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

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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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I. Introduction

The behavior of macroeconomics variables associated to the business cycles has long been of interest to researchers. It has also been of interest the linearity or nonlinearity of the macroeconomic variables movements over phases of the business cycle. The discussion has also covered the symmetric or asymmetric[1] fashion in which such movements take place[2]. Symmetric fluctuations occur when the time distance from peak to trough is similar to that from trough to peak so that contractions are as short and steep as expansions. By contrast, we can think of asymmetries as fluctuations that have different time distance from peak to trough than from trough to peak so that contractions are much shorter and steeper than expansions. This dynamics 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 size of the asymmetry: *deepness* and *steepness*. The former identifies situations in which troughs are further below trend than peaks are above while the latter refers to situations in which contractions are steeper than expansions.

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

[1] 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).

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

as a result production could fall rapidly and expand slowly[3]. In addition, the asymmetric property might also be associated to the relative easy in which a firm may reduce production below full capacity when orders decrease compared with the difficulty of increasing production when capacity constraints are present[4,5].

From the point of view of dynamics, cyclical asymmetries might arise when the propagation mechanism is based on the intertemporal substitution of the labor supply of workers when an adverse technological shocks the economy as in the real business cycle models. Given the existence of a reservation wage, possibly endogenous, when the real wage is below such a reservation wage the labor supply collapses to zero. However, when the shock is positive no exhausting point of the supply is found even assuming that the income effect by large dominates the substitution effect[6].

Given that some evidence (Boldin, 1999) suggests that most econometric models cannot capture empirically important asymmetries and that linear models are incapable of capturing fluctuation asymmetries (Simpsom et al., 1999), we use the method proposed by Granger and Teräsvirta (1993) to study the nonlinear business cycle properties of the industrial production

[3] Chetty and Heckman (1985) and Baldwin and Krugman (1986) present models with this characteristic. Sichel (1993) suggests that this kind of asymmetric costs of upward and downward adjustment can generate steepness in the cycles.

[4] This view is different form that of Acemoglu and Scott (1994) who, independent from the starting point with respect to the potential output, suggest that adverse supply shocks might correspond to recessions while beneficial demand shocks might correspond to expansions.

[5] Sichel (1993) points to this as a potential cause of deepness. For models with this property on prices see, for example, De Long and Summers (1988).

[6] However, this possibility is only a hypothesis to be modeled and checked.

index of five economies[7]: Brazil, Chile, Colombia, Mexico, and Venezuela over the last two decades. The dynamics is also analyzed with the impulse response functions (Potter, 1995) derived from our preferred smooth transition specification.

This work is aimed to obtain some evidence about the regularity associated to asymmetric fluctuations. However, 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 fluctuations 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 countries[8]. This coherence of the movements over the phases of the cycle is explained by external factors such as the capital inflow occurred between 1991 and 1994 (see also Banco de la República, 2001). However, as we have said above, our paper is aimed to check the hypothesis of having asymmetric fluctuations in some Latin American countries.

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 next estimate 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

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[7] 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).

[8] Argentina, Brazil, Chile, Colombia, Peru and Venezuela.

the impulse response functions we show asymmetric responses of the variables depending on the regime the variables are shocked.

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 of monthly data (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)[9].

Figure 1. About here

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:

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

where y_t is the variable of which we are interested in the dynamics, *F* is a 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:

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

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

[9] For the case of Colombia Arango (1998) applied the same approach to the PIB annually dated between 1925 and 1992.

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

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 $\gamma \to \infty$ 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 $\gamma = 0$, (1) becomes an AR(*p*) model. In (3) we observe that the ESTAR model becomes linear [AR(*p*)] both when $\gamma \to 0$ and when $\gamma \to \infty$. In either transition function, the variable y_{t-d} can generate monotonic changes in the parameters of (1) rather than discrete movements between regimes[10].

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.

[10] 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.

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

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

and test the null H_0: $\pi_{1j} = \pi_{2j} = \pi_{3j} = 0$, ($j = 1,...,p$), 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 for small samples. 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:

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

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

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

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,...., 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:

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

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 results[11]. The models fitted appear in Table 1.

Table 1A. About here

Table 1B. About here

Table 1C. About here

Table 1D. About here

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 $\hat{c}$, the threshold, represents the value that triggers the change of one regime to

[11] 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.

the other (see Figure 2). In the case of Brazil we observe a sudden and abrupt, rather than smooth, movement from one regime to the other. It is the consequence of the high value of gamma (27.583). A rather different situation is observed in Chile (1.417), Colombia (4.130) and Mexico (0.606)[12]. The thresholds are statistically equal to zero for Chile and Colombia.

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) where we can observe clear fluctuations of the economy. For Colombia and Chile a smooth 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 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 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.

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,

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

non-remaining nonlinearity, and parameter constancy (Teräsvirta, 1998), are highly satisfactory[13].

The difficulty to interpret 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 function. 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).

Figure 2. About here

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

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

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

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.

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[13] Also available from the authors on request.

Figure 3. Transition function over time

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 a shock:

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

for *k = 1, 2,....* 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.

Table 2. About here

A. Brazil

B. Chile

C. Colombia

D. Mexico

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.

