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UNEMPLOYMENT OR CREDIT: WHO HOLDS THE POTENTIAL? RESULTS FROM A SMALL-OPEN ECONOMY

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Abstract

This paper investigates the importance of unemployment and credit in determining the potential level of real activity for a small-open economy with a low degree of financialization. We estimate a multivariate unobserved component model (MUC) to derive the potential output and its associated output gap for the Lithuanian economy. The model is estimated via Bayesian methods and the time-paths of unobserved variables are extracted via the Kalman filter. We find that the inclusion of unemployment into the MUC model substantially improves the estimates of output gap in real-time. Once information about unemployment is accounted for, adding information about credit does not substantially alter either the estimates of output gap or its performance in real time. We uncover a strong negative correlation between the model-implied unemployment gap (without credit) and real credit growth. This explains the relatively muted impact of the financial variable on the level and dynamics of the output gap. Data revisions appear not to be the primary source of revisions on output gaps estimates.

JEL codes: C11, C32, E24, E32.

Keywords: Potential Output, Output Gap, Multivariate Unobserved Component, Kalman Filter, NAIRU, Real-Financial Cycle, Small-Open Economy

1 Introduction

Potential output and its associated output gap, which is the difference between actual and potential output, are important notions for policy analysis. The former is generally defined as "the maximum production without inflationary pressure- or more precisely- the point of balance between more output and greater stability" (Okun, 1970, pp.132-33). From this view, when output gap is positive, i.e. actual output is greater than potential output, there is an upward pressure on inflation; similarly, disinflation requires actual output to fall below potential output. This relationship therefore provides implications for the conduct of stabilizing policies. Output gap is also of central importance to fiscal policy surveillance because it is an essential ingredient in the calculation of the cyclical component of the budget (see, e.g., Angerer (2014) on the EU Stability and Growth Pact). Recently, the output gap has started playing an increasing role in the operation of macro-prudential policy, e.g. countercyclical capital requirement policy (Suh, 2012; de Resende et al., 2016).

Despite the policy relevance of this concept, the main challenge in its application is the inability to directly observe potential output. Consequently, policy makers need to rely on imperfect measures of its level and dynamics. Several approaches have been proposed for measuring potential output and output gap. The first and more prevalent method is to use Hodrick-Prescott (HP) filter. The appeal of this approach lies at its simplicity and transparency, requiring only GDP data. However, its main drawback is the lack of economic structure, particularly links to inflation and the unemployment rate. These important theoretical concepts underpinning the definition of potential output allow users to check the validity of the derived measure against labor market and inflation dynamics. In addition, the HP filter is notorious for its unusual behavior of cyclical components near the end of the sample (see, e.g., Baxter and King, 1999).

Another widely used method is to rely on a production function approach, therefore approaching the estimation of output from the supply side of the economy. Two main features of this approach are: specifying a functional form of the production function in the first step and then substituting inputs by their corresponding full-employment values (see, e.g, Havik et al., 2014; Fernald, 2014). The advantage of this method is to take the direct link to economic theory into account. Nevertheless, there are two main disadvantages. First, reliable capital-stock data can be hard to obtain. Second, constructing the cyclically adjusted measures of inputs, i.e. total factor production (TFP) and employment components, is an onerous task. In practice, they are often constructed based on *ad-hoc* trend-cycle decompositions, such as HP filter, which are therefore subject to the weaknesses mentioned previously.

The third approach for estimating potential output, which is used in this study, is a semi-structural time series framework and represents a shortcut relative to a more complex supply-side analysis. This method is also known as a multivariate unobserved component (MUC) model which is first proposed by Kuttner (1994) and has been developed and applied in recent studies including Beneš et al. (2010), Blagrave et al. (2015), Alichi (2015) and Melolinna and Tóth (2016) among others. In our baseline, we model potential output of the Lithuanian economy as a latent variable, linking deviations from the trend to inflation and unemployment through a simple Phillips curve and a simple Okun's law relationship, respectively. That is, we use the **joint behavior** of output, inflation and unemployment to derive an estimate of potential output. One strength of this approach is that we can also "back out" an estimate of natural rate of unemployment which is an important concept for policy analysis. Recent papers including Sinclair (2009) and Kamber et al. (forthcoming) show that there is a high correlation between unemployment gap and output gap. Another advantage of our MUC model is that it is sufficiently flexible to adjust rapidly to local variations in the trend (Kuttner, 1994). In addition, it should be easy to implement and can be modified to include more variables when data becomes available. In addition to estimating the output gap, we also study the real-time performance of the MUC model. Our baseline results show that the estimated potential output and output gap capture Lithuanian macroeconomic dynamics reasonably well. More importantly, we show that the inclusion of unemployment does help to improve the performance of MUC models' gap estimates in real-time. Moreover, we affirm the point made by Orphanides and van Norden (2002) that data revisions appear not to be the primary source of revisions on output gaps estimates.

One notable contribution of our paper is to investigate the contribution of financial variables in determining potential output. Borio et al. (2016, 2014) and Melolinna and Tóth (2016) and among others, indicate that the inclusion of financial variables in the estimation of potential output leads to less end-of-sample bias and different qualitative dynamic features of the real cycle. Turning points of the business cycle are influenced by the inclusion of financial information in the estimation exercise, something on notable interest to policy-makers. Unlike most of the applications mentioned above that use data for developed economies with a high degree of financialization, we focus on a small-open economy with relatively low indebtedness level. As compared to the UK or the US, Lithuania has a relatively low level of both government and average household debt.[1] In contrast with the results for high-debt economies, we find that the financial variable (in our case, total real credit) has a relatively small contribution to the estimation of output gap. Although the model with credit produces higher output gap in the pre-crisis, in line with previous studies, the effect is muted. Also, including credit does not change the overall message as far as turning points are concerned. For the recent period (see Figure 10) almost no difference can be noted between the model including and the one excluding real credit. We conjecture that the unemployment rate is carrying most of the information necessary in establishing the level of real activity.

The remainder of the paper proceeds as follows. Section 2 discusses the model used for analysis. Section 3 presents estimation methodology, prior and posterior distributions of parameters. Section 4 analyses the results. Section 5 concludes.

2 The Multivariate Unobserved Component Model

2.1 The Baseline

The multivariate unobserved component model (MUC) considered in this paper includes three observable variables: (log) real GDP (y_t), core inflation (π_t), and the unemployment rate (u_t). The aim is to decompose these variables into a trend and cyclical component simultaneously based on their well-established correspondences in the literature.

