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An unobserved components model for Finland – Estimates of potential output and NAWRU

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Abstract

In this paper, we estimate a potential output model for Finland using an unobserved component model. The model builds on a production function approach, and features price and wage Phillips curves, Okun's law and several resource-utilization indicators. We show that incorporating resource-utilization indicators, i.e. capacity utilization and long-term unemployment, improves real-time reliability of the output gap and NAWRU estimates. Our real-time estimate of the output gap is robust even in an event of a sudden turning point in the economy such as the global financial crisis. It also outperforms the HP filter estimate. Results suggest that Finland's potential output growth slowed significantly in the aftermath of the financial crisis and that the output gap was negative for most of the subsequent decade. The slowdown in potential growth was due mainly to lackluster total factor productivity growth. The real-time results are broadly in line with the ex-post estimates of the IMF and the European Commission.

JEL codes: C51 Model Construction and Estimation, E23 Macroeconomics: Production, E32 Business Fluctuations; Cycles

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1. Introduction

Finnish Gross Domestic Product (GDP) fell by more than 8 % a year during the global financial crisis, and was followed by several more years of contraction. The Finnish economy has since recovered, clawing its way back to its pre-crisis GDP peak. Comparison of GDP levels in itself cannot tell us whether an economy's production factors are fully utilized, of course. For this purpose, we need estimates of the output gap and potential output.

In this paper, we present a model of potential output for Finland using an unobserved components model to decompose time series into separate components such as trend and cycle.[1] The estimate for potential output is based on a production function approach, and, to determine slack in the economy, utilizes theoretical relationships and several indicators that measure the economy's resource utilization. This approach outperforms single univariate filters because of the real-time reliability of the output gap. Moreover, a production-function approach allows detailed and coherent analysis of potential output based on the economy's factors of production.

Access to up-to-date estimates of these measures is a valuable asset for economic policymakers. Such estimates can, for example, be used in assessing price and wage pressures in the economy, in evaluating the appropriateness of the monetary or fiscal policy stance, as well as in determining appropriate stabilization policies. In many cases, it is important that the output gap and potential output estimates are reliable in real time.

One approach to estimate potential output and the output gap would be to use univariate statistical methods.[2] A widely used method of eliminating temporary cyclical effects from economic time-series data is the Hodrick-Prescott (HP) filter.[3] This univariate filter produces a trend component for output and eliminates the presumed cyclical component from observed GDP.

The HP filter is not without its critics. [4] Univariate filters are sensitive to ex-post revisions of the results that undermine their real-time use. In particular, there is the end-of-sample problem or end-point bias, whereby estimates of the current output gap are retroactively revised as new data become available. Even the very notion of discerning potential output from a univariate statistical model is colored by controversy. Such results might be better thought of as statistical trends and not potential output as the method is not based on economic theory.

A semi-structural unobserved components model (UCM) avoids some of the shortcomings of univariate statistical filters). UCM models, which are essentially multivariate filters (MVFs) decompose multiple observable variables into trend and cyclical components by exploiting established structural relationships between macroeconomic variables.

One particular strength of this methodology is that unobserved component models have the potential to mitigate the end-point bias. The methodology's popularity is also explained by its flexibility. The UCM can be augmented with lag structures or additional observable variables if these enhance the estimation of the unobserved variables.

[1] See Harvey (1989) for an introduction to the unobserved components model.
[2] Potential output can be estimated using a variety of methods, including simple univariate filters, multivariate filters, production functions or DSGE modeling. For a brief overview, see e.g. Blagrave et al. (2015).
[3] Hodrick and Prescott (1997).
[4] See e.g. Hamilton (2018) and Orphanides and Van Norden (2002).

Unlike univariate filters, theoretical relationships can be incorporated to these models. One popular starting point is to add structure that links inflation and output through the Phillips curve.

The UCM approach has been used by e.g. Benes et al. (2010) to estimate US and euro area potential output by incorporating the Phillips equation, Okun's law and the capacity-utilization rate into the same framework.[5] It is also hardly a new approach; Laxton (1992) and Kuttner (1994) were constructing unobserved components models to estimate potential output already in the early 1990s.

UCMs can be tailored to an open economy as suggested by Darvas and Simon (2015). Borio et al. (2014) and Melolinna et al. (2016) also propose including financial indicators to mitigate the end-of-sample problem. Blagrave et al. (2015) call for inflation and growth expectations be introduced into MVF models to tackle the same issue. Alichi et al. (2017, 2015) demonstrate that, among other measures, introducing the capacity-utilization rate that contains additional information on the amount of slack in the economy is effective in reducing the ex-post revision of results when estimating potential output and slack in the economy. Alichi et al. (2018) augment their UCM with a monetary policy rule to further improve the reliability of the potential output estimates.

Our potential output model for the Finnish economy is estimated using Bayesian methods. [6] The key outputs are estimates for potential output, the output gap and the NAWRU.[7] The model is a semi-structural unobserved components model with a production function at its core.

Using the production function methodology, potential output is determined by the volume of cyclically-adjusted production factors. To control for the production factors' cyclical components, macroeconomic relationships between wages and unemployment as well as inflation and GDP growth (i.e. the wage and price Phillips curves) are inserted into the model's framework. This is based on the underlying assumption that the rates of inflation and wage growth contain information relevant to the prevailing output and unemployment gaps. The model also incorporates the Okun's law, which depicts an inverse relationship between unemployment and output. Finally, the model includes the observed rates for manufacturing capacity utilization and long-term unemployment to improve estimation of the economy's unused production capacity.

From the policymaking perspective, it is important that the phase of a business cycle is correctly identified in real time. We show that incorporating resource-utilization indicators, i.e. capacity utilization and long-term unemployment, greatly improves the real-time reliability of the output gap and NAWRU estimates. Our real-time estimates are robust and are broadly in line with the ex-post estimates by the IMF and European Commission. Our real-time estimate of the output gap is reliable even in the event of a sudden turning point in the economy such as a global financial crisis. It is also superior to the HP filter.

The results show that potential output growth slowed significantly in the aftermath of the global financial crisis. At the same time, a negative output gap opened up and output remained below potential for almost a decade. Moreover, we also show that the following slowdown of the potential growth was due to lackluster total factor productivity growth. In addition, the detailed production function structure allows us to decompose the total contribution

[5] See Okun (1962).
[6] This paper builds on the original code written by Máté Tóth (Mate.Toth@ecb.int) and work by the WGF potential output task force. See also Szörfi and Tóth (2019).
[7] The difference between gross domestic product and potential output, i.e. the output gap, is denoted as a percentage of potential output. NAWRU stands for the non-accelerating wage rate of unemployment.

of labor input to potential growth into changes in the population trend, the participation rate, average hours worked and the NAWRU.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 illustrates the data and briefly discusses the development of Finnish economy from 1999 to 2017. Section 4 presents the results and sensitivity analysis. Section 5 concludes.

2. The model

The following is a presentation of the key equations of unobserved component model for potential output.

An overview to the model's structure is displayed in Figure 1. The key equations and parameter values are also reported in the Appendix. Discussion on estimation and parameter values is provided in section 3.

We assume that observed output Y_t at time t is formed according to a Cobb-Douglas production function, where ι is the share of labour input and (1- ι) is the share of capital. K_t is the real capital stock, while L_t is the aggregate labor input corresponding to total hours worked in the economy. TFP_t is total factor productivity. This gives:

$$Y_t = TFP_t * {L_t}^{\iota} * {K_t}^{1-\iota}. \tag{1}$$

The aggregate labor input, i.e. total hours worked, is determined by the participation rate (LAX_t), working-age population (LAN_t), unemployment rate (u_t) and average hours worked (AHN_t) such that:[8]

$$L_t = (LAN_t * LAX_t * (1 - u_t)) * AHN_t. \tag{2}$$

By disaggregating the total hours worked into separate factors, we get the Cobb-Douglas production function in log-level form:[9]

$$y_t = tfp_t + \iota(lan_t + lax_t + \ln(1 - u_t) + ahn_t) - (1 - \iota)k_t. \tag{3}$$

An increase in total factor productivity, labor input or capital stock raises GDP. The log aggregate labor input depends on the log participation rate (lax_t), log working-age population (lan_t), unemployment rate (u_t) and log average hours worked (ahn_t).

The next step in creating our unobserved component model is to decompose observed variables into trend and cyclical components, with the trend component of each observable variable corresponding to potential. The general idea is that an increase in a factor input leads to a higher potential output only if the potential level of the given input also rises. Otherwise, the potential output (i.e. trend) is unaffected and the gap (observed relative to potential) increases.

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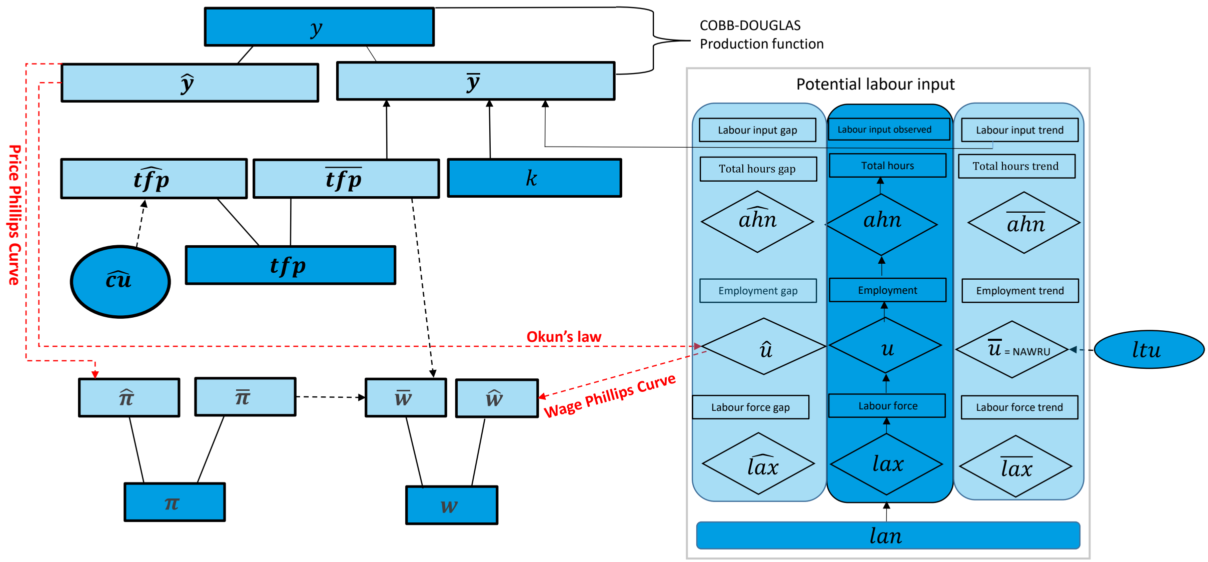
[8] The term $1 - u_t$ accounts for the fact that the unemployed do not participate actively in the production process by deducting the unemployed from the labor force.

