BANCO CENTRAL DE RESERVA DEL PERÚ

Application of Three Alternative Approaches to Identify Business Cycles in Peru

Gabriel Rodríguez*

* Universidad of Ottawa and Central Bank of Peru

DT. N° 2007-007
Serie de Documentos de Trabajo
Working Paper series
Mayo 2007

Application of Three Alternative Approaches to Identify Business Cycles in Peru*

Gabriel Rodríguez[†]
University of Ottawa and Central Bank of Peru

This version: A pril 11, 2007

Abstract

Three alternative econometric approaches are used to estimate business cycles in the Peruvian economy. These approaches are the Plucking model due to Friedman (1964, 1993), the Markov-Switching model proposed by Hamilton (1989) and the Smooth Transition Autoregressive (STAR) model suggested by Teräsvirta (1994). The results show strong rejection of the null hypothesis of linearity, presence of asymmetries and nonlinearities. Furthermore, the methods allow to find the principal episodes of recession for the Peruvian economy.

Keywords: Asymmetries, Business Regional Fluctuations, Markov Switching, Transitory and Permanent Components.

JEL Classification: C22, C52, E32.

*I thank useful comments from participants to the XXIV Meeting of Economists of the Central Bank of Peru.

†Address for Correspondence: University of Ottawa, Department of Economics, P. O. Box 450, Station A, Ottawa, Ontario, Canada, K1N 6N5, Telephone: +613-562-5800 (1750), Fax: +613-562-599, E-mail address: gabrielr@uottawa.ca.

1 Introduction

Interest in business cycles has a long standing history in both theoretical investigations and empirical applications. The important contribution of Burns and Mitchell (1946) paved the ways to measure it. The literature has, however, departed from their methods due to its complicity and the need for subjective evaluations. Instead much of the work has concentrated on easily applicable mechanical and non-subjective methods. In the last few decads, many alternative procedures have been suggested. The need for a quantitative measure of the business cycles arise in great part because most macroeconomic business cycles model deliver implications that pertain to the non-trending component of the series, namely, the deviation from the steady state. In order to confront these models with the data, there is, accordingly, a need to separate the trend and the cycle.

There are, of course, many methods to decompose the trend and the cycle. Some popular methods are the decomposition of Beveridge and Nelson (1981), the decompositions based on unconstrained ARIMA models (Campbell and Mankiw, 1987, Watson, 1986, Cochrane, 1988). There are also the unobserved components model due to Clark (1987), the Hodrick and Prescott (1997) and the band-pass filter of Baxter and King (1999).

Unlike the atheoretical approaches above mentioned, in this paper we use three econometric approaches with economic support. The approaches are the "plucking" model proposed by Friedman (1964, 1993), the markov-switching model due to Hamilton (1989) and the smooth transition regression model proposed by Teräsvirta (1994).

It was Friedman (1964, 1993) who noted that the amplitude of a recession is strongly correlated with the following expansion, but the amplitude of an expansion is not correlated with the amplitude of the succeeding contraction. This striking asymmetry is the basic argument supporting the so named "plucking" model of business cycles[1].

Neftci (1984) presented empirical evidence of the kind of asymmetry advanced by Friedman (1964, 1993), when he found that unemployment rates are characterized by sudden jumps and slower declines. Further evidence was found by Delong and Summers (1986), Falk (1986), and Sichel (1993). As Kim and Nelson (1999b) say, while these kind of asymmetries are consistent with the plucking model, they are also consistent with models where recessions are occasioned by infrequent permanent negative shocks as in the

[1] Another mention of this kind of evidence was also suggested by Keynes (1936): "the substitution of a downward for an upward tendency often takes place suddenly and violently."

Markov-Switching models of Hamilton (1989) and Lam (1990). According to these authors, what distinguishes the plucking model is the prediction that negative shocks are largely transitory, while positive shocks are largely permanent[2]. Another important characteristic of the plucking model is the existence of an upper limit to the output, the so named ceiling output, which is set by the resources available in the economy.

The fact that recessions can essentially result from occasional transitory shocks may suggest that a recession, once it begins, will dissipate in a fairly predictable period of time. However, the length of an expansion is not helpful in predicting the next recession. This is what in the literature of business cycles is called duration dependence which was investigated by Diebold and Rudebusch (1990), Diebold, Rudebusch and Sichel (1993), and Durland and McCurdy (1994) in an univariate context; and Kim and Nelson (1998) in a multivariate context. All these references found empirical support for the existence of duration dependence only for recession times.

Recently, a formal econometric specification of the business cycle was suggested by Kim and Nelson (1999b)[3]. Their specification allows us to decompose measures from economic activity into a trend component and deviations from the trend that show the types of asymmetries implied by the business cycle literature. In this sense, the approach offers more possibilities than standard linear models such as ARIMA models and the unobserved component model of Clark (1987) which cannot account for asymmetries. It may also perform better than other kind of models as the Markov-Switching (Hamilton, 1989; Lam, 1990) where the asymmetric behavior is only accounted in the growth rate or stochastic trend component of real output.

The approach of Kim and Nelson (1999b) has been applied to the output of the G-7 countries by Mills and Wang (2002). Interesting performance of this approach has been also noted by Galvão (2002), where this model is one of the three models capable of reproducing the length of the United States business cycles. In this respect, see the special issue about business cycles published by *Empirical Economics* in 2002.

Other type of models that assume that the transition between regimes is caused by exogenous but not observable (or unknown events) variables is the case of the Markov Switching model, originally proposed by Hamilton (1989). He used an $AR(4)$ model for the growth rate of US output

[2]In this sense, Sichel (1994) also provides support to this fact by showing that postwar real GDP exhibits "peak-reverting behavior". He also argues the existence of a third, high-growth recovery phase, in addition to the usual recession and expansion phases of the business cycle.

[3]See also Kim and Nelson (1999a).

allowing for a changing mean and a constant variance. The results allow to identify phases of recession very close to the dates identified by the NBER which uses a large set of leading indicators. This model has been extended in many forms allowing for changing variance, varying transition probabilities, multivariate analysis, among others. See Godwin (1993), Bodman and Crosby (2000) and the reference there mentioned.

There is another type of model that assumes that the transition between regimes is caused by an observable variable (say s_t). This model is named the Threshold Autoregressive (TAR) model, initially proposed by Tong (1978) and Tong and Lim (1980) and discussed extensively in Tong (1990). A special case arises when the threshold variable, that is the variable determining the changes in regimes, is taken to be a lagged value of the time series itself. The resulting model is called a Self-Exciting TAR (SETAR) model. A drawback of this type of model is that the transition function between regimes is done in a abrupt way. One way to fix that is to consider a smooth transition function. The resulting model is the so called Smooth Transition Autoregressive (STAR) models.

There are two types of STAR models according to the transition function used in the specification. The first STAR model include a logistic function rising the so called LSTAR model which allows to analyze for asymmetries. The other possible selection is to use an exponential function rising the so called ESTAR model. Although there is a testing procedure to decide which of both transition functions are more convenient, we will consider the LSTAR option because we are interested in analizying business cycles.

The rest of the paper is organized in the following manner. Section 2 presents the three alternative methods to be used in the estimations. Section 3 presents and dicusses the results. Section 4 concludes.

2 Methodology

In this section three alternative econometric approaches are briefly described. In all cases, y_t denotes the logarithm of the real output in period t.

