Is the Output Gap a Useful Indicator for Monetary Policy in Moldova?

Igor Pelipas, Robert Kirchner, Enzo Weber

Berlin/Chişinău, April 2015
About the German Economic Team Moldova (GET Moldova)

The German Economic Team Moldova ("GET Moldova"), which has been active in Moldova since 2010, advises the Moldovan government and other state authorities such as the National Bank of Moldova on a wide range of economic policy issues and on financial sector development. Our analytical work is presented and discussed during regular meetings with high-level decision makers. GET Moldova is financed by the German Federal Ministry for Economic Affairs and Energy.

German Economic Team Moldova (GET Moldova)
c/o BE Berlin Economics GmbH
Schillerstr. 59
D-10627 Berlin
Tel: +49 30 / 20 61 34 64 0
Fax: +49 30 / 20 61 34 64 9
info@get-moldau.de
www.get-moldau.de
Follow us on Twitter @BerlinEconomics

© 2015 German Economic Team Moldova
All rights reserved.
Is the Output Gap a Useful Indicator for Monetary Policy in Moldova?

Executive Summary

The linkage between the real economy and inflation is traditionally of great importance for monetary authorities. In this context, the concept of the output gap plays a prominent role in conventional macroeconomic theory, applied research and monetary policy analysis. However, the concept must be operationalized in order to be used for monetary policy purposes. The main problem is that both potential output and the output gap as a derivative value from the former are not directly observable.

The central question of the paper is whether the output gap can be considered as a useful indicator for monetary policy in Moldova. We have tried to address this question from an empirical point of view, allowing the data to speak freely, and bearing in mind the considerations of economic theory. To this end, we considered two methods for estimating potential output and the output gap, where the dynamics of inflation is explicitly taken into account, namely structural vector autoregression (SVAR) and unobserved component (UC) model.

The output gaps derived from univariate and multivariate UC models behave quite similar, and are also correlated to an output gap derived by a simple Hodrick-Prescott (HP) filter. The SVAR model, on the contrary, generates an output gap that is basically uncorrelated with the above mentioned methods. While previously mentioned methods demonstrate a positive output gap at the end of 2013 (the end of our sample period), the SVAR-derived gap is negative, even though it is in the process of closing. Thus, we can infer that the output gap is quite sensitive regarding the model specification chosen.

After we derived the output gaps using the methods mentioned above, we tested for a link between those gaps and inflation, as theory suggests. However, we were only able to detect a rather weak relationship between the output gaps and inflation, and mainly at rather long lags, i.e. the effect is quite delayed. These results, which are not inconsistent with international empirical evidence, suggest further research into its underlying reasons. Possible reasons could be econometric problems (e.g. omitted dynamics and possible nonlinearities), or that the simple models presented above do not fully capture the complex relationship between the variables.

Authors

Igor Pelipas pelipas@research.by +375 17 / 210 01 05
Robert Kirchner kirchner@berlin-economics.com +49 30 / 20 61 34 64 2
Enzo Weber enzo.weber@wiwi.uni-regensburg.de
Contents

1. Introduction .................................................................................................................................................................................. 5
2. Brief review of the concept and main estimation approaches ........................................................................................................ 5
3. Analytical framework ........................................................................................................................................................................ 7
  3.1. Structural VAR model .................................................................................................................................................................... 7
  3.2. Unobserved component model ..................................................................................................................................................... 9
4. Data used and their dynamic characteristics .................................................................................................................................. 11
5. Estimation results ................................................................................................................................................................................. 14
  5.1. Structural vector autoregression model ........................................................................................................................................ 14
  5.2. Unobserved component model ..................................................................................................................................................... 16
  5.3. Comparison of methods ................................................................................................................................................................. 17
  5.4. Output gap as an indicator of inflation .......................................................................................................................................... 18
6. Conclusions and policy implications ............................................................................................................................................... 22
References ............................................................................................................................................................................................ 23

Annex. Data and testing for seasonal unit root test and multiple structural breaks ............................................................................. 25
1. Introduction

The links between the real economy and inflation is traditionally of great importance for monetary authorities\(^1\). In this context, the concept of the output gap plays a prominent role in conventional macroeconomic theory, applied research and monetary policy analysis. Theoretically, the output gap represents the difference between actual and potential output, where potential output is the level of output corresponding to the maximum output level that an economy can produce utilizing all available factors of production without causing inflationary pressures on economy. When actual output exceeds its potential, and the output gap becomes positive, this means there is demand pressure and an upturn in inflation. Such a situation indicates for monetary authorities that monetary policy needs to be tightened. On the contrary, a negative output gap, resulting from actual output below potential output, implies the need for monetary easing.

The concept of the output gap must be operationalized to be implemented for monetary policy. The main problem is that both potential output and the output gap as a derivative value from the former are not directly observable. In accordance with a vivid expression of Billmeier (2009), the output gap is a ghost, which must be caught by the use of statistical and econometric techniques. Thus, to be of practical usage, potential output and the output gap should be estimated. There are various approaches and methods for estimating potential output and the output gap proposed in the literature. It is well known, however, that all these estimates are characterized by substantial uncertainty. Thus, the choice of method of output gap estimation is a nontrivial task for monetary policy analysts.

In this paper, we have tried to address this question from an empirical point of view, allowing the data to speak freely, and bearing in mind the considerations of economic theory. To this end, we considered two methods for estimating potential output and the output gap, where the dynamics of inflation is taken into account in the relevant calculations. On this basis, we have evaluated the information content of the output gap as a variable affecting the dynamics of inflation, and determined its usefulness for monetary policy.

The rest of the paper is organized as follows. The second section briefly reviews the concept of the output gap and its main estimation approaches and methods. In the third section, the analytical framework of our estimations of the output gap is presented, namely two approaches are considered: The first one is based on the SVAR methodology, and the second approach is built around an unobserved component (UC) modelling, or so-called structural time series models. These approaches allow for the inclusion of inflation dynamics in the calculation of the output gap. The fourth section analyses the dynamic characteristics of the data used. In the fifth section the estimation results of the output gap using the methods mentioned above are presented and comparisons are made. Furthermore, the section is devoted to the econometric testing of the output gap as a predictor of inflation. The sixth section concludes and provides some policy implications.

2. Brief review of the concept and main estimation approaches

Potential output and the output gap traditionally play an important role in monetary policy, helping to predict and control inflation at low and stable levels. In general, potential output can be defined as the maximum level of output that an economy is able to produce \textit{without generating an increase of inflation}\(^2\). In accordance with conventional macroeconomic theory potential output is determined by factors of production and technological level and represents the capacity of the national economy to supply goods and services to the consumers.

Within such a framework, the difference between actual output (say, real GDP) and potential output is considered as one of the main determinants of inflation pressure. This difference represents the output gap. In this line of reasoning, a positive output gap means that aggregate demand is higher than potential output, and inflation tends to increase. In turn, a negative output gap implies under-utilization of the economic

---

\(^1\) This paper is based on our analysis for the case of Belarus, see “Is the Output Gap a Useful Indicator for Monetary Policy in Belarus?”, GET Belarus Policy Paper 02/2014.

\(^2\) See Hauptmeier et al. (2009) for details on history and discussion of the concept of potential output and output gap.
potential and a decrease of inflation pressure. It follows that the output gap is an important indicator for modeling inflation dynamics and a useful tool for the conduct of monetary policy.

This elegant theoretical concept is faced with the practical necessity to get estimates of potential output and the output gap. The problem is that potential output, as well as the other variables characterizing the equilibrium states of economy, is directly unobservable and should be derived from observable macroeconomic data using appropriate techniques and models. However, the estimation of potential output is not an easy task. It can be obtained using a variety of approaches, ranging from purely statistical filters to the completely theoretically grounded dynamic stochastic general equilibrium (DSGE) models.

One can emphasize several approaches for estimating potential output and the output gap (see, for instance, Lim Choon Seng, 2007): Direct methods, univariate methods, multivariate and structural methods. This paper does not intend to consider the whole set of methods for potential output and output gap estimation, and refers the interested reader to the extensive literature on this issue. Instead, we focus on some of the most widely used methods of each of the mentioned groups.

