Is There a Brazilian J-Curve?

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Abstract

We show that Marshall-Lerner condition holds for Brazilian trade balance, and discard a J-curve in the short run. We present these results using impulse-response functions in a variety of (linear and nonlinear) models, including Markov-switching, vector error-correction models.

Keywords: Marshall-Lerner condition, J-curve, exchange rate, trade balance, Markov-switching regime, vector error-correction model

JEL Classification: F31, F32, F41

1. Introduction

The hypothesis of a J-curve arises from the anecdotal evidence that, in response to exchange rate depreciation, the trade balance gauged in local currency worsens in the impact period, and then improves. The J-curve thus stands as a short-run departure from Marshall-Lerner condition. A usual rationale for it is that exchange rate depreciation initially means cheaper exports and more expensive imports, making the current account worse (a bigger deficit or smaller surplus). After a while the volume of exports will start to rise because of their lower price to foreign buyers, and domestic consumers will buy fewer of the costlier imports. Eventually the trade balance will improve.

Yet the explanation above does not work for Brazilian trade balance because export contracts are made in foreign currency (dollars). But there is room for a J-curve still, regardless of contracts. This is so if habits and durability in consumption are present (Mansoorian 1998). (Antonucci 2003 provides a brief survey of the theoretical literature.)

Evidence of a J-curve is mixed. Empirical research can be usefully classified into two groups. The first one looks for a J-curve in a two-country (domestic and rest-of-the-world) framework, as in Felmingham (1988). The J-curve is an aggregative phenomenon, and then such an approach seems appropriate. However, a currency can simultaneously depreciate and appreciate relative to others. To take this into account, a second group of research focuses on trade between two partners only, as in Bahmani-Oskooee and Brooks (1999), and Onafowora (2003).

This paper belongs to the first line of research. The problem of simultaneous currency depreciation and appreciation is softened, however, as we take real exchange rates between Brazil and its 16 biggest trading partners.

Onafowora (2003) employs a cointegration approach to the bilateral trade of selected Asian countries. Using Johansen's methodology, he finds that variables cointegrate. He then estimates a linear, vector error-correction model and makes use of impulse-response functions. He finds a J-curve.

We will look for a Brazilian J-curve using a similar cointegration approach. This will enable us to track short- and long-run exchange-rate effects on Brazilian trade balance. Yet we will use a nonlinear Markov-switching, vector error-correction model. This will capture the breaks hitting Brazilian trade balance in the period under scrutiny. These breaks include exchange-rate regime changes, stabilization plans, and shocks from international financial crises.

The rest of this paper is organized as follows. Section 2 presents data, Section 3 analyzes them, and Section 4 concludes.

2. Data

We take monthly data from January 1990 to December 2003 (168 data points) for each of the following variables. Export-import ratio, real exchange rate, gross domestic product (GDP), consumer price index, world imports (as a proxy for income in the rest of the world), and world import price index.

Data from overall Brazilian exports and imports are used to reckon the export-import ratio, which here proxies trade balance (*TB*). (The data are from the Foreign Trade Secretary of the Ministry of Development, Industry, and Foreign Trade.) Taking the export-import ratio to represent trade balance is common in literature. One advantage is to allow one to take logs of trade balance, and then get growth rates (Brada, Kutan, and Zhou 1997). Another advantage of taking the export-import ratio is that it remains constant as units of measurement change. Indeed taking the difference between exports and imports to stand for trade balance demands the use of a deflator to reckon real trade balance. Yet this gauge is sensitive to alternative deflators. By contrast, the export-import ratio is able to represent either nominal or real trade balance (Bahmani-Oskoee 2001).

The real exchange rate (*RER*) data set is that of Institute of Applied Economics Research (IPEA). Brazilian *real*-US dollar nominal exchange rates are deflated with the help of consumer and wholesale price indices of 16 biggest trading partners, weighted by share of each in 2001 Brazilian exports.

