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# Estimating the Potential Output for Switzerland using the Methodology of the European Commission

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**Herausgeber**
Staatssekretariat für Wirtschaft SECO
Holzikofenweg 36, 3003 Bern
Tel. +41 58 469 60 22
wp-sekretariat@seco.admin.ch
www.seco.admin.ch

**Online**
www.seco.admin.ch/studien



**Autoren**
Christian Glocker und Serguei Kaniovski
Austrian Institute of Economic Research (WIFO)
Arsenal, Object 20, AT-1030 Vienna



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**Anmerkungen**
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Der vorliegende Text gibt die Auffassung der Autoren wieder. Diese muss nicht notwendigerweise mit derjenigen des Auftraggebers übereinstimmen.

# Schätzung eines Produktionspotenzials für die Schweiz nach der Methodik der Europäischen Kommission


**Zusammenfassung**

Das Produktionspotenzial beschreibt das Niveau des realen BIP, das mit einer stabilen Lohninflation einhergeht. Die Produktionslücke als relative Abweichung des realen BIP vom Produktionspotenzial gibt die zyklische Position einer Volkswirtschaft wieder. Strukturelle Schätzungen des Produktionspotenzials bestimmen die Wendepunkte eines Konjunkturzyklus und zeigen die Wachstumsbeiträge von Kapital, Arbeit und Produktivität. Die Kenntnis der aktuellen Konjunkturlage ist für die Erstellung von Prognosen und die Wirtschaftspolitik von Relevanz. Die Studie schätzt das Produktionspotenzial der Schweizer Wirtschaft nach der Produktionsfunktionsmethode der Europäischen Kommission (EK). Die Methode fußt auf ökonometrischen Schätzungen des Produktivitätstrends und der natürlichen Arbeitslosenquote (NAWRU).

Darüber hinaus untersucht die Studie die Sensitivität der Schätzungen gegenüber Datenrevisionen auf Basis konsistenter historischer Datensätze. Die Schätzungen nach der Produktionsfunktionsmethode sind anfälliger für Revisionen als mit Zeitreihenfiltern extrahierte Trends. Im Gegensatz zur Produktionsfunktionsmethode bieten Filter jedoch keinen Einblick in die Determinanten des Wirtschaftswachstums. Ein weiterer Aspekt betrifft die strukturelle Komponente der NAWRU, welche mit einem panel-ökonometrischen Ansatz der EK geschätzt wird und als Ankerwert für die Arbeitslosenquote in der langen Frist dienen kann.

Die EK-Methode liefert plausible empirische Ergebnisse für die Schweiz. Die Schätzungen des Produktionspotenzials sind nicht übermäßig prozyklisch, und die Produktionslücke spiegelt die wichtigsten Phasen des Schweizer Konjunkturzyklus wider. Beiden Kennzahlen eignen sich zur Messung von Konjunkturschwankungen in der Schweiz und für mittel- und langfristige Prognosen auf der Grundlage ökonometrischer Schätzungen des Produktivitätstrends und der gleichgewichtigen Arbeitslosenquote.

# Estimation de la production potentielle pour la Suisse selon la méthodologie de la Commission européenne


**Résumé**

La production potentielle correspond au niveau du PIB réel lorsque l'inflation (des salaires) est stable. L'écart de production, soit la différence relative entre le PIB réel et la production potentielle indique la situation dans laquelle se trouve une économie dans le cycle économique. Les estimations structurelles de la production potentielle déterminent les points de retournement du cycle conjoncturel et mettent en évidence la contribution à la croissance des facteurs capital, travail et productivité. Pour des raisons de prévisions et de politique économique, il est important de connaître la situation conjoncturelle du moment. L'étude estime la production potentielle de l'économie suisse selon la méthode de la fonction de production de la Commission européenne (CE), qui repose sur des estimations économétriques de l'évolution de la productivité et du taux de chômage naturel (NAWRU).

L'étude examine en outre la sensibilité des estimations aux révisions de données sur la base de séries temporelles historiques. Les estimations procédant de la méthode de la fonction de production sont plus sensibles aux révisions que les tendances extraites sur la base de filtres de séries temporelles. Contrairement aux méthodes de la fonction de production, les filtres ne permettent néanmoins pas de cerner les déterminants de la croissance. Un autre aspect concerne la composante structurelle du NAWRU, qui est estimée au moyen d'une approche économétrique de données en panel de la CE et peut servir de valeur repère pour le taux de chômage à long terme.

La méthode de la CE livre des résultats empiriques plausibles pour la Suisse. Les estimations de la production potentielle ne sont pas démesurément procycliques et l'écart de production reflète les principales phases du cycle conjoncturel suisse. Les deux instruments sont adéquats pour mesurer les fluctuations conjoncturelles en Suisse et pour établir des prévisions à moyen et à long termes sur la base d'estimations économétriques de l'évolution de la productivité et du taux de chômage d'équilibre.

# Stima del potenziale di produzione della Svizzera secondo la metodologia della Commissione europea


## Riassunto

Il potenziale di produzione rappresenta il livello del PIL reale accompagnato da un'inflazione salariale stabile. Il divario relativo tra PIL reale e potenziale di produzione (output gap) esprime la posizione ciclica di un'economia. Le stime strutturali del potenziale di produzione indicano i punti di svolta di un ciclo congiunturale e mostrano in che misura capitale, lavoro e produttività contribuiscono alla crescita. Conoscere la situazione congiunturale attuale è importante per prevedere e regolare la politica economica. Il presente studio stima il potenziale di produzione e l'output gap dell'economia svizzera applicando la metodologia della funzione di produzione della Commissione europea (CE). Tale approccio si fonda sulle stime econometriche relative all'andamento della produttività e al tasso naturale di disoccupazione (Nawru).

Il presente studio analizza inoltre quanto le stime sono sensibili alle revisioni dei dati svolte sulla base di dati storici coerenti. Le stime effettuate secondo la metodologia della funzione di produzione sono più soggette a revisioni rispetto ad andamenti estrapolati tramite filtri di serie storiche. Tuttavia, a differenza di tale metodologia i filtri non permettono di capire le determinanti della crescita economica. Un ulteriore aspetto concerne il componente strutturale del Nawru – stimato con un approccio della CE basato sull'econometria dei dati panel – che può fungere da valore ancora per il tasso di disoccupazione a lungo termine.

Il metodo della CE fornisce possibili risultati empirici per la Svizzera. Le stime relative al potenziale di produzione non sono eccessivamente procicliche e l'output gap rispecchia le fasi più importanti del ciclo congiunturale svizzero. Le stime risultanti si prestano per misurare fluttuazioni congiunturali in Svizzera e per formulare previsioni a medio e lungo termine basate su stime econometriche relative all'andamento della produttività e al tasso di disoccupazione di equilibrio.

# Estimating the Potential Output for Switzerland using the Methodology of the European Commission


**Summary**

The potential output is the level of output compatible with stable (wage) inflation. The output gap, as a relative deviation of real GDP from potential output, indicates the cyclical position of an economy. Structural estimates of potential output deliver business cycle dating and the contributions of capital, labor and productivity to economic growth. Knowing the current cyclical position is relevant to forecasting and for guiding economic policy. This study estimates potential output and the output gap of the Swiss economy according to the production function approach of the European Commission (EC). The approach is based on econometric estimates of productivity trends and the natural rate of unemployment (NAWRU).

In addition, this study examines the sensitivity of the estimates to data revisions based on consistent historical data sets. Estimates using a production function are more susceptible to revisions than trends extracted with time series filters. However, unlike the production function approach, filters do not provide insight into the determinants of economic growth. A further aspect concerns the structural component of the NAWRU, which is estimated using a panel econometric approach of the EC and can serve as an anchor for the unemployment rate in the long-term.

The EC method provides plausible empirical results for Switzerland. Potential output estimates are not excessively pro-cyclical and the output gap reflects the main phases of the Swiss business cycle. The resulting estimates are suitable for measuring cyclical fluctuations in Switzerland and for medium-term and long-term forecasts based on econometric estimates of productivity trends and equilibrium unemployment rates.

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# 1 Introduction

This report presents estimates of potential output for Switzerland according to the production function of the European Commission (EC) for the years 1980-2017. The production function methodology is generally perceived to be superior to purely statistical trend extraction methods, because it delivers insight into the determinants of economic growth (Cotis, Elmeskov and Mourougane, 2005). The estimates of potential output are compared to the analogous estimates for several EU member states as well as to trends extracted using univariate time series filters. The disadvantages of a structural methodology based on a production function are its complexity, as well as frequent and substantial revisions in view of new data. Another disadvantage is the excessive procyclicality of the potential output estimate, which owes to the difficulty of removing cyclical components from the inputs (Darvas and Simon, 2015; Hristov, Raciborski and Vandermeulen, 2017).

The 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.[1] The report discusses the robustness of the estimates to data revisions. What makes Switzerland an interesting case for a revision analysis is the fact that the Swiss economy experienced a prolonged and severe recession in the 1990s, while it appears to have weathered the global financial and economic crisis of 2008 better than the rest of Europe.

Knowing the current cyclical position of an economy is useful for predicting its future. This makes reliable estimates of output gaps useful for short-term forecasting. By the same token, projections of potential output estimates can be used to develop medium-term extensions of short-term forecasts. The output gap is highly relevant for monetary and fiscal policy. Central banks use output gap estimates when setting interest rates. When the output gap estimates are indicative of the current and future inflationary pressures, they can be used by central banks to meet their inflation targets in the short run. The second use of an output gap as a guide for fiscal policy has certainly been more controversial. In the euro area, estimates of output gaps are also used in budgetary planning. The output gap as a measure of aggregate capacity utilization is used in assessing the current fiscal stance of a member state. A comparison of the output gap to a change in the structural fiscal balance indicates whether the fiscal stance is procyclical or countercyclical. Policy strives for a zero structural fiscal balance over the business cycle. Moreover, fiscal policy should be countercyclical so as to cushion the effect of aggregate fluctuations on

[1] For a comprehensive treatment of such models, see Harvey (1989).

household and firm incomes.

The use of output gap estimates for policy guidance has always been in the focus of economic policy debate. For example, Orphanides (2002) blames incorrect estimates of potential output (according to the Keynesian tradition) for the inability of the central banks to rein in the rise of inflation in the 1970s. The recent criticisms of the use of output gaps for fiscal guidance revolve around the austerity policies that were implemented in response to the financial and economic crisis of 2008. These policies aimed at stabilizing sovereign debt levels. Fatás and Summers (2018) argue, however, that the reliance on too-pessimistic output gap estimates may have increased sovereign debt instead of decreasing it. The result might have even been counterproductive to the budgetary consolidation effort. Excessively procyclical potential output estimates can deprive policy-makers of the budgetary leeway to pursue adequate stabilization policies. This is true especially in the European Union, where the output gaps enter fiscal surveillance and medium-term planning.[2] The second problem is that frequent revisions of the output gap estimates can be counterintuitive, invalidating the instrument in the context of medium-term budgetary planning.

The estimation methods frequently used for the empirical determination of trend output can essentially be divided into three groups. Purely technical methods break GDP down into its components by filtering the long-term trend of the series. Such methods are simple, transparent and easily reproducible. The popular HP filter obtains the trend output by minimizing the deviation of the trend output from the actual output and the fluctuations of the trend output itself. The main drawback of using filters is that they are liable to produce spurious dynamic relations, particularly at the end of the sample (Hamilton, 2017). Systematically incorrect trend-cycle decompositions at the end of the sample entail the risk of misjudging the structural budget balance and can trigger early discretionary measures for budget restructuring. Unlike filters, which are based only on the time series of real GDP, structural approaches rely on a theoretical model. The production function approach describes the relationship between GDP and the production factors capital and labor, as well as a measure of productivity, and in the simplest case the total factor productivity (TFP). Once the levels of production factors corresponding to normal utilization (or a steady state) are determined using structural econometric models, a production function composes them into a time series for trend output. The third group includes hybrid approaches, which are further developments of purely statistical models,

[2] Also see, Turner, Cavalleri, Guillemette, Kopoin, Ollivaud and Rusticelli (2016), as well as Coibion, Gorodnichenko and Ulate (2017) and Fatás (2018).

extended by economic relationships such as the Phillips curve. The EC method represents a hybrid approach, in which filters and structural econometric models are combined to estimate the time series for productivity and input factor trends.

# 2 Institutional Background

Since the introduction of the Economic and Monetary Union, the economic policy in the EU has been characterized by the asymmetry between central monetary policy and national fiscal policies. With the Maastricht Treaty of 1992, the member states agreed to comply with the EU convergence criteria. Since 1997, fiscal policy has been coordinated within the framework of the Stability and Growth Pact (SGP). The pact laid down the principles for the monitoring of national budgets by the EC and the Council. As part of the early warning system, the EC examines annual stability programs of the member states for excessive deficits. Originally, the SGP contained no reference to the cyclical position of a member state. The first reform of the pact took place in 2005 and for the first time considered the cyclical position of a member state when setting the medium-term budget target. However, at the time the EC did not set any targets for the cyclical adjustment of the budget balance.

