A Robust Assessment of the Romanian Business Cycle

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Abstract

The paper provides potential output and output gap estimates for the Romanian economy in the period 1998 – 2008. Our approach consists in combining the structural method of the production function with several non-structural statistical detrending methods: Hodrick-Prescott, Kalman, band-pass, and wavelet transform filters. In this way, the obtained results benefit both from the economic foundations the production function method is relying on, as well as from the flexibility of the detrending techniques.

The contribution of our analysis to the scarce literature dealing with the estimation of the cyclical position of the Romanian economy is twofold. First, we identify the contribution of the production factors to the potential output growth. Second, we aggregate the results obtained through filtering techniques in a consensus estimate ascribing to each method a weight inversely related to its revision stability.

Our results suggest for the period 2000-2008 an average annual growth rate of the potential output equal to 5.8%, but on a descendant slope at the end of the analyzed period, due to the adverse developments in the macroeconomic context.

Keywords: potential GDP, output gap, NAIRU, business cycle.
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1 Introduction

Potential GDP is a measure of the economy's productive capacity, reflecting "full-employment" GDP, the level of GDP attainable when the economy is operating at a high rate of resource use. Potential GDP can also be defined as the level of output corresponding to a balanced state of the economy characterized by stable inflation (*i.e.* consistent with NAIRU). The potential GDP and the output gap (i.e. the difference between actual and potential output) attracted sustained interest by researchers over a long period of time. As early as Okun (1962), it was pointed out the importance of these variables in assessing the cyclical position of the economy. Nowadays the potential GDP is widely employed for macroeconomic modeling, policy analysis, assessment of fiscal sustainability, and quantifying the structural budget balance. Output gap estimations are used in central bank's monetary policy response function such as in the Taylor rule (Taylor, 1993) or in the inflation targeting framework (Svensson, 1999). In the long-run, the level of potential output depends on the growth of the productive capacity of the economy, which in turn depends on total factor productivity and the growth rates of physical capital and of the potential labor force. Thus, the potential output reflects the optimum potential supply of an economy and facilitates an estimate of non-inflationary growth. In the short run, it reflects the potential impact of economic growth on macroeconomic stability indicators, such as inflation. A positive output gap is associated with excess demand, which may lead to inflationary pressures. Orphanides (2002) argues that during the 1970s the Fed estimated the output gap to be much more negative than in reality, which led to policy actions that overheated the economy.

Due to the fact that potential output is not observable, researchers are forced to rely on uncertain estimates, computed using statistical methods and theoretical models. There is a wide range of methods for estimating potential GDP, beginning with analysis of time-series data and trend-based analysis, to more complex assessments based on the production function and structural equations. Various statistical methods have been proposed to estimate the potential output as a trend of the actual level of output. One of the easiest ways is to consider a moving average of actual output as the potential GDP. The HP filter, proposed by Hodrick and Prescott (1997), is widely used. Other methods include band-pass filters (Baxter and King, 1999; Christiano and Fitzgerald, 2003), wavelet-based filters, and unobserved components models (Harvey and Jaeger, 1993), estimated using the Kalman filter. The multivariate statistical approach to potential GDP estimation consists in connecting the output-gap with other macroeconomic variables, such as inflation (Phillips curve) or unemployment (Okun's law). Laxton and

Tetlow (1992) extended the HP filter to a multivariate setting and computed potential output linked to inflation fluctuations. Kuttner (1994) considered potential output as an unobserved stochastic trend and applied the Kalman filter to extract it, using simplified output and inflation equations.

The main drawback of the pure statistical methods approach is the lack of economic content. The production function approach can be employed in order to take into account the economic structure. In this approach, an aggregate production function is estimated and then normal amount of inputs are substituted in it to calculate the potential output. Another structural estimation of the potential GDP consists in econometrically estimating or calibrating large-scale DSGE models and extracting a model-consistent output-gap. This approach was employed by Edge *et al.* (2008) for the U.S. economy and by Smets and Wouters (2003) for the Euro Area. One has to be careful in assessing the estimated output gap using this method, since it is sensitive to the model parameters, particularly to alternative specifications of the monetary policy rule.

Since there is no ideal method for measuring the output-gap, researchers usually employ different methods instead of relying on a single measure. Various studies compared the estimation techniques and concluded that there are similarities in the shape, but divergences on the magnitude of the output gap estimates (Cerra and Saxena, 2000; Cotis *et al.*, 2003; Billmeier, 2004). As Bjornland *et al.* (2005) points out, professional judgment is needed to analyze and interpret the economic significance of the results. Darvas and Vadas (2002) reviewed some univariate de-trending methods which can be applied in the estimation of the potential output and of the output gap. Since all the methods have weaknesses, the authors derive a consensus estimate of potential output by weighting the results from these statistical methods. The weights are derived based on revisions of the output gap for all dates by recursively estimating the models. The conclusion is that consensus estimate can provide a useful indicator for the stance of the economy, especially for transition countries that might have more volatile macroeconomic dynamics, and are more often subject to structural shifts.

Due to the lack of data, to the structural breaks present in it, or to numerous structural shifts our economy faced in its short post-revolutionary history, the literature concerned with the estimation of potential GPD and other structural macroeconomic variables for Romania is scarce. There are, however, a number of noticeable studies, among which we must mention Bucsa (2001), Stanica (2005), Dobrescu (2006), and Galatescu *et al.* (2007)[1].

[1] Among the work dedicated to the estimation of the potential GDP in Romania we must also mention the joint efforts of the DOFIN, Ministry of Finance and National Commission

In the present study we propose an eclectic approach to the estimation of the potential GDP and of the output-gap for the Romanian economy, by employing a battery of statistical and theoretical methods.

The rest of the paper is organized in three sections. In the second section, we estimate the levels of potential employment and capital stock and combine them using the production function method to obtain potential GDP. In the third section we estimate the output gap by a consensus measure using different econometric filters. The final section concludes.

2 Estimating the Potential Output using the Production Function Methodology

Production function (PF) approach models explicitly the dependence of the output on the production factors, therefore reflecting the supply side of the economy. Based on the definition of potential GDP as a measure of the productive capacity of the economy, the PF methodology estimates potential output in a natural manner, replacing the inputs in the production function with their potential level.

The specification of the production function generally relies on two simplifying assumptions: constant returns to scale and constant elasticity of substitution between the production factors.

Estimating the potential output in an economic framework built around the production function has a series of advantages, since: (1) allows explicit growth accounting, detailing the sources of growth in terms of capital, labor and total factor productivity (TFP) contributions; (2) creates the opportunity of establishing a meaningful link between policy reform measures and actual outcomes; (3) supports forecasting, or scenario building on growth prospects, by making explicit assumptions on the evolution of demographic, institutional and technological trends; (4) uses (as other structural methods) a larger information set, information which is then interpreted through the relations between variables suggested by the economic theory.

The main drawback of the production function approach is that the potential level of the TFP is obtained by applying statistical detrending techniques to the "Solow residual," which is generally computed by inverting the production function. In this way, the production function approach inherits, eventually, the vulnerabilities of the statistical method used to detrend the technical progress factor. A common feature of these filtering techniques is that they may give poor approximation at the end of the sample. In addition,

for Economic Forecasting, conducted in the process of preparing the Convergence Program.

the PF often delivers the same result as a basic statistical filter of the GDP.

The PF approach requires the estimation of the potential levels of employment and capital. The potential level of employment is usually computed on the basis of trend participation rate and NAIRU. While the trend participation rate is obtained by a filtering technique, NAIRU is obtained through a more elaborated methodology, but is still influenced by incertitude. Assuming full capacity utilization, the potential level of capital is considered to be equal to the actual one. The capital stock is commonly computed as the accumulation of quarterly national account investment flows by assuming an ad-hoc constant rate of capital depreciation, although several corrections are sometimes introduced.

We assume for the Romanian economy a Cobb-Douglas (C-D) aggregate production function with constant returns to scale. The C-D production function represents the output (Y) as a combination of factor inputs – labor (L) and capital (K) – and of TFP (A) , which includes the degree of excess capacity, adjusted for the level of efficiency:

$$Y = A \cdot L^{\alpha} \cdot K^{1-\alpha}. \tag{1}$$

The Cobb-Douglas specification for the production function is widely used by the major economic institutions as OECD (Beffy *et al.*, 2007), European Central Bank (Cahn and Saint-Guilhem, 2007) and the European Commission (Denis *et al.*, 2006).