We take monthly GDP data from Brazilian central bank. To get real GDP (*RGDP*), GDPs are deflated by the consumer price index (INPC) reckoned by the Brazilian Institute of Geography and Statistics (IBGE). World imports (*WI*) are obtained from IMF's *International Financial Statistics*. They are deflated by world import prices.

3. Analysis

Figures 1a–1d suggest at the naked eye that our series are nonstationary. We take the series both in levels and first differences, and carry out augmented Dickey-Fuller (ADF)-type unit-root tests only to confirm that (Table 1). All series possess a unit root in levels and get stationary in first differences. Yet structural breaks are present in the series of exchange rate and trade balance. Such breaks can distort the unit root tests. We then check for stationarity using Perron (1997)'s test, which endogenously determines dates for structural breaks. Nonstationarity continues to emerge (Table 2).

Because of nonstationarity we check whether the series cointegrate, in which case an error correction model can be estimated. Yet we first should learn how many lags to employ. To this end, we estimate a vector auto-regression (VAR) for the variables in levels. Then we pick the best model, having in mind the information criterion of Akaike (AIC) and that of Schwarz (BIC) (Table 3). We find that four lags make it possible to evaluate a model dynamics parsimoniously.

We thus employ Johansen (1988)'s cointegration test with four lags and find a cointegration vector (Table 4). The cointegration vector in logs is

$$\beta = (1, -1.811856, 1.158394, 1.383791, -2.176329).$$

And the equation describing the long run relationship between the variables is

$$TB = 2.176329 + 1.811856RER - 1.158394WI - 1.383791RGDP. \quad (1)$$

This equation shows that long-run exchange-rate elasticity to trade balance is positive. Thus real depreciation improves real trade balance. A one-percent depreciation raises trade balance to 1.811856 percent on average. Thus Marshall-Lerner condition holds.

Because the cointegration test reveals the existence of a unique long-run relationship (equation (1)), we estimate a vector error-correction model (VECM) with four lags (Table 5). The coefficient of the error correction term is significant at one percent. This means that the trade balance moves toward the unique long-run equilibrium after a shock. The equation of ΔTB conveys information about the long-run relationship between variables because it contains the error correction term. Short-run trade imbalances are monthly corrected at a pace of 20 percent.

Impulse-response functions are a convenient way of displaying estimated coefficients of a VAR. Here they are particularly useful to capture short run dynamics of the trade balance response to exchange rate shocks. Figure 2 shows the response of TB to innovations of one standard deviation in RER. Trade balance increases in the aftermath of a shock. The maximum occurs after roughly four months. Afterward trade balance reduces, and then stabilizes after nearly ten months. Thus the impulse-response function shows no J-curve in this linear error-correction model.

Whenever a time series is plagued with structural breaks, nonlinearity is present. Series are also unlikely to be normally distributed as well as stationary. Markov-switching regime models attempt to cope with nonlinearity. They assume that while parameters are time-varying, they also depend on regime changes s_t. The process generating the regime changes is an ergodic Markov chain with finite number of states s_t = 1, ..., M. These are defined by transition probabilities, i.e.

$$p_{\mathrm{ij}} = \Pr\left(s_{t+1} = j \middle| s_t = i\right),\ \sum_{j=1}^{M} p_{ij} = 1\ \forall\ i, j \in \{1, ..., M\}$$

where $p_{iM} = 1 - p_{i1} - ... - p_{iM-1}$ for $i = 1, ..., M$ (Hamilton 1994).

A cointegrated VAR(p) with M Markovian regimes is dubbed MS(M)-VECM(p). The linear VECM(p) collapses to the particular case where M = 1. Generally,

$$\Delta y_t - \mu(s_t) = v(s_t) + \sum_{i=1}^{p} \Gamma(s_t)_i \left[\Delta y_{t-i} - \mu(s_{t-i})\right] + \alpha(s_t)\beta(s_t) y_{t-1} + u_t,$$

where $u_t \sim N(0, \Sigma s_t)$ (Krolzig 1997).