The European sovereign debt crisis that followed the global financial and economic crisis of 2008 has shown negative external effects of excessive national deficits on other countries in the monetary union. They arise from a spillover of higher interest rates on sovereign debt from a country with an excessive deficit to the other countries. The sovereign debt crisis prompted a series of far-reaching reforms of the SGP, which were further tightened and supplemented by additional legislative measures to reform the Stability and Growth Pact in 2011 (Sixpack and Twopack). With the Fiscal Compact as part of the Fiscal Stability Treaty of 2012, the member states agreed to maintain a balanced general government budget. In the current institutional framework, the most important fiscal policy control variables of the fiscal pact are adjusted for cyclical fluctuations. Today, the EC provides estimates of potential output and output gap as a part of a forecasting exercise and as a key element of fiscal surveillance of the member states.

The EC uses extensions of short-term forecasts for fiscal planning up to $t + 10$ and for assessments of the budgetary impact of the ageing population beyond 2050. Comprehensive short-term forecasts are published twice a year. The spring forecast covers the current and the next year ($t+1$), whereas the autumn forecast updates the spring forecast and extends it by an additional year ($t+2$). The medium-term forecast extends the short by additional three years ($t+5$, currently until 2023). The medium-term forecast essentially describes the transition from short-term business cycle fluctuations to long-term steady-state growth driven by demographic developments and technical progress. The output gap is assumed to close at the end of the medium-term horizon in $t+5$ and the unemployment rate to converge to the NAWRU in $t+10$. The NAWRU represents an equilibrium unemployment rate, which is determined by purely structural factors shaped by labor market institutions as well as several nonstructural factors and persistent cyclical factors. The long-term projections underlying the EC Ageing Reports assume a gradual convergence of country-specific NAWRU to a country-specific long-term anchor. The NAWRU anchor is an estimate of the rate of unemployment which can be traced back to purely structural determinants such as labor-market institutions (European Commission, 2017). The EC updates the anchor estimates every few years. The current estimate uses the data available until 2015.

# 3 The Production Function Methodology

The concept of the output gap as a measure of aggregate capacity utilization has a long and tangled lineage.[3] The differences between Keynesian and monetarist concepts of output gap owe to different views of the causes of macroeconomic fluctuations and the role of economic policy. The key conceptual elements go back to Keynes, and especially to Phillips, whose work on the relationship between the level of unemployment and the rate of wage inflation was fundamental. Much of the early research on potential output in the Keynesian tradition was conducted by Okun, who coined the term “Potential GNP”. Okun’s concept of potential output corresponds to the full employment output that can be achieved without triggering inflationary pressure. The gap is negative except at full employment, where it is zero. Full employment should be the primary goal of economic policy, subject to a trade-off between inflation and unemployment. Friedman and Phelps challenged the Keynesian view and policy prescription, advocating inflation targeting as the primary policy objective. In the monetarist view, the actual output fluctuates around a natural rate of output, so that the output gap can be positive as well as negative. The second important difference between the Keynesian and the monetarist views is the relationship between the output gap and inflation. Okun believed that inflation

[3] For a conceptual history of the output gap, see Congdon (2008).

is related to the output gap, whereas the monetary conception embodied in Friedman's accelerationist hypothesis relates the change in inflation to the output gap.

The monetarist view has prevailed. The output gap as a deviation from a long-run trend is a common element of many macroeconomic models today. An early example of the contemporary formalism is the paper by Perloff and Wachter (1979), whose ideas were further developed by the IMF and the OECD in the late 1980s. Since the 1990s these institutions have published estimates of potential output and output gaps as a part of their macroeconomic forecasts. The output gap is the central concept in the New Keynesian theory, where it enters the New Keynesian Economics Phillips curve and the Taylor Rule governing the monetary policy (Clarida, Galí and Gertler, 1999).

The EC methodology views potential output as the level of GDP compatible with a constant rate of inflation. Conceptually, the estimate of potential output is a trend around which the actual output fluctuates over the course of a business cycle. The output gap as a relative deviation of real GDP from potential output indicates the cyclical position of an economy. Knowing the current cyclical position is helpful for economic forecasting and an assessment of the fiscal stance. The latter is the main goal of the EC. Being non-observable, potential output must be estimated. The following exposition describes the steps required in estimating potential output according to the EC methodology.[4] The point of departure is an aggregate production function that describes the current level of actual GDP (chain-linked volumes at 2010 reference levels). The actual output ($Y_t$) is modeled using a Cobb-Douglas production function, with capital stock ($K_t$) and total hours worked ($L_t$) as the factor inputs:

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

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 Residuum, or the part of growth in real GDP not explicable by changes in the amount of labor and capital used in production.

[4] 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, Mc Morrow, Orlandi, Planas, Raciborski, Roeger, Rossi, Thum-Thysen and Vandermeulen (2014).

## 3.1 Total Factor Productivity (TFP)

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 $(UL_t, UK_t)$,

$$TFP_t = \underbrace{EL_t^{\alpha} \cdot EK_t^{1-\alpha}}_{trend} \cdot \underbrace{UL_t^{\alpha} \cdot UK_t^{1-\alpha}}_{cycle}, \tag{2}$$

or, taking the natural logarithms,

$$F_t \equiv \log(TFP_t) = \underbrace{\log(EL_t^{\alpha} \cdot EK_t^{1-\alpha})}_{f_t} + \underbrace{\log(UL_t^{\alpha} \cdot UK_t^{1-\alpha})}_{c_t}. \tag{3}$$

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 $c_t$. The cyclical component is identified using the variations in the rate of capacity utilization sourced from business sentiment surveys. The estimates are obtained by applying a Kalman filter to the following model:

$$F_t = f_t + c_t\,, \tag{4}$$

$$\left.\begin{aligned} \Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^{\eta} \end{aligned}\right\} \quad \text{trend}\,, \tag{5}$$

$$\left.\begin{aligned} c_t &= \varphi_1 c_{t-1} + \varphi_2 c_{t-2} + a_t^c \\ CU_t &= \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \beta_1 c_t + a_t^{cu} \end{aligned}\right\} \quad \text{cycle}\,, \tag{6}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\ a_t^{\eta} \sim N(0, \sigma^2_{a^{\eta}}),\ a_t^c \sim N(0, \sigma^2_{a^c}),\ a_t^{cu} \sim MA(1) \quad \text{error terms.}$$

The observable variables, denoted by capital letters, include the logarithm of the observed TFP, $F_t$, and the mean-centered aggregate capacity utilization $CU_t$. The trend $f_t$ follows a random walk with a drift. The parameter $\mu_p$ is the long-run (gain) value of $\Delta f_t$ as a result of a random shock $a_t^{\eta}$. The damping parameter $\rho \in (0, 1)$ gauges the rate of convergence to the gain value. The cycle $c_t$ follows an $AR(2)$ process. The measurement equation featuring the series for capacity utilization $CU_t$ depends on the cycle $c_t$ and an error term $a_t^{cu}$ that follows an $MA(1)$ process. Since $CU_t$ is mean-centered, the estimate of $\mu_{cu}$ should be close to zero. All error terms are assumed to be (over time and in a cross-section) independent and identically distributed normal variates with zero means.

The 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.[5] The EC estimates the above unobserved component model using a Bayesian approach. The main 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. On the other hand, since the error bands for the productivity trend cannot be transferred to the estimate of the output gap, the benefit of a Bayesian approach in the current context is not evident. We therefore rely on the Maximum Likelihood estimates.

## 3.2 Capital

The capital stock describes the available inventory of gross fixed assets. The capital stock is accumulated using a perpetual inventory method. The EC methodology does not model capital utilization directly; formally, $\bar{K}_t = K_t$. Part of the reason is the fact that empirical (e.g. survey) data on utilization of capital goods are not readily available. Any cyclical fluctuations in capital utilization are assumed to be removed by the cyclical adjustment of the total factor productivity in the decomposition (2).

## 3.3 Non-accelerating Wage Rate of Unemployment (NAWRU)

According to the Common Methodology of the EC, potential output is defined as the level of output associated with constant wage inflation. The output gap as the relative deviation of real GDP from trend output describes the aggregate capacity utilization. A positive output gap indicates overutilization and rising inflationary pressures. Inflationary pressures should ease once the capacity becomes underutilized. To identify the average utilization of labor, we first decompose total hours worked as:

$$L_t = POP_t \cdot PRT_t \cdot (1 - U_t) \cdot H_t, \tag{7}$$

where $POP_t$ denotes the working-age population aged between 15 and 64, $PRT_t$ the participation rate in percent of the labor force, $U_t$ the unemployment rate and $H_t$ the

[5]For a technical documentation, see Planas and Rossi (2018).

hours worked per persons 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,

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

All of the above quantities, except the population, 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 $\lambda = 10$ is set following the recommendations for the annual data in Baxter and King (1995).[6] Since the HP-filter is particularly susceptible to spurious behavior at the end of the sample, both time series are extended by three years using ARIMA(1,1,0) models prior to applying the filter.

The trend of the unemployment rate is defined as the non-accelerating wage rate of unemployment (NAWRU), which is the dominant macroeconomic equilibrium concept for the labor market (Layard, Nickell and Jackmann, 2005). 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

[6] This values is somewhat higher than 6.25 that is found optimal for the annual real GDP by Ravn and Uhlig (2002). Since hours per persons employed tend to fluctuate more than the participation rate over the business cycle, it might be reasonable to smooth them stronger.

approach is implemented in the following unobserved component model (Hristov, Planas, Roeger and Rossi, 2017).

Let $\nu_t$ 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 (Galí 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 following system is estimated using the Kalman filter.

$$U_t = \nu_t + z_t \,, \tag{8}$$

$$\Delta\nu_t = \xi_t^{\nu} \qquad \text{trend}\,, \tag{9}$$

$$\left.\begin{aligned} & z_t = \vartheta_1 z_{t-1} + \vartheta_2 z_{t-2} + \xi_t^z \\ & \Delta^2 W_t = \mu_w + \gamma_1 z_t + \gamma_2 z_{t-1} + \alpha_1 \Delta^2 tot_t + \alpha_2 \Delta^2 prod_t + \alpha_3 \Delta^2 ls_t + \xi_t^w \end{aligned}\right\} \quad \text{cycle}\,, \tag{10}$$

$$\xi_t^{\nu} \sim N(0, \sigma^2_{\xi^{\nu}}),\ \xi_t^z \sim N(0, \sigma^2_{\xi^z}),\ \xi_t^w \sim N(0, \sigma^2_{\xi^w}) \qquad \text{error terms.} \tag{11}$$

The above unobserved component model places emphasis on modeling the cycle of the unemployment rate, $z_t$, while its trend $\nu_t$ is modeled rather parsimoniously as a 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 that also contains 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.

# 4 Data and Implementation

## 4.1 Data Sources

The report closely follows the methodology of the EC. The aim is to ensure comparability with potential output estimates for the EU member states and the USA disclosed by the EC following the publication of their macroeconomic forecasts.[7] The key source for Swiss data is the AMECO database, which contains mainly annual macroeconomic data from the National Accounts. Additional data, e.g. the measure of aggregate capacity utilization, are drawn either from Macrobond or national sources. The appendix provides a list of variables required for estimating the potential output.

The project uses data covering the period 1980-2017.[8] The current debate on the reliability of potential output estimates in real time revolves around the years immediately following the outbreak of the crisis in 2008. This focus is natural, given the large revisions made during this period and the far-reaching consequences they may have had for economic policies. Since AMECO does not provide comprehensive archives that include the pre-crisis data vintages for Switzerland, we construct a real-time AMECO database using the data found in WIFO repositories, which are reasonably complete. The revision analysis uses vintages of AMECO data starting from spring 2002. Potentially, a total of 34 vintages of AMECO exist, with two vintages (spring and autumn) for each year between 2002 and 2018. We have used the 17 spring vintages for all calculations in this project. The current release from spring 2018 includes data up to 2017, plus a two-year forecast made in the first half of 2018.

Several time series in AMECO (historical or current) have questionable quality prior to 1991. All such cases were resolved using one of the following four approaches: 1) the series was replaced by an equivalent one from a national source (Bundesamt für Statistik); 2) the series was replaced by a more plausible version of the same series found in another vintage; 3) the series was spliced using more plausible growth rates of the same series found in another vintage; or 4) the series was spliced using growth rates of a proxy series. In all such cases we tried to balance three criteria: the length of the sample, the plausibility of the data and the comparability between the vintage data and the current release. The comparability ensures that conclusions drawn from the revision analysis apply to the current situation. We therefore only switched from AMECO to the alternate

[7] The estimates and program codes can be found at: `https://circabc.europa.eu/`.
[8] We explore the robustness of the model using a shorter sample, as is documented in Appendix B.

national source when the AMECO version of a time series was implausible, e.g. because it displayed significant structural breaks. This was the case for the persons employed (employees and self-employed) and the total hours worked. Both series exhibited large structural breaks around 1991.