The direct methods of potential output estimation are based on surveys of firms which provide useful insight on the degree of production capacities utilization of enterprises. However, it is difficult to operationalize the concept of potential output in questionnaires. Such data represents important first-hand information concerning the evaluation of capacity utilization, rather than a level of the production potential. Thus, direct methods are mostly adapted for the identification of business cycle turning points. The subjectivity of responses should also be taken into account.

The univariate statistical methods are widespread when estimating potential output and the output gap. These methods use only information contained in a single time series. The univariate HP-filter (Hodrick, Prescott, 1997) is apparently one of the most popular among them. The idea of HP-filter is to decompose a time series into unobservable components, namely trend and cycle, by using a two-sided moving average approach. A clear advantage of this method is its simplicity and availability in all practically econometric packages. The trend obtained from the HP-filter implies potential output, while the cycle represents the output gap. Flexibility of estimation is assured by setting a special smoothing parameter \( \lambda \) (for quarterly data, this parameter is usually set equal to 1600). The main drawbacks of this method are also well-known: The arbitrariness of setting the smoothing parameter and the end-sample bias (the level of potential output is more affected by variations in actual output at the beginning and at the end of the sample), the possibility of spurious cyclicity when applying the HP-filter to integrated or near-integrated time series and the excessive smoothening of structural breaks.

There are other univariate methods that are used for potential output and output gap estimations: The univariate Beveridge-Nelson decomposition, Baxter-King and Cristiano-Fitzgerald filters, the univariate unobserved component model, etc. All these methods are available in various popular econometric packages. It is necessary to note one peculiarity of all these methods: They are purely statistical in nature, do not involve any theoretical considerations, and essentially produce a trend in the dynamics of real output. The output gap is eventually the deviation from this trend.

Multivariate and structural methods tend to introduce economic theory while estimating potential output and the output gap. Among them, one can mentioned the multivariate HP-filter, the multivariate unobserved component model, SVAR, production function approach and DSGE modeling. All multivariate methods permit to include additional variables which may be relevant from the point of view of economic theory. For a more detailed discussion on the various alternative methods of potential output estimation and its implication for economic policy analysis, see Cotis et al. (2004).

Additional words should be said about potential output estimation within various DSGE\(^3\) models, which have become rather popular over the last decade. In Vetlov, et al. (2011) the notions of potential output within DSGE models are examined conceptually and empirically. Concerning the topic of our paper, the authors draw some interesting conclusions: (1) the comparison of DSGE model-based estimates of the output gap with traditional measures reveals that the two approaches may deliver significantly different estimates

---

\(^3\) See Morley (2010) for critical review of DSGE models.
of the output gap. Like traditional estimates, DSGE model-based estimates of potential output are subject to high uncertainty that reflects real-time uncertainty, parameter uncertainty, as well as critical assumptions underlying the identification of the models’ structural shocks; (2) there is no conclusive evidence proving that empirical estimates of model-consistent output gaps derived from larger and more realistic DSGE models are significantly better indicators of inflationary pressures than traditional measures; (3) the effects of the output gap on inflation and the size of the trade-off between output and inflation stabilization depends on the type of shocks and other structural features of the analyzed economy.

The existing variety of methods that can be used in estimations of potential output and the output gap leads to a substantial divergences of output gap estimates available for policy makers. A choice of the methods for better potential output and output gap estimation looks like a ghostbusting (Billmeier, 2004; 2009) in economic analysis. The unobservable nature of these variables makes it practically impossible to find the best measure, since the precise statistical errors of potential output estimates will never be known. In such a situation, different methods can lead to different policy recommendations. Which one, if any, should be chosen for practical usage?

In our view, the answer is straightforward: To be useful for monetary policy, output gap estimates should demonstrate statistically significant influence on inflation with the theoretically expected sign (a positive output gap should lead to an increase of inflation, while a negative output gap should lead to a decrease of inflation). Without such a requirement, the output gap becomes a worthless indicator for the conduct of monetary policy and can be used only as a measure of the discrepancy between actual and trend output in business cycle analysis without any relation to inflation. Of course, some reservations should be made. In case we must rely on poor-quality or distorted statistics, or observe a problematic conduct of economic policy, which breaks the natural links between macroeconomic indicators, an otherwise useful indicator might be rendered practically useless under such adverse conditions.

It is important to note that inflation dynamics can be influenced by the various structural breaks, characterizing the different regimes of economic policy, internal and external shocks. These structural breaks can mask the real underlying relationship between the output gap and inflation. Therefore, such breaks should be taken into account while estimating the output gap and its link with inflation.

An essential requirement for choosing the method for potential output and output gap estimation is the availability of reliable data. Consequently, when macroeconomic data of interest are limited, a simpler method may be preferred, rather than more advanced methods with stronger theoretical grounds.

Thus, choosing from a variety of approaches and methods for potential output and output gap estimation, we rested on the following: (1) theoretical consideration should be taken into account explicitly in the model (at least, inflation dynamics should be incorporated into the model, so we need multivariate approaches); 2) data used for estimations should be immediately observable, available and reliable. Two of the above-mentioned methods meet the requirements, namely: SVAR and multivariate unobserved component model.

3. Analytical framework

In this paper we applied two methods of potential output and output gap estimation. The first one is based on a well-known and frequently cited paper by Blanchard, Quah (1989), where a Structural VAR (SVAR) model with long run identification restriction based on economic theory was used to estimate potential output and the output gap. The second one is built on the rather new paper by Harvey (2011), where the relationship between inflation and the output gap (Philips curve) is done with univariate and multivariate unobserved component models. The models used in our paper for potential output and output gap estimation are discussed below.

3.1. Structural VAR model

In Blanchard, Quah (1989) a macroeconomic model with only two variables (real GDP and the unemployment rate) is proposed, where real output is affected by two shocks: demand and supply. In accordance with the natural rate hypothesis, demand shocks have no long-run impact on the level of real GDP (demand shocks can have an effect on GDP in the short run only). On the contrary, supply-side or productivity shocks
are supposed to have a permanent effect on output. The authors estimate a vector autoregression model with two variables and identify structural shocks, imposing the long-run restriction that demand shocks have only a temporary effect on real output.

Thus, the main idea of this bivariate SVAR model is to decompose real output into three components, namely (1) deterministic trend, (2) component determined by shocks, having a permanent effect on the supply side of the economy, (3) component determined by shocks that affect demand in the short run. The first two components represent potential GDP, while the latter can be considered as the output gap. It should be noted that within this model potential output and the output gap are determined simultaneously.

In our paper we adopted this method, using inflation instead of the unemployment rate. Thus, we use a bivariate SVAR model, included real GDP growth (seasonally adjusted), $\Delta \text{rgdp}_{t}^{sa}$ and inflation (seasonally adjusted), $\Delta \text{cpi}_{t}^{sa}$. Thus, our system can be presented as vector of stationary covariance variables with

$$
x_{t} = A(L)\varepsilon_{t} = \sum_{i=0}^{\infty} A_{i} \varepsilon_{t-i},
$$

where $A(L)$ is a $2 \times 2$ lag polynomial; $\varepsilon_{t} = [\varepsilon_{t}^{s}, \varepsilon_{t}^{d}]'$ is a vector of exogenous, unobserved structural shocks (supply and demand shock respectively), that satisfies $E[\varepsilon_{t}] = 0$ and $E[\varepsilon_{t}\varepsilon_{t}'] = I$.

In order to identify the structural model, one should estimate the following reduced-form VAR:

$$
x_{t} = \Phi(L)x_{t} + e_{t} = \sum_{i=0}^{p} \Phi_{i} x_{t-i} + e_{t},
$$

where $\Phi(L)$ is a $2 \times 2$ lag polynomial of order $p$; $e_{t}$ is a vector of estimated reduced-form residuals with $E[e_{t}] = 0$, and $E[e_{t}e_{t}'] = \Sigma$.

The reduced form can be inverted using the Wold decomposition, resulting in the reduced-form moving-average representation:

$$
x_{t} = C(L)e_{t} = \sum_{i=0}^{\infty} C_{i} e_{t-i},
$$

where $C(L)$ is a lag polynomial that can be expressed in terms of $\Phi(L)$ as follows: $C(L) = [1 - \Phi(L)L]^{-1}$.

