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Estimating a Quarterly Potential Output Series for Switzerland

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Schätzung eines vierteljährlichen Produktions-potenzials für die Schweiz

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.

Aufbauend auf dem Vorgängerprojekt "Estimating the Potential Output Using the Methodology of the European Commission" widmet sich dieses Projekt dem Produktionspotenzial der Schweiz auf vierteljährlicher Basis. Die Verwendung einer vierteljährlichen Frequenz ermöglicht eine zeitnahe Schätzung der aktuellen Konjunkturlage und erweitert den Umfang der ökonometrischen Verfahren, die effektiv eingesetzt werden können. Das Jahresmodell wurde aktualisiert, um die Konsistenz mit dem Quartalsmodell zu gewährleisten. Beide Modelle verwenden denselben makroökonomischen Datensatz für den Zeitraum von 1980 bis 2018. Die Modelle können genutzt werden, um konsistente Prognosen über das kurz-, mittel- und langfristige Produktionspotenzial zu entwickeln.

Das optimale Modell ergibt sich durch die Anwendung eines transparenten Kriterienkataloges auf eine Vielzahl von potenziellen Spezifikationen. Dieses Modell sollte über eine möglichst gute Vorhersagekraft für die beobachtete zyklische Größe verfügen: die Kapazitätsauslastung im Falle des TFP-Trends oder die Veränderung der Lohninflation im Falle einer Phillips-Kurve (NAWRU). Die daraus resultierenden Wachstumsraten des Produktionspotenzials sollten nicht zu volatil oder zu prozyklisch sein. Ein weiteres Kriterium maximiert die Kongruenz zwischen einer Jahres- und einer Quartalsschätzung, da beide Schätzungen möglichst gut übereinstimmen sollen.

Wir überprüfen die Robustheit anhand einer Stichprobe ab 1991, die aufgrund eines strukturellen Bruchs in den Daten einen natürlichen Beginn der Stützperiode darstellt. Die NAWRU-Schätzungen auf Grundlage der kürzeren Stichprobe sind jedoch weniger plausibel als jene auf Basis der gesamten Stichprobe.

Die jährlichen und die annualisierten Quartalsschätzungen für die Schweiz sind mit den Schätzungen der Europäischen Kommission für die EU15 vergleichbar in Bezug auf Volatilität und Zyklizität. Die vierteljährliche Schätzung der Produktionslücke trifft, die von der OECD für die Schweiz veröffentlichten Konjunkturwendepunkte gut. Für die jüngste Vergangenheit stimmt sie mit der von der Schweizerischen Nationalbank veröffentlichten Produktionslücke gut überein.

Estimation d’une production potentielle trimestrielle pour la Suisse

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 la politique économique, il est important de connaître la situation conjoncturelle du moment.

Prenant le relais du projet antérieur « Estimating the Potential Output Using the Methodology of the European Commission », le présent projet est dédié à la production potentielle de la Suisse sur une base trimestrielle. Le recours à une fréquence trimestrielle permet une estimation de la situation conjoncturelle du moment à brève échéance et multiplie les possibilités d’application des méthodes économétriques. Le modèle annuel a été mis à jour afin de garantir la cohérence avec le modèle trimestriel. Les deux modèles utilisent les mêmes séries macroéconomiques pour la période allant de 1980 à 2018. Ils peuvent servir au développement de prévisions cohérentes relatives à la production potentielle à court, moyen et long termes.

Le modèle optimal découle de l’utilisation d’un catalogue de critères transparents pour une multitude de spécifications potentielles. Il doit idéalement avoir une bonne capacité de prédiction pour la variable cyclique observée : l’utilisation des capacités de production dans le cas de la tendance de la productivité totale des facteurs (en anglais : TFP) ou l’évolution de l’inflation des salaires dans le cas d’une courbe de Phillips (NAWRU). Les taux de croissance de la production potentielle en résultant ne doivent pas être trop volatils ni trop procycliques. Un autre critère maximise l’adéquation entre les estimations annuelles et les estimations trimestrielles, puisqu’elles devraient dans la mesure du possible être concordantes.

Nous contrôlons la validité sur la base d’un échantillon commençant en 1991, un point de départ naturel pour la période de contrôle du fait d’une rupture structurelle des données cette année-là. Les estimations NAWRU qui se fondent sur l’échantillon plus court sont toutefois moins plausibles que celles reposant sur l’échantillon intégral.

Les estimations annuelles et les estimations trimestrielles annualisées pour la Suisse sont comparables aux estimations de la Commission européenne pour l’UE15 en termes de volatilité et de cyclicité. L’estimation trimestrielle de l’écart de production concorde avec les points de retournement de la conjoncture publiés par l’OCDE pour la Suisse. Pour le passé récent, elle se recoupe avec l’écart de production publié par la Banque nationale suisse.

Stima del potenziale trimestrale di produzione della Svizzera

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 di tale potenziale 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.

Sulla base del precedente progetto «Estimating the Potential Output Using the Methodology of the European Commission», il presente studio espone il potenziale di produzione della Svizzera su base trimestrale. Tale frequenza permette una stima tempestiva della situazione congiunturale e amplia la gamma di procedure econometriche attuabili in modo efficace. Il modello su base annua è stato aggiornato in modo da garantire una coerenza con il modello su base trimestrale. Entrambi i modelli utilizzano gli stessi dati macroeconomici concernenti il periodo tra il 1980 e il 2018 e possono essere applicati per formulare previsioni coerenti relative al potenziale di produzione a breve, medio e lungo termine.

L'analisi applica una serie trasparente di criteri per la selezione di modelli a un gran numero di potenziali specificazioni. Il modello ottimale va strutturato in modo da poter prevedere in modo sufficientemente preciso la dimensione ciclica osservata: l'utilizzo delle capacità nel caso del trend della produttività totale dei fattori oppure la variazione dell'inflazione salariale nel caso di una curva di Phillips (Nawru). I tassi di crescita del potenziale di produzione risultanti non devono essere troppo volatili o prociclici. Un'ulteriore ottimizzazione massimizza la coerenza tra una stima annuale e una stima trimestrale, dato che queste devono coincidere il più possibile.