Let $\bar{y}_t$ denote the unobserved trend component of log real GDP and $\hat{y}_t$ its cycle (or output gap), so the decomposition of y_t is written as follows:

$$y_t = \bar{y}_t + \hat{y}_t \tag{1}$$

The model structure for GDP comprises three equations and is subject to three shocks as follows:

$$\bar{y}_t = \bar{y}_{t-1} + g_{t-1} + \varepsilon_t^{\bar{y}} \tag{2}$$

[1] Public debt stands at roughly 45% of GDP

$$g_t = g_{t-1} + \varepsilon_t^g \tag{3}$$

$$\hat{y}_t = \rho_1 \hat{y}_{t-1} + \varepsilon_t^{\hat{y}} \tag{4}$$

where $\varepsilon' s$ are normally distributed independent white noise processes with zero means. To model the trend, we follow Harvey and Todd (1983), Harvey (1985) and Harvey et al. (2007) in which the level $\bar{y}_t$ and slope g_t, i.e. potential growth, both change slowly overtime according to a random walk mechanism. These features imply a local approximation to a linear trend, or are often referred to as a 'smooth linear trend'. The time-varying potential growth is desirable for our study in order to capture a wide-range of structural reforms implemented in Lithuania since the mid-1990s. Meanwhile, the output gap in (4) is assumed to follow an autoregressive process with coefficient ρ_1 similar to Melolinna and Tóth (2016). The white-noise $\varepsilon_t^{\bar{y}}$, ε_t^g, and $\varepsilon_t^{\hat{y}}$ represent shocks to the level of potential output, the growth rate of potential and output gap. The first two shocks cause a permanent change in output, whereas the latter only causes a temporary deviation of output from potential. This may be understood a temporary demand shock.

We incorporate the labour market structure to provide further identifying information for the estimation of potential output. Potential output is defined as the full-employment level of output, the recognition of this definitional relationship is one of the strengths of the adopted methodology. In this structure, unemployment rate is modelled as a sum of trend (or natural rate of unemployment) and cyclical component:

$$u_t = \bar{u}_t + \hat{u}_t, \tag{5}$$

where the trend and cyclical component is given by,

$$\bar{u}_t = \bar{u}_{t-1} + \varepsilon_t^{\bar{u}}, \tag{6}$$

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} - \gamma_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{u}}. \tag{7}$$

As shown in (6), the natural rate of unemployment $\bar{u}_t$ is allowed to be time-varying to capture possible changes in the labour market over time as in Laubach (2001). The unemployment gap $\hat{u}_t$ is modeled based on an Okun's law relationship. A similar specification is applied in Ebeke and Everaert (2014). With this framework, we are able to derive a measure of natural rate of unemployment which helps to assess if the labour market is in equilibrium as well as the size of imbalances if any present.

A system of motion equations describing the evolution of inflation is also incorporated in the model, in line with Kuttner (1994) and Melolinna and Tóth (2016):

$$\pi_t = \bar{\pi}_t + \hat{\pi}_t, \tag{8}$$

$$\bar{\pi}_t = \bar{\pi}_{t-1} + \varepsilon_t^{\bar{\pi}}, \tag{9}$$

$$\hat{\pi}_t = \alpha_1 \hat{\pi}_{t-1} + \alpha_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{\pi}}. \tag{10}$$

Similar to Stock and Watson (2016), inflation is decomposed into trend inflation, $\bar{\pi}_t$, and deviations from the trend, $\hat{\pi}_t$ as shown in (8). The trend inflation in (9) is allowed to be time-varying to capture possible changes in the stead-state values of inflation over time and subject to a trend shock $\varepsilon_t^{\bar{\pi}}$. The cyclical inflation component is linked to the evolution of the output gap based on a Phillips curve with coefficients α_1 and α_2. Therefore, the potential output series extracted from this specification is consistent with a steady-state-inflation measure. As noted in Kuttner (1994), such "accelerationist" specifications are in line with expectations-augmented Phillips curve models in which expected inflation is set equal to the lagged inflation rate. Although there is no guarantee that this ad-hoc treatment of expectations represents a genuine output-inflation trade-off, the strength of this specification lies in its straightforward connection to the structural processes of output and unemployment.

2.2 Model with Credit

As mentioned above, recent studies including Borio et al. (2016, 2014) suggest that financial variables can help improve real-time estimates of output gap (the studies analyze the UK, US and Spain). This suggestion seems natural as credit-to-GDP ratios in these countries over the 1999-2016 period are 150 percent, 163 percent, and 173 percent respectively. One of the possible channels through which debt affects the real side of the economy at high leverage ratio is the pressure on the debt service coverage ratio. Increasing cost of debt can have outsized effects on highly leveraged firms and households. When servicing debt becomes cumbersome, firms curtail investment and employment, households diminish consumption. We explore the role of financial factors for the estimation of output gap in Lithuania by focusing on the evolution of total credit. To do so, we follow a relatively parsimonious approach suggested by Melolinna and Tóth (2016) which embed financial information in the spirit of Borio et al. (2016, 2014) into a multivariate unobserved component framework. Specifically, the financial variable is assumed to affect the output gap with a lag and, therefore, the dynamics of output gap in Equation 4 is adjusted as follows:

$$\hat{y}_t = \rho_1 \hat{y}_{t-1} + \delta \bar{f}_{t-1} + \varepsilon_t^{\hat{y}}. \tag{11}$$

This variable follows an AR(1) process and is observed with errors:

$$\bar{f}_t = \beta \bar{f}_{t-1} + \varepsilon_t^{\bar{f}}, \tag{12}$$

$$f_t = \bar{f}_{t-1} + \varepsilon_t^{f}. \tag{13}$$

where f_t is the observed financial indicator, i.e. the growth of real credit which is standard in the literature on the effects of financial factor on real economy, and $\bar{f}_t$ is the unobserved part that effects the output gap. Combine (11), (12), and (13) with other dynamics described in Section 2, we obtain a new MUC framework including the financial sector. It is important to note that by construction, the financial sector does not affect the fundamental level of potential output but is assumed to act only through the transitory gap component. In this study, we use the growth of real credit as a financial indicator. This choice is standard in the literature on the effects of the financial sector on the real economy.

3 Estimation

The baseline model is estimated with real GDP, inflation and unemployment rate over the sample period from 1998:Q1 to 2016:Q3 given the availability of data.[2] First, we write the 10 equations (1)-(10) in a state space form and then apply the Bayesian approach for analysis. Extending the baseline model's state space specification to include the growth of credit is straightforward.