From (1) and (2) one can see that the reduced-form innovations $e$ are linearly related to the structural innovations $\varepsilon$:

$$
e_{t} = A_{0} \varepsilon_{t},
$$

where $A_{0}$ is a $2 \times 2$ matrix of the contemporaneous effects of structural innovations. Herewith

$$
E[e_{t}e_{t}'] = A_{0}E[\varepsilon_{t}\varepsilon_{t}']A_{0}'.
$$

Since $E[e_{t}e_{t}'] = I$, then

$$
A_{0}A_{0}' = \Sigma.
$$

In order to recover the structural innovations, it is necessary to impose sufficient identification restrictions to identify the elements of matrix $A_{0}$. Three pieces of information are obtained from the symmetric $2 \times 2$ matrix $\Sigma = A_{0}A_{0}'$. Thus, one identification restriction is needed to be imposed in order to recover the four

---

4 The nomenclature of the variables used is presented in Table 1.
unknown elements in $A_0$. This restriction is based on economic theory and supposes that demand shocks have no long-run effect on real GDP:\(^5\)

$$
\sum_{i=0}^{\infty} A_i(1, 2) = 0.
$$

(7)

where $A_i(i, j)$ represents the elements in row $i$ and column $j$ of matrix $A_i$.

The residuals from the unrestricted VAR and the estimated parameters of $A_0$ can be used to construct the vector of exogenous structural shocks. Since potential GDP corresponds to the permanent component of GDP in the system, the equation for growth of potential GDP can be obtained using the vector of supply shocks:

$$
\Delta \text{rgdp}_t^{\text{sa, potential}} = \sum_{i=0}^{\infty} A_i(1, 1) \varepsilon_t.
$$

(8)

Similarly, growth of the output gap can be derived as follows:

$$
\Delta \text{rgdp}_t^{\text{sa, gap}} = \sum_{i=0}^{\infty} A_i(1, 2) \varepsilon_t.
$$

(9)

The levels of potential output and the output gap can be easily obtained.

For estimation of potential output and the output gap using the methodology described above, we utilize the Add-in procedure in Eviews econometric software (HDecomp) that provides a procedure that decomposes the historical values of time series from a VAR estimations\(^6\).

3.2. Unobserved component model

In Harvey (2011) the relationship between inflation and the output gap is modelled by an unobserved component model. Both univariate and multivariate models are discussed. In the first case, the output gap is obtained by using a univariate unobserved component model for output. Then the output gap is included in a univariate model of inflation. In a multivariate case, output, inflation and the output gap are modelled simultaneously.

In the univariate model, the output gap can be estimated from the unobserved component model for real output. A trend-cycle model can be expressed as follows:

$$
\text{rgdp}_t^{\text{sa}} = \mu_t + \psi_t + \varepsilon_t, \quad t = 1, ..., T,
$$

(10)

where $\mu_t$ is an integrated random walk,

$$
\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t,
$$

$$
\beta_t = \beta_{t-1} + \xi_t, \quad t = 1, ..., T,
$$

(11)

$\psi$ is a stochastic cycle, $\beta_t$-slope, $\varepsilon_t \sim \text{NID}(0, \sigma^2)$, $\eta_t \sim \text{NID}(0, \sigma^2_{\eta})$, and $\xi_t \sim \text{NID}(0, \sigma^2_{\xi})$.

The stochastic cycle

$$
\begin{bmatrix}
\psi_t \\
\psi'_t
\end{bmatrix} = \rho
\begin{bmatrix}
\cos \lambda_c & \sin \lambda_c \\
-\sin \lambda_c & \cos \lambda_c
\end{bmatrix}
\begin{bmatrix}
\psi_{t-1} \\
\psi'_{t-1}
\end{bmatrix} + \begin{bmatrix}
\kappa_t \\
\kappa'_t
\end{bmatrix}, \quad t = 1, ..., T,
$$

(12)

where $\lambda_c$ is frequency in radians, $\rho$ is a damping factor, with $0 \leq \rho \leq 1$, and $\kappa_t$, $\kappa'_t$ are two mutually independent white noise disturbances with zero mean and common variance $\sigma^2_k$. The disturbances $\varepsilon_t, \xi_t, \kappa_t, \kappa'_t$ are serially and mutually uncorrelated with variances $\sigma^2_{\varepsilon}$ and $\sigma^2_{\xi}$ for irregular and slope.

---

\(^5\) For the role of persistence when using long-run restrictions, see Tschernig et al. (2013, 2014).

\(^6\) This Add-in procedure is provided by Eren Ocakverdi, see http://www.eviews.com/Addins/addins.shtml.
In this model, the smoothed estimates of the cycle can be considered as the output gap. It should be noted that the HP-filter can be considered as a special case of this unobserved component model. However, the unobserved component model has no “end of the sample problem”, and can be used for forecasting of potential output and the output gap.

Since trend inflation is well approximated by a driftless random walk, it can be modelled as a random walk plus noise or local level model:

\[ \Delta \text{cpi}_{t}^\text{sa} = \mu_t + \varepsilon_t, \quad \varepsilon_t \sim \text{NID}(0, \sigma^2), \quad t = 1, \ldots, T, \]  
\[ \mu_t = \mu_{t-1} + \eta_t, \quad \eta_t \sim \text{NID}(0, \sigma^2), \quad t = 1, \ldots, T. \]  

The disturbances \( \varepsilon_t \) and \( \eta_t \) are serially and mutually uncorrelated, normally and independently distributed with zero mean and variance \( \sigma^2 \).

In fact, \( \mu_t \) in (11) represents core (trend) inflation. By analogy to the model for output, a stochastic cycle \( \psi_t \) can also be added to the model of inflation. To test a relationship between inflation and output gap in a univariate setting, a model of inflation should be expanded by inclusion of output gap with some lags:

\[ \Delta \text{cpi}_{t}^\text{sa} = \mu_t + \psi_t + a_t \chi_{t-j} + \varepsilon_t, \quad t = 1, \ldots, T, \]  
where \( \chi_{t-j} \) is the output gap from the model (11–12), and \( j = 0, 1, 2 \) in our case.\(^7\)

In a multivariate setting inflation and output are modelled simultaneously as follows:

\[
\begin{bmatrix}
\Delta \text{cpi}_{t}^\text{sa} \\
\text{rgdp}_{t}^\text{sa}
\end{bmatrix}
= \begin{bmatrix}
\mu_{t}^\text{cpi} \\
\mu_{t}^\text{rgdp}
\end{bmatrix}
+ \begin{bmatrix}
\psi_{t}^\text{cpi} \\
\psi_{t}^\text{rgdp}
\end{bmatrix}
+ \begin{bmatrix}
\varepsilon_{t}^\text{cpi} \\
\varepsilon_{t}^\text{rgdp}
\end{bmatrix},
\]  

where \( \mu_{t}^\text{cpi} \) is a random walk as in (14) and \( \mu_{t}^\text{rgdp} \) is an integrate random walk as in (11).

The stochastic cycles are modelled as ‘similar cycles’, so that if \( \psi_t = (\psi_{t}^\text{cpi}, \psi_{t}^\text{rgdp})' \), then

\[
\begin{bmatrix}
\psi_t \\
\psi_t'
\end{bmatrix}
= \rho \begin{pmatrix}
\cos \lambda \circ \sin \lambda \\
-\sin \lambda \circ \cos \lambda
\end{pmatrix}
\otimes I_2
\begin{bmatrix}
\psi_{t-1} \\
\psi_{t-1}'
\end{bmatrix}
+ \begin{bmatrix}
\kappa_t \\
\kappa_t'
\end{bmatrix}, \quad t = 1, \ldots, T,
\]  
where \( \kappa_t \) and \( \kappa_t' \) are \( 2 \times 1 \) vector of the disturbances such as \( E(\kappa_t, \kappa_t') = \Sigma_k \), where \( \Sigma_k \) is a \( 2 \times 2 \) covariance matrix, and \( E(\kappa_t, \kappa_t') = 0 \).