Nel presente lavoro viene esaminata la robustezza sulla base di un campione a partire dal 1991, momento che rappresenta un inizio naturale vista una rottura strutturale dei dati. Tuttavia, le stime Nawru basate sul campione costituito su un lasso di tempo più breve sono meno affidabili di quelle basate sul campione totale.

Per quanto riguarda volatilità e ciclicità, le stime annuali e le stime su base trimestrale annualizzate per la Svizzera sono comparabili con quelle effettuate dalla Commissione europea per l'UE15. La stima su base trimestrale dell'output gap rappresenta in modo accurato i punti di svolta del ciclo economico in Svizzera pubblicati dall'OCSE e – per quanto concerne il passato recente – è molto vicina all'output gap pubblicato dalla Banca nazionale svizzera.

Estimating a Quarterly Potential Output Series for Switzerland

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.

Building on a previous project "Estimating the Potential Output Using the Methodology of the European Commission", this project estimates potential output for Switzerland on a quarterly basis. Using a quarterly frequency yields a timely estimate of the cyclical position and expands the scope of econometric techniques that can be effectively applied. The annual model has been updated to ensure consistency with the quarterly model. Both models use the same set of macroeconomic data covering the period from 1980 to 2018. Together, they can be used to develop mutually consistent projections of potential output for Switzerland at the short, medium and long term.

The analysis applies a transparent set of criteria for model selection to a large set of potential specifications. The optimal model should have reasonable predictive power for an observed cyclical quantity, which is either capacity utilization in the case of the TFP trend, or the change in wage-inflation in the case of a Phillips curve (NAWRU). The resulting growth rates of potential output should not be too volatile or too pro-cyclical. Further optimization maximizes congruence between an annual and a quarterly estimate, as we would like the two estimates to be mutually consistent.

We check the robustness using a sample starting in 1991, which is a natural starting point due to a structural break in the data. The NAWRU estimates based on the shorter sample are, however, less plausible than those based on the full sample.

The annual and the annualized quarterly estimates for Switzerland are comparable to the estimates by the European Commission for the EU15 in terms of their volatility and cyclicality. The quarterly estimate of the output gap closely traces the business cycle turning points published by the OECD for Switzerland; in the recent past, it closely agrees with the output gap published by the Swiss National Bank.

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1 Introduction

Potential output is the level of output compatible with stable (wage) inflation. The output gap, as a relative deviation of the actual output given by real GDP from potential output, indicates the cyclical position of an economy. Gauging the current cyclical position is important for economic forecasting and for formulating economic policy. Being a key indicator of inflationary pressures, the output gap is highly relevant for monetary policy. Estimates of the output gap also guide fiscal policy that aims to mitigate the effect of the business cycle on incomes, while safeguarding the sustainability of public finances in the medium term. A comparison of the output gap to a change in the primary fiscal balance indicates whether a country adopts a pro-cyclical or a counter-cyclical fiscal stance.

This work follows the project entitled *Estimating the Potential Output for Switzerland using the Methodology of the European Commission (EC)*.[1] The precursor project delivered plausible annual estimates of potential output. The annual estimate of the output gap shows good agreement with the main phases of the Swiss business cycle according to the OECD, and can be directly compared to the estimates by the EC for the EU Member States, which are routinely used for developing projections underlying fiscal planning and surveillance in the EU. Nevertheless, picking variations in the business cycle that occur during a year requires quarterly output gap estimates. The quarterly frequency is the 'native' frequency of a business cycle forecast. This is one reason why institutions that use output gaps for forecasting, e.g. the US Congressional Budget Office, the IMF and the OECD, rely on quarterly estimates.

The principal aim of the project is to estimate potential output for Switzerland on a quarterly basis. The annual model has been updated to ensure mutual consistency. Both models use the same set of macroeconomic data covering the period from 1980 to 2018. A pair of such models can be used to develop consistent projections of potential output for Switzerland in the short (2 years), medium (5 years) and long term (more than 5 years).

The next section offers general considerations on how to estimate potential output as an unobserved quantity. It emphasizes the role of model uncertainty and benchmarking for validating such estimates. The report then proceeds with an overview of the production function methodology of the European Commission, followed by an extensive specification search. We then compare the estimates for Switzerland with the estimates of the EC for several EU member states. The final section discusses how to develop projections for the medium and long term. Alternative smoothing methods are discussed in an appendix.

[1] See, Glocker and Kaniovski (2019).

2 Estimating and Validating Potential Output

The methods used to estimate potential output can be roughly 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 relatively simple, transparent and easily reproducible. Popular detrending methods include deterministic time-series filters such as the Hodrick-Prescott filter[2] and unobserved component models estimated by the method of Maximum Likelihood or Bayesian techniques. Alternative detrending methods such as LOESS regressions, singular spectrum analysis or wavelet-based methods are used less frequently. Unlike filters and statistical models using the time series of real GDP as sole input, 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 (e.g., 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 that combine purely technical methods with structural models borne by economic relationships such as the Phillips curve. The EC method represents a hybrid approach that combines filters and structural econometric models to estimate the time series for productivity and input factor trends. The identification of fluctuation in potential output, which itself remains unobserved, is thus based on a score of other macroeconomic quantities that should be indicative of the economies' cyclical position. Such additional variables may include various prices, interest rates and direct measures of capacity utilization.

The main challenge in estimating potential output is how to validate an estimate, given that the underlying quantity is not observed. In its theoretical conception, potential output represents the level of output around which the actual output (real GDP) fluctuates in the course of a business cycle. We should therefore expect the level of an estimate of potential output to be a trend of the level of actual output, i.e. to have a centering property vis-a-vis actual output. Beyond that, no convincing case can be made for or against a certain volatility of the growth rates of potential output, other than the trivial requirement of them being less volatile than the actual output. By the same token, there are no compelling economic reasons for an estimate of potential output to have certain persistence in the sense of not changing much when new economic data is added

[2] See, Hodrick and Prescott (1997).

to the estimation sample. While it is true that potential output represents a long-run phenomenon, i.e. the growth prospects of an economy, and should therefore have persistence, it is equally true that, paraphrasing Paul Samuelson, we ought to be able to change our minds in light of new evidence.

