Assessing the Potential Output for Switzerland: Determinants, trends and drivers*

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Abstract

Based on a novel data set for the productive capital stock and labor supply, we present a quarterly estimation of the Swiss potential output. We apply the production function methodology put forth by the European Commission to estimate the trend of total factor productivity and the natural rate of unemployment, obtained by means of unobserved component models. The estimates of potential output are compared to the analogous estimates for several industrialized economies and to the trends in real GDP extracted by means of alternative time series filters. We find that potential output growth neither features excessive volatility nor procyclicality. By means of a pseudo real-time revision analysis, we show that our production function based output gap aligns well with evidence previously found in the literature.

JEL class: E24, E32, E37

Keywords: Productivity trend, NAWRU, potential output, output gap

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1 Introduction

The output gap is one of the most important economic indicators for assessing an economy's position in the business cycle. It is therefore of crucial importance to policymakers when deciding on cyclical stabilization measures for the macroeconomy. While this measure has long been a mainstay of monetary policy decisions (Boschen et al., 1990), it has recently gained additional significance due to its adoption for fiscal policy decisions in many countries (all current EU member states) – both for the purpose of cyclical fiscal policies and public debt management (see Duarte Lledo et al., 2019, among others). Its increasing popularity and importance for policy continues to contrast, however, with the difficulties encountered in its measurement.

Formally, the output gap is defined as the (relative) difference between the actual level of output (that is, Gross Domestic Product, GDP) to an economy's potential output. While the former is measured directly and readily available–ignoring the recurrent data revisions–the latter is not. Consequently, the output gap is not based on directly measured quantities. The difficulty arises as to how to measure and identify the potential output. This is the focus of the present study.

As the potential output cannot be observed directly, it has to be estimated from the data. Consequently, any estimate of potential output is inherently subject to both model uncertainty and parameter uncertainty. Model uncertainty arises from the choice and specification of the model used, while parameter uncertainty stems from the estimation process itself. These uncertainties are compounded by data-induced revisions, which are often substantial (see Grigoli et al., 2015; Kangur et al., 2019, among others). It's important to note that while model uncertainty defines the concept of the output gap, it differs from estimation uncertainty. Model uncertainty pertains to the structure of the model itself, while estimation uncertainty relates to the accuracy of parameter estimates within the chosen model. Nevertheless, both types of uncertainty contribute to imprecise estimates of the output gap, introducing uncertainty regarding the economy's position within the business cycle.

This in turn requires statistical estimation which renders any estimate of the potential output subject to model uncertainty and parameter uncertainty. All of these are exacerbated by uncertainties arising from data-induced revisions which are in general substantial (see Grigoli et al., 2015; Kangur et al., 2019, among others). The uncertainties surrounding the estimation of the potential output map into imprecise estimates for the output gap which gives rise to uncertainties as to the position of the economy in the business cycle.

In this paper we address these problems. To this purpose, we present estimates of potential output for Switzerland according to the production function approach for the years 1980-2022. We rely on the version put forth by the European Commission (EC) outlined in Havik et al. (2014) and adapted to Switzerland by SECO as of the end of 2019.[1] This methodology features estimates of the trend in total factor productivity and the natural rate of unemployment (NAWRU) obtained by applying the Kalman filter to unobserved component models. We construct a consistent database to this purpose including quarterly time series for the productive capital stock and labor supply variables, starting as early as 1980, which forms the basis for the estimation of distinct potential output measures. We then test this methodology's ability to produce reliable measures for the potential output and the output gap alike. We focus on three aspects in this respect.

First, we compare the results from our baseline model to international evidence and alternative estimates for the potential output (and the output gap) obtained by the application of a series of univariate filters and a frequently used multivariate filter. We consider the following univariate models in this context: (i) Hodrick-Prescott (HP), (ii) Christiano-Fitzgerald (CF) and (iii) Hamilton (HAM) filter. The multivariate model follows the methodology of Alichi (2015) implemented at the IMF, including unemployment, inflation and the capacity utilization as exogenous variables. We apply each of the models to the quarterly time series of real GDP.

Second, we examine the sensitivity of the estimates for the potential output (and the output gap) with respect to the anchor values used for the non-accelerating wage rate of unemployment (NAWRU). As the anchor value shapes the convergence of the actual unemployment rate to its medium-run level, it hence comprises a crucial element for separating cyclical from trend fluctuations in the estimate for the potential output.

Third, we examine the changes in the estimates for the potential output (and the output gap) that arise due to ex-post data revisions in GDP. Our focus concerns an assessment of the extent of the revision in the output gap based on a real-time data set. This serves to examine the reliability of the output gap estimates in real-time, which is hence of crucial importance for practitioners.

Related literature. The poor quality of output gap estimates has been well documented in the literature. For instance, Nelson and Nikolov (2003) find that errors in real-time estimates of the output gap have likely contributed to monetary policy mistakes in the United Kingdom in the 1970s. In their second fiscal risks report, the Office for Budget Responsibility (2019) highlights output gap mis-measurement as a fiscal risk. Kangur et al. (2019) show that real-time output gap estimates exhibit large and negative biases and are not useful to predict inflation. Despite being widely used to formulate policy recommendations, initial output gap estimates are characterized by large uncertainty. This has been extensively documented in the literature. For instance, Orphanides and van Norden (2002) show

[1]The data are made available to the public on the website `https://www.seco.admin.ch/potential-growth`. It is updated quarterly with a delay of around 75 days.

how real-time estimates of the US output gap have often proven highly inaccurate. Ley and Misch (2013) highlight this phenomenon across a broad range of countries. In a somewhat related fashion Ho and Mauro (2016) find that long-term growth forecasts are upward biased ("optimism bias") which applies especially to countries whose recent growth performance was disappointing. Grigoli et al. (2015) show that there is a tendency of overestimating the extent of economic slack, especially during recessions, and that uncertainty in initial output gap estimates persists several years.

Albeit discussed controversially in the literature, the output gap and potential output play a highly important role in fiscal and monetary policy-making as well as in assessing the slack in the economy. We thus contribute to this vast and growing literature by providing a new and detailed measurement of the output gap for Switzerland along with potential output and its input factors. In the Swiss case, the Swiss National Bank (SNB) provides three measures of the output gap.[2] Apart from Leist and Neusser (2010), who estimate an output gap based on a DSGE model, we are the first to discuss in depth the characteristics of the Swiss potential output and its determinants. Moreover, with the newly established, publicly available data set, we contribute to the public good and debate.

The rest of the paper is structured as follows: Section 2 outlines the production function methodology as put forth by the European Commission to determine potential output. We then present the construction of the relevant input data along with the specification of the unobserved component models in Section 3. In Section 4, we report the resulting potential output for the Swiss economy along with its underlying determinants, together with the output gap. We discuss the robustness of these results in Section 5. Section 6 concludes.

2 The Production Function Methodology

In the following, we present the methodology to estimate potential output by means of a production function as implemented by the European Commission (Havik et al., 2014).[3]

2.1 Defining potential output

The aggregate production function models the current level of actual GDP, Y_t, using a Cobb-Douglas specification, with capital stock (K_t) and total hours worked (L_t) as factor inputs:

$$Y_t = TFP_t \cdot L_t^{\alpha} \cdot K_t^{1-\alpha}, \text{ where } \alpha \in (0,1). \tag{2.1}$$

[2] A production function based measure, an estimate from a multivariate unobserved components model and an HP-Filter based estimate. See https://data.snb.ch/en/topics/snb/chart/snbprodluch for details.

[3] The methodology is constantly being updated, refined and improved. This conceptual work is being carried out by the Output Gap Working Group (OGWG) in close cooperation with the EU member states. For a more detailed exposition and country-specific results, see Havik et al. (2014). See also Glocker and Kaniovski (2020b,a) for an evaluation of the Swiss case.

The production function shows constant returns to scale. This, together with the neoclassical assumption that factor inputs are paid their marginal products, implies constant shares of income spent on each factor. These shares are equal to the respective output elasticities of labor, α, and capital, $1-\alpha$.[4] Based on a panel-econometric estimate of the average output elasticities of labor of 0.63 for the EU15 member states between 1960-2003, and the observation that estimates of the output gap are not overly sensitive to the choice of α, the methodology sets $\alpha = 0.65$ for all member states (see p. 10 in Havik et al. (2014)). In the case of Switzerland, the average share of compensation of employees in GDP at current prices between 1980 and 2021 equals 0.56. Once the labor share is adjusted for the income of self-employed, the share increases to 0.61 on average. The adjustment assumes that the average wage of self-employed is identical to that of employees. For reasons of comparability, we thus retain the value of the output elasticity of labor assumed by the EC.[5]

The observed total factor productivity (TFP_t) represents the part of the actual output which cannot be explained by the labor and capital input. The growth rate of the observed total factor productivity is usually called the Solow Residual, or the part of growth in real GDP that is not explained by changes in labor and capital used in production.

The Cobb-Douglas functional form entails the equivalence of the Hicks-neutral and factor-augmenting technical change. This implies that the observed total factor productivity TFP_t conflates the efficiency in the use of the two inputs (EL_t, EK_t) with the degree of their utilization (UL_t, UK_t),

$$TFP_t = \underbrace{EL_t^{\alpha} \cdot EK_t^{1-\alpha}}_{trend} \cdot \underbrace{UL_t^{\alpha} \cdot UK_t^{1-\alpha}}_{cycle}, \tag{2.2}$$

or, taking the natural logarithms,

$$F_t \equiv \log(TFP_t) = \underbrace{\log(EL_t^{\alpha} \cdot EK_t^{1-\alpha})}_{f_t} + \underbrace{\log(UL_t^{\alpha} \cdot UK_t^{1-\alpha})}_{c_t}. \tag{2.3}$$

Neither of the two components can be observed. Identifying the trend f_t thus requires removing cyclical fluctuations in the two input factors L_t and K_t given by c_t.

To identify the average utilization of labor, we first decompose total hours worked:

$$L_t = POP_t \cdot PRT_t \cdot (1 - U_t) \cdot H_t, \tag{2.4}$$

where POP_t denotes the working population aged 15+ (labor force), PRT_t the participation rate in percent of the labor force, U_t the unemployment rate and H_t the hours worked per

[4]See for instance Zellner et al. (1966); Douglas (1976).

[5]Figure 11 in the Appendix shows the adjusted share of compensation of employees in GDP at current prices between 1980 and 2021. During this period the share increased, on average, by 0.24 percentage points per year. The small size of this drift makes the technical assumption of a constant labor share tenable. Moreover, based on estimates of the Federal Statistical Office (FSO), the average share of costs in total factor productivity between 1995 and 2021 has been 65.4% (see: Bundesamt für Statistik - WPS).

person employed, i.e., employees and self-employed persons. The above definition uses the identity $LS_t \cdot (1 - U_t) = LD_t$, involving the labor supply LS_t, the number of persons employed LD_t and the unemployment rate U_t. Then,

$$L_t = POP_t \cdot \underbrace{\frac{LS_t}{POP_t}}_{PRT_t} \cdot (1 - U_t) \cdot \underbrace{\frac{L_t}{LD_t}}_{H_t}. \tag{2.5}$$

The capital stock, K_t, describes the available inventory of gross fixed assets. It is accumulated using a perpetual inventory method. The EC methodology does not model capital utilization directly; formally, $\bar{K}_t = K_t$. Any cyclical fluctuations in capital utilization are assumed to be removed by the cyclical adjustment of the total factor productivity in the decomposition (2.2).

Potential output, $\bar{Y}_t$, is defined as the level of output associated with constant (wage) inflation. It is defined as:

$$\bar{Y}_t = f_t \cdot \bar{L}_t^{\alpha} \cdot \bar{K}_t^{1-\alpha}, \tag{2.6}$$

in which $\bar{L}_t$ is the trend component given by the variables of equation 2.4. Except of population, all other quantities to determine trend labor input experience business cycle fluctuations that must be removed when computing their trends. With respect to determining the trend of the participation rate and the average working hours, the EC methodology follows a pragmatic approach by applying the Hodrick and Prescott (1997) filter. The value of the smoothing parameter $\lambda = 1600$ is set following the recommendations for the quarterly data in Baxter and King (1999). The trend of the unemployment rate $\bar{U}_t$ is defined as the non-accelerating wage rate of unemployment (NAWRU), denoted by ν_t, which is the dominant macroeconomic equilibrium concept for the labor market (Layard et al., 2005).

