

Final Report
for the research project (RRC IV-057)
“Adapted models to estimate potential GDP in the candidate countries”

Introduction

The central point of our research project is estimation of the potential GDP for the Romanian economy during transition. The potential GDP for the Romanian economy is estimated using the real GDP series. The data needed to our analysis are real quarterly GDP series computed by National Institute for Statistics for the period 1994-2004 and annual series for the period 1992-2004.

The particularities of the Romanian economy - the lack of well functioning markets and well-organized institutions - make difficult the elaborating of an "ideal" method of potential GDP estimation - this is the reason why we intend to consider two different methods: statistical de-trending methods and economic approaches based on the production function model (PF).

The set of statistical methods we have in view includes various unobserved components methods estimated with the Kalman filter (univariate and bivariate) as well as econometric VAR methods based on Blanchard-Quah decomposition. The set of production function methods estimates the potential output by making specific assumptions on the functional form of the production activity in the Romanian economy, as well as on the “optimal” utilization of the production factors.

Moreover, we shall try to respond to an important issue, namely if it is desirable to use of either statistical or economic methods for the potential GDP estimation. It should be underlined that both approaches have natural advantages in particular policy domains, for example Kalman filter being well suited to policy surveillance areas requiring rapid and non-judgmental updating and the PF approach being adequate in the medium term analysis, where more economic rationale is required. The PF model has the main disadvantage that it requires specific assumptions on the trend technical progress and the potential utilization of factors (unobserved). Also, the definition of the potential contribution of employment to output is difficult to establish. The definition that we therefore apply is the level of employment consistent with stable, non-accelerating (wage) inflation (NAWRU) and it is estimates by the statistical methods developed in our research.

The Final Report is composed by two parts (four papers): in the first part we evaluate the potential output and the output gap by univariate and multivariate filers and econometrically by VAR, by considering a database of quarterly series. In the second part we evaluate the potential output and the output gap starting from the evaluation of the NAIRU for the Romanian economy with the help of H-P filter and by the production function method with annually series databases.

First Part

Chapter 1. Unobserved components methods to estimate potential GDP (Case of Romania)¹

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The estimation of potential output and output gap is useful for the identification of a sustainable growth rate without inflationary pressures. In order to derive the potential output decomposition statistical methods and structural relationships estimation methods are used. The former tries to separate a series into a permanent and a cyclical component, and the latter tries to isolate the structural and cyclical influences upon the aggregate output using the economic theory.

The statistical methods include the Hodrick-Prescott filter, the Beveridge-Nelson decomposition and various methods with unobserved components. The methods that estimate the structural relationships include the structural VAR, production function, and demand-side models.

In order to estimate the potential GDP for the Romanian economy I applied only models with unobserved components. They decompose the data series into two independent unobserved components and an irregular component:

- the stochastic trend;
- the stochastic cycle as a measure of the output gap (the business cycle component);
- the irregular component, assumed to be mean zero and normally distributed.

In this case, the shocks that impact upon the trend will be not correlated with those that impact upon the cycle.

The models used for the estimation of the unobserved components fall within two broad classes:

- *Univariate models*: assume that the relevant information is embodied in the values of the series that has to be decomposed and therefore the unobserved components can be determined without reference to any other economic variable;
- *Multivariate models*: use also other economic variables in order to explain the evolution of the output components. In the case of GDP, such variables may be the inflation rate, the unemployment rate, the interest rate, the industrial output, etc. Since the introduction of more variables into the model leads to more complex computation methods, in practice bivariate models are used, as the most viable way of estimating the unobserved components in the entire class of multivariate models.

The univariate models cannot explain the economic significances of the trend and the gap, in other words one may not know whether the trend corresponds to the potential output considered by the economic theory. However, these models are useful because they provide an overall picture of the series' dynamics in the long run. Especially interesting is the information concerning the presence

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of the structural breaks within the trend and the slope and the identification of the supply side shocks that produced those breaks.

The unobserved components are computed using the Kalman filter. In order to be estimated with the Kalman filter algorithm, the equations are written in the state-space framework.

Applications of the univariate models to the Romanian economy

The univariate model adapted to the Romanian economy has the general form:

$$y_t = \mu_t + \psi_t + \gamma_t + \mathbf{z}'_t \boldsymbol{\delta}_t + \varepsilon_t, \quad t = 1, \dots, n \quad (1)$$

where y_t is the observed series (the log of the real GDP),

μ_t is the trend,

ψ_t is the cycle,

γ_t is the seasonal component,

ε_t is the irregular component with mean zero and normally distributed,

\mathbf{z}_t is a $(p \times 1)$ vector including the observed explanatory variables (the dummy variables that capture the effect of the structural breaks),

$\boldsymbol{\delta}_t$ is the $(p \times 1)$ vector of unknown parameters. If the vector $\boldsymbol{\delta}_t$ does not depend on time, then $\boldsymbol{\delta}_t = \boldsymbol{\delta}_{t-1}$.

The cyclical component is assumed to be stationary second-order autoregressive process while the trend is assumed to follow a random walk with drift. The drift, in turn, is also assumed to follow a random walk (Harvey, A.C., and Jaeger, A., 1993):

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad (2)$$

$$\beta_t = \beta_{t-1} + \xi_t \quad (3)$$

where β_t is the slope (drift term). The disturbances η_t and ξ_t are mutually uncorrelated and normally distributed with mean zero. The general model described by the equations (2) and (3) considers both the trend and the slope as time-dependent stochastic series.

The stochastic cyclical component ψ_t is described in its turn by the vector equation (the translation in the state-space framework of an ARMA(2, 1) process):

$$\begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} = \rho \begin{pmatrix} \cos \lambda_c & \sin \lambda_c \\ -\sin \lambda_c & \cos \lambda_c \end{pmatrix} \begin{pmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{pmatrix} + \begin{pmatrix} \kappa_t \\ \kappa_t^* \end{pmatrix}, \quad t = 1, 2, \dots, n \quad (4)$$

where λ_c is the cycle's frequency in radians, with values within the interval $[0, \pi]$, κ_t and κ_t^* are uncorrelated disturbances with normal distribution and common variance σ_κ^2 , and ρ is the damping (attenuation) factor, with values within the interval $(0, 1]$. The period of the cycle is determined by the relationship $T_c = 2\pi/\lambda_c$. Since the damping factor ρ is lower than unit, it results that the ψ_t series is stationary and describes an ARMA(2, 1) process where the terms AR and MA are restricted (Harvey, Andrew C., 1994).

The stochastic seasonal component γ_t may be also trigonometrically defined, as in the case of the cycle. It decomposes into the series $\gamma_{i,t}$ of frequencies $\lambda_i = 2\pi i/s$ where $i = 1, 2, \dots, s/2$ (for quarterly data $s = 4$) according to the equations (Harvey, 1985):

$$\begin{pmatrix} \gamma_{i,t} \\ \gamma_{i,t}^* \end{pmatrix} = \begin{pmatrix} \cos \lambda_i & \sin \lambda_i \\ -\sin \lambda_i & \cos \lambda_i \end{pmatrix} \begin{pmatrix} \gamma_{i,t-1} \\ \gamma_{i,t-1}^* \end{pmatrix} + \begin{pmatrix} \omega_{i,t} \\ \omega_{i,t}^* \end{pmatrix}, \quad t = 1, 2, \dots, n; \quad i = 1, 2, \dots, s/2 \quad (5)$$

ω_t and ω_t^* are uncorrelated disturbances with normal distribution and common variance σ_ω^2 .

The hypotheses upon which the estimating algorithm is based consider that all the disturbances in the equations (1)-(5) are uncorrelated. There are several ways in which the observed series y_t may be modelled according to the properties of the disturbances in the trend and slope equations, as follows:

- (i) $\sigma_\eta^2 \neq 0$ and $\sigma_\xi^2 \neq 0$: both the trend and the slope are stochastic series; in this case we have a local linear trend model;
- (ii) $\sigma_\eta^2 \neq 0$ and $\sigma_\xi^2 = 0$: the trend is stochastic and the slope is constant; in this case the trend becomes a random walk I(1) with (constant) drift;
- (iii) $\sigma_\eta^2 = 0$ and $\sigma_\xi^2 \neq 0$: the slope is stochastic, while the trend's level is fixed; the trend has the properties of an integrated series of second order I(2). Such a model characterizes a trend with a smooth evolution;
- (iv) $\sigma_\eta^2 = 0$ and $\sigma_\xi^2 = 0$: both the slope and the trend are fixed; in this case the trend becomes deterministic, that is $\mu_t = \mu_0 + \beta t$.

I could also exclude, under certain circumstances, the slope or the trend from the model if after performing the computations I found that they are statistically insignificant (such a feature is indicated by the t-student ratio of the final state vector).

After determining the values of the hyperparameters ($\sigma_\varepsilon, \sigma_\eta, \sigma_\xi, \sigma_\kappa, \sigma_\omega, \rho, \lambda_c$) the trend, slope, and cyclical and seasonal components are estimated, as well as the coefficients of the explanatory variables by applying a smoothing algorithm. The computations may be performed with the GAUSS, STAMP (Koopman S.J., Harvey, A.C., Doornik, J.A. and Shephard, N., 1995) or EViews packages.

The data

Next, I will analyze the quarterly GDP series with statistical data over the interval 1994-2003. It could be mentioned that quarterly GDP in constant prices of 1994 was computed by specialists of Romanian National Institute of Statistics with a financing from the CERGE-GDN project „Adapted models to estimate potential GDP in the candidate countries”. For the beginning, I will try to estimate the model (1)-(5) without explanatory variables, with the dependent variable y_t equals to the log of (seasonally adjusted) GDP. Such an analysis will lead us to a subsequent improvement of the model taking into account the effects of the outliers.

Figure 1 shows the graphs of log quarterly real GDP (Lgdp) and the corresponding seasonally adjusted series (Lgdps) over the period 1994:1-2003:4. A strong seasonal pattern of the Lgdp series is visible, hiding the long-term behaviour revealed by the trend's properties, as well as the medium-term behaviour revealed by the cycle's properties. Thus, the first step in my analysis is to

eliminate the seasonality. The seasonally adjusted series Lgdps will follow the annual GDP trend, but will be partly influenced also by the events specific to the quarterly level. There are two ways of dealing with seasonality: either to eliminate it and subsequently to apply the Kalman filter upon the log of seasonally adjusted series or to estimate the seasonal component within the model, together with the other components.

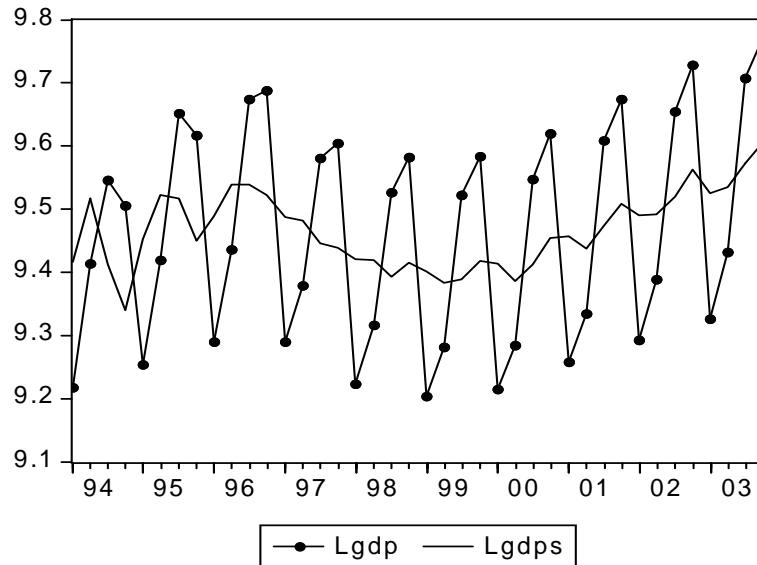


Figure 1. Log of GDP and seasonally adjusted GDP in Romania over the period 1994:1-2003:4

Source: National Institute of Statistics and author's own computations

Three types of seasonality are documented in the literature (Harvey, Andrew, 1994): trigonometric, dummy and fixed. Several models were estimated for each seasonal „pattern”, and were found that the first two types generally induce similar results, while the fixed seasonality influences the properties of the output gap. The trigonometric (dummy) seasonal component estimated within the model is stochastic, taking over certain random tendencies of the trend and cycle, and at the same time eliminating the disturbance ε_t from the measurement equation (1).

Model 1

Because I'm interested to have control on the seasonality I have chosen the fixed seasonality. First, using STAMP, I have formulated a model consisting of a "Local Trend" and a "Fixed Seasonality" to generate the seasonally adjusted series $Lgdps = Trend$. Then, I've estimated the Harvey-Jaeger model (1)-(5) (the case with stochastic trend) with the dependent variable $y_t = Lgdps$ and without explanatory variables:

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t \quad (1)$$

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad (2)$$

$$\beta_t = \beta_{t-1} + \xi_t \quad (3)$$

$$\psi_t = \text{medium term cycle } (\kappa_t \text{ disturbance}) \quad (4)$$

$$\gamma_t = \text{quarterly cycle } (\omega_t \text{ disturbance}) \quad (5)$$

The method of fixed seasonality used to extract Lgdps could determine the ε_t -perturbations to incorporate residual seasonal effects for the observations at the end of the sample. Thus, for modelling this residual seasonality, we keep γ_t in the measurement equation (1) as a cyclical stochastic component at a high frequency.

Indeed, the empirical results show the presence of two cycle components where the quarterly cycle γ_t appears to be almost irregular.

Below are given the values of the hyperparameters estimated with the STAMP programme:

The standard deviations of disturbances

$$\sigma_\varepsilon = 0.00574; \sigma_\eta = 0; \sigma_\xi = 0.00362;$$

$$\sigma_\kappa = 0.00530; \sigma_\omega = 0.01027;$$

The parameters of cycles

$$\text{the damping factors: } \rho_\kappa = 0.984; \rho_\omega = 0.965;$$

$$\text{the frequencies: } \lambda_\kappa = 0.26142; \lambda_\omega = 1.49471;$$

$$\text{the amplitudes: } \alpha_\kappa = 0.0205; \alpha_\omega = 0.0320$$

All the series include stochastic elements, except the level of the trend that is estimated to be fixed. In this case the trend has the properties of an integrated series of second order I(2). The cyclical components are sinusoidal waves that levels down over time with a 98%-97% attenuation factor. The estimated frequencies correspond to the periods of approximately six years and one year, respectively.

The significant stochastic behaviour of the quarterly cycle γ_t determines the large differences between consecutive gaps and has no an economic explanation. A statistical explanation is that of the change in the seasonal pattern specific to the period 1994:1-1995:4 where the last quarter of the year had lower values as compared to the previous one, followed by a steadily increasing of the quarterly trend recorded since 1996.

Figure 2 shows the components of Lgdps as according to the model's estimates, namely the estimated trend with a smooth evolution, the stochastic slope, and the stochastic cycles.

The empirical results indicate that the log output gap (the interference between the two cyclical components) is still dominated by seasonal factors with a high degree of uncertainty. The distance between the extreme points of the trend (minimum and maximum values) is $D_{\text{trend}} = 0.1433$, while the amplitudes of the cycles are $\alpha_\kappa = 0.0205$ and $\alpha_\omega = 0.0320$. This model is one specific for an I(2) trend although the Augmented Dickey-Fuller test found that Lgdps series is I(1) (see the next paper "*Determining the output gap and the inflationary shocks dynamics, the case of Romania*").

This result if possible from a statistical point of view: in the cases when the standard deviation of the slope is relatively small (as compared with the standard deviation of the quarterly cycle, in our example) the I(2) component may be difficult to detect by the ARIMA methodology.

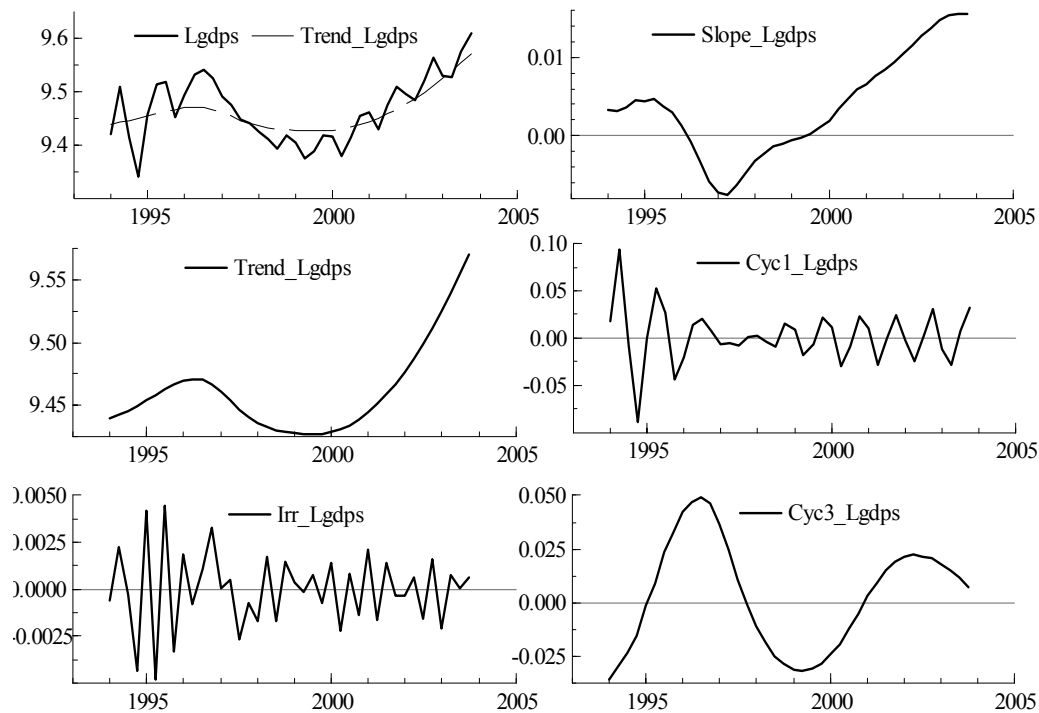


Figure 2. Log of seasonally adjusted GDP (Lgdps) in Romania over the period 1994:1-2003:4 with trend, slope, cycles, random component
Source: National Institute of Statistics and author's own computations.

Harvey and Jaeger (1993) have tried to bring economic arguments in the favour of this situation: “A trend plus cycle model of the form (1-5) with $\sigma_{\eta} = 0$ has stationary components with no persistence and a smooth $I(2)$ trend with infinite persistence. But since the trend reflects slow long-term changes in growth rates, perhaps arising from demographic changes, innovations in technology, changes in savings behavior, or increasing integration of capital and goods markets, the shock which drive the smooth trend may have no connection with short-term economic policy. Following the extensive literature on the productivity slowdown phenomenon, we may well argue that understanding the reasons for persistent changes in growth rates is one of the key problems in macroeconomics” (Harvey, A.C. and Jaeger, A., 1993).

Their conclusion regarding ARIMA modeling is the same as that of Watson (1986): “For purposes of short-term forecasting a parsimonious ARIMA model, such as ARIMA(1,1,0), may well be perfectly adequate compared with a trend plus cycle model. But as a descriptive device it may have little meaning and may even be misleading” (Harvey, A.C. and Jaeger, A., 1993).

The other important hyperparameters that indicate the goodness of fit of the model are:

- Strong convergence reached after 44 iterations
- $R^2 = 0,806$; $\sigma^2 = 0.00070$; $Rd^2 = 0.598$;
- $DW = 1.9399$; $N = 3.2628$; $H(12) = 0.2157$; $Q(14, 6) = 12.976$

If the model is correctly specified, then in the case of a large number of observations DW has the distribution $N(2, 4/T)$, N has the distribution $\chi^2(2)$ (null hypothesis = normal distribution); H(m) has the distribution $F(m, m)$ (null hypothesis = absence of heteroscedasticity), Q(P, q) has the distribution $\chi^2(q)$ (null hypothesis = absence of serial correlation). These statistics have the following significance:

R^2 is the coefficient of determination;

σ^2 is the estimated one-step-ahead prediction error variance;

Rd^2 is the coefficient of determination based on differences, equal to 1 minus the ratio of the estimated one-step-ahead prediction error variance to the variance of the first differences of the observations;

DW is the Durbin-Watson test statistics,

N comes from the *normality* test of Doornik and Hansen (1994);

H(m) is a test statistics for *heteroscedasticity*, equal to the ratio of the last m to the first m sums of squares of residuals (m is less than a third of the total number of observations, n, minus the number d of non zero deviations among $\sigma_\eta, \sigma_\xi, \sigma_\kappa$);

Q(P, q) is the statistics of the Box-Ljung test for *residual serial correlation* based on the first P residual autocorrelations and q is equal to P+1 minus the number of hyperparameters

The results of the tests reveal the lack of heteroscedasticity and the presence of serial correlation between the residuals for the superior lags. The probability of a normal error distribution reaches only 20%. The high values of the determination coefficients R^2 and Rd^2 show as satisfactorily the way the Lgdps series was decomposed into unobservable components. The model built with series in levels leads to better statistical results than a model with series in differences.

The parameters of economic interest presented in Table 1 are those of the unobserved components at the end of the period. Such values known as "estimated coefficients of the final state vector" are used in order to build up the series within the forecasting period. In the table are also included the standard error and the t-ratio with the two-sided Prob. for each coefficient, needed for testing the null hypothesis of a zero value. The results in Table 1 indicate that the level and the slope are significant, concluding once again that the trend is an I(2) process.

Table 1. Estimated coefficients of final state vector in the Harvey model

Variable	Coefficient	R.m.s.e.	t – value	Probability
Level	9.5702	0.025027	382.39	0.0000
Slope	0.015518	0.0077799	1.995	0.0533
ψ Cycle 1	0.031635	0.011421		
ψ Cycle 2	-0.0050383	0.013184		
γ Cycle 1	0.0072881	0.020620		
γ Cycle 2	-0.019169	0.019100		

Figure 3 shows the residuals of the fitted model (they capture the random influences of all the unobserved variables), the correlogram and the estimated spectral density of residuals. The distribution function estimated by the model is compared with the normal distribution. The sum of

the variances of all the components in the measurement equation (1) and the variance of the irregular should, in theory, must be equal to the variance of the observed variable.

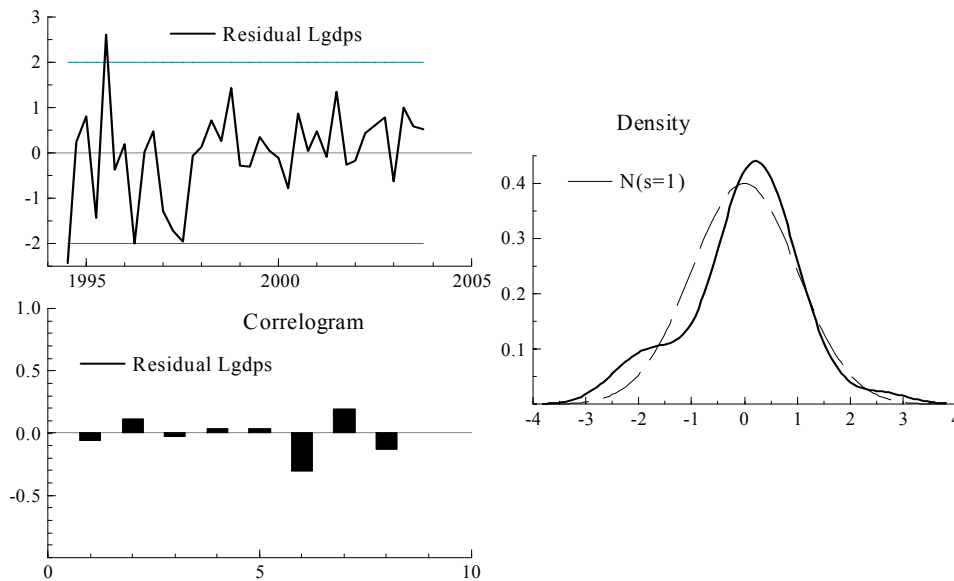


Figure 3. Residuals of the adjusted model, its correlogram and spectral density

Based on the above-mentioned arguments resulted from the statistical tests, as well as on the overall picture provided by the Figures 2 and 3, I can conclude that the Harvey model of the log seasonally adjusted GDP of the Romanian economy is satisfactorily, but requires subsequent improvements. It may be improved by introducing certain dummy, step or staircase variables able to correct the imperfections generated by the outliers and structural breaks. Their existence may be detected from the analysis of the auxiliary residuals of the observed series, of the level and slope, which are generated by the Kalman filter algorithm (Abril, 1997, Harvey, 1994). The graphs of the auxiliary residuals for the Harvey model are presented in Figure 4.

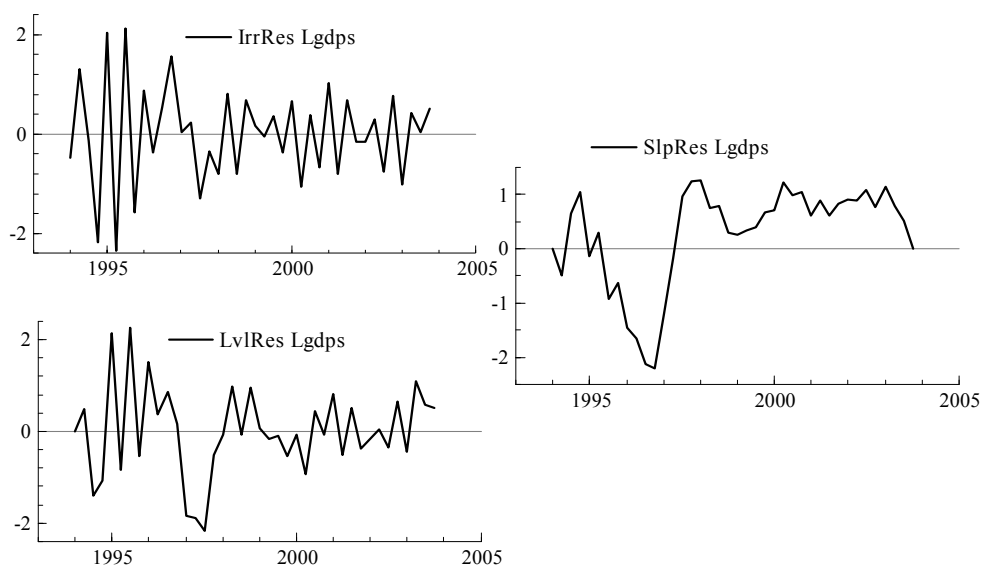


Figure 4. The auxiliary residuals for the observed series, level, and slope

The auxiliary residuals of the observed series reach high values in the interval 1994:2-1995:4, which means that applying certain impulse interventions at these moments the statistical results of the model might be improved. The auxiliary residuals of the trend's level reach high values in 1995:1 and 1995:3, and the slope's auxiliary residuals in 1996:3 and 1995:4. The latter ones exhibit a probability distribution farther than the normal distribution as compared to the trend and the observed series residuals, as the statistics of the N test of Doornik and Hansen reveal.

Model 2

The Harvey model has the inconvenience of an $I(2)$ trend that is not easy to be explained by the economic theory. Next, I'll analyse the case of the model with the level of the trend set at a fixed value (in equation (2) does not exist an irregular term). The simulations performed with the log GDP series show that both the model with stochastic slope and that with constant slope lead to identical statistical results; in both cases the estimated trend is linear deterministic.