Having said the above, the stability of potential output estimates is desirable if potential output is to be used for policy guidance. This is especially true with respect to fiscal policy, because fiscal measures take longer to implement and unfold their intended effects gradually over time. Fiscal planning and surveillance over the course of several years can be greatly hampered by frequent and substantial revisions of potential output estimates. That "a method that generates very large revisions will be considered as uncertain" (Cotis et al. 2005, p. 7) is a wide-spread sentiment among economists and policy makers. This sentiment is entirely understandable, given the conceptual underpinning of potential output as a long-term trend and the dependability required by economic policy. The revision stability of annual estimates for Switzerland has been studied in the precursor project. A similar study cannot be conducted with the Swiss quarterly data due to the lack of required data vintages.

Further problematic characteristics include excessive volatility and, especially, excessive cyclicality of potential output estimates. Excessive volatility is undesirable for largely the same reasons, as it is prone to large revisions. Excessive pro-cyclicality means that changes in potential output closely follow changes in the actual output. Excessive volatility and excessive procyclicality together make the output gaps smaller. The main consequence of excessive volatility is significant revisions in the presence of boom-bust cycles, when expansions of productive capacity due to credit expansion and raising asset prices are followed by contractions due to debt-deflation, with the accompanying asset revaluation and hysteresis effects on investment and labor force. The effect of excessive procyclicality in the EU estimates, for example, was exposed following the outbreak of the global financial and economic crisis in 2008 and the ensuing sovereign debt crisis in several EU member states. A sharp downward revision of potential output made the output gap less indicative of the current cyclical position and removed the pressure for a countervailing policy response. Several authors have critically discussed how hysteresis effects have contributed to this, e.g. Fatás (2018) and Fatás and Summers (2018).[3]

In view of the existing experience in estimating potential outputs and using them as a policy guidance, applied economic literature, e.g. the much-quoted "A Practitioner's

[3] `https://voxeu.org/article/hysteresis-and-fiscal-policy-during-global-crisis`

Guide to Potential Output and the Output Gap" by EU Independent Fiscal Institutions (the main users of underlying methods), has established a set of best practices (EU IFIs, 2018). The essence is that estimates should be backed up by econometric quality and benchmark comparisons. Model uncertainty plays a central role in gauging econometric quality, as potential output is not observable. The analysis presented in this report puts an emphasis on model uncertainty by carrying out an extensive specification search in the framework of the EC production function methodology, as well as offering several alternative estimates obtained using more parsimonious techniques. The main advantage of a production function methodology is that it yields economically interpretable details on the determinants of economic growth. The main disadvantages include an inevitable reliance on many theoretical and not-so-theoretical assumptions, excessive procyclicality and relatively low resilience to data revisions.[4]

This report uses a transparent set of criteria for model selection. The model should have reasonable predictive power for an observed cyclical quantity, such as capacity utilization in the case of the TFP trend, or the change in wage-inflation in the case of a Phillips curve. It should not produce too volatile or too cyclical growth rates of potential output relative to the actual output. The final criterion is the congruence between an annual and a quarterly estimate. This criterion is applied for practical reasons, as we desire the two estimates to form a consistent set of tools. As for benchmarking, EU IFIs (2018) suggests comparing estimates from alternative methods, from other institutions or for other countries. Following this advice, we compare the annual estimates for Switzerland with the current annual estimates by the European Commission for the EU15 (old member states). The estimates for the new member states are excluded because they rely on much shorter samples and their quality appears to be less consistent. The comparison of annual estimates is sufficient, since the annualized quarterly estimates are very close to their true annual counterparts. In addition, we compare the quarterly estimates of the output gap to the estimates published by the Swiss National Bank (SNB).

3 The Production Function Methodology

The aggregate production function models the current level of actual GDP (chain-linked volumes at 2010 reference levels), Y_t, using a Cobb-Douglas specification, with capital

[4]The last fact has been documented in several studies, e.g. Turner, et al. (2016). See also, Dovern and Zuber (2019), who decompose the revisions of potential output estimates for the EU member states following the outbreak of the crisis.

stock (K_t) and total hours worked (L_t) as factor inputs:

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

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 Residual, or the part of growth in real GDP that is not explained by changes in labor and capital used in production.

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

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

or, taking the natural logarithms,

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

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 cycle c_t is identified using changes in the rate of capacity utilization sourced from business sentiment surveys.

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, $\bar{K}_t = K_t$. Any cyclical fluctuations in capital utilization are assumed to be removed by the cyclical adjustment of the total factor productivity in the decomposition (2).

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, such that a positive output gap indicates over-utilization and rising inflationary pressures, which should ease once the capacity becomes underutilized. To identify the average utilization of labor, we first decompose total hours worked:

$$L_t = POP_t \cdot PRT_t \cdot (1 - U_t) \cdot H_t, \tag{4}$$

where POP_t denotes the working population aged between 15 and 64 (labor force), PRT_t the participation rate in percent of the labor force, U_t the unemployment rate and H_t the hours worked per person employed, i.e. employees and self-employed persons. The above definition uses the identity $LS_t \cdot (1 - U_t) = LD_t$, involving the labor supply LS_t, the number of persons employed LD_t and the unemployment rate U_t. Then,

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

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

$$GAP_t = 100 \cdot \frac{Y_t - \bar{Y}_t}{\bar{Y}_t}. \tag{5}$$

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

$$l_t = 100 \cdot \alpha \frac{\bar{L}_t - \bar{L}_{t-1}}{\bar{L}_{t-1}}, \quad \text{where} \quad \bar{L}_t = POP_t \cdot \overline{PRT_t} \cdot (1 - \nu_t) \cdot \bar{H}_t, \tag{6}$$