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.

## 4.2 Implementation

The current implementation by the EC is scattered across several proprietary software packages. The main Maximum Likelihood and Bayesian estimation routines for unobserved component models are written in FORTRAN provided in a compiled form. This project uses the routine `GAP50.EXE` to estimate the TFP trend and the NAWRU with the method of Maximum Likelihood. The `GAP50.EXE` requires a model file containing the specification of an unobserved component model and the data required to estimate it.[9] This information is supplied in a text file carrying an extension `NML`. An example of the invocation command is: `C:\MYGAP50\GAP50.EXE NAWRU_MOD.NML`.

The programs provided by the EC embed `GAP50.EXE` and supplementary MATLAB routines used for Bayesian estimations in EXCEL. These programs include the functionality for entering the data, the specification of the model, the bounds on model parameters or the priors for them, as well as functionality for tabling and plotting the estimates. The auxiliary panel-econometric estimate of the NAWRU anchor is implemented in STATA. The NAWRU anchor is used in medium-term and long-term projections. It enters the EXCEL file as an exogenous parameter. In a final step, a RATS program combines the estimates of the TFP trend and the NAWRU with the remaining data of the structural model to compute the historical potential output and a medium-term projection.

To reduce the required number of software packages, we provide a unified implementation in R. The basic data is assumed to be available in an EXCEL file. The R-program reads these data and then computes and inserts the estimation sample into a `GAP50.EXE`

[9]The technical details of this implementation are discussed by Planas and Rossi (2018), who also provide a user-manual.

model file. The `GAP50.EXE` is subsequently called within the R-program, which then performs all subsequent calculations and generates the output described in the text. The software required to replicate the estimates discussed in this report is thus limited to the `GAP50.EXE` program provided by the EC and the main program written in R. The filtered series are used to either construct the trends of factor inputs in the production function methodology or obtain alternate series for potential output by filtering the real GDP. The panel-econometric estimates of the NAWRU anchor are also implemented in R using the `plm` package. We use the R package `mFilter` to filter individual time series.

# 5 Results

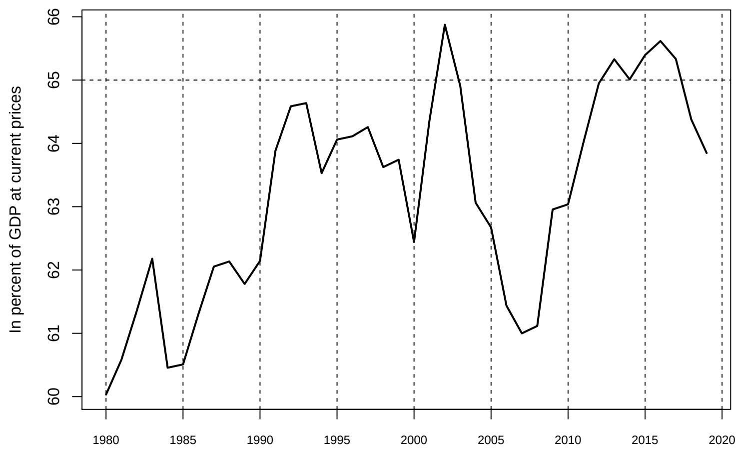
The productivity trend and average utilization of production factors cannot be observed and must be estimated. The EC methodology integrates two estimates into a single structural model, whereby trends of productivity and labor input enter the production function for potential output. The main trend estimates are obtained using two unobserved component models: one for TFP and the other for the non-accelerating wage rate of unemployment (NAWRU). The potential output $\bar{Y}$ is calculated from trend inputs as:

$$\bar{Y}_t = F_t \cdot \bar{L}_t^{\alpha} \cdot \bar{K}_t^{1-\alpha}. \tag{12}$$

## 5.1 Labor Share

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 $\alpha$ and capital $1 - \alpha$. 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 $\alpha$, 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 2017 equals 0.57. We retain the value of the output elasticity of labor assumed by the EC, since it is close to the average labor share of 0.631 adjusted for the income of self-employed. The adjustment assumes that the average wage of self-employed is identical to that of employees. Figure 1 shows the adjusted share of compensation of employees in GDP at current prices between 1980 and 2017. During

Figure 1: 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.

this period the share increased, on average, by 0.14 percentage points per year. The small size of this drift makes the technical assumption of a constant labor share tenable.

## 5.2 Trend in Total Factor Productivity (TFP)

Table 1 summarizes the estimates of the unobserved component model for the TFP trend. Figure 2 shows the growth rates of $\exp(F_t)$ and its trend $\exp(f_t)$. The compound annual growth rate of the trend between 1980 and 2017 equals 0.76 percent. With an output elasticity of labor of 0.65 this value is roughly equivalent to $0.76/0.65 \approx 1.17$ percent growth in labor productivity. The observed total factor productivity grew by 0.7 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 $0.7 = 0.76 - 0.06$.

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 a potential output should be. A visual inspection of Figure 2 already suggests that the growth rate of the trend is substantially lower than that of the observed TFP series, with the variance of the growth rate of the trend of 0.17 against the variance of the growth rate of the observed TFP of 1.9. The correlation between the two growth rates equals 0.36, but the correlation between the GDP growth and that of the trend is 0.16. We can therefore claim with some degree of certainty that the estimated productivity trend is not excessively procyclical.[10]

Table 1: Estimates of the TFP trend model

| | Estimate | S.E. | t-stat |
|---|---|---|---|
| $\mu_p$ | 0.007 | 0.002 | 3.945 |
| $\rho$ | 0.773 | 0.233 | 3.315 |
| $\varphi_1$ | 0.576 | 0.188 | 3.069 |
| $\varphi_2$ | -0.358 | 0.165 | -2.164 |
| $\mu_{cu}/(1-\alpha_1-\alpha_2)$ | -0.001 | 0.005 | -0.100 |
| $\beta/(1-\alpha_1-\alpha_2)$ | 1.552 | 0.224 | 6.938 |
| DIAGNOSTICS | Stat. | | p-val |
| Cycle Ljung-Box stat. Q(4) | 1.340 | | 0.855 |
| Capacity Utilization Ljung-Box stat. Q(4) | 0.855 | | 0.931 |
| $R^2$ (one-step-ahead predictions) | 0.415 | | |

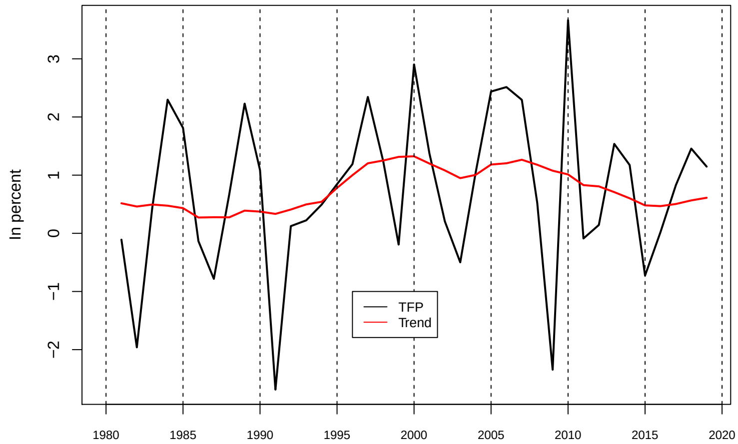
Likelihood maximized by sequential quadratic programming method. Standard errors computed using information matrix. The estimates were obtained using GAP 5.0.

### 5.3 Capital

Figure 3 shows the growth of capital stock and the capital coefficient, defined as $100 \cdot K_t/Y_t$ since 1980. It shows a reduction in the growth rate of 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 and capital to hours worked has not risen to the extent one would expect it to rise during a recovery. Between 1980 and 2017, Swiss capital stock grew with the compound annual growth rate of 1.5 percent. This rate slowed down to 1.1 percent after the crisis (2009-2017). The evolution of the ratio of the capital stock to real GDP paints a similar picture. The capital coefficient decreased at a rate of 0.5 percentage points of real GDP per year prior to the crisis (1980-2007). This rate more than tripled to -1.9 percentage points of real GDP per year after the crisis (2009-2017).

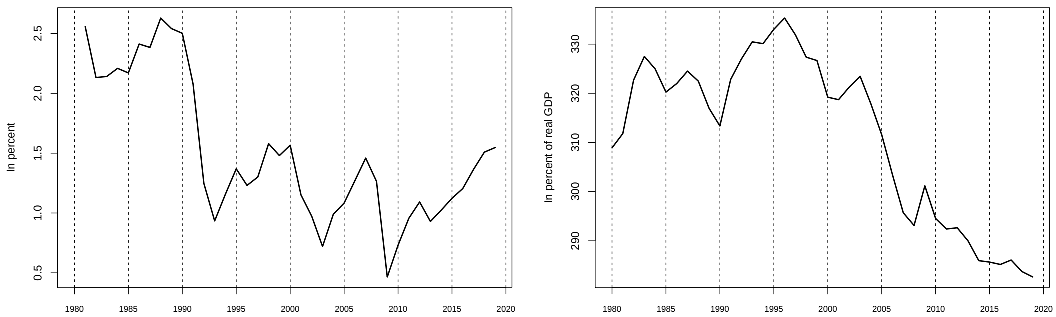
[10] All correlation coefficients discussed in this report are the Pearson product-moment coefficients.

Figure 2: Growth of observed TFP and TFP trend



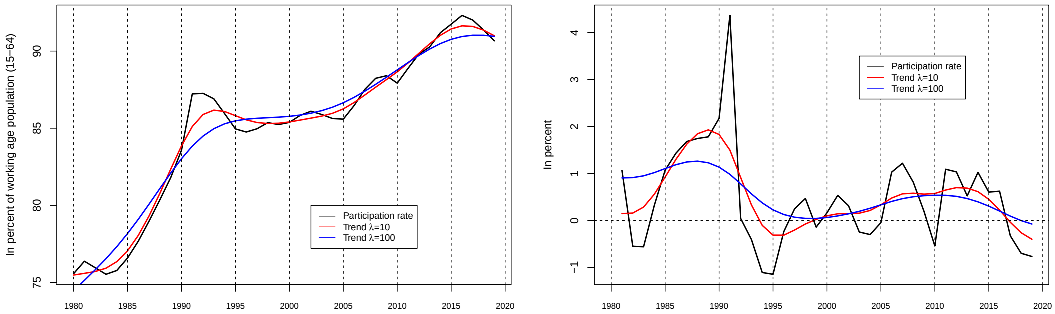

The trend of the logarithm of total factor productivity $f_t$ is estimated using the model defined by equations (4)-(6). The figure shows the annual growth rate of TFP ($\exp(F_t)$, black) and its trend ($\exp(f_t)$, red).

Figure 3: Growth of capital stock and the capital coefficient




The capital stock grew with the compound annual growth rate of 1.5 percent between 1980 and 2017, slowing down to 1.1 percent in the period after the crisis (2009-2017). The capital coefficient decreased at a rate of 0.5 percentage points per year prior to the recent crisis (1980-2007). This rate increased to -1.9 percentage points after the crisis (2009-2017).

Figure 4: Participation rate




The trend is extracted using the HP filter with $\lambda = 10$ (red) and $\lambda = 100$ (blue). To alleviate the end of the sample problem, the original time series was extended by four years using ARIMA(1,1,0) models prior to applying the filter. The right panel shows the corresponding annual average growth rates.

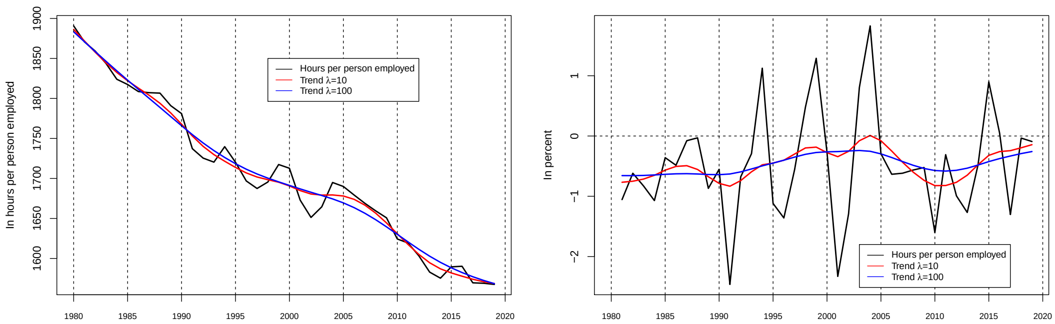
## 5.4 Trend in Participation and Average Hours Worked

Figures 4 and 5 show 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 HP filter smoothes over the structural break, but explicit modeling of the trend before and after the break might be more appropriate. The recent participation rates are nearly constant or slightly decreasing, as is also seen in most of European countries (p. 74-75 in ILO, 2018). The average hours worked have been on a nearly continuous decline, reflecting the trend to more part-time work.