Figure 5 shows the components of Lgdps as according to the estimates of the model, namely the linear deterministic trend, the slope of trend equal to 0.00281, and the stochastic cycles.

As in the previous Harvey model we have two cycles, but the amplitude of the cycle in the medium term (0.0622) becomes significantly superior to that corresponding to the quarterly cycle (0.0359). The cyclical components are sinusoidal stochastic waves that levels down over time with a 98%-97% damping factor. The estimated value of the medium term cycle's frequency corresponds to a period of 31.4902 quarters, namely approximately 7 years and 10 months.

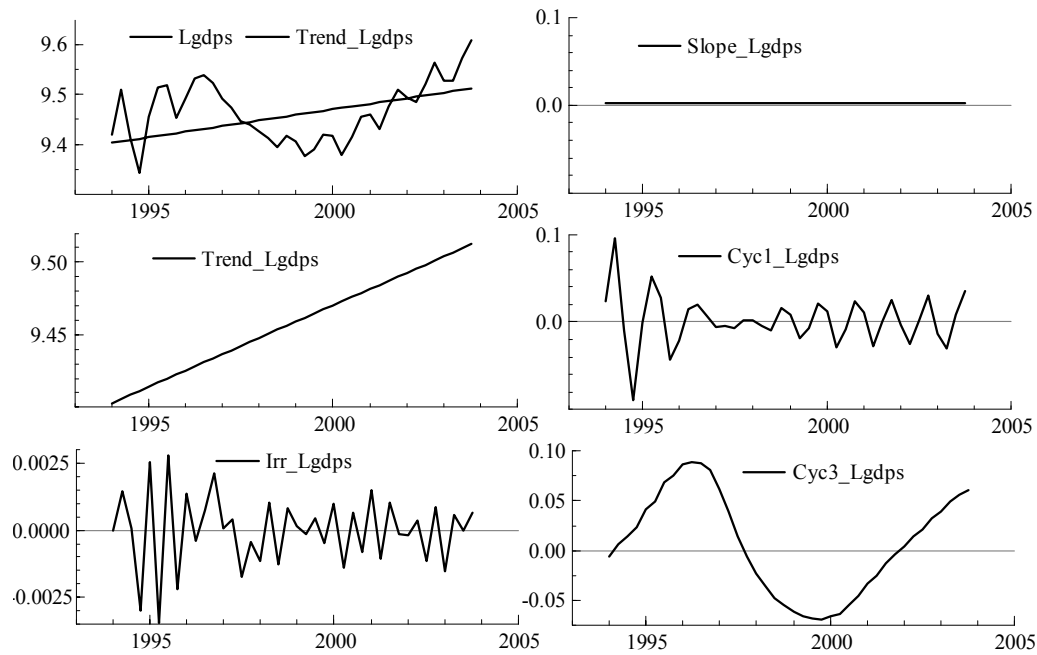


Figure 5. Log of seasonally adjusted GDP in Romania over the period 1994:1-2003:4 with deterministic trend, constant slope, cycles and random component
Source: National Institute of Statistics and author's own computations

The values of the hyperparameters estimated with STAMP are the follows:

The standard deviations of disturbances

$$\sigma_{\varepsilon} = 0.0046821; \sigma_{\xi} = 0.0;$$

$$\sigma_{\kappa} = 0.0084181; \sigma_{\omega} = 0.010366;$$

The parameters of cycles

$$\text{the damping factors: } \rho_{\kappa} = 0.986; \rho_{\omega} = 0.967;$$

$$\text{the frequencies: } \lambda_{\kappa} = 0.19953; \lambda_{\omega} = 1.48532;$$

$$\text{the amplitudes: } \alpha_{\kappa} = 0.0622; \alpha_{\omega} = 0.0359$$

In order to test the validity of the estimated parameters, the following statistics were computed:

- Average convergence reached after 63 iterations
- $R^2 = 0.849$; $\sigma^2 = 0.00055$; $Rd^2 = 0.686$ -slight improvement as compared with Harvey
- $DW = 1.9409$; $H(12) = 0.2023$; $Q(13, 6) = 12.127$; $N = 2.3615$ -close to the Harvey statistics - there are no differences between the models as regards validity.

Moreover, the residuals series (of the adjusted model) for the two types of analyzed models are quite equivalent, as one may notice from Figure 6.

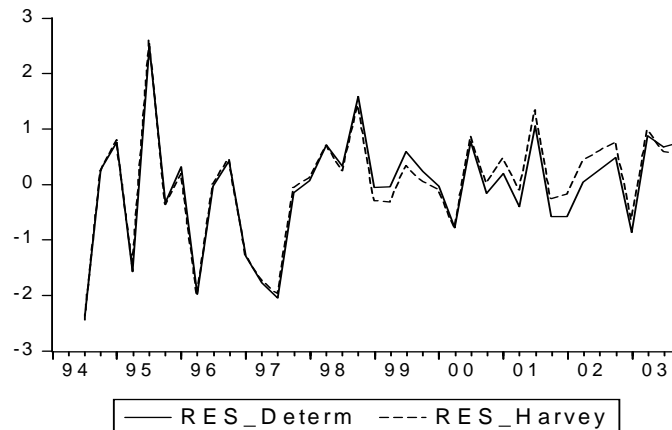


Figure 6. Comparison between the residuals of the Harvey model and those of the deterministic trend model

Based on the arguments resulted from the statistical tests, as well as on the comparisons of the data series in Figure 6, I can conclude that the Harvey model and the deterministic trend model are equivalent as concerns the degree of validity.

Model 3

In the last section of the analysis of the univariate class models with unobserved components, I'll try to generalize the standard univariate model by taking into account the impact of the structural breaks and outliers.

The central idea is not to introduce in the model structural interventions beginning with the year 1996, because I believe that one of the causes of the misspecification of the model is some uncertainty in the estimation of quarterly GDP for 1994:1-1996:4. It is known that Romanian National Institute of Statistics (RNIS) publishes the quarterly GDP beginning with 1997. Also, the specialists of RNIS computed the complete series for the 1994-2003 used in this study with financing from the CERGE-GDN project „*Adapted models to estimate potential GDP in the candidate countries*”. In their opinion, the problems related to the estimation of the quarterly series of the National Accounts appear due to the changes in the methodology of the monthly indicators starting with 1996-1997. In this case, some extrapolations and re-computations of some relevant indicators were made. The statistic-econometric methods for the detection of the incertitude in the quarterly national accounts were already applied on the Romanian economy*.

Before applying the univariate model with interventions to estimate the potential GDP I'll introduce the notions of *outlier* and *structural break*. An outlier is an observation isolated from the rest of the observations, which if included in the estimating algorithm of the parameters would determine a bias in the average evolutionary trend given by the other observations. The effect of

* Lawrence R. Klein, Andrei Roudoi, Cristian Stanica (2003), “Quarterly GDP data correction using principal components analysis. The case of Romanian economy - GDP expenditures side”, *Romanian Journal of Economic Forecasting*, Supplement 2004, Expert Publishing House.

such an observation may be eliminated by a dummy explanatory variable in the measurement equation (1), also named *impulse intervention variable*. This variable has value 1 at the moment of the outlier and zero for any other moment in time.

A structural break in the level occurs when the y_t level of series suddenly jumps up or down, usually due to a specific event. Such a sudden variation is modelled by a *step intervention variable* included in the measurement equation (1), which has zero value before the event and 1 at the moment when the event occurs and afterwards. It may be also modelled by an explanatory dummy variable in the transition equation (2).

A structural break in the slope may be modelled by a *staircase intervention variable* in the measurement equation (1), which takes values 1, 2, 3, ..., starting with the moment of the break. It may be also used a dummy variable in the transition equation (3).

It worth noticing that the outliers and structural breaks may be seen as effects of certain impulse interventions introduced in the equations (1), (2) or (3) that describe the evolutions of the observed series, of the trend and of the slope, respectively. At the same time, under certain circumstances is more useful to consider these structural changes as a consequence of the occurrence of too large values within the irregular disturbances ε_t , η_t , and ξ_t . Thus, interventions can be seen as fixed or random effects; however, the random effects approach is more flexible.

Taking into account the above mentioned I'll consider three explanatory variables in the measurement equation (1) that correspond to the outliers at the moments 1994:2, 1994:4 and 1995:4, respectively (according to the auxiliary residuals estimated with the Harvey model):

$$\begin{aligned} z_{1,t} &= 1 \text{ for } t = 2 \text{ (quarter 1994:2) and } 0, \text{ otherwise} \\ z_{2,t} &= 1 \text{ for } t = 4 \text{ (quarter 1994:4) and } 0, \text{ otherwise} \\ z_{3,t} &= 1 \text{ for } t = 8 \text{ (quarter 1995:4) and } 0, \text{ otherwise} \end{aligned}$$

With the help of the Kalman filter the values of hyperparameters are estimated, and they will be further used for the generation of the unobservable series:

The standard deviations of disturbances

$$\begin{aligned} \sigma_\varepsilon &= 0.00249 \text{ (0.00574 Harvey)}; \quad \sigma_\eta = 0.0 \text{ (0.0 Harvey)}; \quad \sigma_\xi = 0.00499 \text{ (0.00362 Harvey)}; \\ \sigma_\kappa &= 0.0 \text{ (0.00530 Harvey)}; \quad \sigma_\omega = 0.00774 \text{ (0.01027 Harvey)}; \end{aligned}$$

The parameters of cycles

$$\begin{aligned} \text{the damping factors: } &\rho_\kappa = 1.000 \text{ (0.984 Harvey)}; \quad \rho_\omega = 0.917 \text{ (0.965 Harvey)}; \\ \text{the frequencies: } &\lambda_\kappa = 0.29938 \text{ (0.26142 Harvey)}; \quad \lambda_\omega = 1.4871 \text{ (1.49471 Harvey)}; \\ \text{the amplitudes: } &\alpha_\kappa = 0.0263 \text{ (0.0205 Harvey)}; \quad \alpha_\omega = 0.0251 \text{ (0.0320)} \end{aligned}$$

The diagnostic and goodness of fit statistics are:

- Strong convergence reached after 45 (44 Harvey) iterations
- $R^2 = 0.907$ (0,806 Harvey); $\sigma^2 = 0.0003$ (0.0007 Harvey); $Rd^2 = 0.807$ (0.598 Harvey);

- DW = 1.835 (1.940 Harvey); Q(17, 6) = 17.767 (12.976 Harvey);
- N = 0.150 (3.263 Harvey); H(12) = 0.8178 (0.2157 Harvey);

The Harvey model with interventions presents similar properties as the univariate Harvey model. Again we detect the presence of two cyclical components, one at the quarterly level, which measures the residual seasonal effects, another in the medium term with a period of 5 years and 3 months.

The effect of the quarterly cycle (hard to interpret from an economic point of view) is the same in both models but only for 1996-2003. The irregular component has negligible amplitude as compared to the dimension of the other components' variation, which allows us to incorporate it in the random cycle γ_t without modifying the statistical properties of the model.

By analysing the goodness of fit statistics I can conclude that the model with interventions is more appropriate for the data as compared to the previous two models, except the serial correlation of the errors, which is significant. The properties of the quarterly random cycle as well as the negligible values of the irregular component, allows us to consider the model with interventions in a different way. This model is a Harvey-type one with one deterministic cycle and a random transitory component. The transitory component (ε_t) is modelled as a stationary second-order autoregressive process while the trend is assumed I(2):

$$\begin{aligned}
 y_t &= \mu_t + \psi_t + \varepsilon_t + \delta_1 z_{1,t} + \delta_2 z_{2,t} + \delta_3 z_{3,t} \\
 \mu_t &= \mu_{t-1} + \beta_{t-1} + \eta_t \\
 \beta_t &= \beta_{t-1} + \xi_t
 \end{aligned}$$

Figure 7 shows the components of log seasonally adjusted GDP as according to the estimates of the model, namely the I(2) trend, the stochastic slope, the deterministic cycle and the random transitory component.

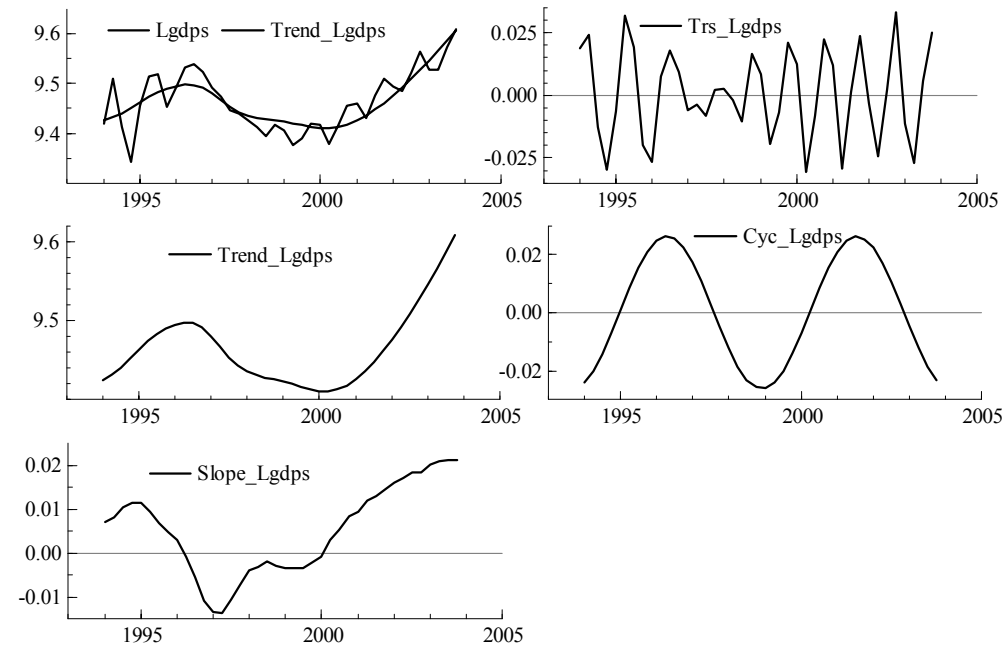


Figure 7. Log of seasonally adjusted GDP in Romania over the period 1994:1-2003:4 with I(2) trend, stochastic slope, deterministic cycle and transitory component
 Source: National Institute of Statistics and author's own computations

It is also required to check up the importance of the explanatory variables. Table 2 includes the estimated values of the coefficients of those variables together with the standard error and the t-ratio value for each coefficient. The t-test values reveal that the observed outliers in the log GDP series are significant.

Table 2. Estimated coefficients of explanatory variables

Coefficient	Estimated value	R.m.s.e.	t – value	Probability
δ_1	0.072734	0.014732	4.9371	0.0000
δ_2	-0.072724	0.012846	-5.6614	0.0000
δ_3	-0.038933	0.010882	-3.5777	0.0010

From the analysis of the diagnostic and goodness of fit statistics I consider the Harvey model with interventions as the most appropriate univariate model (with interventions) to estimate the unobserved components of log quarterly GDP in the Romanian economy. This model has two important features: a deterministic cycle having a period of 5 years and 3 months and a trend component modelled as a I(2) process.

References

- De Brower, Gordon (1998), „*Estimating Output Gaps*”, Reserve Bank of Australia, Economic Research Department, Research Discussion Paper 9809, August
- Cerra, V. and S. Chaman Saxena (2000), “*Alternative Methods of Estimating Potential Output and the Output Gap: An Application to Sweden*”, IMF Working Paper 00/59
- Clarida, R., J. Gali and M. Gertler (1999), “*The Science of Monetary Policy: A New Keynesian Perspective*”, Journal of Economic Literature, 37, p. 1661 – 1707
- Claus, Iris (2000), “*Is the Output Gap a Useful Indicator of Inflation*”, Reserve Bank of New Zealand, Discussion Paper Series No.5, March
- Claus, Iris (1999), “*Estimating Potential Output for New Zealand*”, Reserve bank of New Zealand, Discussion Paper Series, No. 3, July
- Conway, Paul, and Ben Hunt (1997), “*Estimating Potential Output – a semi-structural approach*”, Discussion Paper Series, No. 9, December
- Dupasquier, Chantal, Alain Guay, and Pierre St-Aman, “*A Comparison of Alternative Methodologies for Estimating the Potential Output and the Output Gap*”, Bank of Canada, Working Paper No. 5, February
- Gerlach, S. and F. Smets (1997), “*Output Gap and Inflation: Unobservable Components Estimates for the G-7 Countries*”, Bank of International Settlements mimeo, Basel
- Harvey, A.C. and A. Jaeger (1993), “*Detrending, Stylized Facts, and the Business Cycle*”, Journal of Applied Econometrics, 8, p. 231 – 247
- Jensen, Ch. And B.T. McCallum (2002), “*The Non-Optimality of Proposed Monetary Policy Rules under Timeless - Perspective Commitment*”, NBER Working Paper No. 8882
- Kamada, K. and K. Masuda (2000), “*Effects of Measurement Error on the Output Gap in Japan*”, Bank of Japan, Research and Statistics Department Working Paper No. 00-15
- Kikian, Maral (1999), “*Measuring potential Output within a State-Space Framework*”, Bank of Canada, Working Paper No. 9, April
- Kuttner, K. N. (1994), “*Estimating Potential Output as a Latent Variable*”, Journal of Business and Economic Statistics, 12, p. 361 – 368
- McCallum, B.T. (2001), “*Should Monetary Policy Respond Strongly to Output Gaps?*” American Economic Review, 91, p. 258 – 262
- McCallum, B.T. and E. Nelson (2000), “*Timeless Perspective vs. Discretionary Monetary Policy in Forward - Looking Models*”, NBER Working Paper No. 7915
- Orphanides, A. and S. van Norden (2001), “*The Unreliability of Output Gap Estimates in Real Time*”, CIRANO, Scientific Series, No. 57
- Schnabel, G. (2002), “*Output Trends and Okun’s Law*”, BIS Working Paper No. 111
- Scott Alasdair (2000), “*A Multivariate Unobserved Components Model of Cyclical Activity*”, Reserve bank of New Zealand, Discussion Paper Series, No. 4, January
- Smets, F. (1998), “*Output Gap Uncertainty: Does It Matter for the Taylor Rule?*”, BIS Working Paper No. 60

St-Aman, Pierre, Simon van Norden, “*Measurement of the Output Gap: A discussion of the Recent Research at the bank of Canada*”, Bank of Canada, Technical Report No. 79, August

Svensson, L.E.O. (1999), “*How Should Monetary Policy Be Conducted in an Era of Price Stability*”, in “New Challenges for Monetary Policy”, Federal Reserve Bank of Kansas City, p. 195 – 259

Svensson, L.E.O. and M. Woodford (2000), “*Indicator Variables for Optimal Policy*”, NBER Working paper No. 7953, October

Tanizaki, H. (1996), “*State – Space Models in Linear Case*”, Paper published by The Faculty of Economics, Kobe University

Walsh, C. (2001), “*The Output Gap and Optimal Monetary Policy*”, Paper published by The Department of Economics, University of California, Santa Cruz

Watson, M.W. (1986), “*Univariate Detrending Methods with Stochastic Trends*”, Journal of Monetary Economics, 18, p. 49 – 75

Woodford, M. (1999), “*Optimal Policy Inertia*”, NBER Working Paper No. 7261

Annex 1. (Bibliography) – The state-space representation of the general model

In order to be estimated with the Kalman filter, the general model (1)-(5) with unobserved series must be translated in a compact representation named the *state-space framework*. The equations (1)-(5) are turned into a system with two vector equations where the observed variables \mathbf{y}_t are connected with the unobserved ones $\boldsymbol{\alpha}_t$:

$$\begin{aligned}\mathbf{y}_t &= \mathbf{H}_t \boldsymbol{\alpha}_t + \mathbf{A}_t + \mathbf{N}_t \boldsymbol{\varepsilon}_t \\ \boldsymbol{\alpha}_t &= \mathbf{F}_t \boldsymbol{\alpha}_{t-1} + \mathbf{B}_t + \mathbf{R}_t \boldsymbol{\eta}_t\end{aligned}$$

where $\boldsymbol{\alpha}_t$ is a $m \times 1$ state vector comprising the unobserved variables (trend, cycle, seasonal component) that we want to estimate.

The first equation is called the *measurement equation*, where the vector of observed variables \mathbf{y}_t is connected with the state vector $\boldsymbol{\alpha}_t$. The second equation is called the *transition equation* and describes the dynamics of the $\boldsymbol{\alpha}_t$ vector. In both equations the disturbance vectors are multi-normally distributed:

$$\begin{pmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{\eta}_t \end{pmatrix} \approx \mathbf{N} \left(\begin{pmatrix} \mathbf{0} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0} & \mathbf{G} \end{pmatrix} \right)$$

The matrices \mathbf{H}_t , \mathbf{A}_t , \mathbf{N}_t , \mathbf{F}_t , \mathbf{B}_t , \mathbf{R}_t and the covariance matrices \mathbf{Q} and \mathbf{G} are estimated in the Kalman filter algorithm through the rule of maximizing the log likelihood function of the model with starting conditions $\boldsymbol{\alpha}_1 = \mathbf{B}_1 + \mathbf{R}_1 \boldsymbol{\eta}_1$.

The general model defined by the equations (1)-(5) may be translated in the state space representation. In this case, we assume that the vector $\boldsymbol{\delta}_t$ is constant and has the order p , y_t is a scalar, the matrices \mathbf{A}_t and \mathbf{B}_t are zero and $\mathbf{N}_t = 1$ reduces to a constant scalar dimension. The $(7 + p) \times 1$ state vector $\boldsymbol{\alpha}_t$ becomes:

$$\boldsymbol{\alpha}_t = (\mu_t \quad \beta_t \quad \psi_t \quad \psi_t^* \quad \gamma_{1,t} \quad \gamma_{1,t}^* \quad \gamma_{2,t} \quad \boldsymbol{\delta}'_t)'$$

while the matrix \mathbf{H}_t is a $1 \times (7 + p)$ vector:

$$\mathbf{H}_t = (1 \quad 0 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \quad \mathbf{z}'_t)$$

In order to write in a simplified way the matrices \mathbf{F}_t and \mathbf{R}_t we consider the null column vector $\mathbf{0}$ of order $p \times 1$ and the $p \times p$ unit matrix \mathbf{I}_p . The matrices \mathbf{F}_t and \mathbf{R}_t of order $(7 + p) \times (7 + p)$ and $(7 + p) \times 7$, respectively, are computed as follows:

$$\mathbf{F}_t = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \mathbf{0}' \\ 0 & 0 & \rho \cos \lambda_c & \rho \sin \lambda_c & 0 & 0 & 0 & \mathbf{0}' \\ 0 & 0 & -\rho \sin \lambda_c & \rho \cos \lambda_c & 0 & 0 & 0 & \mathbf{0}' \\ 0 & 0 & 0 & 0 & \cos(\pi/2) & \sin(\pi/2) & 0 & \mathbf{0}' \\ 0 & 0 & 0 & 0 & -\sin(\pi/2) & \cos(\pi/2) & 0 & \mathbf{0}' \\ 0 & 0 & 0 & 0 & 0 & 0 & (-1) & \mathbf{0}' \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{I}_p \end{bmatrix}$$

$$\mathbf{R}_t = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{bmatrix}$$

Finally, the 7 x 1 disturbance vector $\boldsymbol{\eta}_t$ and the 7 x 7 covariance matrix \mathbf{G}_t are:

$$\boldsymbol{\eta}_t = \begin{bmatrix} \eta_t \\ \xi_t \\ \kappa_t \\ \kappa_t^* \\ \omega_{1,t} \\ \omega_{1,t}^* \\ \omega_{2,t} \end{bmatrix}, \quad \mathbf{G}_t = \begin{bmatrix} \sigma_\eta^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_\xi^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_\kappa^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_\kappa^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_\omega^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_\omega^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma_\omega^2 \end{bmatrix}$$

Appendix 2 – Output gap series

	Model1 gap1	Model2 gap2	Model3 gap3
94Q1	-2491.7	-2044.0	-2319.2
94Q2	-353.4	102.6	-227.3
94Q3	1344.1	1805.6	1406.7
94Q4	738.5	1211.0	715.3
95Q1	-2305.5	-1809.1	-2417.1
95Q2	-489.3	29.2	-693.6
95Q3	2664.6	3209.7	2400.0
95Q4	2090.3	2648.3	1783.4
96Q1	-2126.6	-1565.1	-2457.9
96Q2	-439.4	103.3	-793.9
96Q3	2921.8	3420.5	2570.0
96Q4	3203.6	3625.8	2883.6
97Q1	-2023.7	-1711.4	-2275.2
97Q2	-921.0	-736.4	-1089.7
97Q3	1813.3	1867.9	1727.6
97Q4	2249.7	2189.9	2218.3
98Q1	-2396.6	-2551.7	-2396.9
98Q2	-1361.1	-1591.9	-1351.8
98Q3	1267.4	972.4	1289.4
98Q4	2059.2	1712.1	2090.0
99Q1	-2496.2	-2891.1	-2441.1
99Q2	-1689.5	-2128.1	-1598.7
99Q3	1251.3	774.1	1383.4
99Q4	2105.8	1595.8	2284.2
20Q1	-2389.9	-2922.3	-2171.7
20Q2	-1697.7	-2241.9	-1444.7
20Q3	1496.1	958.5	1756.9
20Q4	2500.1	1984.2	2753.2
21Q1	-2144.4	-2622.8	-1920.9
21Q2	-1391.2	-1822.5	-1201.4
21Q3	2079.0	1708.6	2214.8
21Q4	2980.1	2680.6	3057.9
22Q1	-2192.9	-2408.0	-2182.4
22Q2	-1224.4	-1340.0	-1288.8
22Q3	2249.2	2248.5	2109.9
22Q4	3286.1	3419.2	3066.5
23Q1	-2462.0	-2181.2	-2750.8
23Q2	-1420.7	-974.2	-1791.8
23Q3	2322.1	2944.6	1863.0
23Q4	3241.8	4047.1	2690.4

Chapter 2. Determining the Output Gap and the Inflationary Shocks Dynamics. The Case of Romania^{*}

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Cristian Stănică^{***}

Abstract

This paper evaluates the output gap and the effects of the inflationist shocks to the Romanian Economy. We use an extension of the Blanchard-Quah decomposition. The model takes into consideration three variables: the real output, the unemployment rate and the inflation. Three types of shocks are evaluated: the productivity shocks (on the supply side), the adverse shocks in the labor market and the adverse shocks in the good and services market, with a focus on the inflationist shocks. The seasonal pattern of the data regarding quarterly GDP imposes a de-seasoned approach. The analysis of the dynamics of the shocks is confirmed by the real evolutions in the Romanian economy in the period 1994-2003; also a Phillips relationship between inflation and unemployment is emphasized. A provisional *ex post* estimate for 2004 was done, and the results included a forecast of the evolution in 2005. The conclusions confirmed the relevance of the labor market shocks and the productivity shocks upon unemployment. The equilibrium was reached in about 4 years – same as in the case of the output. As regards the productivity shocks, it was found that they did not have relevance on the market of goods and services.

Introduction:

In order to analyze and forecast the macroeconomic policies, one may use the concept of potential output, or potential GDP, defined as the level of GDP that is reachable without generating inflationary tensions. That output level corresponds to the full utilization of productive capacities and to that level of employment corresponding to the non-accelerating wage inflation.