Here we employ an MS-VECM to tackle the breaks in our series. Finding the proper number of regimes in an MS-VECM is not that straightforward, however. Thanks to the presence of nuisance parameters, we cannot rely on likelihood ratio because it ends up with no asymptotic distribution. Although Hansen (1992) and Garcia (1993) have developed a technique to derive the asymptotic distribution in such cases, it is useless for practical purposes. This is because the distribution stands dependent on both data and model parameters, and then an asymptotic distribution needs to be reckoned every time one runs a test (Krolzig 1997). Yet both AIC and BIC never underestimate the minimum number of regimes (Ryden 1995). For that reason, we employ such criteria here. Results are in Table 6.

The best nonlinear model seems to be an MSMH(2)-VECM(4). Here mean and variance are dependent on ongoing regime, and after a regime switch there occurs an instant jump toward the mean, i.e.

$$\Delta y_t - \mu(s_t) = v + \sum_{i=1}^{4} \Gamma_i \left[\Delta y_{t-i} - \mu(s_{t-i})\right] + \alpha z_{t-1} + u_t,$$

where s_t = 1, 2, and $z_t = \beta' y_t$. After normalizing the model to make TB the dependent variable, we estimate elasticities (Table 7).

The coefficient of the exogenous series conveys information about the long run relationship between variables and stands significant at the one-percent level. Mean of regime 1 is greater than that of regime 2. And standard deviation of regime 2 is 37 percent higher than that of regime 1. As can be seen, only the trade balance coefficient of first lag is significant at 5 percent. Table 8 presents starting and final dates estimated for each regime, and Table 9 shows the transition probability matrix together with duration of regimes. Figures 3a and 3b display smooth probabilities of the regimes.

Note that although our data set starts at January 1990 and ends at December 2003, we miss the five initial data points thanks to the four lags and differentiation of data. Historical facts roughly match the regimes in Table 8 and are described elsewhere (e.g. Bonomo and Terra 1999, and monthly central bank reports at http://www.bcb.gov.br/?RELCAMBIO).

Again, we rely on impulse-response functions to evaluate the results of the MSMH(2)-VECM(4). Figure 4 shows that there is no J-curve in our nonlinear model. There is no such thing as an impact-period worsening of the trade balance. Marshall-Lerner still holds, because the full impact of the exchange rate shock to trade balance only occurs after one year has elapsed.

4. Conclusion

We find evidence that Marshall-Lerner condition holds true for Brazilian trade balance, and no evidence of a short-run J-curve. We show that a nonlinear model outperforms a linear model of our data set, and select a Markov-switching, vector error-correction model (i.e. an MSMH(2)-VECM(4)) as the best nonlinear model.

Impulse-response functions from both linear and nonlinear models are clear-cut. There is no J-curve, and Marshall-Lerner condition holds. Brazilian trade balance does improve following exchange rate depreciation. And there is no room for short-run dynamics of temporary worsening of the trade balance.

Table 1 Augmented Dickey-Fuller Test

	Levels			First Differences		
Series	$\boxed{\tau_\tau}$	$\boxed{\tau_\mu}$	$\boxed{\tau}$	$\boxed{\tau_\tau}$	$\boxed{\tau_\mu}$	$\boxed{\tau}$
TB	–2.118219	–2.261872	–1.888342	**–18.7365**	**–18.74535**	**–18.80222**
RER	–2.12053	–1.665742	1.171722	**–9.561508**	**–9.597206**	**–9.502779**
RGDP	–3.413373	–3.212559	–0.305698	**–7.547178**	**–10.62408**	**–10.65189**
WI	–2.533028	–0.359855	1.322549	**–6.868682**	**–3.921123**	**–16.24827**

Note
Bold values mean rejection of the null hypothesis of unit root at the 5 percent significance level.