## 5.5 Trend in Unemployment Rate (NAWRU)

Table 2 summarizes the estimates of the unobserved component model for the trend of the actual unemployment rate (NAWRU). The actual rate of unemployment according to the ILO definition and the estimated NAWRU are shown in Figure 6. The NAWRU is much smoother than the actual unemployment rate. The estimated NAWRU assumes of adaptive expectations. The empirical framework of the common methodology can accommodate forward-looking expectations of wage setters. This alternate estimate is shown as a blue line in Figure 6. We decided to retain the above estimate implicitly based on adaptive (backward-looking) expectations, because the forward-looking alternative produces estimates that are significantly less smooth and more procyclical.

Figure 5: Average hours worked



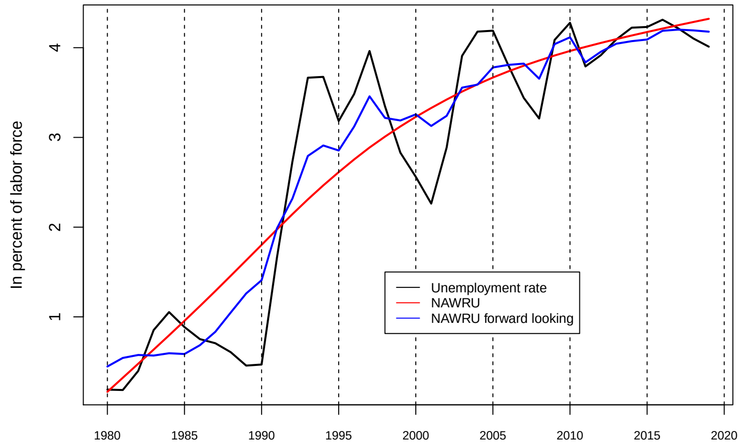

The trend is extracted using the HP filter with $\lambda = 10$ (red) and $\lambda = 100$ (blue). To alleviate the end of the sample problem, the original time series was extended by four years using ARIMA(1,1,0) models prior to applying the filter. The right panel shows the corresponding annual average growth rates.

Table 2: Estimates of the NAWRU model

| | Estimate | S.E. | t-stat |
|---|---|---|---|
| $\vartheta_1$ | 1.188 | 0.133 | 8.956 |
| $\vartheta_2$ | -0.558 | 0.127 | -4.404 |
| $\mu_w$ | -0.002 | 0.002 | -0.799 |
| $\gamma_1$ | -0.011 | 0.005 | -2.344 |
| $\gamma_2$ | 0.007 | 0.005 | 1.507 |
| $\alpha_1$ | -0.293 | 0.240 | -1.218 |
| $\alpha_2$ | 0.641 | 0.189 | 3.394 |
| $\alpha_3$ | 0.372 | 0.164 | 2.261 |
| DIAGNOSTICS | Stat. | | p-val |
| Cycle Ljung-Box stat. Q(4) | 2.151 | | 0.708 |
| Phillips Curve Ljung-Box stat. Q(4) | 4.195 | | 0.380 |
| $R^2$(one-step-ahead predictions) | 0.246 | | |

Likelihood maximized by sequential quadratic programming method. Standard errors computed using information matrix. The estimates were obtained using GAP 5.0.

Figure 6: Unemployment rate and NAWRU




The trend $\nu_t$ (red) is estimated using the unobserved component model defined by equations (8)-(10). The alternate estimate based on forward-looking expectations is significantly more procyclical (blue).

## 5.6 Growth of Potential Output and Output Gap

We can now insert the estimates for the trends of productivity $\exp(f_t)$, working-age population $POP_t$, participation rate $\overline{PRT}_t$, unemployment rate $\nu_t$ and average working hours in the production function to obtain a time series for potential output:

$$\bar{Y}_t = \exp(f_t) \cdot (POP_t \cdot \overline{PRT}_t \cdot (1 - \nu_t) \cdot \bar{H}_t)^{\alpha} \cdot K_t^{1-\alpha}. \tag{13}$$

The output gap is defined as the relative deviation of real GDP from the potential:

$$GAP_t = 100 \cdot \frac{Y_t - \bar{Y}_t}{\bar{Y}_t}. \tag{14}$$

Figure 7 compares the growth of real GDP with the growth of potential output, with the main variant shown in red. The figure shows that the growth of potential output 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 0.47, which is moderately high. Since the estimates of the TFP trend and NAWRU do not appear to be excessively procyclical, a reduction of this correlation can be achieved by applying a stronger smoothing of the participation rate and the average hours worked. These trend series indeed show high variation in transition to the recession period of the 1990s, which is likely to cause excess procyclicality of potential output growth. To assess the possible effect of a stronger smoothing, we apply $\lambda = 100$ instead of $\lambda = 10$ to both series. The results in the growth of potential output are shown as a blue line in Figure 7. The correlation coefficient with the growth of real GDP now equals 0.32. Note also that the two variants of potential output growth differ prior to 2000. 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.

The left panel of Figure 8 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 as follows:

$$l_t = 100 \cdot \alpha \frac{\bar{L}_t - \bar{L}_{t-1}}{\bar{L}_{t-1}} \quad \text{where} \quad \bar{L}_t = POP_t \cdot \overline{PRT_t} \cdot (1 - \nu_t) \cdot \bar{H}_t. \tag{15}$$

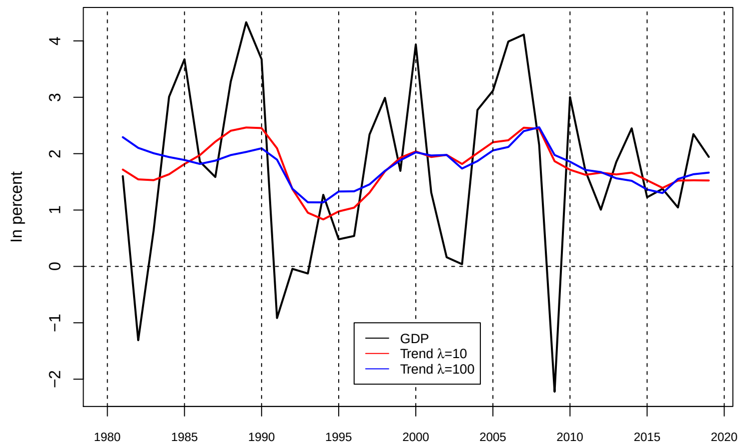
$$k_t = 100 \cdot (1 - \alpha) \frac{K_t - K_{t-1}}{K_{t-1}}. \tag{16}$$

The contribution of TFP is computed as a remainder:

$$f_t = g_t - l_t - k_t \quad \text{where} \quad g_t = 100 \cdot \frac{\bar{Y}_t - \bar{Y}_{t-1}}{\bar{Y}_{t-1}}. \tag{17}$$

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 technolo-

Figure 7: Growth of real GDP and potential output




The red line (main variant) shows the growth of potential output when the trend of participation rate and average hours worked are obtained using the HP-filter with $\lambda = 10$. The blue line shows an alternate calculation with a stronger smoothing of these two times series. Assuming $\lambda = 100$ reduces the correlation coefficient between the growth of real GDP and the growth of potential output from 0.47 to 0.32.

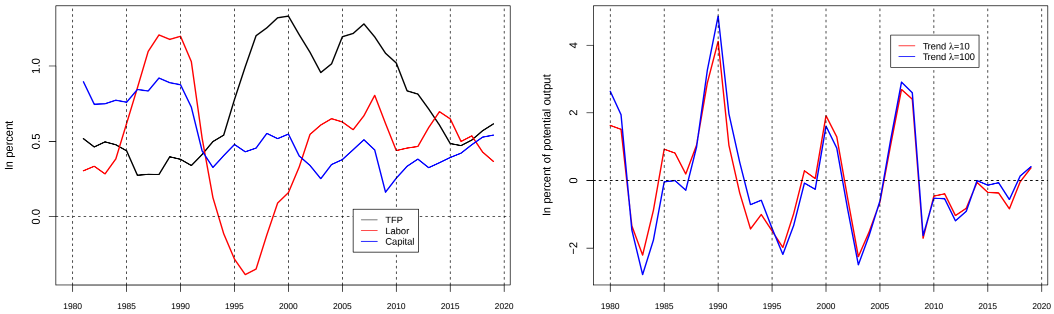
gies and automation. The increase in automation may have been the key factor behind persistent jobless-growth observed in many countries, or the fact that employment reacts very sluggishly to economic recoveries.

Table 3 summarizes the key economic indicators required to determine potential output. The sample is divided into decades, with the observations of the recent two decades separated into before-crisis-period and after-crisis-period groups, and the current two-year forecast reported separately.[11] The compound annual growth rates are computed over the indicated period, e.g., between the years 1980 and 1990. The table shows two episodes of depressed potential growth, one in the 1990s and the other following the 2008 crisis. The first episode is characterized by a negative labor contribution, whereas the second period reflects a productivity slowdown. Turning to the averages in the lower part of the table, we see that the output gaps were negative on average in the two episodes. The averages also reveal two long-term trends: a rising unemployment rate, both actual and NAWRU, and a falling capital coefficient.

The Swiss economy appears to have performed better than most industrialized coun-

[11] The AMECO includes a recent macroeconomic forecast.

Figure 8: Decomposition of potential output growth and output gap

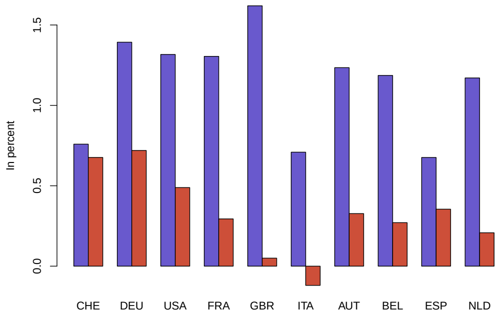


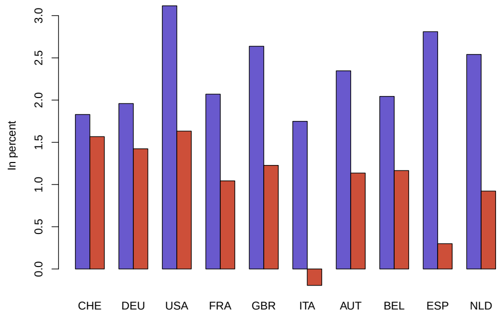

The left panel shows the contributions of TFP ($f_t$, black), labor ($l_t$, red) and capital ($k_t$, blue) to the growth of potential output. The contributions are defined by equations (15), (16) and (17). The three contributions add to the annual growth of potential output $g_t$. The right panel shows the output gap as defined by equation (14).

tries in the aftermath of the recent global financial and economic crisis of 2008. The EC provides estimates of potential output for all member states of the EU and for the USA. Figure 9 compares the pre-crisis to post-crisis estimates of Switzerland's major trading partners, for which comparable results are available in the EC Spring 2018 Economic Forecast.[12] The countries are sorted according to their share in total Swiss exports in 2017. A comparison of the estimates before the crisis (1980-2007) and after the crisis (2009-2017) shows that the impact of the crisis on the trend growth of Switzerland (right panel) has been the smallest, with the difference in growth rates being -0.3 percentage points. The next smallest values pertain to Germany (-0.5) and Belgium (-0.9), whereas all other countries have lowered their potential growth estimates by more than 1 percentage point. The largest downward adjustments apply to Spain (-2.5) and Italy (-1.9), the countries that were hit hardest by the sovereign debt crisis that followed the global crisis.

[12]The export shares of countries included in this comparison in total Swiss exports are: Germany (15.1), United States (12.3), France (5.7), United Kingdom (5.7), Italy (5.3), Austria (2.7), Belgium (2.3), Spain (1.9) and the Netherlands (1.8). The major destinations which are not covered by this source include China (8.2), India (6.6), Hong Kong (5.3), Japan (2.5), Singapore (2.5) and Turkey (2). The shares were sourced from the UN Comtrade Database. The underlying export values include the exports of Liechtenstein.

Figure 9: The effect of the 2008 crisis on potential output growth




The figure compares the estimates of the compound average annual growth in TFP trend (left panel) and growth of potential output (right panel) for Switzerland with those of its major trading partners. The averages for the years before the crisis are shown as a blue line (1980-2007), and those for the years after the crisis as a red line (2009-2017).