[9] Note that in the model this identity holds even though it is not declared directly in the model equations.

Figure 1. Structure of potential output model.



y = output
tfp = total factor productivity
k = capital stock
ahn = average hours worked
u = unemployment rate
lax = participation rate
lan = working age population

ltu = long term unemployment rate
cu = manufacturing capacity utilization rate
π = inflation
w = wage inflation.

$\hat{}$ denotes gap
$\bar{}$ denotes trend

2.1 Decomposition to trend and cycle

We now define decompositions to the trends and cyclical components of each observable variable.

The measurement equation of observed log GDP (y_t) is the sum of unobserved potential log output ($\bar{y}_t$) and the output gap ($\hat{y}_t$): [10]

$$y_t = \bar{y}_t + \hat{y}_t \,. \tag{4}$$

Similarly, we obtain the log trend total factor productivity ($\overline{tfp}_t$) and the total factor productivity gap ($\widehat{tfp}_t$) from the model:[11]

$$tfp_t = \overline{tfp}_t + \widehat{tfp}_t \,. \tag{5}$$

Total factor productivity is not directly observed but can be calculated as residual according to the above equation.

The observed unemployment rate (u_t) is decomposed into a trend unemployment rate that corresponds to NAWRU ($\bar{u}_t$) and into an unemployment gap ($\hat{u}_t$):

$$u_t = \bar{u}_t + \hat{u}_t \,. \tag{6}$$

Similar decompositions are introduced for log participation rate (lax_t) and log average worked hours (ahn_t) where the observed variables are decomposed into trend and cycle:

$$lax_t = \overline{lax}_t + \widehat{lax}_t \tag{7}$$

$$ahn_t = \overline{ahn}_t + \widehat{ahn}_t. \tag{8}$$

We do not separate the capital stock into a trend and a gap because the observable capital stock itself is a slow-moving variable by its nature. The same applies for the working-age population. It would be hard to justify a cyclical component in the evolution of the working-age population.

Beyond the inputs that enter the production function, a number of measurement equations are introduced in the nominal side as well. Motivation for modeling the nominal side is the notion

[10] In other words, log output gap is $\hat{y}_t = \ln(\frac{Y_t}{\bar{Y}_t})$, where Y_t is the observed GDP level and $\bar{Y}_t$ is the potential level.

[11] Note that this identity in the model holds even though it is not declared as a measurement equation.

that the price and wage inflation hold information about the business cycle, which can be captured explicitly through the Phillips curve.

The measurement equation for the observed year-on-year price inflation (π_t) consists of the inflation trend ($\bar{\pi}_t$) and the inflation gap ($\hat{\pi}_t$). Observed year-on-year wage inflation (w_t) is decomposed into a wage inflation trend ($\bar{w}_t$) and a wage inflation gap ($\hat{w}_t$):

$$\pi_t = \bar{\pi}_t + \hat{\pi}_t \tag{9}$$

$$w_t = \bar{w}_t + \hat{w}_t \, . \tag{10}$$

We use these variables later on in sections 2.2 and 2.3 to model the trend equations and the cycles.

2.2 Trend specifications

The log potential output ($\bar{y}_t$) is determined by a Cobb-Douglas production function. An increase in either the log total factor productivity trend, log labor input trend or observed log capital stock (k_t) will raise potential output. More specifically, the labor input trend can be increased by a higher log trend participation rate ($\overline{lax}_t$), log trend average hours worked ($\overline{ahn}_t$), log working-age population (lan_t), as well as by a lower NAWRU ($\bar{u}_t$) such that:

$$\bar{y}_t = \overline{tfp}_t \; + \; \iota\left(lan_t + \overline{lax}_t + \overline{ahn}_t \; + \; \ln(1-\bar{u}_t)\right) \; + \; (1-\iota)k_t. \tag{11}$$

The total factor productivity trend ($\overline{tfp}_t$) follows a double unit-root process:

$$\overline{tfp}_t = \overline{tfp}_{t-1} + \widetilde{tfp}_t \tag{12}$$

$$\widetilde{tfp}_t = \widetilde{tfp}_{t-1} + \varepsilon_t^{\widetilde{tfp}}, \tag{13}$$

where $\widetilde{tfp}_t$ is the TFP trend growth shifter and $\varepsilon_t^{\widetilde{tfp}}$ is a shock to the trend growth shifter. In other words, $\varepsilon_t^{\widetilde{tfp}}$ is a permanent shock to the growth rate. The implication of an assumed double-unit process is that we do not need to fix the trend growth rate of TFP a priori. The unemployment trend (NAWRU) is affected by its lagged value and the observed structure of unemployment: [12]

$$\bar{u}_t = \bar{u}_{t-1} + \; \tilde{u}_t \tag{14}$$

$$\tilde{u}_t = \kappa\,\Delta\, ltu_t + \varepsilon_t^{\tilde{u}} \tag{15}$$

$$ltu_t = (1-\lambda)ltu^* + \lambda ltu_{t-1} + \varepsilon_t^{ltu}. \tag{16}$$

The trend unemployment rate responds to changes in $\tilde{u}_t$, which carries information about long-term unemployment.[13] In turn, an increase in the observed long-term unemployment rate (ltu_t) results in a higher unemployment trend, which depends on the parameter κ. We do not know a priori the extent to which an increase in long-term unemployment leads to an increase

[12] Here, we say our unemployment trend is NAWRU and we use a wage Phillips curve to connect the unemployment gap to the wage gap. Hence, our NAWRU is the lowest unemployment attainable with stable wage development. This approach is different to the structural unemployment indicator derived for Finland by Juvonen and Obstbaum (2018). Their empirical structural unemployment indicator is estimated via labor market flows, and based on labor market search theory and equilibrium unemployment.

[13] The job-finding rate of the long-term unemployed is typically much lower than for newly unemployed workers. Therefore, long-term unemployment effectively constrains the available supply of labor.

in the NAWRU. Hence, parameter κ, which defines this, is estimated rather than calibrated to unity. We define long-term unemployment as being unemployed for more than a year.

Finally, a higher unemployment trend will have a negative impact on potential output. Therefore, the equation linking $\tilde{u}_t$ and ltu_t is important for model outcomes. Of similar importance is the equation connecting observed capacity utilization with cyclical component of total factor productivity. These resource-utilization indicators are displayed in Figure A3 in Appendix A.

The motivation for an equation linking trend unemployment and long-term unemployment is hysteresis as discussed in Blanchard and Summers (1986). A rise in the observed unemployment rate can lead to an increase in structural unemployment. For example, the NAWRU rises if longer unemployment spells lead to weaker job search intensity, skill deterioration or both. In the long run, long-term unemployment rate is pinned down by ltu^*, which is calibrated to the long-run average of the long-term unemployment rate.

To complete the trend inputs of the production function, a number of auxiliary equations are added to the model. Trend equations for both participation rate ($\overline{lax_t}$) and average worked hours ($\overline{ahn_t}$) are double unit-root processes, whereby:

$$\overline{lax}_t = \overline{lax}_{t-1} + \widetilde{lax}_t \tag{17}$$

$$\widetilde{lax}_t = \widetilde{lax}_{t-1} + \varepsilon_t^{\widetilde{lax}} \tag{18}$$

$$\overline{ahn}_t = \overline{ahn}_{t-1} + \widetilde{ahn}_t \tag{19}$$

$$\widetilde{ahn}_t = \widetilde{ahn}_{t-1} + \varepsilon_t^{\widetilde{ahn}}\ . \tag{20}$$

Regarding the observed population (lan_t) and the observed capital stock (k_t), which also enter the production function, auxiliary transition equations are introduced. They, too, are assumed to follow double unit-root processes such that:

$$lan_t = lan_{t-1} + \widetilde{lan}_t \tag{21}$$

$$\widetilde{lan}_t = \widetilde{lan}_{t-1} + \varepsilon_t^{\widetilde{lan}} \tag{22}$$

$$k_t = k_{t-1} + \tilde{k}_t \tag{23}$$

$$\tilde{k}_t = \tilde{k}_{t-1} + \varepsilon_t^{\tilde{k}}\ . \tag{24}$$

Turning to the nominal side, we say the inflation trend ($\bar{\pi}_t$) follows an AR(1) process with a weight on a fixed value (π^*). π^* is calibrated to past average inflation. This gives:

$$\bar{\pi}_t = (1-\varphi)\pi^* + \varphi\bar{\pi}_{t-1} + \varepsilon_t^{\bar{\pi}}. \tag{25}$$

Annual trend wage inflation ($\bar{w}_t$), in turn, is the sum of trend price inflation and the hourly trend in labor productivity growth. This assumption stems from standard micro-economic theory. Trend growth of labor productivity per hour is defined as growth of trend output subtracted by growth of trend labor input.[14] We multiply productivity by 4 as both wage and price inflation are defined in annual terms, such that:

$$\bar{w}_t = \bar{\pi}_t + 4 * \Big(\Delta\,\bar{y}_t - \big(\Delta lan_t + \Delta\overline{lax}_t + \Delta\overline{ahn}_t + \Delta\ln(1-\bar{u}_t)\big)\Big) + \varepsilon_t^{\bar{w}}. \tag{26}$$

[14] Sign and size of the output gap does not change significantly if the index for wage earnings (*ansiotasoindeksi* in Finnish) is used to measure wage inflation in the data, instead of compensation of employees per hours worked. Labor productivity is defined as labor productivity per employee.