Table 2 Unit-Root Perron Test

Model	*TB*	*RER*	*RGDP*	*WI*
1	–4.26519	–3.89801	**–6.86492**	–3.75716
2	–4.52955	**–5.33981**	**–8.78159**	–3.39941
3	–2.96843	–4.32458	–4.23698	–2.69416

Note
Bold values mean rejection of the null hypothesis of unit root at the 5 percent significance level.

Table 3 Selection of Number of Lags Using AIC and BIC

Number of Lags	AIC	BIC
7	–10.9106	–8.690424
6	–11.1417	–9.235736
5	–11.0883	–9.493935
4	–10.8902	–9.604841
3	–10.7539	–9.775046
2	–10.5183	–9.843404
1	–10.1921	–9.818636

Table 4 Cointegration Tests

H_0	$\boxed{r = 0}$	$\boxed{r \leq 1}$	$\boxed{r \leq 2}$
Eigenvalue	0.190723	0.134642	0.02508
Trace	62.23588	27.7427	4.170876
Critical Value at 5%	47.21	29.68	15.41

Table 5 Estimation of a VECM with Four Lags

Variable	Coefficient	Standard Deviation	*t*-Statistics
Constant	–0.0075	–0.01039	–0.72165
$\Delta TB(-1)$	–0.345346	–0.08286	–4.16791
$\Delta TB(-2)$	–0.005552	–0.08486	–0.06543
$\Delta TB(-3)$	0.078976	–0.08396	0.94066
$\Delta TB(-4)$	0.059713	–0.07797	0.76580
$\Delta RER(-1)$	0.105307	–0.24902	0.42288
$\Delta RER(-2)$	0.158494	–0.27091	0.58505
$\Delta RER(-3)$	0.296454	–0.25768	1.15046
$\Delta RER(-4)$	–0.377392	–0.24223	–1.55799
$\Delta WI(-1)$	–0.071862	–0.21965	–0.32717
$\Delta WI(-2)$	0.244983	–0.25481	0.96142
$\Delta WI(-3)$	0.34979	–0.23943	1.46093
$\Delta WI(-4)$	0.258443	–0.19742	1.30909
$\Delta RGDP(-1)$	0.303673	–0.25922	1.17150
$\Delta RGDP(-2)$	0.022641	–0.20727	0.10923
$\Delta RGDP(-3)$	–0.210954	–0.20083	–1.05040
$\Delta RGDP(-4)$	–0.029536	–0.20425	–0.14461
Error Correction Term	–0.207923	–0.04995	–4.16258

Table 6 Selecting a Model

Model	AIC	BIC
MSIAH(3)	**−12.558**	−7.775
MSMAH(3)	−7.293	−2.510
MSIA(3)	−12.020	−7.617
MSMA(3)	−7.539	−3.135
MSIH(3)	....	....
MSMH(3)	−11.863	−9.661
MSI(3)	−11.761	−9.939
MSM(3)	....	....
MSIAH(2)	−11.754	−8.604
MSMAH(2)	−8.023	−4.872
MSIA(2)	−11.710	−8.749
MSMA(2)	−8.146	−5.185
MSIH(2)	−12.090	−10.230
MSMH(2)	−12.115	**−10.255**
MSI(2)	−11.571	−9.900
MSM(2)	−11.479	−9.809
Linear	−11.494	−9.937

Table 7 Estimates from the MSMH(2)-VECM(4)