Table 3: Key macroeconomic indicators

| | 1980-1990 | 1990-2000 | 2000-2007 | 2009-2017 | 2017-2019 |
|---|---|---|---|---|---|
| | Compound annual growth rate (in percent) | | | | |
| Growth of real GDP | 2.2 | 1.2 | 2.2 | 1.7 | 2.1 |
| Growth of TFP trend | 0.4 | 0.9 | 1.1 | 0.7 | 0.6 |
| Growth of Potential Output | 2.0 | 1.4 | 2.1 | 1.6 | 1.5 |
| - Contribution of TFP trend | 0.4 | 0.9 | 1.1 | 0.7 | 0.6 |
| - Contribution of Labor | 0.7 | 0.1 | 0.6 | 0.5 | 0.4 |
| - Contribution of Capital | 0.8 | 0.5 | 0.4 | 0.4 | 0.5 |
| | 1981-1990 | 1991-2000 | 2001-2007 | 2010-2017 | 2018-2019 |
| | Average (in percent) | | | | |
| Output Gap | 0.7 | -0.4 | 0.0 | -0.5 | 0.2 |
| Unemployment Rate | 0.6 | 3.1 | 3.5 | 4.1 | 4.1 |
| NAWRU | 1.0 | 2.7 | 3.6 | 4.1 | 4.3 |
| Adj. Labor Share | 61.5 | 63.9 | 63.3 | 64.8 | 64.1 |
| Capital Coefficient | 320.6 | 328.4 | 313.1 | 289.1 | 283.2 |

The three contributions measured in percentage points add to the growth of potential output.

# 6 Validation and Robustness

## 6.1 A Comparison with Univariate Filters

The production function methodology yields an estimate of the output gap as a measure of aggregate capacity utilization. Fluctuations in the output gap reflect aggregate cyclical fluctuations of the economy. To assess the plausibility of the estimated output gap, we first compare it to an annual indicator series for economic upturns and downturns in Switzerland since 1980. The OECD publishes a monthly series that indicates the turning points of the Swiss business cycle since 1960. In the first step, the monthly turning points are used to delimit consecutive upturn and downturn phases in the business cycle. In a second step, we identify a downturn year if more than six months of that year were downturn months. The remaining years are called upturn years.

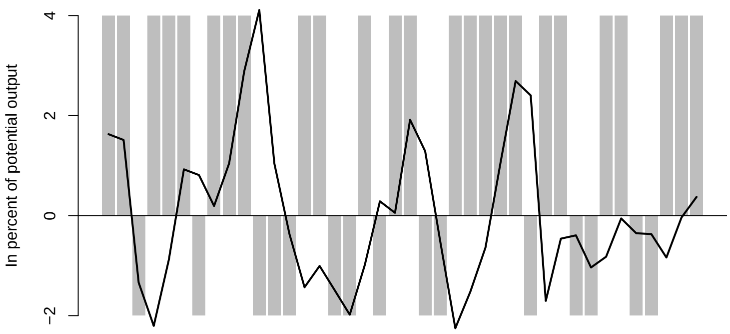
The identification of upturns and downturns is usually based on the growth rates of real GDP. We should expect the output gap to track upturn and downturn phases in general. However, the relation between growth rates and the output gap as a ratio of two levels of output is not trivial. The gap depends on a ratio of cumulative rather than instantaneous growth rates of the real GDP and potential output, as shown in the following representation:

$$\frac{GAP_T}{100} + 1 = \frac{Y_0}{\bar{Y}_0} \cdot \frac{\prod_{t=1}^{T}(1+g_t)}{\prod_{t=1}^{T}(1+\bar{g}_t)}. \tag{18}$$

The above representation shows that the gap depends on the initial ratio of the actual to potential GDP ($Y_0/\bar{Y}_0$) and the ratio of the cumulative growth rates. A characterization of the dynamic of an output gap in terms of cumulative growth rates is only accurate if the economy was at the equilibrium aggregate capacity utilization initially, or when $Y_0 = \bar{Y}_0$. Figure 10 shows the output gap according to the production function methodology against the backdrop of upturns shown by the positive bars and downturns shown by the negative bars. The output gap traces the successions of business cycle phases closely, but with a small delay. The delay is due to the gap being a function of the cumulative rather than instantaneous growth rates. Estimating potential output using higher frequency (e.g., quarterly) data may mitigate the delay to some extent, which suggests using the quarterly output gap estimates to nowcast annual series (e.g., inflation).

In a second step, we compare the output gap to alternate measures obtained by the application of three univariate time series filters – Hodrick-Prescott (HP), Baxter-King

Figure 10: Output gap vs. phases of the business cycle




The output gap obtained using the production function methodology tracks changes between the phases of upturns (positive bars) and downturns (negative bars) reasonably accurately, though with some delay. The delay is due to the output gap being a function of the cumulative rather than instantaneous growth rates of the actual and potential output.

filter (BK) and Christiano-Fitzgerald (CF) – to the annual 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 HP is a highpass filter that targets the high frequency components of a time series. The BK and CF are bandpass filters. They can suppress both the low frequency trend components and the high frequency components. The sole smoothing parameter of the HP filter is set at $\lambda = 10$ in accordance with the trend extractions applied to the labor input. The parameters of the BK and CF filters are set at their recommended values for annual data: $p_l = 2$, $p_h = 8$ and $k = 3$. The parameters $p_l$ and $p_h$ control the minimum and maximum admissible periodicity in the trend. The parameter $k$ sets the length of the lag and lead property of the filter. The BK and CF filters assume a unit root in real GDP.

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 (1995) 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. Hamilton (2017) advocates the use of regression analysis instead of the HP -filter. Yet despite all the problems associated with the use of univariate time series filters, they remain popular in applied work.

Figure 15 compares the four output gaps. Table 4 shows the summary statistics of the four estimates. According to the sample mean, all four estimates are nearly centered over the sample. The output gap according to the production function methodology shows the largest 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. Table 5 testifies to the high correlation between all four measures, which is also evident upon a visual inspection of Figure 15.

Table 4: Output gaps: Summary statistics

| | PF | HP | BK | CF |
|---|---|---|---|---|
| Min. | -2.25 | -2.05 | -1.85 | -1.91 |
| Mean | 0.04 | -0.01 | -0.06 | -0.05 |
| Max. | 4.11 | 3.07 | 2.71 | 2.30 |
| Sd. | 1.48 | 1.17 | 1.06 | 0.93 |
| Acf. (lag 1) | 0.55 | 0.40 | 0.28 | 0.15 |

Table 5: Output gaps: Correlation

| | PF | HP | BK | CF |
|---|---|---|---|---|
| PF | 1.00 | 0.91 | 0.89 | 0.84 |
| HP | 0.91 | 1.00 | 0.98 | 0.95 |
| BK | 0.89 | 0.98 | 1.00 | 0.99 |
| CF | 0.84 | 0.95 | 0.99 | 1.00 |

## 6.2 Analysis of Revisions

The sensitivity of estimates of potential output to large revisions has always been a thorn in the side of the economic policy practitioner. Cotis, Elmeskov and Mourougane (2005) remark that: “It is also important that data updates do not imply very large and unwarranted revisions in estimates to ensure the credibility of the method. Indeed, a method that generates very large revisions will be considered as uncertain” (p.7). Since the current debate on the reliability of potential output estimates in real time revolves around the aftermath of the 2008 crisis, our analysis shall specifically focus on the revisions made during that period. As we already pointed out above, the Swiss economy recovered from the effects of the 2008 crisis remarkably swiftly, despite a sharp decline in real GDP in 2009. In an ex-post consideration, we should therefore not expect a drastic revision of potential growth as a result of the crisis in Switzerland.

This section compares different real-time revisions for each year of the 1980-2017 sample and real-time revisions for each year with the current version. To obtain the estimates of the TFP trend and the NAWRU, we specify and estimate the corresponding unobserved component models for each vintage of the sample. The first vintage of the sample of 2002 covers the 1980-2001 period. The last vintage of 2018 covers the period 1980-2017. The vintage data does not include forecasts, as they were not available for most of the years in the past.

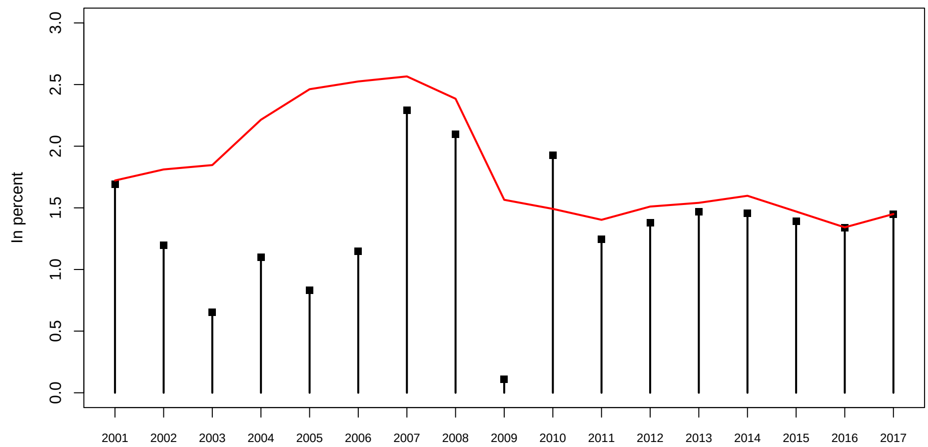
Figure 16 shows the revisions in estimates of potential growth since 2002 as box and whisker plots for the years between 1980 and 2017. The four methods compared are the production function approach and the three univariate time series filters: the Hodrick-Prescott (HP), Baxter-King (BK) and Christiano-Fitzgerald (CF) filters. The filters were applied using their usual parameter settings for annual data. The staples protruding from the box (dashed lines) show the minimum and maximum estimates for each year.

Several aspects become apparent from the estimate spreads. First, the filters show smaller revisions for the 1980s and 1990s. This is because the key quantities in production function methodology involve statistical estimates that depend on the entire sample. Augmenting the sample with new observations changes the fit at each sample point and, consequently, also the estimate of potential output for each year in the past. On the contrary, the trends extracted by the application of filters are more stable, at least in the absence of significant structural breaks in the underlying series of real GDP. In the presence of structural breaks, such filters can produce very misleading results due to a reliance on future data to estimate the current level of trend (symmetric window).

Figure 11 shows the real-time estimates of potential output growth for the years 2001-2017 using the data vintages 2002-2018. The real-time estimates prior to the global crisis in 2008 are generally lower than the estimates based on the current 2018 vintage shown as a red line. The pre-crisis (2001-2008) mean growth rate of real GDP is close to its post-crisis (2010-2017) counterpart, but the standard deviation of the estimates after the crisis is considerably lower (0.2 compared to 0.6 before the crisis).

Figure 12 considers the revisions of growth contributions to potential output growth estimated for the years close to the outbreak of the global financial and economic crisis of 2008 using the data vintages 2009-2012. The three contributions add up to the growth

Figure 11: Real-time estimates of potential growth (2001-2017)




The figure shows the real-time estimates of potential output growth for the years 2001-2017 based on the data vintages spring 2002 to spring 2018. The red line shows the estimate based on the current vintage of spring 2018. The downward revision following the global financial crisis is clearly seen in 2009. The volatility of growth estimates was higher prior to the crisis than after the crisis.

Figure 12: Revisions in growth contributions (2009-2012)


The figure shows the revisions in the growth contributions to the potential output estimated for the years immediately following the outbreak of the global financial and economic crisis of 2008 using the data vintages (2009-2012). The revision of the labor contribution has been the largest. The three contributions add up to the growth of potential output.

of potential output. The revision of the labor contribution was negative and the largest in 2009 in the 2010 vintage.

The largest revisions are observed prior to the outbreak of the global financial and economic crisis in 2008. The magnitude of these revisions is largest for the production function estimate and the HP filter. The HP filter is known to be particularly problematic in the presence of structural breaks common to macroeconomic time series (Pollock, 2000). Structural breaks cause problems to all three filters, as is witnessed by large revisions in the years prior to the crisis. By smoothing over the structural break caused by the crisis, they lower the trend estimate in the run up to the crisis. The HP filter is also particularly susceptible to the elimination of low frequency cycles relevant to the trend and an underestimation of high-frequency cycles close to the end of the sample (Baxter and King, 1995). This end-of-sample problem, however, can be alleviated by extending the sample through forecasts. The estimates according to the production function methodology are affected by the problems associated with the HP filter because they used it in extracting the trends in the participation rate and the average hours worked.