2.3 Cycle specifications

Output gap ($\hat{y}_t$) is assumed to follow a simple AR(2) process. This specification captures the persistence in output gap movements without complicating the model. Inflation pressures are connected to output gap through the Phillips curve equation.[15] $\varepsilon_t^{\hat{y}}$ is an idiosyncratic shock to the output gap equation. It can be interpreted, for example, as a demand shock since prices and output move in the same direction after a shock. We thus obtain:

$$\hat{y}_t = \alpha_1 \hat{y}_{t-1} - \alpha_2 \hat{y}_{t-2} + \varepsilon_t^{\hat{y}} \,. \tag{27}$$

We next introduce a dynamic version of Okun's law to link unemployment and output cycles. Okun's law, which says GDP growth is proportional to the unemployment rate, allows for a dependency between the output gap and the unemployment gap. We note that the data suggest a lag from changes in output to changes in employment, and therefore define the unemployment gap equation in such a way that the current unemployment gap is affected by the previous output gap. The equation is further adjusted by the AR(1) term, which accounts for the assumed persistency of the unemployment gap such that:

$$\hat{u}_t = \gamma_1 \hat{u}_{t-1} - \gamma_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{u}} \,. \tag{28}$$

The cyclical variation in output and unemployment are then linked to the nominal side of the economy. As usual, inflation depends on output gap through the price Phillips curve relation, i.e.:

$$\hat{\pi}_t = \beta_1 \hat{\pi}_{t-1} + \beta_2 \hat{y}_{t-1} + \varepsilon_t^{\hat{\pi}} \,. \tag{29}$$

Similarly, we introduce a wage Phillips curve relation that links the unemployment gap to the wage inflation gap such that:

$$\widehat{w}_t = \beta_3 \widehat{w}_{t-1} - \beta_4 \hat{u}_{t-1} + \varepsilon_t^{\widehat{w}}. \tag{30}$$

[15] We assume away the interest rate in the model to keep the output gap equation simple. Otherwise, the model is designed to analyze observed data or to interpret forecasts made with other tools.

The capacity utilization rate serves to provide the model with additional information on prevailing cyclical conditions. This is accomplished by connecting the cyclical component of total factor productivity $\left(\widehat{tfp}_t\right)$ with the deviation of the observed capacity utilization rate from its long-term average $(\widehat{cu}_t)$. [16] A transitory shock term $\epsilon_t^{\widehat{cu}}$ is added to the capacity utilization gap to address possible measurement errors in the data. Thus, we obtain:

$$\widehat{cu}_t = \omega \widehat{tfp}_t + \epsilon_t^{\widehat{cu}} \, . \tag{31}$$

Observed capacity utilization helps pin down the TFP gap and improves the model's real-time reliability considerably. The resource utilization indicators are displayed in Appendix A Figure A3. Equation 31 implies that when the capacity utilization rate in manufacturing is above (below) its average trend, it associated with positive (negative) productivity gap, and increasing the positive (negative) output gap of the whole economy.

Next, we define gaps for the participation rate and average worked hours $(\widehat{lax}_t, \widehat{ahn}_t)$ as simple transitory stochastic shocks $(\varepsilon_t^{\widehat{lax}}, \varepsilon_t^{\widehat{ahn}})$ that capture all deviations from trend:

$$\widehat{lax}_t = \varepsilon_t^{\widehat{lax}} \tag{32}$$

$$\widehat{ahn}_t = \varepsilon_t^{\widehat{ahn}} \, . \tag{33}$$

Finally, the cyclical component of total factor productivity (TFP) is defined as the difference between the output gap and the labor market gap. This ensures that the gaps in the factors of production add up to the output gap. This gives us our final equation:

$$\widehat{tfp}_t = \hat{y}_t - \iota(\widehat{lax}_t + \widehat{ahn}_t + \ln(1 - \hat{u}_t)) \ . \tag{34}$$

[16] The European Commission (EC) exploits capacity utilization in extracting the total factor productivity gap in their potential output framework. The EC notes that capacity utilization strongly moves together with the TFP gap and can help to produce unbiased estimates of the TFP cycle – even at the end of the sample.[16] This holds for our model as well. See Havik, McMorrow, Orlandi, Planas, Raciborski, Roger, Rossi, Thum-Tysen and Vandermeulen (2014).

3. The Data

The model utilizes the following time-series data on the Finnish economy: log real GDP (y_t), log participation rate (lax_t), log average hours worked (ahn), manufacturing capacity utilization as a percentage of its long-term average rate ($\widehat{cu}_t$), log 15–74 year-old working-age population (lan_t), log aggregate capital stock (k_t), unemployment rate (u_t), long-term unemployed (over 12 months) as a share of the labor force (ltu_t), annual underlying inflation as per HICP inflation excluding energy and food (π_t) and annual wage inflation as per compensation of employees per hours worked (w_t). Estimation is based on quarterly time-series data over the period 1999Q1–2017Q4. The original data sources are reported in Table A1 of Appendix A. Resource utilization indicators, e.g. capacity utilization, are displayed in Figure A3 of Appendix A.

The broad trends in the Finnish economy over the sample period (1999–2017) are illustrated in Figure 2. An overview of the general trends suggests that the Finnish economy experienced significant shifts in composition of the economy's production factors.

Up to 2008, productivity per hour worked increased and the economy grew growing rather steadily. Meanwhile (with the exception of the mini-recession at the turn of the millennium), the participation rate strengthened and further bolstered economic growth. Since the global financial crisis, however, the Finnish economy's performance has been exceptionally weak. Productivity, labor market participation and output have all displayed lackluster growth until quite recently. Indeed, during 2008–2015, average labor productivity growth was slightly negative (-0.1%).

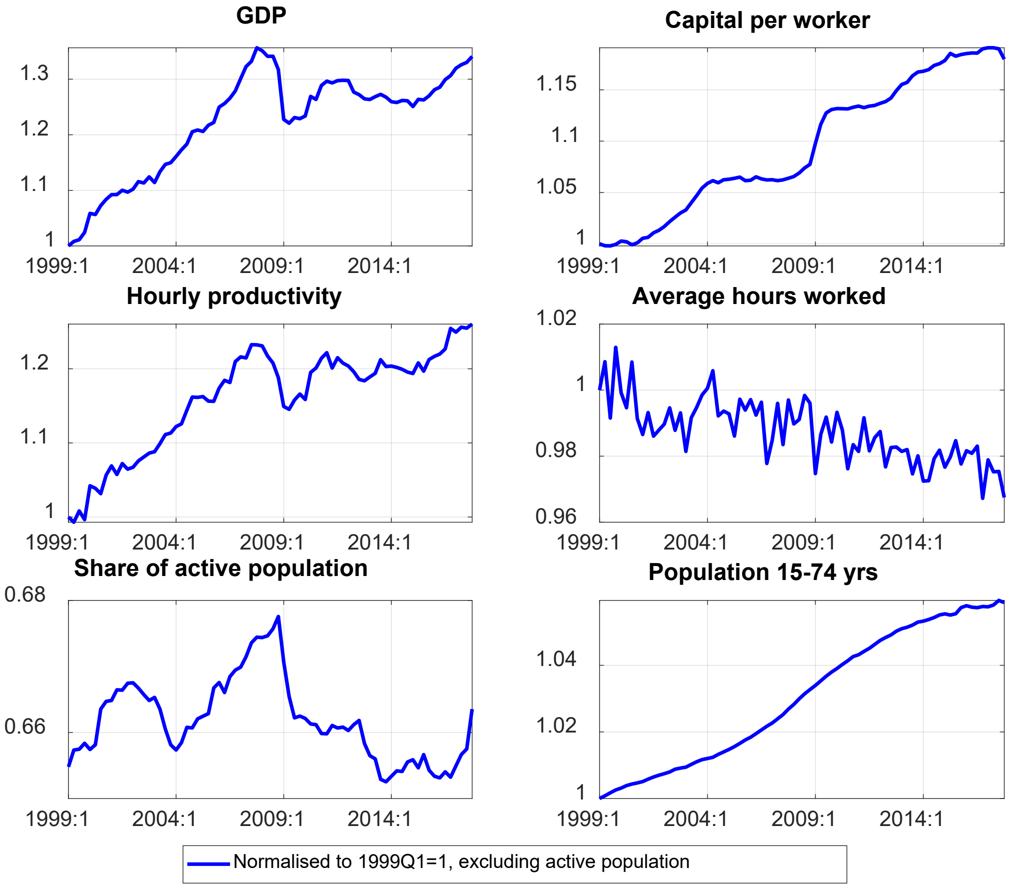
Average hours worked and the capital stock follow different trajectories than productivity, labor market participation and output. Average hours worked per employee declines throughout the sample period. The amount of available capital per worker increases, i.e. capital intensity increases during the years of the financial crisis when the employment weakens considerably, which results in more capital per worker.[17] The participation rate of 15–74 year-olds, i.e. the share of employed and unemployed persons of the working age population decreases considerably. The participation rate has been constrained by lackluster employment growth despite an expanding cohort of 15–74 year-olds.

The Finnish population is aging. It is telling that the expansion of the 15–74-year-old population is solely the result of growth in the cohort of over-64-year-olds.The number of people in the 15–64-year-old group declines. In other words, a growing share of the 15–74-year-old population are retirees who have departed the labor market.

All of these phenomena – weak productivity growth, declining labor input and an expanding larger capital base – impact the economy's growth potential in the period after the financial crisis.

[17] Capital refers to, in real terms, economy's total net capital stock, including dwellings.

Figure 2. Finnish economy, 1999–2017.



Sources: Statistics Finland and author's calculations. See Table A1 in Appendix A for details on data sources and definitions.