3.1 State-space Form

The state-space form of the model includes three observable variables $Y_t = [y_t,\ u_t,\ \pi_t]'$, seven state variables $X_t = [\hat{y}_t,\ \bar{y}_t,\ g_t,\ \hat{\pi}_t,\ \bar{\pi}_t,\ \hat{u}_t,\ \bar{u}_t]'$, and seven state innovations $W_t = [\varepsilon_t^{\hat{y}}, \varepsilon_t^{\bar{y}}, \varepsilon_t^{g}, \varepsilon_t^{\hat{\pi}}, \varepsilon_t^{\bar{\pi}}, \varepsilon_t^{\hat{u}}, \varepsilon_t^{\bar{u}}]'$ as follows:

[2] All these data are collected from Eurostat Database.

$$
\begin{aligned}
Y_t &= HX_t + MV_t \qquad V_t \sim iidN(0,R) &(14)\\
X_t &= FX_{t-1} + NW_t \qquad W_t \sim iidN(0,Q), &(15)
\end{aligned}
$$

where

$$H = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}, \tag{16}$$

$$F = \begin{bmatrix} \rho_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ \alpha_2 & 0 & 0 & \alpha_1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ -\gamma_2 & 0 & 0 & 0 & 0 & \gamma_1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}, \tag{17}$$

$$Q = \begin{bmatrix} \sigma^2_{\varepsilon_{\hat{y}}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{\varepsilon_{\bar{y}}} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{\varepsilon_g} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{\varepsilon_{\hat{\pi}}} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon_{\bar{\pi}}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon_{\hat{u}}} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{\varepsilon_{\bar{u}}} \end{bmatrix}. \tag{18}$$

In addition, R is a 3×3 zero matrix because there is no measurement error, M is a 3×3 identity matrix, and N is a 7×7 identity matrix. The parameters are collected in the vector $\theta = [\rho_1, \alpha_2, \alpha_1, \gamma_2, \gamma_1, diag(Q)']'$. Given the fact that the sample size is relatively short, we use Bayesian estimation techniques for our analysis, which thus help to downweigh regions of the parameter space that are at odds with observations not contained in the estimation sample. To do so, we first estimate the mode of the posterior distribution by maximizing the log posterior function, which combines the prior information on the parameters with the likelihood of the data evaluated by Kalman filter. In the second step, we sample from the posterior with a Markov Chain Monte Carlo to obtain the posterior distribution.

3.2 Prior Distribution

The prior distributions are similar to those used in Melolinna and Tóth (2016) reflecting prior beliefs about the behavior of parameters. First, the cyclical components are assumed to be fairly persistent, so the AR(1) parameters, ρ_1, α_1, and γ_1, are Beta distributed, whose domain is between 0 and 1, with mean 0.70 and standard deviation 0.20. Second, output gap is assumed to be an important source of the deviations of inflation and unemployment from their respective trends, in line with the well-established economic relationships in the literature captured by Phillips curve and Okun's law. Therefore, output-gap-related parameters, α_2 and γ_2, should be positive and are described by Gamma distribution, whose domain is $\mathbb{R}^+$, with mean 0.50 and standard deviation 0.30. In addition, the key drivers of fluctuations in observable variables are cyclical rather than trend shocks, so the variance of innovations are assumed to follow an inverse-gamma-2 distribution with mean of 1.00 and 0.01 for cyclical and trend components, respectively, and with infinite standard deviation. Table 1 summarizes the prior distribution of the parameters.

Table 1 – Prior and Posterior Distribution

		Prior distribution			**Posterior Distribution**		
	Domain.	Distr.	Mean	St. Dev.	Mean	$[2.5\%, 97.5\%]$	PSRF
ρ_1	(0,1)	Beta	0.70	0.20	0.9038	[0.7001, 0.9945]	1.007
α_1	(0,1)	Beta	0.70	0.20	0.8594	[0.4677, 0.9933]	1.010
α_2	$\mathbb{R}^+$	Gamma	0.50	0.30	0.1439	[0.0299, 0.3400]	1.002
γ_1	(0,1)	Beta	0.70	0.20	0.8696	[0.5590, 0.9936]	1.002
γ_2	$\mathbb{R}^+$	Gamma	0.50	0.30	0.1415	[0.0296, 0.3350]	1.002
$\sigma^2_{\varepsilon_{\hat{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	∞	0.0311	[0.0225, 0.0426]	1.000
$\sigma^2_{\varepsilon_{\bar{y}}}$	$\mathbb{R}^+$	Inv.Gam.2	0.01	∞	0.0026	[0.0012, 0.0054]	1.002
$\sigma^2_{\varepsilon_g}$	$\mathbb{R}^+$	Inv.Gam.2	0.01	∞	0.0018	[0.0009, 0.0034]	1.001
$\sigma^2_{\varepsilon_{\hat{\pi}}}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	∞	0.0297	[0.0213, 0.0414]	1.001
$\sigma^2_{\varepsilon_{\bar{\pi}}}$	$\mathbb{R}^+$	Inv.Gam.2	0.01	∞	0.0024	[0.0011, 0.0047]	1.000
$\sigma^2_{\varepsilon_{\hat{u}}}$	$\mathbb{R}^+$	Inv.Gam.2	1.00	∞	0.0295	[0.0214, 0.0405]	1.000
$\sigma^2_{\varepsilon_{\bar{u}}}$	$\mathbb{R}^+$	Inv.Gam.2	0.01	∞	0.0024	[0.0011, 0.0047]	1.000

Note: The posterior distribution is obtained using the Metropolis-Hastings algorithm. PSRF- Potential Scale Reduction Factor.

3.3 Posterior Distribution

To generate draws from the posterior distribution of θ, we apply the Random Walk Metropolis Hastings Algorithm.[3] This algorithm requires the evaluation of the posterior density, i.e. the product of likelihood function and prior density. Because the prior is relied on well-known densities, the computation of prior density is straightforward. To evaluate the likelihood

[3] See Chib and Greenberg (1995) for a detailed exposition of the algorithm.

function of the state-space model, we rely on the Kalman filter as documented in Hamilton (1994).

The posterior mode is obtained by using a quasi-Newton method with BFGS update.[4] From the posterior mode, we generate 200,000 draws and discard the first half as burn-in period.[5] The acceptance rate of our draws is 32% which is in the range $20-40\%$ as suggested by, for instance, Gelman et al. (1996) and Gelman et al. (2014, ch.11, p.314) among others.[6] In order to check if the chains have converged to the target distribution, we create another sequence of draws and evaluate the potential scale reduction factor ($PSRF$) proposed by Gelman and Rubin (1992). As $PSRF$ is close to 1 - and smaller than 1.2- for all the estimates, the approximate convergence has been reached and the draws are close to the target distribution. As shown in the last column of Table 1, $PSFR$ are nearly one for all the parameters; we, therefore, can make inferences about posterior means and variances.

The mean and the 95% confidence interval of the posterior distribution of the parameters are shown in Columns 6-8 of Table 1. Overall, the data appear to be very informative. The cyclical components are estimated to be persistent, around 0.90, and much higher than the prior values. The response of inflation gap to output gap, α_2, is 0.14 indicating that for 1% deviation of output from the potential output, inflation deviates from its trend by 0.14%. This value is in the range $0.05 - 0.30$ obtained by Blagrave et al. (2015) for a group of countries. For the effect of output gap on unemployment gap γ_2, we obtain an estimate of 0.14, close to the lower range $0.1 - 0.4$ documented in Blagrave et al. (2015).[7] Regarding the variance of innovations, we find higher values for cyclical than trend components (0.03 vs. 0.002), implying a larger role for transitory disturbances than permanent ones. Such a result is somewhat expected given our prior specifications, but the differences between prior and posterior means indicate that estimates are substantially affected by the information provided by data.