The output gap as the relative deviation of real GDP from trend output describes the aggregate capacity utilization, such that a positive output gap indicates over-utilization and rising inflationary pressures, which should ease once the capacity becomes underutilized. It can be derived by:

$$GAP_t = 100 \cdot \frac{Y_t - \bar{Y}_t}{\bar{Y}_t}. \tag{2.7}$$

The contributions of labor and capital to the growth of potential output are defined as follows:

$$l_t = 100 \cdot \alpha \frac{\bar{L}_t - \bar{L}_{t-1}}{\bar{L}_{t-1}}, \quad \text{where} \quad \bar{L}_t = \overline{POP}_t \cdot \overline{PRT}_t \cdot (1 - \nu_t) \cdot \bar{H}_t, \tag{2.8}$$

$$k_t = 100 \cdot (1 - \alpha) \frac{K_t - K_{t-1}}{K_{t-1}}. \tag{2.9}$$

The contribution of TFP is computed as a remainder:

$$f_t = g_t - l_t - k_t, \quad \text{where} \quad g_t = 100 \cdot \frac{\bar{Y}_t - \bar{Y}_{t-1}}{\bar{Y}_{t-1}}. \tag{2.10}$$

It has to be acknowledged that the production function outlined here abstracts from different elements frequently discussed in the literature (see Colacchio and Soci (2003) for a critical discussion, among others). For instance, the fact that the production function does not include exogenous or endogenous determinants of technical change such as R&D stock or human capital makes the model unsuitable for a causal analysis of the drivers of TFP growth. This caveat limits the usefulness of the model for long-term forecasts and scenario analyses, where the endogenous determinants of technological change are expected to be relevant. The focus of the EC method is on short to medium-term forecasts, and an univariate extrapolation of the current TFP trend is appropriate within this narrow context. The second caveat relates to the limited selection of input factors, which, for example, excludes energy. The reason for this limited selection goes back to the fact that the EC methodology uses short-term expert forecasts as an input, and such forecasts typically exclude energy and other factors of production. In summary, the EC methodology is suitable for insample analysis – such as the one presented here – up to medium-term forecasts, given the high persistence of the TFP trend; but it is clearly unsuitable for a causal analysis of the determinants of TFP growth in the past and for long-term forecasts where endogenous determinants of TFP growth should be taken into account.

2.2 The unobserved component model

The trends in total factor productivity and the natural rate of unemployment (NAWRU) are estimated using unobserved component models. The following example of a simple unobserved component model splits the main observable variable into a trend and a cycle. The cycle is assumed to be influenced by another observable variable. This adds a second measurement equation to the system. The model can include exogenous variables. For example, a typical backward-looking Phillips curve may include changes in terms of trade, labor productivity and the labor share as exogenous variables.

Consider a simple canonical unobserved component model:

$$X_t = f_t + c_t\,, \quad \text{first measurement} \tag{2.11}$$

$$\Delta f_t \sim N(\mu, \sigma^2_{a^p}) \qquad \text{trend}\,, \tag{2.12}$$

$$\left.\begin{aligned} c_t &= \phi_1 c_{t-1} + a^c_t \sim N(0, \sigma^2_{a^c}) \\ Y_t &= \mu_y + \beta c_t + a^y_t \sim N(0, \sigma^2_{a^y}) \quad \text{second measurement} \end{aligned}\right\} \quad \text{cycle.} \tag{2.13}$$

The first measurement equation decomposes the observed variable X_t in an unobserved trend f_t and an unobserved cycle c_t. The trend is a simple (Gaussian) random walk with drift that fluctuates around a deterministic linear trend with the slope μ. This specification implies an $I(1)$ process for the trend. The cycle is an $AR(1)$ process with a (Gaussian) white noise error. Each error term is assumed to be independent and identically distributed, but the distributional parameters of error terms can differ in the cross-section. For example, in the case of the TFP trend, $X_t = \log(TFP_t)$ (the observed total factor productivity) and $Y_t = CU_t$ (rate of capacity utilization). In the case of the NAWRU, $X_t = U_t$ (actual unemployment rate) and in the spirit of a typical backward-looking Phillips curve, $Y_t = \Delta^2 W_t$ (change in wage inflation). Since the cycle feeds into an observable variable Y_t, the above system has two measurement equations and two state equations. Additionally, the model can include exogenous variables.

The above model can be extended in several ways, each of which potentially allows to better capture the complex dynamics of observed and unobserved time series. The assumption of a deterministic trend can be relaxed by replacing a random walk having a constant drift (RW drift) with a nested random walk. The 2^{nd} order random walk implies a more erratic stochastic trend that may be more appropriate for capturing multiple overlapping aggregate shocks to an economy. This specification is given by

$$\left.\begin{aligned} \Delta f_t &= \eta_{t-1} + a_t^f \\ \Delta \eta_t &= a_t^\eta \end{aligned}\right\} \qquad \text{trend } (2^{nd} \text{ order RW})\,, \tag{2.14}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{2.15}$$

We can further enrich the trend by including a damping term. The damping helps to produce a smoother trend that is still sufficiently flexible. We have,

$$\left.\begin{aligned} \Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^\eta \end{aligned}\right\} \qquad \text{trend (Damped)}\,, \tag{2.16}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{2.17}$$

The parameter ρ influences the long-run (gain) value of Δf_t as a result of a random shock a_t^η. The 2^{nd} order random walk is an $I(2)$ process. The damped trend is a random walk with a stationary $AR(1)$ drift. The resulting trend process is $I(1)$.

The flexibility of the unobserved cycle c_t influences the smoothness of the unobserved trend f_t, since the two add up to the observable variable X_t. We expect a quarterly model to require more lags in order to adequately capture the higher cyclical variation observed in the quarterly data than a model based on annual data. The minimal adequate specification for the cycle is $AR(1)$. This already introduces a degree of persistence assumed to exist in the unobserved cyclical variation. The inclusion of a second lag is a valid approach to improve the fit. We have,

$$c_t = \phi_1 c_{t-1} + a_t^c \text{ and } c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + a_t^c, \text{ where } a_t^c \sim N(0, \sigma^2_{a^c}). \tag{2.18}$$

The fit of the second measurement equation depends on the lag structure and the error process. We include 0-2 lags of the dependent variable and 0-4 lags of the cycle for a total of 15 distinct lag structures for this equation. In the order of increasing complexity,

$$Y_t = \beta_1 c_t + a_t^Y \,, \tag{2.19}$$

$$Y_t = \alpha_1 Y_{t-1} + \beta_1 c_t + a_t^Y \,, \tag{2.20}$$

$$\dots \tag{2.21}$$

$$Y_t = \mu_Y + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \tag{2.22}$$

$$+ \beta_1 c_t + \beta_2 c_{t-1} + \beta_3 c_{t-2} + \beta_4 c_{t-3} + \beta_5 c_{t-4} + a_t^Y \,. \tag{2.23}$$

Finally, the Gaussian white noise model for the error term in the second measurement equation can be replaced by an $MA(1)$.

The chosen model is estimated using the method of Maximum Likelihood by the application of a Kalman filter. The maximum of the likelihood function is obtained using sequential quadratic programming.[6]

The modeling tool provided by the European Commission offers a finite set of model parametrizations for the NAWRU and the TFP equations. This motivates our model selection procedure as an exhaustive specification search on the set of all feasible specifications for a given set of explanatory variables described in Section 3.2 below. The EC estimates the above unobserved component models using a Bayesian approach, which has some advantages.[7] Nevertheless, the frequentist approach is generally more scalable to large numbers of candidate models due to less computational demand per model. The high computation demand per model is the main reason why the European Commission and the member states estimate the relatively more complex NAWRU model using a frequentist approach. An exhaustive specification search over a large set of potential models cannot be reasonably performed using a Bayesian approach with informative priors, given the need to tune the prior distribution for each specification. We therefore opted for a frequentist estimation using the Kalman filter.[8]

[6]For a technical documentation, see Planas and Rossi (2010).

[7]For example, one advantage of a Bayesian approach is that the bounds imposed on the various parameters of the model in the Maximum Likelihood estimation can be relaxed using prior distributions, effectively eliminating any boundary solutions for the estimates.

[8]We estimate the models using the software R. In particular, our routines are based on the package "RGap" (Streicher, 2022). The software renders equal results to the existing software by the European Commission, however its easier and more transparent in use, particularly in recursive applications.

3 Data and model specification

In the following, we first describe how we construct the data set for the estimation of the Swiss potential output. Second, we elaborate on how the unobserved component models are set up to estimate the NAWRU and the trend component of TFP.

3.1 Construction of input data

Swiss quarterly GDP is available since 1980. In order to provide estimates for potential output and the output gaps since 1980, we need to construct the input series. Where available, quarterly data are drawn directly from their original sources such as GDP from SECO or employment from FSO.[9] Nevertheless, in their original sources both the labor input and the capital stock are only available at an annual frequency, in both cases starting later than 1980. Moreover, prior to 1990 the availability of quarterly data with respect to the labor market is rather scarce in the case of Switzerland. Therefore, we have put particular emphasis in constructing proper quarterly series for capital and labor spanning as far back as possible. Additional data, e.g. the measure of aggregate capacity utilization, are drawn from national sources. The appendix provides a list of variables required for estimating the potential output (see Appendix A1).[10]

To ensure comparability with the current estimates of the NAWRU anchor by the EC, we add the Swiss data to the sample of old EU member states. The Swiss data used to obtain an estimate of the NAWRU anchor were sourced from several OECD databases, including the Labor Statistics, the Main Economic Indicators (MEI) and the Structural Policy Indicators Database for Economic Research (SPIDER). The variables and data sources for the anchor estimate are provided in the appendix (see Table 10).

Data editing requires retropolation and interpolation at various points. With this in mind, we highlight the potential implications of these adjustments, as they may lead to discrepancies between the performance of the model under review and the reliability perceived by policymakers.

3.1.1 Labor supply

The estimation of the production function takes into account the labor input measured by the total hours worked, i.e., the actual labor volume L_t. Total hours worked are given by

[9] SECO: Swiss State Secretariat for Economic Affairs; FSO: Federal statistics office. If not stated otherwise, we use the real, seasonally, calendar and sport event adjusted GDP as of 2022:Q3. For more information on the importance of sport related events in GDP and their adjustment consider `https://www.seco.admin.ch/gdp`.

[10] On an annual basis, the EC gathers and provides data on the AMECO database. For Switzerland, many series are also provided there, in particular annual macroeconomic data from the National Accounts.

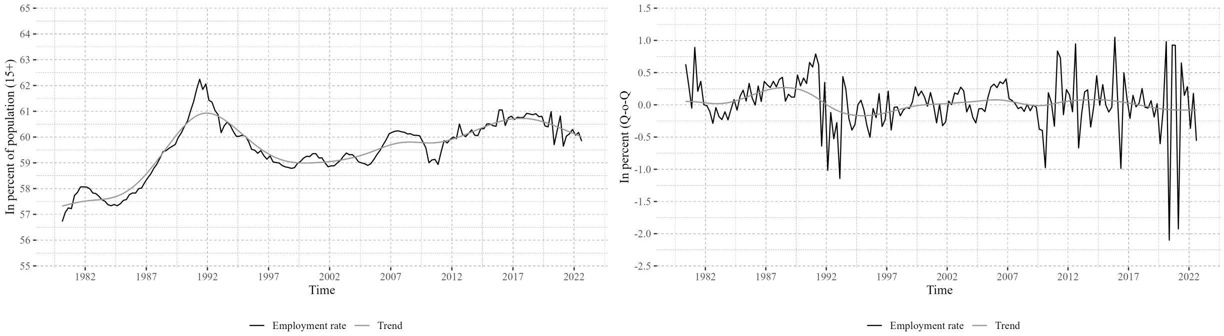
$L_t = l_t \cdot h_t$, in which l_t equals the number of employed persons in full-time equivalents (90% - 100%, FTE), and h_t equals the average hours worked per employed person in FTE. On an annual basis, the actual volume of work is surveyed and published by the FSO as part of the Swiss Labor Force Survey (SLFS, AVOL, 1991-2021). In order to obtain a quarterly time series from 1980 onward, the series must first be retropolated and then be temporally disaggregated. We proceed as follows: (*i*): The annual series for hours worked is extended back to 1975 with data from Siegenthaler (2015); (*ii*): The annual volume of work is broken down into its components l_t and h_t on an annual basis, where h_t is determined as residual; (*iii*): Retropolate the number of employed persons in FTE, l_t, (annual frequency) until 1975 with internal historical data; (*iv*): Temporally disaggregate l_t with the employment statistic (source: FSO) according to the domestic concept (i.e. people employed in Switzerland). This statistic is available since 1975 on a FTE basis. A detailed list of data sources is provided in Appendix Table 8.