The effect of revisions on the estimates of the output gap are shown in Figure 17. Figure 18 focuses on the years since 2000. We see that the output gap estimates for the 1980s and 1990s are practically unaffected by the later revisions, especially in the case of the BK and CF filters. The gaps extracted by the BK and CF filters are also more stable around the crisis years. The most serious disadvantage of these two filters is that losing three years at the end of the sample due to the assumed lag structure ($k = 3$) makes them nearly useless to produce timely estimates for policy guidance.

# 7 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 the 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.[13]

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

[13] See, for example, Martín, Moral-Benito and Schmitz (2018) for the case of Spain.

new member states.[14] The panel for the old member states is unbalanced. Barring a few cases of missing observations, the model for the old member states covers the period from 1985 to 2015, 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, $tw_{i,t}$. In the case of Switzerland, the data sources as well as the splicing that has been applied when the original time series was not available for the sample 1985-2015 are given in Table 9. For all other countries we used the original data in Orlandi's set.

Prior to discussing the estimates, we shall briefly touch on the computation of the unemployment benefits replacement rate and the active labor market policy indicator. To obtain the average replacement rate $rr_{i,t}$ for a country, Orlandi (2012) weights the replacement rate during the initial year of an unemployment spell $rr_t^{su}$ (short-term unemployed) and the replacement rate for unemployment spells in excess of one year $rr_t^{lu}$ (long-term unemployed). The replacement rates $A_t$ and $B_t$ are computed by aggregating various individual replacement rates that apply to recipients who earn either 100 percent or 67 percent of average wage income, have no children, are either single or married with a partner that has no income or have a partner that has an income. The weights reflect the probabilities of an unemployment spell being shorter or longer than one year.

Since we were unable to obtain sufficiently detailed data to replicate Orlandi's measure of unemployment benefits replacement rates, we constructed a proxy for Switzerland using the data from the OECD labor statistics and the OECD-SPIDER database of structural indicators. Suppressing a country index, let $d_t$ denote the average duration of

[14]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.

unemployment in months according to the OECD labor statistics. If the probability of finding a job is constant each month (constant hazard assumption), the probability of an unemployment spell lasting for one year can be expressed by the following sum

$$\theta_t = \frac{1}{d_t} \sum_{i=0}^{11} \left(1 - \frac{1}{d_t}\right)^i . \tag{19}$$

This probability is used to weight two average unemployment benefits replacement rates sourced from the OECD. Let $\widehat{rr}_t^{su}$ be the average initial replacement rate, and $\widehat{rr}_t^{lu}$ the average of net replacement rates over 60 months of unemployment for a family that does not qualify for cash housing assistance or social assistance top-ups. Let $\widetilde{rr}_t^{su}$ and $\widetilde{rr}_t^{lu}$ denote the analogous rates for a family that does qualify for housing assistance. Then,

$$rr_t = \frac{1}{2}\left[\theta_t \widehat{rr}_t^{su} + (1-\theta_t)\widehat{rr}_t^{lu}\right] + \frac{1}{2}\left[\theta_t \widetilde{rr}_t^{su} + (1-\theta_t)\widetilde{rr}_t^{lu}\right] . \tag{20}$$

The active labor market policy indicator for Switzerland is computed using the data provided by the OECD-SPIDER database. Individual expenditure items (in percent of nominal GDP) include: public employment services and benefit administration, training[15], job rotation and job sharing, employment incentives, supported employment and rehabilitation, direct job creation and start-up incentives. To obtain $almp_{i,t}$, the cumulative share of expenditure on these items (items 10-70 in the OECD-SPIDER databank) in nominal GDP is divided by the share of unemployed in the population. This last normalization step is required for better comparability of the resulting weighted average replacement rates across the countries.

[15]This includes institutional training, workplace training, integrated training and special support for apprenticeship.

Table 6: Fixed-effects estimates of NAWRU panel

| | 13 EU member states | | | | 13 EU member states and Switzerland | | | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | S.E. | t-stat | | Estimate | S.E. | t-stat | |
| *cons* | -0.614 | 0.058 | -10.622 | *** | -0.635 | 0.056 | -11.388 | *** |
| $r$ | 0.134 | 0.030 | 4.430 | *** | 0.138 | 0.030 | 4.673 | *** |
| $tfp$ | -0.181 | 0.038 | -4.768 | *** | -0.163 | 0.036 | -4.519 | *** |
| $ud$ | 0.045 | 0.013 | 3.587 | *** | 0.040 | 0.012 | 3.223 | ** |
| $tw$ | 0.246 | 0.021 | 11.467 | *** | 0.241 | 0.021 | 11.454 | *** |
| $almp$ | -0.059 | 0.004 | -13.992 | *** | -0.055 | 0.004 | -13.915 | *** |
| $rr$ | 0.043 | 0.013 | 3.192 | ** | 0.036 | 0.013 | 2.725 | ** |
| $n$ | 13 | | | | 14 | | | |
| $T$ | 16 | | | | 16 | | | |
| $N$ | 395 | | | | 426 | | | |
| Adj. $R^2$ | 0.624 | | | | 0.616 | | | |
| F-stat: | 96.031 | | | *** | 100.427 | | | *** |

The sample covers the period 1985-2015 for Switzerland and Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and United Kingdom.
Significance: *** 0.1 percent; ** 1 percent.

Table 6 shows the estimates of the panel regression model. The first model (on the left) is estimated using the data currently used by the EC for the thirteen old member states. The second model (on the right) includes the Swiss data as the fourteenth country. Both models explain roughly sixty percent of the variation in the NAWRU rates, with all the explanatory variables being highly statistically significant. A highly significant test statistic of the Hausman specification test ($\chi^2(7) = 201.29$) for the second model (on the right) indicates that the fixed effects model is appropriate.

Table 7 provides the NAWRU anchor values. 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 is the panel-fixed effects, which capture the country-specific, time-invariant factors. A comparison with the estimates of the two models and the corresponding anchor estimates shows that including Switzerland does not have a large effect on the estimates of the panel model.

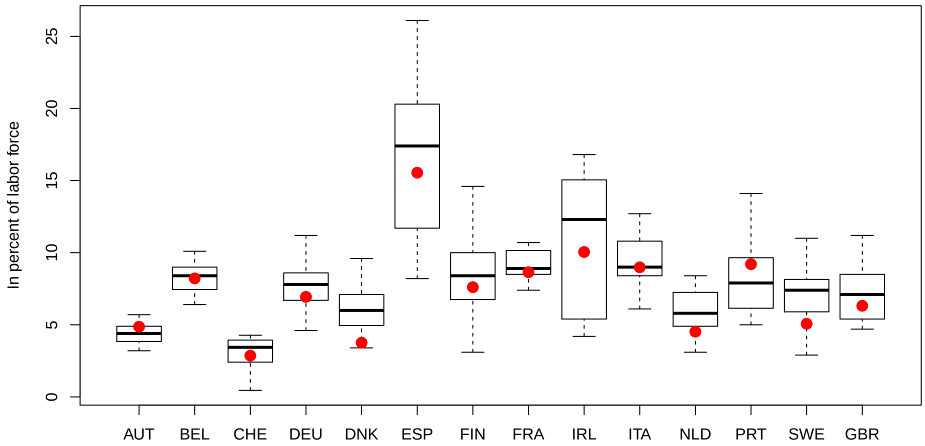
Table 7: NAWRU anchors

| | 13 EU member states | 13 EU member states and Switzerland |
|---|---|---|
| Austria (AUT) | 4.838 | 4.869 |
| Belgium (BEL) | 8.235 | 8.219 |
| Switzerland (CHE) | - | 2.865 |
| Germany (DEU) | 6.854 | 6.938 |
| Denmark (DNK) | 3.654 | 3.759 |
| Spain (ESP) | 15.508 | 15.547 |
| Finland (FIN) | 7.564 | 7.612 |
| France (FRA) | 8.641 | 8.648 |
| Ireland (IRL) | 10.012 | 10.049 |
| Italy (ITA) | 9.043 | 8.989 |
| Netherlands (NLD) | 4.525 | 4.524 |
| Portugal (PRT) | 9.192 | 9.205 |
| Sweden (SWE) | 4.983 | 5.073 |
| United Kingdom (GBR) | 6.247 | 6.320 |

How does the anchor compare to the actual unemployment rates in the past? This question is relevant for assessing the plausibility of long-term projections in view of historical unemployment data. Figure 13 compares the estimated anchor with the range of variation of the unemployment rate observed over the estimation sample 1985-2015. With few exceptions, which include Denmark, the Netherlands and Sweden, the anchor lies in the inter-quartile range of the observed variation.

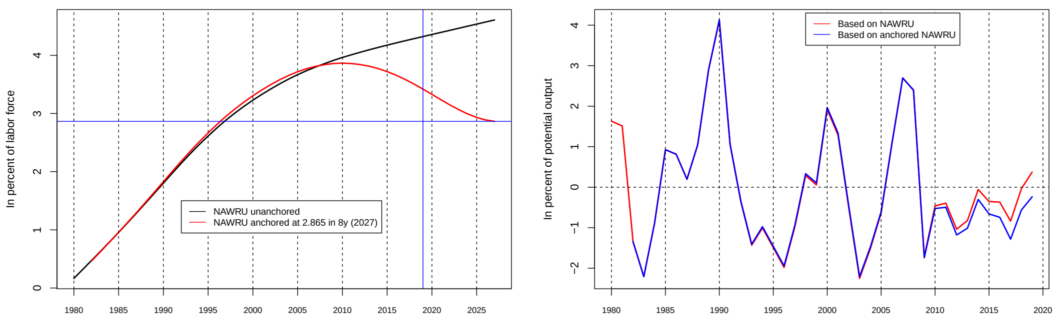
Figure 14 compares a constrained (anchored) NAWRU projection to its unconstrained counterpart. It is important to emphasize that anchoring may change the in-sample NAWRU estimate and, consequently, also the estimate of potential output and the output gap. The effect of anchoring on historical NAWRU estimates 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, as illustrated in the right panel for the output gap.

Figure 13: Unemployment rates and NAWRU anchors




Box and whisker plots show the dispersion of the unemployment rates between 1985-2015, using the conventional definition of the box and staples as *max-75q-median-25q-min*. The red point shows the estimate of the NAWRU anchor obtained using the panel regression.

Figure 14: The anchored NAWRU




The left panel compares a constrained (anchored) NAWRU projection (red) to its unconstrained counterpart (black). The constrained NAWRU projection is set to converge to the estimated anchor value of 2,865 in 8 years (2020-2027), 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. The actual unemployment rates were taken from AMECO.

# 8 Summary and Ideas on Further Research

The estimates of potential output based on the annual data from AMECO and national sources yields plausible empirical results for Switzerland that can be compared to the analogous estimates by the European Commission for the EU member states. The estimates of potential output growth are not excessively pro-cyclical and the output gap reflects the main phases of the Swiss business cycle. The two instruments can be used to gauge business cycle fluctuations in Switzerland and develop medium-term and long-term projections based on econometric estimates of the productivity trend and the equilibrium rate of unemployment.

Using historical vintages of the AMECO data allows us to carry out a revision analysis in a manner consistent with the results based on the current release. The consistency is ensured overall (barring few exceptions) by using the data that was available in the past and the same modeling approach, even though the unobserved component models had to be adjusted for older vintages. All the issues associated with the use of the Hodrick-Prescott univariate time series filter to estimate the trends of the participation rate and the average hours worked also affect the results of the production function approach. The main issues are the inability to adequately deal with structural breaks and the end-of-sample problem, although the latter can to some extent be dealt with by extending the sample with technical forecasts. The more advanced Baxter-King and Christiano-Fitzgerald bandpass filters appear to yield more stable estimates. However, they have two significant shortcomings. As purely technical filters they do not yield economically interpretable details that can be provided by an appropriate structural model and, more importantly, the loss of several data points at the end of the sample due to the assumed lag structure renders them incapable of delivering timely estimates at the end of a sample, which is crucial for policy guidance.

The auxiliary panel-econometric estimate of the NAWRU anchor appears to yield a plausible estimate of the structural component of the unemployment rate. Since anchoring the NAWRU by requiring convergence to an anchor at some future point may significantly change the in-sample estimates of the NAWRU and its short-term projections, it should be reserved for long-term projections. The routines used to estimate the TFP trend and the NAWRU can yield forecasts for up to thirty periods, thus allowing to develop long-run projections of an economy on an annual basis.

Broad comparability with the EC estimates and the feasibility of conducting a comprehensive revision analysis make the annual estimates an attractive first step. Pursuing an implementation based on quarterly data appears to be a worthwhile endeavor for further research. Aside from the obvious synergy of quarterly estimates supplementing and validating their annual counterparts, having more observations enables the use of advanced trend extraction (smoothing) and validation techniques. Smoothing methods based on non-parametric regressions, for example the LOESS regression, may contribute to the production function methodology by improving the quality of the trends extracted from the input time series. These more advanced smoothing methods have the potential to reconcile the desired smoothness of trend while still recognizing structural breaks.