[4]For the optimization with quasi-Newton method, we use the popular Matlab-based "csminwel" codes which can be downloaded from Chris Sims's Page at http://sims.princeton.edu/yftp/optimize/.

[5]The Hessian resulting from the optimization procedure was used for defining the transition probability function that generates the new proposed draw.

[6]High acceptance ratio implies that the jumps are so short that the simulations moves very slowly through the target distribution; whereas low acceptance rate implies that the jumps are nearly all into low-probability areas of the target density, causing the Markov chain to stand still most of the time (Gelman et al., 1996).

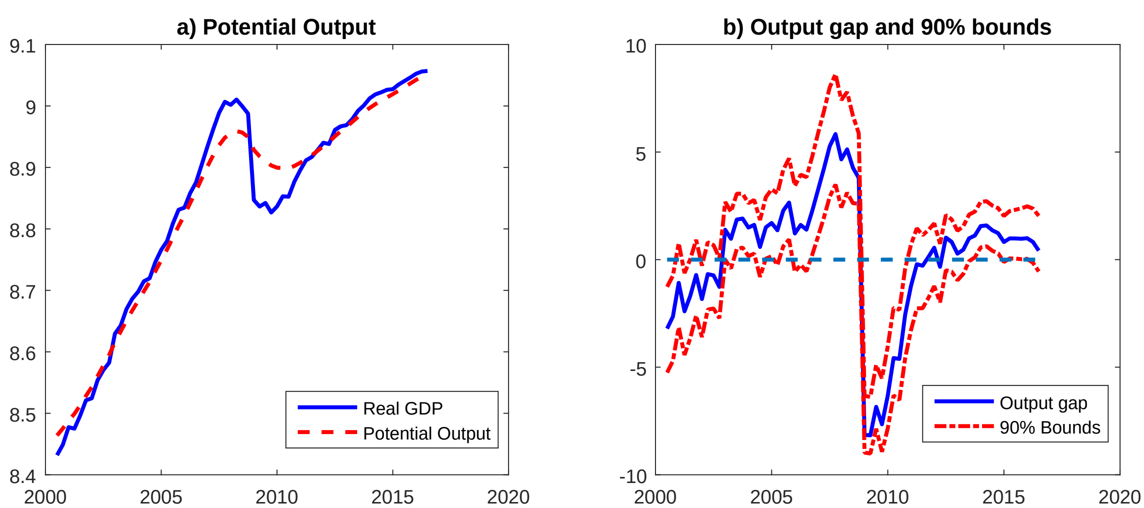
[7]Note that γ_2 is not the same with the Okun parameter usually defined in the literature as: $\hat{u}_t = \beta \hat{y}_t + \varepsilon_t$. Using the measures of output gap and unemployment gap, we obtain an estimate of $\beta = -0.6$, which is similar to the one obtained by Ebeke and Everaert (2014) for Lithuania.

4 Analysis

4.1 Potential Output Estimation

Figure 1 displays the Kalman smoothed series of (log of) potential output $\bar{y}_t$ and its associated output gap $\hat{y}_t$.[8] Actual output was continuously above potential output from 2003:Q1 to the occurrence of financial crisis in 2008, with output gap reaching the peak of 6 percent in 2007:Q4. During the crisis, both actual and potential output decrease and output gap plummeted by nearly 12 percentage points from 4 percent in 2008:Q4 to -8 percent in 2009:Q1. The gap was closed gradually in three years, became positive in the early 2012, and has remained above zero (around 1 percent) since then. To capture the uncertainty of output gap estimate, we calculate its 90 percent confidence intervals based on each parameter draw (after burn-in period). As it can be seen, the bounds also detect the pre-crisis expansion, with output gap being between 2 and 8 percent, and the post-crisis recession with output gap between -6 and -9 percent. In recent periods, the lower and upper bounds of output gap are 0 and 2 percent, respectively.

Figure 1 – Potential Output and Output Gap



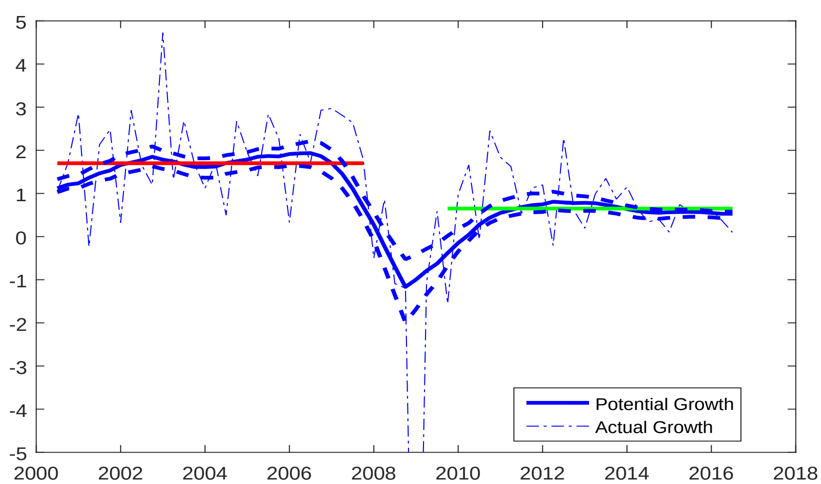
Notes: The graph shows the smoothed sequences of (log of) potential output in the left panel and its associated output gap with 90% bounds in the right panel.

Another important feature of potential output is its growth g_t, whose fluctuations reflect

[8] We use the Rauch–Tung–Striebel algorithm to obtain the smoothed state variables.

supply conditions, such as changes in the production inputs of capital, labor, and their productivity, as well as variations in investment and the degree of unemployment persistence. We find that potential growth was about 1.7 percent (per quarter) in the pre-crisis period and fell temporarily to -1 percent in the early 2009 when the actual output dropped by 15 percent. The potential growth recovered gradually and has remained around 0.6 percent (equivalent to 2.4 percent per year) since 2010. Therefore, the potential growth in the post-crisis is about 1.1 percentage points per quarter (or 4.4 percentage points per annual) lower than the pre-crisis level, suggesting the long-run impact of the crisis on potential output. A similar finding is obtained by Podpiera et al. (2017) for Lithuania. This result is also consistent with IMF (2015) which finds that the financial crisis has lowered potential growth in both advanced and emerging market economies. In addition, according to IMF (2015), the ageing population is another potential factor contributing to the decline of potential output growth.

Figure 2 – Potential Growth

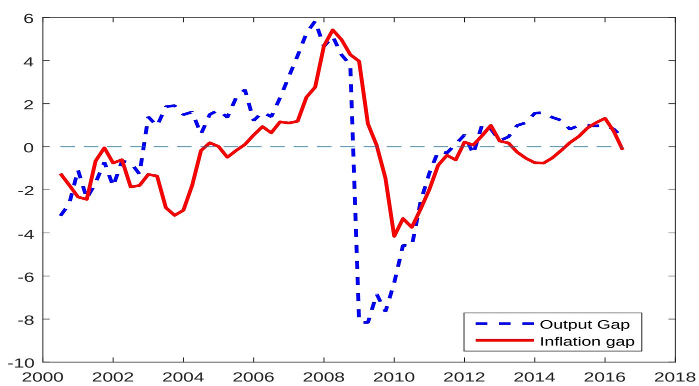


Notes: The graph shows the potential growth (%) and its 90 percent bounds together with the actual output growth (%). The red and green lines illustrate the average of potential growth in the pre- and post-crisis, respectively.