In addition, in order to take into account the important role of cross-border commuters in the Swiss context, equation 2.4 has to be slightly reformulated. We thus define:

$$L_t = l_t \cdot h_t = L_{s,t} \cdot (1 - u_t) \cdot h_t = prt_t \cdot pop_t \cdot (1 - u_t) \cdot h_t. \tag{3.1}$$

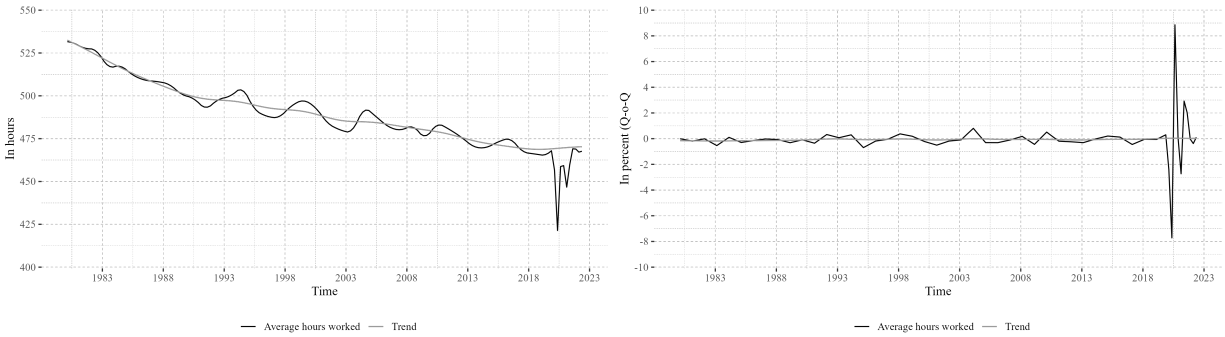
We can further disentangle the previous equation into $l_t \cdot h_t = [(L_{s,t}^{CH}) \cdot (1 - u_{ft,t}) + cbc_t] \cdot h_t = [prt_t^{CH} \cdot pop_t \cdot (1 - u_{ft,t}) + cbc_t] \cdot h_t$, where $L_{s,t}^{CH}$ is the domestic labor force excluding cross-border commuters, $u_{ft,t}$ is the unemployment rate including partial unemployment, cbc_t the amount of cross-border commuters in FTE, prt_t^{CH} the domestic participation rate and pop_t the working age population (15+). As no data for the unemployment rate in full-time equivalents are available, we simplify the expression above and use $L_{s,t}$ as the labor force including cross-border commuters and u_t as the unemployment rate. For the estimation of the NAWRU according to the EC method from 1980 onward, certain series are needed further back, since they are included in first and second differences. Therefore, numerous variables are directly retropolated to 1975.

Figure 1: Participation rate



The trend is extracted using the HP filter with $\lambda = 1600$ (grey). The right panel shows the corresponding quarterly growth rates.

Figure 2: Average hours worked

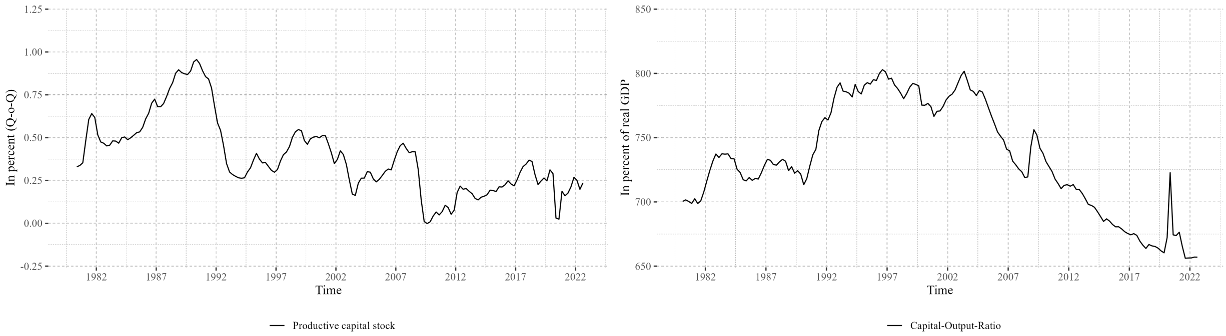


The trend is extracted using the HP filter with $\lambda = 1600$ (grey). The right panel shows the corresponding quarterly growth rates.

Figures 1 and 2 show the participation rate prt_t and the average hours worked per employed person together h_t with the trends extracted by the application of the HP-filter. The recession of the early 1990s is clearly visible in both series. Note the spike in the participation rate in 1990. The recent participation rates are nearly constant or slightly decreasing, as is also seen in most of European countries. The average hours worked have been on a nearly continuous decline, reflecting the trend to more part-time work and more holidays.

From 2020 to the begin of 2022, hours worked remained on markedly lower levels due to short-time work in the wake of restrictions such as shop-closing orders. We assume that the loss of hours due to short-time work during the Covid-19 pandemic did not affect the potential hours worked. The trend of hours worked is, therefore, obtained by applying the HP-filter to a series of hours worked including short-time work.

Figure 3: Growth of capital stock and the capital coefficient



3.1.2 Capital Stock

The effective capital input, K_t, is obtained from the mean *productive* capital stock, K_{Prod}, of periods t and $t-1$, as the capital stock measures end-of-period stocks. In particular,

$$K_t = \frac{K_{Prod,t} + K_{Prod,t-1}}{2}, \tag{3.2}$$

The aggregate productive capital stock consists of the capital stock of fixed assets $K_{A,t}$ plus that of buildings, excluding residential buildings, $K_{BX,t}$, such that

$$K_{Prod,t} = K_{BX,t} + K_{A,t}, \tag{3.3}$$

Residential construction $K_{W,t}$ is excluded from the construction aggregate $K_{B,t}$ because it does not contribute to productive capital. Residential construction is a service in the broader sense and does not serve production. It holds that $K_{BX,t} = K_{B,t} - K_{W,t}$. The capital stocks $K_{A,t}$ and $K_{BX,t}$ are calculated using the *Perpetual Inventory Method* (Berlemann and Wesselhöft, 2014). Therefore, today's capital stock consists of the capital stock of the previous period $t-1$, reduced by the depreciation rate $\delta_{i,t}$, plus the new investments $I_{i,t}$:

$$K_{A,t} = K_{A,t-1} \cdot (1 - \delta_{A,t}) + I_{A,t}, \tag{3.4}$$

$$K_{BX,t} = K_{BX,t-1} \cdot (1 - \delta_{B,t}) + I_{BX,t}. \tag{3.5}$$

In order to obtain a quarterly series for the capital stock starting in 1980, the following steps are necessary: (*i*) retropolate nominal and real investment in residential construction $I_{W,t}$ back until 1980 with historical data; (*ii*) Derive a historical series for productive construction investment $I_{BX,t} = I_{B,t} - I_{W,t}$; (*iii*) construct capital stocks for fixed assets and construction based on historical data; (*iv*) derive implicit depreciation rates; (*v*) apply temporal disaggregation methods to the annual series; (*vi*) apply recursively the perpetual inventory method. The detailed data sources are reported in Appendix Table 9.

Figure 3 shows the quarterly growth of the capital stock and the capital coefficient, defined as $100 \cdot K_t / Y_t$ since 1980. It shows a sizable reduction in the growth rate of the capital stock during the recession of the 1990s. Since the mid-1990s, the average annual growth of capital stock was lower than that of real GDP, which resulted in a downward trend of the capital coefficient. Following the global financial and economic crisis of 2008, the ratio of capital to GDP has not risen to the extent one would expect it to rise during a recovery. Between 1980 and 2021, the Swiss productive capital stock grew with a compound annual rate of 1.6 percent. Considering only the period after the crisis of 2008, the rate was substantially lower at 0.7 percent. The evolution of the ratio of the capital stock to real GDP paints a similar picture. The capital coefficient grew at an average rate of 0.2 percentage points of real GDP per year prior to the crisis (1980-2007). After the crisis, the ratio decreased at an average rate of -0.7 percentage points of real GDP per year.

3.2 Estimation of Unobserved Component Models

The unobserved component models outlined in Section 2.2 can be cast into a state space representation and subsequently estimated using the Kalman filter. The search for an optimal pair of NAWRU and TFP trend models. The defined optimal model is the one that minimizes the volatility and procyclicality of potential growth and maximizes the persistence of the TFP trend. Low volatility and procyclicality are standard requirements mentioned in the literature (Seco Justo and Szörfi, 2021; Casey et al., 2021), whereas the persistence of the TFP trend is inspired by models of economic growth in which technological progress is modeled as a persistent AR(1) process.

The formal model selection criteria involve volatility and procyclicality of potential output growth and the persistence of the TFP trend. Let Δf_t, $\Delta \bar{Y}_t$, ΔY_t be the growth rates of the TFP trend, potential output, and real GDP:

1. **Volatility** of potential output growth: $\sigma_{\Delta \bar{Y}_t}$,
2. **Procyclicality** of potential output growth: $\rho(\Delta \bar{Y}_t, \Delta Y_t)$,
3. **Persistence** of the TFP trend: $\rho(\Delta f_t, \Delta f_{t-1})$,

where $\rho(\cdot,\cdot)$ is the coefficient of correlation.[11] If no single pair of NAWRU and TFP models optimizes all criteria simultaneously, models with the lower BIC values are selected from the set of pairs that optimize at least one criterion. The BIC is a popular model selection criterion that balances the performance of a model and its complexity measured by the number of parameters in the model. The final step involves checking the usual regression diagnostics such as the (pseudo) R^2 as a conventional fit measure for a model with an unobserved

[11] All correlation coefficients discussed in this report are the Pearson product-moment coefficients.

component, which reflects the one-step prediction error of the model, autocorrelations in the residuals and finally the overall plausibility of the selected pair of TFP and NAWRU models.

In the following we present the models estimated with data spanning from 1978:Q1 to 2022:Q3 for the NAWRU, respectively starting in 1980:Q1 for the TFP trend.

3.2.1 Observed unemployment rate and NAWRU

The existing approaches for modeling the NAWRU and its companion concept of the non-accelerating inflation rate of unemployment (NAIRU) come in many flavors. Structural specifications of a Phillips curve view inflation as a function of discounted expected future marginal costs, where unobservable marginal costs are approximated by the labor share. Purely structural models often incorporate price and wage stickiness characteristic of the New Keynesian paradigm (Schorfheide, 2008). The NAWRU follows from a set of structural equations under the assumption that the labor market is in a long-term equilibrium. The second group of methods estimates the NAWRU directly using a variety of statistical techniques for decomposing the unemployment rate into a cycle and a trend. The EC methodology follows a middle path between purely structural and purely reduced-form models. It allows the NAWRU to be estimated on the basis of a Phillips curve, while also allowing it to vary by assuming that it follows a random walk (Gordon, 1997). This approach has the advantage of allowing an equilibrium unemployment rate that is consistent with economic theory to be determined directly by imposing the condition of stable wage inflation. This approach is implemented in the following unobserved component model (Hristov et al., 2017).

Let ν_t denote the NAWRU, or the trend of the actual unemployment rate U_t. The cyclical variation in the labor market z_t equals the difference between the actual rate of unemployment and NAWRU (unemployment gap). The Phillips curve postulates a negative relationship between wage inflation and the unemployment gap. An actual unemployment rate above NAWRU puts downward pressure on the rate of growth of nominal wages. The opposite is the case if the unemployment rate falls below NAWRU. The other key variables include labor productivity and marginal costs approximated by the labor share. The terms of trade may play a role if the wage setters target the GDP inflation rather than consumer price inflation, or when the export sector dominates the outcomes of wage bargaining (Galı and Gertler, 1999). The Phillips curve thus captures the short-term variation of nominal wage inflation to changes in labor productivity, aggregate marginal costs and the employment gap represented by the cyclical component of the actual unemployment rate. The system is specified as follows:

$$U_t = \nu_t + z_t\,, \tag{3.6}$$

$$\left.\begin{aligned} \nu_t &= \nu_{t-1} + \eta_{t-1} + \xi_t^{\nu} \\ \eta_t &= \eta_{t-1} + \xi_t^{\eta} \end{aligned}\right\} \quad \text{trend}\,, \tag{3.7}$$

$$\left.\begin{aligned} &z_t = \vartheta_1 z_{t-1} + \vartheta_2 z_{t-2} + \xi_t^z \\ &\Delta^2 W_t = \mu_w + \gamma_1 z_t + \gamma_2 z_{t-1} + \gamma_3 z_{t-2} + \gamma_4 z_{t-3} + \\ &\alpha_1 \Delta^2 tot_t + \alpha_2 \Delta^2 prod_t + \alpha_3 \Delta^2 ls_t + \xi_t^w \\ &\xi_t^w = \rho_1 \xi_{t-1}^w + \ldots + \rho_5 \xi_{t-5}^w + \epsilon_t \end{aligned}\right\} \quad \text{cycle}\,, \tag{3.8}$$

$$\xi_t^{\nu} \sim N(0, \sigma^2_{\xi^{\nu}}),\; \xi_t^z \sim N(0, \sigma^2_{\xi^z}),\; \epsilon_t \sim N(0, \sigma^2_{\epsilon}) \quad \text{error terms.} \tag{3.9}$$

The above unobserved component model places emphasis on modeling the cycle of the unemployment rate, z_t, while its trend ν_t is modeled rather parsimoniously as a second order random walk. The cycle is modeled as an $AR(2)$ process. The variable W_t denotes the average compensation of employees. The cycle enters the Phillips curve contemporaneously along with three lags and three exogenous variables in second differences: the terms of trade tot_t, the average labor productivity $prod_t$ and the logarithm of labor share ls_t. The terms of trade are given by the difference between the inflation rate of the deflator of private consumption and the inflation rate of the GDP deflator. The average labor productivity equals real GDP divided by total employment (employees and self-employed). The (adjusted) labor share is the share of compensation per employees in nominal GDP per person employed. The error of the Phillips curve ξ_t^w follows an AR(5)-process with $\rho_i \;\forall\; i \in 1 \ldots 5$ auto-regressive parameters.