2.1 The Plucking Model

Following the literature of unobserved components (see Watson, 1986), it is possible to decompose y_t into a trend component and a transitory component, which are denoted as τ_t and c_t, respectively. That is,

$$y_t = \tau_t + c_t. \tag{1}$$

Adopting a similar notation as in Kim and Nelson (1999b), I assume that shocks to the transitory component are a mixture of two different types of shocks, which will be denoted π_{s_t} and u_t, respectively. This allows us to account for regime shifts or asymmetric deviations of y_t from its trend component. In formal terms, the transitory component and the shocks affecting their behavior are specified as follow:

$$\begin{aligned}
c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + u_t^*, && (2)\\
u_t^* &= \pi_{s_t} + u_t, && (3)\\
\pi_{s_t} &= \pi s_t, && (4)\\
u_t &\sim N(0, \sigma^2_{u,s_t}), && (5)\\
\sigma^2_{u,s_t} &= \sigma^2_{u,0}(1-s_t) + \sigma^2_{u,1} s_t, && (6)\\
s_t &= 0, 1 && (7)
\end{aligned}$$

where $\pi \neq 0$. In the above specification, the term u_t is the usual symmetric shock. The term π_{s_t} is an asymmetric and discrete shock which is dependent upon an unobserved variable denoted by s_t which is an indicator variable that determines the nature of the shocks to the economy. When the economy is near the potential or trend output, it can be qualified as normal times. In this case, $s_t = 0$ which implies that $\pi_{s_t} = 0$. In the opposite situation, which could be qualified as a period of recession, the economy is hit by a transitory shock potentially with a negative expected value, that is, $\pi_{s_t} = \pi < 0$. In this case, aggregate or other disturbances are plucking the output down.

Note that equations (5) and (6) allow for the possibility that the variance of the symmetric shock u_t be different during normal and recession times. In order to account for a persistence of normal periods or periods of recession, it is assumed that s_t evolves according to a first-order Markov-switching process as in Hamilton (1989). It means that

$$\begin{aligned}
\Pr[s_t &= 1|s_{t-1} = 1] = q\\
\Pr[s_t &= 0|s_{t-1} = 0] = p.
\end{aligned}$$

As mentioned by Kim and Nelson (1999b), the above specification for the transitory component of output shares the same idea with the literature on "stochastic frontier production function", initially motivated by Aigner, Lowell and Schmidt (1977). See also Goodwin and Sweeney (1993).

The model is completed with the specification of τ_t, the permanent component. In this respect, Friedman (1993) suggested that the potential output, or what he named "the ceiling maximum feasible output", can be approximated by a pure random walk. In this case, all possible sorts of shocks can produce disturbances on it. In formal terms, this means that the permanent component can be specified as follows:

$$\begin{aligned}
\tau_t &= g_{t-1} + \tau_{t-1} + v_t, & (8)\\
g_t &= g_{t-1} + w_t, & (9)\\
w_t &\sim N(0, \sigma_w^2), & (10)\\
v_t &\sim N(0, \sigma_{v,s_t}^2), & (11)\\
\sigma_{v,s_t}^2 &= \sigma_{v,0}^2(1 - s_t) + \sigma_{v,1}^2 s_t, & (12)
\end{aligned}$$

where, according to (10) and (11), the permanent component τ_t is subject to shocks to the level and shocks to the growth rate. These shocks are given by v_t and w_t, respectively. Note that it is allowed for the possibility that the variance of the shock to the level may be different during normal and recession times. However, variance of the shock to the growth rate is not likely to be systematically different during the normal and the recession times.

The model can be written in state-space form. The observation equation is

$$\begin{aligned}
y_t &= \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ c_{t-1} \\ g_t \end{bmatrix} \\
&= H\xi_t, \qquad (13)
\end{aligned}$$

while the state equation is

$$\begin{aligned}
\xi_t &= \begin{bmatrix} 0 \\ \pi_{s_t} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \xi_{t-1} + \begin{bmatrix} v_t \\ u_t \\ 0 \\ w_t \end{bmatrix} \\
&= \overline{\mu}_{s_t} + F\xi_{t-1} + V_t \qquad (14)
\end{aligned}$$

where $E(V_t V_t') = Q_{s_t}$ and

$$Q_{s_t} = \begin{bmatrix} \sigma_{v,s_t}^2 & 0 & 0 & 1 \\ 0 & \sigma_{u,s_t}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_w^2 \end{bmatrix}.$$

Notice that the model expressed by (13) and (14) nests the model suggested by Clark (1987). As it is well known, the model of Clark (1987) does not account for asymmetries, which in the context of the specification (13) and (14) implies that $p = q = 0$. On the other hand, in the model of Clark (1987), we have $\sigma_{v,0} = \sigma_{v,1} = \sigma_v$, and $\sigma_{u,0} = \sigma_{u,1} = \sigma_u$. In the empirical section, the plucking model is tested against the symmetric model proposed by Clark (1987).

2.2 The Markov-Switching Model

Let Δy_t denotes the growth rate of real output in quarter t. Hamilton (1989) proposes the following model to estimate US business cycles:

$$\Delta y_t - \mu_{s_t} = \phi_1(\Delta y_{t-1} - \mu_{s_{t-1}}) - ... - \phi_4(\Delta_{yt-4} - \mu_{s_{t-4}}) + u_t, \tag{15}$$

where s_t is an unobserved variable indicating the state of the economy, and $u_t \sim i.i.d.\ N(0, \sigma^2)$. A full description of the dynamics of Δy_t is obtained if we have a probabilistic description of how the economy changes from one regime to another. The simplest such model is a Markov chain, that is a model where

$$\begin{aligned} \Pr[s_t &= j|s_{t-1} = i, s_{t-2} = k, ..., y_{t-1}, y_{t-2}, ...] = \Pr[s_t = j|s_{t-1} = i] \\ &= p_{ij} \end{aligned}$$

with $\sum_{j=1}^{M} p_{ij} = 1$, $\forall\ i, j \in \{1, 2, ..., M\}$. Therefore we have a matrix of transition probabilities

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1M} \\ p_{21} & p_{22} & \cdots & p_{2M} \\ .... & .... & \cdots & \cdots \\ p_{M1} & p_{M2} & \cdots & P_{MM} \end{bmatrix} \tag{16}$$

with $p_{iM} = 1 - p_{i1} - p_{i2} - ... - p_{iM-1}$, for $i = 1, 2, ..., M$.

In the model (15) only the value of the mean is regime dependent. It is denoted as MSM(2)-AR(4) which denotes a Markov switching model with mean regime dependent, two regimes and an autoregression of order 4. Other specifications are available. For example, a model where the mean, the variance and the autoregressive coefficients are regime dependent is denoted by MSMAH(m)-AR(k) where m indicates the number of states and k reflects the order of the autoregression. In some cases instead of modeling the mean as regime dependent parameter, it is considered the intercept as regime dependent. The model where the mean and the intercept are regime dependent are not equivalent. They imply different dynamics of adjustment of the variables after a change in regime.

The maximization of the likelihood function of an MS-AR model entails an iterative technique. This technique gives us the parameters of the autoregression and the transition probabilities governing the Markov chain of the unobserved states. Denote this parameter vector by $\lambda = (\theta, \rho)$.

Maximum likelihood estimation of the model is based on the Expectation Maximization (EM) algorithm proposed by Hamilton (1990). Each iteration of the EM algorithm consists of two steps: the *expectation* step and the *maximization* step. Calculations are simplified using the recursive and smoothing algorithms discussed in Krolzig (1997). With that, inference for ξ_t given a specified observation set Y_τ, $\tau \leq T$ is possible. It reconstructs the time path of the regime $\{\xi_t\}_{t=1}^T$, under alternative information sets: *predicted* regime probabilities $\widehat{\xi}_{t|\tau}$ when $\tau < t$ *filtered* probabilities $\widehat{\xi}_{t|\tau}$, when $\tau = t$, *smoothed* probabilities $\widehat{\xi}_{t|\tau}$ when $t < \tau \leq T$.