The cycle of inflation can be broken down into two independent parts, one of which depends on real GDP cycle, that is \( \psi_{t}^\text{cpi} = \beta \psi_{t}^\text{rgdp} + \psi_{t}^\text{cpi\textsuperscript{+}} \), where

\[ \beta = \text{Cov}(\psi_{t}^\text{cpi}, \psi_{t}^\text{rgdp}) / \text{Var}(\psi_{t}^\text{rgdp}) = \text{Cov}(\kappa_{t}^\text{cpi}, \kappa_{t}^\text{rgdp}) / \text{Var}(\kappa_{t}^\text{rgdp}), \]  
and \( \psi_{t}^\text{cpi\textsuperscript{+}} \) is cyclical component specific to inflation.

Substituting in the inflation equation in (16) gives

\[ \Delta \text{cpi}_{t}^\text{sa} = \mu_{t}^\text{cpi} + \beta \psi_{t}^\text{rgdp} + \psi_{t}^\text{cpi\textsuperscript{+}} + \varepsilon_{t}^\text{cpi}, \]  
If the cycle disturbances \( \kappa_{t}^\text{cpi} \) and \( \kappa_{t}^\text{rgdp} \) are perfectly correlated, (19) corresponds to the relationship between inflation and the output gap with zero lag.

\[^7\text{Only one lag is used at a time in the equation (15).}\]
We estimated univariate and multivariate unobserved component models using module Stamp 8.3 of OxMetrics 7.0 software. It should be noted that possible structural breaks in the variables have to be introduced into UC models to render their dynamics properly. In the next section we detect multiple structural breaks in the variables and use them in the following estimations. Besides, in STAMP 8.3 an automatic detection procedure for detection of outliers, level shifts and trend breaks is implemented. The program is able to propose a set of potential outliers, level shifts and trend breaks for univariate and multivariate time series on the basis of two-step procedure based on the auxiliary residuals. First the selected model is estimated and the diagnostics are investigated. Then a first set of potential outliers, shifts and breaks are selected from the auxiliary residuals. After re-estimation of the model, only those interventions survive that are sufficiently significant (see Koopman et al. (2009)). This procedure is also utilized in further analysis.

4. Data used and their dynamic characteristics

For econometric modelling, we used quarterly data of real GDP in average 2010 prices and CPI index over 1995q1–2013q4 (76 observations). The quarterly CPI index is obtained by averaging monthly data, 2010=1.

The time series are seasonally unadjusted.

Then the raw data (see Annex, Table A1) were tested for seasonality and, if necessary, the appropriate adjustment was made. We used X-13ARIMA-SEATS procedure for seasonal adjustment. To obtain seasonally adjusted data, it is necessary to specify correctly the ARIMA(\(p, d, q\)(\(P, D, Q\) model. Within X-13ARIMA-SEATS the choice of \(d\) and \(D\) can be done automatically. However, the order of integration of data determined in the automatic mode is sometimes not consistent with the actual dynamic characteristics of the time series. Therefore, to determine the order of integration of the variables, we tested them for seasonal unit root, using HEGY-test (Hylleberg, Engle, Granger, Yoo, 1990).

In both variables, a clear and significant pattern of seasonality is identified. For real GDP, there are both regular and seasonal unit roots in the data (see Table A1 in the Annex). So in ARIMA(\(p, d, q\)(\(P, D, Q\) \(d\) and \(D\) should be equal to 1. Semi-automatic seasonal adjustment has been done with fixed \(d=1\) and \(D=1\). For the CPI series, there is only regular unit root in the data and there is no evidence of seasonal unit roots (there is a deterministic and not a stochastic seasonality if any). Thus, a seasonal differencing is not appropriate option here. In this case we use semi-automatic seasonal adjustment fixing \(d=1\) and \(D=0\), and adding deterministic seasonal dummies into the model. The codes for seasonal adjustment of real GDP and CPI used in this paper are presented below:

<table>
<thead>
<tr>
<th><strong>RGDP</strong></th>
<th><strong>CPI</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>series{</td>
<td>series{</td>
</tr>
<tr>
<td>title = &quot;RGDP&quot;</td>
<td>title = &quot;CPI&quot;</td>
</tr>
<tr>
<td>start = 1995.1</td>
<td>start = 1995.1</td>
</tr>
<tr>
<td>period = 4</td>
<td>period = 4</td>
</tr>
<tr>
<td>name = &quot;RGDP&quot;</td>
<td>name = &quot;CPI&quot;</td>
</tr>
<tr>
<td>file = &quot;C:\USERS\PELIPAS\EV_TEMP\EVX13TMP.DAT&quot;</td>
<td>file = &quot;C:\USERS\PELIPAS\EV_TEMP\EVX13TMP.DAT&quot;</td>
</tr>
<tr>
<td>decimals = 1</td>
<td>decimals = 1</td>
</tr>
<tr>
<td>transform{</td>
<td>transform{</td>
</tr>
<tr>
<td>function = auto</td>
<td>function = auto</td>
</tr>
<tr>
<td>}</td>
<td>}</td>
</tr>
<tr>
<td>outlier{</td>
<td>automdl{</td>
</tr>
<tr>
<td>types = (ao ls )</td>
<td>diff = (1,0)</td>
</tr>
<tr>
<td>span = (1995.1 , 2013.4)</td>
<td>maxorder = (2,1)</td>
</tr>
<tr>
<td>}</td>
<td>mixed = no</td>
</tr>
<tr>
<td>automdl{</td>
<td>fcstlim = 15</td>
</tr>
<tr>
<td>diff = (1,1)</td>
<td>}</td>
</tr>
</tbody>
</table>

---

8 See Koopman, Harvey, Doornik, Shephard (2009).
9 For details see http://www.census.gov/srd/www/x13as.
10 See Annex, Table A1.
Seasonally adjusted time series in natural logarithms are presented in Figure 1. The first difference of these time series approximate the growth rate of the real GDP and inflation. Visual inspection of data and a formal econometric analysis suggests that the real GDP and CPI indices are non-stationary variables and contain unit roots.

Figure 1. Data used (log scale, seasonally adjusted)

Conventional unit root tests suggest that the data are non-stationary in the levels and stationary in the first differences. Augmented ADF test for $rgdp_{t}^{sa}$ is equal to −2.40 (constant + trend, lag=0, null hypothesis of unit root is not rejected) and for $\Delta rgdp_{t}^{sa}$ the ADF test is equal to −6.83 (constant, lag=0, null hypothesis of unit root is clearly rejected). Augmented ADF test for $cpi_{t}^{sa}$ is equal to −2.97 (constant + trend, lag=1, null hypothesis of unit root is not rejected) and for $\Delta cpi_{t}^{sa}$ the ADF test is equal to −4.70 (constant, lag=0, null hypothesis of unit root is clearly rejected).
Visual inspection of the time series shows that multiple structural breaks (level shifts) in the first differences of the analyzed data (Figure 1) may exist, that can affect the estimates of the output gap. Bearing in mind that conventional unit root test are strongly affected by such breaks, we first specify them in a formal setting. To identify such structural breaks we employed the Bai-Perron multiple breakpoint test (Bai, Perron, 1998; 2003) for the first differences of the time series. Within this approach, the sum of squared residuals is minimized in order to identify the dates of \( k \) structural breaks in time series \( \Delta y_t \), and, thereby, determine \( k + 1 \) regime in dynamics of the examined variable, on the basis of the following model: \( \Delta y_t = \gamma_{k+1} + \tau_t \), where \( \Delta y_t \) is a variable of interest; \( \gamma_{k+1} \) is a series of \( k + 1 \) constants, that characterized the means of the variable in each of \( k + 1 \) regimes; \( \tau_t \) are regression residuals. This is corrected for autocorrelation by reservation of a certain share of the sample corresponding to minimal regime duration (0.05 from the total sample in our case). The final model is chosen using Bayesian information criterion (BIC).

Figure 2 depicts the results of these tests in graphical form\(^{11}\). As one can see, five break points were found for inflation (1996q4, 1998q4, 1999q4, 2000q4, 2008q3) and three for real GDP (1999q4, 2004q4, 2009q1) according to the Schwarz criterion.

This fact plays an important role in analyzing the relationship between inflation and the output gap, and appropriate step dummies (if significant) should be included in econometric models to reflect properly the dynamics of inflation.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure2}
\caption{Bai-Perron test for multiple structural breaks}
\end{figure}

Below we present a detailed description of the data and all transformations of the time series used in this study.