Table 1a summarizes the estimates of the above described unobserved component model for the trend of the actual unemployment rate (NAWRU).[12] The parameters $\vartheta_{1,2}$ capture the auto-regressive coefficients of the cycle. As is to be expected, μ_w is close to zero. The parameters in the Phillips curve have the expected sign, for instance γ_1 is negative. The actual rate of unemployment according to the ILO definition and the estimated NAWRU are shown in Figure 4. It displays the filtered and smoothed state estimate for the NAWRU. While both estimates are noticeably smoother than the actual unemployment rate, the filtered state estimate shows more short-term variation due to the limited information set used to compute it compared to the extended information set used to compute the smoothed state estimate. The confidence interval added to the smoothed state estimate is rather narrow while involving both filter uncertainty and parameter uncertainty.

[12]The Ljung-Box statistic is computed on the first-four autocorrelations of the innovations ξ_t^w and a_t^{cu} with its p-value. Rejection of the null-hypothesis implies the data are independently distributed, i.e., there is no residual auto-correlation in the innovations. The signal-to-noise ratio is defined as $q := \frac{\sigma_p^2 + \sigma_\eta^2}{\sigma_c^2}$, with σ_c^2 being the cycle variance, σ_p^s the trend variance and σ_η^2 the variance of the trend drift.

Table 1: Estimates

(a) NAWRU

	Estimate	S.E.	t-stat
ϑ_1	1.868	0.028	67.258
ϑ_2	-0.919	0.027	-33.659
μ_w	-0.005	0.044	-0.104
γ_1	-3.658	1.370	-2.669
γ_2	10.309	3.675	2.805
γ_3	-9.802	3.689	-2.657
γ_4	3.202	1.382	2.317
α_1	17.305	8.858	1.953
α_2	-137.148	7.380	-18.584
α_3	25.954	17.266	1.503
σ_{ξ^v}	0.003	0.0003	8.870
σ_{ξ^z}	0.00002	0.00003	0.637
σ_ϵ	0.916	0.097	9.436
DIAGNOSTICS	Stat.		p-val
Ljung-Box Q(4)	16.900		0.077
Log-Likelihood	8.119		
Signal-to-noise	0.007		
R^2	0.780		
BIC	66.760		
Observations	179		

Note: Likelihood maximized by sequential quadratic programming method. Standard errors computed using information matrix.

(b) TFP

	Estimate	S.E.	t-stat
ϕ_1	0.926	0.039	23.720
μ_{cu}	0.087	0.107	0.811
β_1	0.645	0.146	4.430
β_2	-0.109	0.213	-0.510
β_3	-0.363	0.210	-1.727
β_4	-0.091	0.148	-0.614
α_1	1.222	0.065	18.947
α_2	-0.373	0.201	-1.856
σ_{a^η}	0.433	0.048	9.080
σ_{a^c}	0.00011	0.0002	0.649
$\sigma_{a^{cu}}$	1.355	0.148	9.136
DIAGNOSTICS	Stat.		p-val
Ljung-Box Q(4)	9.718		0.045
Log-Likelihood	-446.6		
Signal-to-noise	0.0003		
R^2	0.881		
BIC	956		
Observations	171		

Note: Likelihood maximized by sequential quadratic programming method. Standard errors computed using information matrix.

The empirical framework accommodates adaptive, backward-looking expectations of wage setters. Alternatively, we tested also models with forward-looking expectations. However, such specifications rendered the estimates more procyclical and volatile.

3.2.2 Observed TFP and TFP trend

We specify and estimate the following model for the trend-cycle decomposition of the observed TFP (F_t):

$$F_t = f_t + c_t\,, \tag{3.10}$$

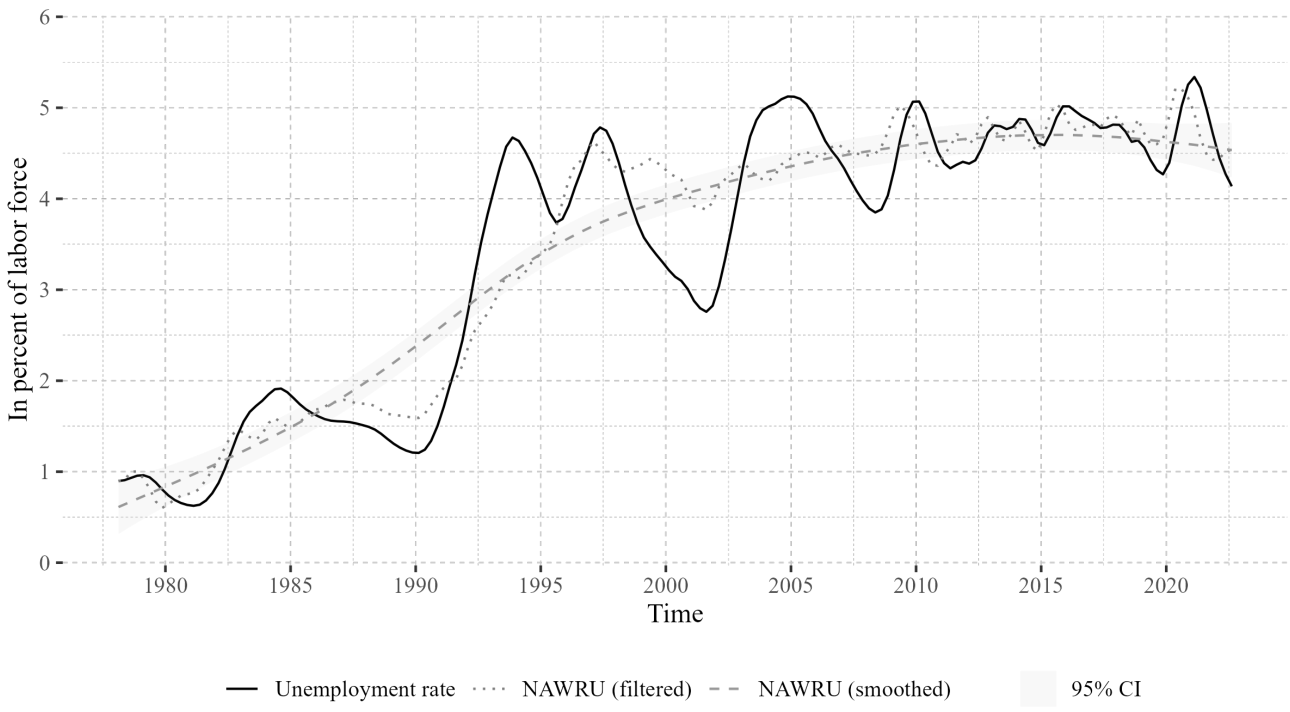
$$\left.\begin{aligned} f_t &= f_{t-1} + \eta_{t-1} + a_t^f \\ \eta_t &= \eta_{t-1} + a_t^\eta \end{aligned}\right\} \qquad \text{trend}\,, \tag{3.11}$$

$$\left.\begin{aligned} &c_t = \phi_1 c_{t-1} + a_t^c \\ &CU_t = \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \\ &\beta_1 c_t + \beta_2 c_{t-1} + \beta_3 c_{t-2} + \beta_4 c_{t-3} + a_t^{cu} \end{aligned}\right\} \qquad \text{cycle}\,, \tag{3.12}$$

$$a_t^\eta \sim N(0, \sigma^2_{a^\eta}),\ a_t^c \sim N(0, \sigma^2_{a^c}),\ a_t^{cu} \sim N(0, \sigma^2_{a^{cu}}) \qquad \text{error terms.}$$

The observable variables, denoted by capital letters, include the logarithm of the observed TFP, F_t, and aggregate capacity utilization CU_t. For capacity utilization, we use the

Figure 4: Unemployment rate and NAWRU

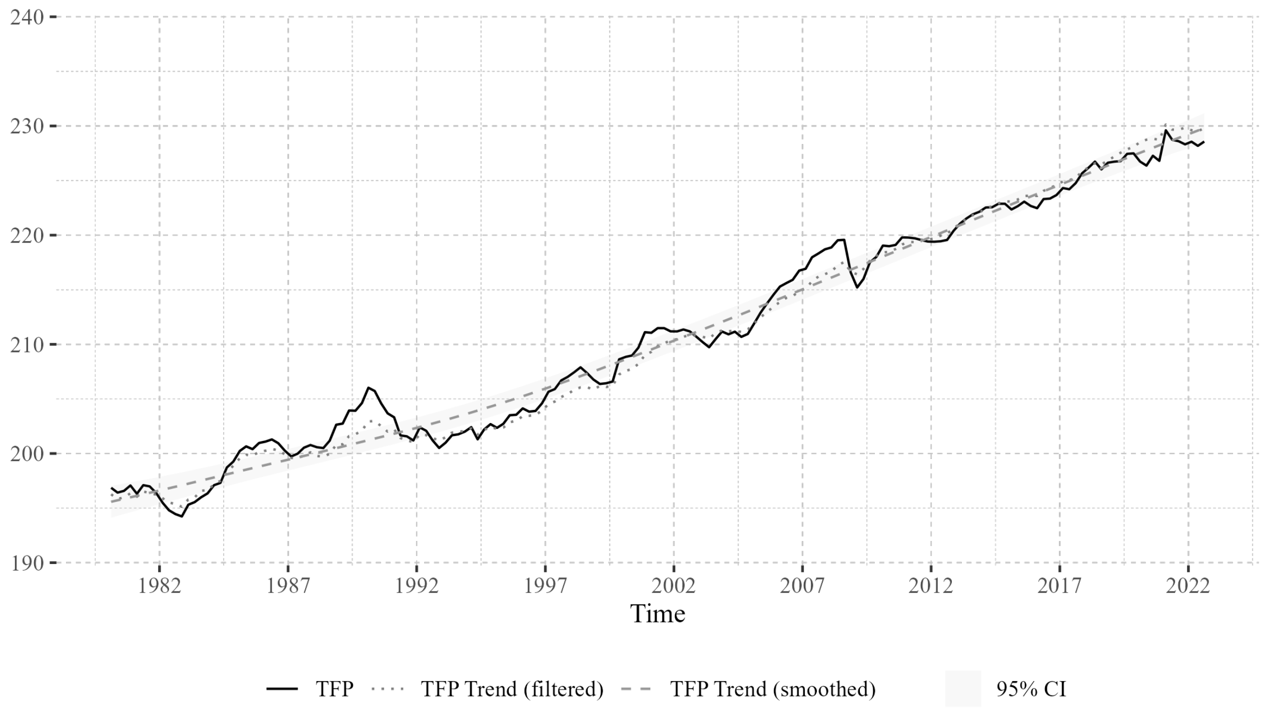


weighted mean of manufacturing and services.[13] The TFP trend f_t follows a second order random walk and the cycle c_t an $AR(1)$ process. The measurement equation featuring the series for capacity utilization CU_t depends on the cycle c_t along with three lags and an error term a_t^{cu}. The constant μ_{cu} corresponds approximately to the mean of CU_t. All error terms are assumed to be (over time and in a cross-section) independent and identically distributed normal variates with zero means.