In order to assess the price and wage dynamics, one may use the „output gap” variable, defined as the difference between the real and the potential GDP. A real output level exceeding the potential one (a *positive output gap*) is a source of inflationary pressures and a signal that the monetary authorities interested in avoiding acceleration of inflation had to enforce a restrictive monetary policy. A real GDP level below the potential GDP (a *negative output gap*) corresponds to the intervals when inflation calms down and allows for a relaxation of the monetary policy. In the case of the countries that set as goal a certain inflation „target” as determining element of the monetary policies (such as Romania during the pre-accession period), the output-gap estimate and forecast might prove as a very useful tool in elaborating the monetary policies.

Nevertheless, the measuring of the *output gap* (unobservable variable) is not an easy task. Usually, certain assumptions are made as regards the potential output dynamics². Different sets of

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hypotheses, combined with various econometric techniques are used to obtain different assessments of the *output gap*; but what really matters is if the estimates' dynamics is similar, since it shows the course which the dynamics of the economic policy variables will follow.

For the decision-making process is also important the assessment of other directly non-observable macroeconomic variables, such as the NAIRU, the NAWRU, the structural budget balance (as share of the potential GDP), which exhibit different responses to the shocks occurred during the economic process.

Blanchard and Quah (1989) analyzed the way in which the perturbations (shocks) within the economy impact upon the output – viewed as a unit-root non-stationary process. They considered the hypothesis that the perturbations impacting upon the output were of two types, permanent (in the long run) and transitory (in the short run), and that these impact differently upon the other macroeconomic variables. If only a single type of perturbations within the economy would have existed, such a perturbation (shock) influenced the economy in a way that might have been characterized by univariate-moving average representations. The matter would have been then simply to have found out the substance of that perturbation and why its dynamics impacted upon the output. In addition, if the real output would have consisted of a stationary component and a simple linear trend, then the output gap might have been measured as being formed by the residuals of a regression of the output on a linear trend. If the output has been influenced by more than a single type of perturbations, the interpretation was not anymore that simple: in such a case, the output's univariate-moving average representations were a combination (resultant) of the output's dynamic response to each of these perturbations, and the individual influence of a certain perturbation could not be revealed. The above-mentioned authors considered that, given the possibility that output was influenced by more than a single type of perturbations, *a priori* restrictions might have been imposed upon the output's response to each type of perturbations, or that the information provided by other macroeconomic variables that the output might have been exploited.

The Blanchard-Quah (1989) decomposition provide a solution to such a type of problems, and most of the authors that approached that issue used the method proposed by the two authors, in different ways.

Blanchard and Quah take into account the common behavior of output and unemployment. St. Amant and van Norden (1997), Lalonde *et al.* (1998) expanded the Blanchard-Quah decomposition to the common behavior of output, unemployment and inflation, and Goran Hjelm (2003) considered the output, unemployment and the deficit consolidated budget deficit, for all using a non-restricted VAR.

² The building of econometric models is based on the assumption that economy is a process within which many factors act at random; such a hypothesis allows for the use of econometric descriptions and interpretations. Beside this fundamental hypothesis, it is accepted that the output is reasonably characterized by a non-stationary process integrated of order 1 (I(1), with unit root). Justification of such an approach is provided by the fact that the output is subject to perturbations that act in different directions and have effects over different time intervals, so that their resultant cannot have zero average and constant dispersion. This statistical characterization is accepted by most of the authors that considered the issue Campbell and Mankiw (1987), Cochrane (1988) and Blanchard and Quah (1989), St. Amant and van Norden (1997), Lalonde *et al.* (1998), Hjelm (2003).

Based on the Blanchard-Quah decomposition (1989), St. Amant and van Norden (1997)³ analyze the filtering methods with many variables that use the autoregressive vectors (VAR) incorporating long-term restrictions in comparison with the univariate methods, based on the Blanchard and Quah (1989) decomposition. Differently from the univariate filters (Hodrick-Prescott) such methods do not exhibit the end of sample difficulties and allow for the forecasting of the output gap values. The authors study the consequences of imposing long-term restrictions upon the real output (following the route of the Blanchard-Quah decomposition), then simultaneously upon the real output and inflation. They reveal the fact that the latter approach should interest the decision-makers that are focusing their attention upon the movements in the real output associated to the inflation trend.

The paper attempts to use the Blanchard-Quah decomposition in the case of the Romanian economy output over the transition period. The available data represent a small size sample (quarterly data over the interval Q1:1994 – Q4:2003), so that the conclusions require a certain degree of caution. The strong GDP seasonality, revealed by the output data series expressed in real terms, is due to the high share of agriculture in the Romanian economy (a type of agriculture based on the family small-size farm, with subsistence activities, highly influenced by the seasonal fluctuations), as well as to the seasonal dynamics of services and construction activities. Appendix 2 presents an analysis of the shocks on the de-seasoned data series. In addition, we attempted the same type of analysis for the output's industrial component (see Appendix 3). The results led to the same conclusions, with small differences in the last two cases. They revealed the behavior of the three components of the model against supply side shocks (productivity shocks), and adverse (inflationary) shocks on the labor and goods and services markets.

The transition interval was a true crisis for the Romanian economy. The shocks that acted upon the output were both permanent (influencing the supply through the decrease in labor productivity) and transitory (as, for instance, the shocks that influenced the demand through the decrease in purchasing power). Due to reasons that in our view were not imputable only to the economic side of transition, but to the social and institutional components as well (whose development was much delayed), long-term perturbations occurred not only on the supply side, but also on the demand side (the fast income polarization), which complicated the analysis. In order to reveal them we preferred the analysis of a non-restricted VAR with stationary variables (I(0)) (see Section 3). This approach corresponds to that used by Hjelm (2003) for the analysis of shocks' impacts upon the output, unemployment and structural budget balance.

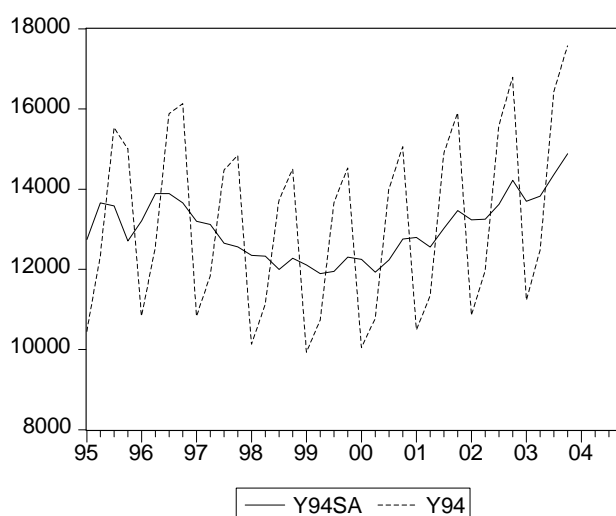
³ Pierre St-Amant and Simon van Norden shows that Cochrane (1994) uses a bivariate VAR including the output (expressed as GNP) and consumption in order to identify the permanent and transitory components of the output. The bivariate representation is developed with the ratio of the lags of consumption rate to the output. The permanent income theory involves a random character of consumption (for a constant real interest rate). Moreover, if one assumes that output and consumption are co integrated, then the output's fluctuations at a constant consumption must be perceived as transitory. On such a basis Cochrane decomposes the real output into two components: a permanent and a transitory one. In order to extract the potential output, the errors provided by VAR are orthogonalized in such a way that consumption does not respond to the shocks simultaneously with the output. Cochrane shows that if the output and consumption are co integrated and the consumption has a random character the Blanchard-Quah identification and the conventional orthogonalization are equivalent. Moreover, if consumption is of random nature, the Cochrane decomposition corresponds to the Beveridge-Nelson decomposition based on output and consumption.

Briefly, if in the Blanchard-Quah model a two variables VAR is estimated – namely output and unemployment – subject to the influence of two perturbations (shocks) – the one generated by supply and the one generated by demand – with the restriction that a single shock – the one generated by supply – impacts in the long run upon the output, the model proposed by Hjelm uses three variables, unemployment (u), output (y) and consolidated budget deficit (bb). It is also considered that unemployment and output are non-stationary of order 1, and that the consolidated budget deficit is stationary. It is assumed that these variables are subject to shocks on the labor market, which influence both unemployment and output in the long run, to productivity shocks (supply shocks), which influence only the output in the long run, and to business cycle shocks (demand shocks), which influence in the long run neither the output nor the unemployment.

1. The data

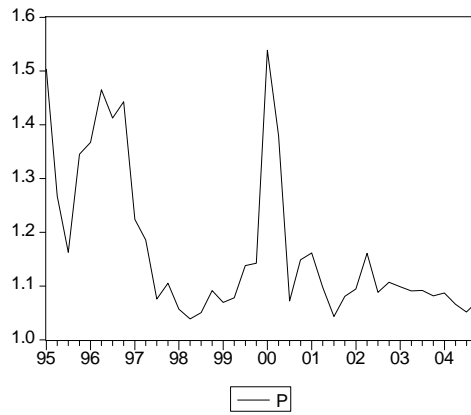
The model has three variables: output (y), unemployment (u) and inflation (p)⁴. Figure 1 shows the statistical data. We assume that the real output growth rate (Δy) follows a stationary stochastic process that responds to two types of structural shocks: permanent (ε_p) and transitory (ε_T).

Figure 1. Data: Total GDP, constant 1994 prices (y94) and the de-seasoned component (y94sa). Period: QI-994, QIV-2003

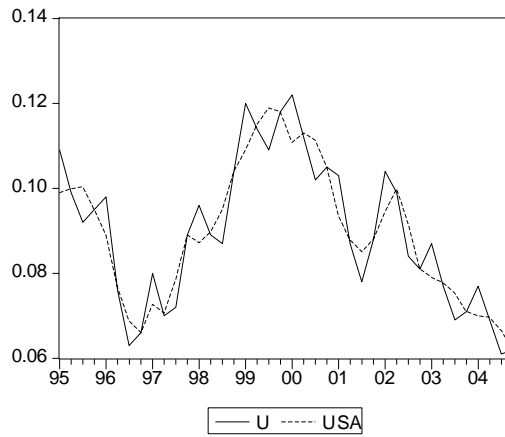


⁴ The output is the quarterly GDP computed by the National Institute of Statistics, in current prices (the model uses the real output logarithm); the unemployment is given by the unemployment rate (official data published in the Statistical Bulletins), and inflation is given by the consumer price index (total). The interval is quarter I-1994 – quarter IV-2003.

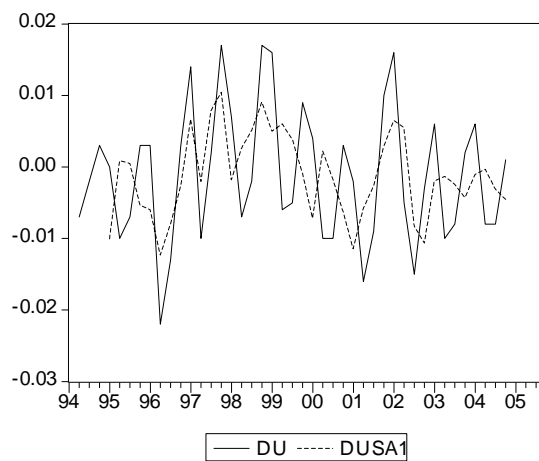
Chain-base consumer price indices. Period: QI-994, QIV-2004



Unemployment rate and its de-seasoned component. Period: QI-994, QIV-2004



Order 1 differences of unemployment rate and of its de-seasoned component



The quarterly output (total GDP), expressed in constant 1994 prices, is a series with strong seasonality, due to the high shares of agriculture and constructions, sectors that in the Romanian economy are highly depending on the weather conditions, which give them a strong seasonal character. Econometrics for data series with seasonality is in deficit in the case that a seasonal common pattern exist among the analyzed data series. Such a pattern is possible to occur between the GDP and unemployment data series (the labor employment in the above-mentioned sectors being able to influence significantly the unemployment rate). As regards the inflation rate, the component concerning the food products prices is influenced by the agricultural output, and exhibits a high seasonality over the summer-autumn interval. The correlation matrix for the gross variables (real output, unemployment rate and inflation) reveals the presence of a common seasonal pattern between the real output and unemployment rate (Appendix 1: Data series); the correlation between output and inflation being too weak to take into account a common pattern of the two variables. However, the correlation matrix for the variables used in the model (real output logarithm, order 1 differences of unemployment rate and inflation) does not reveal a common seasonal pattern among the three variables. In such a case, we considered it would be interesting to asses the results obtained by building two models for GDP and unemployment: one for the gross data series, and the other for the de-seasoned data series (the univariate-moving average representations method – Appendix 6). The designated Appendix also includes the results of the two models – the comparison of results is presented in the „Conclusions” part of this paper.

We analyze the gross data series stationarity. The output is non-stationary of order 1 I(1); the unemployment given by the unemployment rate is I(1) and inflation, given by the total consumer price index with chain base is I(0) (see Table 1). In the VAR estimation we shall include the first differences in the real output logarithm, in u and in p (Δy_{94} , Δu , p).

Table 1. Data stationarity (Augmented Dickey-Fuller Unit Root test)

	Intercept	Trend and intercept	None	Stationarity
y	0.97 (-2.61 [*])	-1.89 (-3.20 [*])	2.11(-1.62 [*])	I(1)
Δy	-6.23 (-3.62 ^{**})	-6.99 (-4.23 ^{**})	-5.22 (-2.62 ^{**})	I(0)
y₉₄	-9.48 (-3.62 ^{**})	-9.70 (-4.23 ^{**})	-0.34 (-1.62 [*])	I(0)
ly₉₄	-9.89 (-3.61 [*])	-10.16 (-4.22 [*])	0.21 (-1.62 ^{**})	I(0)
Δly_{94}	-13.56(-3.62 [*])	-13.37(-4.22 [*])	-13.70(-2.63 [*])	I(0)
u	-2.22 (-2.60 [*])	-2.31 (-3.19 [*])	-0.98 (-1.62 [*])	I(1)
Δu	-8.39 (-3.60 ^{**})	-8.29 (-4.20 ^{**})	-8.24 (-2.62 ^{**})	I(0)
p	-2.67 (-2.60 [*])	-3.44 (-3.19 [*])	-0.67 (-1.62 [*])	I(0)

*Rejection of the unit root hypothesis at the 10 per cent level

**With 2 lags

2. The model

Following the approach developed by Hjelm (2003), we define the variables' stationary vector as: $\Delta x' = [\Delta y_{94}, \Delta u, p]$; the system's moving average representation will be given by:

$$\Delta x_t = \mu + C(L) \varepsilon_t \quad (1)$$

$$= \mu + C_0 \varepsilon_t + C_1 \varepsilon_{t-1} + C_2 \varepsilon_{t-2} + \dots$$

where μ is the vector of constants, of 3x1 dimension, L is the lags' operator, and

$$\varepsilon_t' = [\varepsilon_t^P, \varepsilon_t^{LM}, \varepsilon_t^I]$$

is the vector of unobserved structural shocks, orthogonal by hypothesis. Thus, the system is affected by three shocks that may be described as follows:

- **Hypothesis 1.** The supply side shock, given by productivity (ε_t^P): it refers to the changes in the aggregate supply due to the productivity shocks. During transition, a decrease in productivity occurred, so that these kinds of shocks had a negative impact. We accept the hypothesis that these shocks had long-term impact upon the output but not upon unemployment, whose causes are of a different nature (the hidden unemployment during the centrally-planned economy, personnel layoffs due to restructuring, fraudulent privatization of certain companies).
- **Hypothesis 2.** The labor market shocks (ε_t^{LM}), which influence the unemployment, have negative impacts in the sense of increasing the numbers of unemployed persons. They are due more to the above-mentioned realities of the transition (the hidden unemployment during the centrally-planned economy, personnel layoffs due to restructuring, fraudulent privatization of certain companies), which express themselves as a crisis of the economic system, than due to certain changes in the social security system. Significant demographical changes have also occurred, such as the decrease in birth rate and in the total population⁵. The effects, both upon output and unemployment, are long-term ones.
- **Hypothesis 3.** Because the inflation is stationary, by definition the inflationary shocks do not influence the other variables in the long run, being transitory shocks that influence the output and unemployment in the short run. They are demand side shocks, due to the adopted strategy of gradual price liberalization, with all the successive stages and the wage indexations connected to these stages. There were also involved the shocks due to the national currency devaluation in the interval prior to adopting the flexible exchange rate, as well as the monetary shocks.

Since these structural shocks are unobservable, a non-structured VAR model has to be estimated (UVAR) in order to assess the reduced form of shocks. The associated mobile average representation is:

$$\begin{aligned} \Delta x_t &= \mu + R(L) v_t & (2) \\ &= \mu + v_t + R_1 v_{t-1} + R_2 v_{t-2} + \dots \end{aligned}$$

where v_t is the vector of the reduced form of shocks, of 3x1 dimensions. The equations (1) and (2) involve a linear relationship between the structural residuals and those of the reduced form:

⁵ The last census (2002) revealed a decrease in the total population of around 1 million people as compared to the previous one (1992).

$$\varepsilon_t = C(L)^{-1} R(L) v_t \quad (3)$$

Considering the three above-mentioned long-term restrictions, we obtain the following representation of equation (1) in the long run:

$$[\Delta y_{94}, \Delta u, p]' = \mu + C(1) \varepsilon_t = [\mu_y, \mu_u, \mu_p]' + \quad (4)$$

$$\begin{bmatrix} \sum_{k=0}^{\infty} c_{11}(k) & 0 & 0 \\ \sum_{k=0}^{\infty} c_{21}(k) & \sum_{k=0}^{\infty} c_{22}(k) & 0 \\ \sum_{k=0}^{\infty} c_{31}(k) & \sum_{k=0}^{\infty} c_{32}(k) & \sum_{k=0}^{\infty} c_{33}(k) \end{bmatrix} [\varepsilon_t^P, \varepsilon_t^{LM}, \varepsilon_t^I]'$$

where $C(1)$ is the long-term impact matrix; $\sum_{k=0}^{\infty} c_{11}(k) \varepsilon_t^P$ is the long-term effect of productivity shocks upon the output; $\sum_{k=0}^{\infty} c_{21}(k) \varepsilon_t^P + \sum_{k=0}^{\infty} c_{22}(k) \varepsilon_t^{LM}$ is the effect upon employment of the combined productivity and labor market shocks, and $\sum_{k=0}^{\infty} c_{31}(k) \varepsilon_t^P + \sum_{k=0}^{\infty} c_{32}(k) \varepsilon_t^{LM} + \sum_{k=0}^{\infty} c_{33}(k) \varepsilon_t^I$ is the effect upon prices of the combined productivity, labor market and inflationary shocks. Since $R(0) = I$, in (2), we notice that $C(0) \varepsilon_t = R(0)$ and $R(j) C(0) = C(j)$. Our aim is to find $C(0)$ in such a way that $C(L)$ and, consequently, the structural shocks to be identified through the equation (3). The inflationary shock ε_t^I is restricted not to have a long-term impact upon the output and unemployment, and the adverse labor market shock is restricted not to have long-term impact upon the output.

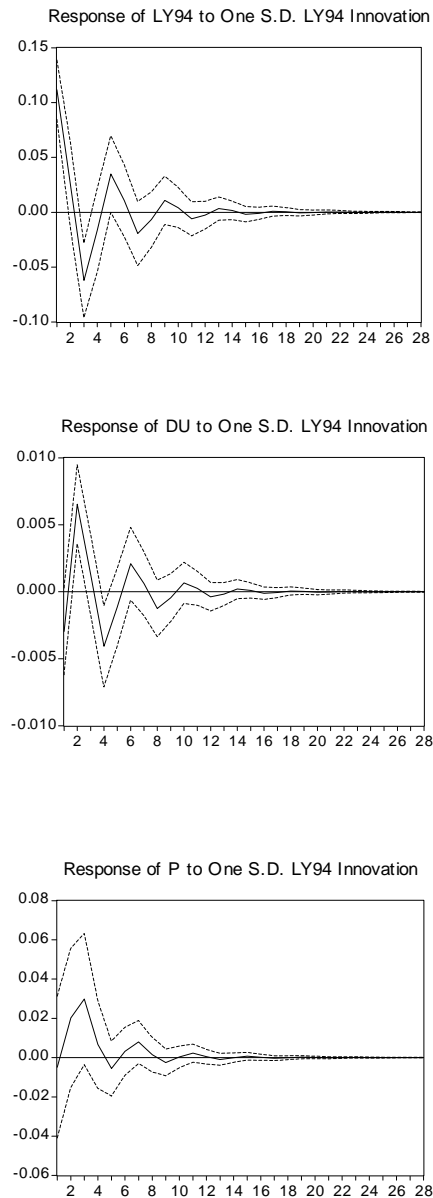
3. The results

These restrictions cannot be statistically tested. However, we may examine the way in which the chosen variables respond to different shocks. If they respond the way we expect, according to the interpretations associated to the shocks we have a support (not a demonstration) for the identification of the system. Figure 2 provides an interpretation to these three shocks:

a) The productivity shock (on the supply side):

- For a positive shock on the supply side (an increase in productivity), the output positively responds in the first quarter, then oscillatory (increases in each first quarter of the next year), and the shock is absorbed in approximately 4-5 years (16-20 quarters); the oscillatory „shape” of the response is due to the statistical data seasonality. We shall approach the same topic using the de-seasoned statistical series, in order to study the phenomenon's base reaction (see Appendix 1).
- The unemployment has a counter-clock response as compared to that of the output, revealing a decrease followed by a gradual absorption in near 5 years (20 quarters); the unemployment response dynamics differed from that of the output because, as Blanchard-Quah (1989) showed, an increase in productivity has initially led to an increase in unemployment, followed by a decrease when the positive effect of the shock upon the output has diminished:
- After a slight decrease due to the increase in the output in the first quarter, inflation significantly increases as a reaction to the decrease in the output in the 3rd quarter; its dynamics is counter-clock as compared to that of the output; the shock is absorbed a little bit faster, in approximately 18-19 quarters.

Figure 2. The response of the three variables to a productivity shock

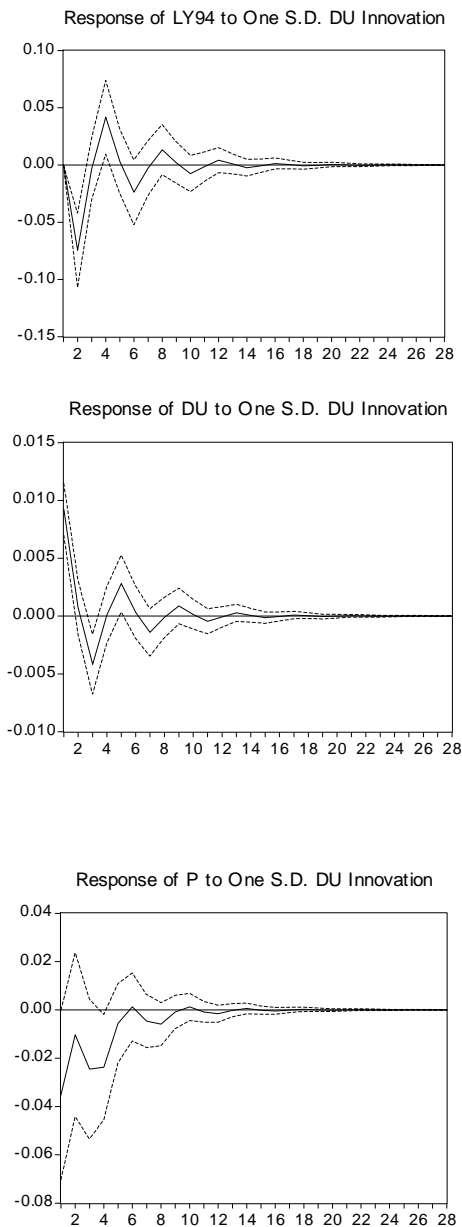


b) Adverse shock on the labor market

- The output's response to an adverse labor market shock (sudden increase in unemployment) is a sudden decrease in output, followed by an „adjustment” that is absorbed in 18-24 quarters (4-6 years);
- The labor market response to an adverse shock: the high shock in the first quarter is very slowly absorbed, in around 4-6 years;

- It is interesting the reaction on the goods and services market, where a shock on the labor market is transmitted into prices through an oscillatory decrease in prices (an inverse relationship, as according to the Phillips curve), shock whose absorption closely follows that of the labor market response (4-6 years), suggesting a very strong dependency between these two phenomena, much stronger than that suggested by the transition economy phenomena.

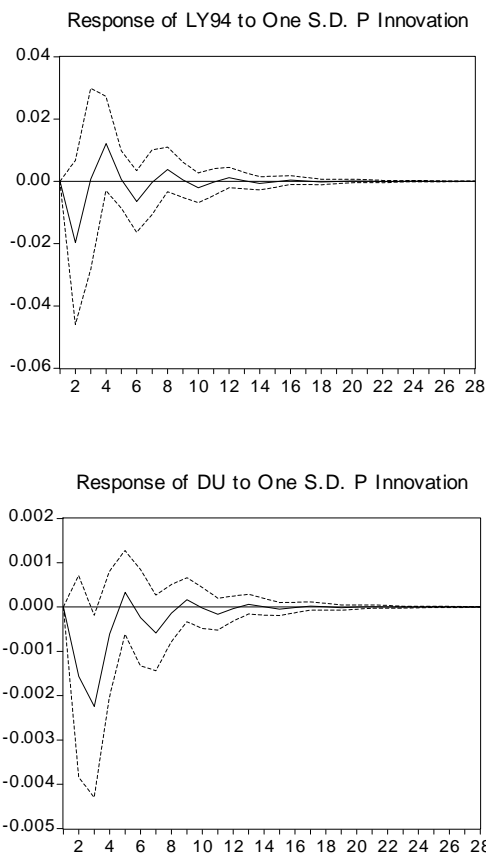
Figure 3. The response of the three variables to an adverse labor market shock

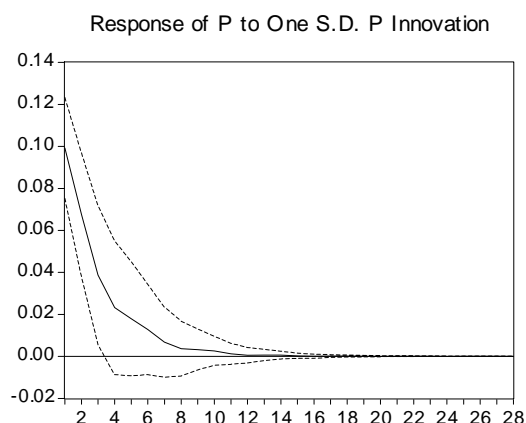


c) Adverse shock on the goods and services market (prices)

- The output's response to an adverse shock (increase in inflation) on the goods and services market is the decrease in output in the first quarters, with an adjustment that begins after approximately three years and lasts between 3.5 and 5.5 years;
- The response of unemployment to inflation reveals the same inverse dependency, as well as a special sensitiveness of the relationship between the two variables; the absorption of the shock begins after around 3.5 years and does not end before 7 years;
- On the goods and services market the inflationary shock is high in the first quarter, but does not reveal seasonality phenomena as the other variables and is absorbed faster, in around 4-5.5 years.