For nonlinear models the situation is rather different since the *IRF* does not have restrictions about symmetry while being time dependent (see Koop, Pesaran and Potter, 1996). Potter (1995) defined the following measure of asymmetry:

$$ASYM(\delta, t)_k = IRF(\delta,\ t)_k + IRF(-\delta,\ t)_k \tag{11}$$

for $k = 1,\ 2, \ldots$. In contrast to the linear specification, for 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 dates each corresponding to a each regime (as close to the extreme as possible)[14]. Each picture contains three lines showing the effect of the shock on the variables in levels , the superior and inferior line represent the *IRF* given a positive and a negative shock, respectively. The one in the middle represents the *ASYM* measure given in the equation (11).

As we can see from the Figure 4, the variables exhibit asymmetric responses[15]. 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 fluctuations in the selected Latin American countries.

Figure 4. About here

A. Brazil. About here

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 since no clear contraction period can be pointed out from the industrial production index (Figure 2).

B. Brazil. About here

[14] The results are obtained from 1,000 bootstrapping replications.

[15] That is, the *ASYM* measure is not zero.

C. Chile. Abut here

D. Chile. About here

E. Colombia. About here

F. Colombia. About here

G. Mexico. About here

H. Mexico. About here

In all the cases, except for Brazil, we can see that the asymmetry measure 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.

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 autorregresive 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.

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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).