Variable	ΔTB	Standard Deviation	*t*-Statistics
Mean (Regime 1)	0.795951	0.2065	3.8544
Mean (Regime 2)	0.788046	0.2044	3.8554
$\Delta TB(-1)$	–0.3183	0.094	–3.3852
$\Delta TB(-2)$	0.009631	0.0768	0.1253
$\Delta TB(-3)$	0.119602	0.077	1.5541
$\Delta TB(-4)$	0.121797	0.0738	1.6494
$\Delta RER(-1)$	0.012341	0.2768	–0.0446
$\Delta RER(-2)$	0.29702	0.2955	1.0053
$\Delta RER(-3)$	0.350168	0.2881	1.2154
$\Delta RER(-4)$	–0.32299	0.2394	–1.3492
$\Delta WI(-1)$	–0.12236	0.1965	–0.6227
$\Delta WI(-2)$	0.136474	0.2329	0.5860
$\Delta WI(-3)$	0.147492	0.2370	0.6223
$\Delta WI(-4)$	0.180132	0.1800	1.0010
$\Delta RGDP(-1)$	0.224533	0.2437	0.9214
$\Delta RGDP(-2)$	0.002029	0.2105	0.0096
$\Delta RGDP(-3)$	–0.19808	0.1994	–0.9932
$\Delta RGDP(-4)$	–0.16155	0.1981	–0.8154
Error Correction Term	–0.21396	0.0502	–4.2631
Standard Deviation (Regime 1)	0.100029		
Standard Deviation (Regime 2)	0.137412		

Table 8 Regime Dates

Regime 1 Low Volatility	Regime 2 High Volatility
1991:01 — 1991:02	1990:06 — 1990:12
1991:07 — 1991:09	1991:03 — 1991:06
1992:01 — 1994:06	1991:10 — 1991:12
1994:08 — 1995:02	1994:07 — 1994:07
1995:07 — 1998:12	1995:03 — 1995:06
1999:11 — 2001:02	1999:01 — 1999:10
2003:05 — 2003:12	2001:03 — 2003:04

Table 9 Transition probability matrix and duration of regimes

	Regime 1	Regime 2	Data Points	Probability	Duration
Regime 1	0.9381	0.0619	106.8	0.6797	16.14
Regime 2	0.1315	0.8685	56.2	0.3203	7.61

Figure 1a Trade balance

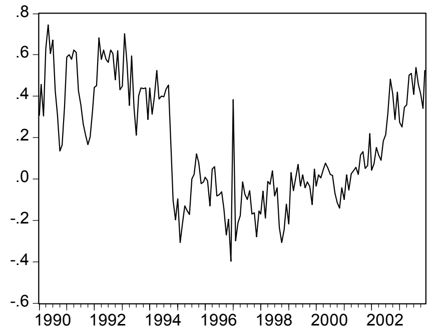


Figure 1b Real exchange rate

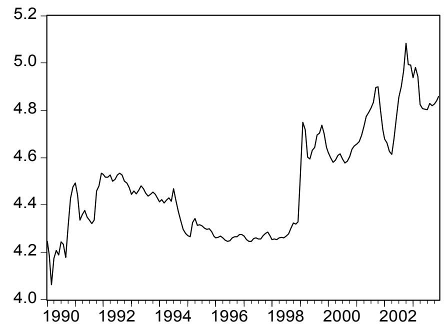


Figure 1c World imports

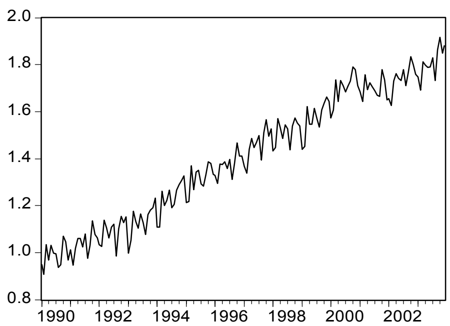


Figure 1d Real gross domestic product

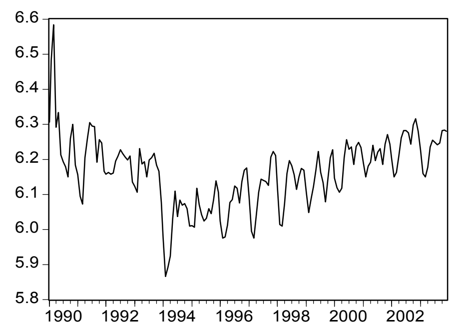


Figure 2 Linear model: response of trade balance to innovations of one standard deviation in real exchange rate