4. Results

4.1 Parameter estimation

The model parameters are estimated using Bayesian statistical methods.[18] The estimation sample is 1999Q1–2017Q4. In total, 13 semi-structural parameters are estimated, as well as 14 standard deviations of the shocks.[19] Two parameters were calibrated to match their average rate in the sample: long-term unemployment rate was calibrated to 2.03 % and inflation to 1.49 %. [20] Standard deviations of the shocks $\varepsilon_t^{\tilde{k}}$ *and* $\varepsilon_t^{\widetilde{lan}}$ were calibrated to 0.1 %.

The prior assumptions and the estimation results are reported in Tables A2 and A3 of Appendix A. We mainly use gamma and beta distributions for priors, and choose relatively uninformative priors with the exception of the Cobb-Douglas share parameter (ι), which was given a tight prior.

A beta prior is assumed when a parameter is limited between 0 and 1, otherwise a gamma prior is mainly chosen for parameters assumed to be strictly positive. Regarding standard deviations of the shocks, an inverse gamma is applied and the prior mean is assumed large for gap shocks (e.g. shock to the Phillips curve $\varepsilon_t^{\hat{\pi}}$) compared to shocks more directly linked to trends (e.g. shock to the inflation trend $\varepsilon_t^{\overline{\pi}}$).

The simulations in the following sections are based on the medians of the posterior distributions. [21] We now discuss some of the estimated values of the key parameters.

The Cobb-Douglas parameter (ι) is 0.6 and represents the share of labor in the production function.[22] The parameter estimate for lagged output gap (β_2) in the price Phillips curve is 0.09 with a 60 % credible set between 0.06 and 0.13.[23] This parameter value is quite similar to the estimate of Kortela, Oinonen and Vilmi (2018) for the euro area.

The parameter for the lagged output gap (γ_2) in the Okun's law equation is 0.11. The posterior distribution is tightly centered around the median (60 % credible set between 0.07 and 0.15). The parameter ω links the movements in TFP to the capacity utilization gap. The estimate for ω exceeds unity (2.2), which is reasonable since fluctuations in the manufacturing sector are higher than in the economy overall.

Estimation results for shock standard deviations are also intuitive, i.e. estimates are higher for shocks related to gaps than those related to trends. That is as expected. For example, the output gap fluctuates more than potential output.

In the wage Phillips curve, the data appear to be somewhat uninformative with respect to the parameter for the lagged unemployment gap (β_4). The parameter estimate is 0.49 with 60 % credible set between 0.27 and 0.68. The posterior mean is high compared, for example, to the

[18] In the framework, model is written in state-space form and Kalman filter is used. The posterior distributions of the parameters were simulated using Metropolis-Hastings algorithm. A precise description of the method can be found for example in Hamilton (1994), Andrle (2013) or Durbin and Koopman (2012).
[19] The parameters were estimated using Iris Macroeconomic modeling toolbox version 20151016. See https://github.com/IRIS-Solutions-Team/IRIS-Toolbox/wiki/IRIS-Macroeconomic-Modeling-Toolbox
[20] The average inflation rate in the sample refers to the annual underlying inflation as per HICP inflation, excluding energy and food.
[21] The number of accepted draws in the adaptive Metropolis-Hastings procedure for the posterior distribution was 2,500,000 after a burn-in of 2,500,000.
[22] We have applied a very tight prior to guide the share parameter close to the value calculated in the data.
[23] For those interested in the Phillips curve, see e.g. the discussion of Gordon (2011) on the history of Phillips curve.

estimates of Bonam, de Haan and van Limbergen (2018) for the five largest euro area countries.

The parameter κ (0.39) connects observed long-term unemployment to the unemployment trend. For example, if the data signals that the observed long-term unemployment rate has increased by 1 percentage point, it implies a 0.39 percentage-point increase in the long-term unemployment rate of the model framework.[24] Furthermore, this is connected with a temporary decrease in potential output by ¼ %, while a higher NAWRU implies a lower potential labor input. The magnitude of the drop in potential output is determined by the Cobb-Douglas share parameter.

For illustration, impulse responses for a temporary widening of the output gap (e.g. demand shock) are reported in Figure A2 of Appendix A. We observe that the widening of the output gap lowers the unemployment rate temporarily and leads, as expected, to higher inflation. A 1 % temporary increase in the output gap results in 0.2 percentage point peak effect in annual core inflation over the horizon of 1- 1.5 years. Nominal wages also rise, but with a longer lag. The lag in nominal wages results to lower real wages during the first 1.5 years after the initial shock as price inflation outpaces wage inflation. This is reversed after wages also pick up. Note that these nominal and real effects stemming from an initial increase in the output gap materialize only in the gaps, whereas e.g. potential output and the inflation trend remain unaffected.

[24] This estimate appears broadly in line with cross-country observations of the euro area after the global financial crisis. There are country differences, however. See chart 37 on the link between long-term and structural unemployment developments in the report of the Ad Hoc Team of the ESCB (2015).

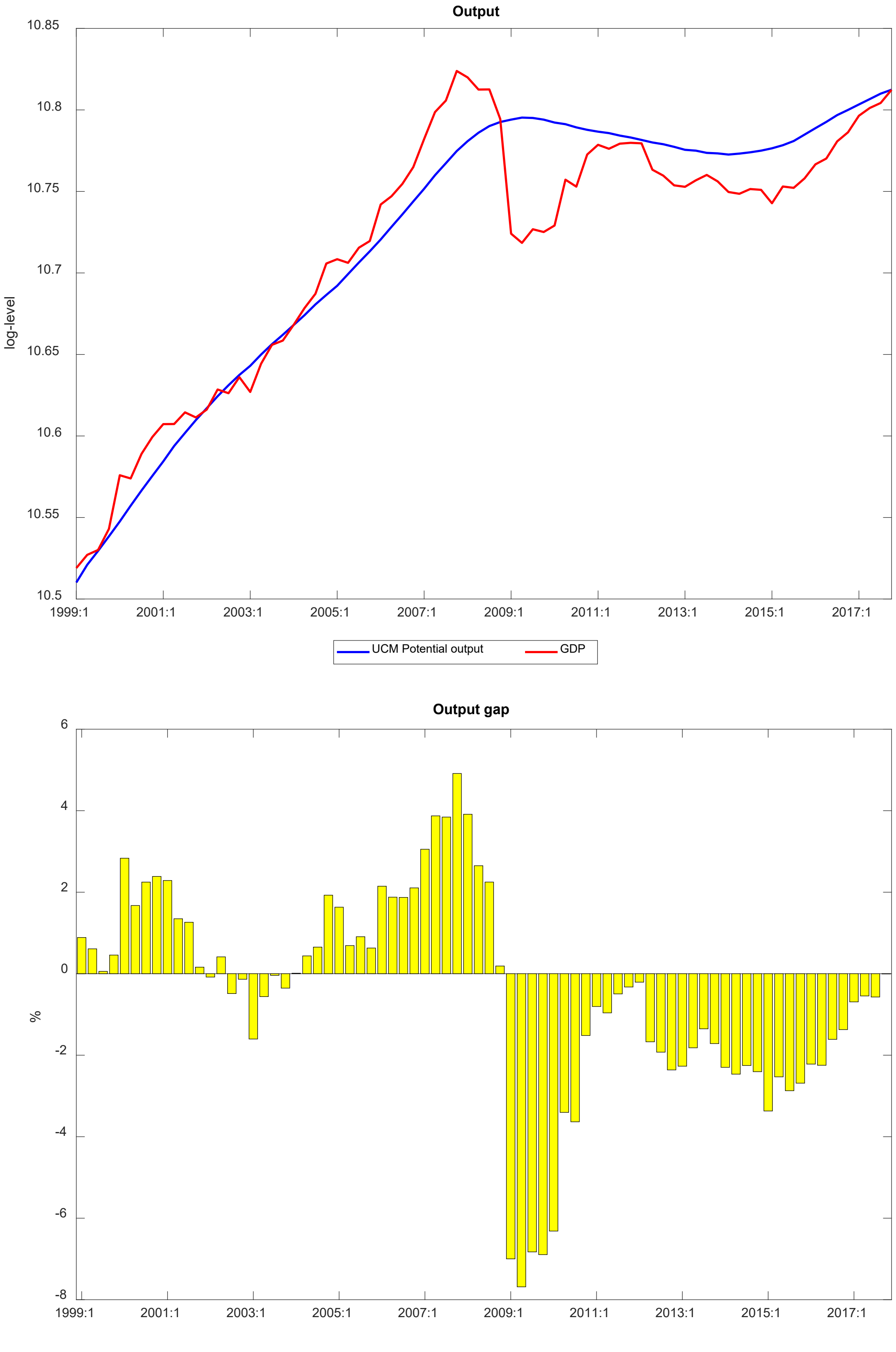
4.2 Estimates of potential growth, output gap and the NAWRU

In this section, we present the main results of the model. Besides reporting the potential growth and the NAWRU, we disaggregate potential growth into contributions of different production factors as implied by the model's production function. The results are discussed in light of the literature.

In line with the historical narrative, the model interprets the pre-financial-crises period as one of rapid growth of potential output (Figure 3). After the financial crisis, potential output growth slows significantly, while a negative output gap opens and output remains below potential for most of the decade.

In the early 2000s, potential output peaked at just over 3 % p.a. on the back of strong growth in total factor productivity. The opposite effect can be observed during the prolonged recession. As the crisis emerged, potential growth slowed. For several years, TFP contributed negatively to potential growth. The contributions from other supply factors (capital and labor) also weakened (Figure 4). While potential growth has gathered strength in recent years, it remains considerably lower than in the pre-crisis period. These results suggest that the lackluster economic growth and long recession cannot be explained entirely by cyclical factors.

Figure 3. Actual GDP, potential output (top) and output gap (bottom). UCM potential output refers to potential output produced by the model in log levels. Output gap is real GDP relative to potential output in percent.



Sources: Statistics Finland and author's own calculations.

The model does not provide explanations as to why TFP growth has been subdued since the financial crisis. Blanchard (2018), for example, discusses potential reasons that TFP might be affected by a recession. For example, if TFP is simply determined by R&D efforts, lower R&D could reduce TFP. Similarly, speed of adoption of inventions could slow in a recession and adversely affect TFP. Another suggested channel that could influence TFP is creative destruction, i.e. the reallocation of resources from low-productivity firms to high-productivity firms.