The output elasticities of labor and capital are represented by α $(0 < \alpha < 1)$, and $(1-\alpha)$ respectively. In order to produce 1 unit of GDP, the economy uses α units of labor, and $(1-\alpha)$ units of capital.

From (1) and its potential counterpart, it is obvious to see that

$$y - \bar{y} = (a - \bar{a}) + \alpha \cdot \left(l - \bar{l}\right) + (1-\alpha) \cdot \left(k - \bar{k}\right), \tag{2}$$

where lowercase symbols represent logs (*i.e.* $y = \log Y$), and hats indicate the potential level.

Thus, the output gap computed using the PF approach built on a C-D specification is the weighted average of the TFP, employment and physical capital gaps. Unlike the labor input and TFP, the capital input does not need to be cyclically adjusted to create a "potential" level. Although use of the capital stock varies greatly during the business cycle, the potential flow of capital services will always be related to the total size of the capital stock, not to the amount currently being used (CBO, 2004). With the capital used at full capacity, the output gap is given by

$$y - \bar{y} = (a - \bar{a}) + \alpha \cdot \left(l - \bar{l}\right). \tag{3}$$

(3) shows that, under the PF method assumptions, the output gap is influenced explicitly by the employment and the TFP gaps, and implicitly by the capital stock, through the TFP gap.

We set the output elasticity in respect to labor to 0.65, a value consistent with those employed in similar studies (Denis *et al.*, 2006; Dobrescu, 2006; Galatescu *et al.*, 2007). There are two alternatives to the ad-hoc setting of the production function parameter α: econometric estimation and direct computation using the data from National Accounts. As Galatescu *et al.* (2007) show, trying to estimate capital and labor contributions to the output in the C-D production function doesn't yield economically meaningful results in the case of Romania. As it concerns using the National Accounts information, α is computed as the ratio between the compensation of employees and the gross valued added. The average value of the compensation of employees gross value added ratio computed for yearly data on the time span 2000-2008 for the Romanian economy is 0.44. However, as Bergoeing *et al.* (2002) suggest, measured labor compensation fails to account for the income of most self-employed and family workers. They also point out that a high capital share (implied in the hypothesis of constant returns to scale by a low labor share) implies implausibly high rates of return on capital.

2.1 The Labor Input

We define the labor input as employment, multiplied by the average number of actual weekly hours. The potential level for the labor input can be estimated as

$$\bar{L} = N \cdot \bar{q} \cdot (1 - \bar{u}) \cdot \bar{H}, \tag{4}$$

where N stands for the population of working age (between 15 and 64 years old), $\bar{q}$ for the trend participation rate, $\bar{H}$ for the trend in the number of actual weekly hours worked, and $\bar{u}$ for NAIRU. To ensure a higher degree of robustness to the results, we estimate the trends for the participation rate and the number of hours using a principal component consensus of the HP and Kalman filters.

The approaches broadly adopted in the definition and modeling of NAIRU either distinguish a series of labor market variables as being potential empirical determinants of the NAIRU, either employ a number of statistical methods in which the time series properties of the macroeconomic variables in question are used to identify NAIRU. Since it allows a better economic interpretation of the results, we choose to follow the structural approach of Denis *et al.* (2006), relying on Kuttner (1994) bivariate model. Kuttner's model associates to a classical decomposition a regression whose regressors include unobserved quantities such as the gap and its lags.

The unemployment rate (u_t) is the summation of the unemployment gap (x_t) to a trend component ($\bar{u}_t$):

$$u_t = \bar{u}_t + x_t. \tag{5}$$

A Phillips type curve links the change in wage inflation ($\Delta\pi_t^w$) and the unemployment gap:

$$\left(1 - \gamma_1 L - \gamma_2 L^2\right) \cdot \Delta\pi_t^w = \beta \cdot x_t + \left(1 + \theta_1 L + \theta_2 L^2\right) \cdot \varepsilon_t^\pi, \tag{6}$$

where ε_t^π is the error term, modeled as white noise, and L is the lag operator.

The cyclical component of unemployment is assumes to be a second order autocorrelated stationary process with a sample mean of zero:

$$\left(1 - \phi_1 L - \phi_2 L^2\right) \cdot x_t = \varepsilon_t^x, \tag{7}$$

where stationarity requires $\phi_1 + \phi_2 < 1$. The trend component is modeled as a random walk with drift

$$(1 - L) \cdot \bar{u}_t = \mu_t + z_t, \tag{8}$$

where the drift term itself is allowed to follow a random walk

$$(1 - L) \cdot \mu_t = a_t. \tag{9}$$

ε_t^π, ε_t^x, z_t, a_t and are all IID.

The equations of the model described above are estimated with maximum likelihood on quarterly data over the period 1999Q1 to 2009Q1. The series were seasonally adjusted using the X12 ARIMA procedure in Demetra.

Using the employment data available for Romania involves overcoming several difficulties. The first problem is related to the presence of a structural break in the series (see Figure 1). We addressed this issue in a two-step procedure. First, we removed the seasonal component for each series, before and after the structural break point. Then, by assuming that the growth rate of the seasonally adjusted variable in the structural break point is zero, we re-constructed backward the values using the growth rates of the seasonally adjusted series before the structural break.

Another feature to be dealt of when using Romanian employment data is that there are two series for the unemployment rate, reflecting different methodologies:

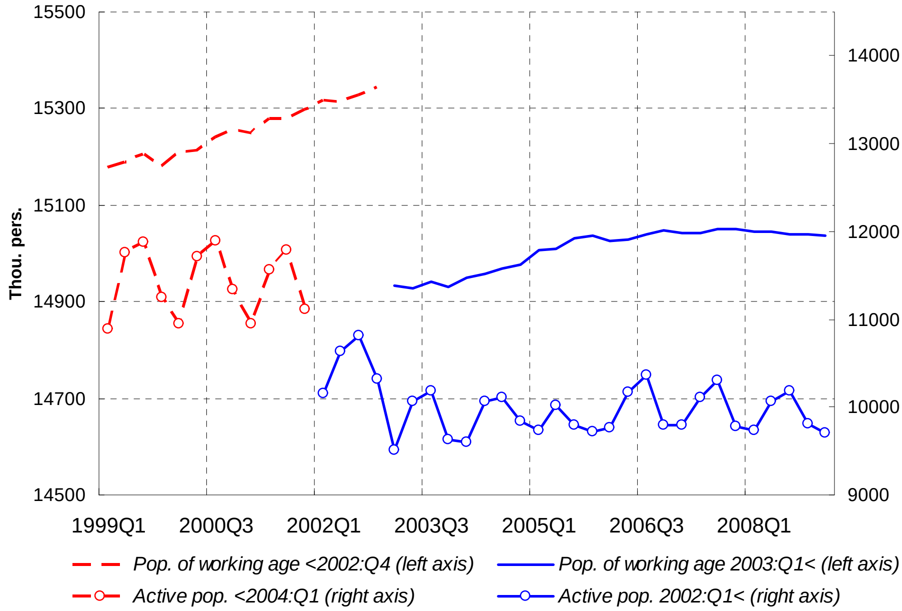

Figure 1: Structural break in the employment data.
Source: EUROSTAT

- ILO (International Labor Office) unemployment rate, representing the ratio between the number of ILO unemployed and active population. Economically active population (active persons) comprises all persons aged 15 years and over, providing available labor force for the production of goods and services.

- registered unemployment rate, representing the ratio between the number of unemployed (registered at the agencies for employment) and civil economically active population (unemployed + civil employment). Civil employment includes, according to the methodology used for the labor force balance, all persons who, during the reference year, carried out a socio-economic lucrative activity, excepting military staff and similar, political and community organizations employees and the convicts (NIS, 2007).

While the ILO unemployment rate is calculated on a quarterly basis, the registered unemployment rate is calculated monthly, but using the last annual civil employment available data.