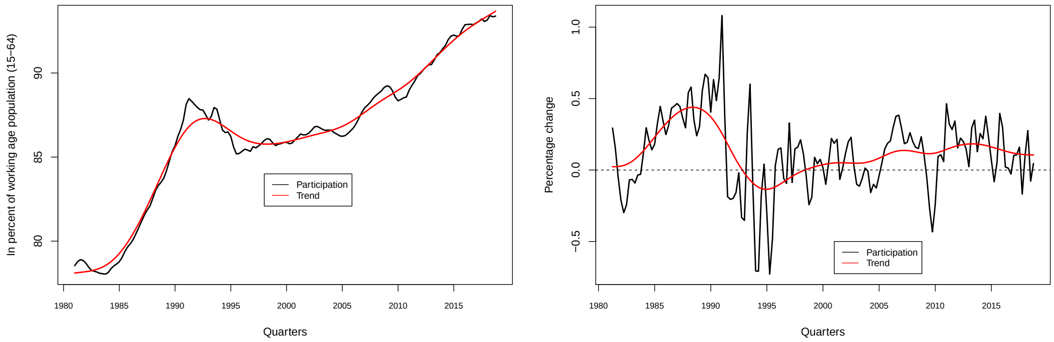
$$k_t = 100 \cdot (1 - \alpha) \frac{K_t - K_{t-1}}{K_{t-1}}. \tag{7}$$

The contribution of TFP is computed as a remainder:

$$f_t = g_t - l_t - k_t, \quad \text{where} \quad g_t = 100 \cdot \frac{\bar{Y}_t - \bar{Y}_{t-1}}{\bar{Y}_{t-1}}. \tag{8}$$

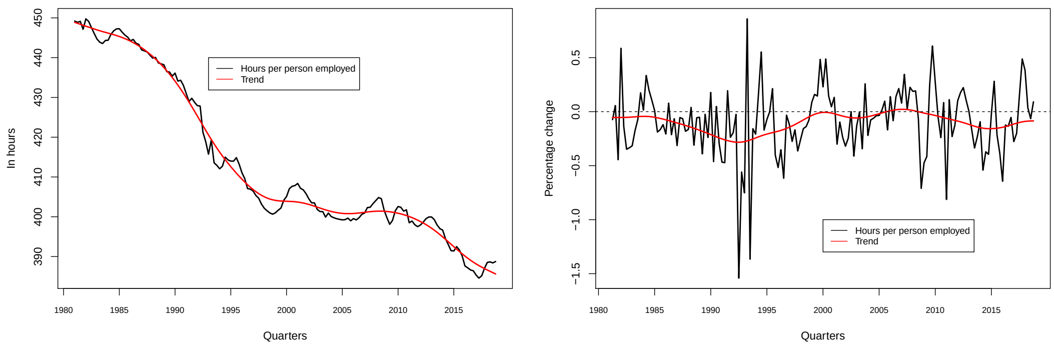
The business cycle influences the total factor productivity TFP_t, the participation rate in percent of the labor force PRT_t, the unemployment rate U_t and the hours worked per person employed H_t. Next, we discuss how to decompose each of the series into a trend and a cycle, the latter being removed when computing potential output.

Figure 1: Participation rate



The trend is extracted using the HP-filter with $\lambda = 1600$.

Figure 2: Average hours worked



The trend is extracted using the HP-filter with $\lambda = 1600$.

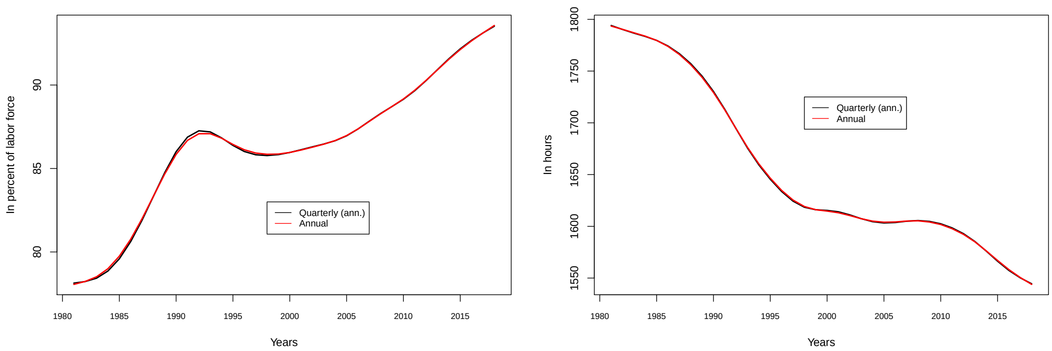
3.1 Trend in participation rate and average hours worked

The EC applies the Hodrick-Prescott filter (HP-filter) to annual series of the participation rate and the average working hours. The quarterly series are smoothed using $\lambda = 1600$, the value typically recommended for quarterly data (Baxter and King 1995). Figures 1 and 2 show the respective quarterly trends. Both are compared to their annual counterparts in Figure 3.

3.2 The unobserved component model

The trend in total factor productivity and the natural rate of unemployment (NAWRU) are estimated using unobserved component models. The following example of a simple

Figure 3: Participation rate and average hours worked



The figures compare the quarterly trend aggregated to the annual frequency to the trend estimated using annual data. We use means of the quarterly values to aggregate the participation trend and sums of the quarterly values to aggregate the trend of the hours worked.

unobserved component model splits the main observable variable into a trend and a cycle. The cycle is assumed to be influenced by another observable variable. This adds a second measurement equation to the system. The model can include exogenous variables. For example, a typical backward-looking Phillips curve may include changes in terms of trade, labor productivity and the labor share as exogenous variables.

Consider a simple unobserved component model:

$$X_t = f_t + c_t\,, \quad \text{first measurement} \tag{9}$$

$$\Delta f_t \sim N(\mu, \sigma^2_{a^p}) \qquad \text{trend}\,, \tag{10}$$

$$\left.\begin{aligned} c_t &= \varphi_1 c_{t-1} + a^c_t \sim N(0, \sigma^2_{a^c}) \\ Y_t &= \mu_{cu} + \beta c_t + a^{cu}_t \sim N(0, \sigma^2_{a^{cu}}) \quad \text{second measurement} \end{aligned}\right\} \quad \text{cycle.} \tag{11}$$

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

3.2.1 Model variations

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

$$\left.\begin{aligned}\Delta f_t &= \eta_{t-1} + a_t^f \\ \Delta \eta_t &= a_t^\eta\end{aligned}\right\} \qquad \text{trend } (2^{nd} \text{ order RW})\,, \tag{12}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{13}$$

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

$$\left.\begin{aligned}\Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^\eta\end{aligned}\right\} \qquad \text{trend (Damped)}\,, \tag{14}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{15}$$

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

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

$$c_t = \varphi_1 c_{t-1} + a_t^c \text{ and } c_t = \varphi_1 c_{t-1} + \varphi_2 c_{t-2} + a_t^c, \text{ where } a_t^c \sim N(0, \sigma^2_{a^c}). \tag{16}$$

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

$$CU_t = \beta_1 c_t + a_t^{cu} \,, \tag{17}$$

$$CU_t = \alpha_1 CU_{t-1} + \beta_1 c_t + a_t^{cu} \,, \tag{18}$$

$$\dots \tag{19}$$

$$CU_t = \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \tag{20}$$

$$+ \beta_1 c_t + \beta_2 c_{t-1} + \beta_3 c_{t-2} + \beta_4 c_{t-3} + \beta_5 c_{t-4} + a_t^{cu} \,. \tag{21}$$

Finally, we also replace the Gaussian white noise model for the error term in the second measurement equation by $MA(1)$. The model variations can be summarized as follows:

3 **Trend**(s).