2.3 The Smooth Transition Autoregressive (STAR) Model

Following the same notation as in van Dijk, Franses, and Teräsvirta (2002), the smooth transition autoregressive ($STAR$) model for a time series Δy_t observed at $t = 1-p, 1-(p-1), ..., -1, 0, 1..., T-1, T$, is represented by

$$\Delta y_t = \phi_1' x_t[1 - F(s_t; \gamma, c)] + \phi_2' x_t[F(s_t; \gamma, c)] + \epsilon_t \tag{17}$$

where $x_t = (1, \tilde{x}_t')$ with $\tilde{x}_t = (\Delta y_{t-1}, ..., \Delta y_{t-p})'$ and $\phi_i = (\phi_{i,0}, \phi_{i,1}, ..., \phi_{i,p})'$, $i = 1, 2$ and $F(.)$ is named the transition function. The term ϵ_t is a martingale difference sequence with respect to the set of information up to and including time $t-1$ (denoted by Ω_{t-1}). In addition, it is assumed that the conditional variance of ε_t is constant, $E[\varepsilon_t^2|\Omega_{t-1}] = \sigma^2$.[4]

The transition variable (denoted by s_t) can be a lagged endogenous variable, $s_t = y_{t-d}$ for $d > 0$ or it can also be an exogenous variable $s_t = z_t$ or a function of lagged endogenous variables $s_t = g(\tilde{x}_t; \alpha)$ for some function g, which depends on the $q \times 1$ parameter vector α . Lastly, the transition variable can be a linear time trend $s_t = t$ giving a model with smoothly changing parameters as discussed in Lin and Teräsvirta (1994).

Therefore, the regime that occurs at time t is determined by the observable variable s_t and the associated values of $F(s_t; \gamma, c)$. Different choices for the transition function $F(s_t; \gamma, c)$ give rise to different types of regime-switching behavior. Two popular choices are the logistic and the exponential

[4] The inclusion of exogenous variables is discussed in Teräsvirta (1998). Lundbergh and Teräsvirta (1998) discuss inclusion of ARCH dynamics.

functions given origin to the so called Logistic STAR (LSTAR) and Exponential STAR (ESTAR) models, respectively.

Although a statistical test exists to decide which function is preferred, we decided to use the logistic function given our interest in modeling recessions and expansions[5]. The first-order logistic function is defined by

$$F(s_t;\gamma,c) = (1+\exp\{-\gamma\{s_t-c)\})^{-1}, \tag{18}$$

with $\gamma > 0$. In the $LSTAR$ model, the parameter c in (17) or (18) can be interpreted as the threshold between the two regimes, in the sense that the logistic function changes monotonically between 0 and 1 as s_t increases. The parameter γ determines the smoothness of the change in the value of the logistic function and thus, the smoothness of the transition from one regime to the other. As γ becomes very large, the logistic function $F(s_t;\gamma,c)$ approaches the indicator function $I[s_t > c]$, defined as $I[A] = 1$ if A is true and $I[A] = 0$ otherwise, and, consequently, the change of $F(s_t;\gamma,c)$ from 0 and 1 becomes almost instantaneous at $s_t = c$. Hence, the $LSTAR$ model (17) with (18) nests a two-regime threshold autoregressive (TAR) model as a special case[6].

Note that the transition function (18) is a special case of the general nth-order logistic function, defined by[7]

$$F(s_t;\gamma,c) = \{1+\exp[-\gamma\prod_{i=1}^{n}(s_t-c_i)]\}^{-1}, \tag{19}$$

where $\gamma > 0, c_1 \leqslant c_2 \leqslant ... \leqslant c_n$. This function can be used to obtain multiple switches between the two regimes.

---

[5] However, in certain cases the regime-switching behaviour might be derived by the size of the deviations between the transition variable and the threshold. Therefore, in this circumstance the regimes are associated with small and large absolute values of s_t, which is represented by the exponential function, that is $F(s_t;\gamma,c) = (1-\exp\{-\gamma\{s_t-c)\})^2$, and the model is the ESTAR model. A drawback of the exponential function is that for either $\gamma \to 0$ or $\gamma \to \infty$, the function collapses to a constant (0 and 1, respectively) becoming linear and then, the ESTAR model does not nest a SETAR model. The more frequent empirical application of this type of model corresponds to the analysis of real exchange rates, see Michael, Nobay, and Peel (1997), Taylor, Peel, and Sarno (2001).

[6] In the case where $s_t = y_{t-d}$, the model is called a self-exciting TAR (SETAR) model. See Tong (1990) for an extensive presentation of TAR and SETAR models.

[7] For example, Jansen and Terasvirta (1996) used a second-order logistic function.

The approach suggested by Teräsvirta (1994) allows the construction of a suitable model starting from a general model and proceeding to a more parsimonious model by performing diagnostic testing of the model's adequacy. The method consists of the following six steps: i) specify a linear model of order p for the time series under investigation; ii) test the null hypothesis of linearity against the alternative of $STAR$ nonlinearity. If linearity is rejected, choose the appropriate transition variable s_t and the form of the transition function $F(s_t;\gamma,c)$; iii) estimate the parameters of the chosen $STAR$ model; iv) evaluate the model, using both diagnostic testing and impulse response analysis; v) modify the model if warranted; vi) use the model to forecast or describe situations. In this paper we are only interested in (i)-(iii)[8].

In the $LSTAR$ models, the two regimes are associated with small and large values of the transition variable s_t relative to the parameter c. This type of regime-switching can be convenient for modelling, for example, business cycle asymmetries in distinguishing expansions and recessions. It is clear that if Δy_t is the growth rate of an output variable, and if $c \approx 0$, the model distinguish between periods of positive and negative growth, that is, between expansions and recessions. The $LSTAR$ models has been successfully applied by Teräsvirta and Anderson (1992) and Teräsvirta, Tjøstheim and Granger (1994) to characterize the different dynamics of industrial production indexes in a number of OECD countries during both regimes[9].

[8] For more technical details regarding estimation issues and the issues described here, see van Dijk, Franses, and Teräsvirta (2002).

[9] After estimating the model, the fourth step in the $STAR$ modeling cycle is to evaluate the soundness of the nonlinear model. Following Eitrheim and Teräsvirta (1996), this step is concerned with the quality of the model regarding the hypotheses of: i) no residual autocorrelation; ii) no remaining nonlinearity; and iii) parameter constancy. The $LM-$test for no serial correlation in the residuals $\widehat{\varepsilon}_t$ is calculated using TR^2, where R^2 is the coefficient of determination from the regression of $\hat{\varepsilon}_t$ on $\nabla F(x_t;\hat{\theta}) = \partial\nabla F(x_t;\hat{\theta})/\partial\theta$, with $\theta = (\phi_1, \phi_2, \gamma, c)'$, and q lagged residuals $\hat{\varepsilon}_{t-1}, ..., \hat{\varepsilon}_{t-q}$. The test statistic, $LM_{SI(q)}$, is asymptotically χ^2 distributed with q degrees of freedom.

On another hand, Eitrheim and Teräsvirta (1996) have developed an LM statistic to test the two-regime $LSTAR$ model against the alternative of an additive $STAR$ model. In testing for the null hypothesis, a third-order Taylor approximation is used and the test statistic is denoted by $LM_{AMR,3}$ and it has an asymptotic χ^2 distribution with $3(p+1)$ degrees of freedom, where the notation AMR indicates additive multiple regime. Notice, that by testing the null hypothesis, we can test for parameter constancy in the two regime $STAR$ model against the alternative of smoothly changing parameters. The $LM-type$ statistic is based on a third-order approximation of $F_2(t;\gamma_2,c_2)$, and is represented as $LM_{C,3}$.

The evaluation of the models is based on measures of the in-sample fit, such as the $\overline{R}^2$ and information criteria (AIC, SIC, and HQ). The ratio of the variance of the residuals

3 Empirical Results

The models presented in the last section are estimated using the growth rates of the logarithm of the quarterly GDP of Peru covering the period 1979:1 to 2005:4. For the Plucking model, we use the seasonal adjusted output. In order to perform some comparisons, a linear $AR(k)$ model has also been estimated.

As we mentioned in the previous section, the model suggested by Clark (1987) is nested by the plucking model. Estimation of the model of Clark (1987) gives a value of the log likelihood of 180.819. A likelihood ratio is used to compare the unrestricted Plucking model (see second column of Table 1) with the model of Clark (1987). The value is 43.632 which compared with a $\chi^2_{(5)}$ gives a p-value of 0.00; therefore the model of Clark (1987) is strongly rejected. It means that there are asymmetries in the data.