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

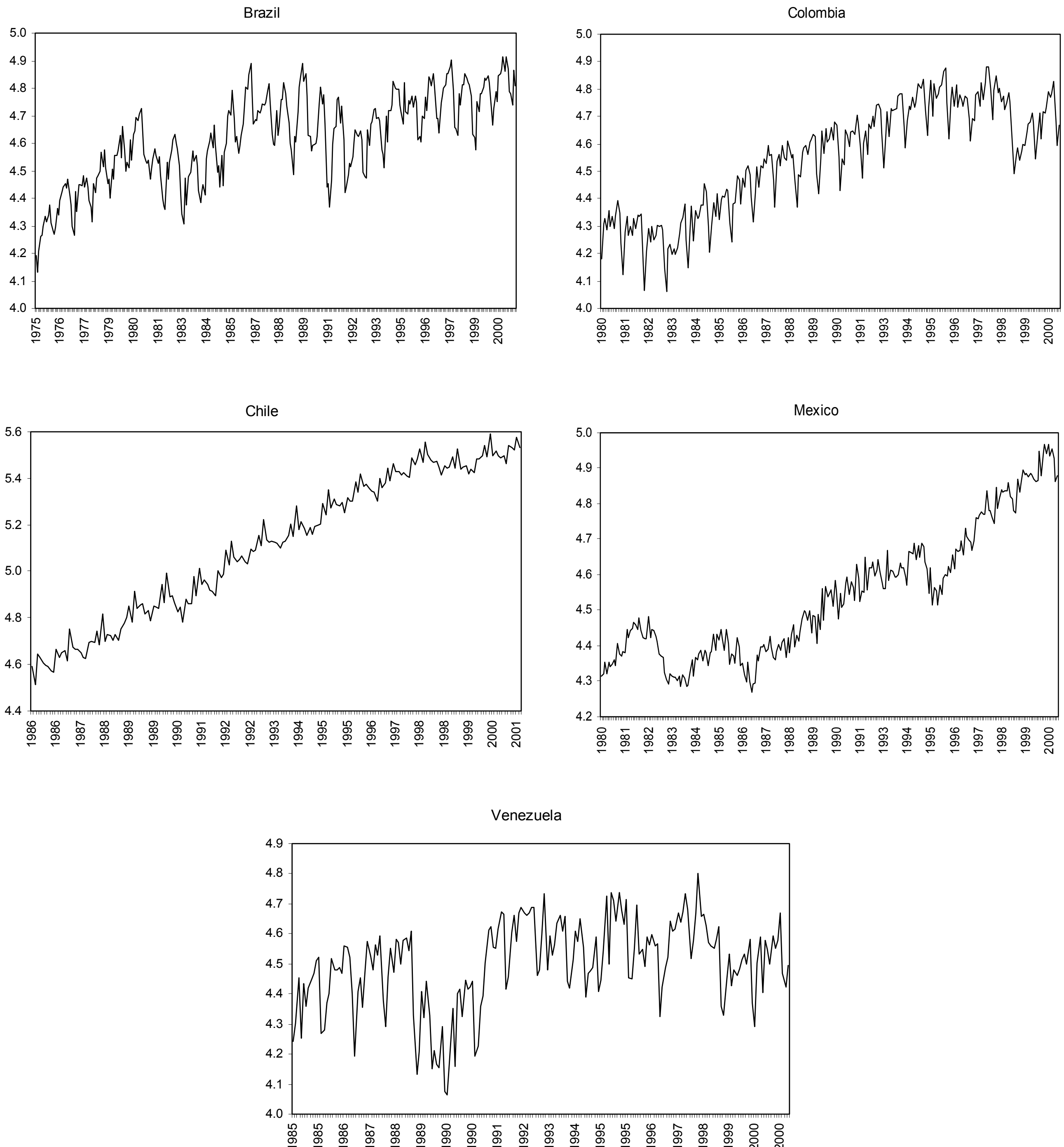


Figure 2. Transition function

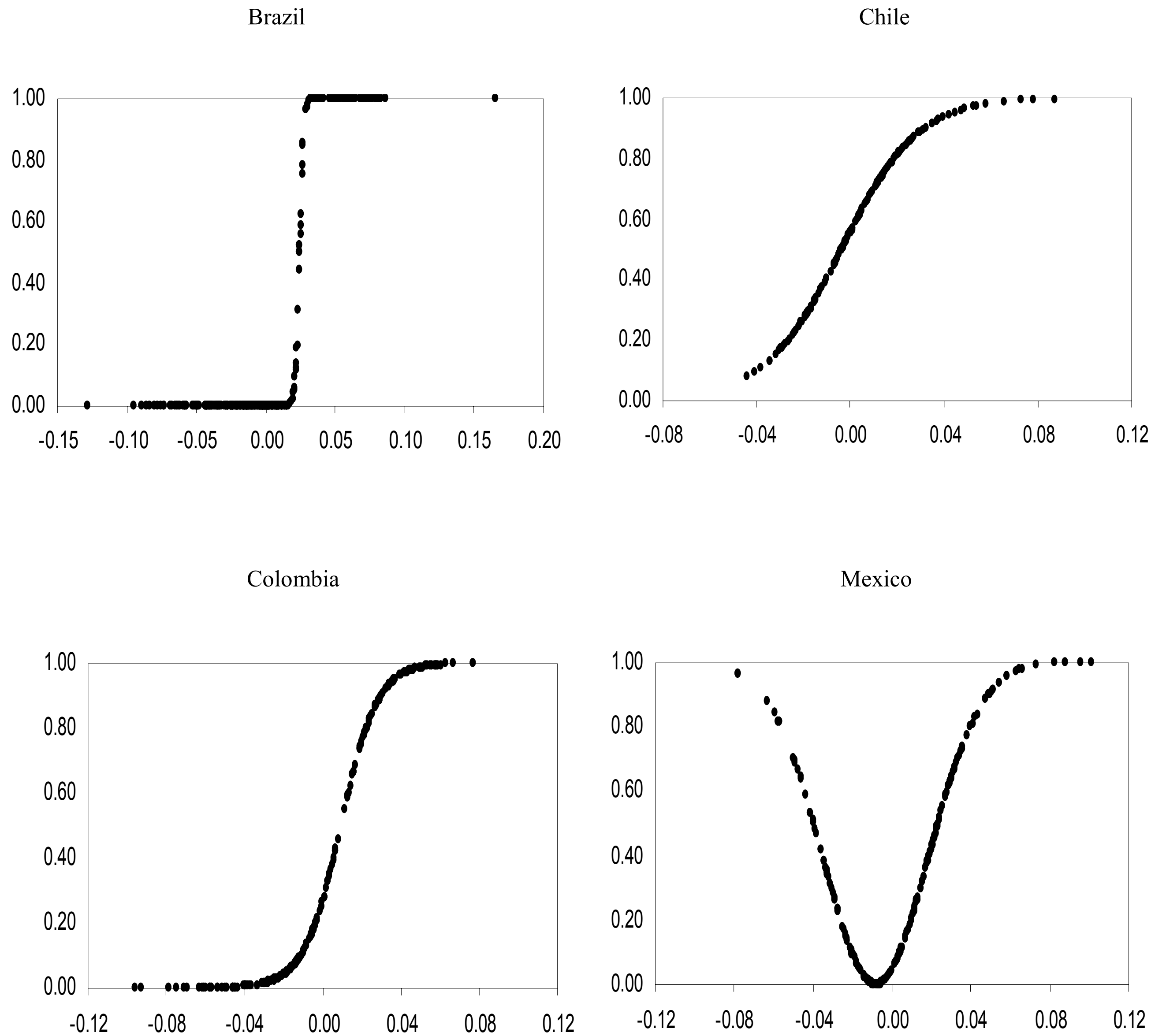