Given the importance of TFP, it is worthwhile to review several explanations provided in the literature. Anzoategui, Comin, Gertler and Martinez (2016) develop and estimate a model with endogenous TFP that considers both R&D and technology adoption. They argue that demand shocks have important supply-side effects as well. They note, for example, that in the US after the Great Recession slow speed of adoption of innovations is the reason for low TFP and it was caused by the recession. [25] Along similar lines applying an endogenous TFP model for the euro area, Schmöller and Spitzer (2018) find that the TFP slowdown that started in the early 2000s can be explained by the decrease in R&D intensity. After the Great Recession, a demand shock is identified as the main driver of weak endogenous TFP.

Foster, Grim and Haltiwanger (2014), for example, note that reallocation is closely linked with productivity in the US economy. Reallocation increases in recessions as firms with weaker productivity exit and more productive firms continue. Thus, reallocation improves productivity more in recessions than in normal times. Importantly, they note that the Great Recession was different in this respect as this normal "cleansing effect" was impaired. [26]

Fernald (2014) provides an alternative view for the TFP slowdown. He notes that the TFP slowdown in the US started prior to the Great Recession and TFP growth has merely settled back to more normal levels after the mid-1990s acceleration. Industry TFP data show that the exceptional TFP growth of early 2000s is linked to the industries using or producing IT. As Fernald notes: "By the mid-2000s, the low-hanging fruit of IT had been plucked."

Indeed, R&D investment seems to have diminished significantly in Finland. R&D expenditure stood at 5.2% of GDP in 2007–2010, but fell to 4.2 % during 2015–2017.[27] Reallocation of resources has also been witnessed in Finland as the labor share in high-productivity manufacturing has shrunk . Since 2008, the manufacturing sector has lost 90,000 jobs and the highly productive ICT-sector's share of total output has declined since the turn of the millennium. Empirical work on technology diffusion and the speed of adoption of innovation in Finland after 2008 might provide additional insight into sluggish TFP development.

Turning to our second supply factor, the capital stock, we observe that, despite the subdued level of investment seen during the recession, it contributed positively to the potential growth rate throughout 2000–2017. On the other hand, the capital stock's relative contribution to the potential growth rate declined quite significantly during the prolonged recession. Investment has since picked up, strengthening the capital base (Figure 4). All in all, the capital base

[25] Andrews, Criscuolo and Gal (2015) provide micro-evidence on OECD countries, noting that productivity growth at global frontier firms remained robust in the 2000s, while the productivity gap with other firms increased. This raises questions on the pace of technology diffusion.

[26] See Caballero and Hammour (1994) for early literature on the cleansing effect. They study how industry responds to demand fluctuations and note "…that the fact that job destruction is much more responsive than creation to the business cycle leads to the view that recessions are a time of cleansing, when outdated or unprofitable techniques and products are pruned out of the productive system."

[27] Research and development investments are detailed in Statistic Finland's Quarterly National Accounts under the time-series entitled "Cultivated assets and intellectual property products."

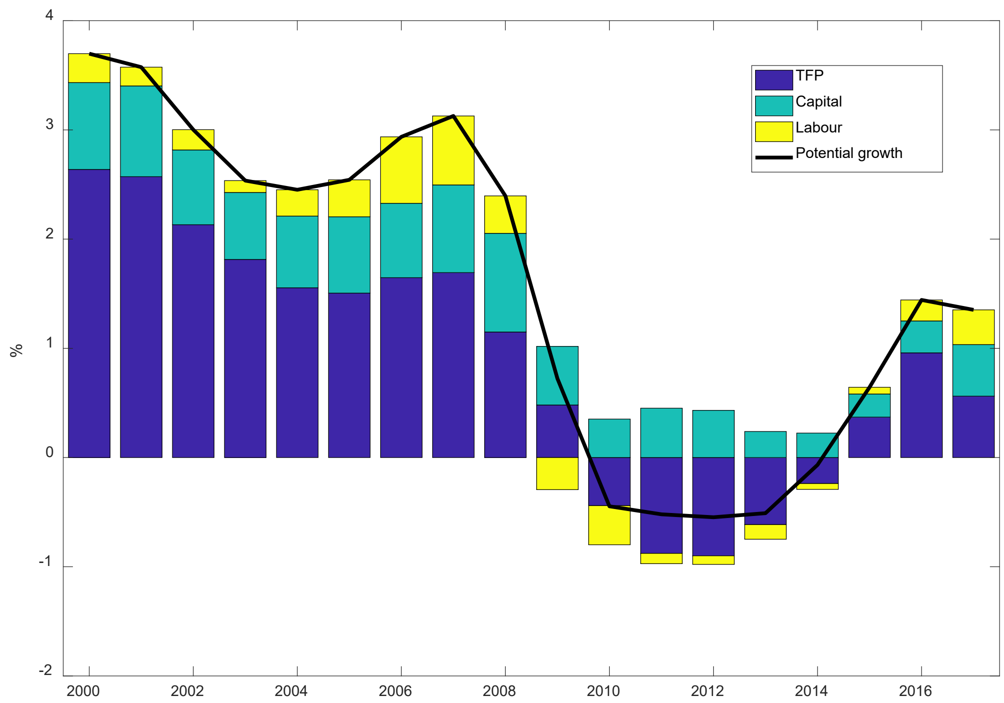
evolves slowly as new fixed capital investment is slightly offset by the rate of capital depreciation.

The increased uncertainty and weakening of corporate profitability that followed the financial crisis could explain the low level of investment activity seen in Finland in spite of accommodative financing conditions. Maliranta et al. (2017) point out that Finland's relative dearth of manufacturing investment is largely caused by subdued expectations with respect to productivity growth.

Recessions can also restrict growth in the capital stock when failed businesses are left with unused capital, effectively rendering part of the productive capital obsolete. Indeed, the diminution of Finland's mobile phone industry and subsequent contraction of the entire electrical engineering and electronics sector is undoubtedly part of the reason for the capital base's weaker growth since 2011.

The capital stock in the important and capital-intensive paper and pulp industry began to shrink in the early 2000s and gained steam after the financial crisis. Hence, the paper and pulp industry's contribution to the economy's total capital stock has been negative over the business cycle.

Figure 4. Contributions to potential growth.



The third supply factor, labor input, had a negative contribution to potential growth during the recession, albeit to a lesser degree than that of total factor productivity. Quite recently, however, labor has again started to support potential growth (Figure 5).

The aggregate contribution of labor input can be decomposed into changes in population, the participation rate, average hours worked and the NAWRU. Long-term trends can be identified in the components of labor input. The persistent decline in the average number of hours worked per employee has reduced the potential growth rate. Meanwhile, the 15–74-year-old working-age population, i.e. the potential pool of labor, has expanded and contributed to the volume of potential output. The decline in the participation rate has especially weakened potential growth since 2008; contraction in the labor force is both a consequence of the economy's double-dip recession and a natural result of population ageing as discussed in section 3.

The NAWRU has also increased slightly and weighed on the potential growth rate during the financial crisis (Figure 5). A high NAWRU estimate is consistent with the Bank of Finland's structural unemployment indicator, which is estimated using labor market flows (Bank of Finland Bulletin 2018). A prolonged recession can result in the long-term displacement of part of the labor force. Extensive periods of unemployment erode worker skills and turn cyclical unemployment into something persistent, raising the NAWRU (hysteresis). As noted by Obstbaum and Sariola (2017), a skills mismatch in the labor market or weakened incentives to work may also contribute to structural unemployment.

Figure 5. Labor contribution to potential growth.

Source: Author.

4.3 Comparison with other estimates

In this section, we compare the main results to the estimates produced by the IMF and the European Commission (Figure 6). While the general results of our unobserved component model (UCM), i.e. deceleration of potential output growth, large output gap swings and a high NAWRU, are broadly in line with the IMF and the EC, small differences emerge. For example, the UCM's estimate of the output gap peak preceding the global financial crisis was slightly smaller than the IMF estimate, while the trough of the output gap was deeper, reflecting slightly more rapid potential output growth before the crisis. Indeed, compared to the IMF and the EC estimates, potential output growth in the UCM model is somewhat faster in 2006 and 2007 and the subsequent deceleration more substantial.