There is no clear relation between the values of the two series such as to obscure the methodological differences. Moreover, both series present an out-

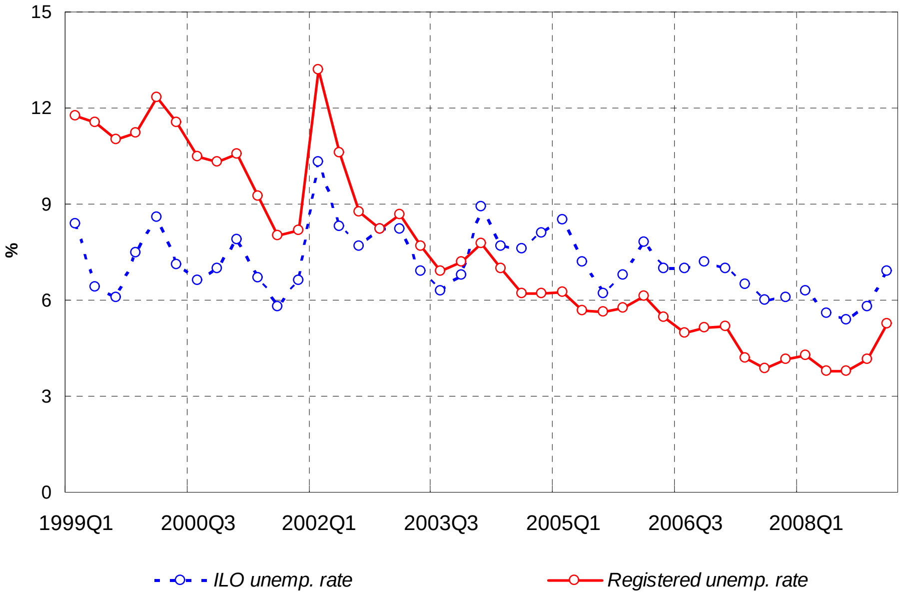

Figure 2: ILO and registered unemployment rates
Source: NIS, EUROSTAT

lier value, occurring in 2002Q1 as a result of a change in the legislation (Law No. 416/2001 concerning minimum guaranteed wage). As one can observe in Figure 2, the outlier has a much greater impact on the registered unemployment rate, than on the ILO rate. Taking this into consideration, and also the fact that the denominator for the registered unemployment is updated only on a yearly basis, we decided to use further the ILO unemployment rate.

The estimation results for the equations (6)-(9) are presented in Table 1. It is worth noting that the results are consistent with the theory. The equations were estimated by Maximum Likelihood. Since using the wage inflation $\Delta\pi^w$ led to economically inconsistent results, we replace in the estimations with the deviation of the wage inflation from a HP trend. The coefficient of the unemployment cyclical component in the Phillips equation is significant and negative. The unemployment gap exhibits clear cyclical behavior, confirmed by the statistic relevance of the AR(2) coefficients.

Table 1 *NAIRU bivariate model estimates*

	Unemployment eq.
ϕ_1	0.7912 (0.1807) [4.3788]
ϕ_2	-0.1616 (0.1756) [-0.9200]
	Phillips curve
β	-1.0707 (0.3951) [-2.7098]
γ_1	0.2437 (0.1130) [2.1574]
γ_2	-0.6413 (0.1101) [-5.8268]
θ_1	-0.4239 (0.1085) [-3.9081]
θ_2	1.0000 (0.1597) [6.2606]

Note: In parenthesis are reported the standard errors, and in brackets the values of the corresponding t-statistics.

The estimated values of NAIRU range between 6.48% in 2008Q4 and 7.52% in 2002Q1. Beginning with 2006Q1 the size of NAIRU situated below the value of 7%.

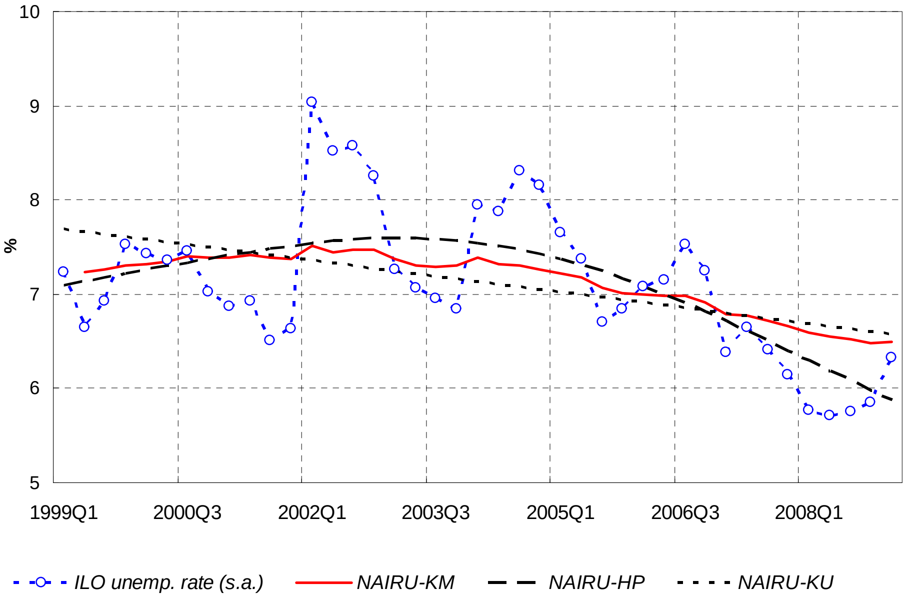

Figure 3: Actual and NAIRU unemployment
Source: INS, EUROSTAT, own calculations

Figure 3 displays the values obtained for NAIRU using the bivariate Kalman filter, and, also, for comparison reasons the values obtained by applying a HP filter (NAIRU-HP) and a Kalman univariate filter (NAIRU-KU). The values obtained with the bivariate Kalman filter range between the values computed using the two univariate methods.

Table 2 *NAIRU and unemployment gap*

	ILO unemp. rate (%)	NAIRU	Unemp. gap
1999	7.08	7.27	-0.18
2000	7.32	7.36	-0.04
2001	6.73	7.39	-0.66
2002	8.60	7.47	1.13
2003	7.03	7.32	-0.29
2004	8.07	7.32	0.75
2005	7.15	7.12	0.03
2006	7.25	6.97	0.28
2007	6.40	6.74	-0.34
2008	5.77	6.54	-0.76

Note: Annual values were computed as average of the quarterly ones.

The annualized values of NAIRU and of the unemployment gap for are presented in Table 2.

It is possible to elude some of the difficulties raised by the employment data in the case of Romania by considering the labor input variable in the production function as the number of employees. Accordingly, the potential level of the labor input is computed by applying a filtering technique. Figure 4 depicts the labor input gap obtained by the structural method described above (excluding the average number of hours worked), and by applying a HP filter to the number of employees.

The two measures of the labor input gap have a similar shape since 2004Q4, but they differ significantly, both in shape, as well as in magnitude, before.

A number of arguments favor the use of employment data instead of the number of employees. First, it is obvious that employment data include those who contributed to the creation of the domestic production, but are not included in the number of employees because they don't fit the statistical definition of the employee (they don't have an individual labor contract). Second, a structural method involving a Phillips curve applied to employment data is more suitable than a detrending method applied to the number of employees data, since the resulting potential GDP corresponds more to the