Figure 3. Transition function over time

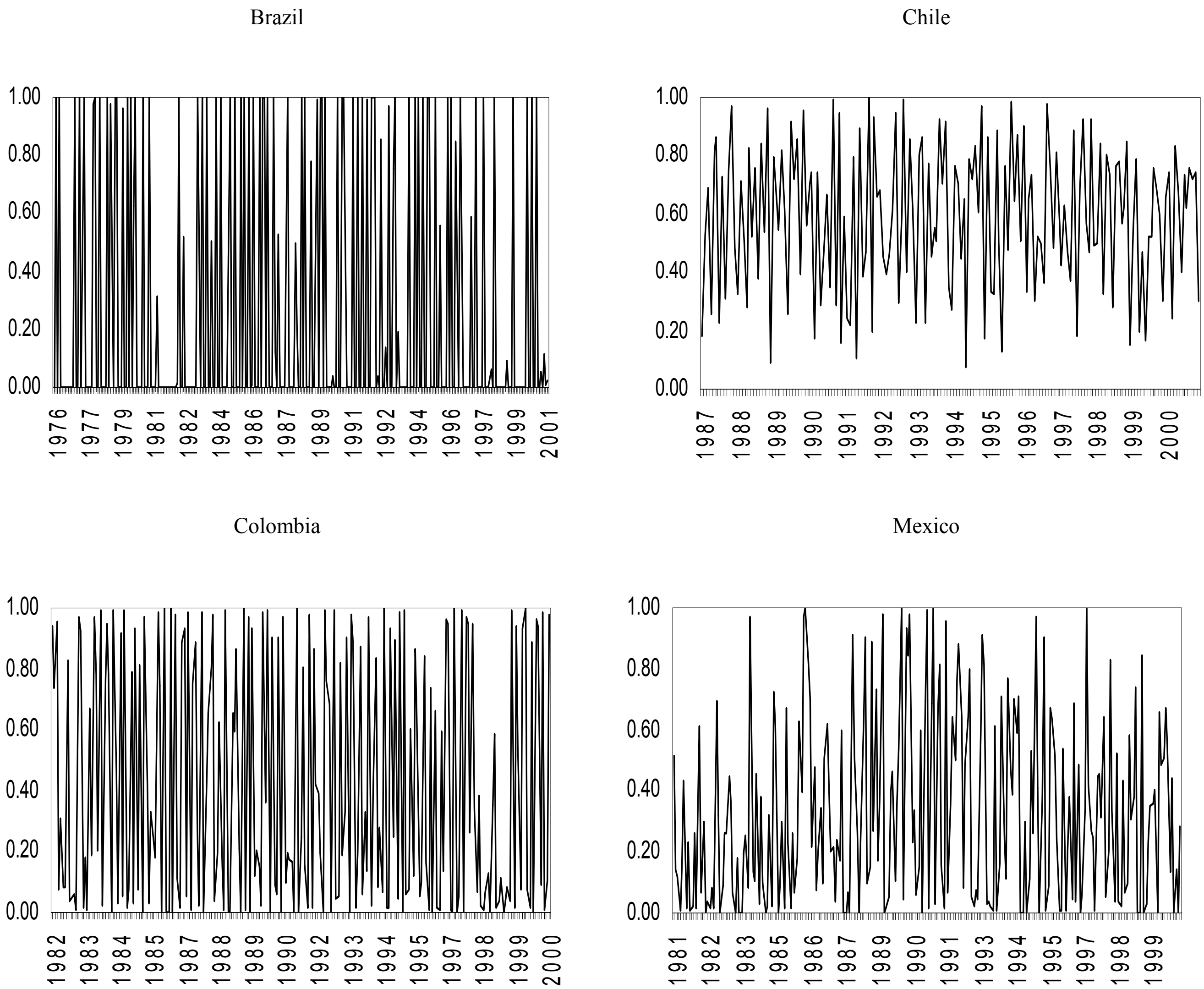
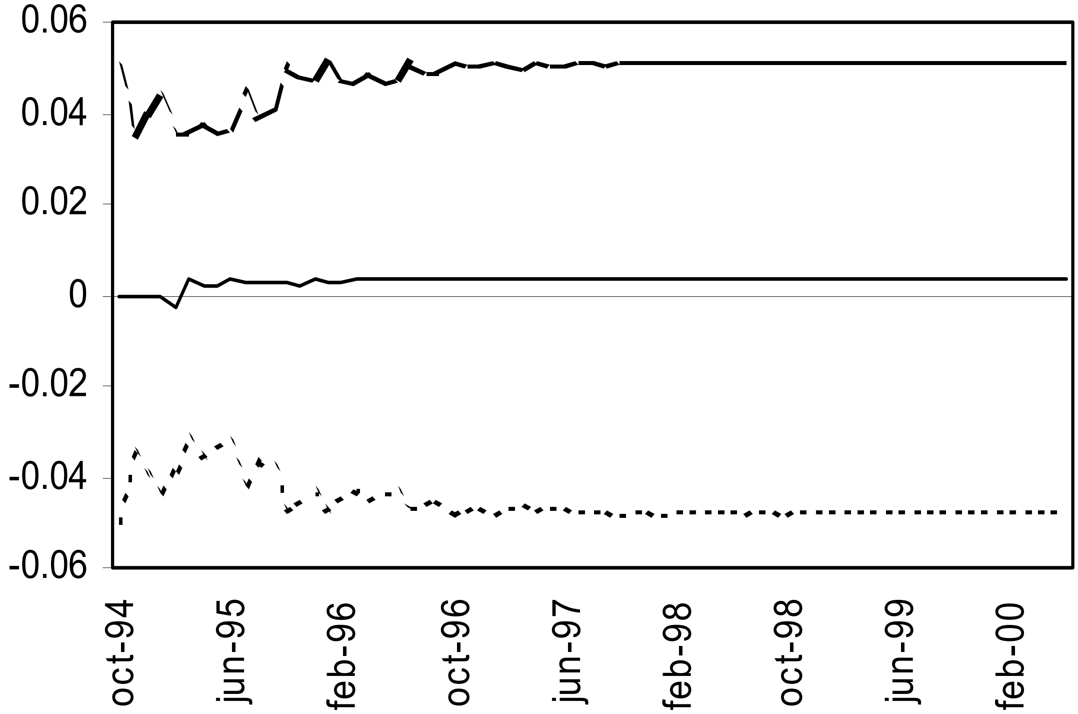
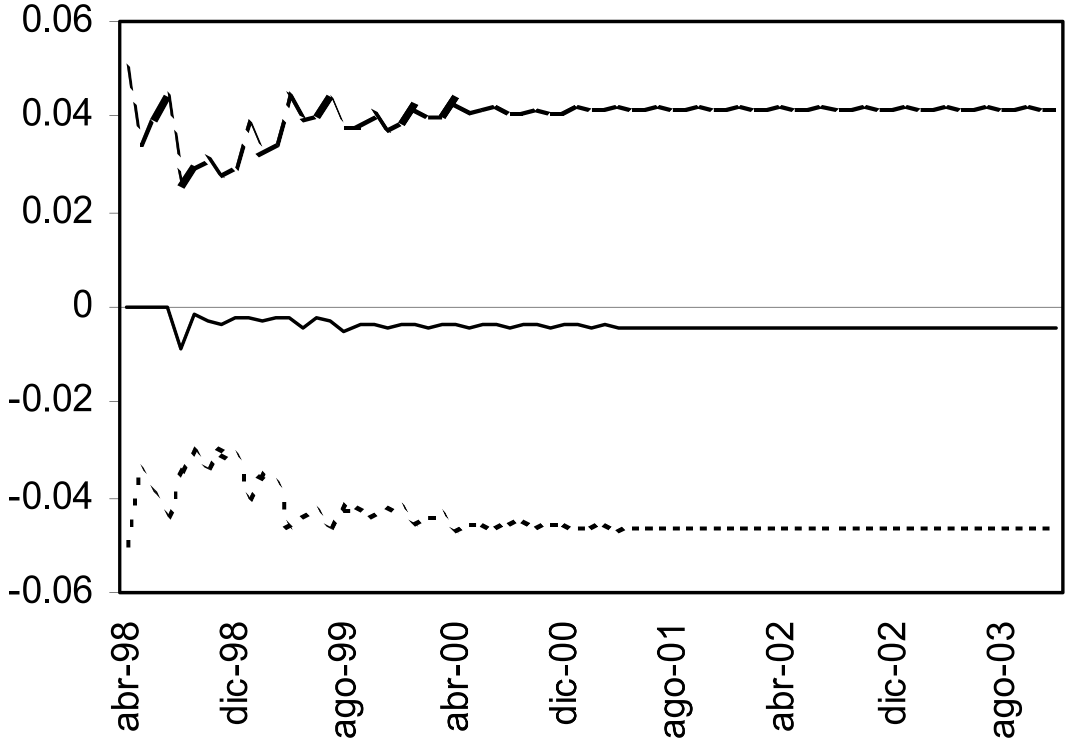