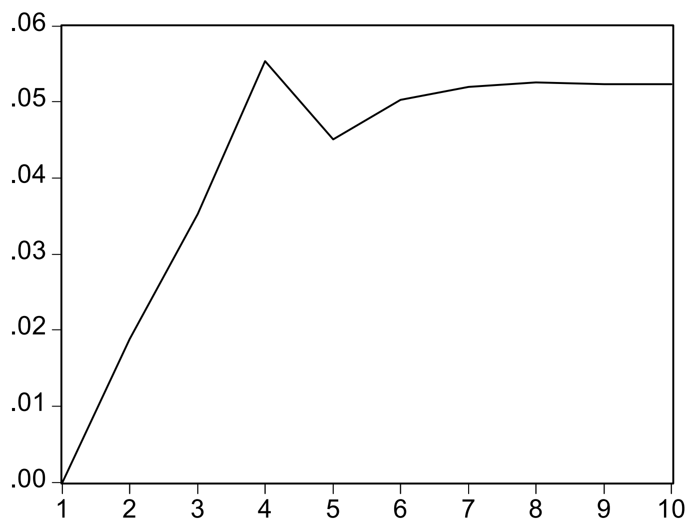


Figure 3a Smooth Probabilities of Regime 1

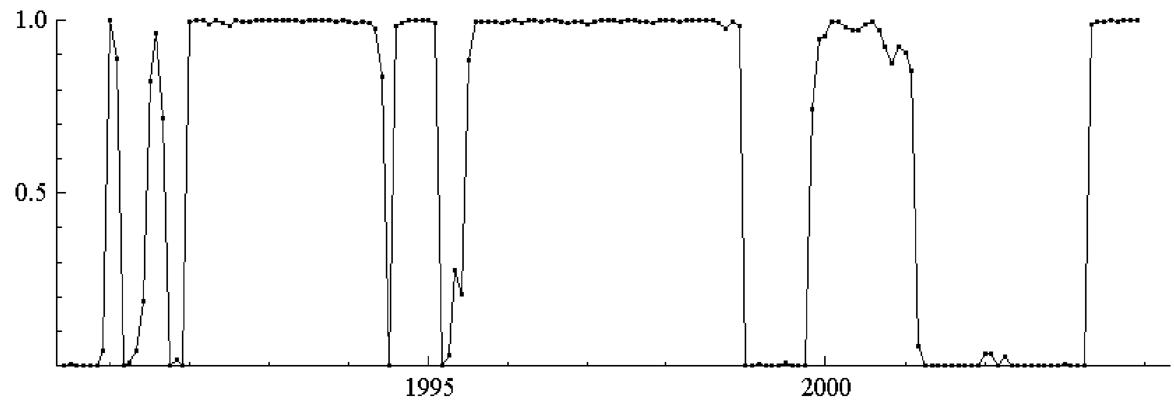


Figure 3b Smooth Probabilities of Regime 2