Table 1 presents the estimates obtained using the plucking model. The second column shows the estimates from the unrestricted model. The second autoregressive parameter is not statistically significant. Similar observations are applied to the parameters $\sigma^2_{u_0}$, $\sigma^2_{v_0}$, $\sigma^2_{v_1}$, σ^2_w and the discrete shock π Furthermore, the estimate value of the probability of normal times ($s_t = 0$) indicates strong persistence. According to this estimate the expected duration of this regime is around 166 quarter which appears to be excessively large.

Because the non significance of some coefficients, the third column of Table 1 shows estimates obtained from a restricted model. In this restricted model, I impose the null hypothesis that $\sigma^2_w = 0$. This hypothesis is equivalent to arguing that the trend growth component has been constant. The log likelihood value of this model is very close to the value obtained for the unrestricted model. Therefore, a LR statistic of 1.526 is obtained. Comparing this value with a $\chi^2_{(1)}$ gives a p-value of 0.217; therefore the null hypothesis is not rejected. In this model most of the coefficients are significant. The only exception is $\sigma^2_{u_1}$ which seems to indicate that the symmetric shock does not have effect on the time series. In the estimated restricted model of the third column of Table 1, the sum of the autoregressive coefficients is 0.914.

The fourth column of Table 1 presents a restricted model where the restrictions are $\sigma^2_{u_0} = 0$ and $\sigma^2_{u_1} = 0$. This is equivalent to arguing that the asymmetries in the transitory component are not derived from the term u_t, and therefore, they account exclusively for the asymmetric discrete shock

from the non-linear model with respect to the linear model is also used to calculate the improvement of one model with respect to the other model.

π_{s_t}. A LR statistic of 0.708 (p-value of 0.400) supports the null hypothesis suggesting that the principal source of the asymmetries in the transitory component comes from the asymmetric discrete shock. Furthermore, the sum of the autoregressive coefficients is 0.941 and the value of σ_w^2 is not statistically significant. The expected durations are 9.7 and 27.0 quarters, for recession and normal times, respectively.

Last column of Table 1 shows the estimates of a restricted model where the restrictions are $\sigma_w^2 = 0$ and $\sigma_{u_0}^2 = 0$ and $\sigma_{u_1}^2 = 0$ have been imposed. A LR statistic of 0.410 (p-value of 0.527) does not reject the null hypothesis. In this model, all coefficients are statistically significant. One interesting result in this model is that the sum of autoregressive coefficients is 0.50 indicating a substantial reduction of the persistence. The expected durations of the recession and normal times are 5.3 and 18.2 quarters, respectively. The coefficient associated to the discrete shock π is negative and highly significant.

In summary, the estimates of the selected restricted Plucking model suggest that during normal times ($s_t = 0$) the Peruvian economy is subject to permanent disturbances and it operates near the trend ceiling. In the other case, during recessions and the recovery periods that follow, the transitory component plays a principal role in the fluctuations of the Peruvian economy. At the same time, given the magnitude of the sum of the autoregressive coefficients, when economy is near the end of a period of recession, and there are no other negative shocks, the fast-decaying negative shocks give origin to a third phase, which Sichel (1994) named high-recovery phase.

Figure 1 and 2 visually summarize the preceding discussions. Notice that all estimates presented in the graphs represent filtered estimates, that is, they are based on information available until time t. Figure 1 shows the evolution of the logarithm of the real output and its trend component $(\tau_t|t)$ for all four models presented in Table 1. Figure 2 shows the estimates of the transitory component $(c_t|t)$ for the same models.

Essentially, Figure 1 indicate that most of the time the Peruvian economy is operating on or near the trend ceiling component. In periods of recession, the economy is operating below the trend ceiling component. Notice that there are some cases where the economy is notably below the ceiling component.

All these issues cam be appreciated more clearly in Figure 2. It is possible to observe that after a trough, the negative transitory shocks are deteriorating, restoring the economy back to the trend ceiling, or the normal level. The transitory component obtained from the unrestricted Plucking model presents periods of recession more pronounced in comparison with the other cases. The cycle obtained from the restricted Plucking model (see last column of Table 1) is less pronounced. Another interesting issue is the fact that after 1995-1996 the economy has been operating on or close to the ceiling level. Therefore, there are not pronounced cycles for this period. Another interpretation is that the Plucking mechanism has not been strong in this period. Figure 3 shows the probabilities to be in periods of recession. There are two issues to worth. First, the recession periods are more clearly identified using the most restricted Plucking model. According to it, the recessions are 1983, 1988 and 1990. Second, after 1995-1996, there are no recessions in the economy.

Now, we consider the results of the MS models where seasonal adjusted data have been also used. In the case of Markov-Switching models, I estimate models where the mean (or the intercept) and the variance are depending of the regime. Table 2a shows the estimates of a MSIH(2)-AR(4) and MSMH(2)-AR(4) models. Both models strongly reject the null hypothesis of linearity. If we use the AIC as a criterium to select the model, the MSM(2)-AR(4) is selected. In both cases only the first and fourth autoregressive coefficient are statistically significant. According to the estimated probabilities, a recession lasts for 7 quarters in both models. The expected duration of expansions are 31 and 34 quarters, for the MSIH(2)-AR(4) and MSMH(2)-AR(4) models, respectively. Observing the standard errors, we see that the periods of recession are more volatile than the periods of expansion.

Figure 4 and 5 present the filtered and smoothed probabilities of periods of recession and expansion for both models, respectively. Filters and smoothed probabilities are very close. Another observation is that both models present very similar behavior for the periods of recession and expansion.

Table 2b shows the results of the estimation of a MSIH(3)-AR(4) and MSMH(3)-AR(4) models, respectively. Strong rejection of the null hypothesis of linearity is clearly observed according to the p-value of the test of Davies. According to the AIC, the MSMH(3)-AR(4) model is preferred. For this model, the three values of the mean are significant. According to these values, the first regime accounts for periods of recession, second regime accounts for normal times and the last period represents high rates of growth of output. The expected duration of the regimes are 7.5, 34.5 and 2.3 quarters, respectively. Figures 6 and 7 present the evolution of the filtered and smoothed probabilities for each regimes.

Table 3 shows the results obtained with the estimation of the LSTAR models. The first set of results are obtained using the first differences of the logarithm of the real output seasonal adjusted (Δy_t^{sa}). The model shows a strong rejection of the null hypothesis of linearity. The transition variable is the first lagged dependent variable. The selected model is a model with two thresholds and the variance of the LSTAR model is 97.6% respect to the variance of the linear model. The smooth parameter (γ) is slow and the the two thresholds are -10.8% and 7.5%, respectivement.

The second set of results use the fourth differences of the logarithm of the non seasonal adjusted output ($\Delta_4 y_t$) As before, there is a strong rejection ofthe null hypothesis of linearity. In this case, the variance of the LSTAR model is 79.7% of the variance of the linear model. The smooth parameter is higher compared tothe previous model and the two threshold are -11.7% and 13.8, respectivemente.

Figures 8 and 9 show the evolution of the transition function against time and also the evolution of the transition function against the transition variable.

Summarizing, the set of used models find the following quarters as periods of recession. The Plucking model finds 1982:3-1984:1, 1988:2-1989:2, 1990:1-1991:1. The two MS model with 2 regimenes find the following periods: 1982:2-1983:1, 1987:3-1990:4 and 1982:2-1983:1, 1987:3-1990:4, respectively. In the case of the MS with 3 regimenes, the selected periods are 1982:2-1983:1, 1987:3-1990:4 and 1982:2-1983:4, 1987:3-1990:4. Finally, two LSTAR models find the following periods 1989:1-1989:1, 1990:4-1991:1 and 1989:4-1990:3, 1991:3-1991:4, respectively.