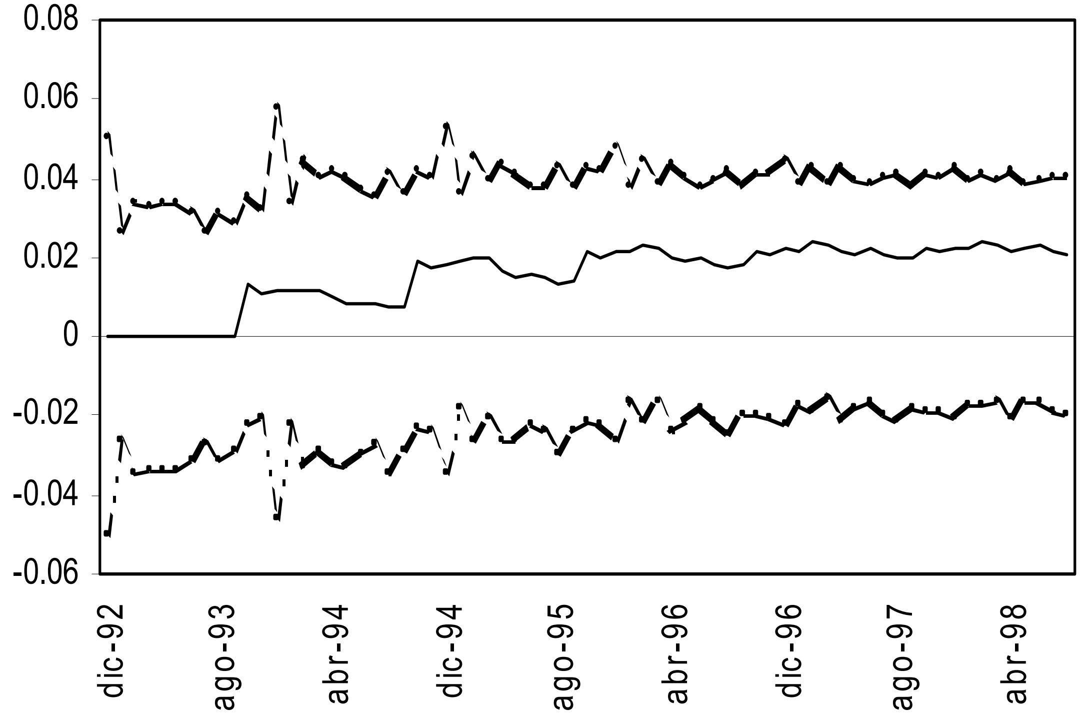
Figure 4. Impulse response functions
A. Brazil. Effect of a shock in the upper regime (September 1994)