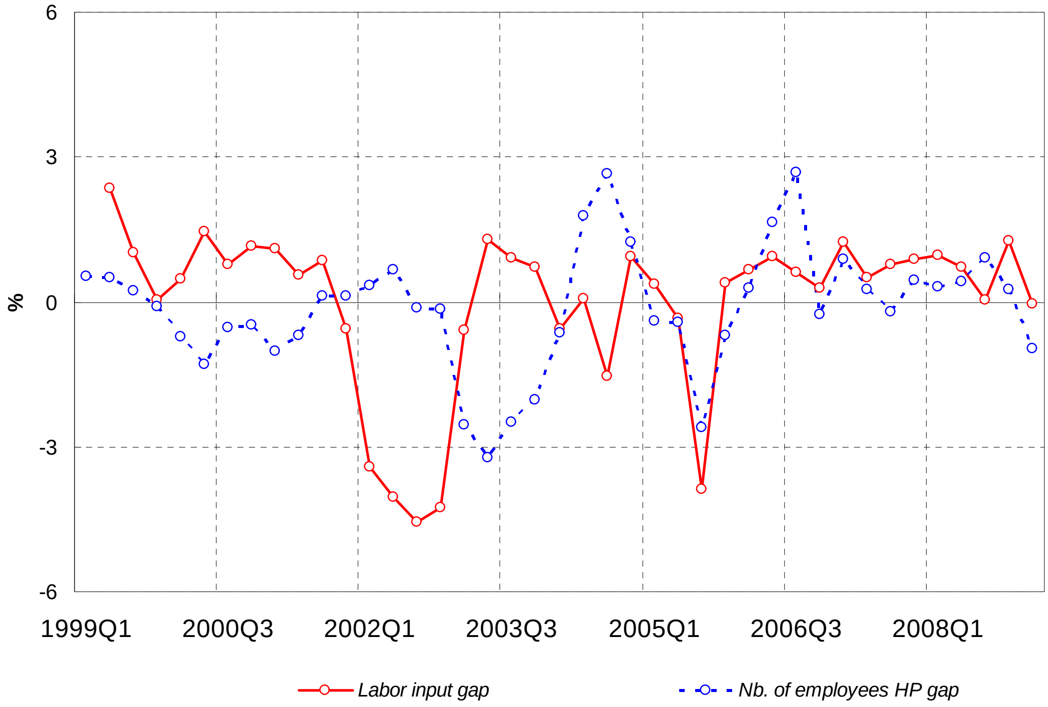

Figure 4: Labor input gap
Data source: INS, EUROSTAT, own calculations

definition as the level where no inflation pressures emerge. Third, using only the number of employees reveals little information on the sources of the labor input gap.

2.2 The Capital Stock

The proper concept of capital in the context of the production function methodology is given by the flow of services of capital in constant prices. The use of the gross capital stock as input in the production function implies the following assumptions: (1) the flow of capital services is a constant proportion of an estimate measure of the capital stock, the rate of change of capital services coinciding over time with the rate of change of the capital stock as estimated by cumulating measurable investment; (2) the aggregate capital stock is made up of assets that generate the same marginal revenues in production.

One of the major problems of using the PF method to estimate the potential GDP for the Romanian economy is the lack of an adequate data series for the capital stock. As relation (3) shows, the severity of this problem is greater for the potential output than for output gap.

In the absence of official statistics, the fixed capital stock in Romania can be estimated using the Perpetual Inventory Method (PIM). The PIM method consists in accumulating past capital formation and deducting the value of assets that have reached the end of their service lives. The basic requirements to apply the PIM to estimate the gross capital stock are:

- an initial benchmark estimate of the capital stock;
- statistics on gross fixed capital formation extending back to the benchmark, or if no benchmark is available, back over the life of the longest-lived asset;
- information on capital depreciation, implicitly comprising: asset price indices, information on the average services lives of different assets, and information on how assets are retired around the average service life (mortality functions).

The PIM approach we employed can be formally stated as:

$$K_t = K_{t-1} \cdot (1-\delta) + I_t = K_0 \cdot (1-\delta)^t + \sum_{j=1}^{t} I_j \cdot (1-\delta)^{t-j}, \qquad (10)$$

where K_t represents the capital stock at time t, K_0 is the initial capital stock, I_j the gross fixed capital formation, and δ the depreciation rate. The value of the capital stock is thus dependant on the path of the gross fixed capital formation, on the initial capital stock, and on the depreciation rate. Statistics on gross fixed capital formation are available since 1990, annual data, with a methodology shift from ESA 1979 to ESA 1995 in 1998, and since 1998, quarterly data. For the depreciation rate we choose a constant value, similar to the one generally used in the literature (see *e.g.* Denis *et al.*, 2006), namely 5 percent annually. Following Denis *et al.* (2006), we set the initial moment for the capital stock to be 1995, and the value of the physical capital to be twice the GDP in that moment. According to the PIM methodology, the initial capital stock is less, and less important as the initial moment is more far away in the past. For an annual depreciation rate equal to 5%, setting the initial moment in 1995 means that, at the end of 2008, only a half of the initial capital is still in use. However, an initial moment very distant in the past is feasible only when a reliable gross fixed capital

formation series is available.
Summarizing, our implementation of the PIM methodology can be stated as:

$$\frac{K_t}{Y_t} = 2, \text{ for } t = 1995$$
$$K_{t+1} = (1-\delta) \cdot K_t + I_t, \text{ with } \delta = 0.05, \text{ for } t = 1996;$$
$$K_{t+1}^Q = (1-\delta_Q)\, K_t^Q + I_t^Q, \text{ with } (1-\delta_Q)^4 = 1-\delta, \text{ for } t > 1996.$$

The annualized capital stock series from 1998 is presented in Table 3. To asses the performance of the capital stock calculation methods we employed, we also present the annual capital-output ratio.

In the interval 1998-2008 the capital-output ratio in the Romanian economy varies from 2.18 to 2.39. The values for the capital stock presented in Table 3 are comparable with those we would have obtained if we used other methods, based on various assumptions regarding the initial value of the capital stock.

Table 3 *Capital stock estimates*

Year	Capital stock (mln. RON 2000 prices)	Capital output ratio
1998	177,270.08	2.22
1999	182,564.79	2.32
2000	188,388.90	2.33
2001	195,402.19	2.29
2002	203,530.04	2.27
2003	212,811.37	2.25
2004	223,757.98	2.18
2005	237,471.11	2.22
2006	255,472.37	2.22
2007	281,237.00	2.30
2008	313,121.86	2.39

Table 4 summarizes the results obtained by employing the methodologies similar to Bergoeing et al. (2002), Harberger (1978), and IMF (2003).

Table 4 *Capital output ratio estimates*

Methodology	Min	Max	Average
Bergoeing et al. (2002)	2.23	2.42	2.32
Denis et al. (2006)	2.18	2.39	2.27
Harberger (1978)	2.33	2.57	2.45
IMF (2003)	1.98	2.30	2.11

In our version of the Bergoieng *et al.* (2002) methodology we consider the time span 1998-2008, and we determine K_{1998} such as $K_{2002}/Y_{2002} = 1/11 \cdot \sum_{t=1998}^{2008} K_t/Y_t$. Harberger (1978) methodology assumes that the economy evolves on the "balanced growth path," implying that the growth rates of the capital stock and of real GDP are equal. We consider the time span 1998-2008, and we determine K_{1998} such as $(K_{2008}/K_{1998})^{1/10} = (Y_{2008}/Y_{1998})^{1/10}$. Similar to IMF (2003) we estimate the initial capital stock using the ratio of the Romanian to Euro Area per capita GDP (at PPS) in 2000, 23%. Departing from the IMF methodology, we consider that only one third of the difference in per capita GDP it can be explained by different real capital endowments, the rest being explained by other factors, such as human capital, institutions setting etc. Assuming a capital share of about 1/3, we obtain $\frac{\left(K_{2000}^{RO}/Y_{2000}^{RO}\right)}{\left(K_{2000}^{EA}/Y_{2000}^{EA}\right)} = \left[3 \cdot \frac{\left(Y_{2000}^{RO}/L_{2000}^{RO}\right)}{\left(Y_{2000}^{EA}/L_{2000}^{EA}\right)}\right]^2 = 0.6888^2 = 0.4744$, meaning that in 2000 the Romanian capital-output ratio is 47.44% of the one for Euro Area. The value of 4.44 for the Euro Area capital-output ratio yields a value of about 2.11 for Romania. It's worth mentioning that computing backwards the values of the annual capital stock the capital-output ratio for 1992 is 1.44, close to the value of 1.3 in the IMF (2003) report.

2.3 The Total Factor Productivity (TFP) estimation

Within the production function framework, potential output refers to the level of output which can be produced with a "normal" level of efficiency of factor inputs. The trend efficiency level is measured as a principal component consensus of the HP and Kalman filtered Sollow residual:

$$a_t = \ln(Y_t) - [\alpha \ln(L_t) + (1-\alpha)\ln(K_t)]. \tag{11}$$

2.4 Potential Output and Output Gap Estimates using the PF Method

Potential output is derived by inserting potential capital stock and potential labor into the production function equation.

Figure 5 represents the output gap obtained in the production function analysis using quarterly data for the period 1999Q2-2009Q1. After a period of positive output gap, between 2006Q1 and 2008Q3, the output gap plunges to a negative value of around -7 percent in 2009Q1. Output gap reached its maximum value in 2008Q3, 3.8%.