\(^{11}\) Formal results of these tests are presented in the Annex, Table A2 and A3.
<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>( RGDP_t )</td>
<td>Real gross domestic product (GDP) in average 2010 prices, quarterly data, millions of MLD</td>
<td>-</td>
<td>Own estimations based on National Bureau of Statistics of the Republic of Moldova</td>
</tr>
<tr>
<td>( CPI_t )</td>
<td>Consumer price index (CPI), quarterly data, 2010=1</td>
<td>Average from monthly data</td>
<td>Own estimations based on National Bureau of Statistics of the Republic of Moldova</td>
</tr>
<tr>
<td>( RGDP_{sa} )</td>
<td>Seasonally adjusted real GDP</td>
<td>X-13ARIMA-SEATS: automatic TRAMO-SEATS procedure with fixed ( d=1, D=1 ) and final specification of ARIMA(0, 1, 1)(0, 1, 1); clearly significant seasonality is identified</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( CPI_{sa} )</td>
<td>Seasonally adjusted CPI</td>
<td>X-13ARIMA-SEATS: automatic TRAMO-SEATS procedure with fixed ( d=1, D=0 ) and seasonal dummies; final specification of ARIMA(1, 1, 0) + seasonal dummies; clearly significant seasonality is identified</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( rgdp_t )</td>
<td>Natural logarithm (ln) of real GDP</td>
<td>( rgdp_t = \ln RGP_t )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( cpi_t )</td>
<td>Natural logarithm (ln) of CPI</td>
<td>( cpi_t = \ln CPI_t )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( \Delta rgdp_t )</td>
<td>Logarithmic first differences of real GDP</td>
<td>( \Delta rgdp_t = rgdp_t - rgdp_{t-1} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( \Delta cpi_t )</td>
<td>Logarithmic first differences of CPI</td>
<td>( \Delta cpi_t = cpi_t - cpi_{t-1} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( \Delta rgdp_{sa} )</td>
<td>Logarithmic fourth (seasonal) differences of real GDP</td>
<td>( \Delta rgdp_{sa} = rgdp_{sa} - rgdp_{sa-4} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( rgdp_{sa} )</td>
<td>Natural logarithm (ln) of seasonally adjusted real GDP</td>
<td>( rgdp_{sa} = \ln RGP_{sa} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( cpi_{sa} )</td>
<td>Natural logarithm (ln) of seasonally adjusted CPI</td>
<td>( cpi_{sa} = \ln CPI_{sa} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( \Delta rgdp_{sa} )</td>
<td>Logarithmic first differences of seasonally adjusted real GDP</td>
<td>( \Delta rgdp_{sa} = rgdp_{sa} - rgdp_{sa-1} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( \Delta cpi_{sa} )</td>
<td>Logarithmic first differences of seasonally adjusted CPI</td>
<td>( \Delta cpi_{sa} = cpi_{sa} - cpi_{sa-1} )</td>
<td>Own estimations</td>
</tr>
<tr>
<td>( GAP_t )</td>
<td>Different measures of output gap, in logs</td>
<td>Estimated by using HP-filter, SVAR model, UC model</td>
<td>Own estimations</td>
</tr>
</tbody>
</table>

5. Estimation results

5.1. Structural vector autoregression model

In order to estimate the output gap within a SVAR model, we specify a VAR with 3 lags and a constant. This specification is consistent with the data. The order of the VAR is chosen on the basis of LR-tests (sequential modified LR test statistic), and a variety of criterions, namely FPE (final prediction error), AIC (Akaike information criterion) and HQ (Hannan-Quinn information criterion). LR-test, FPE and AIC suggest 3 lags, whereas HQ and SC suggest only 1 lag in the model. We preferred the VAR model with 3 lags since it performs better with specification tests. The null hypothesis of no serial correlation up to 3 lags and residual heteroskedasticity are not rejected at any convenient levels. There is evidence of non-normality in residuals in the equation for \( \Delta rgdp_{sa} \). The equation for \( \Delta cpi_{sa} \) passed the residual normality test. Deterministic term (constant) is significant in the chosen specification.
Impulse response functions due to supply and demand shocks are depicted in Figure 3. The dynamic effects of supply and demand shocks are in line with the theoretical considerations. A supply shock leads to an increase in real GDP in the long run that stabilizes after 10 quarters. In turn, inflation at first decreases after a supply shock and then stabilizes after 10 quarters, in fact mirroring the response of real GDP with opposite sign. The impulse responses characterizing the effects of a supply shock on output and inflation are statistically significant according to 95% bootstrap confidence intervals.

A demand shock has a short-run effect on real GDP. It leads to an increase of output up to 2 quarters and then the impulse response function becomes insignificant. Inflation grows after a demand shock and stabilizes after 10–12 quarters. The impulse responses characterizing the effects of a demand shock on inflation are statistically significant at the 95% significance level.

**Figure 3. Impulse response functions**

![Impulse response functions](image)

Note: dashed lines are 95% Hall percentile bootstrap confidence intervals, 2000 pseudo samples were used for bootstrapping.

Source: own estimations

On the basis of SVAR, potential output and the output gap were estimated. It should be noted, that since the VAR model has 3 lags we lose three observations at the beginning of the sample. The obtained results are presented on Figure 4.
5.2. Unobserved component model

Univariate unobserved component model:
To get the potential output and output gap from the UC model, we at first follow Harvey (2011) in utilizing a univariate unobserved component model. There are several possible specifications of such a model and we used a so-called smooth trend model where the level (trend) is fixed and the slope (growth rate of the trend) is stochastic. Since we work with seasonally adjusted data, a seasonal component is excluded from the model. Additionally, the model contains a stochastic cycle of order one and an irregular component.\(^{12}\) The level shift in 2009q1 is taken into account.

The output gap is depicted in Figure 5 with 90% confidence bands that permit to evaluate its significance at different peaks. As one can see from the graph, during the recent past, the output gap showed quite some volatility. A negative output gap in 2012 reversed over the year 2013 when actual output increased beyond its potential.

\(^{12}\) Higher orders of the cycle can also be used, that will lead to a smoother cycle; see Harvey, Trimbur (2003).
Multivariate unobserved component model:
This model permits not only to obtain the output gap, taking into account the dynamics of inflation, but also to verify the existence of the relationship between the output gap and inflation (in accordance with (18–19)). In the system of equations we used the same specification for real GDP as it was discussed above in the univariate case (fixed level and stochastic slope) and include level shift dummy that take structural breaks in 2009q1. The equation for inflation is a so-called local level model (stochastic level and no slope). It also contains dummies characterizing level shifts (Figure 2 and Table A2).

Figure 6. Potential output and output gap: multivariate UC (log scale)

Source: own estimations

The potential output and output gap from the multivariate UC models are shown in Figure 6. There are some minor differences in comparison with derived unobservables from the univariate model, but in general the output gaps in Figures 6 and 5 look similar.

The results from our multivariate UC model do not verify the existence of a Philips curve-like relationship between inflation and the output gap in Moldova. This is different from previous findings for the case of Belarus, where such a relationship was detected once structural breaks in inflation dynamics were taken into account.

In the next section we use the output gaps from univariate and multivariate UC models in UC model of inflation to evaluate the information content of the output gap while predicting inflation in Moldova.

5.3. Comparison of methods
In order to compare the output gaps obtained from different approaches we show them jointly in Figure 7. The output gap based on the HP-filter is added as a benchmark for comparison. Additionally, the correlation matrix of the different output gaps are calculated and presented in Table 2.
As follows from Figure 7 and Table 2, the output gaps obtained by different methods differ considerably in terms of their profiles and correlations with each other. It should be noted immediately that the output gap obtained using SVAR3 differs cardinally from all other measures of the output gap and in fact does not correlate with them. The correlations with other output gaps are in fact negligible. The benchmark output gap estimated on the basis of HP-filter has rather strong correlations with univariate and multivariate UC (around 0.65). Both output gaps from UC models are closely correlated (0.99) and have similar profiles.

