Application of Three Alternative Approaches to Identify Business Cycles in Peru

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

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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.

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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 decades, 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.\footnote{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.”}

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
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 permanent2. 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.

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2 In this sense, Sichel (1994) also provides support to this fact by showing that post-war 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 an 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 analyzing 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 discussses 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 $\tau_t$ and $c_t$, respectively. That is,

$$y_t = \tau_t + c_t. \quad (1)$$
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 \( \pi_{st} \) 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:

\[
\begin{align*}
  c_t &= \phi_1 c_{t-1} + \phi_2 c_{t-2} + u_t^*, \\
  u_t^* &= \pi_{st} + u_t, \\
  \pi_{st} &= \pi_{st}, \\
  u_t &\sim N(0, \sigma_{u, st}^2), \\
  \sigma_{u, st}^2 &= \sigma_{u, 0}^2(1 - s_t) + \sigma_{u, 1}^2 s_t, \\
  s_t &= 0, 1
\end{align*}
\]

where \( \pi \neq 0 \). In the above specification, the term \( u_t \) is the usual symmetric shock. The term \( \pi_{st} \) 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 \( \pi_{st} = 0 \). 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, \( \pi_{st} = \pi < 0 \). 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

\[
\begin{align*}
  \Pr[s_t = 1|s_{t-1} = 1] &= q \\
  \Pr[s_t = 0|s_{t-1} = 0] &= p
\end{align*}
\]

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 \( \tau_t \), 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 per-
manent component can be specified as follows:

\[
\begin{align*}
\tau_t &= g_{t-1} + \tau_{t-1} + vt, \\
g_t &= g_{t-1} + w_t, \\
w_t &\sim N(0, \sigma_w^2), \\
v_t &\sim N(0, \sigma_{v,t}^2), \\
\sigma_{v,t}^2 &= \sigma_{v,0}^2(1 - s_t) + \sigma_{v,1}^2s_t,
\end{align*}
\]  

(8) (9) (10) (11) (12)

where, according to (10) and (11), the permanent component \(\tau_t\) 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

\[
y_t = \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ c_{t-1} \\ g_t \end{bmatrix} = H\xi_t,
\]

(13)

while the state equation is

\[
\xi_t = \begin{bmatrix} 0 \\ \pi_{st} \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & \phi_1 & \phi_2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \xi_{t-1} + \begin{bmatrix} v_t \\ u_t \\ 0 \\ w_t \end{bmatrix} + F\xi_{t-1} + V_t
\]

(14)

where \(E(V_tV_t') = Q_{st}\) and

\[
Q_{st} = \begin{bmatrix}
\sigma_{v,st}^2 & 0 & 0 & 1 \\
0 & \sigma_{u,st}^2 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & \sigma_w^2
\end{bmatrix}.
\]

Notice that the model expressed by (13) and (14) nests the model sug-
gested 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 \( \Delta y_t \) denotes the growth rate of real output in quarter \( t \). Hamilton (1989) proposes the following model to estimate US business cycles:

\[
\Delta y_t - \mu_{s_t} = \phi_1 (\Delta y_{t-1} - \mu_{s_{t-1}}) - \ldots - \phi_4 (\Delta y_{t-4} - \mu_{s_{t-4}}) + u_t, \tag{15}
\]

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 \( \Delta y_t \) 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

\[
\Pr[s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots] = \Pr[s_t = j | s_{t-1} = i]
\]

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

\[
P = \begin{bmatrix}
    p_{11} & p_{12} & \ldots & p_{1M} \\
    p_{21} & p_{22} & \ldots & p_{2M} \\
    \vdots & \vdots & \ddots & \vdots \\
    p_{M1} & p_{M2} & \ldots & p_{MM}
\end{bmatrix} \tag{16}
\]

with \( p_{iM} = 1 - p_{i1} - p_{i2} - \ldots - p_{iM-1} \), for \( i = 1, 2, \ldots, M \).

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 $\xi_t$ given a specified observation set $Y_T$, $\tau \leq T$ is possible. It reconstructs the time path of the regime $\{\xi_t\}_{t=1}^T$, under alternative information sets: predicted regime probabilities $\hat{\xi}_{t|\tau}$ when $\tau < t$, filtered probabilities $\tilde{\xi}_{t|\tau}$, when $\tau = t$, smoothed probabilities $\hat{\xi}_{t|\tau}$ 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 $\Delta y_t$ observed at $t = 1 - p, 1 - (p - 1), ..., -1, 0, 1, ..., T - 1, T$, is represented by

$$\Delta y_t = \phi_1 x_t [1 - F(s_t; \gamma, c)] + \phi_2 x_t [F(s_t; \gamma, c)] + \epsilon_t$$  \hspace{1cm} (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 $\epsilon_t$ is a martingale difference sequence with respect to the set of information up to and including time $t - 1$ (denoted by $\Omega_{t-1}$). In addition, it is assumed that the conditional variance of $\epsilon_t$ is constant, $E[\epsilon_t^2 | \Omega_{t-1}] = \sigma^2$.

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 $\alpha$. 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.

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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. The first-order logistic function is defined by

\[ F(s_t; \gamma, c) = \frac{1}{1 + \exp(-\gamma (s_t - c))}, \quad (18) \]

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 \( \gamma \) 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 \( \gamma \) 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.

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

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

where \( \gamma > 0, c_1 \leq c_2 \leq \ldots \leq c_n \). 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 $\Delta y_t$ 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, Tjostheim and Granger (1994) to characterize the different dynamics of industrial production indexes in a number of OECD countries during both regimes.9

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

9After 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 $\hat{\epsilon}_t$ is calculated using $TR^2$, where $R^2$ is the coefficient of determination from the regression of $\hat{\epsilon}_t$ 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 $\hat{\epsilon}_{t-1}, \ldots, \hat{\epsilon}_{t-q}$. The test statistic, $LM_{ST(q)}$, is asymptotically $\chi^2$ 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 $\chi^2$ 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 $R^2$ 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 $\sigma^2_{u_0}$, $\sigma^2_{v_0}$, $\sigma^2_{v_1}$, $\sigma^2_{w}$ and the discrete shock $\pi$. 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.

\hspace{1cm} 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.
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 $\sigma^2_w$ 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 $\sigma^2_w = 0$ and $\sigma^2_{nu} = 0$ and $\sigma^2_{n1} = 0$ 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 $\pi$ 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 ($\tau_t$) for all four models presented in Table 1. Figure 2 shows the estimates of the transitory component ($c_t$) 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 can 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 \((\Delta y^a_t)\). 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 \((\gamma)\) is slow and the the two thresholds are -10.8\% and 7.5\%, respectively.

The second set of results use the fourth differences of the logarithm of the non seasonal adjusted output \((\Delta_4y_t)\) As before, there is a strong rejection of the 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 to the previous model and the two threshold are -11.7\% and 13.8, respectively.

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.


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 Autoregressive (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 regimes 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 Peruvian economy.

In the last part of 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


Table 1. Estimates of the Plucking Model

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Standard errors in parentheses.
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Table 2b. Estimates of the Markov-Switching Models

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Table 3a. Estimates of a Linear AR(4) and a LSTAR Model using $\Delta y_t^{sa}$

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

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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 Smoothed 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
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