2 lag structures for the dependent variable in the cycle equation (**AR Cyc**).

3 lag structures for the dependent variable in the second measurement equation (**AR CU**).

2 models for the error term in the second measurement equation (**Error MA**).

5 lag structures for the cycle in the second measurement equation (**Cyc Lags CU**).

The resulting 180 models are listed in Table 10 of the Appendix A. This search uses the estimates for the annual sample 1980-2018 and the quarterly sample Q1:1981-Q4:2018. We test the validity of the conclusions based on a shorter sample starting in 1991. In the above taxonomy, the models studied in the precursor project carry the numbers 102 (NAWRU) and 146 (TFP-trend).

3.3 Non-accelerating wage rate of unemployment (NAWRU)

3.3.1 NAWRU model selection

Let ν_t denote the NAWRU, or the trend of the actual unemployment rate U_t. The cyclical variation in the labor market z_t is called the unemployment gap. It equals the difference between the actual rate of unemployment and the NAWRU. The Phillips curve postulates a negative relationship between wage inflation and the unemployment gap. An actual unemployment rate above NAWRU puts downward pressure on nominal wage growth. The opposite is the case if the unemployment rate falls below NAWRU. The Phillips curve is the second measurement equation of the model, with the change in wage inflation as the dependent variable. The Phillips curve captures the short-term variation of nominal wage inflation as a result of changes in labor productivity, aggregate marginal costs and the employment gap represented by the cyclical component of the unemployment rate.

Before committing to an exhaustive specification search over the complete set of models listed in Table 10 of the Appendix A, we considered a representative sample of 36 models listed in Table 9. These 36 representative models are chosen from a partition of the complete set of 180 models according to their trend specification (**Trend**) and the lag structure of the cycle (**Cyc Lags CU**). These two model specification elements were chosen because they deliver good variation of models in the sample, and because their overall effect on the estimation result is more significant than that of other specification elements.

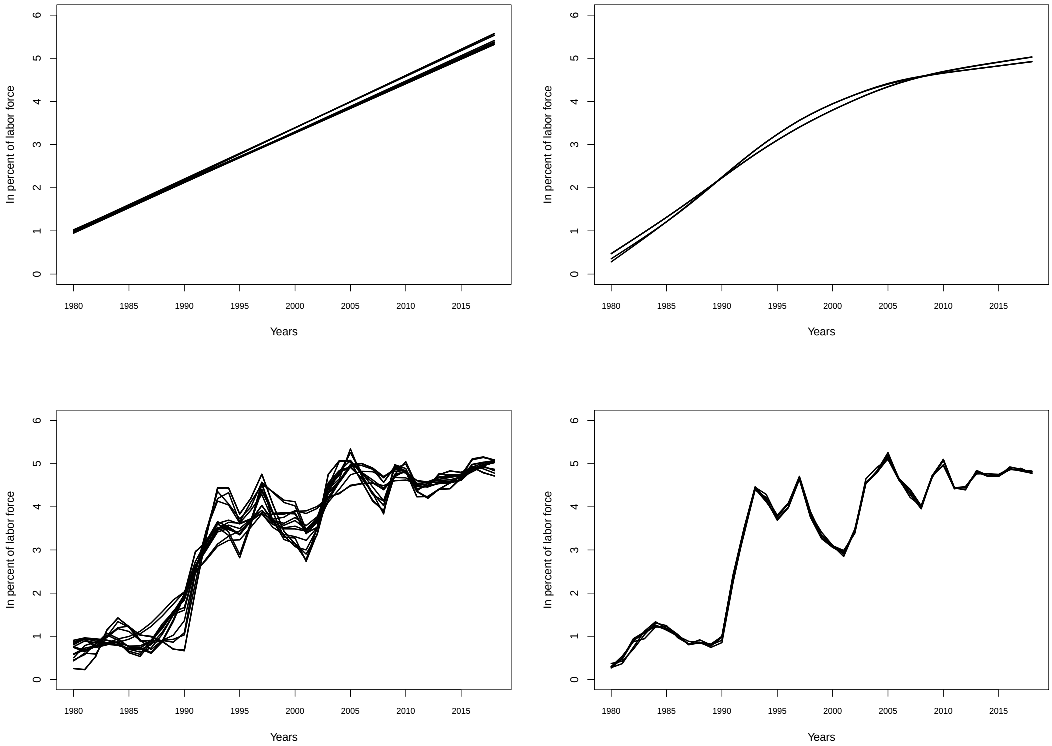
This preliminary search for an optimal NAWRU model has revealed that the quarterly estimates fall into three categories. The first category comprises linear NAWRU estimates (linear), the second category shows some curvature (smooth curve), and the third category plainly equates the trend to the actual unemployment rate (actual). The first and third types of estimates can be discarded on a priori grounds. While a linear NAWRU is conceivable in principle, it is problematic since it assigns all irregular variation in the actual unemployment rate to the cycle (unemployment gap). Equating the trend with the actual unemployment rate results in no decomposition, which is unacceptable. Figure 5 shows the quarterly estimates from each of the three categories of models (linear, smooth curve, actual).