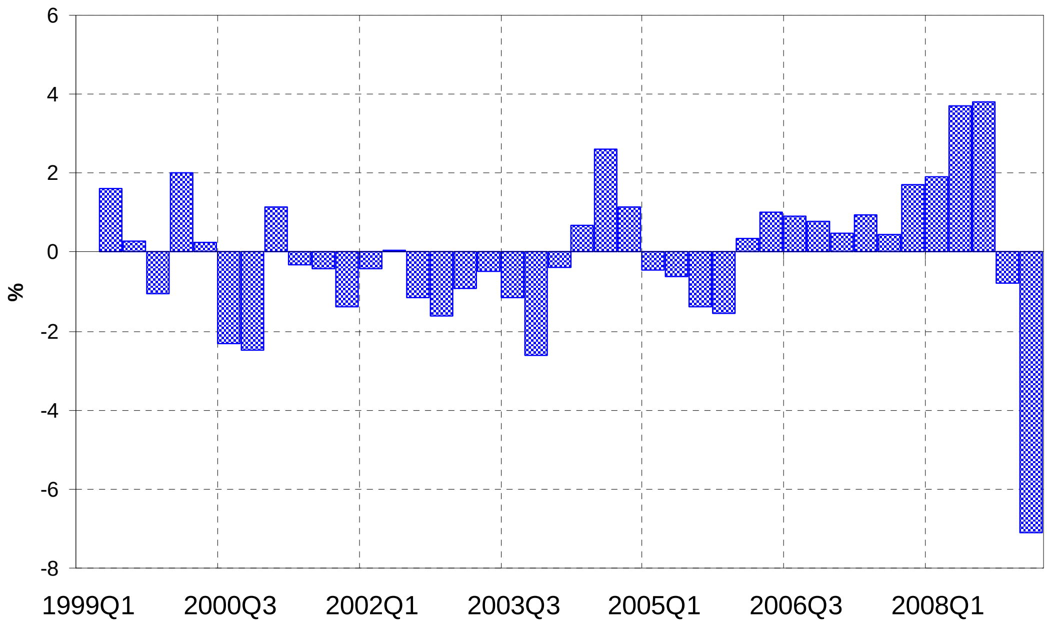

Figure 5: Output gap estimates using the PF approach

Obviously, the shape of the output gap in the last quarters is determined by the actual macroeconomic context, characterized, among others, by the sharp decrease in the external demand, the drop in the governmental expenditures, and the blockage of non-governmental credit.

Table 5 *Annualized potential GDP estimates using the PF methodology*

Year	Output-gap (% of potential GDP)	Potential output (mln. RON 2000 prices)	Potential growth (%)
2000	-0.64	81,508.3	-
2001	-0.25	85,700.94	5.14
2002	-0.79	90,500.01	5.61
2003	-1.29	95,751.49	5.81
2004	1.04	101,473.4	5.97
2005	-1.00	107,834.9	6.27
2006	0.76	114,348.7	6.04
2007	0.90	121,266.7	6.05
2008	2.18	128,248.2	5.76

The growth rate of the potential GDP for the period 2001-2008 situated between 5.1% and 6.3%, with an average of 5.8%. Our findings are similar to those obtained in similar studies, suggesting for the Romanian economy in the last years a potential GDP growth rate of about 6 percent (Dobrescu, 2006; Galatescu *et al.*, 2007).

2.5 Potential Growth Accounting

As we have mentioned before, one of the advantages of using the production function to estimate the potential output consists in assessing separately the contribution of the labor, capital and total factor productivity to potential output growth. To compute the individual factor contribution to GDP growth we use the following relation, obtained by differentiating the production function:

$$\frac{\dot{Y}}{Y} = \frac{\dot{A}}{A} + \alpha \cdot \frac{\dot{L}}{L} + (1-\alpha) \cdot \frac{\dot{K}}{K}. \tag{12}$$

Table 6 presents the part of the annual potential output growth for the period of 2001-2008 which can be assumed by each factor.

Table 6 *Labor, capital and TFP contribution to potential growth*

Year	Labour	Capital	TFP	Potential growth (%)
2001	0.64	1.30	3.20	5.14
2002	0.69	1.46	3.46	5.61
2003	0.56	1.60	3.65	5.81
2004	0.55	1.80	3.62	5.97
2005	0.55	2.14	3.58	6.27
2006	0.06	2.65	3.33	6.04
2007	0.02	3.53	2.50	6.05
2008	-0.10	3.97	1.89	5.76
Average	**0.37**	**2.31**	**3.15**	**5.83**

Figure 6 illustrates the contributions of production factors to the quarterly potential GDP growth, computed relative to the same quarter of the previous year, for the period 2000Q2-2009Q1.

Until 2007Q1, the TFP growth was the main source of potential GDP growth. The TFP contribution first increases from 2.8 in 2000Q2 to 3.6 in 2004Q3, decreasing smoothly after, to 1.5 in 2009Q1.

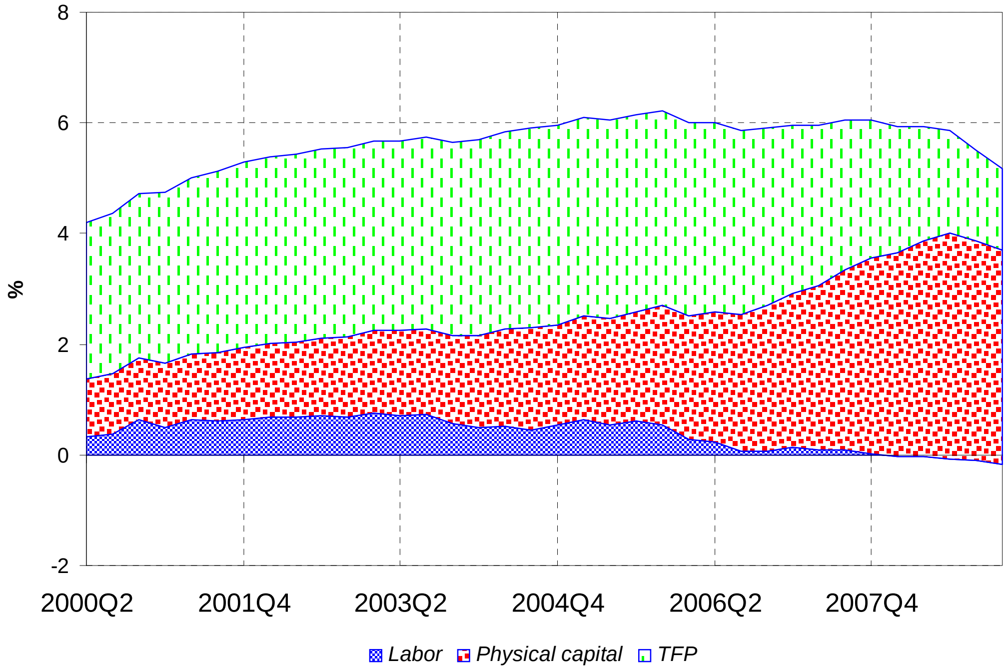

Figure 6: Labor, capital and TFP contribution ot potential growth

Since 2007Q2, the capital growth becomes the main driving factor of GDP growth. Excepting the last two quarters, the capital contribution to potential GDP growth displays an increasing path, ranging from 1.05 in 2000Q2, to 4.1 in 2008Q3. In this time the annual investment ratio, calculated as the ratio between the gross fixed capital formation and GDP, ranged from 18.8% in 1999 to 35.7% in 2008. The 2008Q4 and 2009Q1 quarters witnessed a decline in the contribution of the physical capital to the potential output growth, as the result of the deteriorating macroeconomic environment, characterized among others by a sharp decline in the year on year growth rate of the gross fixed capital formation from 24.3% in 2008Q3 to 2.78% in 2008Q4, and -0.3% in 2009Q1.