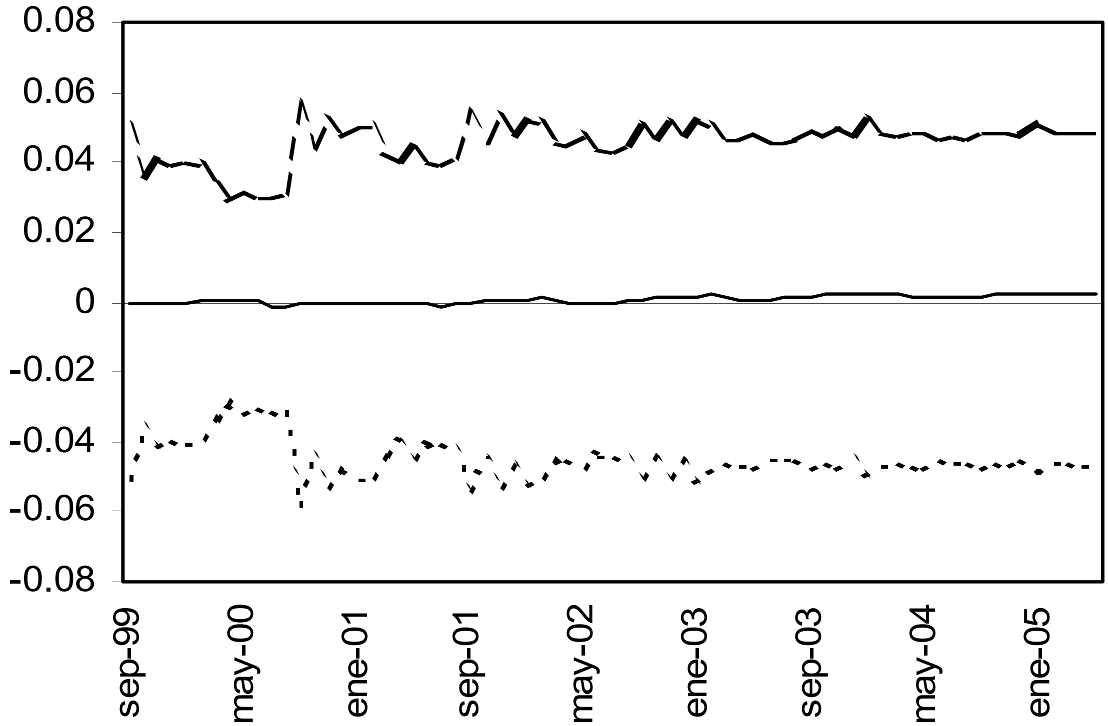
B. Brazil. Effect of a shock in the lower regime (March 1998)



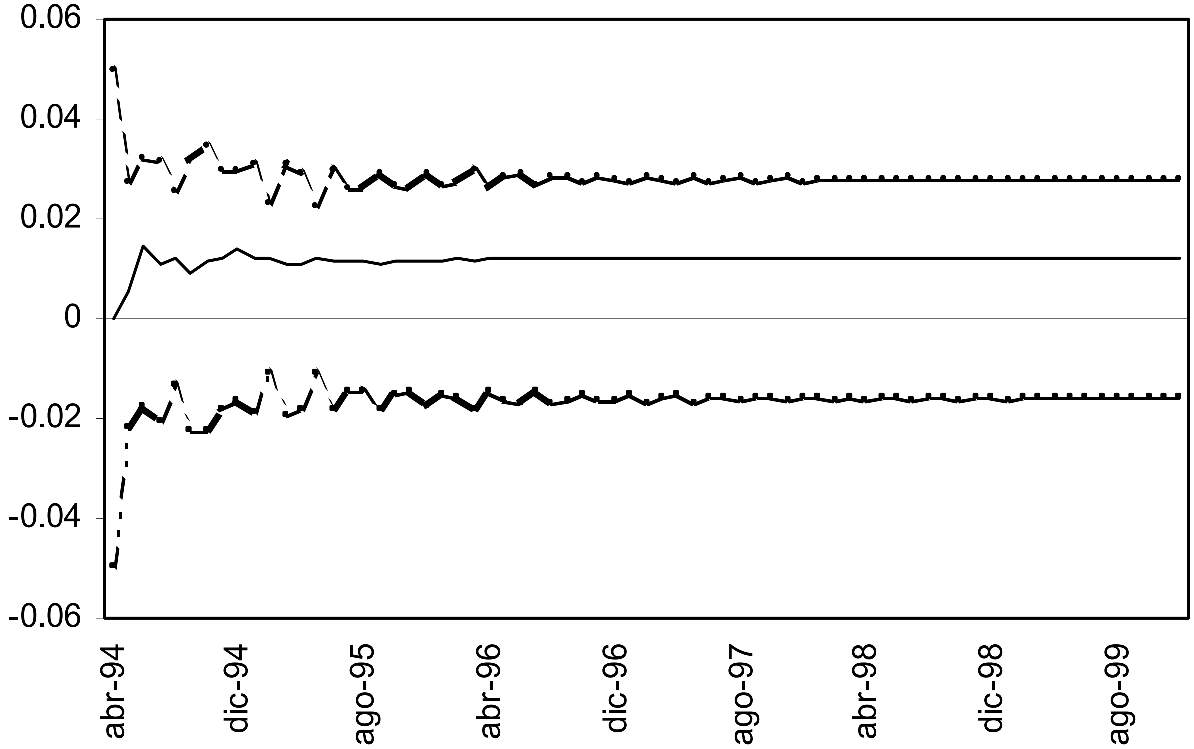
C. Chile. Effect of a shock in the upper regime (November 1992)