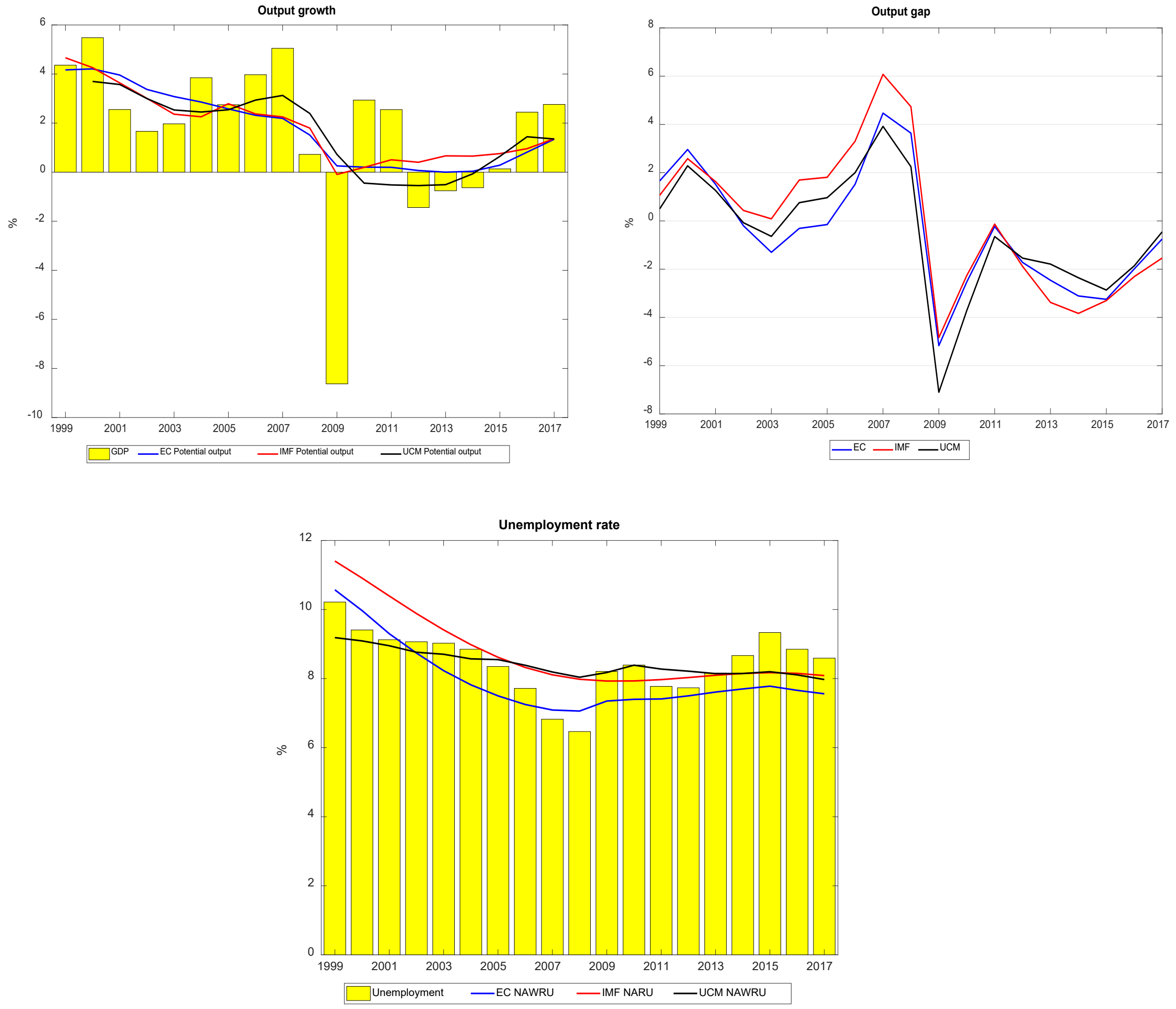
One narrative to support the path of potential growth depicted by the UCM is that the growth in the Finnish economy was dominated by the ICT sector (particularly Nokia) even in 2007. Up to that point, the tangible capital and human capital related to this industry were very productive.[28] In 2008, this turned around as new competing technologies unrelated to the global financial crisis emerged on the market. Along with a change in global preferences, the global demand shifted away from Finland. At least part of the old and previously highly productive capital (fixed and human capital) became obsolete and probably led to a rapid deceleration of potential growth, and perhaps even led to a level-shift in potential output.

Beyond the small ex-post differences between the UCM, the EC and the IMF estimates, it is important to note that the phase of the business cycle should be identified correctly in real-time if the estimate is to be useful for policymakers. Our UCM model, which incorporates resource utilization indicators (capacity utilization and long-term unemployment) is reliable in real time.[29]

Real-time and ex-post estimates of the output gap and the NAWRU by the UCM model are discussed in the next section and presented in Figure 7 (top). Our real-time estimates are robust and broadly in line with the ex-post estimates of the IMF and the European Commission. The real-time estimate of the output gap is reliable even in the event of a sharp business-cycle turning point such as the shift during the global financial crisis. This is not always the case, however. For example, in the spring 2008, prior to the global financial crisis, the European Commission's initial estimate of the Finnish output gap for 2007 was a negligible 0.8 % (although it was later substantially revised to over 4 %, implying a record boom in 2007).[30] In contrast, our UCM real-time estimate of the output gap in 2007 is slightly below 4 %, thereby signaling an overheated economy at that time.

[28] For example, Nokia made a *net profit* of EUR 8 billion in 2007.
[29] Note that the chosen resource-utilization indicators are subject to revisions only stemming from the seasonal adjustment. This helps us eliminate at least one source of real-time uncertainty.
[30] See real-time analysis of the EC method e.g. in McMorrow, Roeger, Vandermeulen and Havik (2015). For EC forecasts, see European Commission forecast spring 2008 (2008) and European Commission forecast autumn 2018 (2018).

Figure 6. Comparison with the IMF and the European Commission (EC).



Sources: IMF, European Commission (EC) and author.

4.4 Sensitivity analysis

The potential output model is also estimated without capacity utilization and long-term unemployment to assess the importance of the chosen resource-utilization indicators. This alternative specification reveals that the exclusion of those observables magnifies the end-point problem, making real-time estimates of the output gap less reliable. Thus, our UCM baseline hereafter only refers to a potential output model that includes both capacity utilization and long-term unemployment.

Real-time sensitivity analysis regarding the output gap and NAWRU is displayed in Figure 7 and Table 1. The real-time exercise is carried out with the baseline model (Figure 7, top), an alternative model without capacity utilization and long-term unemployment (Figure 7, middle) and with Hodrick-Prescott filter (Figure 7, bottom).[31] In the following graphs and tables, we call the HP filter estimates of the unemployment trend as NAWRU simply for the sake of comparison.[32]

In this exercise, both unobserved component models are estimated with the same data sample 1999Q1–2017Q4. [33] In Figure 7, real-time refers to estimates produced by adding new data quarter by quarter. Ex-post estimates are those acquired using the entire data set. Revisions to the output gap and unemployment trend estimates are measured as real-time minus ex-post (gray bars in Figure 7).

Baseline UCM produces output gap and NAWRU estimates with the smallest mean absolute errors. The baseline model gives the most reliable real-time estimates, which holds especially in times of rapid turns of the economy. Furthermore, real-time sensitivity analysis shows that even the alternative unobserved component model outperforms the HP filter estimates in terms of revisions.

Table 1. Revisions to estimates

	Output gap		NAWRU	
	MAE	RMSE	MAE	RMSE
UCM baseline	0.47	0.39	0.21	0.07
UCM alternative	1.14	2.64	0.25	0.10
HP filter	1.29	3.20	0.31	0.16

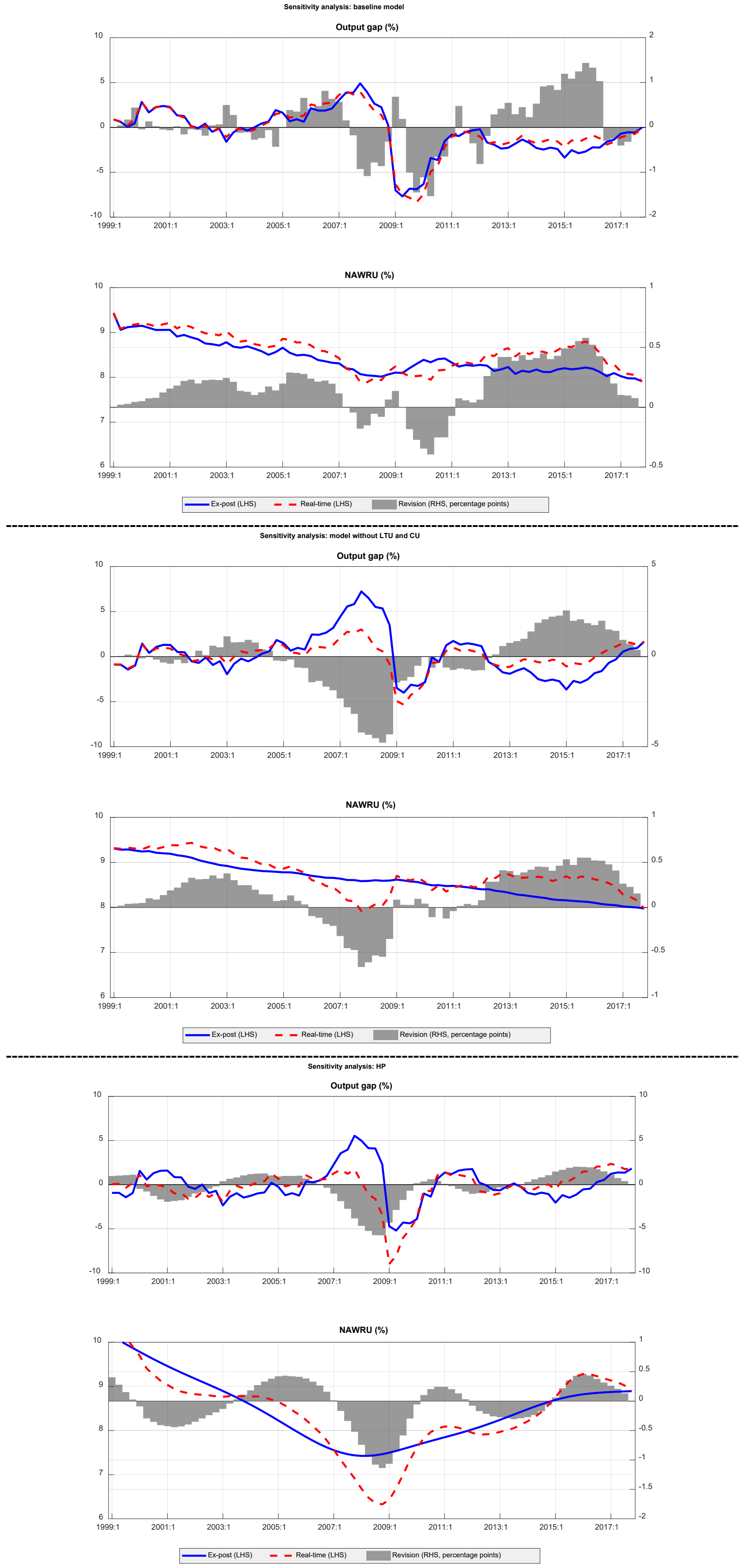
*MAE and RMSE refer to Mean Absolute Error and Root Mean Square Error, respectively. Revision for output gap is calculated using 100*log data. Hence, e.g. HP filter MAE for output gap indicates that in absolute terms average revision has been 1.29 percentage points. The UCM alternative does not include capacity utilization or long-term unemployment. Revision refers to "real-time" minus "ex-post" estimates, in other words, the difference in output gap estimate when the output gap is calculated by adding data quarter by quarter compared to the output gap estimate when the whole sample data set is available. The data sample is 1999Q1–2017Q4. Both UCM models are estimated one time using the entire data sample.*

A direct comparison of the baseline and the alternative unobserved component model results is displayed in Figure A1 of Appendix A. This ex-post comparison of the baseline and alternative unobserved component model shows that the alternative model's assessment of the size

[31] In this alternative model estimation, the same priors and the same number of draws and burn-in sample were used as in the baseline model.
[32] HP filter with smoothing parameter lambda =1,600.
[33] Both models were estimated using the entire sample. Hence, this exercise could be considered a pseudo real-time exercise. A full real-time exercise would require estimating model every time after adding a new quarter and using data series available at each particular point in time.

of output gap in the global financial crisis is smaller. Furthermore, the alternative model's output gap is clearly positive in 2011 – and hence far from the estimates of the IMF and the EC. The alternative model's NAWRU is more persistent compared with the baseline; the downward trend does not reverse even in the deep recession. In contrast, the baseline model's estimates point to an increasing NAWRU during the recession, a finding more in line with the assessment of the European Commission.