Table 1b summarizes the estimates of the unobserved component model for the TFP trend. The parameter μ_{cu} is close to the mean of capacity utilization. The cycle exhibits a high degree of auto-correlation with $\phi_1 = 0.93$. Figure 5 shows the path of the observed TFP (F_t) and two measures for the TFP trend (f_t) based on the filtered and smoothed state estimates. We observe the same pattern as with the NAWRU in the form that the filtered state estimate for the TFP trend shows a more volatile path relative to the smoothed state estimate. Again, the reason for this lies in the different information sets underlying the computations for these state estimates. Additionally, we added a 95 percent confidence interval

[13]The capacity utilization for services starts in 2017:Q3, prior to that date we only use capacity utilization in manufacturing. We use the share of value added in manufacturing and services in GDP as respective weights. Prior to calculating the weighted average, we normalize and rescale the series. We deviate from the *CUBS* indicator used by the European Commission as for Switzerland no harmonized sentiment indicator for services and construction is available from Eurostat. Also, alternative domestically collected sentiment indicators in the service sector or in construction are only available for a limited time period.

Figure 5: TFP and TFP trend



for the smoothed state estimate for the TFP trend. The confidence interval again includes both the filter uncertainty and the parameter uncertainty. A Wald test rejects the null hypothesis that all β coefficients are jointly equal to zero at the 1 percent level of significance. The shows the relevance of the time series for capacity utilization for explaining the cyclical variation in the TFP series (Solow residual). The estimates for the α coefficients fulfill the sufficient conditions for the stability of an AR(2) model.

The compound annual growth rate of the TFP trend (based on the smoothed state estimate) between 1980 and 2021 equals 0.80 percent. With an output elasticity of labor of 0.65 this value is roughly equivalent to $0.80/0.65 \approx 1.22$ percent growth in labor productivity. The observed TFP grew by 0.76 percent per year. The growth contribution of fluctuations in aggregate capacity utilization has been slightly negative overall, as the identity $\Delta \log(TFP_t) = \Delta f_t + \Delta c_t$ translates into $0.76 = 0.80 - 0.04$.

It is important to examine the variation of the TFP trend because excess cyclicality of the trend is likely to directly translate into excess cyclicality of potential output via the production function. The situation is compounded by the fact that there is no rough and ready guideline for how flexible a TFP trend or the potential output should be. A visual inspection of Figure 5 already suggests that the TFP trend is substantially less volatile (this applies to both the filtered and smoothed state estimates for the observed TFP) than that of the observed TFP series itself, with the variance of the growth rate being close to zero against the variance of the growth rate of the observed TFP of 0.19. The correlation between the two growth rates equals 0.19, but the correlation between GDP growth and that of the TFP trend is 0.11. We can therefore claim with some degree of certainty that the estimated TFP trend is not excessively procyclical.

Our approach to computing the TFP trend uses only observed TFP and a measure of aggregate capacity utilization. In a recent paper, Carstensen et al. (2024) estimate the cyclical component of total factor productivity (TFP gap) with a factor structure that includes a wide range of business cycle indicators and show that this extension stabilizes the estimate of the TFP gap (in an application to the five largest EMU countries).

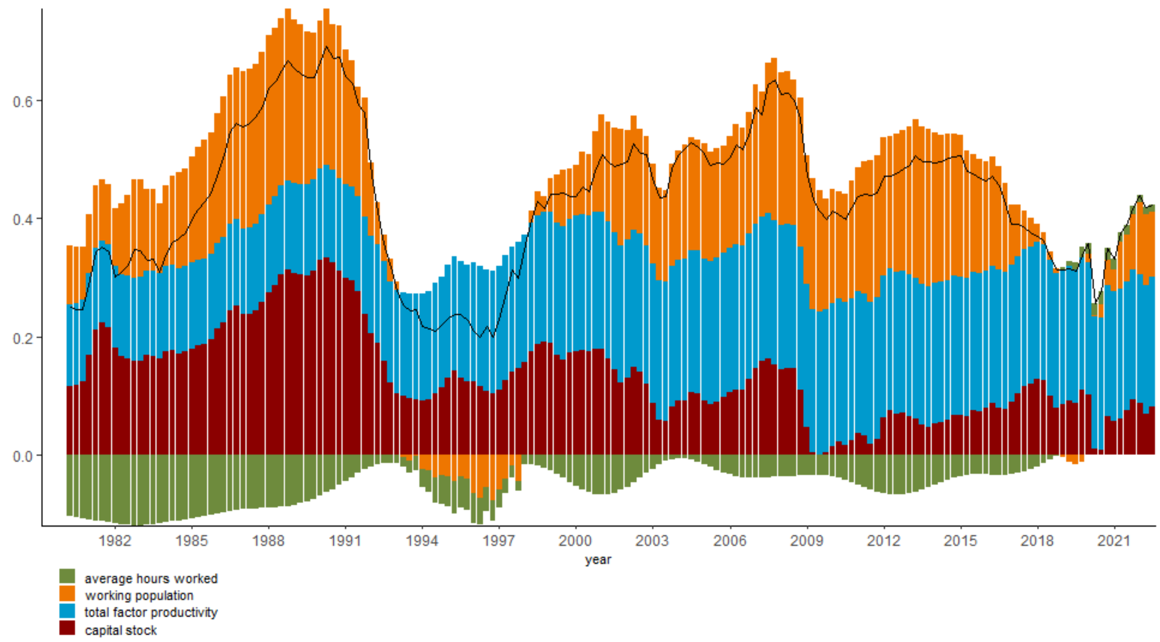
4 Results

This section presents the resulting time series for potential output and the output gap, as defined by equations 2.6 and 2.7. Figure 6 displays the growth of real GDP alongside the growth of potential output. Potential output growth fluctuated less than the growth of actual output, despite having a discernible degree of procyclicality from 1980 until about 2000. The overall correlation coefficient between the two growth rates equals 0.29, which is relatively low. Since the estimates of the TFP trend and NAWRU do not appear to be excessively procyclical, a further reduction of this correlation could be achieved by applying a stronger smoothing of the participation rate and the average hours worked. The aforementioned trend series demonstrate a considerable degree of variability in the transition to the recessionary period of the 1990s. This variability is likely to have contributed to the procyclicality of potential output growth during that period.

In the 1990s the Swiss economy suffered from a prolonged recession. This decade saw a contraction for three consecutive years (1991-1993), which after a brief rebound was followed by two more years of low growth (1995, 1996). The bursting of the dot-com bubble of the early 2000s left a barely discernible dent on potential output. Even the impact of the global financial and economic crisis of 2008 on potential output appears to be smaller than that of the 1990s recession, despite a sharp contraction in 2009. Finally, the sharp recession caused by the pandemic of the Coronavirus in 2020 has not left a deep scar in the growth potential of the Swiss economy.

Figure 6: Growth of real GDP and potential output

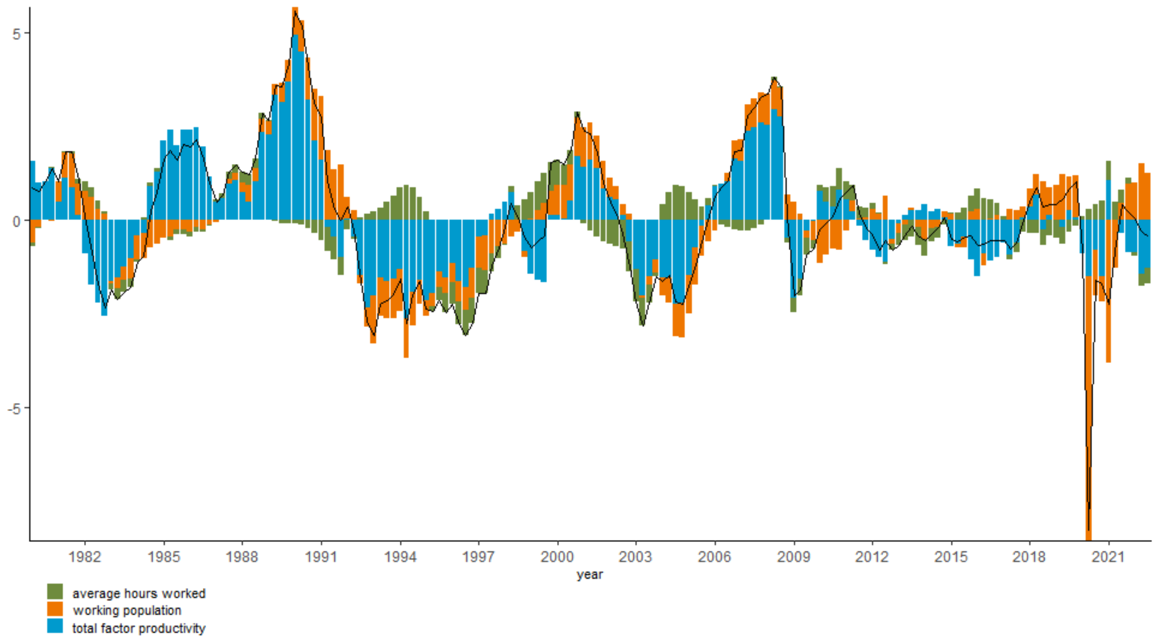
Figure 7: Decomposition of potential output growth



Next, Figure 7 shows an additive decomposition of potential growth in the contribution of the TFP, capital and labor. The contributions of labor and capital to the growth of potential output are defined in equations 2.8, 2.9 and 2.10.

Two observations are immediately apparent: a large drop in labor contribution during the recession of the 1990s and a large increase in the contribution of TFP beginning in late 1990s until the late 2000s. The diminishing labor contribution appears plausible, given the large detrimental effect of the 1990s recession on the Swiss labor market. During this period, the unemployment rate increased for four consecutive years (1991-1994) and again in 1996-1997 after a brief respite in 1995. The increase in the unemployment rate of 1993-1994 and 1996-1997 surpassed those recorded in the aftermath of the global crisis in 2009 and after 2011. The increase in the contribution of the productivity to potential output is likely to have multiple causes. This observation largely coincides with a prolonged period of increased productivity created by the rise of information technologies and automation. The increase in automation may have been the key factor behind persistent jobless-growth observed in many countries, or the fact that employment reacts very sluggishly to economic recoveries.

Figure 8: Decomposition of output gap



Finally, Figure 8 displays the resulting output gap for Switzerland based on the novel data set and the methodology of the EC. In accordance with the common perception of the Swiss business cycle.[14] Prior to the 1991, most of the gap can be explained by fluctuations in TFP. Interestingly, the gap widened sharply during the Covid-19-pandemic of 2020/2021 due to the sharp decline in labor input. With the recovery, the labor input grew above trend, such that the gap closed rapidly.

[14]See for instance OECD business cycle dating.

4.1 Comparison with existing international estimates

Table 2 compares the annualized estimates for Switzerland with those of the EC for the EU15. The comparison is performed in terms of excessive volatility and excessive procyclicality. The volatility is expressed by the ratio of the standard deviation of the growth rates of potential output to the standard deviation of the growth rates of actual output (real GDP). The procyclicality is measured by the correlation between the annual growth rates of potential output and the annual growth rates of real GDP. Since estimates by the EC are only made on the annual frequency, we aggregate the Swiss estimates to the lower frequency. The comparison is presented by decade, with the overall figure provided in the last row of each group.

Table 2: Volatility and procyclicality of potential output

	CH	USA	DEU	ITA	FRA	AUT	UK	BEL	DNK	ESP	IRL	NLD	PRT	Median
Volatility														
1981 - 1990	0.34	0.14		0.16	0.40	0.34	0.30	0.40	0.15	0.58	0.18	0.39	0.34	0.34
1991 - 2000	0.38	0.30	0.55	0.24	0.15	0.34	0.32	0.13	0.13	0.24	0.54	0.16	0.33	0.27
2001 - 2010	0.11	0.36	0.10	0.24	0.18	0.29	0.34	0.23	0.13	0.39	0.70	0.32	0.56	0.30
2011 - 2022	0.18	0.18	0.20	0.10	0.05	0.04	0.07	0.10	0.24	0.11	0.85	0.25	0.29	0.14
1981 - 2022	0.29	0.41	0.25	0.36	0.29	0.35	0.29	0.26	0.22	0.43	0.76	0.46	0.50	0.36
Procyclicality														
1981 - 1990	0.61	0.65		0.80	0.81	0.62	0.77	0.89	0.78	0.89	0.65	0.77	0.93	0.78
1991 - 2000	-0.19	0.77	-0.28	0.08	-0.25	0.26	0.70	0.57	0.66	0.23	0.92	0.90	0.59	0.58
2001 - 2010	0.19	0.55	0.19	0.59	0.62	0.49	0.68	0.39	0.33	0.89	0.77	0.32	0.36	0.52
2011 - 2022	0.26	-0.07	0.07	0.19	0.45	0.64	0.43	0.31	0.43	0.47	0.81	0.44	0.56	0.44
1981 - 2022	0.27	0.53	0.07	0.40	0.39	0.41	0.46	0.44	0.53	0.48	0.82	0.54	0.66	0.47

Series for Germany start in 1991. Source: AMECO

The overall conclusion from the figures reported is that the estimates for Switzerland are neither excessively volatile, nor excessively procyclical. This follows from a comparison of the Swiss figures to the corresponding medians of the EC estimates for the EU15 member states. The period 1991-2000 marks heightened volatility, which is not surprising, given the fact that Switzerland has experienced a recession during this decade and the potential output was not procyclical. This recession was unique to Switzerland and mainly affected the real estate market. Overall, the estimated growth rate of potential output shows smaller volatility relative to the growth rate of real GDP than in the majority of the EU15 member states or the USA. The estimates are also not excessively procyclical, as evidenced by the comparison of the correlation between the two growth rates for Switzerland and the median correlations for the EU15 member states.