4 Conclusion

Three different and alternative econometric approaches have been used to estimate business cycles in the Peruvian economy. The first model is named the Plucking model and it is due to Friedman (1964, 1993). The second approach is the Markov-Switching model as suggested by Hamilton (1989). Finally the last kind of models is the Smooth Transition Auroregressive (STAR) model as suggested by Teräsvirta (1994). All three approaches strongly reject the null hypothesis of linearity and support the existence of nonlinearities and asymmetries.

The Plucking model supports the importance of the asymmetric discrete shock affecting the transitory component. The sum of the autoregressive coefficients is substantially reduced and it indicates a fast decaying of the shocks to the transitory components. Overall, the results support the idea that the economy is operating near to the ceiling level most of the time.

Two different MS models have been estimated. In the first case, two models with two regimenes have been estimated. In one case the model is mean regimen-dependent. In the other case, the model is regimen dependent in the intercept. The second group of estimated models is similar to the above mentioned but with three regimes. All models suggest strong rejection of the null hypothesis of linearity. The model also suggest the recession periods for the Peruvisan economy.

In the last part iof the document two LSTAR models have been estimated. The results suggest the presence of a smooth parameter and two thresholds. Both models capture the principal quarters of recession.

References

[1] Aigner, D., A. K. Lovell, and P. Schmidt (1977), "Formulations and Estimation of Stochastic Frontier Production Models," *Journal of Econometrics* **6**, 21-37.

[2] Baxter, M. and R. G. King (1999), "Measuring Business Ccles: Approximate Band-Pass Filter for Economic Time Series," T*he Review of Economics and Staristics* **79**, 551-563.

[3] Bodman, P. M. and M. Crosby (2000), "Phases of the Canadian Business Cycle", *Canadian Journal of Economics* **33**, 618-633.

[4] Burns, A. F., and W. C. Mitchell (1946), *Measuring Business Cycles*, New York, NBER.

[5] Campbell, J.Y. and N.G. Mankiw (1987b): "Are Output Fluctuations Transitory?" *Quarterly Journal of Economics* **102**, 857-880.

[6] Clark, P. (1987), "The Cyclical Component of US Economic Activity," *Quarterly Journal of Economics* **102**, 797-814.

[7] Cochrane, J.H. (1988): "How Big is the Random Walk in GNP?" *Journal of Political Economy* **96**, 893-920.

[8] Delong, J. Bradford, and L. H. Summers (1986), "Are Business Cycles Symmetrical?," in Gordon, R. (ed.), *American Business Cycle: Continuity and Change*, pp. 166-179. Chicago: University of Chicago Press.

[9] Diebold, F. X., and G. Rudebusch (1990), "A Nonparametric Investigation of Duration Dependence in the American Business Cycle," *Journal of Political Economy* **98**, 596-616.

[10] Diebold, F. X., G. Rudebusch, and D. E. Sichel (1993), "Further Evidence on Business-Cycle Duration Dependence," in Stock, J. and M. Watson (eds.), *Business Cycles, Indicators and Forecasting*, pp. 255-284. University of Chicago Press.

[11] Durland, J. M., and T. H. McCurdy (1994), "Duration-Dependent Transitions in a Markov Model of U.S. GNP Growth," *Journal of Business and Economic Statistics* **12 (3)**, 279-288.

[12] Eitrheim, Ø. and T. Teräsvirta (1996), "Testing the Adequacy of Smooth Transition Autoregressive Models," *Journal of Econometrics* **74**, 59–76.

[13] Falk, B. (1986), "Further Evidence on the Asymmetric Behavior of Economic Time Series over the Business Cycle," *Journal of Political Economy* **94:5**, 1096-1109.

[14] Friedman, M. (1964), "Monetary Studies of the National Bureau," *The National Bureau Enters Its 45th Year*, 44th Annual Report, pp. 7-25.

[15] Friedman, M. (1993), "The 'Plucking Model' of Business Fluctuations revisited," *Economic Inquiry*, 171-177.

[16] Galvão, A. B. C. (2002), "Can Non-Linear Time Series Models Generate US Business Cycle Asymmetric Shape," *Economic Letters* **77**, 187-194.

[17] Goodwin T. H. (1993), "Business-Cycle Analysis With a Markov-Switching Model" *Journal of Business and Economic Statistics* **11**, 331-339.

[18] Goodwin, T. H., and R. J. Sweeney (1993), "International Evidence on Friedman's Theory of the Business Cycle," *Economic Inquiry*, 178-193.

[19] Hamilton, J. D. (1989), "A New approach to the Economic Analysis of Nonstationarity Time Series and the Business Cycle," *Econometrica* 57, 357-384.

[20] Hamilton, James D., (1990, "Analysis of Time Series Subject to Changes in Regimes," *Journal of Econometrics* **45**, 39-70.

[21] Hodrick, R. and E. Prescott (1997), "Postwar US Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking* **29**,1-16.

[22] Jansen, E. S. and, T. Teräsvirta (1996), "Testing parameter constancy and superexogeneity in econometric equations," *Oxford Bulletin of Economics and Statistics* **58**, 735–768.

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

[24] Kim, Ch.-J., and Ch. R. Nelson (1998), "Business Cycle Turning Points. A New Coincident Index, and Tests of Duration Dependence Based on a Dynamic Factor Model with Regime-Switching," *Review of Economics and Statistics* **80**, 188-201.

[25] Kim, Ch.-J., and Ch. R. Nelson (1999a), *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications.* The MIT Press.

[26] Kim, Ch.-J., and Ch. R. Nelson (1999b), "Friedman's Plucking Model of Business Fluctuations: Tests and Estimates of Permanent and Transitory Components," *Journal of Money Credit, and Banking* **31 (3)**,317-334.

[27] Krolzig, H.-M. (1997), *Markov-Switching Vector Autoregressions. Modelling, Statistical Inference, and Application to Business Cycle Analysis*, Lecture Notes in Economics and Mathematical Systems, Volume 454, Berlin: Springer.

[28] Lam, P. S. (1990), "The Hamilton Model with a General Autoregressive Component: Estimation and Comparison with other Models of Economic Time Series," *Journal of Monetary Economics* **26**, 409-432.

[29] Lundbergh, S. and T. Teräsvirta (1998), "Modelling Economic High-Frequency Time Series with STAR-GARCH Models", *Working Paper Series in Economics and Finance* **291,** Stockholm School of Economics.

[30] Michael, P., A. R. Nobay, and D. A. Peel (1997), "Transaction Costs and Nonlinear Adjustment in Real Exchange Rates: An Empirical Investigation," *Journal of Political Economy* **105,** 862–879.

[31] Mills, T. C., and P. Wang (2002), "Plucking Models of Business Cycle Fluctuations: Evidence from the G-7 Countries," *Empirical Economics* **25**, 225-276.

[32] Neftci, S. N. (1984), "Are Economic Time Series Asymmetric Over the Business Cycles?," *Journal of Political Economy* **92 (2)**, 307-328.

[33] Sichel, D. E. (1993), "Business Cycle Asymmetry: A Deeper Look," *Economic Inquiry* April, 224-236.

[34] Sichel, D. E. (1994), "Inventories and the Three Phases of the Business Cycle," *Journal of Business & Economic Statistics* **18**, 29-75.

[35] Taylor, M. P., D. A. Peel, and L. Sarno (2001), "Nonlinear Mean-Reversion in Exchange Rates: Towards a Solution to the Purchasing Power Parity Puzzles," *International Economic Review* **42**, 1015-1042.

[36] Teräsvirta, T. (1994), "Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models," *Journal of the American Statistical Association* **89**, 208–218.

[37] Teräsvirta, T. (1998), "Modelling Economic Relationships with Smooth Transition Regressions," in A. Ullah and D. E. A. Giles (eds.), *Handbook of Applied Economic Statistics*, New York: Marcel Dekker, pp. 507–552.