Figure 7. Real-time sensitivity analysis.



Revision refers to "real-time" minus "ex-post."

5. Conclusions

We presented a model of potential output for Finland that was based on an unobserved component model and a production function approach. The model features both price and wage Phillips curves, as well as an application of Okun's law that links the output gap to the unemployment gap. We show that incorporating resource-utilization indicators and long-term unemployment to the model improves the real-time reliability of the output gap and the NAWRU. Moreover, an advantage of the presented model is that the unobserved components of the economy's input factors can be inserted into a detailed production function to produce a simultaneous and coherent estimate of potential output.

Accurate, real-time assessment of an economy's resource utilization will always be challenging, irrespective of the method. Possible future explorations towards better understanding of endogenous TFP growth could include investigation of how additional observables (e.g. indicators for R&D, educational levels, innovation and technology diffusion) might be incorporated into the model to explain the evolution of potential TFP and further improve the robustness of results.

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Appendix A

Table A1. Data Sources

Indicator (1)	Source
Employment	Statistics Finland
Labor force	Statistics Finland
Hours worked	Statistics Finland
Unemployment rate	Statistics Finland
Real GDP	Statistics Finland
Total real capital stock (net)	Statistics Finland
HICP inflation excluding food and energy	Statistics Finland
Compensation of employees	Statistics Finland
Working-age population	Statistics Finland
Industry capacity utilization	Eurostat (EC survey question INDU_FI_TOT_13_QPS_Q)
Long term (1+ yrs) unemployment rate (of labor force)	Eurostat

(1) Data transformations are made to indicators in order to match model's measurement variable definitions.

Table A2. Estimation results for model parameters, structural parameters

Parameter	Prior distribution			Posterior distribution			
	type	mean	std	Mean	Median	20%	80%
α_1	Γ	1.5	0.5	1.12	1.12	1.04	1.22
α_2	Γ	0.5	0.3	0.27	0.27	0.18	0.36
ι	β	0.6	0.015	0.60	0.60	0.60	0.61
γ_1	β	0.5	0.25	0.68	0.71	0.55	0.84
γ_2	Γ	0.5	0.3	0.11	0.11	0.07	0.15
κ	Γ	0.5	0.3	0.42	0.39	0.23	0.58
λ	β	0.5	0.25	0.93	0.94	0.90	0.96
β_1	β	0.5	0.25	0.67	0.70	0.54	0.81
β_2	Γ	0.5	0.3	0.10	0.09	0.06	0.13
φ	β	0.5	0.25	0.56	0.58	0.37	0.76
β_3	β	0.5	0.25	0.44	0.44	0.31	0.56
β_4	Γ	0.5	0.3	0.49	0.49	0.27	0.68
ω	N	1	2	2.22	2.22	2.01	2.42

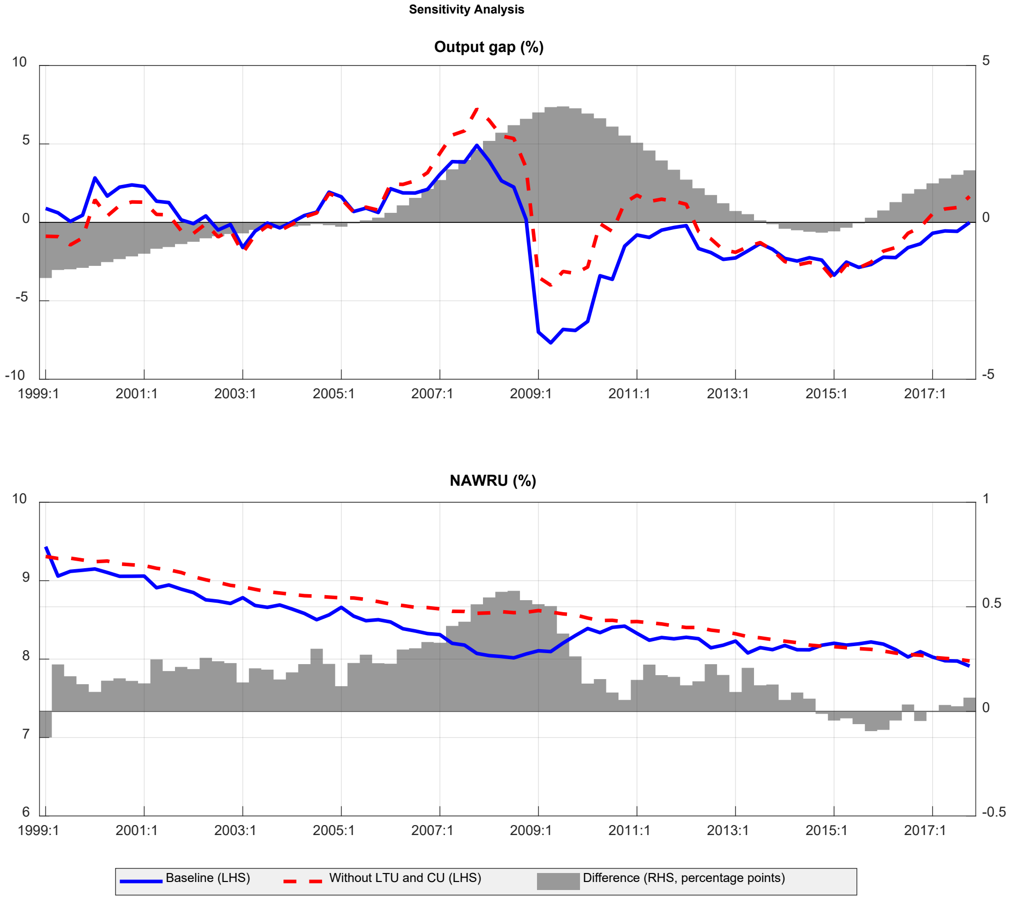
Number of accepted draws for the posterior distribution was 2,500,000 after burn-in of 2,500,000. In addition, ltu^* *and* π^* *were calibrated to their long-term averages of 0.0203 and 0.0149, respectively. Standard deviations of* $\varepsilon_t^{\tilde{k}}$ *and* $\varepsilon_t^{\widetilde{lan}}$ *were calibrated to 0.001.*

Table A3. Estimation results for model parameters, standard deviations

Parameter standard deviation	Prior distribution			Posterior distribution			
	type	mean	std	Mean	Median	20%	80%
$\sigma_{\varepsilon^{\hat{y}}}$	Γ^{-1}	1	inf	0.020	0.019	0.018	0.021
$\sigma_{\varepsilon^{\widetilde{tfp}}}$	Γ^{-1}	0.01	inf	0.001	0.001	0.0011	0.0016
$\sigma_{\varepsilon^{\hat{u}}}$	Γ^{-1}	1	inf	0.014	0.014	0.013	0.015
$\sigma_{\varepsilon^{\bar{u}}}$	Γ^{-1}	0.01	inf	0.002	0.002	0.002	0.002
$\sigma_{\varepsilon^{\widehat{lax}}}$	Γ^{-1}	1	inf	0.015	0.015	0.014	0.017
$\sigma_{\varepsilon^{\widetilde{lax}}}$	Γ^{-1}	0.01	inf	0.001	0.001	0.0010	0.0016
$\sigma_{\varepsilon^{\widehat{ahn}}}$	Γ^{-1}	1	inf	0.017	0.016	0.015	0.018
$\sigma_{\varepsilon^{\widetilde{ahn}}}$	Γ^{-1}	0.01	inf	0.001	0.001	0.0009	0.0015
$\sigma_{\varepsilon^{ltu}}$	Γ^{-1}	0.01	inf	0.002	0.002	0.002	0.002
$\sigma_{\varepsilon^{\hat{\pi}}}$	Γ^{-1}	1	inf	0.014	0.014	0.013	0.016
$\sigma_{\varepsilon^{\overline{\pi}}}$	Γ^{-1}	0.01	inf	0.002	0.002	0.002	0.003
$\sigma_{\varepsilon^{\hat{w}}}$	Γ^{-1}	1	inf	0.022	0.022	0.020	0.024
$\sigma_{\varepsilon^{\overline{w}}}$	Γ^{-1}	0.01	inf	0.003	0.003	0.002	0.004
$\sigma_{\varepsilon^{\widehat{cu}}}$	Γ^{-1}	1	inf	0.032	0.031	0.029	0.034

Number of accepted draws for the posterior distribution was 2,500,000 after burn-in of 2,500,000. In addition, ltu^* *and* π^* *were calibrated to their long-term averages of 0.0203 and 0.0149, respectively. Standard deviations of* $\varepsilon_t^{\tilde{k}}$ *and* $\varepsilon_t^{\widetilde{lan}}$ *were calibrated to 0.001.*

Figure A1. Baseline UCM results compared to model without capacity utilization and long-term unemployment



Source: Author.

Figure A2. Impulse response functions: output gap shock. Impulse responses are reported as percent deviations, excluding unemployment rate and annual inflation, which are reported as percentage points.