The contribution of labor to GDP growth had a relatively stable path in the interval 2000Q2-2005Q4, followed by a decline ending with a negative contribution of -0.17 in 2009Q1. The evolution of employment is determined by the demographic conditions and by the labor market conditions. The factors of the potential labor growth rate are detailed in Figure 7. The main factor was the growth rate of the average hours worked, decreasing from 1%

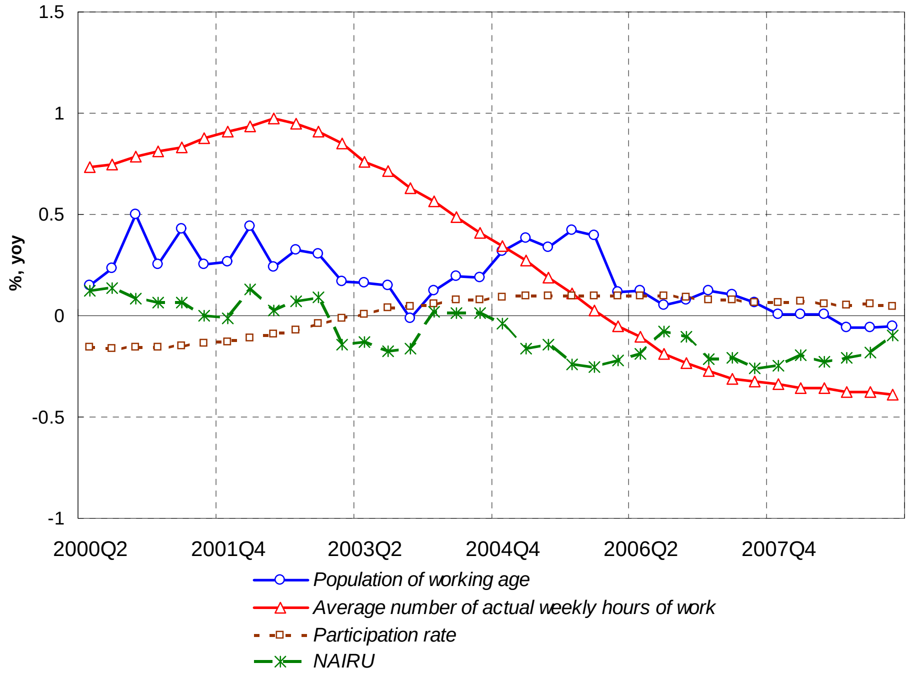

Figure 7: Factors of the labor contribution to potential growth

in 2002Q2 to -0.4% in 2009Q1. The negative contribution of the labor input to the potential GDP growth in the last quarters can be also explained by the increase in NAIRU.

Our decomposition of potential GDP growth rate are comparable with 2002-2005 projections of IMF (2003), which assuming a zero contribution of employment growth and a labor share of 0.5 obtain 3 percent contribution of capital accumulation and 1.9 percent contribution of total factor of productivity.

Table 7 *Sensitivity analysis*

(%)	$\alpha = 0.65$, $\delta = 0.05$	$\alpha = 0.45$, $\delta = 0.05$	$\alpha = 0.65$, $\delta = 0.08$	$\alpha = 0.45$, $\delta = 0.08$
Average	-0.07	0.01	-0.12	-0.06
Std. dev.	1.89	1.76	1.90	1.78
Min	-7.09	-7.02	-7.46	-7.02
Max	3.81	3.22	3.50	3.21
Q min	2009Q1	2009Q1	2009Q1	2009Q1
Q max	2008Q3	2008Q3	2008Q3	2008Q3
Av. of the annualized growth rate of the potential GDP	5.83	5.92	5.85	5.89

We conclude this section with a sensitivity analysis with respect to the parameters α and δ. Table 7 synthesizes the results of the potential output and output gap estimates using the PF approach, under four sets of values: $\{\alpha = 0.65, \delta = 0.05\}$, $\{\alpha = 0.45, \delta = 0.05\}$, $\{\alpha = 0.65, \delta = 0.08\}$, and $\{\alpha = 0.45, \delta = 0.08\}$. Neither the modification of the labor elasticity α, nor that of the depreciation rate δ, don't have a significant effect on the shape and the magnitude of the output gap, or on the average of the annualized growth rate of the potential GDP.

3 Estimating the Potential Output using Econometric Filtering Methods

The estimates of potential GDP and output-gap are greatly influenced by uncertainty and, therefore, require considerable judgment (de Brouwer, 1998; Bjornland et al. 2005). This issue presents a considerable challenge for the policymakers, since different measures of these unobservable variables provide contradictory information on the stance of the economy. Orphanides (1998) stress out that if policymakers mistakenly adopt policies based on wrong estimates of the output gap, they inadvertently induce instability in economic activity. To ensure the robustness of the estimates obtained using the production function methodology, our main objective in this section is to provide alternative output gap estimations employing different statistical approaches. The need to use various econometric filtering methodologies arises due to the fact that one tool may not be robust enough to the specificities of an emerging economy. Since all the methods have weaknesses, we employ four of these methods to compute the output gap, and use the four estimates to compose a consensus measure of the output gap using the methodology outlined in Darvas and Vadas (2002).

3.1 Hodrick-Prescott Filter (HP)

The oldest statistical technique that was utilized to estimate the output gap is the linear trend method, approximating the potential GDP as a simple deterministic function of time. The drawbacks of this technique are well documented in the literature (Diebold and Senhadji 1996; de Brouwer 1998; Billmeier 2004). The shortcomings of the linear trend method have called for alternative detrending methods. The most popular detrending methodology consists in using the Hodrick-Prescott filter (Hodrick and Prescott, 1997), which identifies the long-term trend component of output by minimizing a loss function penalizing the gap between actual and trend output and the rate of change of the trend:

$$L = \sum_{t=1}^{T} \left(y_t - \bar{y}_t\right)^2 + \lambda \sum_{t=2}^{T-1} \left(\Delta\bar{y}_{t+1} - \Delta\bar{y}_t\right)^2 . \tag{13}$$

The smoothing factor λ is an exogenous parameter that was suggested by Hodrick and Prescott (1997) to be 1600 for quarterly data and 100 for annual data. However, some authors have used different values for λ (Billmeier 2004; Ross and Ubide 2001). The shape of the potential GDP varies with the size of the smoothing factor. More precisely, as λapproaches infinity this method resembles the linear trend method, and as λ approaches zero the potential output will be equal to actual output. Giorno et al. (1995) recommends choosing a value of λ that generates a pattern of cycles which is consistent with prior views about past cycles in each country. In this study, we employed a smoothness parameter equal to 1600.

As has been highlighted by various studies, the Hodrick-Prescott filter has end-sample problems, since the estimates of the output gap at the end of the sample may be subject to substantial revision as new data is available. To solve the issue, the most preferred corrective measure is to extend the dataset with forecasts. However, the accuracy of output-gap estimates at the end of the sample depends on the accuracy of the forecasts.

3.2 Kalman Filter (KM)

This methodology uses the insight of Watson (1986) to decompose output into a permanent and a transitory component, which correspond to the potential output and the output gap respectively. More specifically, we employed a Harvey (1989) type univariate model, in which the seasonally adjusted real GDP series is decomposed in a trend component (T) and a cyclical component (C):

$$Y_t = T_t + C_t + \epsilon_t, \tag{14}$$

where $\epsilon_t \sim NID\,(0, \sigma_\epsilon^t)$, $t = 1, ..., T$.

The trend component, which represents the potential output is specified as a first-order autoregressive process (AR(1)):

$$\begin{aligned} T_t &= T_{t-1} + \beta_{t-1} + \eta_t,\ \eta_t \sim NID\left(0, \sigma_\eta^2\right), & (15) \\ \beta_t &= \beta_{t-1} + \xi_t,\ \xi_t \sim NID\left(0, \sigma_\xi^2\right), & (16) \end{aligned}$$

where β_t is the slope of the trend.

The cycle is modeled as a second-order autoregressive process (AR(2)) which can be obtained from processing a trigonometric relation such as:

$$\begin{pmatrix} c_t \\ c_t^* \end{pmatrix} = \rho \begin{pmatrix} \cos \lambda_C & \sin \lambda_C \\ -\sin \lambda_C & \cos \lambda_C \end{pmatrix} \times \begin{pmatrix} c_{t-1} \\ c_{t-1}^* \end{pmatrix} + \begin{pmatrix} k_t \\ k_t^* \end{pmatrix}, \tag{17}$$

where k and k^* are uncorrelated $NID\,(0, \sigma_k^2)$innovations, and λ_C is the frequency of the cycle (*i.e.* the cycle period is $2\pi/\lambda_C$).

The estimates of the parameters of the model and the state variables can be obtained by maximum likelihood estimation using the Kalman filter methodology (Kalman, 1960; Kalman and Bucy, 1961). The main advantage of this methodology consists in its stability when new data is available (*i.e.* reduced end-sample problems).