Figure 4. The response of the three variables to an adverse shock on the goods and services market (prices)





4. The variance decomposition

The variance decomposition presented in Table 2 suggests that the output's cyclical component subject to the productivity shocks is relevant for the output's monitoring, an importance worth considering exhibit the labor market shocks, while the inflationary shocks are not relevant for the total output. It is also interesting the fact that all the three shocks maintain their shares after 12 quarters, namely after around 3 years.

Table 2. Variance decomposition of the real output

Horizon (quarters)	Productivity shock	Labor market shock	Shock on goods and services market
1	100.00	0.00	0.00
2	68.85	29.11	2.02
4	68.76	29.11	2.13
8	68.76	29.16	2.14
12	68.68	29.17	2.14
16	68.68	29.17	2.14
24	68.68	29.17	2.14
Long-term	68.68	29.17	2.14

The analysis of the data in Table 3 confirms the relevance of the labor market and productivity shocks upon employment. As in the case of the output, the equilibrium is reached after nearly 3 years.

Table 3. Variance decomposition of the unemployment rate

Horizon (quarters)	Productivity shock	Labor market shock	Shock on goods and services market
1	9.30	90.70	0.00
2	36.89	61.36	1.75
4	38.61	57.05	4.34
8	38.92	56.86	4.20

12	38.98	56.82	4.19
16	38.98	56.82	4.19
24	38.98	56.82	4.19
Long-term	38.98	56.82	4.19

The data in Table 4 reveal that the productivity shocks have no relevance on the goods and services market. The inflation dynamics in the Romanian transition economy seems to have had causes outside the supply variations: there were the shocks induced by decisions upon the administrated prices: the successive shocks of price liberalizations, those concerning the increase in the energy prices, the demand side shocks, as well as those occurred on the forex market, given by the national currency devaluations.

Table 4. Variance decomposition of the inflation

Horizon (quarters)	Productivity shock	Labor market shock	Shocks on goods and services market
1	0.21	11.16	88.63
2	2.68	8.01	89.00
4	6.73	12.35	80.91
8	7.01	12.33	80.65
12	7.05	12.33	80.60
16	7.05	12.34	80.59
24	7.06	12.35	80.59
Long-term	7.06	12.35	80.59

5. The output gap

Figure 5 reveals the output gap's dynamics in the Romanian economy over the interval 1995-2003. A seasonal phenomenon, of inflation „calming down”, systematically occurred (negative output gap) at the beginning of each year (in quarters I and II); the inflationary pressures systematically showed up again in the quarters III and IV of each year. What emphasizes this figure is the fact that there were inflationary pressures in each year: the quarters III and IV being the quarters characterized by the increase in the aggregate demand.

Over the entire period there is a negative correlation between the output-gap and inflation; the correlation turns positive between the output-gap and the two-lagged inflation data series (Appendix 3), which does not exactly correspond to the general theory regarding the phenomenon, in the sense that there is a pro-cycle dynamics only in the case of the lagged inflation data series. However, under the circumstances of the transition period undergoing in the Romanian economy, such a phenomenon is explainable through the high inertia of the economic reactions, and the analysis of the impulse-response function confirms such an interpretation.

The inflation short-term fluctuations might be due to the transitory fluctuations in the exchange rate, or even in the indirect taxes, which does not justify a change in the exchange rate or the tax policy. In such a sense, it is interesting to reveal the inflationary trend long-term fluctuations, especially in Romania, where the persistence of above two-digits inflation has already a long

history. In such a case, the policy decision-makers might be interested to react to the output's fluctuations associated with long-term variations in inflation.

Figure 5. Output gap dynamics over the period 1995-2003

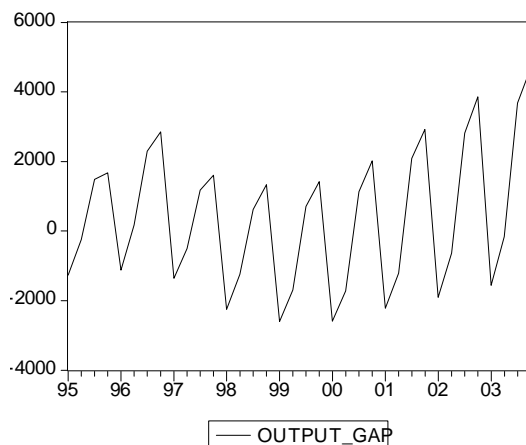
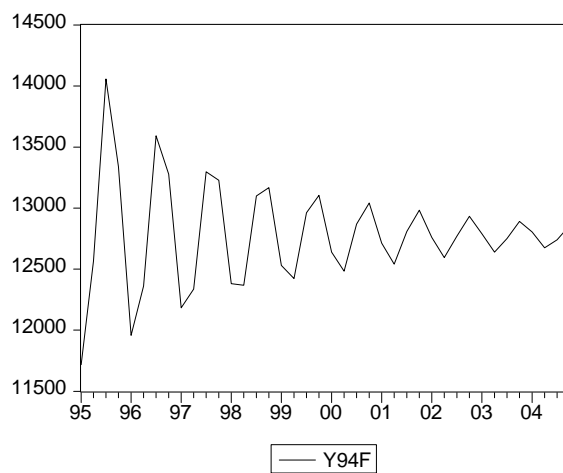


Figure 6. Potential GDP dynamics over the period 1994-2003



Appendices 3 and 4 present data for potential output and output gap.

5. Forecasts and conclusions

Different from the univariate filters (Hodrick-Prescott), the methods based on auto-regressive vectors (VAR) do not exhibit the „gaps” at the end of the sample (St. Amant and van Norden 1997), and allow for forecasting the variables.

In order to assess the forecasts based on the above-elaborated VAR models, two models were used: the first used the gross data series (real output logarithm, **ly94**; order 1 differences of unemployment rate, **du** and inflation, measured by the consumer price index, **p** (Appendix 6, Model 1)); the second took into account the possibility of a common pattern between the seasonalities of real output and unemployment rate data series, and it was elaborated on the basis of the de-seasoned data series (denoted by **ly94sa** for the output and **dusa1** for the unemployment rate) – Appendix 6, Model 2.

The results of the forecasts elaborated on the basis of the two models are presented below. Model 2, built on the de-seasoned data series, provided better results as regards the *ex post* forecast of the output and unemployment rate; as regards the inflation, both models provided much higher values than those recorded by the statistical system in 2003 and 2004. However, the data series used are too short to work with in the previsionsal system, so that the results require a certain degree of caution. Even so, they provide certain conclusions:

- The real GDP seasonality continues to be the same high during the forecasting period, too;
- The forecasted inflation level reveals an increase in both models, which lead to the conclusion that in the next interval an output exceeding the potential GDP level is possible to occur;
- As regards the unemployment rate, the *ex post* forecasts are quite close to the levels recorded by the statistical system, with oscillations around the current level.

Figure 7. Forecasts of the two models for the potential GDP dynamics (2003 – *ex post* forecasts, 2004 and 2005 – forecasts)

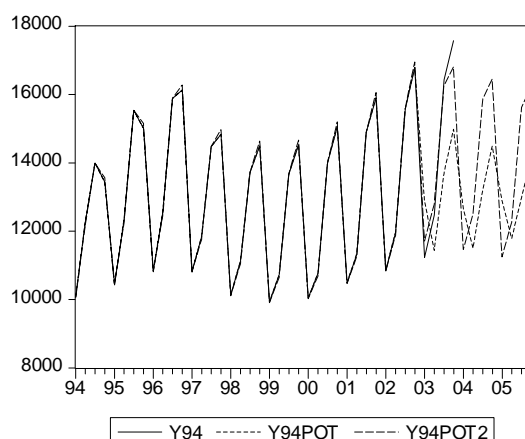


Table 5. Forecasts of the two models for the potential GDP dynamics

	Y94 (real data)	Y94POT1 (Model 1)	Y94POT2 (Model 2)
2003:1	11231.20	12906.90	11711.86
2003:2	12475.90	11435.58	12793.67
2003:3	16432.50	13684.34	16249.13
2003:4	17572.90	14983.86	16810.84
2004:1	NA	12681.37	11464.87
2004:2	NA	11502.54	12479.69
2004:3	NA	13199.99	15863.94
2004:4	NA	14491.06	16451.85
2005:1	NA	12900.99	11247.33
2005:2	NA	11787.26	12268.49
2005:3	NA	12978.91	15623.68
2005:4	NA	14137.69	16228.59

Figure 8. Forecasts of the two models for the unemployment rate dynamics (2003 and 2004 – *ex post* forecasts, 2005 – forecasts)

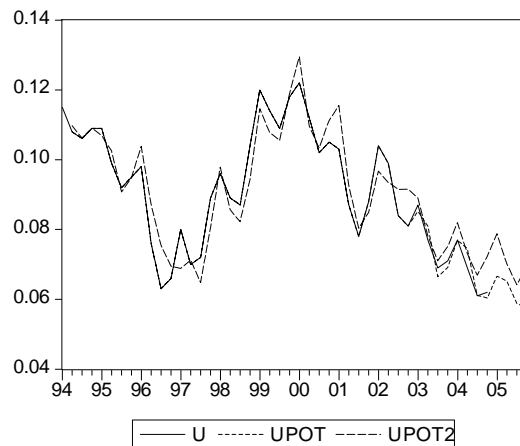


Table 6. Forecasts of the two models for the unemployment rate dynamics

	U	UPOT	UPOT2
2003:1	0.087000	0.085222	0.088981
2003:2	0.077000	0.080997	0.078157
2003:3	0.069000	0.066490	0.071076
2003:4	0.071000	0.069103	0.075118
2004:1	0.077000	0.076860	0.081985
2004:2	0.069000	0.074444	0.073070
2004:3	0.061000	0.061115	0.066949
2004:4	0.062000	0.060345	0.072302
2005:1	NA	0.066595	0.078762

2005:2	NA	0.065208	0.070139
2005:3	NA	0.058846	0.064178
2005:4	NA	0.057468	0.069254

Figure 9. Forecasts of the two models for the inflation dynamics (2003 and 2004 – *ex post* forecasts, 2005 – forecasts)

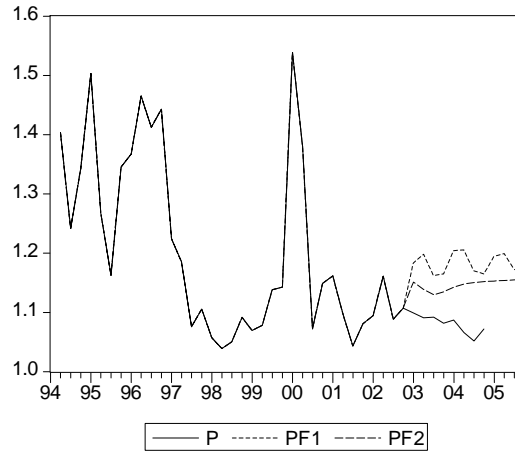


Table 7. Forecasts of the two models for the inflation dynamics

obs	P	PF1	PF2
2003:1	1.098962	1.183478	1.151040
2003:2	1.091026	1.198299	1.138618
2003:3	1.091869	1.162030	1.129304
2003:4	1.081800	1.164837	1.134648
2004:1	1.086848	1.204147	1.142681
2004:2	1.065808	1.205515	1.147582
2004:3	1.051769	1.169880	1.150089
2004:4	1.071924	1.164688	1.151707
2005:1	NA	1.194150	1.152959
2005:2	NA	1.199278	1.153915
2005:3	NA	1.172582	1.154626
2005:4	NA	1.165549	1.155173

Data

Correlation matrix for the gross variables

	Y94	U	P
Y94	1.000000	-0.500947	-0.176693
U	-0.500947	1.000000	0.136241
P	-0.176693	0.136241	1.000000

Correlation matrix for the variables used in the model

	LY94	DU	P
LY94	1.000000	-0.092901	-0.177544
DU	-0.092901	1.000000	-0.162526
P	-0.177544	-0.162526	1.000000

Appendix 2

The response of the three types of shocks in the case of the de-seasoned series

Since the data series regarding the quarterly GDP in the Romanian economy reveal a strong seasonality, in order to trace down the behavioral line not influenced by the seasonal perturbations we considered useful to reveal the reaction to the shocks on the de-seasoned series.

We consider the same variables ($\Delta x' = [\Delta ly94, \Delta u, p]$), with the same types of shocks ($\varepsilon_t' = [\varepsilon_t^P, \varepsilon_t^{LM}, \varepsilon_t^I]$).

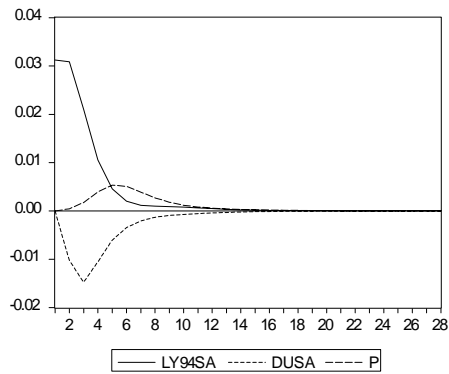
The graphs with the combined responses, which synthesize the 9 graphs in the main text allow for a quick analysis of the responses to the three types of shocks analyzed in the paper.

- a) **The output's response to the three shocks:** The first graph in Figure 6 reveals the de-seasoned output response to the three shocks: supply shock (productivity shock), adverse labor market shock and adverse shock on the goods and services market. A supply shock (by increasing productivity) leads to a significant increase in the output, which, nevertheless, does not last too long, being absorbed in around 3 years; therefore, *several successive productivity increase shocks are necessary for a prolonged GDP growth in the Romanian economy*. An increase in employment leads to a decrease in output with a lag of two quarters, pretty fast absorbed; an increase in inflation measured by the consumer prices leads to a surprisingly weak response of the GDP revealed with a delay (lag) of about a year and a half.
- b) **The unemployment response to the three shocks** (the second graph in Figure 6): the reactions on the labor market are quite weak to the three shocks: to a productivity shock, after a first negative reaction, the unemployment quickly returns to its initial level; the labor market shock itself is absorbed in less than one year; the prices decrease, and the reaction has a two quarters delay.
- c) **The inflation response to the three shocks** (the third graph in Figure 6): we may say that all the shocks upon inflation are transitory, since they are absorbed during an interval between 2.5 and 3.5 years; when a productivity shock occurs, inflation decreases in the beginning, then

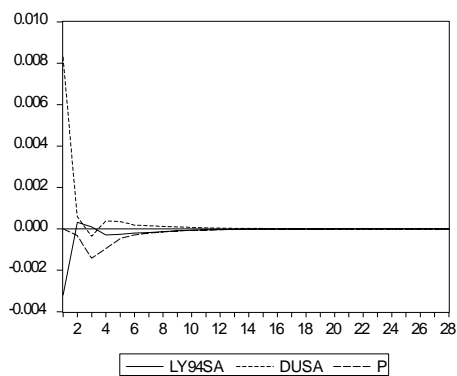
increases and returns to the initial level after near 3.5 years; when an adverse labor market shock occurs (increase in unemployment) the inflation diminishes, then in around one year increases up to near its initial level, and returns to the initial level after around 3.5 years .

Figure 6. The response of the three variables (the model with de-seasoned series) to the three types of shocks

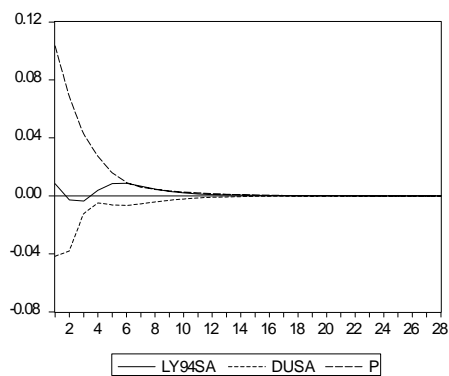
Response of LY94SA to One S.D. Innovations



Response of DUSA to One S.D. Innovations



Response of P to One S.D. Innovations



Appendix 3

The response to the three types of shocks in the case of the industry

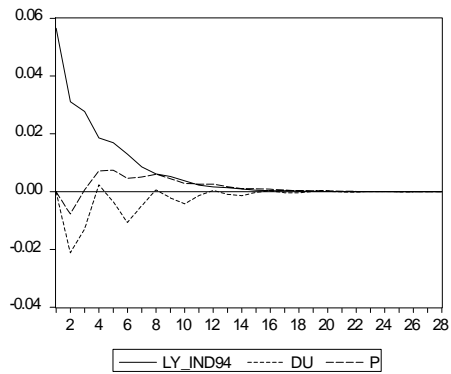
Since the data series regarding the quarterly GDP in the Romanian economy exhibit a high seasonality, we selected the data series corresponding to the industrial output, which reveal seasonality not as high as that of the total output. Since unemployment and prices highly influence the industrial output, we consider the variables ($\Delta x' = [\Delta ly_ind94, \Delta u, p]$), with the same types of shocks ($\varepsilon_t' = [\varepsilon_t^P, \varepsilon_t^{LM}, \varepsilon_t^I]$).

The graphs with the combined responses, which synthesize the 9 graphs in the main text allow for a quick analysis of the responses to the three types of shocks analyzed in the paper.

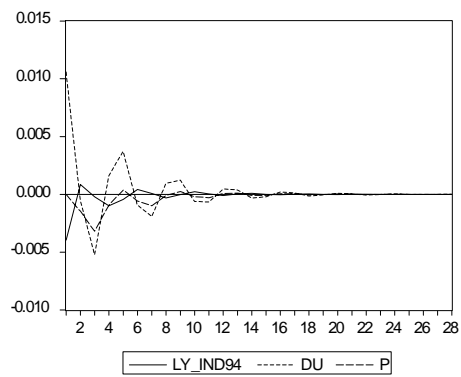
- d) The industrial output response to the three shocks:** The first graph in Figure 7 shows the way the industrial output responds to the three shocks: supply (productivity) shock, adverse labor market shock and adverse shock on the goods and services market. Contrary to the response of the entirely de-seasoned total output (Appendix 1), the industrial output's response to the three shocks is faster. A supply shock (by increasing productivity) leads to a significant increase in output, which does not last long, being absorbed in around 4 years; therefore *several successive productivity increase shocks are necessary for a prolonged growth of the industrial output in the Romanian economy*. An increase in unemployment leads to a decrease in output with a single quarter lag, pretty fast absorbed; an increase in inflation measured by the consumer prices leads to an industrial output response with a delay (lag) of around three quarters.
- e) The response of unemployment to the three shocks** (the second graph in Figure 7): the reactions on the labor market to the three shocks: in the case of a productivity shock in industry, after a first negative reaction, the unemployment slowly returns to its initial level (in around 4 years); the labor market shock itself is even more slowly absorbed, in around 6 years; the prices decrease, with a reaction delayed by 2-3 quarters, which is absorbed in around 4 years.
- f) The response of inflation to the three shocks** (the third graph in Figure 7): we may say that the consumer prices react stronger when the shocks upon the industrial output are considered than in the case of the total output. The shocks upon inflation are absorbed in around 3.5-5.5 years; in the case of a productivity shock, inflation diminishes in the beginning, then increases and returns to the initial level in around 3-5 years; when an adverse labor market shock occurs (an increase in unemployment) the inflation diminishes, then in about one year increases up to near the initial level and returns to it after 3.5 years; a shock on the goods and services market is much faster absorbed, in around 2 years.

Figure 7. The response of the three variables (the model with industrial output) to the three types of shocks

Response of LY_IND94 to One S.D. Innovations



Response of DU to One S.D. Innovations



Response of P to One S.D. Innovations

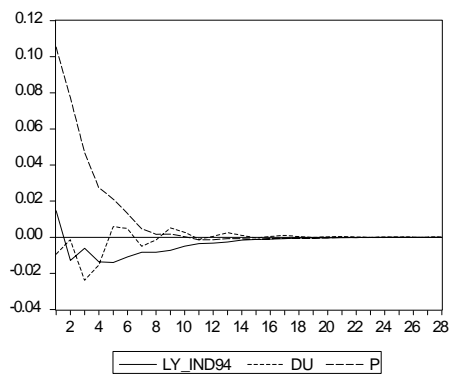


Table 5. Output gap dynamics over the period 1995-2003

1995:1	-1266.698
1995:2	-242.3696
1995:3	1481.946
1995:4	1673.420
1996:1	-1123.448
1996:2	175.2701
1996:3	2297.276
1996:4	2851.431
1997:1	-1357.120
1997:2	-498.8933
1997:3	1178.962
1997:4	1606.693
1998:1	-2252.261
1998:2	-1244.894
1998:3	625.1744
1998:4	1331.017
1999:1	-2598.907
1999:2	-1691.732
1999:3	707.9556
1999:4	1423.666
2000:1	-2593.472
2000:2	-1720.540
2000:3	1130.827
2000:4	2021.516
2001:1	-2221.198
2001:2	-1212.624
2001:3	2088.662
2001:4	2923.540
2002:1	-1905.975
2002:2	-633.9902
2002:3	2814.864
2002:4	3861.550
2003:1	-1557.895
2003:2	-162.7006
2003:3	3682.761
2003:4	4682.026

Correlation matrix for output-gap and inflation (2 lags)

	OUTPUT_GAP	P(-2)
OUTPUT_GAP	1.000000	0.177203
P(-2)	0.177203	1.000000

Table 6. Potential output dynamics over the interval 1995-2003

1994:1	10079.30
1994:2	12260.00
1994:3	13997.10
1994:4	13436.80
1995:1	11717.80
1995:2	12566.17
1995:3	14056.95
1995:4	13338.78
1996:1	11956.95
1996:2	12361.53
1996:3	13591.62
1996:4	13277.87
1997:1	12184.32
1997:2	12336.29
1997:3	13298.14
1997:4	13227.81
1998:1	12380.76
1998:2	12368.79
1998:3	13098.83
1998:4	13168.48
1999:1	12531.21
1999:2	12423.03
1999:3	12961.64
1999:4	13103.93
2000:1	12639.27
2000:2	12483.24
2000:3	12868.87
2000:4	13040.48
2001:1	12713.00
2001:2	12541.52
2001:3	12808.34
2001:4	12982.56
2002:1	12760.57
2002:2	12593.89
2002:3	12770.94
2002:4	12932.45
2003:1	12789.10
2003:2	12638.60
2003:3	12749.74
2003:4	12890.87
2004:1	12804.29
2004:2	12675.28
2004:3	12739.53
2004:4	12857.55

Model with gross data series (Model 1)

Estimation Command:

```
=====
LS 1 2 LY94 DU P @ C
```

VAR Model:

```
=====
LY94 = C(1,1)*LY94(-1) + C(1,2)*LY94(-2) + C(1,3)*DU(-1) + C(1,4)*DU(-2) + C(1,5)*P(-1) + C(1,6)*P(-2) +
C(1,7)
```

```
DU = C(2,1)*LY94(-1) + C(2,2)*LY94(-2) + C(2,3)*DU(-1) + C(2,4)*DU(-2) + C(2,5)*P(-1) + C(2,6)*P(-2) +
C(2,7)
```

```
P = C(3,1)*LY94(-1) + C(3,2)*LY94(-2) + C(3,3)*DU(-1) + C(3,4)*DU(-2) + C(3,5)*P(-1) + C(3,6)*P(-2) +
C(3,7)
```

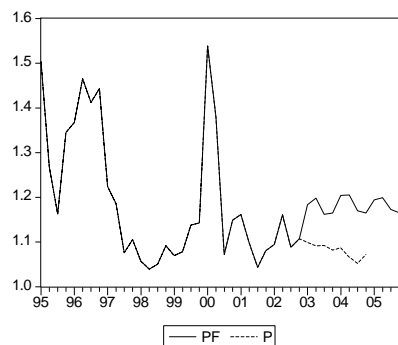
VAR Model - Substituted Coefficients:

```
=====
LY94 = - 0.0157113811*LY94(-1) - 0.1780318141*LY94(-2) - 11.80043572*DU(-1) - 0.2007393451*DU(-2)
- 0.3712729579*P(-1) + 0.2227545677*P(-2) + 11.46726099
```

```
DU = 0.03053220793*LY94(-1) - 0.03967011255*LY94(-2) + 0.7498724696*DU(-1) - 0.3888534324*DU(-2)
+ 0.002958602621*P(-1) - 0.01074991817*P(-2) + 0.09500120417
```

```
P = 0.1288389455*LY94(-1) + 0.01869199239*LY94(-2) + 1.445856125*DU(-1) - 1.400941335*DU(-2) +
0.7062004622*P(-1) - 0.01726402343*P(-2) - 1.030046911
```

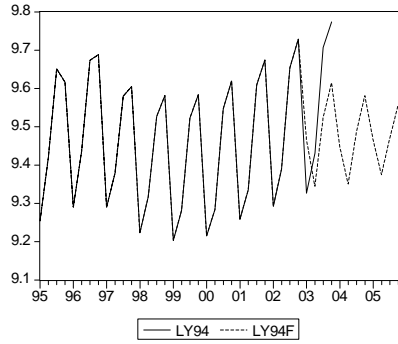
Model 1 : Real inflation and forecasts (ex post for 2003 and 2004 and forecast for 2005)



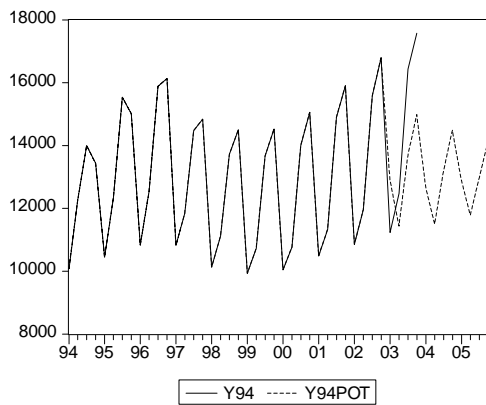
obs	PF	P
2003:1	1.183478	1.098962
2003:2	1.198299	1.091026
2003:3	1.162030	1.091869
2003:4	1.164837	1.081800
2004:1	1.204147	1.086848
2004:2	1.205515	1.065808
2004:3	1.169880	1.051769
2004:4	1.164688	1.071924

2005:1	1.194150	NA
2005:2	1.199278	NA
2005:3	1.172582	NA
2005:4	1.165549	NA

Model 1 : Real GDP logarithm (ex post forecast for 2003, forecast for 2004 and 2005)



obs	LY94	LY94F
2003:1	9.326451	9.465517
2003:2	9.431554	9.344485
2003:3	9.707016	9.524007
2003:4	9.774113	9.614729
2004:1	NA	9.447889
2004:2	NA	9.350323
2004:3	NA	9.487971
2004:4	NA	9.581287
2005:1	NA	9.465059
2005:2	NA	9.374774
2005:3	NA	9.471081
2005:4	NA	9.556600

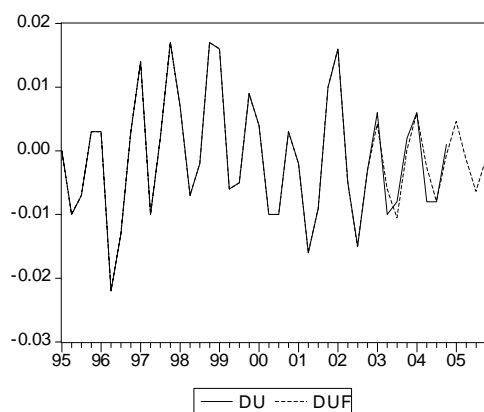


Model 1:

Real and potential GDP evaluated on the basis of the gross data series (*ex post* forecast for 2003; forecast for 2004 and 2005)

obs	Y94	Y94POT
2003:1	11231.20	12906.90
2003:2	12475.90	11435.58
2003:3	16432.50	13684.34
2003:4	17572.90	14983.86
2004:1	NA	12681.37
2004:2	NA	11502.54
2004:3	NA	13199.99
2004:4	NA	14491.06
2005:1	NA	12900.99
2005:2	NA	11787.26
2005:3	NA	12978.91
2005:4	NA	14137.69

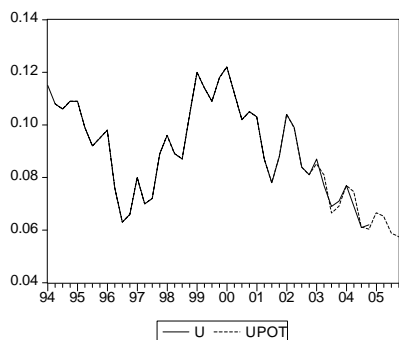
Model 1 : Order 1 differences for the unemployment rate (*ex post* forecast for 2003 and 2004 ; forecast for 2005)



obs	DU	DUF
2003:1	0.006000	0.004222
2003:2	-0.010000	-0.006003
2003:3	-0.008000	-0.010510
2003:4	0.002000	0.000103
2004:1	0.006000	0.005860
2004:2	-0.008000	-0.002556
2004:3	-0.008000	-0.007885
2004:4	0.001000	-0.000655
2005:1	NA	0.004595
2005:2	NA	-0.001387
2005:3	NA	-0.006362
2005:4	NA	-0.001378

Model 1 :

Real unemployment and forecast, in the model evaluated on the basis of data series with seasonality (ex post for 2003 and 2004; forecast for 2005)



obs	U	UPOT
2003:1	0.087000	0.085222
2003:2	0.077000	0.080997
2003:3	0.069000	0.066490
2003:4	0.071000	0.069103
2004:1	0.077000	0.076860
2004:2	0.069000	0.074444
2004:3	0.061000	0.061115
2004:4	0.062000	0.060345
2005:1	NA	0.066595
2005:2	NA	0.065208
2005:3	NA	0.058846
2005:4	NA	0.057468

Model 2 (with de-seasoned data series)

Estimation Command:

```
=====
LS 1 2 LY94SA DUSA1 P @ C
```

VAR Model:

```
=====
LY94SA = C(1,1)*LY94SA(-1) + C(1,2)*LY94SA(-2) + C(1,3)*DUSA1(-1) + C(1,4)*DUSA1(-2) + C(1,5)*P(-1)
+ C(1,6)*P(-2) + C(1,7)
```

```
DUSA1 = C(2,1)*LY94SA(-1) + C(2,2)*LY94SA(-2) + C(2,3)*DUSA1(-1) + C(2,4)*DUSA1(-2) + C(2,5)*P(-1)
+ C(2,6)*P(-2) + C(2,7)
```

```
P = C(3,1)*LY94SA(-1) + C(3,2)*LY94SA(-2) + C(3,3)*DUSA1(-1) + C(3,4)*DUSA1(-2) + C(3,5)*P(-1) +
C(3,6)*P(-2) + C(3,7)
```

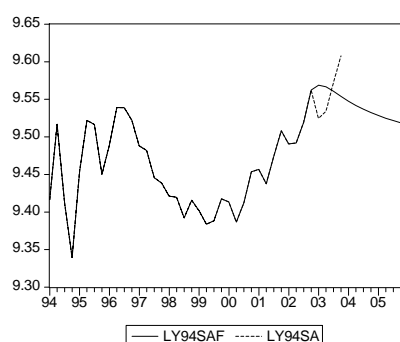
VAR Model - Substituted Coefficients:

$$\text{LY94SA} = 0.922085047 * \text{LY94SA}(-1) - 0.02641068956 * \text{LY94SA}(-2) - 1.035449839 * \text{DUSA1}(-1) - 0.1486677687 * \text{DUSA1}(-2) - 0.05688254553 * \text{P}(-1) + 0.02545512189 * \text{P}(-2) + 1.025960953$$

$$\text{DUSA1} = -0.04247113674 * \text{LY94SA}(-1) + 0.03570365019 * \text{LY94SA}(-2) + 0.5507021403 * \text{DUSA1}(-1) - 0.272620151 * \text{DUSA1}(-2) + 0.002407757799 * \text{P}(-1) - 0.01006759115 * \text{P}(-2) + 0.07261051845$$

$$\text{P} = 0.5200420434 * \text{LY94SA}(-1) - 0.4947936329 * \text{LY94SA}(-2) - 3.082665289 * \text{DUSA1}(-1) + 3.585037648 * \text{DUSA1}(-2) + 0.6798737992 * \text{P}(-1) - 0.01296331873 * \text{P}(-2) + 0.146693393$$

Model 2 : Log GDP on the basis of de-seasoned data series (*ex post* forecast for 2003, forecast for 2004 and 2005)



obs	LY94SAF	LY94SA
2003:1	9.568915	9.524706
2003:2	9.566780	9.534244
2003:3	9.560910	9.572403
2003:4	9.554032	9.607781
2004:1	9.547601	NA
2004:2	9.541933	NA
2004:3	9.536919	NA
2004:4	9.532446	NA
2005:1	9.528444	NA
2005:2	9.524865	NA
2005:3	9.521658	NA
2005:4	9.518782	NA

Model 2 : GDP on the basis of de-seasoned data series (*ex post* forecast for 2003, forecast for 2004 and 2005)

De-seasoning is performed with the help of seasonality coefficients:

Date: 06/12/05 Time:

15:34

Sample: 1995:1 2004:4

Included observations:

36

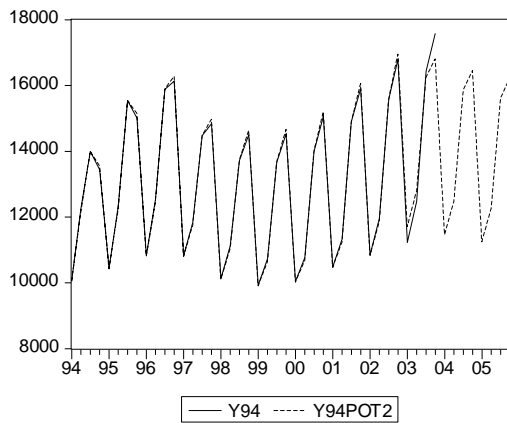
Ratio to Moving Average

Original Series: Y94

Adjusted Series: Y94SA

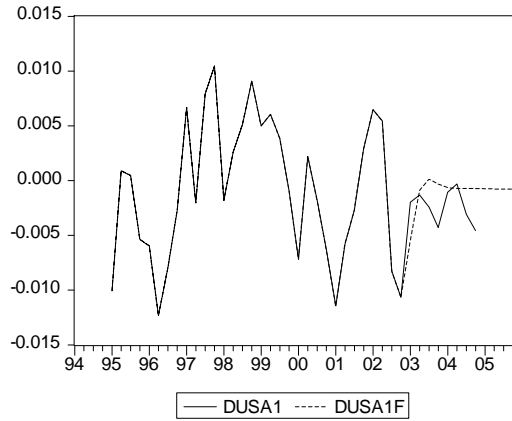
Scaling Factors:

1	0.818274
2	0.895767
3	1.144405
4	1.192137



obs	Y94	Y94POT2
2003:1	11231.20	11711.86
2003:2	12475.90	12793.67
2003:3	16432.50	16249.13
2003:4	17572.90	16810.84
2004:1	NA	11464.87
2004:2	NA	12479.69
2004:3	NA	15863.94
2004:4	NA	16451.85
2005:1	NA	11247.33
2005:2	NA	12268.49
2005:3	NA	15623.68
2005:4	NA	16228.59

Model 2 : Real unemployment and *ex post* forecast for 2003 and 2004 ; forecast for 2005, (for the model with de-seasoned data series)



obs	DUSA1
1994:1	NA
1994:2	NA
1994:3	NA
1994:4	NA
1995:1	-0.010042
1995:2	0.000894
1995:3	0.000463
1995:4	-0.005370
1996:1	-0.005979
1996:2	-0.012324
1996:3	-0.007964
1996:4	-0.002731
1997:1	0.006670
1997:2	-0.002029
1997:3	0.007909
1997:4	0.010450
1998:1	-0.001796
1998:2	0.002611
1998:3	0.005100
1998:4	0.009085
1999:1	0.005005
1999:2	0.006039
1999:3	0.003872
1999:4	-0.000916
2000:1	-0.007178
2000:2	0.002204
2000:3	-0.001746
2000:4	-0.006279
2001:1	-0.011437
2001:2	-0.005766
2001:3	-0.002701
2001:4	0.002904
2002:1	0.006471
2002:2	0.005436
2002:3	-0.008265

2002:4	-0.010642
2003:1	-0.001971
2003:2	-0.001323
2003:3	-0.002428
2003:4	-0.004277
2004:1	-0.001055
2004:2	-0.000313
2004:3	-0.003082
2004:4	-0.004549
2005:1	NA
2005:2	NA
2005:3	NA
2005:4	NA

Coefficients for unemployment rate de-seasoning

Date: 06/12/05

Time: 15:28

Sample: 1995:1

2004:4

Included

observations: 40

Ratio to Moving

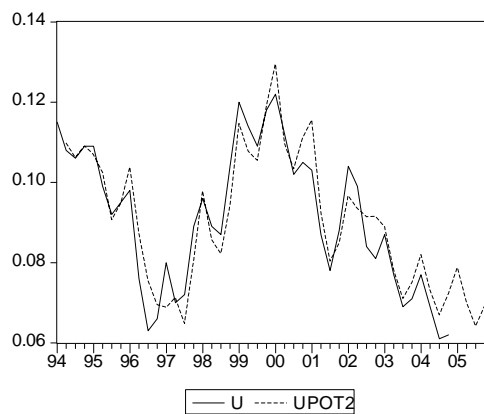
Average

Original Series: U

Adjusted Series: USA

Scaling Factors:

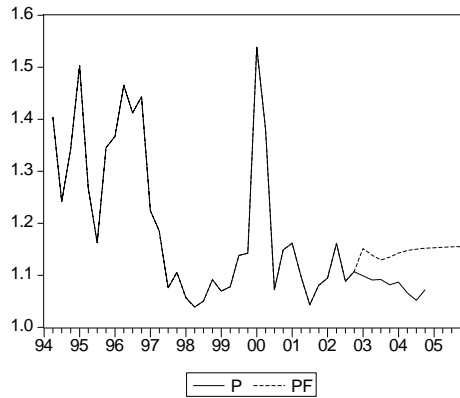
1	1.100892
2	0.990947
3	0.916632
4	1.000022



obs	U	UPOT2
1994:1	0.115000	NA
1994:2	0.108000	0.109761
1994:3	0.106000	0.106260
1994:4	0.109000	0.109055
1995:1	0.109000	0.106934

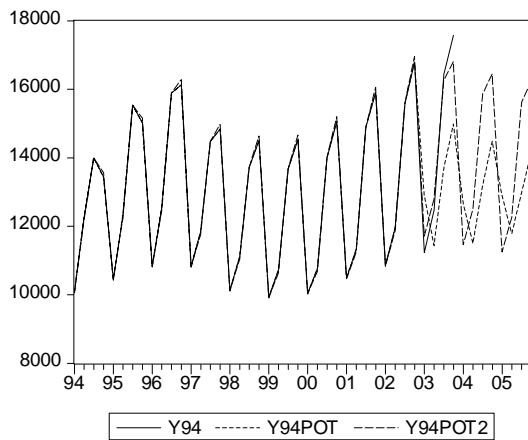
1995:2	0.099000	0.102474
1995:3	0.092000	0.090732
1995:4	0.095000	0.094802
1996:1	0.098000	0.103829
1996:2	0.076000	0.087162
1996:3	0.063000	0.075454
1996:4	0.066000	0.069514
1997:1	0.080000	0.068835
1997:2	0.070000	0.071315
1997:3	0.072000	0.064813
1997:4	0.089000	0.080576
1998:1	0.096000	0.097885
1998:2	0.089000	0.085690
1998:3	0.087000	0.082281
1998:4	0.104000	0.094375
1999:1	0.120000	0.114655
1999:2	0.114000	0.107816
1999:3	0.109000	0.105488
1999:4	0.118000	0.119003
2000:1	0.122000	0.129507
2000:2	0.112000	0.109659
2000:3	0.102000	0.103373
2000:4	0.105000	0.111237
2001:1	0.103000	0.115554
2001:2	0.087000	0.092530
2001:3	0.078000	0.080359
2001:4	0.088000	0.084885
2002:1	0.104000	0.096724
2002:2	0.099000	0.093482
2002:3	0.084000	0.091437
2002:4	0.081000	0.091520
2003:1	0.087000	0.088981
2003:2	0.077000	0.078157
2003:3	0.069000	0.071076
2003:4	0.071000	0.075118
2004:1	0.077000	0.081985
2004:2	0.069000	0.073070
2004:3	0.061000	0.066949
2004:4	0.062000	0.072302
2005:1	NA	0.078762
2005:2	NA	0.070139
2005:3	NA	0.064178
2005:4	NA	0.069254

Model 2 : Inflation (*ex post* forecast for 2003 and 2004 ; forecast for 2005, (for the model with de-seasoned data series)



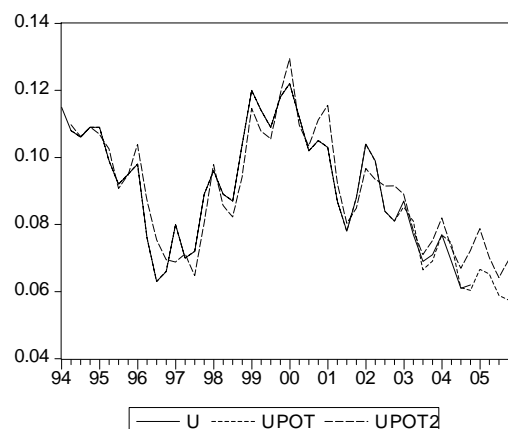
obs	P	PF
2003:1	1.098962	1.151040
2003:2	1.091026	1.138618
2003:3	1.091869	1.129304
2003:4	1.081800	1.134648
2004:1	1.086848	1.142681
2004:2	1.065808	1.147582
2004:3	1.051769	1.150089
2004:4	1.071924	1.151707
2005:1	NA	1.152959
2005:2	NA	1.153915
2005:3	NA	1.154626
2005:4	NA	1.155173

COMPARISONS BETWEEN THE RESULTS OF THE TWO MODELS: output in 1994 prices



obs	Y94	Y94POT (Model 1)	Y94POT2 (Model 2)
1994:1	10079.30	10079.30	10056.12
1994:2	12260.00	12260.00	12169.80
1994:3	13997.10	13997.10	14000.90
1994:4	13436.80	13436.80	13563.91
1995:1	10451.10	10451.10	10427.06
1995:2	12323.80	12323.80	12233.13
1995:3	15538.90	15538.90	15543.11
1995:4	15012.20	15012.20	15154.21
1996:1	10833.50	10833.50	10808.58
1996:2	12536.80	12536.80	12444.56
1996:3	15888.90	15888.90	15893.21
1996:4	16129.30	16129.30	16281.88
1997:1	10827.20	10827.20	10802.30
1997:2	11837.40	11837.40	11750.31
1997:3	14477.10	14477.10	14481.03
1997:4	14834.50	14834.50	14974.83
1998:1	10128.50	10128.50	10105.20
1998:2	11123.90	11123.90	11042.06
1998:3	13724.00	13724.00	13727.72
1998:4	14499.50	14499.50	14636.66
1999:1	9932.300	9932.300	9909.455
1999:2	10731.30	10731.30	10652.35
1999:3	13669.60	13669.60	13673.31
1999:4	14527.60	14527.60	14665.03
2000:1	10045.80	10045.80	10022.69
2000:2	10762.70	10762.70	10683.51
2000:3	13999.70	13999.70	14003.50
2000:4	15062.00	15062.00	15204.49
2001:1	10491.80	10491.80	10467.67
2001:2	11328.90	11328.90	11245.55
2001:3	14897.00	14897.00	14901.04
2001:4	15906.10	15906.10	16056.57
2002:1	10854.60	10854.60	10829.63
2002:2	11959.90	11959.90	11871.91
2002:3	15585.80	15585.80	15590.03
2002:4	16794.00	16794.00	16952.87
2003:1	11231.20	12906.90	11711.86
2003:2	12475.90	11435.58	12793.67
2003:3	16432.50	13684.34	16249.13
2003:4	17572.90	14983.86	16810.84
2004:1	NA	12681.37	11464.87
2004:2	NA	11502.54	12479.69
2004:3	NA	13199.99	15863.94
2004:4	NA	14491.06	16451.85
2005:1	NA	12900.99	11247.33
2005:2	NA	11787.26	12268.49
2005:3	NA	12978.91	15623.68
2005:4	NA	14137.69	16228.59

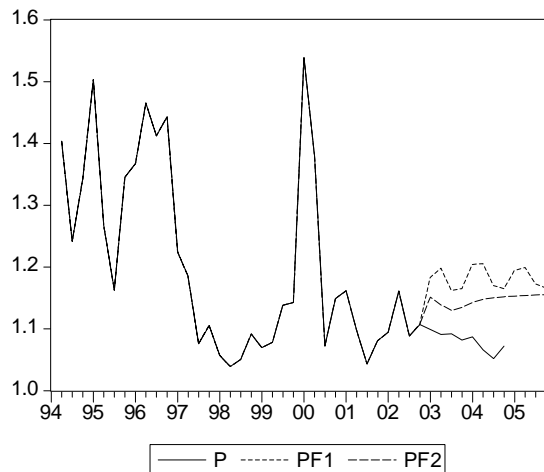
COMPARISONS BETWEEN THE RESULTS OF THE TWO MODELS: unemployment rate



obs	U	UPOT	UPOT2
1994:1	0.115000	NA	NA
1994:2	0.108000	0.108000	0.109761
1994:3	0.106000	0.106000	0.106260
1994:4	0.109000	0.109000	0.109055
1995:1	0.109000	0.109000	0.106934
1995:2	0.099000	0.099000	0.102474
1995:3	0.092000	0.092000	0.090732
1995:4	0.095000	0.095000	0.094802
1996:1	0.098000	0.098000	0.103829
1996:2	0.076000	0.076000	0.087162
1996:3	0.063000	0.063000	0.075454
1996:4	0.066000	0.066000	0.069514
1997:1	0.080000	0.080000	0.068835
1997:2	0.070000	0.070000	0.071315
1997:3	0.072000	0.072000	0.064813
1997:4	0.089000	0.089000	0.080576
1998:1	0.096000	0.096000	0.097885
1998:2	0.089000	0.089000	0.085690
1998:3	0.087000	0.087000	0.082281
1998:4	0.104000	0.104000	0.094375
1999:1	0.120000	0.120000	0.114655
1999:2	0.114000	0.114000	0.107816
1999:3	0.109000	0.109000	0.105488
1999:4	0.118000	0.118000	0.119003
2000:1	0.122000	0.122000	0.129507
2000:2	0.112000	0.112000	0.109659
2000:3	0.102000	0.102000	0.103373
2000:4	0.105000	0.105000	0.111237
2001:1	0.103000	0.103000	0.115554
2001:2	0.087000	0.087000	0.092530
2001:3	0.078000	0.078000	0.080359

2001:4	0.088000	0.088000	0.084885
2002:1	0.104000	0.104000	0.096724
2002:2	0.099000	0.099000	0.093482
2002:3	0.084000	0.084000	0.091437
2002:4	0.081000	0.081000	0.091520
2003:1	0.087000	0.085222	0.088981
2003:2	0.077000	0.080997	0.078157
2003:3	0.069000	0.066490	0.071076
2003:4	0.071000	0.069103	0.075118
2004:1	0.077000	0.076860	0.081985
2004:2	0.069000	0.074444	0.073070
2004:3	0.061000	0.061115	0.066949
2004:4	0.062000	0.060345	0.072302
2005:1	NA	0.066595	0.078762
2005:2	NA	0.065208	0.070139
2005:3	NA	0.058846	0.064178
2005:4	NA	0.057468	0.069254

COMPARISONS BETWEEN THE RESULTS OF THE TWO MODELS: inflation



obs	P	PF1	PF2
1994:1	NA	NA	NA
1994:2	1.403415	1.403415	1.403415
1994:3	1.241684	1.241684	1.241684
1994:4	1.342930	1.342930	1.342930
1995:1	1.503169	1.503169	1.503169
1995:2	1.267378	1.267378	1.267378
1995:3	1.162710	1.162710	1.162710
1995:4	1.345143	1.345143	1.345143
1996:1	1.367229	1.367229	1.367229
1996:2	1.465212	1.465212	1.465212
1996:3	1.412273	1.412273	1.412273
1996:4	1.442855	1.442855	1.442855
1997:1	1.224087	1.224087	1.224087

1997:2	1.185733	1.185733	1.185733
1997:3	1.075965	1.075965	1.075965
1997:4	1.105320	1.105320	1.105320
1998:1	1.057023	1.057023	1.057023
1998:2	1.039103	1.039103	1.039103
1998:3	1.050649	1.050649	1.050649
1998:4	1.091734	1.091734	1.091734
1999:1	1.069415	1.069415	1.069415
1999:2	1.078193	1.078193	1.078193
1999:3	1.138147	1.138147	1.138147
1999:4	1.142674	1.142674	1.142674
2000:1	1.538638	1.538638	1.538638
2000:2	1.379618	1.379618	1.379618
2000:3	1.072360	1.072360	1.072360
2000:4	1.148883	1.148883	1.148883
2001:1	1.161558	1.161558	1.161558
2001:2	1.097392	1.097392	1.097392
2001:3	1.043146	1.043146	1.043146
2001:4	1.080866	1.080866	1.080866
2002:1	1.094517	1.094517	1.094517
2002:2	1.160869	1.160869	1.160869
2002:3	1.088287	1.088287	1.088287
2002:4	1.106961	1.106961	1.106961
2003:1	1.098962	1.183478	1.151040
2003:2	1.091026	1.198299	1.138618
2003:3	1.091869	1.162030	1.129304
2003:4	1.081800	1.164837	1.134648
2004:1	1.086848	1.204147	1.142681
2004:2	1.065808	1.205515	1.147582
2004:3	1.051769	1.169880	1.150089
2004:4	1.071924	1.164688	1.151707
2005:1	NA	1.194150	1.152959
2005:2	NA	1.199278	1.153915
2005:3	NA	1.172582	1.154626
2005:4	NA	1.165549	1.155173

Bibliographical Annex: Basic theoretical models

The Beveridge-Nelson method

Be Z_t a $n \times 1$ vector including a n_1 vector representing a variable integrable of order 1, $I(1)$, and a n_2 vector representing a stationary variable $I(0)$, such as:

$$Z_t = (\Delta X_{1t}', \Delta X_{2t}')'$$

If we apply the Wald decomposition theorem, Z_t may be written in a reduced form as follows:

$$Z_t = \delta(t) + C(L) \varepsilon_t \quad (1)$$

where $\delta(t)$ is the deterministic term, $C(L) = \sum C_i L^i$ (\sum from $i=1$ to ∞) is the polynomial lags' matrix, $C_0 = I_n$ is the identity matrix, the ε_t vector is the forecasting errors vector of Z_t for the next step that provides information about the lags of Z_t and which satisfies the restrictions: $E(\varepsilon_t) = 0$ and $E(\varepsilon_t, \varepsilon_t') = \Omega$, with Ω positively defined.

Beveridge and Nelson show that equation (1) may be decomposed in a long-term (permanent) component and a short-term (transitory) one:

$$Z_t = \delta(t) + C(1) \varepsilon_t + C^*(L) \varepsilon_t \quad (2)$$

with $C(1) = \sum C_i$ (\sum from $i=1$ to ∞) and $C^*(L) = C(L) - C(1)$. We define $C_1(1)$ as the long-term multiplier of the vector X_{1t} . If the rank of $C_1(1)$ is below n_1 , then there is at least one linear combination of the elements of X_{1t} which is $I(0)$ (stationary). In other words, there is at least one co integration relationship among these variables.

The Blanchard-Quah decomposition

The B-Q approach was used in different circumstances, for instance to examine the dynamic effects of the demand and supply shocks in the OECD countries (Bayoumi and Eichengreen 1994, Bergman 1996, Funke and Hall 1998, Gavosto and Pellegrini 1999, Keating and Nye 1999), and in Canada (Pierre St-Amant, Simon van Norden 1997, René Lalonde, Jennifer Page and Pierre St-Amant 1998); to study the response of the Federal Reserve to the supply and demand shocks (Gamber and Hakes 1997); to study the response of inventory and inflation variations to the demand and supply shocks (Hess and Lee 1999); to study the real exchange rate dynamics (Ender and Lee 1997) and (Bergman, Cheung and Lai 2000); to study the dynamics of the NAIRU, output gap and structural budget balance (Hjelm, Göran 2003).

What all these studies have in common is that the inference is based upon bivariate VAR models with a long-term restriction upon the reduced form of the VAR model in order to identify two structural shocks, one on the supply and the other on the demand side.

Blanchard and Quah (1989) assume that a bivariate model comprising the logarithm of output, y_t and unemployment, u_t , is influenced by two types of shocks: one on the supply side, with long-term effects upon the output, but not upon the unemployment, and a transitory shock with short-term effects upon both variables⁶. However, the permanent shock may influence the unemployment in the short and medium run, but not in the long run.

Such restrictions are based upon the argument that the real shocks, such as the changes in labor productivity and labor force have permanent effects only upon the output. Moreover, this restriction is consistent with a labor market model with a Fisher-type (1977) behavior of wages; see Blanchard and Quah (1989) or Bergman (1996). The long-term restrictions require that the output comprises a stochastic trend and the unemployment only a deterministic one. Thus, in a bivariate system we have: a „co integration vector”, the unemployment is stationary and a stochastic trend in output.

Blanchard and Quah assume that Z_t has the following structural representation:

$$Z_t = \delta(t) + \Gamma(L) \eta_t \quad (3)$$

where η_t is the n -dimensional vector of the structural shocks, with $E(\eta_t) = 0$ and $E(\eta_t \eta_t') = I_n$ (normal). We may find the structural form of equation (3) in the reduced form using the following relationships: $\Gamma_0 \Gamma_0' = \Omega$, $\varepsilon_t = \Gamma_0 \eta_t$, and $C(L) = \Gamma(L) \Gamma_0^{-1}$.

The covariance matrix of the reduced form is equal to $C(1) \Omega C(1)'$. From equations (1) and (3) we have:

$$C(1) \Omega C(1)' = \Gamma(1) \Gamma(1)' \quad (4)$$

This relationship suggests that we may identify the Γ_0 matrix using a corresponding number of restrictions upon the structural form covariance matrix. Blanchard and Quah (1989) use long-term restrictions in order to identify the shocks for which $C(1)$ has the rank n_1 .