4.2 Output Gap, Inflation Gap, and Unemployment Gap

Figure 3 displays the links between output gap and inflation gap. These two measures are found to be positively correlated and output gap appears to lead inflation gap.[9] In the expansionary period before 2008, actual output was significantly above the level of potential output, which likely contributed to the inflationary pressures and caused a positive deviation of inflation rate from its trend. On the other hand, during the recent economic downturn, the substantially negative output gap probably led to lower inflationary pressures and then a negative deviation of inflation rate from its trend. However, other factors may be at work too. For instance, in 2014, while output gap was positive, inflation gap was found to be negative which can be partly explained by the fall of oil price.

Figure 3 – Inflation Gap



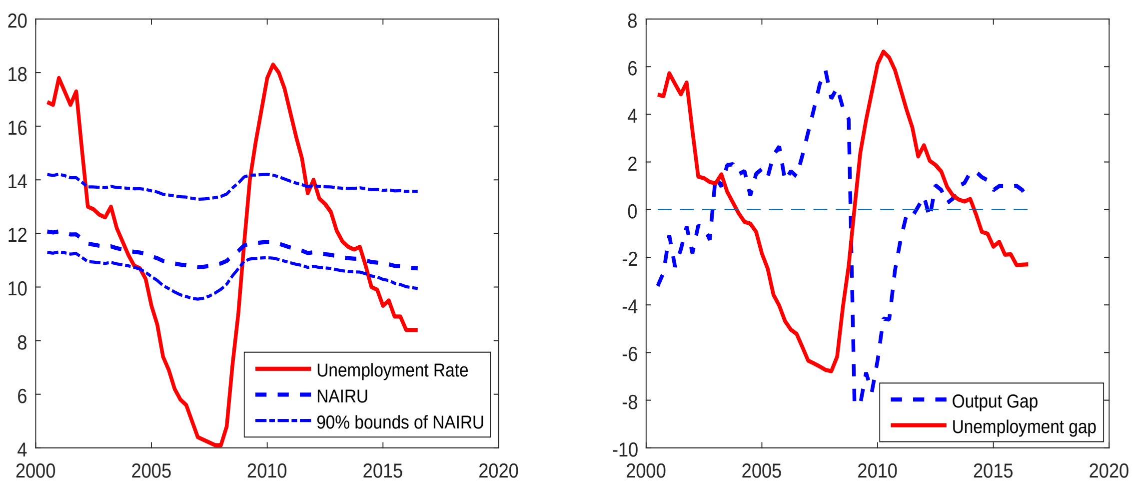
Notes: The graph shows the smoothed sequences of output gap (%) and inflation gap (%).

It may be also interesting to investigate the link between output gap and unemployment gap. These concepts are closely related to each other: deviations of the unemployment rate from its inflation-neutral rate mean that the economy is not running at an efficient rate-either over-working or under-working, therefore suggesting a deviation of output from its potential level. Figure 4 shows the measure of NAIRU on the left panel which has been falling gradually from about 12 percent in the early 2000 to 10.7 percent in 2016, interrupted by a temporary increase during 2009-2010 when actual unemployment rate increased considerably

[9] $Corr(\hat{y}_{t-1}, \pi_t) = 0.63$ ($p \approx 0.00$), $Corr(\hat{y}_t, \pi_t) = 0.45$ ($p \approx 0.00$) and $Corr(\hat{y}_{t+1}, \pi_t) = 0.23$ ($p = 0.06$).

to about 18% due to the financial crisis. These results suggest that there may be hysteresis effects in the labour market as argued by Ball (2009), i.e. the natural rate of unemployment is influenced by the path of actual unemployment.[10] However, it can be also argued that the crisis could have brought structural changes in the economy/labour market leading to an increase in the nature rate of unemployment. The right panel of Figure 4 displays the deviation of unemployment rate from NAIRU together with output gap. It is clear that these two measures are highly negatively correlated, $Corr(\hat{y}_t, \hat{u}_t) = -0.75$ ($p \approx 0.00$) and $Corr(\hat{y}_{t-1}, \hat{u}_t) = -0.80$ ($p \approx 0.00$), therefore corroborating our estimates.

Figure 4 – Unemployment Gap



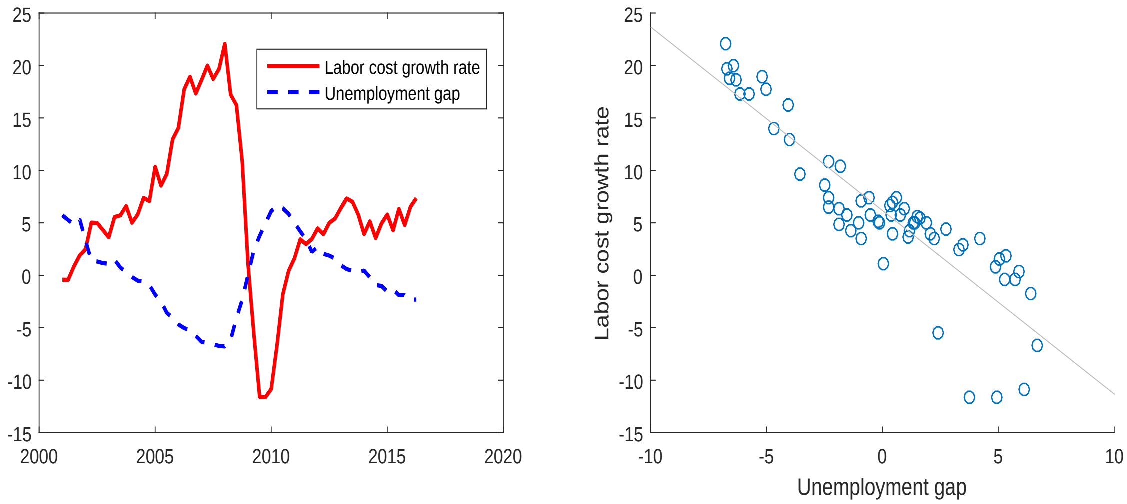
Notes: The graph shows the smoothed sequences of natural rate of unemployment (%) in the left panel and the deviation of unemployment gap from its natural rate (%) in the right panel.