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

[39] Teräsvirta, T., D. Tjøstheim, and C. W. J. Granger (1994), "Aspects of Modelling Nonlinear Time Series," in R. F. Engle and D. L. McFadden (eds.), *Handbook of Econometrics*, Volume **IV**, Amsterdam: Elsevier Science, 2917–2957.

[40] Tong, H. (1990), *Non-Linear Time Series: A Dynamical Systems Approach*, Oxford: Oxford University Press.

[41] van Dijk,D., T. Teräsvirta and P. H. Franses (2002), "Smooth Transition Autoregressive Models. A Survey of Recent Developments," *Econometric Reviews* **21**, 1-47.

[42] Watson, M. W. (1986), "Univariate Detrending Methods with Stochastic Trends," *Journal of Monetary Economics* **18**, 29-75.

Table 1. Estimates of the Plucking Model

Parameters	Unrestricted Model	$\sigma_w^2 = 0$	$\sigma_{u_1}^2 = \sigma_{u_2}^2 = 0$	$\sigma_w^2 = 0, \sigma_{u_1}^2 = \sigma_{u_2}^2 = 0$
q	0.984	0.897	0.938	0.812
	(0.017)	(0.074)	(0.067)	(0.125)
p	0.994	0.963	0.966	0.945
	(0.011)	(0.026)	(0.029)	(0.037)
ϕ_1	1.167	1.507	1.697	1.201
	(0.288)	(0.211)	(0.278)	(0.129)
ϕ_2	-0..353	-0.593	-0.756	-0.701
	(0.279)	(0.196)	(0.242)	(0.130)
σ_{u_0}	0.010	0.012		
	(0.007)	(0.005)		
σ_{u_1}	0.033	0.000		
	(0.002)	(0.001)		
σ_{v_0}	0.010	0.013	0.016	0.019
	(0.008)	(0.004)	(0.002)	(0.002)
σ_{v1}	0.029	0.058	0.055	0.064
	(0.022)	(0.009)	(0.008)	(0.011)
σ_w	0.001		0.000	
	(0.001)		(0.001)	
π	-0.026	-0.014	-0.009	-0.025
	(0.026)	(0.006)	(0.007)	(0.008)
Log Lik	202.635	201.872	201.518	201.313

Standard errors in parentheses.

Table 2a. Estimates of the Markov-Switching Models

	MSIH(2)-AR(4)		MSMH(2)-AR(4)	
	Coefficient	t-value	Coefficient	t-value
μ_1	-0.016	-1.021	-0.024	-1.665
μ_2	0.011	3.090	0.011	4.364
ϕ_1	0.182	1.657	0.163	1.614
ϕ_2	0.023	0.286	0.010	0.133
ϕ_3	-0.009	-0.116	-0.015	-0.621
ϕ_4	-0.236	-3.306	-0.286	-4.038
σ_1	0.064		0.064	
σ_2	0.020		0.019	
p_{11}	0.857		0.859	
p_{22}	0.968		0.971	
Log-Likelihood	223.803		224.843	
AIC	-4.152		-4.172	
LR Linearity Tests	47.105		49.185	
Davies' p-value	(0.000)		(0.000)	

Table 2b. Estimates of the Markov-Switching Models

	MSIH(3)-AR(4)		MSMH(3)-AR(4)	
	Coefficient	t-value	Coefficient	t-value
μ_1	-0.023	-1.511	-0.029	-2.797
μ_2	0.010	2.731	0.006	1.677
μ_3	0.039	5.027	0.037	8.308
ϕ_1	-0.001	-0.008	0.083	0.838
ϕ_2	-0.020	-0.228	-0.017	-0.276
ϕ_3	0.069	-0.865	-0.131	-2.075
ϕ_4	-0.288	-3.921	-0.367	6.041
σ_1	0.059		0.062	
σ_2	0.017		0.016	
σ_3	0.014		0.009	
p_{11}	0.875		0.866	
p_{22}	0.902		0.971	
p_{33}	0.688		0.572	
Log-Likelihood	225.852		228.833	
AIC	-4.075		-4.133	
LR Linearity Tests	51.204		57.166	
Davies' p-value	(0.000)		(0.000)	

Table 3a. Estimates of a Linear AR(4) and a LSTAR Model using Δy_t^{sa}

	Linear Model		LSTAR	
	Coefficient	t-value	Coefficient	t-value
μ_1	0.005	0.146	0.006	0.073
$\phi_{1,1}$	0.319	0.002	0.485	0.001
$\phi_{2,1}$	-0.065	0.533		
$\phi_{3,1}$	-0.026	0.803	-0.112	0.229
$\phi_{4,1}$	-0.132	0.190	-0.248	0.013
μ_2			-1.087	0.055
$\phi_{1,2}$			-4.923	0.089
$\phi_{2,2}$			-8.236	0.006
$\phi_{3,2}$				
$\phi_{4,2}$				
c_1			-0.108	0.000
c_2			0.079	0.000
γ			1.733	0.059
AIC	-6.788		-6.793	
BIC	-6.660		-6.534	
$\overline{R}^2$	0.085		0.315	
p-value of Q(1)	0.818		0.899	
p-value of Q(4)	0.956		0.983	
p-value of Q(8)	0.312		0.219	
p-valueARCH(8)	0.039		0.105	
p-balue of JB	0.001		0.000	
$\widehat{\sigma}_{LSTAR}/\widehat{\sigma}_{Linear}$			0.976	

Table 3b. Estimates of a Linear AR(4) and a LSTAR Model using $\Delta_4 y_t$

	Linear Model		LSTAR	
	Coefficient	t-value	Coefficient	t-value
μ_1	0.005	0.270	0.009	0.054
$\phi_{1,1}$	1.086	0.000	1.104	0.000
$\phi_{2,1}$	-0.311	0.038	-0.185	0.220
$\phi_{3,1}$	-0.147	0.321	-0.131	0.346
$\phi_{4,1}$	0.078	0.439	-0.136	0.191
μ_2			0.013	0.412
$\phi_{1,2}$			-0.153	0.501
$\phi_{2,2}$			-1.343	0.002
$\phi_{3,2}$			0.822	0.119
$\phi_{4,2}$			0.129	0.654
c_1			-0.117	0.000
c_2			0.137	0.000
γ			22.982	0.897
AIC	-6.029		-6.410	
BIC	-5.899		-6.071	
$\overline{R}^2$	0.674		0.808	
p-value of Q(1)	0.729		0.484	
p-value of Q(4)	0.032		0.002	
p-value of Q(8)	0.016		0.013	
p-valueARCH(8)	0.007		0.231	
p-balue of JB	0.461		0.225	
$\widehat{\sigma}_{LSTAR}/\widehat{\sigma}_{Linear}$			0.797	