If we assume that the log (real output) is the first variable of the vector Z_t , we may write:

$$\Delta y_t = \mu_y + \Gamma_1^p(L) \eta_t^p + \Gamma_1^c(L) \eta_t^c \quad (5)$$

where η_t^p is the vector of the permanent shocks that influence the output, η_t^c is the vector of the shocks that have only transitory effects upon the output and $\{ \Gamma_1^p(L), \Gamma_1^c(L) \}$ represent the dynamic effects of these shocks. The increase in the potential output may be defined as:

$$\Delta y_t^p = \mu_y + \Gamma_1^p(L) \eta_t^p \quad (6)$$

Thus, the potential output corresponds to the permanent component of the output. The part of output due to the purely transitory shocks is defined as the „output gap”.

⁶ In particular, they impose the restriction that the effects upon output and unemployment due to the transitory shocks must satisfy the restriction $\lim_{s \rightarrow \infty} \text{resp}(y_{t+s}, u_{t+s}) = 0$. Consequently, they admit the possibility that these shocks might have significant effects in the short and medium run upon both variables.

Extensions of the Blanchard-Quah decomposition

Different extensions of the Blanchard-Quah decomposition allowed to the authors certain distinctions among the different types of transitory shocks. A direct extension is the LRRO model elaborated by St. Amant and van Norden (1997) for the Canadian economy. The authors start from the hypothesis that the real output growth rate (Δy) follows a stationary process (the output is $I(1)$) that responds to two types of shocks: permanent and stationary. In the estimated VAR are included: the first order differences in inflation ($\Delta\pi$), unemployment rate (Δu), which are stationary (inflation and unemployment are integrable of first order), and the real interest rate. It is assumed that there is no co integration relationship among these stationary variables. In the model it is introduced a permanent shock due to supply and three types of transitory shocks. The authors elaborate a model (LRROI) – which is another extension of the Blanchard-Quah decomposition – on the basis of the hypothesis that not only the output is first order non-stationary, but also inflation is better characterized by a first order non-stationary process for the interval considered. The hypothesis regarding inflation is based on the fact that the inflationary process average may vary according to factors such as: the preferences of the monetary authority for a certain type of policy, the political environment the authorities are facing, the stage of the knowledge regarding the costs and benefits when an inflation targeting policy is pursued. Inflation becomes thus a process whose average changes over time, so that it is not stationary, but non-stationary. In the model it is assumed that inflation is a first order non-stationary process.

Thus, with the LRRO method is necessary to assume that only the output is first order integrable ($I(1)$), while the LRROI method is more restrictive, in the sense that asks for an additional hypothesis, namely that inflation is itself a first order non-stationary process ($I(1)$). The LRROI method proposes a measure of the output gap that might be attractive for the decision-makers interested in that part of the real output cyclical component that is associated with the movements in the trend of inflation, by opposing to the data series short-term fluctuations. The results provided by the LRRO method cannot help the decision-makers in this respect. The short-term fluctuations of inflation revealed by the LRRO method may be due to the exchange rate transitory fluctuations or to changes in the tax burden (in the indirect taxes, for instance), and the decision-makers might not accept a change in the fiscal or exchange rate policy only in order to level down the short-term fluctuations. In this respect, it is interesting to reveal the inflationary trend long-term fluctuations, especially in Romania where persistence of two digits inflation already has a long history. In this case, the decision-makers might be interested to react to the output fluctuations associated with the long-term variations in inflation.

We briefly present another extension of the Blanchard-Quah decomposition, namely that proposed by Hjelm (2003). If in the Blanchard-Quah model is estimated a VAR comprising two variables: output and unemployment, subject to the action of two perturbations (shocks), one generated by supply and the other generated by demand, with the restriction that only one of them - that generated by supply – has long-term effects upon the output, in the model proposed by Hjelm, three variables are used: unemployment (u), output (y) and the consolidated budget balance (bb), and it is assumed that unemployment and output are first order non-stationary and the consolidated budget balance is stationary. It is also assumed that these variables are subject to the shocks induced by the labor market, which influence both unemployment and output in the long run, to the (supply) productivity shocks that influence only the output in the long run and to the business

cycle shocks (demand shocks) that have no long-term effects, either upon output or unemployment.

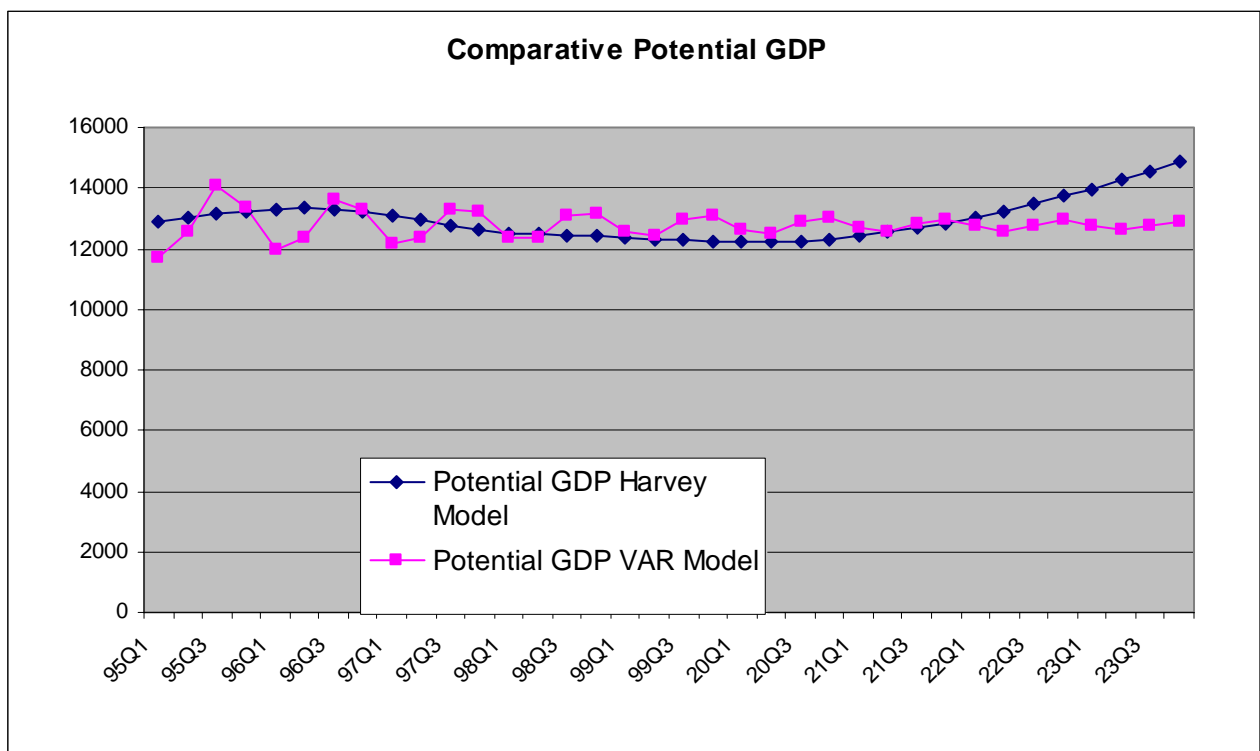
Bibliography

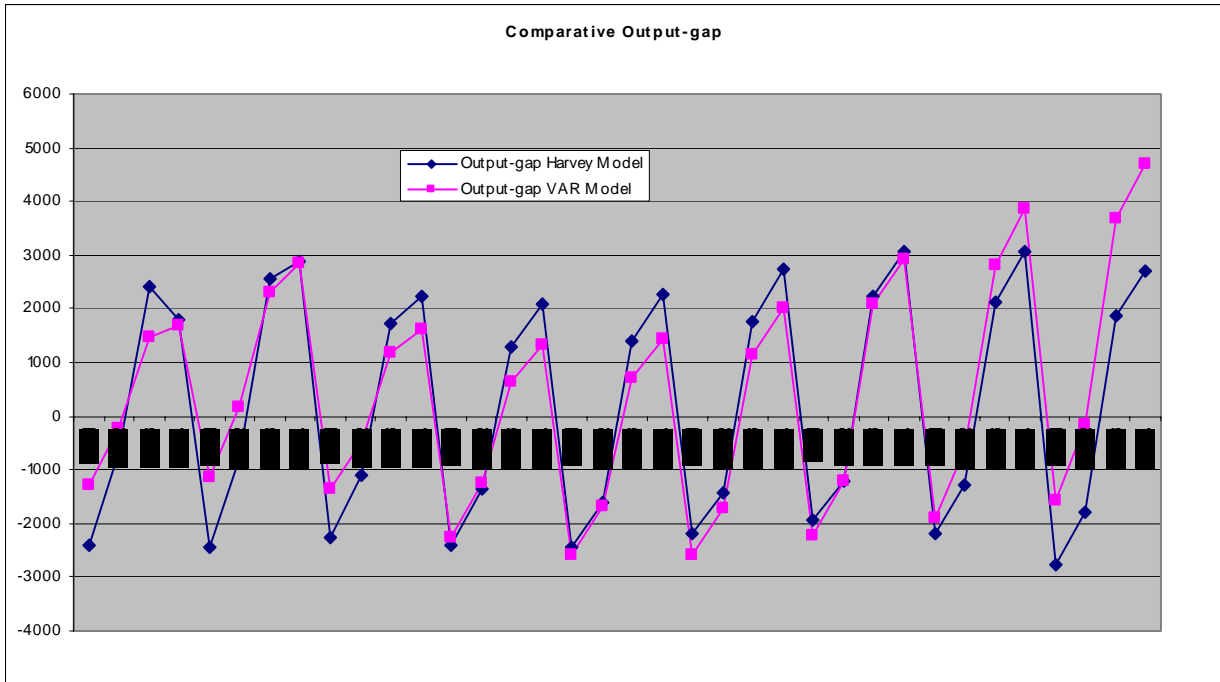
- Albu, Lucian-Liviu**, (2001) „Evolution of Inflation-Unemployment Relationship in the Perspective of Romania’s Accession to EU” *Romanian Journal of Economic Forecasting*, No. 3-4/2001
- Albu, Lucian-Liviu**, (2004) „Dinamica ratei naturale a șomajului în perioada tranziției” *OEconomica*, Nr. 1/2004
- Blanchard, Olivier Jean and Quah, Danny** (1989) „The Dynamic Effects of Aggregate Demand and Supply Disturbance”, *The American Economic Review*, September 1989, Vol. 79, No. 4, pp. 655-673.
- Campbell, John Y. and Mankiw, N. Gregory** (1987), „Are output Fluctuations Transitory?” *Quarterly Journal of Economics*, November 1987, 102, pp. 857-80.
- Cochrane, John**, (1988), „How Big Is the Random Walk in GNP?” *Journal of Political Economy*, October 1988, 96, no. 5, pp. 893-920.
- Cochrane, John**, (1994), „Permanent and Transitory components of GNP and Stock Prices” *Quarterly Journal of Economics* 109 (1), pp. 241-65
- Dăianu, Daniel and Albu, Lucian-Liviu** (1996), “Strain and the Inflation-Unemployment Relationship: A Conceptual and Empirical Investigation” *Research Memorandum ACE Project*, University of Leicester, 15/1996
- Hjelm, Göran** (2003) „Simultaneous Determination of NAIRU, Output Gaps, and Structural Budget Balances: Swedish Evidence”, *Working Paper, No. 81, April 2003, National Institute of Economic Research, Stockholm 2003*.
- Lalonde, René, Page, Jennifer et St-Amant, Pierre** (1998) „Une nouvelle méthode d’estimation de l’écart de production et son application aux États-Unis, au Canada et à l’Allemagne”, *Document de travail 98-21, Banque de Canada, décembre 1998*.
- Mandelbrot, Benoit** (1989) *Fractal geometry: What is it, and what does it do?* *Proc. Royal Society* (London), 1998
- Mandelbrot, Benoit** (1995), *Les objets fractals- Forme, hazard et dimension*, quatrième édition, Flammarion, 1995
- Quah, Danny**, (1988) „The Relative Importance of Permanent and Transitory Components: Identification and Some Theoretical Bounds” MIT Working Paper No. 498, October 1988.
- Pelinescu, Elena, Scutaru-Ungureanu Cornelia** (2001) „A dynamic Model of the Money demand in Romania”, *Romanian Journal of Economic Forecasting*, No. 1-2/2001
- Peters, E.** (1991), *Chaos and Order in the Capital Markets – A new View of Cycles, Prices and Market Volatility*, John Wiley & Sons Inc. , 1991
- Scutaru, Cornelia and Ghiță Adrian** (1999), “Chaos and Order in Transition: Social Costs (Inflation, Unemployment) and Exchange Rate Policy, Case of Romania” *Research Memorandum ACE Project*, University of Leicester, 9/1999
- Scutaru, Cornelia**, (2001), „Answer of an Inflationary Circuit to the Possible Shocks in Economy” *Romanian Journal of Economic Forecasting*, No. 3-4/2001
- St-Amant, Pierre and van Norden, Simon** (1997) „Measurement of the Output Gap: A Discussion of recent Research at the Bank of Canada”, Technical Report No. 79, august 1997, Bank of Canada.

Chapter 3. Comparisons between the obtained results by filtering methods (Chapter 1) and VAR methods (Chapter 2)

For comparing the results we have retained, as the authors suggest, the potential output and the output gap given by the Harvey model and the VAR one which includes the real GDP, the unemployment and the inflation (the variables symbolized by Δy_{94} , Δu , p).

For the potential GDP the Harvey model puts in evidence a smoothed business cycle, while the VAR model maintains the seasonality of the initial data.





Regarding the output gap, the results are coherent, in the sense that they follow the same seasonal pattern, with bigger differences toward the end of the period.

In the Annex we present the comparative data regarding the two indicators.

Anexa 1

	Potential GDP Harvey Model	Potential GDP VAR Model
95Q1	12868.25	11717.8
95Q2	13017.37	12566.17
95Q3	13138.87	14056.95
95Q4	13228.85	13338.78
96Q1	13291.36	11956.95
96Q2	13330.72	12361.53
96Q3	13318.9	13591.62
96Q4	13245.75	13277.87
97Q1	13102.4	12184.32
97Q2	12927.12	12336.29
97Q3	12749.55	13298.14
97Q4	12616.16	13227.81
98Q1	12525.38	12380.76
98Q2	12475.73	12368.79
98Q3	12434.62	13098.83
98Q4	12409.55	13168.48
99Q1	12373.45	12531.21

99Q2	12330.02	12423.03
99Q3	12286.2	12961.64
99Q4	12243.38	13103.93
20Q1	12217.55	12639.27
20Q2	12207.36	12483.24
20Q3	12242.84	12868.87
20Q4	12308.82	13040.48
21Q1	12412.69	12713
21Q2	12530.35	12541.52
21Q3	12682.2	12808.34
21Q4	12848.22	12982.56
22Q1	13037.01	12760.57
22Q2	13248.69	12593.89
22Q3	13475.86	12770.94
22Q4	13727.47	12932.45
23Q1	13981.99	12789.1
23Q2	14267.73	12638.6
23Q3	14569.5	12749.74
23Q4	14882.51	12890.87

Anexa 2

	Output- gap Harvey Model	Output- gap VAR Model
95Q1	-2417.15	-1266.7
95Q2	-693.575	-242.37
95Q3	2400.031	1481.946
95Q4	1783.353	1673.42
96Q1	-2457.86	-1123.45
96Q2	-793.925	175.2701
96Q3	2570.005	2297.276
96Q4	2883.552	2851.431
97Q1	-2275.2	-1357.12
97Q2	-1089.72	-498.893
97Q3	1727.552	1178.962
97Q4	2218.343	1606.693
98Q1	-2396.88	-2252.26
98Q2	-1351.83	-1244.89
98Q3	1289.378	625.1744
98Q4	2089.952	1331.017
99Q1	-2441.15	-2598.91
99Q2	-1598.72	-1691.73
99Q3	1383.4	707.9556
99Q4	2284.222	1423.666
20Q1	-2171.75	-2593.47
20Q2	-1444.66	-1720.54
20Q3	1756.863	1130.827
20Q4	2753.184	2021.516
21Q1	-1920.89	-2221.2

21Q2	-1201.45	-1212.62
21Q3	2214.8	2088.662
21Q4	3057.878	2923.54
22Q1	-2182.41	-1905.98
22Q2	-1288.79	-633.99
22Q3	2109.939	2814.864
22Q4	3066.529	3861.55
23Q1	-2750.79	-1557.9
23Q2	-1791.83	-162.701
23Q3	1862.998	3682.761
23Q4	2690.388	4682.026

Second Part

Chapter 1. Estimating natural unemployment in transitional economies (Case of Romania)*

Lucian-Liviu ALBU**

There are various methods trying to estimate economic cycles during last decades based on natural unemployment rate or NAIRU (“Non-Accelerating Inflation Rate of Unemployment”). Taking into account already accumulated experience on about fifteen years of transition and data today available, we try to estimate the level of natural rate in case of Romanian economy. Our study is coming from a general standard model recently used in order to estimate changes in NAIRU during last decades in USA and to investigate causes of such evolution (Ball and Mankiw, 2002). Moreover, in case of application on the Romanian economy in transition period, in order to verify what is the type of correlation between natural rate and change in productivity we used an outside independent model to estimate the dynamics of so-called pure productivity. Finally, some ways to further continue the research are deduced.

Following some old preoccupations (Dăianu and Albu, 1996; Albu, 1998 and 2001), we present only few conclusions based on an empirical analysis of the inflation-unemployment relationship evolution in European area after 1970. So, empirical studies demonstrate, on the background of business cycles, some major changes of trends in Western countries during last three decades. Among these it can be noted an impressive decrease in inflation followed by a continuing growth of unemployment and general diminution of the yearly growth rate of production (GDP). An important conclusion is that a smaller volume in 3D map (estimated by including the variation of the three macroeconomic indicators) represents a greater economic stability and consequently less strain in economic system. In Appendix 1 it is shown a graphical representation of the evolution during last three decades (1970-2000) in the three-dimensional space (unemployment rate, $u\%$ - annual growth rate, $y\%$ - inflation, $\pi\%$), including ten EU countries (Belgium, Denmark, England, France, Germany, Italy, Ireland, Holland, Portugal, and Spain). Evolution was from a period in which high inflation predominated toward one in which unemployment plays now this role. This evolution could mean that on the unemployment-side occurred a relaxation, higher levels of unemployment being viewed as normal but is not the case for the inflation level. A deeper analysis showed the possibility of some persistent trends and long-run attractors. On the other hand, in Eastern European countries there was an opposite situation at least during the first years of transition after 1989; open inflation rose rapidly in the region whereas unemployment did also rise but at a smaller pace. There are evidences demonstrating that the long-run trends will be similar to those registered in Western countries.

In case of each individual Eastern economy the most important question is how long the transition period will be. Despite of a relatively short period since 1989, in case of Eastern countries it seems to emerge a convergence process relating the natural rate of unemployment. The main problem continues to be a relatively high inflation comparing with the EU standards (especially in case of Romania where the annual inflation will decrease below 10% just last year).

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In case of Western countries in Europe, it would seem that long periods of experiencing high unemployment might have infused a larger acceptance of the system in this matter. This must be viewed in direct connection with a continuous development of social security programs, but also with other variables such as the budget deficit and public debt, their sustainability, number of

strikes, etc. In Eastern countries it seems that the acceptance of large unemployment rate is smaller at least during the incipient stages of transition period. Moreover, in these countries the development of social security programs is only in a re-building phase. It should be underlined that the probable large share of underground sector in their national economy could alter the level of macroeconomic indicators used currently in analyses.

The evolution in Eastern countries in transition period represented only a stage within a long-run wave on the general economic development scale. Also, when the income level per capita rises to a very high level, it was demonstrated a specific evolution process in Western countries, namely that to higher natural rate of unemployment and to a period in which unemployment become more autonomous relating to the dynamics of GDP. Important for the Eastern countries, is that, in actual period of the “new economy” revolution, the converging process do not suppose necessarily a repetition of the Western evolution coming from the ‘60s and its achieving period could be substantially reduced.

Numerous studies trying to estimate economic cycles during last decades are based on natural unemployment rate or NAIRU (“Non-Accelerating Inflation Rate of Unemployment”). Following the cited study of Ball and Mankiw, in which they demonstrated that NAIRU (a useful concept within the business cycle theory) is in fact very similar to the natural rate, in order to estimate its value in case of Romanian economy after 1989, we rewrite the Phillips curve equation as follows:

$$\Delta\pi = aU^* - aU + v \quad (1)$$

where a and U^* are parameters, $\Delta\pi$ is the deviation of actual inflation, π , from expected inflation, π_e , and v is shock on supply side. U^* is named natural rate of unemployment. In case of accepting adaptive expectations, the expected inflation is a weighted average of the past inflation rates. The simplest solution is to consider expected inflation to be equal to the registered inflation in previous period, $\pi_e = \pi_{-1}$.

Supposing that U^* is constant and U is uncorrelated with v , then the value of U^* can be estimated by regressing the change in inflation, $\Delta\pi$, on a constant and unemployment U . So, the ratio of the constant term, noted as $m=aU^*$, to the absolute value of the unemployment coefficient, noted as a , is an estimate of U^* . Applying this exercise for annual US data in period 1960-2000, measuring inflation with the consumer price index, Ball and Mankiw reported a constant term of 3.8 and an unemployment coefficient of -0.63. The resulted NAIRU estimate in case of American economy was 6.1%. Reproducing the same exercise in case of Romanian economy on quarterly data for the period 1994-2004 (QIV1994 – QIV2004) we obtained a value of 6.1 for the constant term m and an unemployment coefficient of -0.69. These values correspond to a NAIRU estimate of 8.9%.

We note the sensibility of two parameters (m and respectively a) to changes in frequency of statistical data (on rule annual, quarterly or monthly data are used), but also a relative stability of the estimated value of NAIRU. For instance, in case of annual data for the period 1991-2004, we obtained a value for the constant term (m) of 122.6 and an unemployment coefficient of -15.3. Based on these values resulted a NAIRU estimate of around 8.0%. In case of using monthly data for the period December 1991 - December 2003, we estimated a value for the constant term of 0.124 and an unemployment coefficient of -0.023. The implicit computed value for NAIRU was around 5.4%.

However, many economists contest the assumption of a constant NAIRU and a growing literature tries to estimate persistent movements in NAIRU. The main hypotheses are based on idea that

changes in U^* are long-term shifts in the unemployment-inflation relation, but the shock v captures short-run fluctuations. Following again the Ball and Mankiw's methodology, we used for application the following equation obtained by rearranging terms:

$$U^* + (v / a) = U + (\Delta\pi / a) \quad (2)$$

Its right-hand side can be computed from statistic data, generating in this way an estimate of $U^* + (v / a)$, which in fact measures the shifts in the Phillips curve. The authors noted that U^* represents the longer-term trends and v/a is proportional to the shorter-term shocks. Consequently we can try to extract U^* from $U^* + v/a$ using a standard approach to estimating the trend in a series. On the rule, in literature it is used the Hodrick-Prescott filter (Hodrick and Prescott, 1997), noted below as HP. In case of using HP filter, we must choose two parameters: the Phillips curve slope, a , and respectively the smoothing parameter λ (this makes the trend, U^* , to be smoothed and not with large oscillations, by replacing the banal procedure of fitting every movement in $U^* + (v / a)$). The selection of a value for parameter λ is very arbitrary.

In case of our experiment on the Romanian economy in transition period, we used in case of annual series 15.3 for coefficient a , value already obtained previously by regressing $\Delta\pi$ function of one constant and the actual rate of unemployment, U . This value can be interpreted in relation with the disinflation cost (so, it means for the transition period in Romania, period characterized generally by a very high level of inflation, that the inflation decreases by 10 percentage points generated in average $10/15.3 = 0.66$ percentage points of unemployment per year). Regarding the selection of HP parameter λ , in literature there are reported numerous experiments. However, few conclusions were outlined, but they derived only on empirical analysis. So, in specialized literature there are recommended a number of values for parameter λ , as follows: 100 in case of annual series (other authors suggest value 1000 in order to obtain a more smoothed trend); 1600 in case of quarterly series; and 14400 in that of monthly series.

In fact, HP filter is equivalent to an interpolation method. Therefore, given a time series, it is natural to consider as candidate every other method permitting to estimate a smooth trend. In our exercise on Romanian economy during transition period, we used three procedures. They can be found within sources-packages in *MathCAD* referring to the classes "Polynomial Regression" and respectively "Smoothing Data". Then we used them in order to estimate the trend of U^* . The concrete estimation functions we chosen are:

- *regress* (vx , vy , k) returns a vector which *interp* uses to find the k th order polynomial that best fits the x and y data values in vx and vy ; it generates a vector permitting interpolation, finally expressed by function *interp* (vs , vx , vy , x); k is a positive integer specifying the order of the polynomial we want to use to fit the data (usually it is recommended to choose $k < 5$);

- *loess* (vx , vy , $span$) returns a vector which *interp* uses to find a set of second order polynomials that best fit a neighborhood of the x and y data values in vx and vy ; it generates a vector permitting interpolation, finally expressed by function *interp* (vs , vx , vy , x); *span* is a positive real number for specifying how big a neighborhood we want to use (usually it is recommended to select larger values of *span* when the data behaves very differently over different ranges of x ; a good default value is *span*=0.75);

- *ksmooth* (vx , vy , b) returns an m -element vector created by smoothing using a Gaussian kernel to return weighted averages of the elements in vy ; b is the bandwidth of the smoothing window (it should be set to a few times the spacing between x data points).

In case of the first two procedures \mathbf{vx} is a vector of real data values in ascending order. These correspond to the x values. \mathbf{vy} is a vector of real data values and they correspond to the y values. The number of elements is the same as \mathbf{vx} . \mathbf{vs} is a vector generated by *regress* function and respectively by *loess* function. x is the value of the independent variable at which we want to evaluate the regression curve. In case of the third procedure \mathbf{vx} is an m -element vector of real numbers and \mathbf{vy} is an m -element vector of real numbers.

For applications in Romanian economy case, we used the following values for parameters: $k = 3$, $\text{span} = 1$ and respectively $b = 5$ (indeed, in case of quarterly or monthly series other values must be attributed to parameters). We used also the HP filter with $\lambda=100$. Some results of our exercise on Romanian economy using annual series are synthetically reported in Table 1 and Figure 1 (also in Figure of Appendix 2 is presented the trend of natural rate in case of using the quarterly data; the key-parameters for the four filters are $k=3$, $\text{span}=1$, $b=16$, and $\lambda=1600$). The natural rate of unemployment estimated by simple regression in case of annual data, relation (1), is noted U_n in order to not be confused with U^* (U_n has an unique value of 8.0% for the 1992-2004 period, but U^* means the trend in long run of natural rate estimated conforming to all filters used).