Table 1: Discrepancies between NAWRU models 1980-2018 and Q1:1981-Q4:2018

	Ann.			
Quart.	102	120	123	174
102	0.0420	0.0669	0.0651	0.0456
108	0.0435	0.0705	0.0689	0.0468
114	0.0465	0.0711	0.0697	0.0497
120	**0.0357**	0.0663	0.0641	0.0410
123	0.0435	0.0704	0.0687	0.0467
174	0.0465	0.0711	0.0698	0.0497

In contrast with the quarterly estimates, the annual estimates of the same set of 36 models contain an additional category (ragged curve). Even though ragged curve estimates are inherently plausible, the final model selection falls on a pair of smooth curve types. This decision is motivated by the desire to minimize the discrepancy between the annual estimate and the annualized quarterly estimate of NAWRU. The annualized quar-

Figure 4: Annual NAWRU models

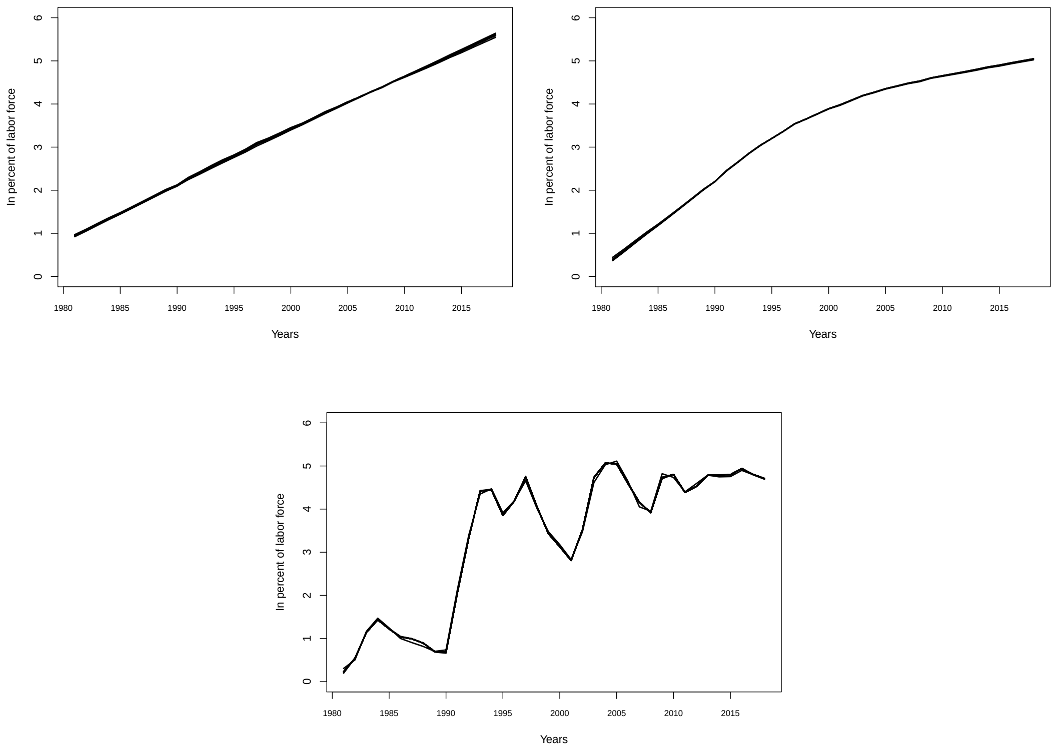


The figure shows the four types of annual estimates for the NAWRU. Their codes are: linear (9, 19, 25, 45, 48, 70, 78, 94, 88, 58), smooth (102, 120, 123, 174), ragged (74, 100, 145, 84, 108, 129, 133, 137, 149, 168, 180, 114, 13, 33, 54, 159), and actual (3, 27, 39, 62, 153, 165). Linear trends and estimates very close to the actual unemployment rate can be rejected on a priori grounds.

terly estimate is obtained by averaging the four quarterly values in a year. The category of smooth estimates includes (102, 120, 123, 174) at the annual frequency and (102, 108, 114, 120, 123, 174) at the quarterly frequency. Converting the quarterly estimates to the annual frequency and cross-tabulating the mean absolute discrepancy between each pair of estimates reveals that a pair of models 102 (annual) and 120 (quarterly) returns the closest set of estimates (Table 1). We therefore choose this pair of models for subsequent estimations.

The choice of exogenous variables in the Phillips curve is standard in the literature, where labor share approximates labor productivity and marginal costs. The terms of trade may play a role if the wage setters target the GDP inflation rather than the consumer price inflation, or when the export sector dominates the outcomes of wage bargaining (Galí and Gertler, 1999). The Phillips curve assumes that all variables are stationary.

Figure 5: Quarterly NAWRU models



The figure shows the three types of quarterly estimates for the NAWRU (annualized). Their codes are: linear (78, 84, 88, 94, 100, 149, 168), smooth (102, 108, 114, 120, 123, 174), actual (3, 9, 13, 19, 25, 27, 33, 39, 45, 48, 54, 58, 62, 70, 74, 129, 133, 137, 145, 153, 159, 165, 180). Since the smooth curve type is the only plausible type available at both frequencies, the final choice falls on a model of this type, which minimizes the discrepancy between the annual and the annualized quarterly estimate.

The specification of the preferred annual model 102 is given by

$$U_t = \nu_t + z_t\,, \tag{22}$$

$$\left.\begin{array}{l} \Delta\nu_t = \eta_{t-1} + a_t^{\nu} \\ \Delta\eta_t = a_t^{\eta} \end{array}\right\} \quad \text{trend}\,, \tag{23}$$

$$\left.\begin{array}{l} z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t^{z} \\ \Delta^2 W_t = \mu_w + \beta_1 z_t + \beta_2 z_{t-1} + \gamma_1 \Delta^2 tot_t + \gamma_2 \Delta^2 prod_t + \gamma_3 \Delta^2 ls_t + a_t^{w} \end{array}\right\} \quad \text{cycle}\,, \tag{24}$$

$$a_t^{\nu} \sim N(0, \sigma^2_{a^{\nu}}),\; a_t^{\eta} \sim N(0, \sigma^2_{a^{\eta}}),\; a_t^{z} \sim N(0, \sigma^2_{a^{z}}),\; a_t^{w} \sim N(0, \sigma^2_{a^{w}}) \quad \text{error terms.}$$

Here, the trend ν_t is a nested random walk and the cycle z_t is an $AR(2)$ process. The variable W_t denotes the average compensation per employee. The cycle enters the Phillips curve together with three exogenous variables in second differences: the terms of trade tot_t, the average labor productivity $prod_t$ and the logarithm of the 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 labor share is the share of compensation of employees in nominal GDP.