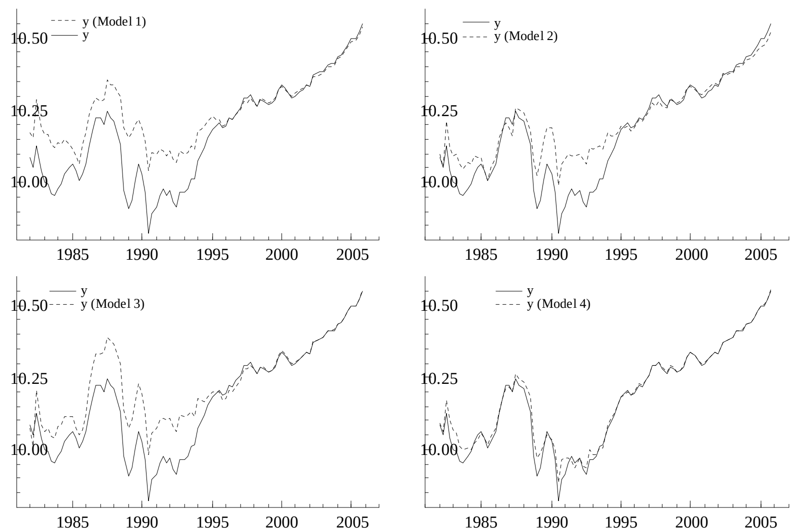

Figure 1. Current and Potential output from the Plucking Model

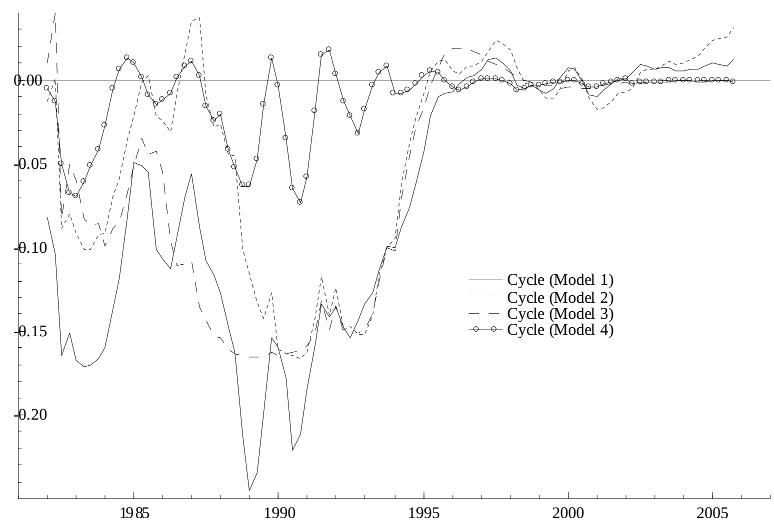

Figure 2. Cycles estimated from the Plucking Model

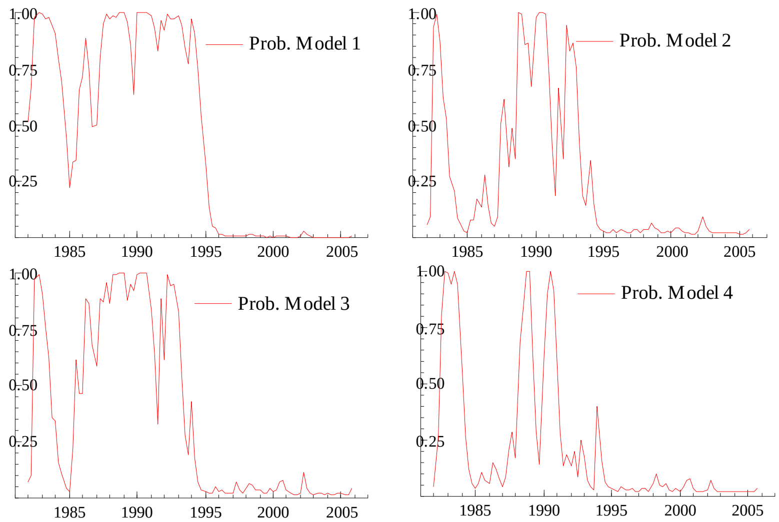

Figure 3. Probabilities of recession times ($s_t = 1$)