To substantiate our measures of NAIRU, we compare to the estimates obtained by the European Commission.[11] Over the sample 2000-2015, the average of natural rate of unemployment obtained by the latter is 10.9 percent which is very close to our estimate of 11.2 percent. Moreover, the correlation between two series is high and statistically significant,

[10] Although we do not restrict the trend path of unemployment rate to be influenced by the (lag of) actual unemployment rate, the trend $\bar{u}_t$ is pinned down by economic relationships relating to the cyclical and trend components of unemployment and output. Therefore, as discussed in Melolinna and Tóth (2016), the hysteresis effect could be captured by our model specifications.

[11] See European Commission's Annual Macro-Economic database. As documented in Havik et al. (2014), the natural rate of unemployment's measure of European Commission is obtained from a standard model of the labour market, with explicitly formulated wage and labour demand equations. In particular it is shown how the Wage Phillips curve, which links the change in wage inflation to the unemployment gap, is shifted by observed and unobserved shocks to the wage rule and the labour demand equations.

Figure 5 – Labor cost



Notes: The graph shows the smoothed sequences of unemployment gap (%) and the labor cost growth rate (%).

$corr = 0.75$ ($p \approx 0.00$). In addition, we investigate if the measure of unemployment gap aligns with the behavior of labor cost- a variable that is not used in our estimation.[12] Basically, the labor cost should accelerate if unemployment gap is negative, i.e. unemployment rate is below its natural rate. As shown in Figure 5, the growth rate of labor cost is highly and negatively correlated with unemployment gap, $corr = -0.89$ ($p \approx 0.00$), therefore confirming our NAIRU estimates.

4.3 Real-Time Performance

It is often argued that the estimates of output gap are particularly unreliable in real time, therefore questioning its usefulness for policy-making purposes. For instance, the HP filter is notorious for its unusual behavior of cyclical components near the end of the sample (see, e.g., Baxter and King, 1999). According to Orphanides and van Norden (2002), the first and probably primary reason that challenges the estimate of potential output in real time arises from the fact that when data in subsequent quarters become available, hindsight may help to clarify our position in the business cycle. This includes the update/revision of the model

[12]The labor cost index is from Eurostat, which shows the short-term development of the total average hourly labor costs, including compensations of employees plus taxes paid minus subsidies received by the employer for business activities in the economy.

given the the arrival of new data. Second, output data is often subject to revisions, therefore the estimate of output gaps from real-time data may differ from those estimated with revised data. For this reason, it is crucial to examine the real-time performance of our model.

Figure 6 – Output gap in Real time

Notes: The pseudo real-time output gap is obtained by recursively estimating the models, MUC *versus* HP, using 1998:Q1-2005:Q1 as the initial sample and adding one by one observation from 2005:Q2-2016:Q3.

In order to investigate the effects of additional information by conducting the following exercise. We use 1998:Q1-2005:Q1 as the initial sample and then estimate the model recursively to the end of the sample, i.e. adding one quarter by one from 2005:Q2-2016:Q3. Therefore, the model is estimated recursively for 46 times. We retain only the end-point estimates of output gap in each estimation and construct the pseudo real-time series of output gap from 2005:Q2-2016:Q3. Note that there is a difference between actual real time and pseudo real-time data. The former is the actual data available in real time, while the latter is constructed based on the final vintage and may be subject to revisions. Given the fact that vintage data is not available in the case of Lithuania, we use the pseudo real-time instead. A consequence of using pseudo real time is that we exclude the issue of data revisions. However, such an exclusion may not be problematic because, according to Orphanides and van Norden (2002), data revisions are not the primary source of revisions on output gaps estimates and, thus, even if the reliability of the underlying real-time data were improved, the improvement of output gaps estimates would not be significant. At the end of this section, we propose a method to evaluate the effects of data revisions on our measures of output gap and affirm the point made by Orphanides and van Norden (2002).

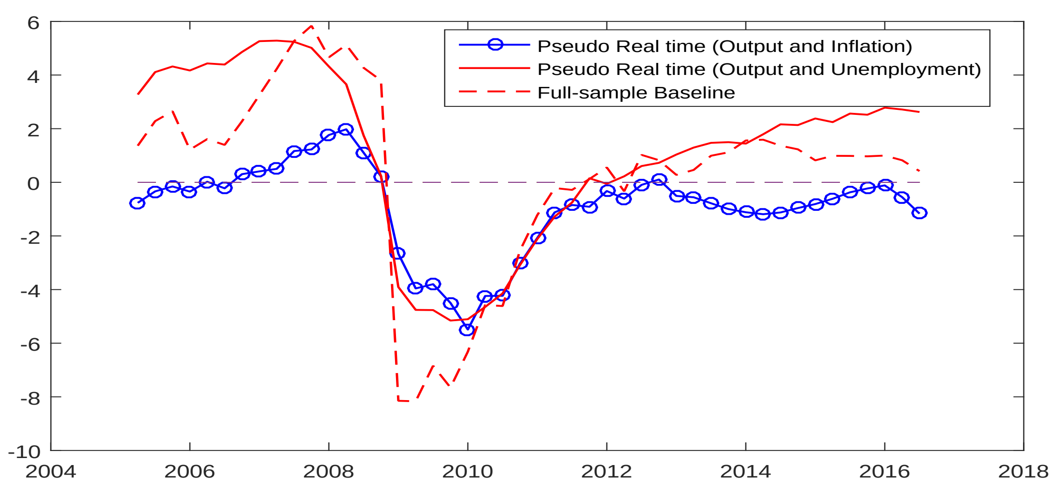
Table 2 – Relative Real-time Performance Based on Standardized Average Errors (SAE)

Model	SAE
MUC	0.27
HP Filter	0.69

Presuming that more information improve output gaps estimates, we evaluate the real-time performance by comparing the full-sample output gap estimates and the end-point real-time estimates. In Figure 6, we present the estimates of the multivariate unobserved component model together with those using HP filter for comparisons. It is apparent that the real-time MUC-based estimates captures the dynamics relatively well and likely performs better than those derived by the real-time HP output gap. To put a numerical value on the relative real-time performance, we follow Melolinna and Tóth (2016) to calculate the mean of absolute deviation of the full sample output gap estimate from the end-point real time estimates and divide by the standard deviation of the full sample gap. This provides a measure of standardized average errors of the two methods. Table 2 reports the results suggesting that the real-time performance of the multivariate unobserved component model is clearly better than the HP filter, therefore emphasizing the importance of using relevant modelling techniques to limit the uncertainty surrounding the end-point estimates.