The specification of the optimal quarterly model is more complex than of its annual counterpart. It features more lags of the observed dependent variable $\Delta^2 W_t$, as well as more lags of the unobserved cyclical component z_t in the Phillips curve. The error in the Phillips curve follows a more complex $MA(1)$ process.

The specification of the quarterly model 120 in the optimal pair of models reads

$$U_t = \nu_t + z_t\,, \tag{25}$$

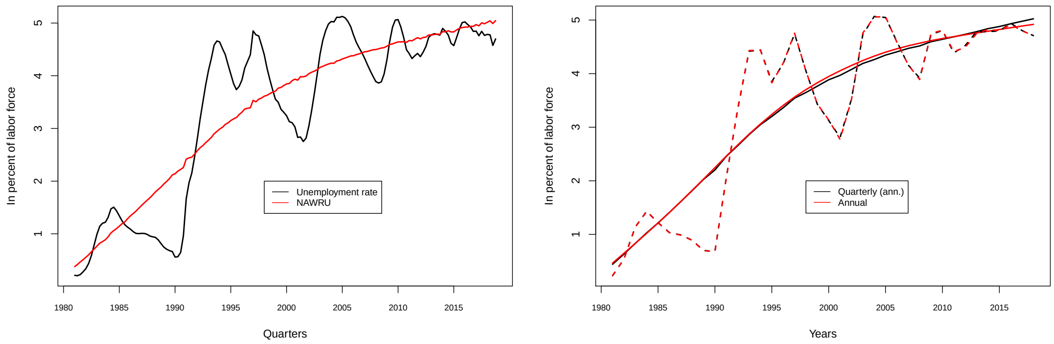
$$\left.\begin{array}{l} \Delta\nu_t = \eta_{t-1} + a_t^{\nu} \\ \Delta\eta_t = a_t^{\eta} \end{array}\right\} \quad \text{trend}\,, \tag{26}$$

$$\left.\begin{array}{l} z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t^{z} \\ \Delta^2 W_t = \mu_w + \alpha_1 \Delta^2 W_{t-1} + \beta_1 z_t + \beta_2 z_{t-1} + \beta_3 z_{t-2} + \beta_4 z_{t-3} + \\ \qquad + \gamma_1 \Delta^2 tot_t + \gamma_2 \Delta^2 prod_t + \gamma_3 \Delta^2 ls_t + a_t^{w} + \psi a_{t-1}^{w} \end{array}\right\} \quad \text{cycle}\,, \tag{27}$$

$$a_t^{\nu} \sim N(0, \sigma^2_{a^{\nu}}),\; a_t^{\eta} \sim N(0, \sigma^2_{a^{\eta}}),\; a_t^{z} \sim N(0, \sigma^2_{a^{z}}),\; a_t^{w} \sim N(0, \sigma^2_{a^{w}}) \quad \text{error terms.}$$

Figure 6 plots the quarterly NAWRU against the actual unemployment rate.

Figure 6: Unemployment rate and NAWRU



The left panel compares the quarterly unemployment rate with the quarterly NAWRU estimate. The right panel compares the actual unemployment rate (dashed) with the annual NAWRU (red, model 102) and the quarterly NAWRU (black, model 120) aggregated to the annual frequency by averaging the quarterly values.

3.4 Total factor productivity (TFP)

3.4.1 TFP model selection

The first step evaluates the goodness of 180 models having different specifications for the TFP trend and the same specification for the NAWRU given by the annual equations (22)-(24) (model 102), or by the quarterly equations (25)-(27) (model 120). The candidate models are selected separately at each frequency. The following criteria are applied to the annual and the quarterly models. The first criterion is the one-step-ahead forecast R^2 for the second measurement equation (**TFP** R^2). The higher it is, the better the model predicts the observed capacity utilization. Next, we define the period-to-period growth of the GDP $g_t = 100 \cdot \frac{Y_t - Y_{t-1}}{Y_{t-1}}$ and equally the rate of potential output $\bar{g}_t$. The following ratio is a very sensitive measure of the excessive volatility of the growth rate of potential output:

$$\frac{\max(\bar{g}_t) - \min(\bar{g}_t)}{\max(g_t) - \min(g_t)}. \tag{28}$$

This measure of relative excessive volatility (**Range PO**) is preferable to the more conservative ratio of standard deviations (**Sd. PO**), because it is extremely sensitive to outliers. A value close to or above unity indicates the presence of excessive volatility in the estimate of potential output growth for at least one time period. The third criterion is the sample correlation coefficient $\mathrm{Corr}[\bar{g}_t \, , g_t]$ between the growth rate of potential output and the growth rate of real GDP (**Cyclic. PO**). A high value of this measure indicates excessive procyclicality.

A candidate model should have reasonable predictive power (high **TFP** R^2), produce not-too-volatile growth rates of potential output (low **Range PO**) and not-too-cyclical growth rates of potential output (low **Cyclic. PO**). Based on this reasoning, the composite selection criterion for a candidate model in the set of 180 models at a given frequency is given by the following three conditions being fulfilled simultaneously:

$$\mathbf{TFP}R^2 \text{ is above the median of all } \mathbf{TFP}R^2\,, \tag{29}$$

$$\mathbf{Range\ PO} \text{ is below the median of all } \mathbf{Range\ PO}\,, \tag{30}$$

$$\mathbf{Cyclic.\ PO} \text{ is below the median of all } \mathbf{Cyclic.\ PO}. \tag{31}$$

The last two criteria (30) and (31) tend to select models that produce exponential TFP trends, or, equivalently, TFP trends with a constant growth rate. This occurs because a constant growth model minimizes the volatility of the trend and, therefore, also the excess volatility measure used for model selection. A constant growth model also tends to minimize correlations with the growth rates of actual output, at least among the models that produce positive correlations. The above criteria bias the model selection towards low volatility trends, which is sensible, given that the baseline theoretical model of exponential growth implies constant growth rates. Nevertheless, it is advisable to remove such models from the full set of all models prior to applying the above three criteria. Constant growth models for the TFP trend assign all irregular variation in the actual TFP to the cycle, which is implausible, given the existence of productivity shocks.