Table 1. Estimated long run trend of NAIRU (in %)

Year	U (1 Jan. of year)	$U_n + (v/a)$	Estimation Function			
			Y TR _i ¹⁾	Y TL _i ²⁾	Y TK _i ³⁾	Y HP _i ⁴⁾
1992	3.0	5.6	6.8	6.4	6.8	6.6
1993	8.2	11.2	6.5	6.7	6.7	6.9
1994	10.4	2.6	6.7	7.0	6.8	7.2
1995	10.9	4.1	7.0	7.4	7.2	7.5
1996	9.5	9.9	7.6	7.8	7.9	7.9
1997	6.6	14.2	8.2	8.3	8.4	8.1
1998	8.9	2.6	8.9	9.3	8.7	8.4
1999	10.4	9.5	9.4	9.6	9.0	8.5
2000	11.8	11.8	9.6	9.6	9.1	8.7
2001	10.5	9.8	9.6	9.3	9.1	8.7
2002	8.8	8.0	9.2	8.8	8.8	8.7
2003	8.4	7.9	8.2	8.1	8.3	8.6
2004	7.4	7.2	6.7	7.0	8.0	8.5
U* minim			6.5	6.4	6.7	6.6
U* maxim			9.6	9.6	9.1	8.7
U* average			8.0	8.1	8.1	8.0

¹⁾ $Y_{TR_i} = \text{interp}(RY, t, Y, t_i)$, where $RY = \text{regress}(t, Y, 3)$, $Y = U + (\Delta\pi/a)$

²⁾ $Y_{TL_i} = \text{interp}(LY, t, Y, t_i)$, where $LY = \text{loess}(t, Y, 1)$, $Y = U + (\Delta\pi/a)$

³⁾ $Y_{TK_i} = \text{ksmooth}(t, Y, 5)$, $Y = U + (\Delta\pi/a)$

⁴⁾ $Y_{HP_i} = \text{Hodrick-Prescott filter}(\lambda = 100)$

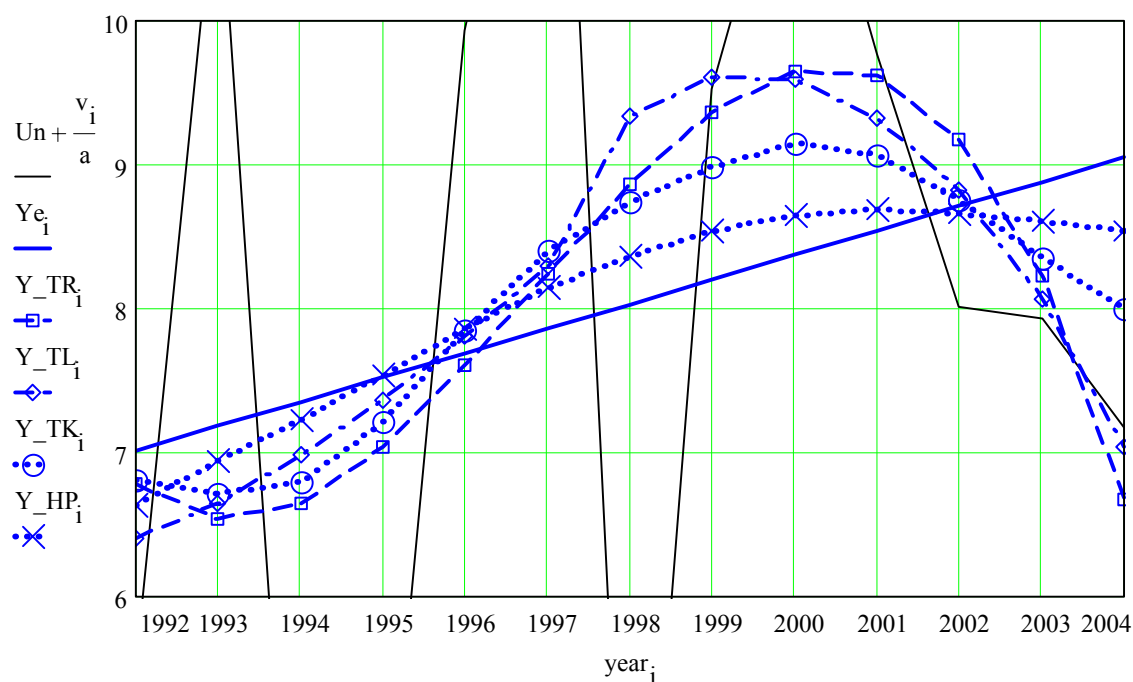


Figure 1.

We can see similar dynamics of the natural rate, U^* , for all estimation procedures: minimal value was registered during the first years of transition (1992-1994), but the maximal value seems to be registered in middle period (1999-2002). Note that the average value of NAIRU is equal to the unique value estimated by the simple regression (8.0%). On the base of simulations, we can also see the unfavorable impact of positive difference between effective unemployment rate and NAIRU on inflation dynamics ($\Delta\pi$). In case of linear trend the gap is $\Delta U = U - Y_e$, but in case of the four selected filters it is noted $\Delta UR = U - Y_{TR}$, $\Delta UL = U - Y_{TL}$, $\Delta UK = U - Y_{TK}$, and respectively $\Delta UH = U - Y_{HP}$. As we can see from the Figure 2, as general rule, the points in 2D space, $\Delta U - \Delta\pi$, are distributed in sectors II and IV (in trigonometric sense) over the right line transcending the origin of coordination axes. Eventual differences (the evading from two mentioned sectors) can be attributed to the short run supply shocks. Also, corresponding to the four used filters, we computed the natural (or potential) level of GDP, as it is shown in table of Appendix 3, and respectively output gap and the correlation coefficient between it and inflation variation in Appendix 4. The general level of correlation coefficient between output gap and variance of inflation ($\Delta\pi$), for the period 1992-2004, was positive (between +0.600 and +0.641). From Figure of Appendix 4, we can see that in the first part of transition period (before 1998) the inflation is accentuated procyclical relating to output gap (correlation coefficient between +0.669 in case of TL filter and +0.714 in case of HP filter). However, after 1998 it is countercyclical (correlation coefficient between -0.420 in case of HP filter and -0.836 in case of TR filter), that could mean a favorable temporary situation when a growth in output may be accompanied by a negative change in inflation. More explanation could be extracted in case of considering the dynamic process of real reforming and restructuring of the national economy: a prolonged and hesitant restructuring process of economy

in first part of transition (before 1998); and a more determinate and accelerated process of it during last years (after 1998).

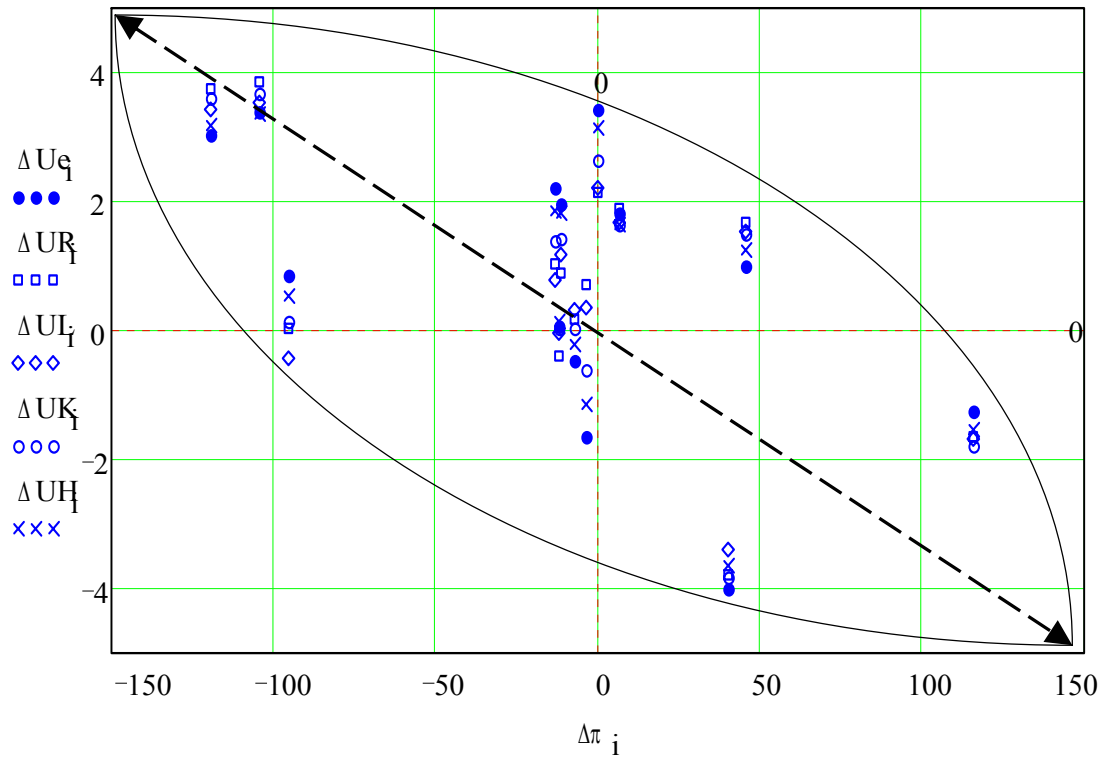


Figure 2.

As many times in literature is supposed, the growth of productivity could affect in a significant way the potential GDP and also the natural rate of unemployment. In order to verify the eventual link between the productivity acceleration and natural rate of unemployment it is essentially to use an independent model to estimate productivity trend. Moreover, taking into account that the current level of productivity is implicitly influenced by the value of unemployment rate, more accurately is to evaluate the level of so-called pure productivity. This level must be independently from short-run variation in employment, being affected more in long-term by factors such as the general technological progress, increasing in education level, expanding of R&D system, impact of extending the share of “new economy” within the whole economic system together with their implications, etc.

In order to estimate the level of pure productivity and its trend in case of Romanian economy, we conceived a simple particular model having as hypotheses the following two equations (the time subscript, t , being omitted):

$$q = A L \alpha = A L^\alpha \mu^\alpha = q_{\max} \mu^\alpha \quad (3)$$

$$s = s_0 L^\alpha \quad (4)$$

where q and s are production (GDP) and respectively all costs implied by its achievement (taking into account that the production function has an alone factor, so the active labor force); q_{max} and s_0 are production under the hypothesis of an integral utilization of labor force ($L_a=L$) and unitary cost (indeed including also salary) per person in active labor force, L_a , respectively; α is a positive and sub-unitary coefficient, which determinates how look the production curve function of employment share, μ , in total labor force, L ($\mu=L_a/L$). For the moment all considered variables are evaluated in real terms, therefore under the hypothesis of constant prices (of a year selected as base).

The difference between q and s can be interpreted as being the profit or net accumulation, therefore the quantity that stimulates entrepreneurs to make future investments and to develop their affaires. It mainly depends on two factors: employment degree, l_a , and respectively coefficient α . Since the evaluation of the employment share in total available labor force is not a problem, to estimate α is an extremely difficult issue, as well as its economic interpretation. Economists generally accept the sub-unitary restriction, as it ensures the concavity of production function. The explanation is: as employment share grows, tending to value one, the average level of labor productivity tends to decrease (as well as the adapting possibilities of entrepreneurs to some permanent moving markets). In order to solve the problem of estimating the production function curvature, we took into account also the long-run price evolution. The hypothesis that we adopted, however very restrictive, is referring to the absence of some pertinent information on the future evolution of prices (as it is the case of an economic system functioning in high inflation, as well as that of Romanian economy in transition period). The remained solution is to compute maximization of the future profit by reporting to actual level of unitary costs (although knowing that in reality this is not the case for the future period). It would be reasonable that even such decision (founded on a highly restrictive hypothesis, like that of basing the maximization of the future profit on maintaining unchanged the specific costs) could yield sweet fruit in the future, in any way larger than in case of no evaluation calculus. The real adjustment to be operated (indeed instantaneously conforming to the “new wave” theory of rational expectations) then when the pressures on cost (such as for instance the trade unions’ pressures) will not confirm the effective pre-evaluation. The implicit hypothesis of this “backward dynamics” mode of interpretation is that the effective change of unemployment rate in current period from precedent period corresponds even to the solution of profit maximization under the hypothesis of maintaining unchanged cost between the two consecutive periods, but also to the modification of total price of production exactly at the value effectively registered. So, the actual level of unemployment rate means even its optimal level, however computed previously on the base of total cost in precedent period together with the index of prices in current period. Since we accept this interpretation, the maximization function will be:

$$Be(\mu) = Q - s = q p - s \quad (5)$$

where Be is the anticipated profit (despite of knowing that the planed benefit will not be integrally obtained), Q is value of production in current prices, p . This function admits a maximum given by the solution of the following equation:

$$p = (\mu^{1-\alpha}) / \alpha \quad (6)$$

The restriction imposed by this equation enabled us to estimate, only by using a special numeric procedure, the values of α coefficient for the period 1990-2004. The model permitted to estimate

also other synthetic indicators characterizing the evolution of the Romanian economy during the transition period, such as:

- Coefficient of using capacity (or the degree of using potential GDP, noted here as qmax)

$$k = q / q_{\max} = \mu^{\alpha} \quad (7)$$

- Share of profit

$$b = B / Q = (Q - s p) / Q = (q - s) / q = 1 - \mu^{1-\alpha} \quad (8)$$

In Table 2 are shown the estimated values of some indicators in the period 1991-2004. Their signification is as follows: qe90 and qmax are actual GDP in constant prices (prices of year 1990) and respectively potential GDP (it is viewed here as the maximum level of GDP obtained in case of no unemployment, u%=0, and differs from natural level of GDP corresponding to the natural rate of unemployment as it was computed previously); w90 and wL90 are the effective productivity and “pure” productivity (corresponding to the case of integrally using of labor force, μ%=100); k is the coefficient of using capacity (in the theoretic case of potential GDP k=1); and b is the proportion of estimated profit in actual GDP.

Table 2. Estimated level of certain indicators in transition period

	qe90 (10 ⁹ ROL)	qmax (10 ⁹ ROL)	w90 (10 ³ ROL)	wL90 (10 ³ ROL)	k (%)	b (%)
1991	747.2	750.5	78.2	68.4	99.6	0.9
1992	681.2	688.0	69.0	61.2	99.0	2.0
1993	691.5	708.7	62.4	62.6	97.6	5.9
1994	719.8	751.4	66.5	67.1	95.8	6.5
1995	771.3	837.6	71.7	74.6	92.1	3.2
1996	802.1	857.3	77.1	81.6	93.6	3.3
1997	753.2	773.4	84.3	77.6	97.4	4.1
1998	717.2	760.0	80.9	76.7	94.4	3.5
1999	708.6	761.1	79.5	77.2	93.1	3.8
2000	723.2	786.1	80.2	82.1	92.0	4.1
2001	764.4	826.4	85.6	86.2	92.5	3.2
2002	803.0	864.0	89.0	91.9	92.9	1.9
2003	845.0	908.4	93.7	100.3	93.0	1.5
2004	915.4	977.5	101.9	109.8	93.6	1.1

In order to identify the type of relation between unemployment and productivity, following some studies existing in literature (Staiger et al., 2001; Ball and Moffitt, 2001; Ball and Mankiw, 2002) we examined the estimated data supplied by the above NAIRU model (Table 1) and respectively by “pure” productivity model together. Many times the authors are using for the productivity growth an inverted scale to reflect better the two supposed inverse movements: the long-run unemployment trend and productivity growth trend. In case of our application on Romanian economy in transition period, we maintained the original scales, but used a calibrating procedure to

force the two trends to come in a closer region of their co-joint space. In Figure 3 we are presenting the same NAIRU trends from Figure 1 together with the growth rate of “pure” productivity (noted as y_{wL90}). In Figure 3, time means the years in period 1992-2004, noted as 2...14 (the estimated NAIRU levels are here considered at the beginning of each year, as it was in Figure 1). From this graphical representation it is an evident inverse correlation between the estimated NAIRU level and productivity growth. So, we could conclude that, at least in case of transition period, the productivity acceleration is accompanied by a decrease in NAIRU level and when the productivity decreases the NAIRU level increases rapidly. This type of correlation is also verified in case of using quarterly data.

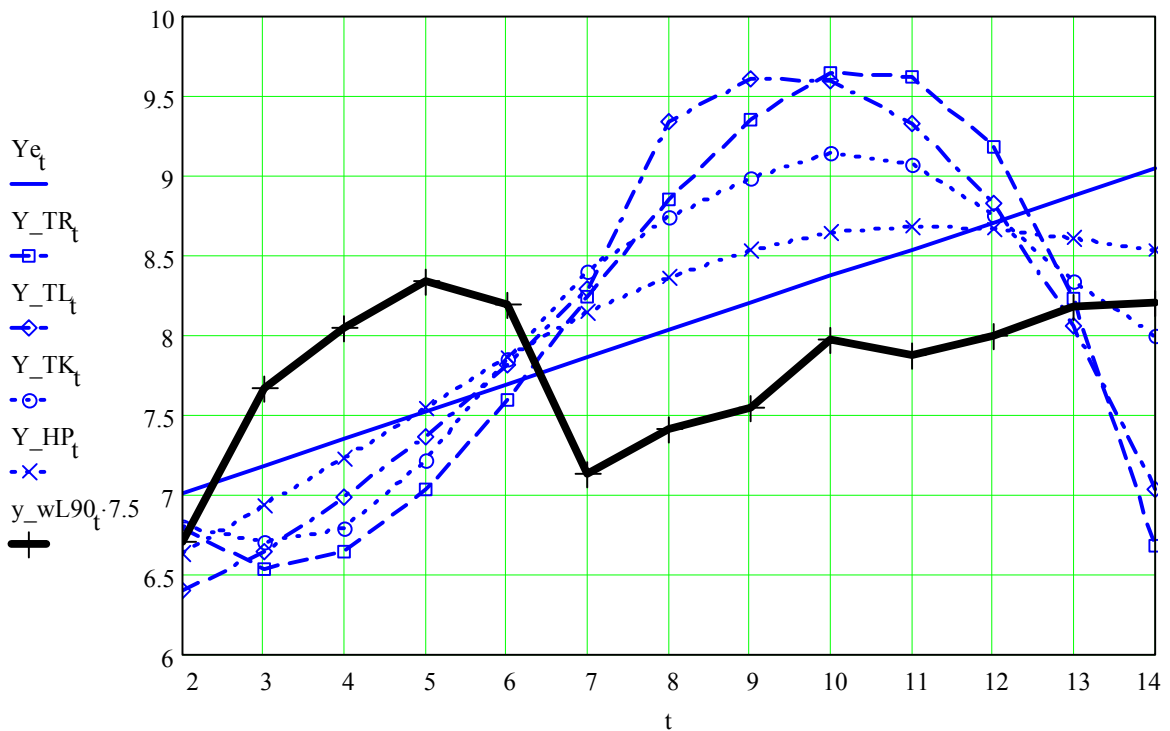


Figure 3.

References

Albu Lucian-Liviu (1998): “Strain and inflation-unemployment relationship in transitional economies: a theoretical and empirical investigation” (monograph), *Final Report, ACE-PHARE-F Project, CEES, January*, University of Leicester, Centre for European Economic Studies, Leicester, Brussels.

Albu Lucian-Liviu (2001): “Evolution of Inflation-Unemployment Relationship in the Perspective of Romania’s Accession to EU”, *Romanian Journal of Economic Forecasting*, 3-4, Bucharest, 5-23.

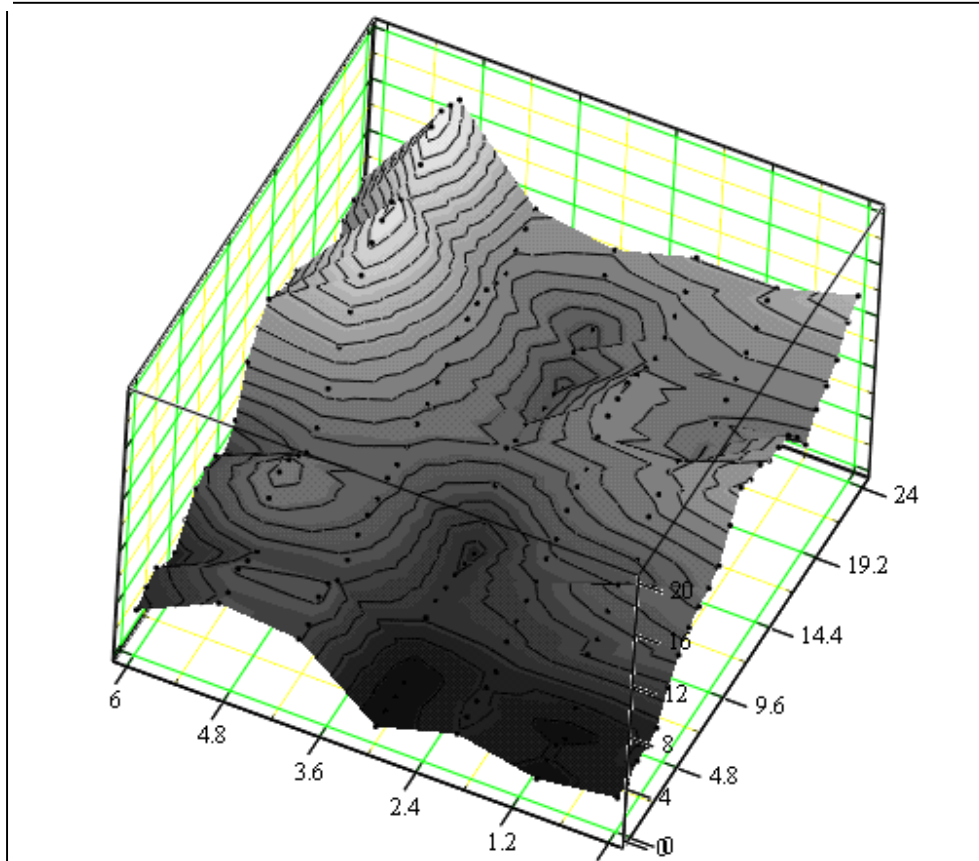
Ball Laurence and Mankiw Gregory (2002): “The NAIRU in Theory and Practice”, *NBER Working Paper Series, 8940*, National Bureau of Economic Research, Cambridge.

Ball Laurence and Robert Moffitt (2001): “Productivity Growth and the Phillips Curve”, *The Roaring Nineties: Can Full Employment Be Sustained?* (eds.: Alan B. Krueger and Robert Solow), New York: The Russell Sage Foundation and The Century Foundation Press.

Daianu Daniel and Albu Lucian-Liviu (1996): “Strain and the Inflation-Unemployment Relationship: A Conceptual and Empirical Investigation”, *Econometric Inference into the Macroeconomic Dynamics of East European Economies, Research Memorandum ACE Project, 15*, University of Leicester, Centre for European Economic Studies, Leicester.

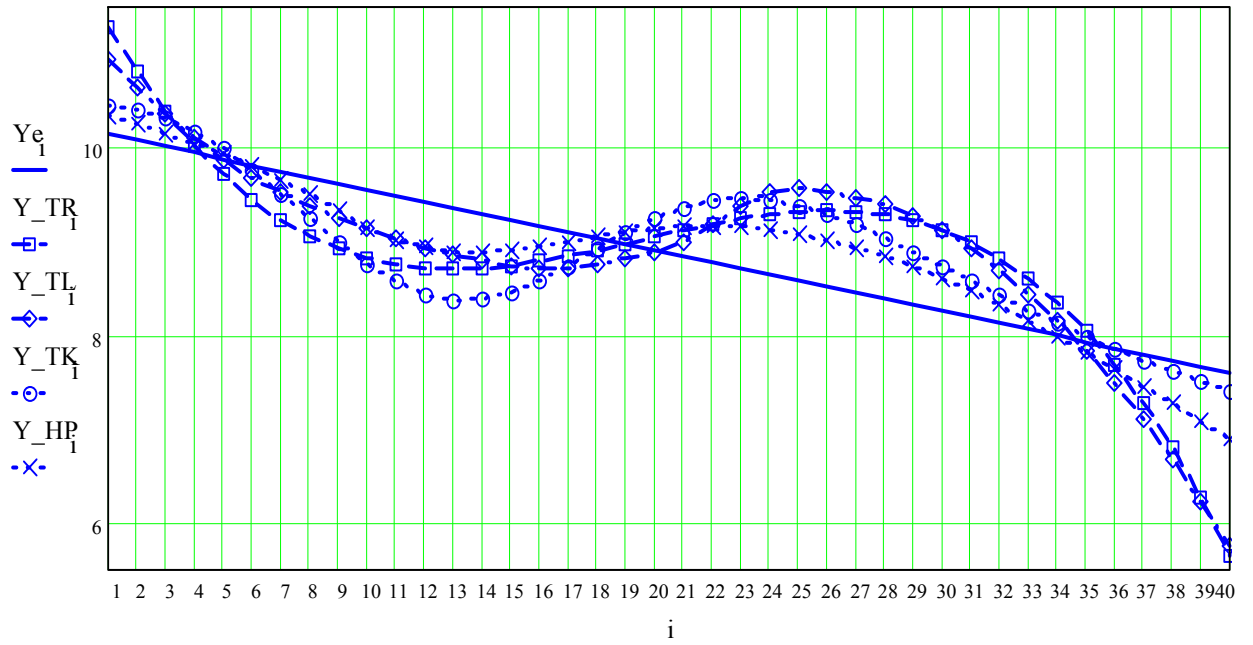
Hodrick Robert and Prescott Edward (1997): “Postwar U.S. Business Cycles: An Empirical Investigation”, *Journal of Money, Credit, and Banking*, 29, 1-16.