4.2 Comparison with alternative filters

To assess the plausibility of the estimated output gap, we compare it to alternative measures obtained by the application of three frequently used univariate time series filters – Hodrick-Prescott (HP), Christiano-Fitzgerald (CF) and Hamilton (HAM) – to the quarterly time series of real GDP. The popularity of the HP-filter owes to its simplicity and the fact that it can be applied to non-stationary time series. The sole smoothing parameter of the HP-filter is set at $\lambda = 1600$ in accordance with the trend extractions applied to the labor input and as it is standard in the literature. The CF-filter is a bandpass filter. It can suppress both the low frequency trend components and the high frequency cycle components. The parameters of the CF-filter are set at their recommended values for quarterly data: $p_l = 2$ and $p_h = 40$. The parameters p_l and p_h control the minimum and maximum admissible periodicity in the trend. Hamilton (2018) advocates the use of regression analysis instead of the HP-filter. The HAM-filter is specified by a linear model on a univariate time series shifted ahead by h periods, regressed against a series of variables constructed from varying lags of the series by some number of periods, p. We follow the recommendations and set $h = 8$ and $p = 4$.

The typical caveats associated with the use of univariate filters include the end-of-sample problem and the generation of artificial cycles. Baxter and King (1999) discuss the properties a sound filter should possess. Christiano and Fitzgerald (2003) discuss approximations to an ideal bandpass filter and provide several computationally cheaper alternatives to the BK filter. Yet despite all the problems associated with the use of univariate time series filters, they remain popular in applied work. Moreover, the single best filter method has so far not been identified. We thus complement the univariate Filters with a multivariate unobserved components model (MVF) as used for instance by the IMF (Alichi, 2015). The model features three exogenous regressors: capacity utilization, inflation and unemployment (deviations from trend). The model is estimated by means of the Kalman Filter.[15]

Table 3 shows the summary statistics of the five different estimates. All five output gap estimates have a sample mean close to zero. The output gap according to the production function methodology shows comparatively high variability and persistence, as measured by the sample standard deviation and first-order autocorrelation, respectively. An output gap as a measure of aggregate capacity utilization is expected to show high persistence, reflecting the aggregate cyclical fluctuations. The Hamilton-Filter exhibits the highest fluctuation in potential output growth, rendering this methodology less attractive compared to the remaining univariate filters. As the estimated trend contains high-frequency noise, it can hardly be interpreted as potential GDP.[16] Table 4 testifies to the high correlation between all

[15] A detailed description of the model can be found in Appendix A3.

[16] In a recent paper, Quast and Wolters (2022) propose a simple modification based on the mean of 4 to 12

four measures.

What concerns the production function, we find several favorable properties: First, the sample mean is close to zero. This implies that, in the long run, a fiscal arrangement based on this particular measure of the output gap (such as the one used in Switzerland) should lead to a balanced budget.[17] Second, potential output growth shows little volatility and a high degree of persistence. This is a desirable property given the fact that potential output is used for medium term forecasts and fiscal planning purposes. It also underscores the notion of inertia in the propagation of technical progress. Finally, the correlation of the output gap and potential output growth is highest with the series resulting from the multivariate filter (MVF). It is important to note that, unlike the univariate filters, which are purely econometric approaches to disentangling the trend and cycle of GDP, the multivariate filter and the production function methodology incorporate more economic content, making the interpretation and analysis of the resulting potential output more appealing.

Table 3: Summary statistics

	Output Gap					Potential Output				
	PF	MVF	HP	CF	HAM	PF	MVF	HP	CF	HAM
Min.	-7.75	-7.30	-7.70	-8.19	-9.46	0.17	0.17	0.12	0.13	-5.83
Mean	-0.01	0.00	0.03	0.05	0.06	0.43	0.44	0.43	0.43	0.43
Max.	5.33	4.14	3.47	3.87	6.20	0.66	0.71	0.69	0.70	5.99
Sd.	1.69	1.69	1.37	1.58	2.70	0.13	0.14	0.14	0.14	0.86
Acf. (1 lag)	0.83	0.82	0.73	0.79	0.87	0.97	0.99	0.99	0.98	-0.06

Table 4: Correlations

	Output Gap					Potential Output				
	PF	MVF	HP	CF	HAM	PF	MVF	HP	CF	HAM
PF	1.00	0.90	0.90	0.86	0.86	1.00	0.79	0.75	0.70	0.21
MVF	0.90	1.00	0.88	0.85	0.76	0.79	1.00	0.81	0.66	0.05
HP	0.90	0.88	1.00	0.98	0.77	0.75	0.81	1.00	0.87	0.06
CF	0.86	0.85	0.98	1.00	0.76	0.70	0.66	0.87	1.00	0.12
HAM	0.86	0.76	0.77	0.76	1.00	0.21	0.05	0.06	0.12	1.00

5 Validation and Robustness

In this Section we validate the results presented above by specifying a model which includes an anchored NAWRU estimate. We then examine the sensitivity of the output gap

quarter ahead forecast errors. They show that this slight modification shares the favorable real-time properties of the Hamilton filter, but leads to a much better coverage of typical business cycle frequencies and a smooth estimated trend. See also Biolsi (2023); Álvarez and Gómez-Loscos (2018) among others for comparisons of different models and output gap characteristics.

[17] See for instance Bodmer et al. (2006); Beljean and Geier (2013).

estimates based on the production function methodology to revisions arising from changing the dataset.

5.1 The role of the NAWRU Anchor

The EC methodology assumes the convergence of the actual unemployment rate to the NAWRU over the medium term, which in turn converges to an anchor value in the long term. The anchor essentially represents the level of the unemployment rate which can be traced to the effect of the labor market institutions alone. Orlandi (2012) argues that the factors typically used in empirical studies to explain actual unemployment rates can also explain the trends of the actual unemployment rates exemplified by the NAWRU. To this end, he proposes estimating a panel-fixed effects model with country-specific NAWRU as the dependent variable.

The theoretical background and empirical methodology for deriving the anchor values are elaborated in Orlandi (2012). The structural factors on the labor demand side may influence the probability of a match between a job seeker and a firm, as well as the subsequent cost of labor to the firm. Successful active labor market policies provide training that may otherwise have to be provided by the employer. They also facilitate the search, thus improving the probability of a successful match. Most of the structural factors on the supply side influence the reservation wage, or the lowest wage rate at which a worker would be willing to accept a job. Increases in labor taxes or unemployment benefits (replacement rates) tend to raise the reservation wage and lower labor supply. Strong trade unions tend to create the insider-outsider situation, in which the unemployed cannot effectively underbid the current wage (Lindbeck and Snower, 2001). In this institutional environment, external adverse shocks to employment may lead to a permanent increase in the rate of unemployment (Blanchard and Summers, 1986).

The nonstructural factors that are likely to affect the equilibrium unemployment rate include the technical process represented by TFP and the real interest rate. Changes in productivity growth affect unemployment through labor demand in the short term and through substitution between labor and capital in a longer perspective. An increase in the real interest rate depresses investment, which in turn lowers labor demand. The relative importance of the construction sector is an example of a persistent cyclical factor. Unsustainable developments in the construction sector have exacerbated the impact on the global financial and economic crisis in several European economies. Housing bubbles are perceived as being a major source of financial instability.[18]

Orlandi (2012) estimates two panel regression models, separately for the old and the new

[18] See, for example, Martín et al. (2021).

member states.[19] The panel for the old member states is unbalanced. Barring a few cases of missing observations, the model for the old member states starts in 1985, except for Germany, whose sample contains growth rates starting in 1992, i.e., one year following German reunification. The model for the fourteen new member states covers a shorter period that starts in 1996 at the earliest. To ensure comparability with the current estimates by the EC, we add the Swiss data to the sample of old member states and re-estimate the regression model.

The anchor values for each country are calculated based on the estimated coefficients of the panel model. The dependent variable is the NAWRU estimated from an unobserved component model within the production function methodology. The independent variables can be divided into two groups. The first group contains nonstructural variables that vary over the business cycle. These include the annual growth rate of the TFP, $tfp_{i,t}$, the share of the construction sector in total employment, $cons_{i,t}$, and the real interest rate, $r_{i,t}$. The second group comprises purely structural variables and includes the unemployment benefit replacement rates, $rr_{i,t}$, expenditure on active labor market policies, $almp_{i,t}$, the degree of trade union density, $ud_{i,t}$, and the tax wedge, $tw_{i,t}$. The data sources are given in Table 11.

Table 5 shows the set of fixed-effects estimates for the old EU member states based on an annual sample for 1991-2021 and the current estimates of the TFP growth (one of the independent variables) and the NAWRU (the dependent variable). The choice of the starting year has been motivated by a structural break in the Swiss labor market data in 1991. This structural break is particularly apparent in the time series of the unemployment rate. Two regressions have been run in order to check the sensitivity of the estimates to the inclusion of Swiss data. The regression model reads:

$$NAWRU_{it} = \alpha_i + \beta_1 cons_{it} + \beta_2 r_{it} + \beta_3 tfp_{it} + \beta_4 almp_{it} + \beta_5 ud_{it} + \beta_6 tw_{it} + \beta_7 rr_{it} + \epsilon_{it}. \quad (5.1)$$

The dependent variable is the annual NAWRU estimate according to the production function methodology. The independent variables comprise non-structural variables, such as the annual growth rate of the TFP, tfp_{it}, the share of the construction sector in total employment, $cons_{it}$, and the real interest rate, r_{it}. The structural variables include the unemployment benefit replacement rates, rr_{it}, expenditure on active labor market policies, $almp_{it}$, the degree of trade union density, ud_{it} and the tax wedge, tw_{it}. The index i refers to a country, where $i = 1, 2, \ldots, 14$ when the sample includes Switzerland. The time index $t = 1, 2, \ldots, 27$ refers to the years between 1991 and 2021. Both models explain roughly fifty percent of the variation in the NAWRU rates, with the value of the Hausman test statistic validating the choice of the estimator.

[19] As of 2016, the group of old member states included: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden and the UK.

Table 5: NAWRU panel estimates

	13 EU member states			including CH		
cons	−0.281	(0.054)	***	−0.301	(0.052)	***
r	0.354	(0.037)	***	0.353	(0.036)	***
tfp	−0.021	(0.027)		−0.018	(0.027)	
ud	−0.010	(0.017)		−0.017	(0.017)	
tw	0.067	(0.025)	**	0.066	(0.025)	**
almp	−0.045	(0.008)	***	−0.043	(0.008)	***
rr	0.045	(0.011)	***	0.040	(0.011)	***
Adj. R^2	0.472			0.456		
Hausman-stat	132.8	***		44.221	***	
Num. obs.	403			434		
n	13			14		
T	31			31		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$ The sample covers the period 1991-2021 for Switzerland and Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and United Kingdom.

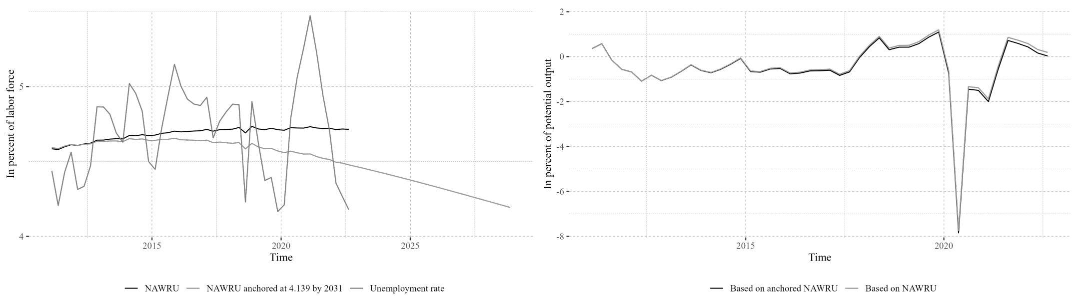
The anchor values for each country are based on the estimated coefficients of the panel models. To derive a country-specific anchor, the nonstructural variables are averaged over the sample to remove any cyclical variation, whereas the structural variable are held at their current values. The third quantity to enter the anchor calculations are the panel-fixed effects, which capture the country-specific, time-invariant factors. Table 6 compares the country estimates for the anchor. The anchor estimate for Switzerland equals 4.193.