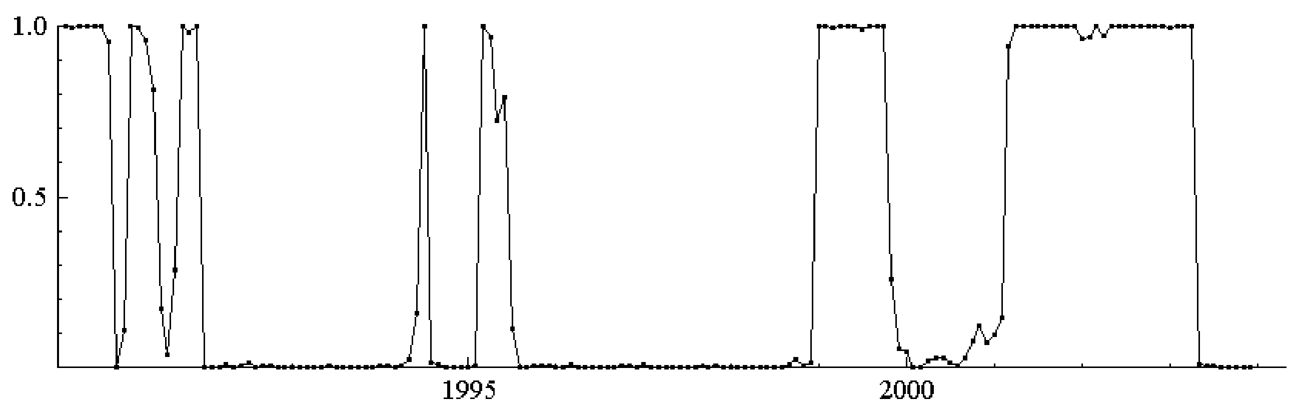
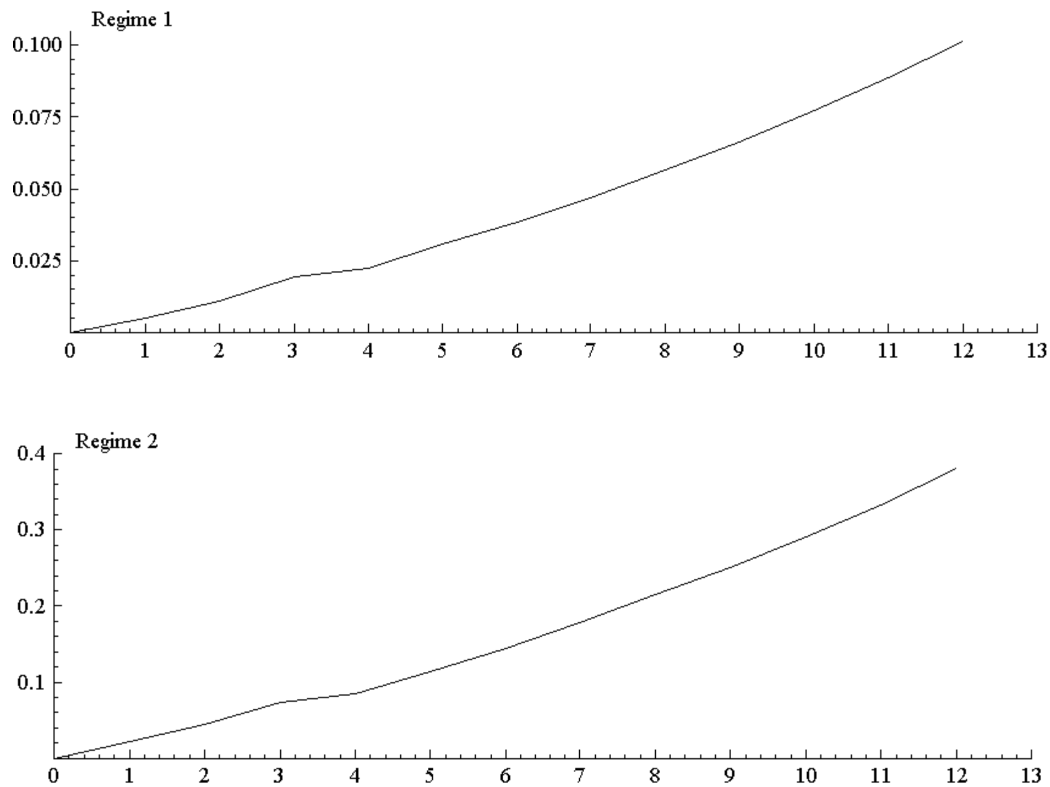


Figure 4 Impulse-Response Functions in the MSMH(2)-VECM(4)



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