Table 2. Different measures of the output gap: correlation matrix

<table>
<thead>
<tr>
<th>Output gap</th>
<th>HP</th>
<th>SVAR3</th>
<th>Univariate UC</th>
<th>Multivariate UC</th>
</tr>
</thead>
<tbody>
<tr>
<td>HP</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVAR3</td>
<td>0.095</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Univariate UC</td>
<td>0.658</td>
<td>0.037</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Multivariate UC</td>
<td>0.650</td>
<td>0.088</td>
<td>0.992</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: sample 1996q1–2013q4 is used to make estimates of the different output gaps comparable.
Source: own estimations

Thus, the different methods of output gap estimation lead to quite distinct results. Three of them (HP, univariate UC, multivariate UC) are clearly positive at the end of the sample without any tendency to be closed. The output gap derived from the SVAR3 model is negative at the end of the sample, but with clear-cut tendency towards closing.

5.4. Output gap as an indicator of inflation

In this section we evaluated the usefulness of different measures of the output gap derived above in predicting inflation. It must be emphasized that our task here is not to get well specified models of inflation, taking into account all possible determinants. On the contrary, we used very simple models of inflation where the output gap is the only explanatory variable in order to determine the sign and test the significance of this variable and to verify its information content in explaining inflation dynamics. The following

13 However, it seems that from 2002/2003 onwards, the SVAR3-derived output gap moved in tandem with the other gaps, whereas before that, it actually behaved in the opposite way.
consideration is behind such kind of analysis: If the output gap is clearly not significant or has a wrong sign in a simple model of inflation, it is rather improbable that the situation will change fundamentally in more complex models.

Before we apply a number of formal models, we look at the correlation between inflation and output gaps derived by the different methods at different lags. Here, we continue to see a similar behaviour of output gaps derived by the HP, univariate UC and multivariate UC methods, while the SVAR3 model is clearly behaving in a very different manner. While the correlation of the latter model with inflation is quite high initially, it quickly fades out. With the previous 3 methods, the correlation coefficient is slowly rising until lag 6, and is then tapering off. The maximum correlation coefficient is never higher than about 0.4 for those 3 methods.

**Figure 8. Correlation between inflation and the output gaps**

![Correlation graph](chart)

Source: own estimations

The modelling strategy is as follows: (1) for all measures of the output gap (HP, SVAR3, univariate UC, multivariate UC) the models with the output gap and inflation with lag 1 (to capture inflation inertia) and a constant were used. The models are estimated using OLS; (2) univariate models of inflation with fixed level and no slope were applied for the output gaps derived from univariate and multivariate UC model. The models are estimated using the Kalman filter.

The output gaps are included into the models with lags 0 to 6. The results obtained are presented in Table 3 and 4. As one can see from Table 3, there is very weak evidence of the relationship between output gap and inflation. In most cases, the estimated coefficients of the output gap are insignificant or have the wrong signs. The output gap derived from the HP-filter demonstrates a positive link with inflation at the 5% significance level, but only at very long lags (5). This is similar in the case of univariate and multivariate UC (lags 5/6), while the SVAR3 model behaves differently, as here lag 0 is highly significant. In sum, one can conclude that these output gaps are not very reliable indicator variables for inflation.
Table 3. Testing output gaps coefficients in AR (1) models of inflation

<table>
<thead>
<tr>
<th>Lag</th>
<th>Output gap (HP)</th>
<th>p-value</th>
<th>Output gap (SVAR3)</th>
<th>p-value</th>
<th>Output gap (univariate UC)</th>
<th>p-value</th>
<th>Output gap (multivariate UC)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>-0.001</td>
<td>0.992</td>
<td>0.989</td>
<td>0.003</td>
<td>-0.074</td>
<td>0.747</td>
<td>0.014</td>
<td>0.953</td>
</tr>
<tr>
<td>1</td>
<td>-0.085</td>
<td>0.371</td>
<td>-0.287</td>
<td>0.279</td>
<td>-0.170</td>
<td>0.461</td>
<td>-0.216</td>
<td>0.366</td>
</tr>
<tr>
<td>2</td>
<td>-0.098</td>
<td>0.303</td>
<td>-0.056</td>
<td>0.793</td>
<td>-0.237</td>
<td>0.312</td>
<td>-0.300</td>
<td>0.215</td>
</tr>
<tr>
<td>3</td>
<td>-0.041</td>
<td>0.659</td>
<td>-0.132</td>
<td>0.518</td>
<td>-0.049</td>
<td>0.831</td>
<td>-0.120</td>
<td>0.614</td>
</tr>
<tr>
<td>4</td>
<td>0.076</td>
<td>0.417</td>
<td>-0.155</td>
<td>0.431</td>
<td>0.307</td>
<td>0.182</td>
<td>0.278</td>
<td>0.246</td>
</tr>
<tr>
<td>5</td>
<td>0.193</td>
<td>0.037</td>
<td>-0.221</td>
<td>0.270</td>
<td>0.571</td>
<td>0.016</td>
<td>0.543</td>
<td>0.027</td>
</tr>
<tr>
<td>6</td>
<td>0.163</td>
<td>0.091</td>
<td>-0.288</td>
<td>0.159</td>
<td>0.624</td>
<td>0.016</td>
<td>0.612</td>
<td>0.021</td>
</tr>
</tbody>
</table>

Source: own estimations

Turning to the second set models, the UC models of inflation, the results are given in Table 4 below. Here, we see for the univariate and the multivariate UC output gap a similar result as before, as only at very long lags (6) significance is assured (at the 1% level). This supports the general conclusion of a weak link between the output gap and inflation, and only at very long lags.

Table 4. Testing output gaps coefficients in the UC inflation models

<table>
<thead>
<tr>
<th>Lag</th>
<th>Output gap (univariate UC)</th>
<th>p-value</th>
<th>Output gap (multivariate UC)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.067</td>
<td>0.795</td>
<td>0.261</td>
<td>0.332</td>
</tr>
<tr>
<td>1</td>
<td>-0.128</td>
<td>0.622</td>
<td>-0.113</td>
<td>0.673</td>
</tr>
<tr>
<td>2</td>
<td>-0.548</td>
<td>0.040</td>
<td>-0.605</td>
<td>0.027</td>
</tr>
<tr>
<td>3</td>
<td>-0.529</td>
<td>0.053</td>
<td>-0.627</td>
<td>0.024</td>
</tr>
<tr>
<td>4</td>
<td>-0.091</td>
<td>0.748</td>
<td>-0.147</td>
<td>0.614</td>
</tr>
<tr>
<td>5</td>
<td>0.518</td>
<td>0.060</td>
<td>0.463</td>
<td>0.105</td>
</tr>
<tr>
<td>6</td>
<td>0.902</td>
<td>0.001</td>
<td>0.883</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Source: own estimations

The graphical illustration of the goodness of fit for the inflation models (AR(1) and UC) with the most significant coefficients of the output gaps (see Table 3 and 4) is given in Figure 9.

Figure 9. Actual and fitted values of inflation

Source: own estimations
In order to evaluate predictive performance of the models without and with the output gap we compared the models having significant coefficients at the output gap, presented in Table 3, with the benchmark model that comprises inflation with lag 1 and a constant. Then, the models from Table 4 were compared with the benchmark model and with the model that has the most significant coefficient at the output gap. To this end, the pseudo out-of-sample 1-step forecasts were estimated for the period 2009q1–2013q4 (20 quarters).

Since in the first case all the models are nested, the test for equal forecast accuracy proposed by Clark and McCracken (2001) is appropriate. This procedure generates pseudo out-of-sample forecasts, estimates forecast errors and tests for equality of mean square error (MSE) and encompassing for each pair of nested models, where the first model is a restricted version of the second model. To compare forecasts two statistics are used, MSE-t and MSE-F. The hypothesis is rejected if MSE-t and MSE-F exceed the appropriate critical values. In other words, we test the null hypothesis that the unrestricted model (with the output gap) forecast MSE is equal to the restricted model (without the output gap) forecast MSE against the one-sided upper tail alternative hypothesis that the unrestricted model forecast MSE is less than the restricted model forecast MSE.