Figure 9 compares in the left panel the constrained (anchored) NAWRU projection to its unconstrained counterpart. Importantly, anchoring may change the in-sample NAWRU estimate and, consequently, also the estimate of potential output and the output gap. The effect of anchoring on historical NAWRU estimates depends on the difference between the current value of the NAWRU and the anchor, but also on the proximity of the convergence point to the most recent sample point. In general, the smaller the difference and the further away the convergence point, the smaller the effect of anchoring on the in-sample fit would be. The effect of anchoring on the estimate of potential output and the output gap can be substantial. In the current situation, however, the effect of the NAWRU anchor on the output gap is limited, as illustrated in the right panel of Figure 9 for the output gap. In the present case, whether the NAWRU is anchored or not does not affect substantially the statistics reported in Table 2.

Table 6: NAWRU anchors

	13 EU member states	13 EU member states and Switzerland
Switzerland	-	4.193
Austria	4.834	4.878
Belgium	7.642	7.671
Denmark	4.862	4.915
France	8.780	8.775
Finland	8.503	8.595
Germany	5.989	6.080
Ireland	9.763	9.784
Italy	10.095	10.020
Netherlands	5.855	5.855
Portugal	9.199	9.238
Spain	15.471	15.517
Sweden	6.335	6.416
UK	6.333	6.368

Figure 9: The anchored NAWRU



The left panel compares a constrained (anchored) NAWRU projection (light grey) to its unconstrained counterpart (grey). The constrained NAWRU projection is set to converge to the estimated anchor value of 4,139 in 6 years (2022-2028), after which it remains constant at that value. Note that imposing the constraint may change the in-sample estimates of the NAWRU. The smaller the difference between the current value of the NAWRU and its anchor, and the further away the convergence point is in time, the smaller is the effect of anchoring. The effect of this change on the output gap is shown in the right panel.

5.2 Sensitivity to revisions

The sensitivity of potential output estimates to revisions has long been a concern for economic policy practitioners (Coibion et al., 2018; Cotis et al., 2004; Orphanides and van Norden, 2002). While major recessions, such as the aftermath of the financial crisis of 2008/2009 and the recent crisis of 2020/2021 due to the Covid-19 pandemic, have undoubtedly fueled this debate, it is important to recognize that the reliability of real-time estimates of potential output is an ongoing issue. Even in periods of swift recovery, such as those experienced by the Swiss economy following these crises, one must remain cautious about expecting sizable revisions to potential growth figures.

Table 7: Summary reliability indicators of Swiss output gap estimates

	CORR[1]	NS[2]	NSR[3]	SIGN-lev[4]	SIGN-ch[5]	MAE[6]
Based on latest GDP vintage						
PF	0.921	0.418	0.504	89.1	95.1	0.606
CF	0.987	0.147	0.256	94.9	98.2	0.142
HAM	0.980	0.197	0.259	94.8	87.1	0.444
HP	0.990	0.113	0.236	98.1	98.7	0.053
MVF	0.659	0.773	0.802	75.1	88.8	1.170
Based on real-time GDP vintages						
PF	0.905	0.445	0.559	89.2	81.4	0.626
CF	0.956	0.282	0.369	93.1	78.7	0.328
HAM	0.949	0.308	0.395	91.1	77.5	0.691
HP	0.951	0.294	0.405	93.3	78.8	0.290
MVF	0.938	0.385	0.475	91.1	79.5	0.600

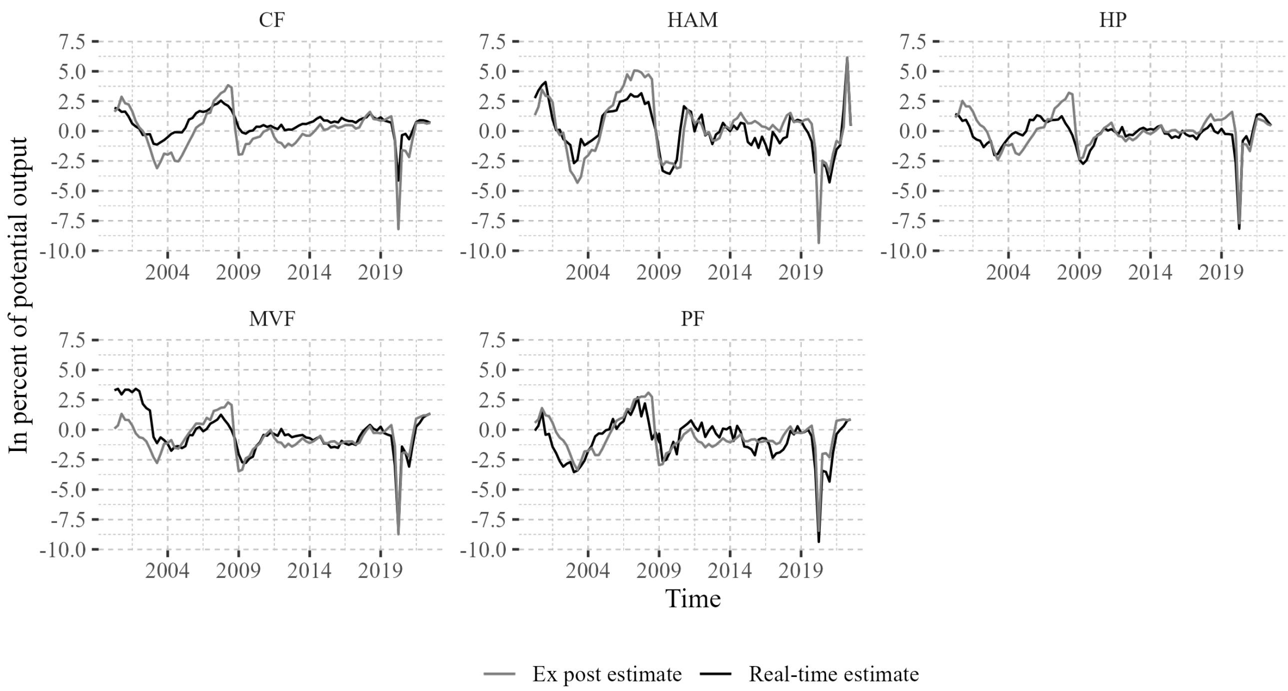
Notes: Estimation sample: 2002:2 to 2022:2 (90 observations); Data starts in 1980:Q1.
[1] CORR: Correlation between (pseudo) real-time estimate and ex post estimate.
[2] NS: Ratio of the standard deviation of the revision to that of the ex post estimate.
[3] NSR: Ratio of the root mean square of the revision to the standard deviation of the ex post estimate.
[4] SIGN-lev: Percentage of times the level of the (pseudo) real-time estimate has the same sign as the level of the ex post estimate.
[5] SIGN-ch: Percentage of times the change in the (pseudo) real-time estimate has the same sign as the change in the ex post estimate.
[6] MAE: Mean absolute revision (ex post minus (pseudo) real-time) error.

In this section, we simulate in a *pseudo* real-time exercise the estimation elaborated above to investigate the revision patterns in potential GDP and the output gap. In doing so, we follow closely the procedure of Marcellino and Musso (2011). Our exercise spans over 90 quarters, starting in 2000:Q2 until 2022:Q3. Given that the data set has been recently established, no true real-time vintages are available for the capital stock nor the labor input.[20] In

[20]For a further robustness analysis, we were able to obtain the *true* real-time vintages of the production function approach presented here from SECO. The sample only starts in 2019:Q4 and covers mostly the volatile crisis period of 2020-2021. Still, we compare the revisions of the true real-time estimates as they were published with the recursive estimates presented here. The MAE of the true real-time estimates (0.25) is substantially lower than of the pseudo real-time estimates (0.55 with real-time GDP; 0.53 final vintage data). This reinforces

order to mimic – at least partially – the exercise of the practitioner in real-time, we perform two different simulations: (i) we use *final* vintage data (i.e., the last available GDP vintage as of 2022:Q3) and perform the recursive simulations. This corresponds to a purely pseudo real-time analysis. (ii) we rely on the available real-time vintages of GDP. By doing so, we are able to capture some of the potential revisions in the raw data.[21] To obtain the estimates of the TFP trend and the NAWRU, we re-estimate the corresponding unobserved component models for each vintage of the sample.[22] Optimal models are chosen every quarter based on the BIC and may differ from the models specified in Section 3.2.[23]

Figure 10: Pseudo-Real-Time and Ex Post Swiss Output Gap Estimates



Units are 100 times natural log deviation from trend. "CF" refers to the bandpass filter of Christiano and Fitzgerald (2003). "HAM" refers to the modified Hamilton filter of Hamilton (2018). "HP" refers to the Hodrick and Prescott filter of (Hodrick and Prescott, 1997). "MVF" refers to the multivariate filter model. "PF" corresponds to the production function approach outlined in this paper.

Table 7 presents the results. Those in the upper part are based on the recursive output

our finding that the production function presented here features many desirable properties for assessing the Swiss output gap in real-time.

[21] Real time GDP data is obtained from Indergand and Leist (2014).

[22] As mentioned in Section 5.1, the Swiss unemployment rate exhibits a significant structural break in 1991. Between 1990 and 1995, the Swiss economy experienced a prolonged period of volatile and stagnant economic development. The crisis was centered on the domestic real estate market and had a strong impact on the labor-intensive construction sector. Regarding the recursive estimation of the NAWRU, we control for the structural break by including a dummy equal to 1 for the period after 1991. Especially for small samples, the inclusion of the dummy helps to find a stable solution and to determine a smooth trend estimate.

[23] The resulting vintages of output gap estimates from the production function are shown in Figure 12.

gap estimations carried out with data from the latest available GDP vintage as of 2022:Q3. In the lower part, the results are based on the 'true' real-time GDP vintages, i.e. the simulated information set available at that point in time. Recursive estimations based on the final GDP vintage give insights into parameter instability and uncertainty. As each model is estimated every quarter, model parameters are prone to substantial uncertainty. Notice that the correlation between the pseudo real-time estimate and the ex post estimate is high in all cases. It is the HP-filter, which exhibits the highest correlation. The lowest correlation corresponds to the MVF model. This should not be surprising, as this model features many parameters to be estimated. This result aligns well with the evidence reported in Marcellino and Musso (2011). As the production function also features two unobserved component models with many parameters to be estimated, the NS and NSR statistics are somewhat higher than in the case of univariate filters. Nevertheless, the level of pseudo-real-time estimates has the same sign as the level of ex post estimate about 90% of the time, which is a comparatively high value. In the case of the production function, it is even higher for the change in the estimates.

Regarding the simulation with real-time GDP vintages, the results in Table 7 provide insight into the role of data revisions in determining the output gap and potential output. Since the impact of data uncertainty may differ between the alternative gap measures, as well as the impact of parameter instability, we now compare the final estimates with the real-time estimates. This is also illustrated in Figure 10, which plots the pseudo real-time and the ex-post (i.e., full sample) estimates of the output gap from the production function along with the various other methods. Overall, the findings with the final data vintage are confirmed: (1) the correlation between real-time and final estimate are above 90%; (2) the production function exhibits the highest noise-to-signal ratios; (3) the HP-filter has the best performance concerning the percentage of times, in which the level of the real-time estimate has the same sign as the final estimate; (4) the production function approach performs best when considering the change in the real-time estimate. Summarized, data revisions in GDP worsen somewhat the reliability of real-time output gap estimates, albeit not drastically. The production function performs similarly well if not better than the comparable multivariate filter, but slightly worse than the univariate filters.

6 Conclusions

In this study, we have proposed a production function approach tailored to Switzerland and operating at a quarterly frequency, with the aim of improving existing methodologies both theoretically and empirically, in line with the framework established by the European Commission. By constructing a comprehensive database going back to 1980, including quarterly productive capital stock and labor supply variables, we have addressed the need for data processing, which requires retropolation and interpolation. However, it is imperative to acknowledge the potential impact of these adjustments, which may lead to discrepancies between model performance and perceived reliability by policy makers. Nevertheless, the structural basis of the proposed method is a significant advantage, facilitating the disentangling of the various components of potential output and their determinants in a coherent and economically meaningful way.