The second and arguably more important advantage, is that quarterly data offer a promising means of validating potential output estimates based on the production function approach. In a recent paper, Coibion et al. (2017) proposed estimating potential output based on the well-known Blanchard and Quah (1989) identification strategy for structural vector autoregression (SVAR) models. The Blanchard-Quah approach allows the identification of transient and permanent shocks. Transient shocks to GDP growth are usually associated with demand and the permanent shocks with supply, where supply-side shocks can pertain to technology, fiscal policy, etc. The idea in the context of potential output estimates is that the latter should not be sensitive to transient shocks. Estimates of transitory and permanent shocks from an appropriate SVAR model can thus be used to validate the estimates of potential output obtained using the production function methodology. However, estimating a reliable SVAR model that can differentiate the relative importance of supply and demand shocks in business cycles requires more observations than typically available on an annual basis, making the transition to quarterly data a logical next step.

The main limitation of quarterly estimates is the impossibility of conducting a revision analysis due to the lack of comprehensive historical quarterly data. Revision analysis would have to rely on annual data. Second, implementing the production function methodology on a quarterly basis may require technical quaternization of several inputs such as the capital stock. This, however, can usually be achieved in an informative way by using the quarterly investment and depreciation as indicators.

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# A Tables and Figures

Table 8: Data and sources

| Variable | Macrobond/AMECO label | Text label | Used to compute |
|---|---|---|---|
| Capacity utilization, industry total, sa, percent | `chprod0090` | $CU_t$ | |
| Compensation of employees: total economy, CHF | `ameco_che_1_0_0_0_uwcd` | | $W_t$, $ls_t$ |
| Employees, persons: all domestic industries (National accounts), persons[1] | `ameco_che_1_0_0_0_nwtd` | | $W_t$ |
| Employment (domestic concept), average of four quarters | BFS | $LD_t$ | $PRT_t$, $prod_t$ |
| (A) Employment, persons: all domestic industries (National accounts), persons | `ameco_che_1_0_0_0_netd` | | |
| Gross domestic product at 2010 reference levels, CHF | `ameco_che_1_1_0_0_ovgd` | $Y_t$ | $prod_t$, $TFP_t$ |
| Gross domestic product at current prices, CHF | `ameco_che_1_0_0_0_uvgd` | | $ls_t$ |
| Net capital stock at 2010 prices: total economy, CHF | `ameco_che_1_0_0_0_oknd` | $K_t$ | $TFP_t$ |
| Population: 15 to 64 years, persons | `ameco_che_1_0_0_0_npan` | $POP_t$ | $PRT_t$ |
| Price deflator gross domestic product, national currency: 2010=100 | `ameco_che_3_1_0_0_pvgd` | | $tot_t$ |
| Price deflator private final consumption expenditure, national currency: 2010=100 | `ameco_che_3_1_0_0_pcph` | | $tot_t$ |
| Total annual hours worked: total economy | BFS | $L_t$ | $H_t$, $TFP_t$ |
| (A) Total annual hours worked: total economy, number | `ameco_che_1_0_0_0_nlht` | | |
| Unemployment rate: EUROSTAT definition, percentage of active population | `ameco_che_1_0_0_0_zutn` | $U_t$ | |

A - Alternative series from AMECO.

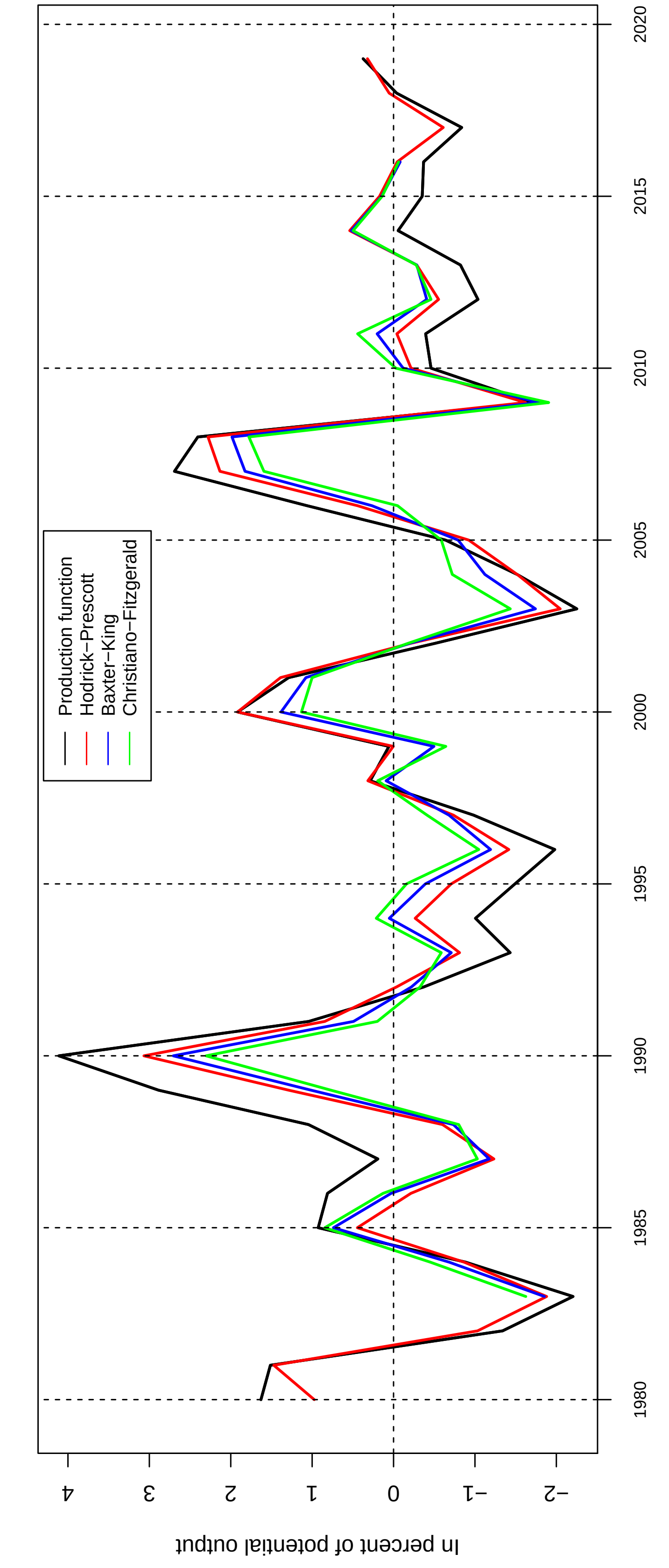
[1] Prior to 1992 spliced with BFS series: Employment (domestic concept), average of four quarters.

Table 9: 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 (`avg_tws`) | $tw_{i,t}$ |
| 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_EXPPCT110`, `pop_wdi`, `UN`) | $almp_{i,t}$ |
| Employment in construction in percent of employment total | BESTA | $cons_{i,t}$ |
| Real interest rate[4] | OECD-MEI, OECD-SPIDER | $r_{i,t}$ |

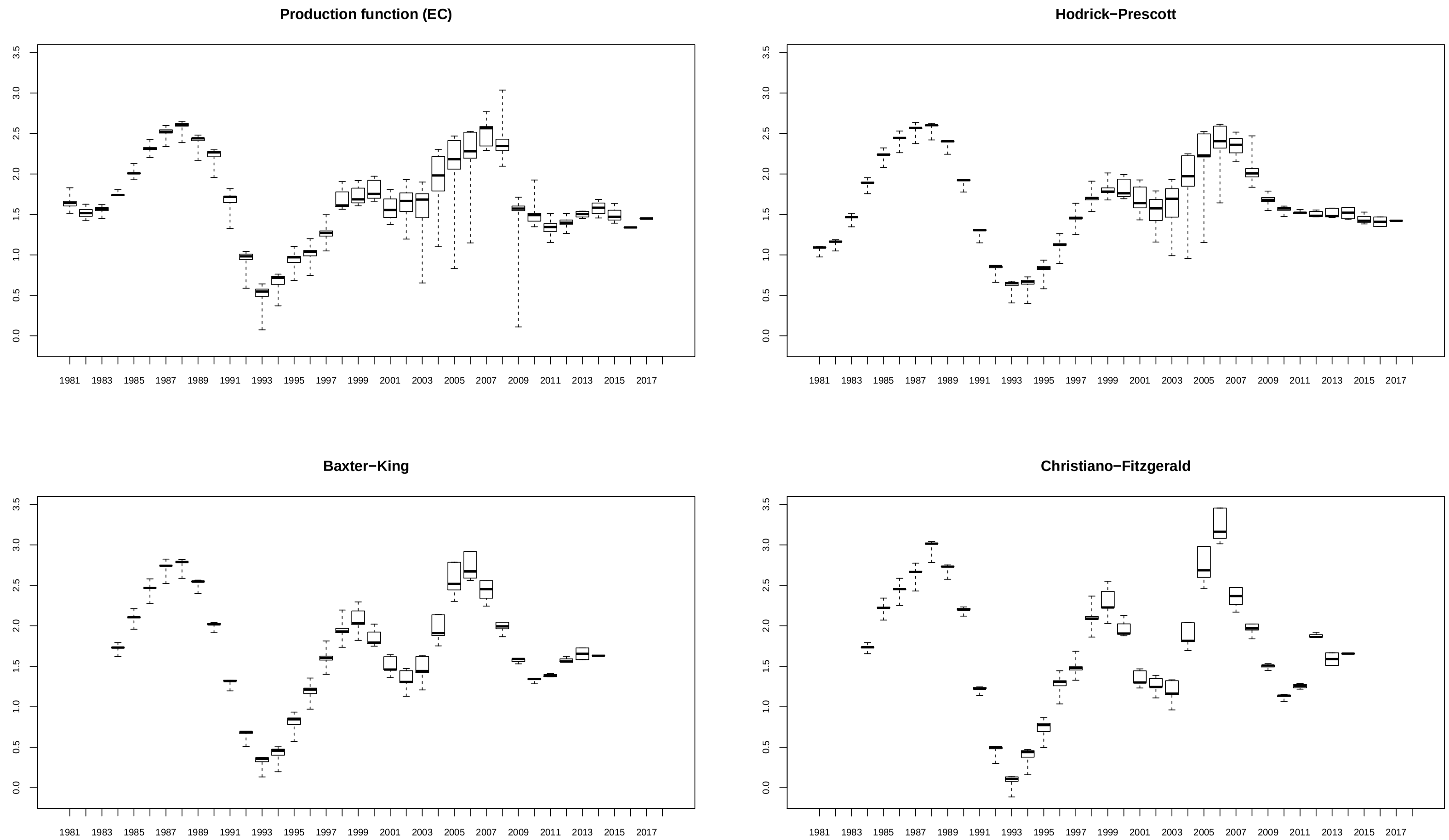
[1] Single person at 67 percent of average earnings, no child. Spliced with OECD-SPIDER tax wedge for single person prior to 2000.
[2] Prior to 2001 spliced with Van Vliet and Caminada (2012) welfare state entitlements data.
[3] Share of expenditure on items 10-70 in nominal GDP, divided by the share of unemployed in the population.
[4] 10-year government bond yields, minus inflation rate of the GDP deflator averaged over 5-years.