Further statistics in Clark-McCracken test are ENC-t and ENC-F which relate to the concept of forecast encompassing. In this context, if the restricted model forecast (without the output gap) encompass the unrestricted model forecast (with the output gap), the output gap provides no useful additional information for prediction inflation. If forecast encompassing is rejected, then the output gap does contain information content useful for predicting dynamics of inflation. Performing Clark-McCracken tests for equal forecast accuracy the recursive scheme is applied, where forecasting models estimated with more data as forecasting moves forward in time. The results are presented in Table 5.

As follows from the results obtained, not all MSEs for the models with the output gap are less than MSE for the benchmark model of inflation, but some are even higher. Formal testing the differences between the mean square errors does not support in general the conclusion that models with the output gap are superior in out-of-sample forecasting than the simple benchmark AR (1) model; the evidence is rather mixed.

Table 5. Clark-McCracken tests for equal forecast accuracy (out-of-sample forecast for 2009q1–2013q4)

<table>
<thead>
<tr>
<th>Model</th>
<th>MSE</th>
<th>MSE-t</th>
<th>MSE-F</th>
<th>ENC-t</th>
<th>ENC-F</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1) with constant (benchmark) vs.:</td>
<td>0.00022</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>AR(1) with constant + output gap (HP5)</td>
<td>0.00021</td>
<td>0.122</td>
<td>0.555</td>
<td>1.198</td>
<td>3.176</td>
</tr>
<tr>
<td>AR(1) with constant + output gap (SVAR30)</td>
<td>0.00016</td>
<td>0.715</td>
<td>8.429</td>
<td>2.096</td>
<td>15.137</td>
</tr>
<tr>
<td>AR(1) with constant + output gap (UUC6)</td>
<td>0.00026</td>
<td>-0.565</td>
<td>-2.968</td>
<td>0.693</td>
<td>1.909</td>
</tr>
<tr>
<td>AR(1) with constant + output gap (MUC6)</td>
<td>0.00025</td>
<td>-0.476</td>
<td>-2.346</td>
<td>0.723</td>
<td>1.796</td>
</tr>
</tbody>
</table>

Critical values

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1%</td>
<td>1.659</td>
<td>2.631</td>
<td>2.004</td>
<td>1.948</td>
</tr>
<tr>
<td>5%</td>
<td>1.019</td>
<td>1.242</td>
<td>1.343</td>
<td>1.007</td>
</tr>
</tbody>
</table>

Note: HP5 is an output gap derived from HP-filter with lag 5; SVAR30 is an output gap derived from SVAR3 model with lag 0; UUC6 and MUC6 are the output gaps derived from the univariate and multivariate UC models respectively with lag 6.

Source: own estimations

To evaluate pseudo out-of-sample performance of the UC models presented in Table 4, in comparison with three benchmark models (the first one is AR (1) model with constant, the second one is the AR(1) with constant + output gap (HP5), and the third is AR(1) with constant + output gap (SVAR30)), we employed Diebold and Mariano test (1995) for equal forecast accuracy suited for non-nested models. Diebold-Mariano utilizes the actual time series of inflation and pairs of competing predictions, applying a loss criterion (MSE in our case) and calculating a measure of predictive accuracy that allow the null hypothesis of equal forecasts ac-
accuracy to be tested. The S (1) statistic tests the mean difference between the loss criteria for two predictions is zero, using a long-run estimate of the variance of the difference time series. If the null hypothesis is rejected, than pseudo out-of-sample forecast from competing model outperform the forecast from the benchmark model.

Table 6. Diebold-Mariano tests for equal forecast accuracy (out-of-sample forecast for 2009q1–2013q4)

<table>
<thead>
<tr>
<th>Diebold-Mariano test</th>
<th>UUC6</th>
<th>MUC6</th>
</tr>
</thead>
<tbody>
<tr>
<td>vs. AR(1)with constant</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE(tested)−MSE (benchmark)</td>
<td>0.00004</td>
<td>0.00005</td>
</tr>
<tr>
<td>S(1)</td>
<td>0.422</td>
<td>0.619</td>
</tr>
<tr>
<td>p-value</td>
<td>0.673</td>
<td>0.536</td>
</tr>
<tr>
<td>vs. AR(1)with constant + output gap (HP5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE(tested)−MSE (benchmark)</td>
<td>0.00003</td>
<td>0.00004</td>
</tr>
<tr>
<td>S(1)</td>
<td>0.409</td>
<td>0.746</td>
</tr>
<tr>
<td>p-value</td>
<td>0.683</td>
<td>0.456</td>
</tr>
<tr>
<td>vs. AR(1)with constant + output gap (SVAR30)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSE(tested)−MSE (benchmark)</td>
<td>−0.00005</td>
<td>−0.00004</td>
</tr>
<tr>
<td>S(1)</td>
<td>−0.548</td>
<td>−0.523</td>
</tr>
<tr>
<td>p-value</td>
<td>0.584</td>
<td>0.601</td>
</tr>
</tbody>
</table>

Note: maximum order of the lag using in calculating the long-run variance of the difference series from its autocovariance function calculated from the Schwert criterion as a function of the sample size. The uniform kernel is employed in calculations. UUC6 and MUC6 are the output gaps derived from the univariate and multivariate UC models respectively with lag 6.

Source: own estimations

The results of Diebold-Mariano tests for equal forecast accuracy are presented in Table 6. As one can see from the obtained results, our conclusions from the previous tests in Table 5 are even strengthened, as all results are insignificant.

6. Conclusions and policy implications

The existing linkage between real economy and inflation is traditionally of great importance for monetary authorities. In this context, the concept of the output gap plays a prominent role in conventional macroeconomic theory, applied research and monetary policy analysis. In this study, we used structural vector autoregression and unobserved component models to obtain new measures of the output gap in Moldova, and tried to relate them to inflation. The output gap, based on a HP-filter approach, is considered as a benchmark. The following conclusions can be drawn from our research:

1. The estimates of the output gaps using different methods demonstrate quite different results, and are sensitive to model specification. In particular the results obtained from the SVAR model show a relatively low correlation with the other methods. This method stands out due to its different methodology, while the other methods are based on similar foundations.

2. All output gaps, apart from the SVAR model, are positive at the end of the sample. While the SVAR model exhibits a negative output gap, there is a clear tendency towards a closure of this gap.

3. There is in general a rather weak relationship between different measures of the output gap and inflation in the sample. We are able to confirm such links, but the effect is more delayed, and usually only present at very long lags (the exception is the SVAR model, where the effect is immediate).

4. While a rather weak link between the output gap, i.e. the business cycle and inflation is not inconsistent with mixed international evidence [ECB, 2011], further analysis should be devoted to the underlying reasons, in particular for the big time lag, which remains a puzzle. These reasons could be econometric pitfalls (e.g. omitted dynamics and possible nonlinearities), but it could also be the case that the simple models presented above do not fully captured the complex relationship between the variables.
References


Annex. Data and testing for seasonal unit root test and multiple structural breaks

Table A1. HEGY seasonal unit root test

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model specification</th>
<th>Deterministic terms</th>
<th>Number of lags</th>
<th>$H_0$</th>
<th>Test</th>
<th>Test statistics</th>
<th>Critical values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_t \text{rgdp}$</td>
<td>Constant, 1</td>
<td>$H_0 : \pi_1 = 0$</td>
<td>$t_{x_1}$</td>
<td>-1.42</td>
<td>-3.41</td>
<td>-2.84</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Trend, 1</td>
<td>$H_0 : \pi_2 = 0$</td>
<td>$t_{x_2}$</td>
<td>-4.81</td>
<td>-3.41</td>
<td>-2.83</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Seasonals</td>
<td>$H_0 : \pi_3 = \pi_4 = 0$</td>
<td>$F_{34}$</td>
<td>27.22</td>
<td>8.79</td>
<td>6.57</td>
<td></td>
</tr>
<tr>
<td>$cpi$</td>
<td>Constant, 0</td>
<td>$H_0 : \pi_1 = 0$</td>
<td>$t_{x_1}$</td>
<td>-1.59</td>
<td>-3.96</td>
<td>-3.39</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Trend, 1</td>
<td>$H_0 : \pi_2 = 0$</td>
<td>$t_{x_2}$</td>
<td>-4.94</td>
<td>-3.41</td>
<td>-2.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Seasonals</td>
<td>$H_0 : \pi_3 = \pi_4 = 0$</td>
<td>$F_{34}$</td>
<td>29.31</td>
<td>8.79</td>
<td>6.55</td>
<td></td>
</tr>
</tbody>
</table>