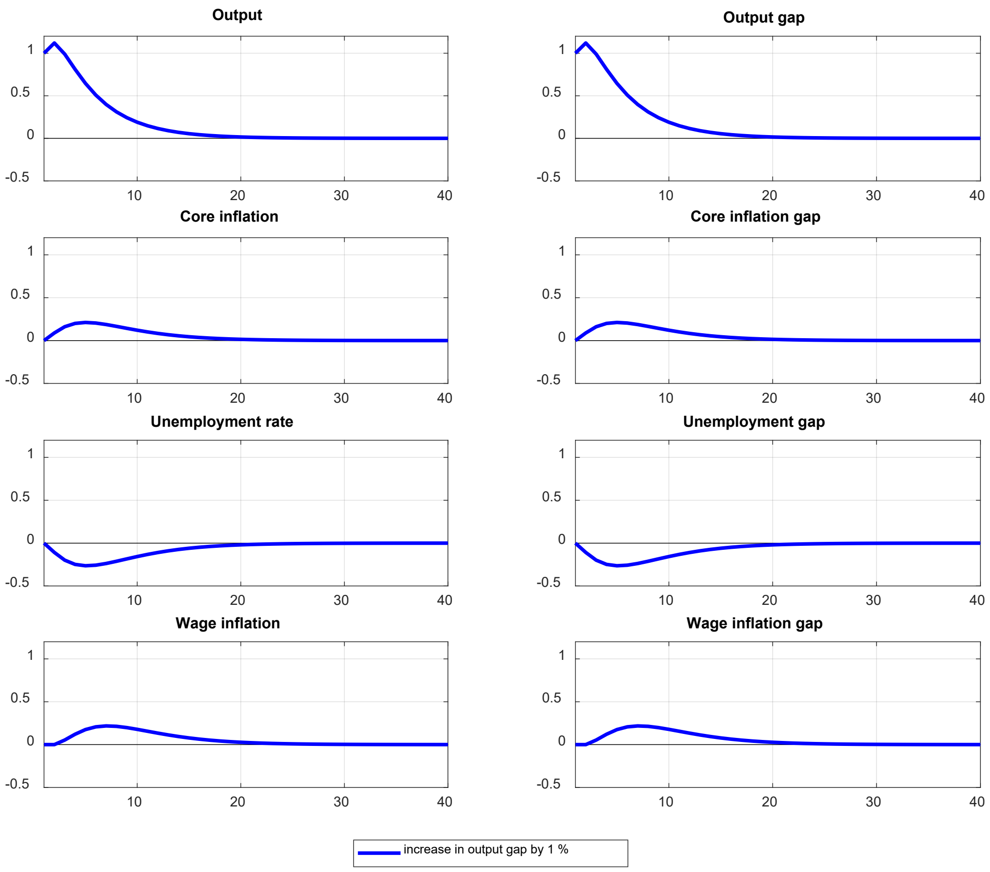
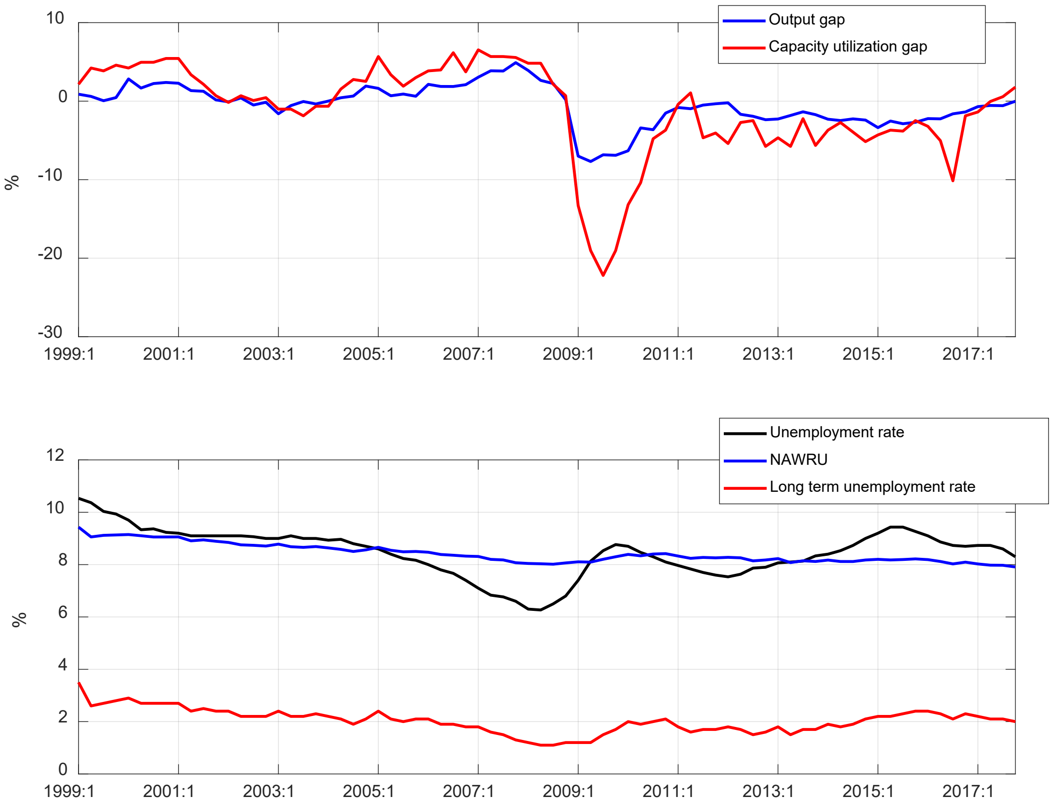


Figure A3. Resource utilization indicators. The capacity utilization gap refers to the manufacturing capacity utilization as a percentage of its long-term average rate. The long-term unemployment rate refers to long-term unemployed (over 12 months) as a share of the active population i.e. the labor force. The estimates of the output gap and the NAWRU are from the baseline UCM.



Sources: Statistics Finland, Eurostat and author's calculations.

Appendix B: Model equations and parametrization

Measurement equations

Y=Y_HAT+Y_BAR;

UNR=UNR_HAT+UNR_BAR;

LAX=LAX_HAT+LAX_BAR;

AHN=AHN_HAT+AHN_BAR;

LAN=LAN_;

K=K_;

PIE=PIE_HAT+PIE_BAR;

WIE=WIE_HAT+WIE_BAR;

LTU=LTU_;

CUGAP=omega*TFP_HAT+EPS_CU;

Transition equations

Y_HAT=alpha1*Y_HAT{-1}-alpha2*Y_HAT{-2}+EPS_Y_HAT;

Y_BAR=Y_BAR{-1}+Y_SFT+iota*(((LAN_)-(LAN_{-1}))+((LAX_BAR)-(LAX_BAR{-1}))+((AHN_BAR)-(AHN_BAR{-1}))+((log(1-UNR_BAR))-(log(1-UNR_BAR{-1}))))+(1-iota)*((K_)-(K_{-1}));

Y_SFT=Y_SFT{-1}+EPS_Y_SFT;

UNR_HAT=gamma1*UNR_HAT{-1}-gamma2*Y_HAT{-1}+EPS_UNR_HAT;

UNR_BAR=UNR_BAR{-1}+UNR_SFT;

UNR_SFT=kappa*((LTU_)-(LTU_{-1}))+EPS_UNR_SFT;

LAX_HAT=EPS_LAX_HAT;

LAX_BAR=LAX_BAR{-1}+LAX_SFT;

LAX_SFT=LAX_SFT{-1}+EPS_LAX_SFT;

AHN_HAT=EPS_AHN_HAT;

AHN_BAR=AHN_BAR{-1}+AHN_SFT;

AHN_SFT=AHN_SFT{-1}+EPS_AHN_SFT;

LAN_=LAN_{-1}+LAN_SFT;

K_=K_{-1}+K_SFT;

LAN_SFT=LAN_SFT{-1}+EPS_LAN_;

K_SFT=K_SFT{-1}+EPS_K_;

dY=((Y_BAR+Y_HAT)-(Y_BAR{-1}+Y_HAT{-1}));

TFP_HAT=Y_HAT-iota*(LAX_HAT+log(1-UNR_HAT)+AHN_HAT);

TFP_BAR=Y_BAR-iota*(LAN_+LAX_BAR+AHN_BAR+log(1-UNR_BAR))-(1-iota)*K_;

PIE_HAT=beta1*PIE_HAT{-1}+beta2*Y_HAT{-1}+EPS_PIE_HAT;

PIE_BAR=(1-phi)*phi0+phi*PIE_BAR{-1}+EPS_PIE_BAR;

WIE_HAT=beta3*WIE_HAT{-1}-beta4*UNR_HAT{-1}+EPS_WIE_HAT;

WIE_BAR=PIE_BAR+4*(((Y_BAR)-(Y_BAR{-1}))-(((LAN_)-(LAN_{-1}))+((LAX_BAR)-(LAX_BAR{-1}))+((AHN_BAR)-(AHN_BAR{-1}))+((log(1-UNR_BAR))-(log(1-UNR_BAR{-1})))))+EPS_WIE_BAR;

LTU_=(1-lambda)*ltu0+lambda*LTU_{-1}+EPS_LTU_;

Parameters

alpha1	1.1204
alpha2	0.2656
gamma1	0.7089
gamma2	0.1085
iota	0.6026
kappa	0.3913
beta1	0.6950
beta2	0.0890
phi0	0.0149
phi	0.5802
beta3	0.4433
beta4	0.4904
lambda	0.9356
ltu0	0.0203
omega	2.2194

std_EPS_CU	0.0314
std_EPS_UNR_HAT	0.0139
std_EPS_UNR_SFT	0.0019
std_EPS_Y_HAT	0.0193
std_EPS_Y_SFT	0.0013
std_EPS_LAX_HAT	0.0151
std_EPS_LAX_SFT	0.0012
std_EPS_AHN_HAT	0.0163
std_EPS_AHN_SFT	0.0011
std_EPS_LAN_	0.0010
std_EPS_K_	0.0010
std_EPS_PIE_HAT	0.0143
std_EPS_PIE_BAR	0.0022
std_EPS_WIE_HAT	0.0219
std_EPS_WIE_BAR	0.0031
std_EPS_LTU_	0.0019