Figure 15: A comparison of output gaps



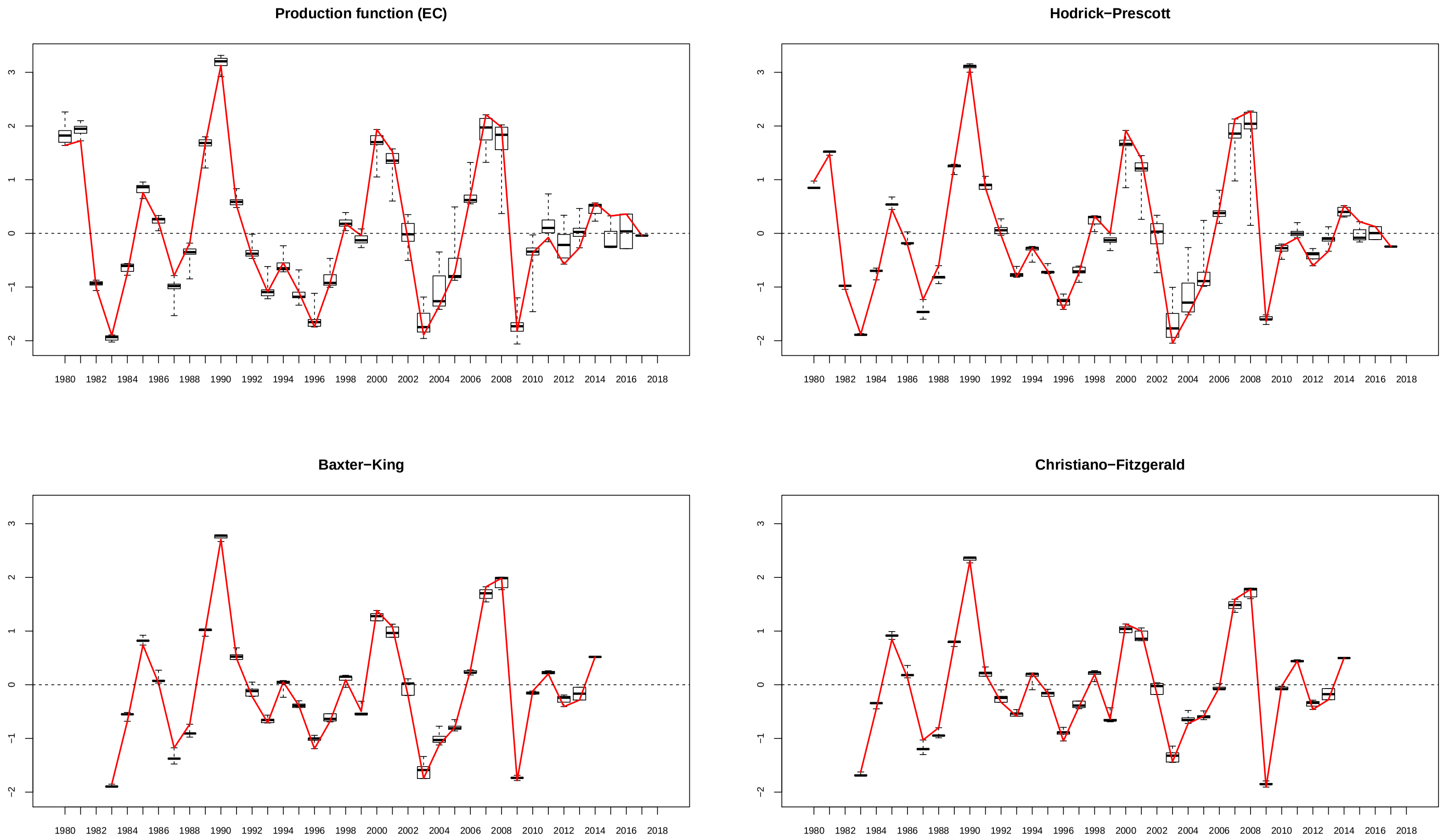

The output gaps according to the production function methodology (black), Hodrick-Prescott filter with $\lambda = 10$ (red), Baxter-King filter with $p_l = 2$ and $p_h = 8$ (blue), and Christiano-Fitzgerald with $p_l = 2$ and $p_h = 8$ (green).

Figure 16: Revisions in estimates of potential output growth since 2002 (1980-2017)



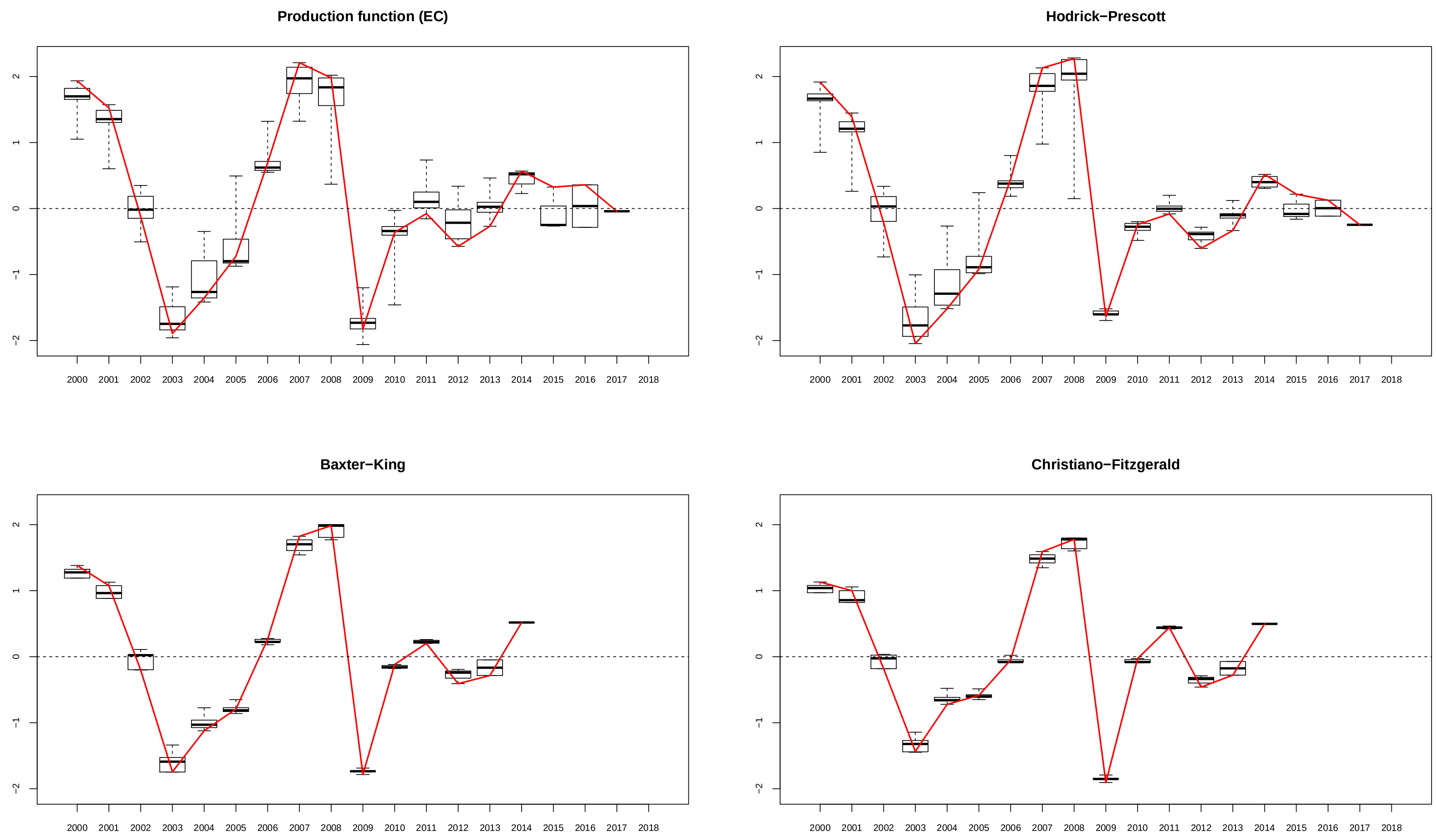

Box and whisker plots show the dispersion of the estimates for each year, using the conventional definition of the box and staples as *max-75q-median-25q-min.* The parameters are $\lambda = 10$ for the Hodrick-Prescott filter, and $p_l = 2$ and $p_h = 8$ for the Baxter-King and Christiano-Fitzgerald filters.

Figure 17: Revisions in estimates of output gap since 2002 (1980-2017)




Box and whisker plots show the dispersion of the estimates for each year, using the conventional definition of the box and staples as *max-75q-median-25q-min*. The red line shows the most recent (spring 2018) estimate. The parameters are $\lambda = 10$ for the Hodrick-Prescott filter, $p_l = 2$ and $p_h = 8$ for the Baxter-King and Christiano-Fitzgerald filters.

Figure 18: Revisions in estimates of output gap since 2002 (2000-2017)




Box and whisker plots show the dispersion of the estimates for each year, using the conventional definition of the box and staples as *max-75q-median-25q-min*. The red line shows the most recent (spring 2018) estimate. The parameters are $\lambda = 10$ for the Hodrick-Prescott filter, and $p_l = 2$ and $p_h = 8$ for the Baxter-King and Christiano-Fitzgerald filters.

# B Restricting the Sample to 1991-2017

Empirical identification of productivity and unemployment trends using unobserved component models requires sufficiently long time series. Relying on short series can significantly complicate finding a flexible specification, especially if the time series are non-stationary and short. This often results in over-simplified models that are either unable to adequately capture the dynamics of the cycle or return an excessively rigid trend.

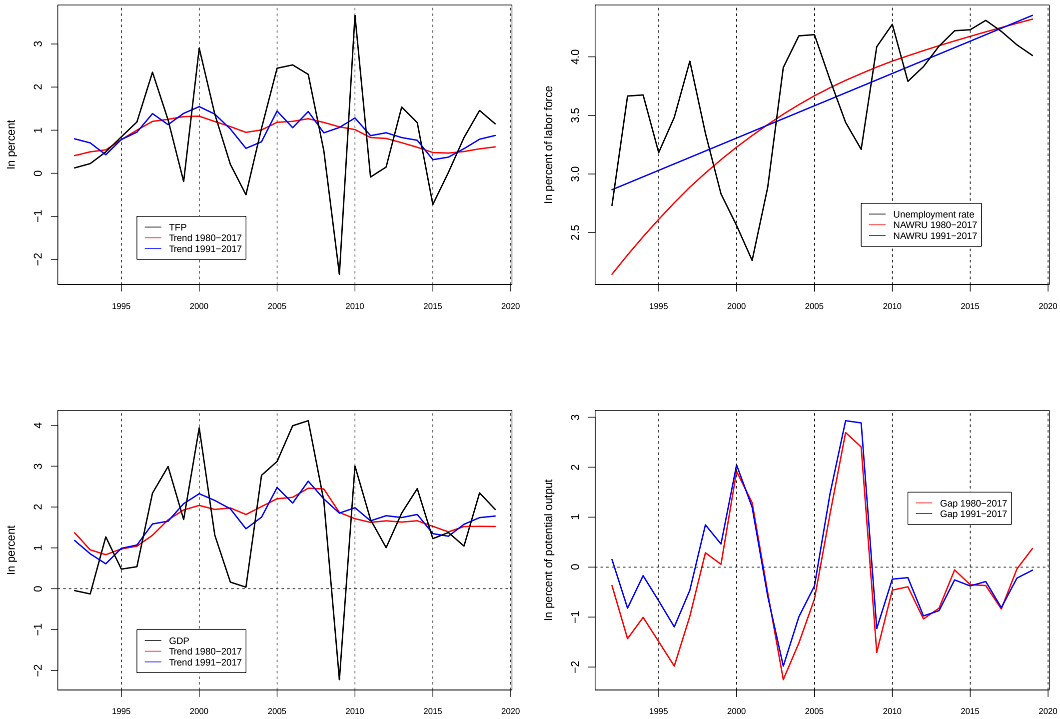
For this reason, we use the AMECO database, which offers a sample that is larger than that typically used in empirical macroeconomic research for Switzerland. The AMECO data used in the project extends the available time span to 1980. Using a longer sample comes at the cost of consistency. In this section, we explore the robustness of the model by starting the estimation sample in 1991 instead of 1980. An alternate sample starts in 1991, the first year that is available from the current vintage of national macroeconomic data, after having computed all the differences and lagged values of the exogenous variables for the Phillips curve.

The empirically-minded macroeconomist often faces a trade-off between the length of a time series and its temporal consistency. Over a longer term, the consistency of macroeconomic time series is punctuated by regular changes in the System of National Accounts (SNA) and in the associated methods of data collection. Following major changes in the SNA, national statistical agencies partially or fully restore the consistency of the series by updating historical data using the new regulation.

Like most European countries, Switzerland has seen several changes in the European System of National Accounts (ESA). The most recent changes are the adoption of ESA 78 in 1997, then ESA 95 and finally the current ESA 2010 in 2014. There was also a major change in the scope and methodology in the collection of labor market statistics in 1991. One consequence of this change is that the annual sample typically used in the empirical analysis of the Swiss economy begins in 1991.

Figure 19 shows the estimates obtained using the two samples, 1980-2017 and 1991-2017. The largest discrepancy between the output gaps is seen in the 1990s and is due to pronounced differences in the estimate of the NAWRU. The shorter sample returns an essentially linear trend of the actual unemployment rate and a slightly more ragged and pro-cyclical estimate of the TFP trend. Notwithstanding these differences, the two models produce comparable estimates for the growth rates of potential output. The more pronounced effect on the output gap is caused by the accumulation of these differences over time, since the gap is a ratio of two levels according to formula (18). Our tenta-

Figure 19: Restricting the sample to 1991-2017




The figure compares the estimates obtained using the same pair of unobserved component models for the two samples: 1980-2017 (red) and 1991-2017 (blue). In each case, the trends in the participation rate and the average hours worked are extracted by setting $\lambda = 10$ as the value of the smoothing parameter in the HP filter. The estimates obtained using the longer sample correspond to the main variant discussed in the text.

tive conclusion is that, even though estimates of potential growth are not too dissimilar between the two samples, relying on the shorter sample would require a different and probably simpler specification for the NAWRU.