Our results indicate a favorable performance in this regard, as evidenced by the reduced procyclicality of potential output estimates relative to alternative methods, including international benchmarks. The stability of output gap estimates across pseudo real-time assessments further underscores the usefulness of the production function as a tool for assessing the cyclical stance of the Swiss economy.

Looking ahead, there are several avenues for extending the research conducted in this study. First, future efforts could examine the effects of revisions to variables beyond GDP, with a particular focus on productivity, to gain a more complete understanding of their impact on model reliability. In addition, an examination of the effects of interpolation and retropolation on simulated real-time reliability would provide valuable insights into the robustness of the proposed methodology under different conditions.

Moreover, while our study focused primarily on stable estimates of the total factor productivity (TFP) gap across data vintages, future research could incorporate Bayesian model comparison techniques, such as those proposed by Grant and Chan (2017), to assess in-sample fit more comprehensively. This would involve conducting a rigorous specification search to compare and select models based on their adequacy in capturing the underlying economic dynamics and additional variables, as suggested in Carstensen et al. (2024).

Furthermore, the investigation of out-of-sample forecast accuracy, although computationally intensive, represents a promising avenue for improving model specification. By subjecting the proposed methodology to rigorous forecasting exercises, researchers can refine its predictive capabilities and assess its robustness in capturing economic fluctuations beyond the sample period. Moreover, continued research efforts aimed at extending the scope and refining the methodology employed here will contribute to advancing our understanding of the Swiss economy and its dynamics in the broader international context.

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A1 Data Sources

The construction of the labor input makes use of the following series:

Table 8: Data sources to construct labor input

Series	Source	Freq.	Start
Permanent resident population (15+)	FSO	Y	1981
Permanent resident population	FSO	Y	1975
Permanent resident population	FSO/SECO/SEM	M	1969
Actual annual volume of work (AVOL)	FSO	Y	1991
Actual annual working time, Full-time (90%-100%)	FSO	Y	1991
Employed Persons (domestic concept)	FSO	Q	1975
Employed Persons, seasonally adjusted	FSO	Q	2010
Employed Persons, FTE, seasonally adjusted in VZA	FSO	Q	2010
Employees	FSO	Q	2010
Employees*	FSO	Y	1991
Short-time working compensation	SECO	M	2000
Employment, FTE	FSO	Q	1991
Unemployment rate (ILO-concept)	FSO	Q	1991
Unemployed (ILO-concept)	FSO	Q	1991
Compensation of employees	SECO	Q	1980
Indicator wage contributions	CCO/SECO	M	1980
Permanent resident population (15+)	Historical Data	Y	1975
Actual annual volume of work	Siegenthaler (KOF)	Y	1975
Actual annual working time	Siegenthaler (KOF)	Y	1975
Employed Persons	Historical Data	Q	1975
Unemployed Persons	Historical Data	Q	1971

Note: CCO: Central Compensation Office, historical data stem from internal database.
* From 1991 to 2009, the Swiss Labor Force Survey (SLFS) was conducted in the second quarter of each year. Since 2010, the SLFS data has been collected quarterly (continuous survey).
See https://www.bfs.admin.ch/bfs/en/home/statistics/work-income/surveys/slfs.html

The construction of the capital stock makes use of the following series:

Table 9: Data sources to construct capital stock

Series	Source	Type	Frequency	Start
K: Equipment investment	FSO	Real	Y	1996
K: R&D	FSO	Real	Y	1996
K: IT equipment	FSO	Real	Y	1996
K: Building construction	FSO	Real	Y	1996
K: Civil engineering	FSO	Real	Y	1996
Inv: Residential Construction	FSO	Nominal	Y	1995
Inv: Residential Construction y-o-y	FSO	Real	Y	1996
Inv: Equipment investment	FSO	Real	Y	1980
Inv: Construction	FSO	Real	Y	1980
Inv: Residential Construction	FSO	Real	Y	1995
Inv: Equipment investment	SECO	Real	Q	1980
Inv: Construction	SECO	Real	Q	1980
Inv: Residential Construction	SECO	Real	Q	1995
Inv: Residential Construction	FSO	Nominal	Y	1990
Inv: Residential Construction y-o-y	FSO	Real	Y	1991
K: Equipment investment	Historical Data	Real	Y	1975
K: Construction	Historical Data	Real	Y	1980
K: Residential Construction	Historical Data	Real	Y	1980
Inv: Residential Construction	Historical Data	Real	Y	1980

Notes: K: Capital stock; historical data drawn from www.hsso.ch

The construction of capacity utilization makes use of the following series:

Table 10: Further data sources

Series	Source	Frequency	Start
Capacity utilization manufacturing	KOF	Q	1980
Capacity utilization services	KOF	Q	2017
Value added in manufacturing	SECO	Q	1980
Value added in services	SECO	Q	1980

Notes: Value added is used to construct the respective sector weights

To estimate the NAWRU-Anchor, the following data series are considered.

Table 11: Panel data and sources (NAWRU anchor)

Variable	Source	Text label
NAWRU	Own estimate	$nawru_{i,t}$
TFP growth	Own estimate	$tfp_{i,t}$
Labor tax wedge[1]	OECD/OECD-SPIDER	$tw_{i,t}$
Degree of trade union density	OECD	$ud_{i,t}$
Unemployment benefits replacement rate[2]	OECD	$rr_{i,t}$
Expenditure on active labor market policies[3]	OECD-SPIDER	$almp_{i,t}$
Employment in construction share	BESTA	$cons_{i,t}$
Real interest rate[4]	OECD-MEI, OECD-SPIDER	$r_{i,t}$

[1] Single person at 67 percent of average earnings, no child. Spliced with OECD-SPIDER tax wedge for single person prior to 2000.

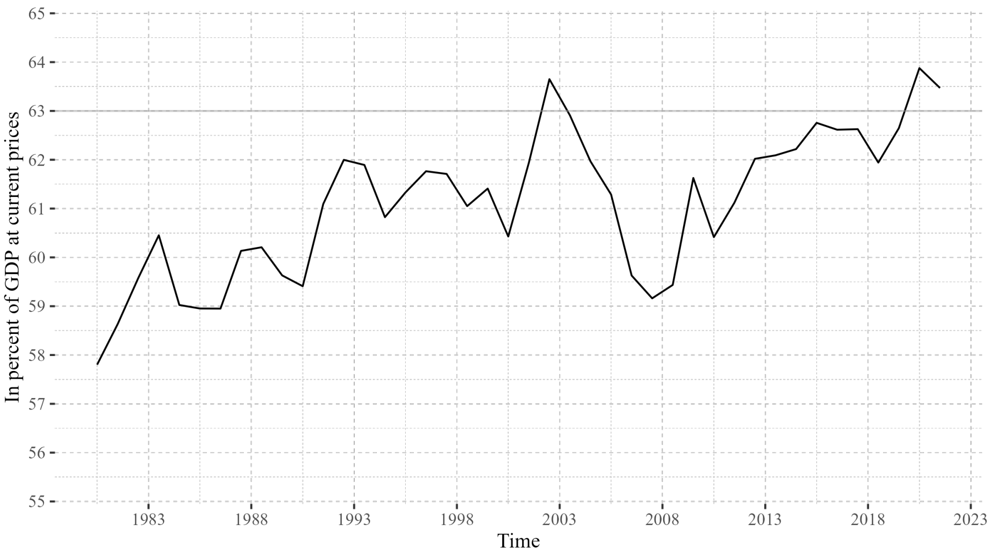
[2] Prior to 2001 spliced with Van Vliet and Caminada (2012) welfare state entitlements data.

[3] Share of expenditure on items 10-70 in nominal GDP, divided by the share of unemployed in the population.

[4] 10-year government bond yields, minus inflation rate of the GDP deflator averaged over 5-years.

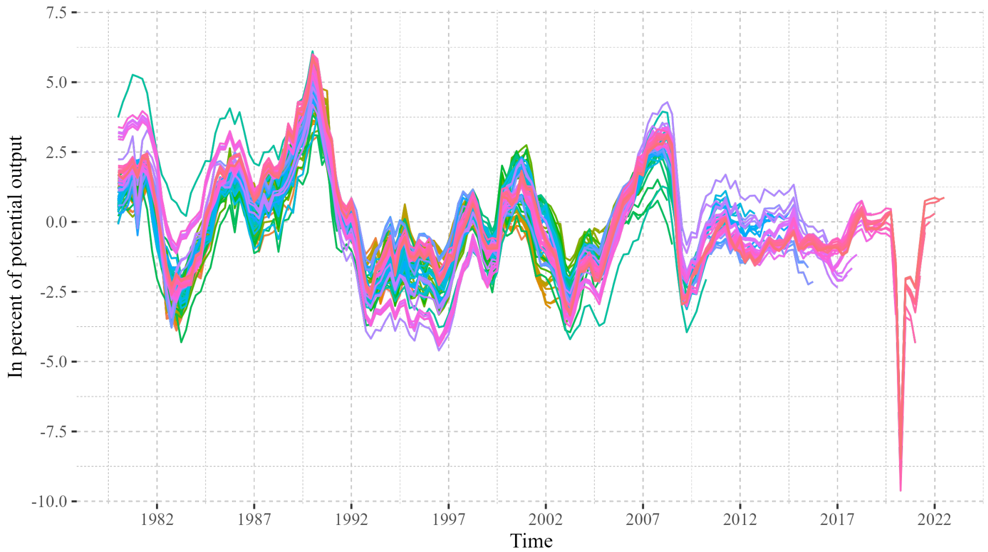
A2 Additional Figures and Tables

Figure 11: Adjusted labor share



The figure shows the labor share adjusted for the income of self-employed persons, under the assumption that the average wage of the self-employed is identical to that of employees. The output elasticity of labor in the production function is set to 0.65.

Figure 12: Vintages of output gap estimates from the production function



The figure shows the recursively estimated output gap based on the real-time vintages of GDP. It is the baseline for the calculations provided in the lower part of Table 7.

A3 The multivariate filter

Multivariate filters extend the informational basis by including data in addition to GDP, using equations that map the unobserved output gap to observed variables like the inflation rate (Phillips curve) or the unemployment rate (Okun's law). The basic multivariate model is given by the following equations:

$$Y_t = \bar{Y}_t + \epsilon_t^y \tag{A3.1}$$

$$\bar{Y}_t = \bar{Y}_{t-1} + g_t \qquad \epsilon_t^y \sim \mathcal{N}(0, \sigma_y^2) \qquad \sigma_y^2 = \lambda \sigma_g^2 \tag{A3.2}$$

$$g_t = g_{t-1} + \epsilon_t^g \qquad \epsilon_t^g \sim \mathcal{N}(0, \sigma_g^2) \qquad \sigma_g^2 = e^{\theta_1} \tag{A3.3}$$

$$duc_t = \beta_1 + \beta_2 \epsilon_t^y + \epsilon_t^{duc} \qquad \epsilon_t^{duc} \sim \mathcal{N}(0, \sigma_{duc}^2) \qquad \sigma_{duc}^2 = e^{\theta_2} \tag{A3.4}$$

$$\pi_t = \beta_3 + \beta_4 \epsilon_t^y + \epsilon_t^{\pi} \qquad \epsilon_t^{\pi} \sim \mathcal{N}(0, \sigma_{\pi}^2) \qquad \sigma_{\pi}^2 = e^{\theta_3} \tag{A3.5}$$

$$ur_t = \beta_5 + \beta_6 \epsilon_t^y + \epsilon_t^{ur} \qquad \epsilon_t^{ur} \sim \mathcal{N}(0, \sigma_{ur}^2) \qquad \sigma_{ur}^2 = e^{\theta_4} \tag{A3.6}$$

Note that ϵ_t^y corresponds to the output gap, duc is the capacity utilization, π is the inflation rate and ur is the unemployment rate. The first three equations represent the traditional HP-filter with $\lambda = 1600$. The multivariate extensions consist of mapping the latent output gap in equations A3.4 to A3.5 to other observable variables. These conditioning variables are industrial capacity utilization (KOF survey), the unemployment rate and the inflation rate. The multivariate unobserved components model is solved by maximum likelihood estimation via non-linear least squares and estimated by running the Kalman filter and smoother.

Declarations

Competing Interests

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Authors' Contributions

All authors jointly developed the idea, conducted data analysis, interpreted the results, and were major contributors in writing the manuscript. All authors proof-read and approved the manuscript.