Note: The following regression is used to conduct the HEGY seasonal unit root test:

$$\Delta_4 y_t = \pi_1 z_{4,t-4} + \pi_2 z_{2,t-1} + \pi_3 z_{3,t-2} + \pi_4 z_{4,t-1} + \sum_{j=1}^{p-4} \alpha_j \Delta_4 y_{t-j} + \delta_t,$$

where $\Delta_4 y_t = (1 - L^4) y_t - y_{t-4}$; $z_{4,t} = (1 + L + L^2 + L^3) y_t$; $z_{2,t} = (-1 + L + L^2 + L^3) y_t$; $z_{3,t} = (-1 - L^2) y_t$; with $L$ being the lag operator; $\delta_t$ are residuals. The deterministic terms such as constant, trend and seasonal dummies can be added to the regression. The number of lagged seasonal differences is chosen to eliminate residual autocorrelation. The null hypothesis $H_0 : \pi_1 = 0$, $H_0 : \pi_2 = 0$ and $H_0 : \pi_3 = \pi_4 = 0$ corresponds to test for regular, semiannual and annual unit root, respectively. The regression is estimated by OLS and the hypotheses are tested using corresponding t-test for
the first two hypotheses \((t_{i1}, t_{i2})\) and \(F\)-test for the third one \((F_{i3})\). The critical values are taken from Franses, Hobijn (1997). Rejections of the null hypotheses are marked in gray.

*Source: own estimations*

**Table A2. Bai-Perron multiple breakpoint test for inflation**

Multiple breakpoint tests

Compare information criteria for 0 to M globally determined breaks

Sample: 1995Q2 2013Q4

Included observations: 75

Breakpoint variables: C

Break test options: Trimming 0.05, Max. breaks 5

Allow heterogeneous error distributions across breaks

Schwarz criterion selected breaks: 5
LWZ criterion selected breaks: 3

<table>
<thead>
<tr>
<th>Breaks</th>
<th># of Coefs.</th>
<th>Sum of Sq. Resids.</th>
<th>Log-L</th>
<th>Schwarz* Criterion</th>
<th>LWZ* Criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0.054249</td>
<td>164.7670</td>
<td>-7.174098</td>
<td>-7.132222</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>0.038267</td>
<td>177.8539</td>
<td>-7.407948</td>
<td>-7.281768</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>0.027677</td>
<td>190.0040</td>
<td>-7.616817</td>
<td>-7.405561</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>0.022141</td>
<td>198.3734</td>
<td>-7.724869</td>
<td>-7.427720</td>
</tr>
<tr>
<td>4</td>
<td>9</td>
<td>0.019504</td>
<td>203.1273</td>
<td>-7.736507</td>
<td>-7.352599</td>
</tr>
<tr>
<td>5</td>
<td>11</td>
<td>0.016982</td>
<td>208.3209</td>
<td>-7.759870</td>
<td>-7.288286</td>
</tr>
</tbody>
</table>

* Minimum information criterion values displayed with shading

Estimated break dates:

1: 2000Q4
2: 1998Q4, 2000Q4
3: 1996Q4, 1998Q4, 2000Q4

*Source: own estimations using Eviews 8 econometric software*
Table A3. Bai-Perron multiple breakpoint test real GDP growth

Multiple breakpoint tests
Compare information criteria for 0 to M globally determined breaks
Sample: 1995Q1 2013Q4
Included observations: 76
Breakpoint variables: C @TREND
Break test options: Trimming 0.15, Max. breaks 5
Allow heterogeneous error distributions across breaks

Schwarz criterion selected breaks: 3
LWZ criterion selected breaks: 2

<table>
<thead>
<tr>
<th>Breaks</th>
<th># of Coefs.</th>
<th>Sum of Sq. Resids.</th>
<th>Log-L</th>
<th>Schwarz* Criterion</th>
<th>LWZ* Criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>2</td>
<td>0.444664</td>
<td>87.52511</td>
<td>-5.027203</td>
<td>-4.943631</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>0.101375</td>
<td>143.7078</td>
<td>-6.334745</td>
<td>-6.124432</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
<td>0.028429</td>
<td>192.0219</td>
<td>-7.435219</td>
<td>-7.096378</td>
</tr>
<tr>
<td>3</td>
<td>11</td>
<td>0.021505</td>
<td>202.6289</td>
<td>-7.543401</td>
<td>-7.074084</td>
</tr>
<tr>
<td>4</td>
<td>14</td>
<td>0.020734</td>
<td>204.0152</td>
<td>-7.408930</td>
<td>-6.807006</td>
</tr>
<tr>
<td>5</td>
<td>17</td>
<td>0.022698</td>
<td>200.5761</td>
<td>-7.147478</td>
<td>-6.410601</td>
</tr>
</tbody>
</table>

* Minimum information criterion values displayed with shading

Estimated break dates:
1: 2001Q3
2: 1999Q4, 2009Q1
3: 1999Q4, 2004Q4, 2009Q1
4: 1998Q2, 2001Q1, 2004Q4, 2009Q1
5: 1998Q1, 2000Q4, 2003Q3, 2006Q2, 2009Q1

Source: own estimations using Eviews 8 econometric software

Figure A1. Data used (log scale, seasonally unadjusted)

Source: own estimations based on National Bureau of Statistics of the Republic of Moldova data
List of recent Policy Papers

- Overcoming Barriers to Investment, by Ulrike Bechmann and Jörg Radeke, Policy Paper PP/05/2014
- Measures to reduce informal employment in Moldova, by Ulrike Bechmann and Jörg Radeke, Policy Paper PP/04/2014
- Remittances from Russia: Macroeconomic implications of possible negative shocks, by David Saha and Ricardo Giucci, Policy Paper PP/03/2014
- A Blue Print for an Information Technology Park in Moldova, by Jörg Radeke, Policy Paper PP/02/2014
- Proposal for Reforming the Pension System, by Ulrike Bechmann and Adrian Lupusor, Policy Paper PP/01/2014
- Realising the Potential of Moldova’s Information Technology Sector, by Jörg Radeke, Policy Paper PP/04/2013
- Moldova’s trade policy: Strategy, DCFTA and Customs Union, by Jörg Radeke, Ricardo Giucci and Adrian Lupusor, Policy Paper PP/03/2013
- Liberal Professions in Moldova – Neglected Economic Potential, by Alexander Knuth and Marcel Chistruga, Policy Paper PP/02/2013
- Current Account Sustainability in Moldova: Policy Implications, by Ricardo Giucci and Robert Kirchner, Policy Paper PP/01/2013

List of recent Policy Briefings

- Benefits in kind: Best international practice and lessons for Moldova, by Jörg Radeke, Veronica Vragaleva and Daniela Heitele, Policy Briefing PB/12/2014
- The cost of Russian trade sanctions, by Jörg Radeke, Policy Briefing PB/11/2014
- Moldova’s exports to Russia: Sectorial exposure, by Jörg Radeke and Woldemar Walter, Policy Briefing PB/10/2014
- Measures to reduce informal employment in Moldova: Summary of results, by Ulrike Bechmann and Jörg Radeke, Policy Briefing PB/09/2014
- Moldova’s fruit exports: Measures to reduce the impact of a potential Russian import ban, by Jörg Radeke and Ricardo Giucci, Policy Briefing PB/08/2014
- Moldova between East and West: Perspectives for free trade with both sides, by Ricardo Giucci, Policy Briefing PB/07/2014
- Macroeconomic effects of possible shocks to remittances from Russia to Moldova: Summary of Results, by David Saha and Ricardo Giucci, Policy Briefing PB/06/2014
- Moldova’s fruit exports: Can the EU substitute the Russian market?, by Jörg Radeke, Policy Briefing PB/05/2014
- A Blue Print for an Information Technology Park in Moldova, by Jörg Radeke and Philip Steden, Policy Briefing PB/04/2014

All papers and briefings can be downloaded free of charge under [http://www.get-moldau.de/wordpress/de/publikationen/](http://www.get-moldau.de/wordpress/de/publikationen/). For more information please contact the German Economic Team Moldova on info@get-moldau.de.