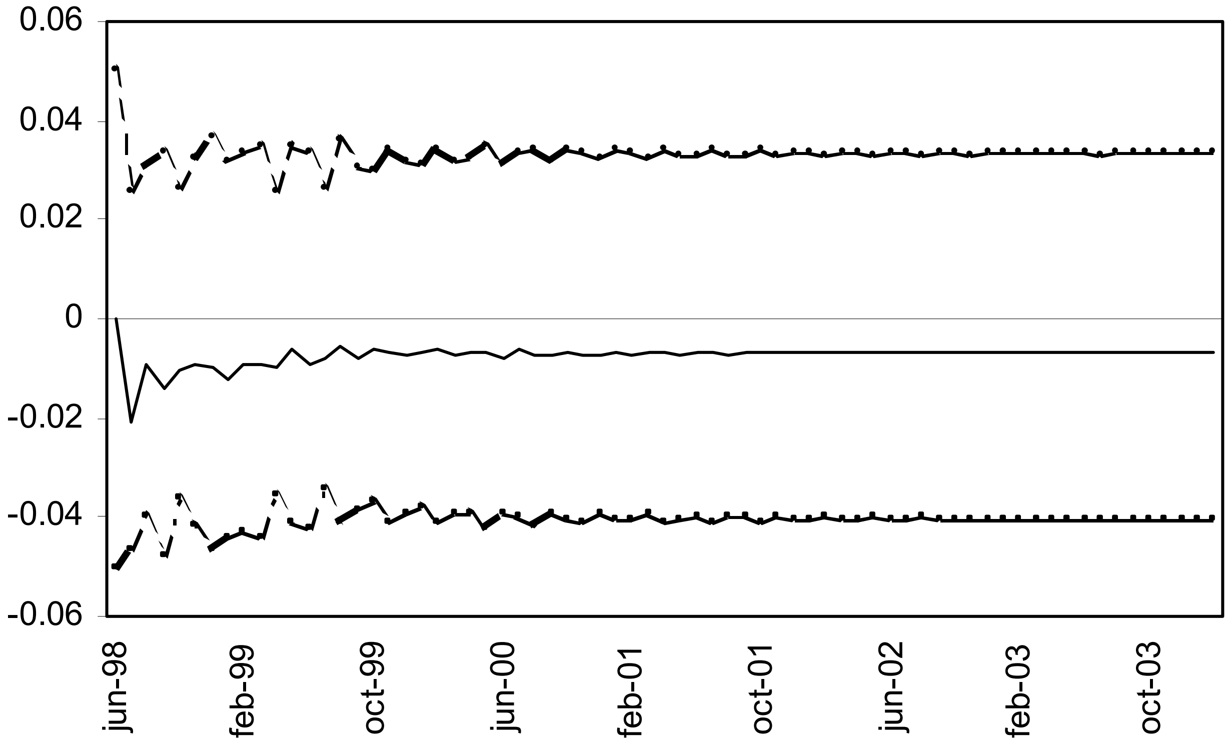
D. Chile. Effect of a shock in the lower regime (August 1999)