It is also noticeable that the real-time output gap based on the MUC model for Lithuania does indicate a positive output gap before crisis. This result has been struggled to obtain in some other countries, including UK, US and some countries in the Euro area. In these countries, only after the crisis did the measures of output gap, i.e. estimates by the OECD, IMF and those based on simple HP filter, suggest that output had been above its potential level. For this reason, Borio et al. (2016) emphasize to incorporate the financial factor into consideration to capture the relationship between financial factors and business fluctuations. For Lithuania, we notice that, as shown in Figure 4, there is a strong relationship between the output gap and the unemployment gap, indicating the usefulness of the labor market indicator in our multivariate unobserved component models for the real-time estimation. Prior to the crisis, unemployment rate was far below its natural level (as shown by our estimates or implied by a significant increase in labor cost), which therefore helps to identify the fact that output was above its potential level. As a robustness check, we consider two alternative models: the first model includes output and inflation, therefore excluding labor market indicator from the baseline, and the second one only uses the data of output and unemployment rate. We conduct the pseudo real time measures of output gap in the same procedure with recursive estimations and present the results in Figure 7. It is clear that output is far above its potential level in the model with unemployment rate than in the model without it. On the other hand, both models can successfully produce a real-time slump of output in 2009-2010. Based on these results, the model with labor market indicator is more preferred than the one without it. Comparing the baseline model with the model having only output and unemployment, we find that the unemployment/output gaps estimated from the former have higher correlations with the labor cost growth than those from the latter. Moreover, the behavior of output gap in the baseline model appears to be more consistent with the dynamics of inflation than the model without inflation information.

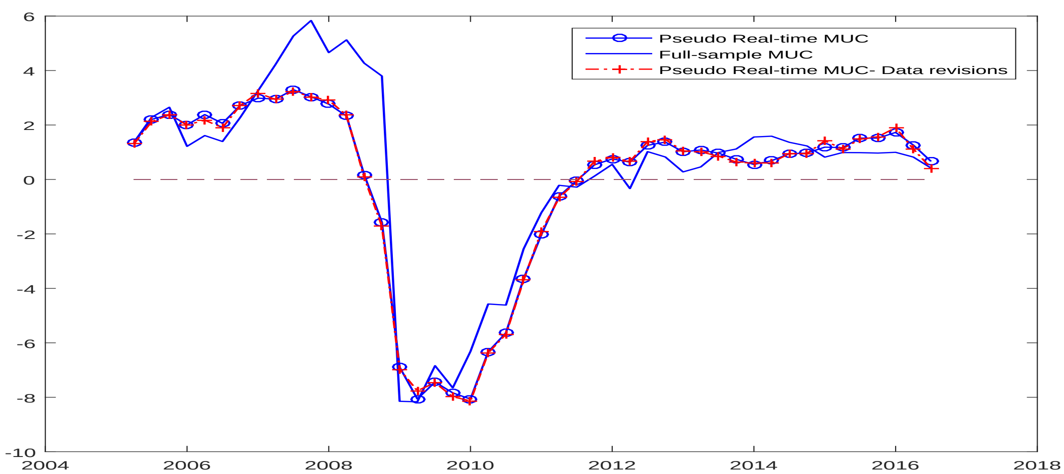
Figure 7 – Output gap in Real time: Two Alternative Models



Notes: Two alternative models are: the MUC model with output and inflation and the MUC with output and unemployment rate. The pseudo real-time output gap is obtained by recursively estimating the models using 1998:Q1-2005:Q1 as the initial sample and adding one quarter by one from 2005:Q2-2016:Q3.

In another exercise, we study the effect of data revisions on the estimate of potential output in real time. Note that the revisions in inflation and unemployment rate are negligible, so we only focus on revisions in real GDP. For real-time performance evaluation, we also use the 1998:Q1-2005:Q1 period as the initial sample and then estimate the model recursively to the end of the sample, i.e. adding one quarter by one from 2005:Q2-2016:Q3. However, at each period of estimation, the recent four quarters are assumed to be observed with errors. Specifically, we add random values to the original real GDP in those quarters so that the difference between the new and original values are about 5 percent of the original values with a confidence level of 95 percent. For instance, if the actual real GDP is 9000 millions (in Euro), the observed value is between $[9000 - 0.05 \times 9000; 9000 + 0.05 \times 9000]$ with a confidence level of 95 percent. We generate 50 different values of real GDP at each time, calculate the end-point output gap estimate, and then take the average. As shown in Figure 8, the pseudo real-time estimates of output gap are similar with the ones without measurement errors. We therefore affirm the point made by Orphanides and van Norden (2002) that data revisions are not the primary source of revisions on output gaps estimates.

Figure 8 – Output gap in Real time: Data with Measurement Errors



Notes: The pseudo real-time output gap is obtained by recursively estimating the models, with actual data and data with errors, using 1998:Q1-2005:Q1 as the initial sample and adding one quarter by one from 2005:Q2-2016:Q3.

4.4 Including the Financial Sector

Real credit data is only available with quarterly frequency from 2003:Q4 to 2016:Q2 and with annual frequency before that[13]. To deal with this issue, we first treat the annual data

[13] Real credit is defined as total loans to non-financial corporations and households, including non-profit institutions serving households, and debt securities issued by non-financial corporations. The real credit

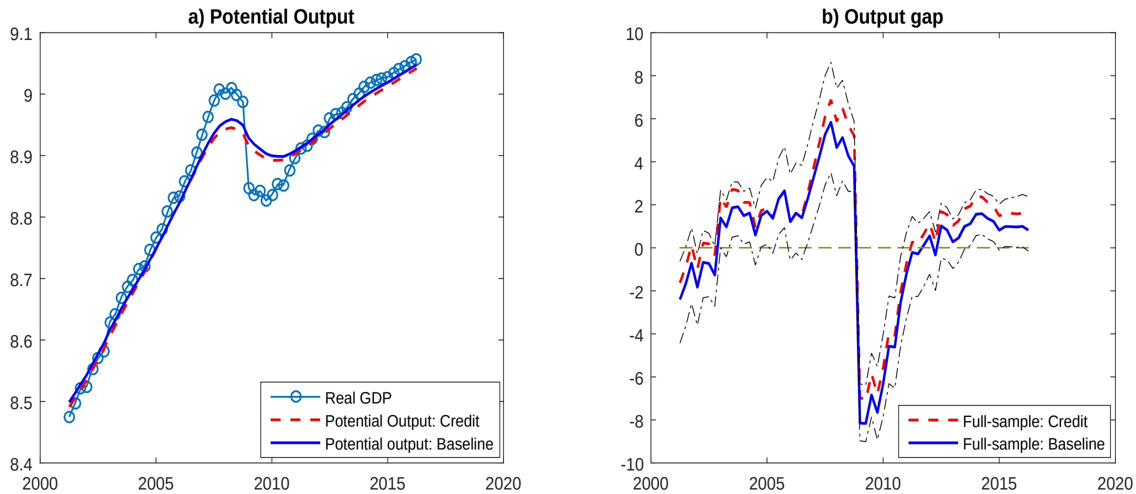
of credit, which is a stock, as the data of quarter 4 in the corresponding year. Hence, in terms of credit growth, we have quarterly data from 2004:Q4 to 2016:Q2 and the data at quarter 4 only in the previous years (i.e. missing observations in the first three quarters of each year). We then handle the issue of missing observations via Kalman filtering process as documented in Durbin and Koopman (2012). This thus allows us to estimate the MUC model with real credit growth using a similar sample as in the baseline running from 1998:Q4 to 2016:Q2. Regarding prior distributions, as above we use a Beta distribution for the autoregressive parameter β with mean 0.7 and standard deviation 0.2 reflecting a prior belief on the persistence of financial factor. Meanwhile, little is known about the effect of credit growth on output gap in Lithuania; we use a Gamma prior for δ with mean 0.01, which is close to the estimate of HP-filter gap on its lag and real credit growth, and standard deviation equal to half of the mean value.[14] By using the Gamma distribution, we assume that δ should be positive. However, the relative strength of the force is determined by the data. In addition, to evaluate the real-time estimates of output gap, we follow the above procedure by using the first 30 quarters as initial sample and then estimating the model recursively by adding one quarter by one until the end of the sample.