3.3 Band-Pass Filter (BP)

In general, the GDP can be decomposed into components of different frequencies: high-frequency, medium-frequency and low-frequency. The high-frequency component consists in seasonal movements, whereas the low frequency component is the trend of the time series variable. Medium-frequency component, the main focus of a Band-pass filter, can be interpreted as the cyclical component. More specifically, this methodology consists of a combination between high-pass and low-pass filters which passes only the components of the series with frequencies between an inferior and superior limit thereby isolating the cycles. The Band-pass filter methodology was first employed in the measuring of business cycles by Baxter and King (1999).

This method is superior to the Hodrick-Prescott filter, since Cogley and Nason (1995) shows that the latter works as a high-pass filter, suppressing cycles with higher frequencies while letting low frequency cycles go through without change. Also, Harvey and Jaeger (1993) pointed out that the Hodrick-Prescott-filter creates spurious cycles in detrended random walks and I(2) processes. This kind of filtering has also several limitations. Since, it can not handle non-stationary time series variables in the frequency domain it must be transformed into the time domain, implying the loss of several observations at the beginning and at the end of the sample. Since it is in fact a centered moving average with symmetric weights, this filter is also criticized on the basis that it might generate spurious dynamics in the cyclical component.

3.4 Wavelet Transform (WT)

Although the wavelet transform is quite a new concept, it has become a popular method in economics as well as in other fields of research. Conway and Frame (2000) and uses the wavelet transform to analyze New Zealand output gap in comparison to other non-theoretic methods. They compare the frequency component of different output gaps estimates concluding that they have common cyclical characteristics. Swagel and Scacciavillani (2002) also compare the wavelet transform with other methods in the case of Israel and conclude that all these methods provide qualitatively similar output gap estimates. Darvas and Vadas (2003) employed the wavelet transform in the case of Hungary.

The roots of the wavelet transform go back to the Fourier transform developed at beginning of the 19th century. Similarly to the Fourier analysis, the wavelet transform converts a data series from time domain to the frequency domain. However, there are several important differences. The main drawback of the Fourier transform is that it can only handle data series with the property that all frequency components in the series exist at all times. This is called the time localization problem. To handle this problem, mathematicians developed the Gabor transform. In this approach the original data series is divided into smaller parts using a rolling window with appropriate width. Thus, the Fourier transform at different times can be computed, and a time-frequency representation of the data series can be obtained. However, one cannot know what spectral components exist at what points in time, or put another way, one can only know which time intervals exist in a certain band of frequencies. This is called the resolution problem. Narrow windows

provide good time resolution, but poor frequency resolution, while wide windows provide good frequency resolution, but poor time resolution.
This is where the wavelet transformation improves spectral analysis. The width of window in the wavelet transform is variable, so that the wavelet transform has good time and poor frequency resolution at high frequencies and good frequency and poor time resolution at low frequencies. The wavelet transform adapts itself to capture features across a wide range of frequencies and thus has the ability to capture events that are local in time. This makes the wavelet transform an ideal tool for studying non-stationary times series. Unlike sinuses and cosines in Fourier transformation the wavelet transform employs wavelets as mathematical basis for decomposing the data series into different frequency components. The wavelet function is non-zero over a finite length. Several wavelet forms can be used such as the Haar wavelet, the Mexican hat wavelet, or the Morlet wavelets. The most frequently used wavelets are the Daubechies wavelet family developed by Daubechies (1988). Wavelets within the family are characterized by the number of their filters. Increasing the number of filter elements makes the wavelet smoother. In this paper we employed a Daubechies wavelet with 16 filter elements.
The methodology for estimating the potential GDP and the output-gap consists in using the multi-resolution analysis of the wavelet transform. The multi-resolution analysis is implemented as a pyramid algorithm passing the data series through a sequence of low-band and high-band filters. This procedure decomposes the data series (y_t) into components of different frequencies:

$$y_t = \sum_{i=1}^{J+1} d_{i,t}, \tag{18}$$

where $J = \log_2(N)$, N is the length of the data series, and d_i is the i-level wavelet detail associated with changes in the data series at scale of length $\lambda_i = 2^{i-1}$.

Therefore one can decompose the GDP data series (y_t) into two components:

$$y_t = \bar{y}_t + og_t, \tag{19}$$

where

$$\bar{y}_t = \sum_{i=\bar{J}+1}^{J} d_{i,t}, \tag{20}$$

$$og_t = \sum_{i=1}^{\bar{J}} d_{i,t}, \tag{21}$$

and $\bar{J} < J$ the level of detail of the multi-resolution analysis.

The component $\bar{y}_t$ (*i.e.* the potential GDP) is a cumulative sum of elements at scales of length $\lambda_i, i > \bar{J}$ and will be smoother and smoother as $\bar{J}$ increases. The component og_t (*i.e.* the output-gap) contains only the elements with high frequency lower scale details. In this paper, we employed a 4-scale multi-resolution decomposition (*i.e.* $\bar{J} = 4$).

3.5 The Consensus Output Gap and Potential GDP estimates

We employed the quarterly GDP data series for the period 1998Q1-2009Q1. Figure 8 depicts the output gap estimates using the four econometric methods that we previously described. Although the amplitude of the estimates varies, the shapes of the curves describing the output gap from four methods are comparable. Using the Kalman filter estimate of the unobserved component model, the period of the business cycle resulted to be 8.14 years. Although the other estimates do not allow for an analytic computation of the length period, a visual inspection of the graph also indicates a period around 8 years. These results are consistent with de definition of a business cycle consisting of periodic components whose frequencies lie between 2 and 8 years per cycle (Burns and Mitchell, 1946; Hodrick and Prescott, 1997; Baxter and King, 1999).

The most challenging task is the evaluation of the estimations resulted from these methods. Considering the weak stability of the various econometric methods of output gap estimation, a problem which was encountered in all the countries, a synthetic index for the output gap should be constructed Therefore, we will compute a consensus estimate using the methodology outlined in Darvas and Vadas (2002). The consensus estimate consists in weighting the individual estimates with weights proportional to the inverse of revisions of the output gap for all dates estimated for recursive samples. Therefore, the methods that lead to more stable results are given more weight.

The stability analysis of the estimations obtained using the four methods has shown that the most stable estimation is provided by the Kalman filter estimate. Also, the output gap estimation using the Band Pass filter (BP) proved to be stable enough. Based on the stability analysis performed for the four estimations, the weights for the synthetic index ("consensus output gap estimator") were chosen equal to 32.97% for the Kalman filter (KM), 29.7 % for the Band Pass filter (BP), 25.45 % for the Hodrick-Prescott filter (HP) and 11.88% for the wavelet transform (WT). Figure 9 depicts the consensus estimate of the output-gap.

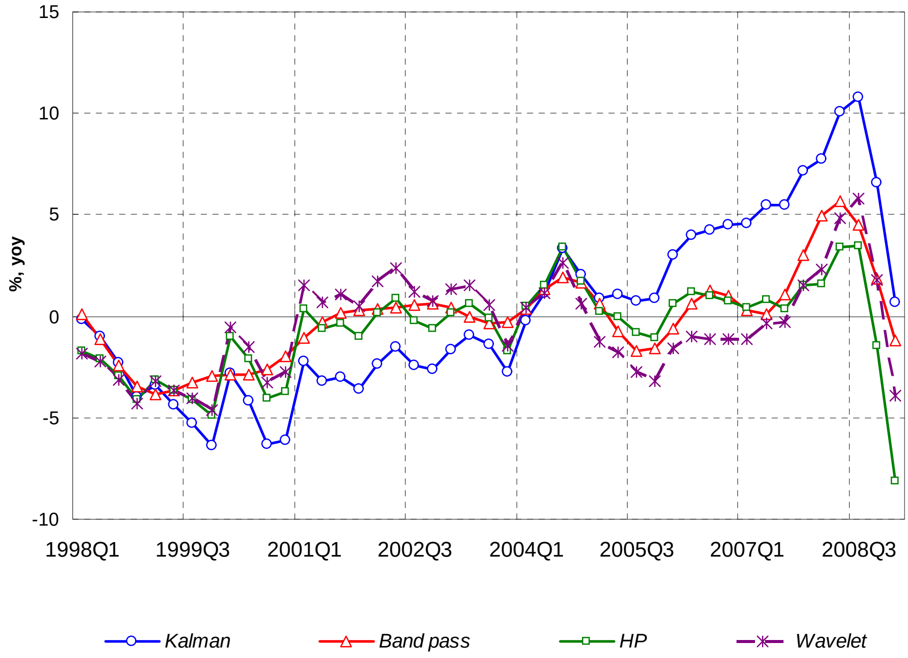

Figure 8: Output gap estimates using econometric filters

The shape of the consensus output gap trajectory is similar to that obtained thought the production function methodology. However, the amplitude of the cycle is quite different. Between 2006Q1 and 2008Q4, the output gap was positive reaching a maximum of 6.47% in 2008Q3. Due to the actual macroeconomic conditions, the output gap was negative, around -2.5%, in 2009Q1. The amplitude in 2009Q1 is much lower that the value obtained using the production function methodology of around -7%.