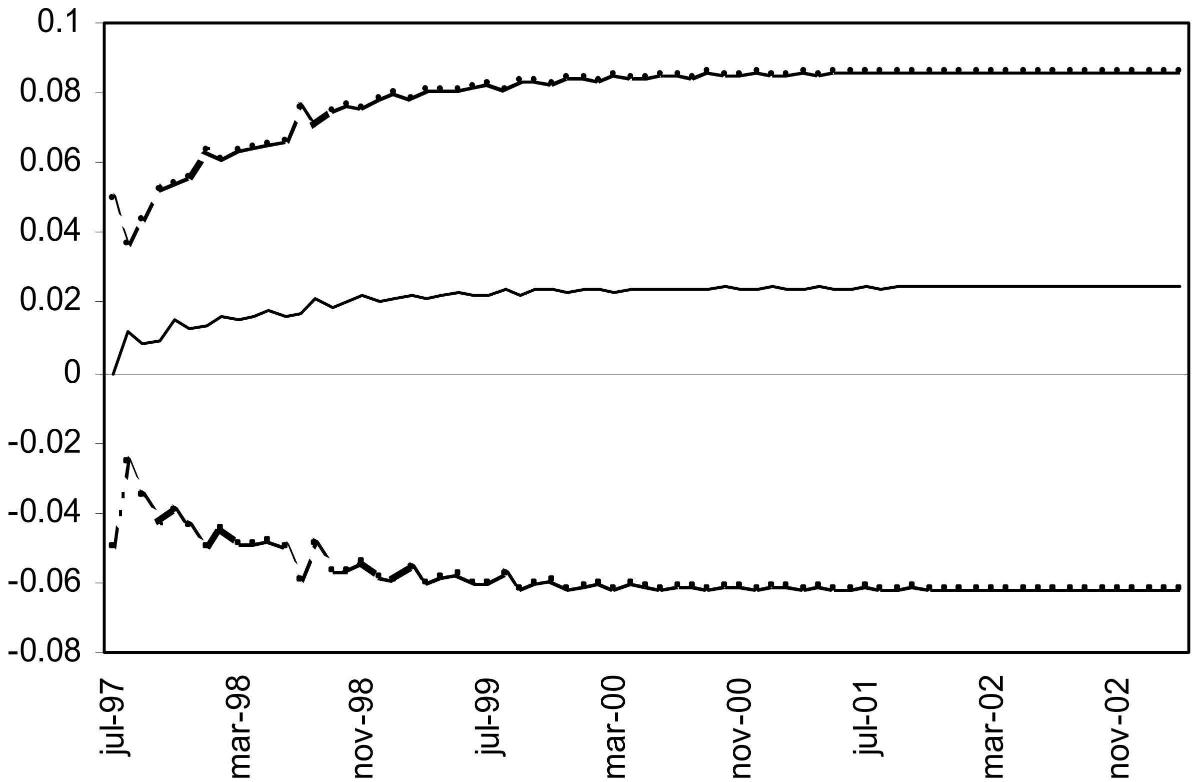
E. Colombia. Effect of a shock in the upper regime (March1994)



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



G. Mexico. Effect of a shock in the upper regime (June 1997)



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

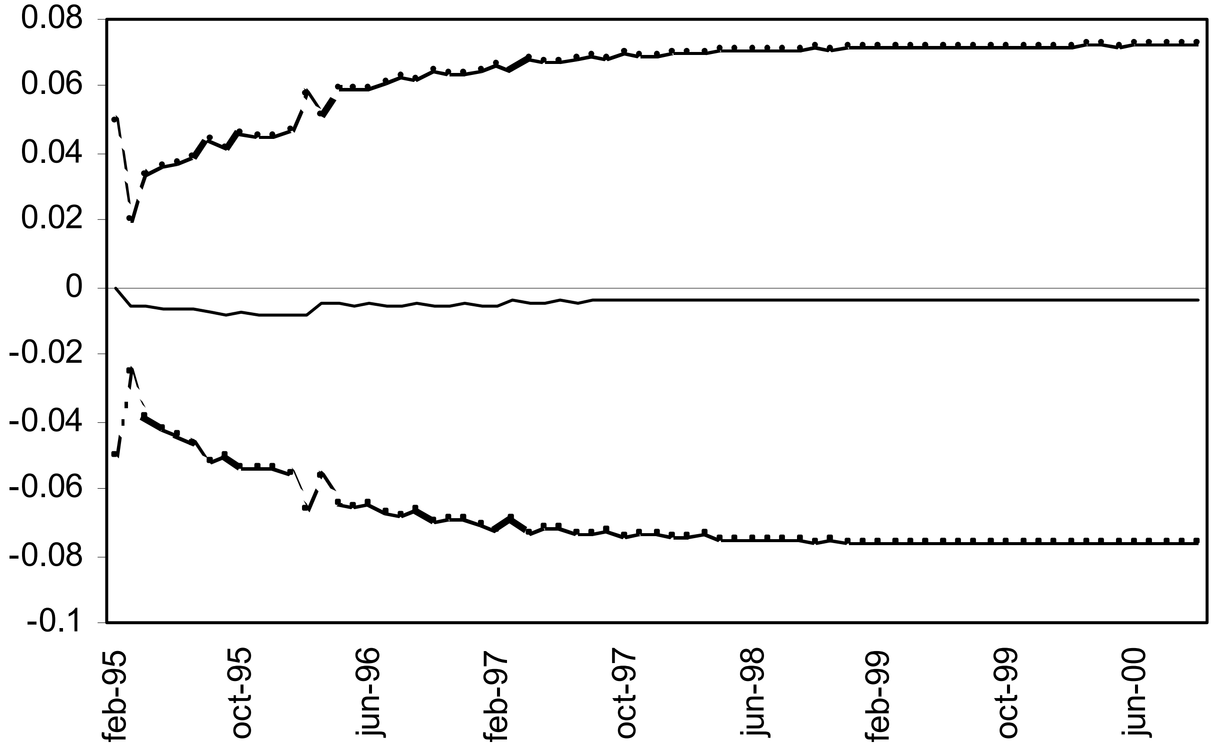


Table 1A. LSTAR model for Brazil

	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

Table 1B. LSTAR model for Chile

	Coefficient	**S. D.**	***t*-value**	***p*-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

Table 1C. LSTAR model for Colombia

	Coefficient	**S. D.**	***t*-value**	***p*-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
$\hat{\gamma}$	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

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
$\hat{\gamma}$	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

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