Figure 9 illustrates the smoothed series of potential output and output gap in the model with credit (red and dashed) together with the estimates of the baseline (blue lines). Including credit growth results in higher pre-crisis output gaps, which is therefore in line with Borio et al. (2016, 2014) and Melolinna and Tóth (2016). However, the difference appears not to be substantial and the smoothed series in the model with credit is well in the 90 percent bounds of the baseline estimates as shown in Figure 9. We conjuncture this may be due to the smaller financial depth of the Lithuanian economy (with a credit-to-GDP ratio of 45 percent, compared to 150 percent in the UK or 174 percent in Spain). We also conduct an exercise with pseudo-real-time data and obtain similar conclusions as shown in Figure 10. Nevertheless, such a result does not strictly imply that the financial factor is not important in Lithuania. Instead, if the developments in the financial market leaded to significant changes in prices and the labor market, then using a multivariate unobserved component models incorporating both inflation and unemployment rates could capture indirectly the effects of

series is obtained by dividing the nominal series by the GDP deflator. All these data are collected from Eurostat Database.

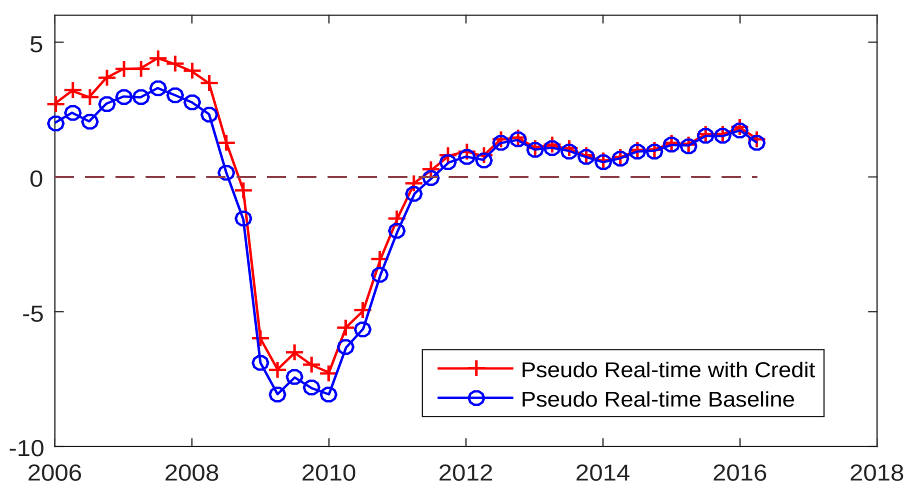
[14]We obtain a similar result when using a Uniform distribution for δ.

Figure 9 – Output gap in the Model with Credit



Notes: The graph shows in the left panel the smoothed sequences of (log of) potential output in the model with credit and the baseline model and their associated output gaps in the right panel. The dotted lines in the right panel are 90 percent bounds of the baseline estimates.

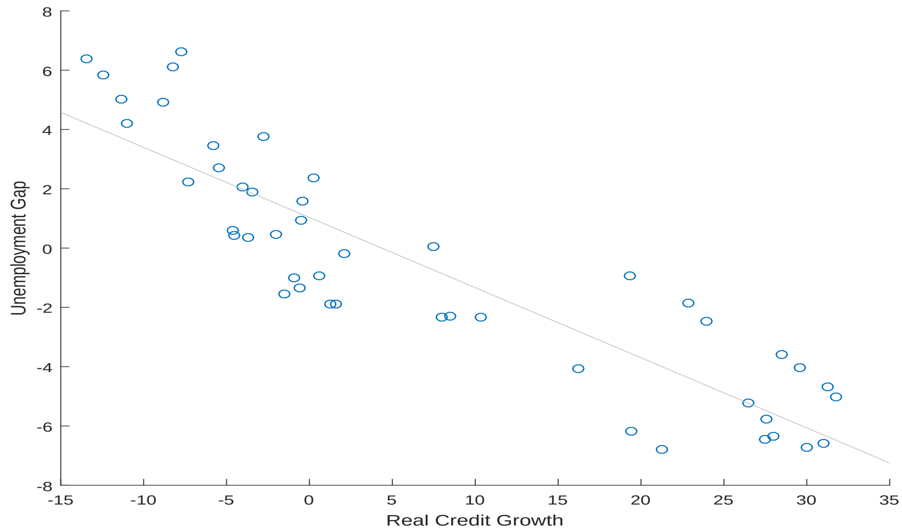
Figure 10 – Output gap in Real time: Model with Credit



Notes: The graph shows the real-time estimates of output gaps in the model with credit and the baseline model. The pseudo real-time output gap series is a collection of the end-point measures obtained by estimating the relevant model recursively by adding one quarter by one till the end of the sample.

financial developments on the measure of potential output and output gap. This possibility is supported by Figure 11 which shows that the real credit growth and the unemployment gap estimated from the baseline model (without the financial factor) are highly and negatively

Figure 11 – Credit and Unemployment: 2004Q4 - 2016Q2



Notes: Real credit growth (%) and unemployment gap estimated from the baseline model (%).

correlated with $Corr(f_t, \hat{u}_t) = -0.89$ ($p \approx 0.00$). In such a scenario, including financial variables may not result in substantial differences in the estimates of output gap if the labor market is taken into account. This indicates that, as far as the Lithuanian economy is concerned, the evolution of the unemployment rate captures most of the underlying structural information needed to compute potential output. A further important observation is related to the information conveyed by credit. As indicated in Figure 10, real credit signals a higher output gap right before the 2008 crisis as compared to the baseline model yet carries almost no additional information from 2010 onwards.

5 Conclusion

In this paper, we used a multivariate unobserved component model (MUC) to measure the unobserved potential output of the Lithuania economy. Specifically, we back-out the potential output based on its relationships with inflation and unemployment through a simple version of the Phillips curve and Okun's law. The model was written in a state-space form and subsequently estimated via Bayesian methods. Our results show that the estimated gap measures track Lithuanian macroeconomic dynamics reasonably well. With the inclusion of labor market indicator, the MUC models' gap estimates perform better in real-time than the ones derived by the popular HP filter. The inclusion of real credit, to account for the impact of the financial market, does not produce fundamentally different results. This is at odds with results from countries featuring a more prominent financial sector. We show that data revisions are not the primary source of revisions on output gaps estimates.

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