowitz, V. [1992], *Business Cycles, Theory, History, Indicators, and Forecasting*. The University of Chicago Press. London.

Appendix 1

Data Sources:

Brasil: *Produção industrial – indústria geral - quantum - índice dessaz. – Mensal*". Monthly data from 1975:1 to 2001:1. WEBSITE of the “*Instituto de Pesquisa Econômica Aplicada*”.

Chile: Economic Activity Monthly Index (IMACEC). Monthly data from 1986:1 to 2001:2. WEBSITE of the *Banco Central de Chile*.

Colombia: Real Industrial Production Index. Monthly data from 1980:1 to 2001:2. *DANE* Data bases.

Mexico: Physical Volume Industrial Activity Index. Monthly data from 1980:1 to 2001:1. *INEGI* Data bases.

Venezuela: Laspeyres Volume Production Index corresponding to the private manufacturing industry. Monthly data from 1985:1 to 2001:2. *Banco Central de Venezuela* Data bases.

Periods used as references of A: slump (/ contraction / deceleration) and B: boom (/ expansion / acceleration / recovery).

Source: CEPAL, Estudio Económico de América Latina y el Caribe (1999) y (1999-2000)

Brazil:

A: 1981, 1983, 1985, 1989; 1993*; 1994, 1996, 1998, 1999.

B: 1986, 1991, 1997

Chile:

A: 1990*, 1996*, 1998*, 1999.

B: 1989, 1992, 1995.

Colombia:

A: 1982*, 1996*, 1998*, 1999.

B: 1986, 1994.

México:

A: 1982*, 1983, 1986, 1995.

B: 1981, 1990, 1997.

Venezuela:

A: 1985, 1989, 1993*, 1994, 1996, 1998, 1999.

B: 1986, 1991, 1997.

* represents a deceleration (qualification from the authors).