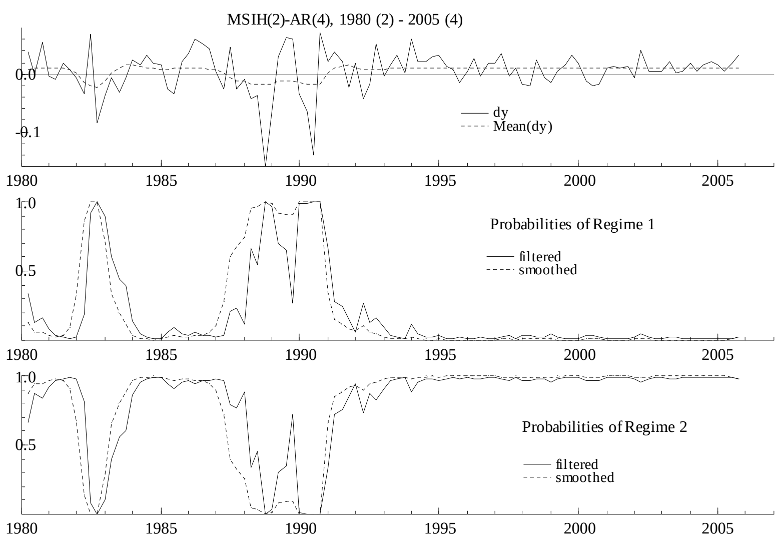

Figure 4. Filtered and Smoothed probabilities; MSIH(2)-AR(4) Model

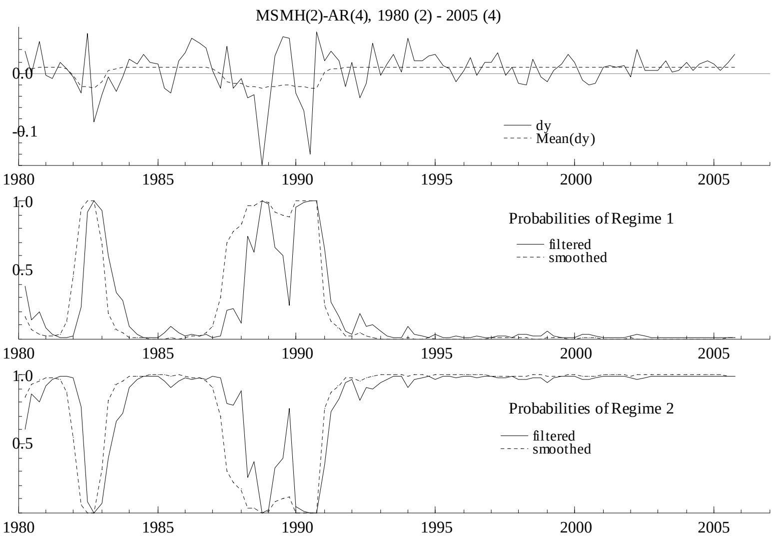

Figure 5. Filtered and Smoothed probabilities; MSMH(2)-AR(4) Model

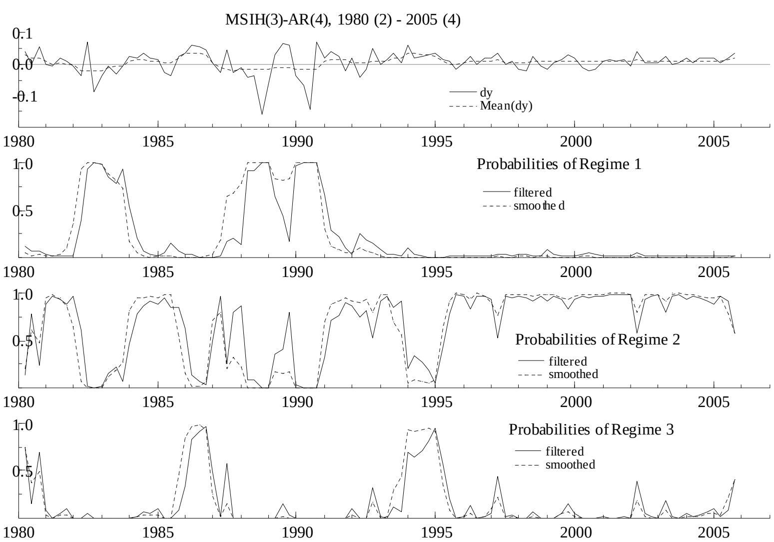

Figure 6. Filtered and Snoothed probabilities; MSIH(3)-AR(4) Model

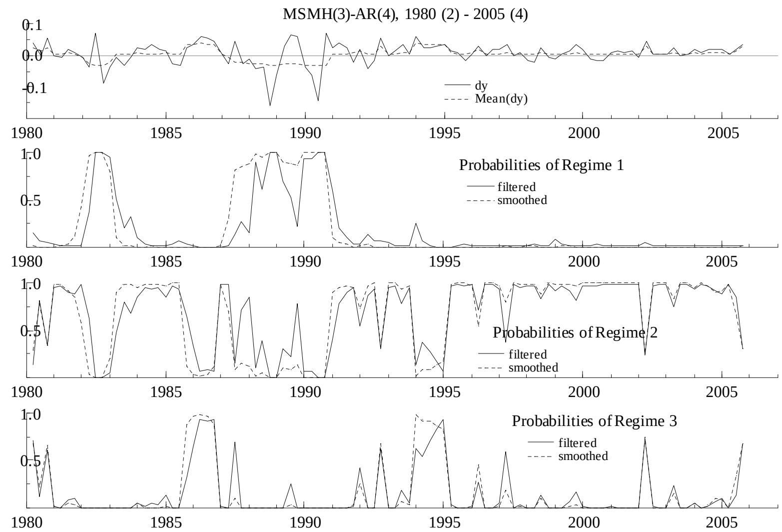

Figure 7. Filtered and Smoothed probabilities, MSMH(3)-AR(4) Model

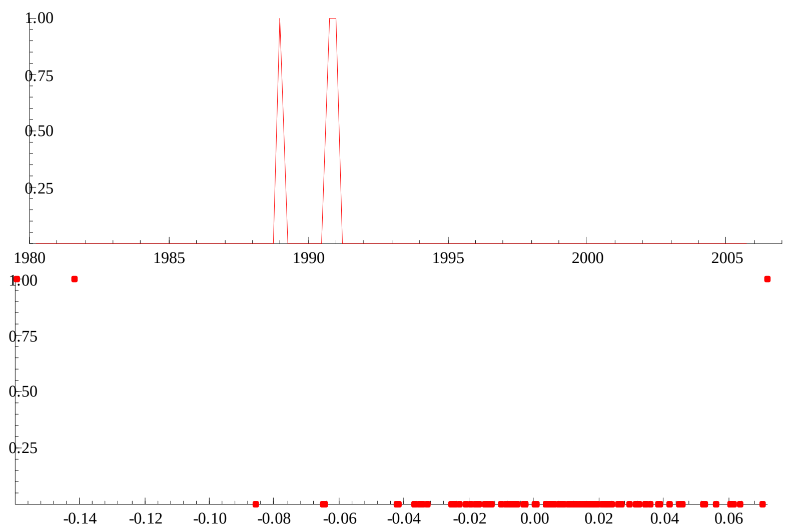

Figure 8. Transition Function against Time and Transition Function against Transition Variable

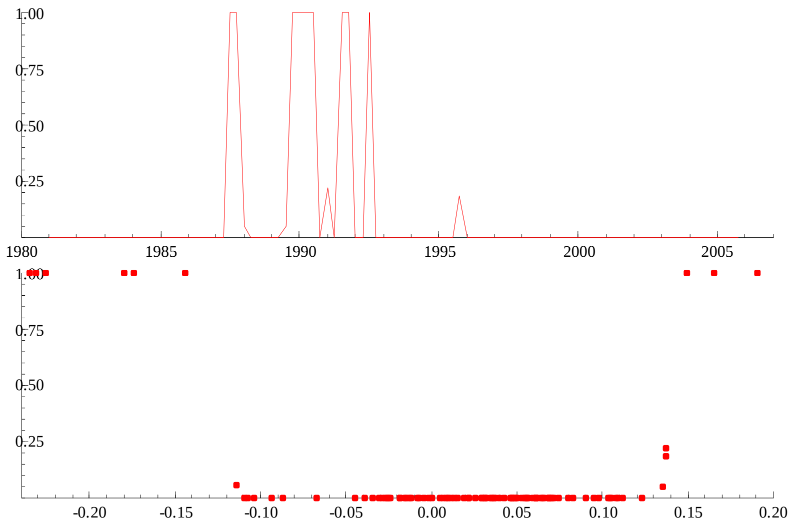

Figure 9. Transition Function against Time and Transition Function against Transition Variable

Documentos de Trabajo publicados
Working Papers published

La serie de Documentos de Trabajo puede obtenerse de manera gratuita en formato pdf en la siguiente dirección electrónica:
http://www.bcrp.gob.pe/

The Working Paper series can be downloaded free of charge in pdf format from:
http://www.bcrp.gob.pe/

2007

Abril \ April

DT N° 2007-006
Monetary Policy in a Dual Currency Environment
Guillermo Felices, Vicente Tuesta

Marzo \ March

DT N° 2007-005
Monetary Policy, Regime Shift and Inflation Uncertainty in Peru (1949-2006)
Paul Castillo, Alberto Humala, Vicente Tuesta

DT N° 2007-004
Dollarization Persistence and Individual Heterogeneity
Paul Castillo y Diego Winkelried

DT N° 2007-003
Why Central Banks Smooth Interest Rates? A Political Economy Explanation
Carlos Montoro

Febrero \ February

DT N° 2007-002
Comercio y crecimiento: Una revisión de la hipótesis "Aprendizaje por las Exportaciones"
Raymundo Chirinos Cabrejos

Enero \ January

DT N° 2007-001
Perú: Grado de inversión, un reto de corto plazo
Gladys Choy Chong

2006

Octubre \ October

DT N° 2006-010
Dolarización financiera, el enfoque de portafolio y expectativas:
Evidencia para América Latina (1995-2005)
Alan Sánchez

DT N° 2006-009
Pass–through del tipo de cambio y política monetaria:
Evidencia empírica de los países de la OECD
César Carrera, Mahir Binici

Agosto \ August

DT N° 2006-008
Efectos no lineales de choques de política monetaria y de tipo de cambio real en economías parcialmente dolarizadas: un análisis empírico para el Perú
Saki Bigio, Jorge Salas

Junio \ June

DT N° 2006-007
Corrupción e Indicadores de Desarrollo: Una Revisión Empírica
Saki Bigio, Nelson Ramírez-Rondán

DT N° 2006-006
Tipo de Cambio Real de Equilibrio en el Perú: modelos BEER y construcción de bandas de confianza
Jesús Ferreyra y Jorge Salas

DT N° 2006-005
Hechos Estilizados de la Economía Peruana
Paul Castillo, Carlos Montoro y Vicente Tuesta

DT N° 2006-004
El costo del crédito en el Perú, revisión de la evolución reciente
Gerencia de Estabilidad Financiera

DT N° 2006-003
Estimación de la tasa natural de interés para la economía peruana
Paul Castillo, Carlos Montoro y Vicente Tuesta

Mayo \ May

DT N° 2006-02
El Efecto Traspaso de la tasa de interés y la política monetaria en el Perú: 1995-2004
Alberto Humala

Marzo \ March

DT N° 2006-01
¿Cambia la Inflación Cuando los Países Adoptan Metas Explícitas de Inflación?
Marco Vega y Diego Winkelreid

2005

Diciembre \ December

DT N° 2005-008
El efecto traspaso de la tasa de interés y la política monetaria en el Perú 1995-2004
Erick Lahura

Noviembre \ November

DT N° 2005-007
Un Modelo de Proyección BVAR Para la Inflación Peruana
Gonzalo Llosa, Vicente Tuesta y Marco Vega

DT N° 2005-006
Proyecciones desagregadas de la variación del Índice de Precios al Consumidor (IPC), del Índice de Precios al Por Mayor (IPM) y del Crecimiento del Producto Real (PBI)
Carlos R. Barrera Chaupis

Marzo \ March

DT N° 2005-005
Crisis de Inflación y Productividad Total de los Factores en Latinoamérica
Nelson Ramírez Rondán y Juan Carlos Aquino.

DT N° 2005-004
Usando información adicional en la estimación de la brecha producto en el Perú: una aproximación multivariada de componentes no observados
Gonzalo Llosa y Shirley Miller.

DT N° 2005-003
Efectos del Salario Mínimo en el Mercado Laboral Peruano
Nikita R. Céspedes Reynaga

Enero \ January

DT N° 2005-002
Can Fluctuations in the Consumption-Wealth Ratio Help to Predict Exchange Rates?
Jorge Selaive y Vicente Tuesta

DT N° 2005-001
How does a Global disinflation drag inflation in small open economies?
Marco Vega y Diego Winkelreid