Table 8 presents the annual consensus output gap estimate, the consensus potential GDP, and the potential GDP growth. The results of the consensus estimate of the output gap using various non-theoretic statistical methods are similar to the result obtained using the PF methodology. The higher values for the output gaps in 2007 and 2008 are reflected in lower growth rates of the potential GDP.

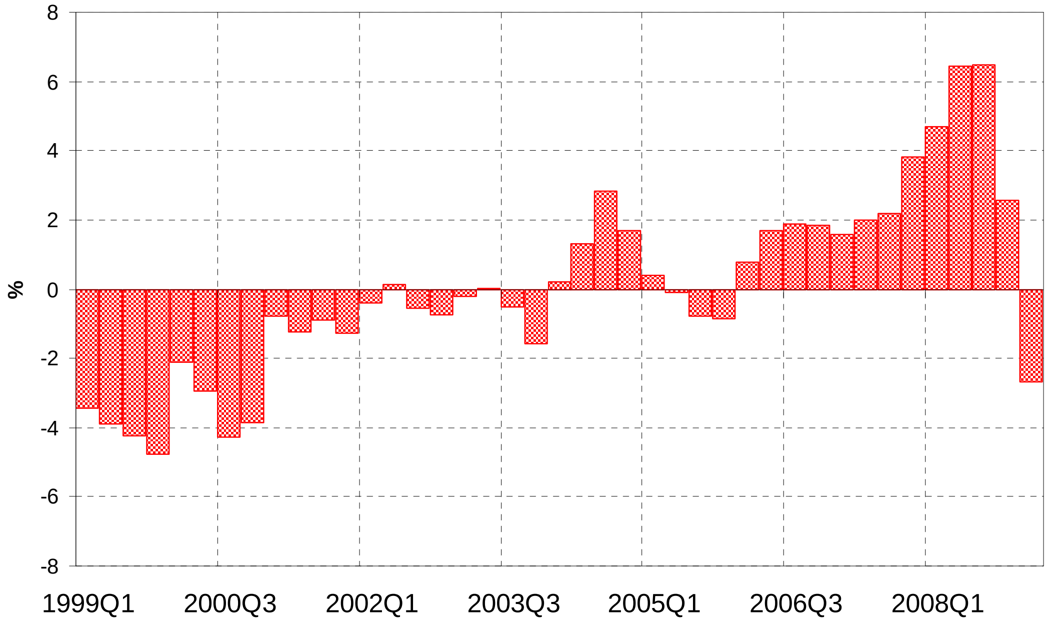

Figure 9: Consensus output gap estimate

Table 8 *Annualized consensus output gap and potential GDP*

Year	Output-gap (% of potential GDP)	Potential output (mln. RON 2000 prices)	Potential growth (%)
2000	-3.24	83,700.23	1.96
2001	-1.04	86,379.98	3.20
2002	-0.39	90,139.76	4.35
2003	-0.58	95,068.21	5.47
2004	1.54	100,971.90	6.21
2005	-0.34	107,121.81	6.09
2006	1.57	113,441.05	5.90
2007	2.44	119,449.69	5.30
2008	5.18	124,590.09	4.30

The growth rate of the potential GDP for the period 2000-2008 was between 1.96% and 6.21%, with an average of 4.75%. If we consider only the period covered using the production function methodology, 2001-2008, the annual average potential growth rate is around 5.1%.

Table 9 *Comparative analysis of the individual potential output and output gap estimation methods*

	PF	HP	KM	BP	WT	Consensus
Correlation between the output gap estimates						
PF	1.00	0.76	0.52	0.48	0.56	0.62
HP		1.00	0.65	0.75	0.78	0.84
KM			1.00	0.81	0.53	0.94
BP				1.00	0.81	0.93
WT					1.00	0.76
Consensus						1.00
Output gap descriptive statistics (%)						
Average	-0.07	-0.37	0.53	0.13	-0.18	0.10
Std. dev.	1.89	2.33	4.49	2.10	2.34	2.68
Min	-7.09	-8.15	-6.35	-3.68	-4.64	-4.76
Max	3.81	3.49	10.78	5.67	5.79	6.47
Q min	2009Q1	2009Q1	1999Q4	1999Q2	1999Q4	1999Q4
Q max	2008Q3	2008Q3	2008Q3	2008Q2	2008Q3	2008Q3
Growth rate of the potential GDP (%, yoy) 2000Q2-2009Q1						
Average	5.70	5.29	4.24	4.93	5.00	4.80
Std. dev.	0.51	1.55	0.66	1.89	2.28	1.35
Min	4.27	1.29	2.68	1.12	0.69	1.83
Max	6.35	6.52	5.05	8.27	7.95	6.60
Growth rate of the potential GDP (%, yoy) 2004Q1-2009Q1						
Average	5.97	6.30	4.48	5.67	5.90	5.46
Std. dev.	0.28	0.20	0.54	1.65	2.00	0.89
Min	5.09	5.90	3.10	2.13	2.19	3.41
Max	6.35	6.52	5.05	8.27	7.95	6.60

The correlation degree between the output gap estimates obtained using the PF, and the detrending methods: HP, KM, BP, and WT is relatively high, ranging between 0.48, and 0.81. Correlation is lowest for the pair PF and BP, and highest for BP with KM, and WT, respectively. The PF output gap estimates are correlated most with those obtained using the HP filter. As it concerns the standard deviation of the output gap estimates, the most volatile series is that resulted in the KM approach, the least volatile being the result of the PF approach.

An interesting feature issuing from Table 9 is that all of the five individual methods, as well as the consensus of the detrending methods, agree on the quarter with the largest positive output gap (although the magnitudes differ).

Analyzing the year on year growth rate of the potential GDP, we see that the average computed for the time span 2000Q2-2009Q1 is between 4.24% and 5.7%, while the same average computed for the time span 2004Q1-2009Q1 is between 4.48%, and 6.3%, indicating an acceleration of the potential GDP in the last years.

4 Concluding Remarks

This study assembles a battery of theoretical and statistical methods, both structural, as well as non-structural, in order to obtain a reliable estimate for the cyclical position of the Romanian economy. Potential output and output gap are matters of outmost importance for the decisions taken by the policymakers in normal periods: monetary policy actions dealing with excess demand, fiscal policy actions to interfere (or not) with automatic stabilizers, but especially in the periods characterized by financial, economic, and trade distress.

Our methodology combines the production function method with econometric filtering techniques: Hodrick-Prescott, Kalman, band-pass and wavelet transform. Thus, the potential output and output gap estimates benefit from the advantages of both methods.

The results indicate a continuously increase in the growth rate of the potential output until the third quarter of 2008, followed by a decline in 2008Q4 and 2009Q1. For the period lasting until 2007Q3, the main driving force in the potential growth was the technical progress, but in the final period under analysis the major contribution is that of physical capital. According to the production function approach, the decline in the growth rate of potential GDP in the last two quarters analyzed is mainly due to the decrease in the investment to GDP ratio, to a reduced growth rate in the trend of the hours worked, and to the increase in the NAIRU.

Although the four statistical estimates have been combined into a consensus measure using an explicit methodology, further aggregation of this measure with the estimate obtained using the production function methodology is beyond the scope of the present study, and should be subject to further research and expert judgment. As a rule of thumb, an equal weighting scheme might be used to obtain a single estimate of the output gap.

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