Staiger Douglas, James H. Stock, and Mark W. Watson (2001): “Prices, Wages, and the U.S. NAIRU in the 1990s”, *The Roaring Nineties: Can Full Employment Be Sustained?* (eds.: Alan B. Krueger and Robert Solow), New York: The Russell Sage Foundation and The Century Foundation Press.



u%, y%, $\pi\%$

Appendix 2



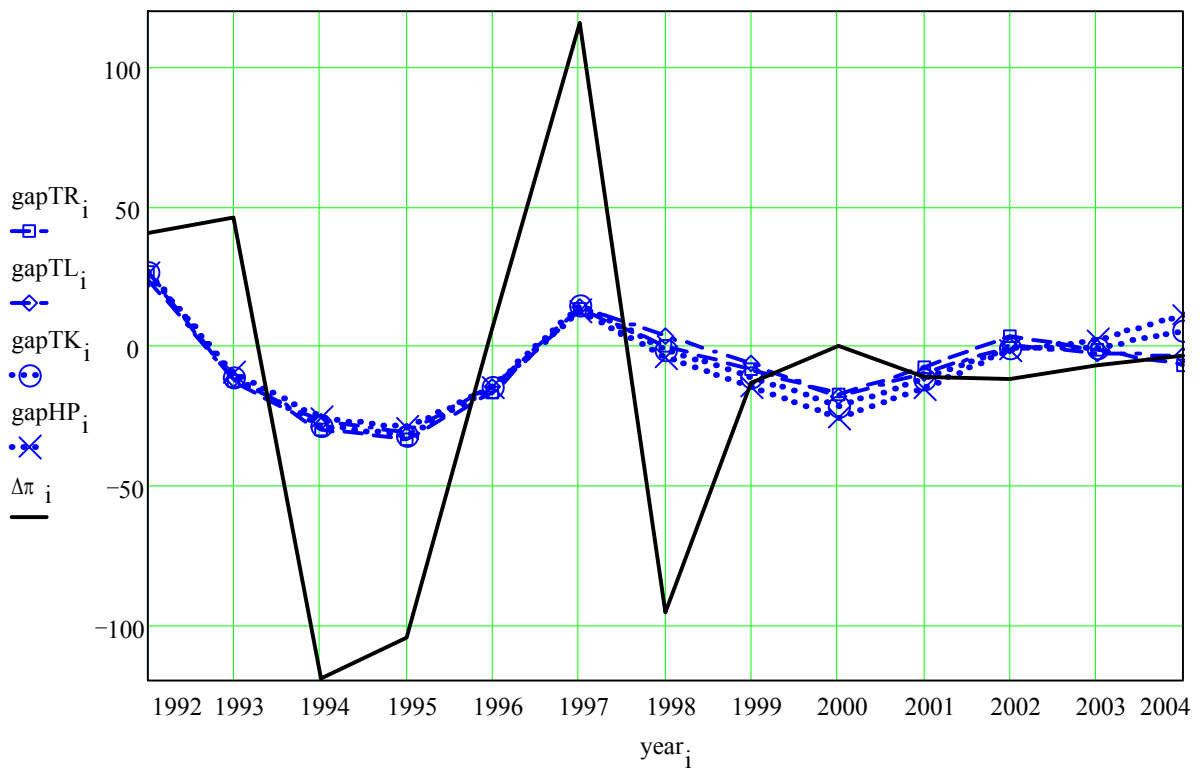
Appendix 3

Estimated natural level of GDP in case of the four filters, in 1990 prices (10⁹ ROL)

	Real GDP	GDP TR	GDP TL	GDP TK	GDP HP
1990	857.9				
1991	747.2				
1992	681.2	654.6	657.3	654.5	655.6
1993	691.5	704.0	703.2	702.7	701.0
1994	719.8	749.9	747.2	748.7	745.3
1995	771.3	804.7	801.9	803.2	800.3
1996	802.1	818.9	817.0	816.7	816.6
1997	753.2	740.0	739.5	738.7	740.7
1998	717.2	717.5	713.7	718.4	721.4
1999	708.6	716.8	714.8	719.7	723.3
2000	723.2	740.9	741.3	745.0	749.0
2001	764.4	772.0	774.4	776.6	779.9
2002	803.0	799.7	802.8	803.4	804.2
2003	845.0	846.6	848.1	845.5	843.1
2004	915.4	922.5	919.0	909.5	904.2

Estimated level of output gap in case of the four filters, in 1990 prices (10^9 ROL)

	GapTR	GapTL	GapTK	GapHP
1992	26.6	23.9	26.7	25.6
1993	-12.5	-11.7	-11.2	-9.5
1994	-30.1	-27.4	-28.9	-25.5
1995	-33.4	-30.6	-31.9	-29.0
1996	-16.8	-14.9	-14.6	-14.5
1997	13.2	13.7	14.5	12.5
1998	-0.3	3.5	-1.2	-4.2
1999	-8.2	-6.2	-11.1	-14.7
2000	-17.7	-18.1	-21.8	-25.8
2001	-7.6	-10	-12.2	-15.5
2002	3.3	0.2	-0.4	-1.2
2003	-1.6	-3.1	-0.5	1.9
2004	-7.1	-3.6	5.9	11.2
Correlation coefficient ($\Delta\pi$, output gap)	0.641	0.617	0.641	0.600



Chapter 2. COBB DOUGLAS PRODUCTION FUNCTION: case of the Romanian economy⁷

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Mariana NICOLAE***

Introduction

Direct single equation estimation of a production function typically Cobb Douglas for evaluation of the potential output gives implausible results. This is because one cannot really treat capital and labor as independent variables and proceed to estimate by Ordinary Least Squares (OLS), because the inputs are chosen in some optimal fashion by the producers and therefore the ergogeneity assumptions required for OLS will not hold (Griliches and Mairesse, 1995). Bernanke and Gurkaynak (2001) note that estimates of the production function coefficients are not always reasonable and problems with the estimation of production relationships are not uncommon. It is necessary to develop a simultaneous system of equations, which consists of first order conditions from optimization of the production function. Under the assumption of competitive factor markets and imperfect competition in the product market, profit maximization results in a three-equation supply-side system. In this paper only the Cobb Douglas production function results are presented.

1. MODEL DESCRIPTION:

⁷ Paper prepared for the Final Report of GDN research project “Adapted models to estimate potential GDP in the candidate countries” (RRC IV-057).

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The Cobb Douglas production function is given by:

$$Y_t = AK_t^\beta L_t^{1-\beta} e^{(1-\beta)\alpha t} \quad (1)$$

where Y_t is real GDP at constant market prices, K_t is the capital stock, L_t is the number of people employed, t is a time trend, and A is a scale factor. Equation (1) assumes constant returns to scale, β is the capital share and α is the rate of growth of labour-augmenting, Harrod neutral technological progress.

Potential output in logs is defined as:

$$\log(Y_t^*) = \log(A) + \beta \log(K_t) + (1 - \beta) \log(L_t) + (1 - \beta)\alpha t \quad (2)$$

Finally, the output gap is defined as:

$$GAP_t = Y_t - Y_t^* \quad (3)$$

An alternative to using a linear trend (t) as a determinant of technological progress is also examined and Total Factor Productivity is calculated as a Solow Residual, i.e.:

$$TFP_t = \log(Y_t) - \beta^* \log(K_t) - (1 - \beta^*) \log(L_t) \quad (4)$$

where β^* is the estimate of β obtained when through the computing of the equations system (formed by the equations 4-6), in logs. Since productivity growth changes over time, a linear trend may be inappropriate, and thus TFP_t is HP-filtered (TFP_t^*), with $\lambda=25$. The sensitivity of the output gap estimates to the use of a linear time trend or HP filtered Total Factor Productivity (TFP) as a proxy for technological progress is assessed. Technological progress is treated as a linear time trend under the Cobb Douglas specification. After estimating the production function using the time trend as an explanatory variable for technical progress, a HP filter is applied to the residual implied by the first stage estimates. The result of the HP filter is used as an exogenous technology component. The system is then re-estimated. This procedure is then repeated until convergence is attained.

Potential output in logs based on this method is:

$$\log(Y_t^*) = \beta \log(K_t) + (1 - \beta) \log(L_t) + TFP_t^* \quad (5)$$

Output gap is constructed on the basis of a Cobb Douglas production function, which relates potential output to the availability of factors of production and technological change.

A simultaneous system of equations, which comprises a production function and first order conditions from optimisation of the production function will be specified for the final report. Profit maximisation results in a three-equation supply-side system. This yields more reliable and plausible results than direct estimation of the production function. Part of this exercise involves estimating the NAWRU (Non-Accelerating Wage Rate of Unemployment), or the equilibrium unemployment rate, which is used to calculate potential employment. The NAWRU is derived

using Elmeskov's (1993) method, which assumes that the change in wage inflation is proportional to the unemployment gap.

2. APPLICATION FOR THE ROMANIAN TRANSITION ECONOMY

This paper is a first application of the model presented in the previous chapter for the Romanian transition economy in order to determine the Potential GDP and the output gap. We will use the equation number 22, in which TFP is evaluated with the help of the Hodrick-Prescott filter for $\lambda = 25$.

The Data

The series used for the construction of the production function (see eq. 5) are: the real GDP (denoted by Y90), the capital stock (denoted by FA90) and the employment (L). For evaluating the stationarity of the series we used the ADF test. The results are presented in Table 1. We have denoted by I the index of the base series and by L the logarithm of the series.

Table 1. Data stationarity (Augmented Dickey-Fuller Unit Root test)

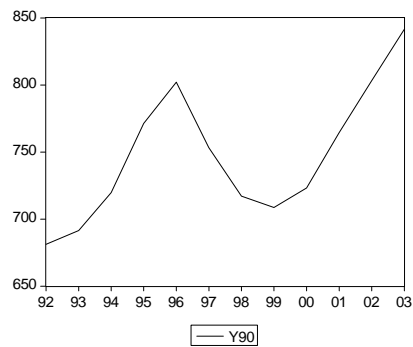
The Series	The Level of stationarity	Characteristics
Y90	I(0) (-2.7732)*	10%, Intercept, 1 lag
IY90	I(0) (-2.7720)**	10%, Intercept, 2 lag
LIY90	I(0)	5%, Intercept+Trend, 1 lag
L	I(2)	1%, Intercept+Trend, 1 lag
IL	I(0)	10%, Intercept, 0 lag
LIL	I(0)	5%, none, 0 lag
FA90	I(2)	5%, none, 1 lag
IFA90	I(1)	10%, Intercept+Trend, 1 lag
LIFA90	I(0)	10%, Intercept, 1 lag

*Compared with the critical value de -2.7349 la 10%

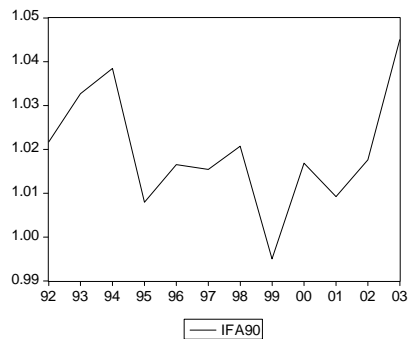
**Compared with critical value de -2.7822 la 10%

We present in the following graphs the data series which were used to build the equation of the potential GDP.

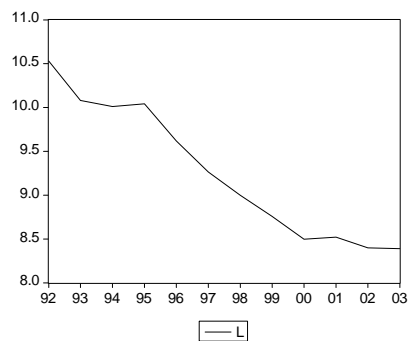
Graph. 1 The Dynamics of the real GDP over the Period 1992-2003



Graph. 2 The Index of Capital Stock over the Period 1992-2003



Graph. 3 The Dynamics of Employment over the Period 1992-2003



The Empirical Model

The empirical model is based on the equation 5 from the previous paragraph. The series used in the computations are short series, which raise some problems in interpreting the statistical tests. The stationarity of the processes is at the lower limit of the scale, and in these conditions, by using these data series we are obliged to a very prudent interpretation of the results.

The evaluation of the equation 5 for the hypothesis of the linear trend as a proxy for the technical progress is:

$$\text{LOG}(IY90)=0.05683086563-0.2294396533*\text{LOG}(IFA90)+(1+0.2294396533)*\text{LOG}(IL)+$$

$$(1.200198) \quad (-0.382524) \quad (-0.382524)$$

$$(1+0.2294396533)*-0.0007941408038*T$$

$$(-0.382524) \quad (-0.256389)$$

$$R^2 = 0.357 \quad DW = 1.357 \quad (1)$$

Because it is obvious that the linear trend hypothesis regarding the the technical progress is not acceptable, we have evaluated the technical progress TFPt as a HP filter, with lambda equal to 25. In the equation 5 we have replaced $A_t = \log(A) + (1-\beta) \alpha T$ with TFPt. We have obtained the equation:

$$\text{LOG}(IY90)=0.04960422951+A1+1.244017727*\text{LOG}(IL)+(1-1.244017727)*\text{LOG}(IFA90)$$

$$(2.462198) \quad (2.781627) \quad (2.781627)$$

$$R^2 = 0.541 \quad DW = 1.779 \quad (2)$$

The next iteration is given by the equation :

$$\text{LOG}(IY90)=0.04996047373+A2+1.252999663*\text{LOG}(IL)+(1-1.252999663)*\text{LOG}(IFA90)$$

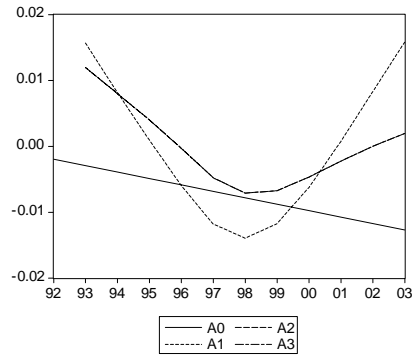
$$(2.308561) \quad (2.608158) \quad (2.608158)$$

$$R^2 = 0.470 \quad DW = 1.578 \quad (3)$$

Because the convergence is already obtained (at the next iteration β has practically the same value : 1.2530) for the evaluation of the potential GDP and the output gap we have considered the equation (3).

In the next paragraphs we present the approximations of the TFP analyzed above: A0 is a linear trend, A1, A2, A3 are the three iterations of the HP filter, convergence being attained for A2=A3. What is significant is that both iterations emphasize a minimum reached in 1998.

Graphic no. 4. Approximations for the TFP



The Results

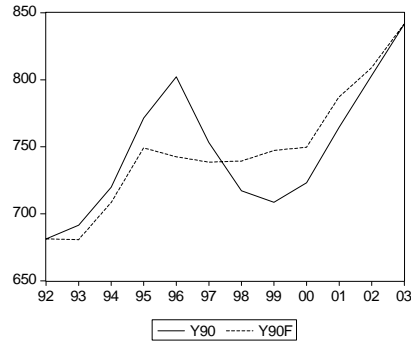
The empirical model used in this stage gives as partial results the potential GDP and the corresponding output gap. For the final report we will develop the model for the equations 19-21 from the previous paragraph. Table 2 presents the real GDP, the potential GDP obtained by the equation (3), the corresponding output gap and the differences of the first order of the index of consumer prices. With the exception of the years 1994 and 1995, the interpretation of the correlation between the inflation and the output gap corresponds to the economic reality.

Table 2. The real GDP, the potential GDP, the output-gap and $\Delta\pi$

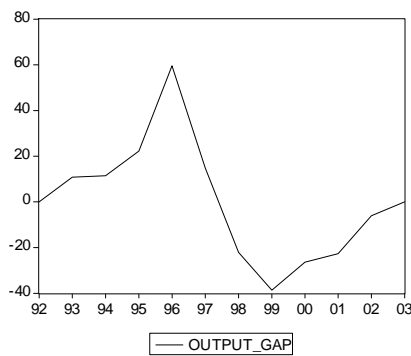
obs	Y90	Y90 potential	OUTPUT_GAP	DCPI
1993	691.5	680.6765	10.82349	79.40000
1994	719.8	708.2958	11.50419	-153.6000
1995	771.3	749.0408	22.25917	-104.4000
1996	802.1	742.5138	59.58625	6.500000
1997	753.2	738.3848	14.81517	116.0000
1998	717.2	739.2759	-22.07594	-95.70000
1999	708.6	747.1862	-38.58615	-13.30000
2000	723.2	749.5889	-26.38888	-0.100000
2001	764.4	787.1022	-22.70217	-11.20000
2002	803.0	809.0200	-6.019992	-12.00000
2003	841.6	841.6000	1.64E-08	-7.200000

The correlation between the output gap and the DCPI is positive but weak (0.08 for the period 1993-2003 and 0.64 for the period 1997-2003), which confirms the interpretation of the output gap as an indicator of the inflationary tendencies in the analyzed period.

Graph. 5 The Real GDP and the Potential GDP, over the Period 1992-2003



Graph. 6 The Output Gap over the Period 1992-2003



References

Adams C., and D. T. Coe, 1990. "A Systems Approach to Estimating the Natural Rate of Unemployment and Potential Output for the United States", *IMF Staff Papers*, Vol. 37 No.2.

Artus. J., 1977. "Measures of Potential Output in Manufacturing for Eight Industrial Countries, 1955-78", *IMF Staff Papers*, Vol. 24, pp. 1-35.

Bernanke B., and R.S. Gurkaynak, 2001. "Is Growth Exogenous? Taking Mankiw, Romer and Weil Seriously", *NBER Working Paper Series*, No. W8365.

Blanchard O., and D. Quah, 1989. "The Dynamic Effects of Aggregate Demand and Aggregate Supply Disturbances", *American Economic Review*, Vol. 79.

- Bolt W., and P.J.A. van Els, 1998. "Output Gap and Inflation in the EU", *De Nederlandsche Bank Working Paper Series* No. 550.
- Claus I., P. Conway and A. Scott, 2000. "The Output Gap: Measurement, Comparisons and Assessment", *Reserve Bank of New Zealand Research Paper* No. 44.
- De Masi P., 1997. "IMF Estimates of Potential Output: Theory and Practice", *International Monetary Fund Working Paper*, WP/97/177.
- Elmeskov, J. and M. MacFarland (1993). "Unemployment Persistence". *OECD Economic Studies*, (21), 59—88.
- Fabiani S., and R. Mestre, 2000. "Alternative Measures of the NAIRU in the Euro Area: Estimates and Assessment", *European Central Bank Working Paper* No.17.
- Fitzgerald J., and J. Hore, 2001. "Wage Determination in Economies in Transition: Ireland Spain and Portugal", *Economic and Social Research Institute, Working Paper*, forthcoming.
- Frain J., 1990. "Borrow and Prosper? Notes on the User Cost of Capital", *Central Bank of Ireland Technical Paper Series*, No. 3/RT/90.
- Giorno C., P. Richardson, D. Roseveare and P. van den Noord, 1995. "Potential Output, Output Gaps and Structural Budget Balances", *OECD Economic Studies* No.24, 1995/I.
- Granger C.W.J., and P. Newbold, 1974. "Spurious Regressions in Econometrics", *Journal of Econometrics* 2, pp. 111-120.
- Griliches Z., and J. Mairesse, 1995. "Production Functions: The Search for Identification", *NBER Working Paper* No. 5067.
- Hodrick, R.J., and E. C. Prescott, 1980. "Post-war U.S. Business Cycles: an Empirical Investigation", Discussion Paper No. 451, *Carnegie Mellon University*.
- McMorrow K., and W. Roeger, 2000. "Time – Varying Nairu/Nawru Estimates for the EU's Member States", *Directorate-General for Economic and Financial Affairs (ECFIN) of the European Commission Economic Papers* No. 145.
- McMorrow K., and W. Roeger, 2001. "Potential Output: Measurement Methods, "New" Economy Influences and Scenarios for 2001-2010 – A Comparison of the EU15 and the US", *Economic Papers European Commission Directorate-General for Economic and Financial Affairs Working Paper* No. 150.
- Ravn M., and H. Uhlig, 1997. "On Adjusting the HP-Filter for the Frequency of Observations", *CEPR Working Paper* No. 9750.
- Razzak W., and R. Dennis, 1996. "The output gap using the Hodrick-Prescott filter with a non-constant smoothing parameter: an application to New Zealand", *Reserve Bank of New Zealand Discussion Paper Series* G95/8.
- Senhadji A., 2000. "Sources of Economic Growth: An Extensive Growth Accounting Exercise", *International Monetary Fund Staff Papers* Vol. 47, No.1.

Torres R., and J.P. Martin, 1989. "Potential Output in the Seven Major OECD Countries", *OECD Working Paper* No. 66.

Marit Rõõm, „Potential Output Estimates for Central and East European Countries Using Production Function Method”, Tallinn 2001

Gordon de Brouwer, „Estimating Output Gaps”, Research Discussion Paper, 9809, Economic Research Department, Reserve Bank of Australia, 1998

Alpo Willman, “Euro area Production function and Potential Output: a Supply Side System Approach”, European Central Bank, Working Paper series, 2002

Andre a. Hofman, Heriberto Tapia, “Potential output in Latin America: a standard approach for the 1950-2002 period”, Serie Statistics and Economic Projections Division, Santiago, Chile, 2003

Tommaso Proietti, Alberto Musso, Thomas Westermann, “Estimating Potential Output and Output Gap for the Euro Area: a Model—Based Production Function Approach”, EU I Working Paper ECO N0. 2002/9

Cécile Denis, Kieran Mc Morrow and Werner Röger, “Production function approach to calculating potential growth and output gaps – estimates for the EU Member States and the US” EUROPEAN ECONOMY. ECONOMIC PAPERS. No. 176. September 2002, European Commission. Brussels

Methodological Appendix: Current stage of using the production function method to estimate the potential GDP

Potential output estimations have a long tradition in the economic science and go back as far as Adam Smith⁸. The development of production functions (Young, Cobb-Douglas, Tinbergen) and the growth theories (Harrod-Domar and Solow) in the twentieth century made potential growth and capacity utilization studies possible and they became widespread in the literature. The Keynesian revolution and Europe's post-war reconstruction planning was also important in the development of tools such as potential growth estimation. More recently, the new growth theories and advances in econometrics have started up a new brand of potential growth studies. The number of books and papers dedicated to potential GDP estimation by the production function method is impressive, and in the following we shall review only a few recent such applications.

Thus, Marit Rõõm (2001) estimates the potential output of four Central and East European countries (the Czech Republic and the Baltic countries: Estonia, Latvia and Lithuania) using the Cobb-Douglas production function. The Estonian production function uses data regarding employment, sectoral restructuring, estimated capital stock and foreign direct investments. For these countries the author estimates the capital stock and level of technology using the same form of production function and parameter estimates of the Estonian economy. Also, the potential output is calculated using the long-term unemployment in order to approximate the potential labour input in production.

⁸ Smith (1776) uses the term idleness and describes the relationship between capital and industry in the chapter on the accumulation of the capital of productive and unproductiv labour

Alpo Willman, presents in his paper (2002) a three equation supply-side model based on aggregation across sectors, with sector specific mark-ups and the technology parameters of the production function. The model has been applied to euro area data from the 1970s assuming that the underlying production function is either CES or Cobb-Douglas. Estimation results support the Cobb-Douglas case and the estimated supply-side model accounts satisfactorily for the stylised features of the data, i.e. the hump shape in the labour income share coupled with the relatively stable capital-to-labour income ratio and a noticeable change in profit margins and sectoral production shares. The author also made estimates of potential output and the output gap conditional on estimated production functions and examine the sensitivity of output gap estimates with respect to the alternative parameterisation of the production function.

Tommaso Proietti (University of Udine and European University Institute), Alberto Musso (European University Institute, Euro Area Macroeconomic Developments, Frankfurt am Main) and Thomas Westermann (Euro Area Macroeconomic Developments, Central Bank, Frankfurt am Main) estimated in 2002 the potential output and the output gap for the Euro Area using a model-based production function approach. In their paper, the authors evaluated unobserved components models based on production function approach (PFA) for estimating the output gap and potential output for the Euro Area. They fit and validated, against a bivariate model of output and inflation, a system of five time series equations for the Solow's residual, labour force participation, the employment rate, capacity utilisation and the consumer price index. The first four equations were used to define the output gap, whereas the price equation related the latter to the underlying inflation, according to a triangular model. The conclusion of their paper is that, although the PFA models cannot outperform a bivariate model of output and inflation, they can be valuable for growth accounting and for reducing the uncertainty surrounding the output gap estimates.

For Australian GDP data, five methods were used (Gordon de Brouwer, 1998): linear time trends, Hodrick-Prescott (HP) filter trends, multivariate HP filter trends, unobservable components models and a production function model. Estimates of the gap vary with the method used and are sensitive to changes in model specification and sample period. While gap estimates at any particular point in time are imprecise, the broad profile of the gap is similar across the range of methods examined.

However, following the ECOFIN Council meeting of 12 July 2002, the production function (PF) approach for the estimation of output gaps constitutes the reference method when assessing the stability and convergence programmes, starting with the 2002 set of programmes. During a "short" transition period, during which the PF method will be periodically reviewed and amended if necessary, the Hodrick-Prescott (HP) filter will be used as a backup method. For Spain the HP filter method will be used to assess the 2002 stability programme. Also, Germany and Austria expressed the view that some time was needed before estimates using the production function were considered as sufficiently reliable in deriving policy assessments.

In this sense, the PF estimates were prepared by Cécile Denis, Kieran Mc Morrow and Werner Röger (Production function approach to calculating potential growth and output gaps – estimates for the EU Member States and the US, EUROPEAN ECONOMY. ECONOMIC PAPERS. No. 176. September 2002. European Commission. Brussels), and must therefore be assessed in the light of the above set of predetermined requirements and given the difficult trade-offs involved. The primary use of the methodology described in the above-mentioned paper is as an operational

surveillance tool in the assessment of the annual stability/convergence programmes of the EU's Member States, so that it was important that the methodology respected a number of basic principles given the politically sensitive nature of the dossier. The main requirements of this PF approach is that it should be a simple and fully transparent methodology where the key inputs and outputs are clearly delineated and where equal treatment of all of the EU's Member States is assured. In addition, given that the estimates are to be used for budgetary surveillance purposes, it was felt important to take a prudent view regarding the assessment of the past and future evolution of potential growth in the EU.

The output gaps are calculated according to both methods (HP filter and PF). The cyclically adjusted balances are calculated according to the production function approach. For Spain, Germany and Austria an exception was made and the cyclically adjusted balances for these countries were calculated on the basis of output gaps estimated according to the HP filter. Therefore, the cyclically adjusted data for aggregates were a mixture of the two approaches.

One of the key objectives laid out for the new PF methodology was to reduce the degree of cyclicity of the potential growth estimates to an absolute minimum in order to avoid the mistakes of the past. This bias towards a prudent or cautious view is evident in all aspects of the PF estimation process, including for the elaboration of the medium-term extension to the method for the period 2004-2006. It should be stressed that the methodology described in the paper should not be seen in static terms since there is a strong likelihood that specific details of the approach will continue to be amended in the years to come on the basis of the practical experience garnered from using the methodology in the annual budgetary surveillance exercises.

Chapter 3. Comparisons between the results from Chapter 1 and Chapter 2

In the following paragraphs, we will present the comparisons between the results obtained for the potential GDP and the output gap with the two methods presented in the second part of this study: the method used by L.L. Albu in the first chapter and the method used by M. Altar, C. Scutaru and M. Nicolae in the second chapter.

Estimated the natural level of GDP in the case of the four filters, in 1990 prices (10⁹ ROL) and in the case of the production function method

	Real GDP	GDP_TR*	GDP_TL*	GDP_TK*	GDP_HP*	Potential GDP**
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1993	691.5	704.4	703.1	702.5	701.6	680.7
1994	719.8	750.7	747.6	748.4	745.8	708.3
1995	771.3	805.4	802.9	802.8	800.7	749.0
1996	802.1	819.0	818.6	816.5	816.7	742.5
1997	753.2	739.3	739.7	738.6	740.6	738.4
1998	717.2	716.3	716.0	718.4	720.9	739.3
1999	708.6	714.5	713.9	718.9	721.5	747.2
2000	723.2	739.6	741.3	744.6	747.2	749.6
2001	764.4	771.7	774.5	775.5	777.1	787.1
2002	803.0	801.6	803.3	801.2	800.1	809.0
2003	841.6	848.8	845.7	838.7	834.0	841.6

* Results obtained by L.L.Albu in chapter 1.

** Results obtained using the production function method in chapter 2.

Estimated level of the output gap in the case of the four filters, in 1990 prices (10⁹ ROL) and in the case of the production function method

	GapTR*	GapTL*	GapTK*	GapHP*	OUTPUT_GAP**
1993	12.9	11.6	11.0	10.1	10.8
1994	30.9	27.8	28.6	26.0	11.5
1995	34.1	31.6	31.5	29.4	22.2
1996	16.9	16.5	14.4	14.6	59.6
1997	-13.9	-13.5	-14.6	-12.6	14.8
1998	-0.9	-1.2	1.2	3.7	-22.1
1999	5.9	5.3	10.3	12.9	-38.6
2000	16.4	18.1	21.4	24.0	-26.4
2001	7.3	10.1	11.1	12.7	-22.7
2002	-1.4	0.3	-1.8	-2.9	-6.0
2003	7.2	4.1	-2.9	-7.6	0.0

* Results obtained by L.L.Albu in chapter 1.

** Results obtained using the production function method in chapter 2.

Analysing the results presented in these tables, one can observe that the methods based on filters offer different results as compared to those obtained using the production function method: the correlation between the output-gap and the inflation differential is negative when one uses the methods based on filters and positive when one uses the production function method.