Briefly anticipating the results, there will be no constant growth model among the annual models estimated from 1980, nor among the quarterly models estimated from Q1:1981. However, there will be several such cases among the quarterly models estimated from Q1:1991, where the model complexity coupled with a shorter sample leads to some estimates of slope parameters hitting their lower bound of zero.

In a second step, we search the set of candidate models for those model pairs which maximize coherency between the quarterly and the annual implementation. To this end, we consider the pair of candidate models – one quarterly and one annual – that minimizes the average of the discrepancy between the annualized quarterly estimate of the output gap, GAP_t^*, and the output gap estimated using an annual model GAP_t in terms of mean absolute deviation (**MAE Gap**):

$$\frac{1}{N}\sum_{i=1}^{N}|GAP_t^* - GAP_t|, \tag{32}$$

and the pair that minimizes the discrepancy between the annualized quarterly estimate of potential output growth, $\Delta\log(\bar{Y}_t^*)$, and the annual estimate of potential output growth $\Delta\log(\bar{Y}_t)$ (**MAE PO**)

$$\frac{1}{N}\sum_{i=1}^{N}|\Delta\log(\bar{Y}_t^*) - \Delta\log(\bar{Y}_t)|. \tag{33}$$

The above discrepancies are computed by converting the quarterly estimates to the annual frequency rather than the other way around, because temporal disaggregation requires additional assumptions while temporal aggregation does not. We thus aggregate the quarterly estimates by summing up the levels of quarterly potential output for each year and compute the growth rate of potential output along with the output gap.

It should be noted that a small discrepancy in growth rates of potential output for every observation implies that the output gaps are also similar for every observation. In general, however, discrepancies in the output gap tend to be more sensitive to the choice of models. This occurs because a single discrepancy between the growth rates has a lasting effect on discrepancy between the gaps. The gap depends on a ratio of cumulative rather than instantaneous growth rates of the real GDP and the potential output, as is shown in the following representation:

$$\frac{GAP_T}{100} + 1 = \frac{Y_0}{\bar{Y}_0}\cdot\frac{\prod_{t=1}^{T}(1+g_t)}{\prod_{t=1}^{T}(1+\bar{g}_t)}. \tag{34}$$

This higher sensitivity may result in a larger misalignment between gap estimates of distinct models. A single discrepancy between the growth rates can cause a protracted discrepancy between the gaps. To minimize the risk of this happening, we select the optimal model based on the following simple composite criterion:

$$\frac{1}{2N}\sum_{i=1}^{N}|GAP_t^* - GAP_t| + \frac{1}{2N}\sum_{i=1}^{N}|\Delta\log(\bar{Y}_t^*) - \Delta\log(\bar{Y}_t)|. \tag{35}$$

Using the *average criterion* ensures the proximity of the two output gaps.

Further criteria applied to all models at both frequencies include the usual model diagnostics, such as the absence of auto-correlations in the residuals of the trend and cycle equations (Ljung-Box statistic) and the absence of parameter estimates hitting their boundary values (except perhaps some standard deviations in more complex models). The issue of boundary values frequently occurs when estimating unobserved component models using the method of Maximum Likelihood.

4 Results

4.1 The best model

Table 11 in the Appendix A presents the values of the selection criteria for the annual and the quarterly models. The application of the three criteria to the set of annual models returns a subset of 33 candidate models listed in Table 2. The same criteria applied to the quarterly models yield the 23 candidate models listed in Table 3. Both tables also report the median value of the criteria for the *remaining* models (**Med**, bottom row). In general, the candidate models are among the more complex models in terms of the trend specification and the lag structure in the cyclical part. While all models have similar predictive power, the selected candidate models clearly outperform the hypothetical median remaining model by having a smaller excessive volatility and a smaller excessive procyclicality.

Refining the set of 33×23 candidate models, we seek the pair of models that minimizes the average of

1. discrepancy between the annualized quarterly estimate of the output gap and the annual estimate of the output gap,

2. discrepancy between the annualized quarterly estimate of the growth rate of potential output and the annual estimate of the growth rate of potential output.

The optimal pair of models fulfilling the *average criterion* is:[5]

160 (quarterly), label = 2 ARord = 1 2 MAord = 0 lagvar = 6,

171 (annual), label = 2 ARord = 2 2 MAord = 0 lagvar = 2.

[5]In this particular case, the pair of models was also the one that minimizes the second of the two discrepancies defined above.

Together with the results of the model-by-model evaluation undertaken in the first step, the second step of the search process shows that the pair of models 160 (quarterly) and 171 (annual) possesses good individual quality as well as internal consistency.

The specification of the optimal quarterly model 160 is given by:

$$F_t = f_t + c_t\,, \tag{36}$$

$$\left.\begin{aligned}\Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^\eta\end{aligned}\right\} \quad \text{trend}\,, \tag{37}$$

$$\left.\begin{aligned}c_t &= \varphi_1 c_{t-1} + a_t^c \\ CU_t &= \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \beta_1 c_t + \cdots + \beta_4 c_{t-3} + \beta_5 c_{t-4} + a_t^{cu}\end{aligned}\right\} \quad \text{cycle}\,, \tag{38}$$

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

The observable variables include the logarithm of the observed TFP, F_t, and the mean-centered aggregate capacity utilization CU_t. The trend f_t follows a damped trend. The parameter μ_p gauges the long-run (gain) value of Δf_t as a result of a random shock a_t^η. The damping parameter $\rho \in (0,1)$ gauges the rate of convergence to the gain value. This specification implies that the trend is a random walk, where the drift is an $AR(1)$ process. The cycle c_t also follows an $AR(1)$ process. The measurement equation featuring the series for capacity utilization CU_t includes four lagged values of the cycle c_t.

The specification of the optimal annual model 171 is:

$$F_t = f_t + c_t\,, \tag{39}$$

$$\left.\begin{aligned}\Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^\eta\end{aligned}\right\} \quad \text{trend}\,, \tag{40}$$

$$\left.\begin{aligned}c_t &= \varphi_1 c_{t-1} + \varphi_1 c_{t-2} + a_t^c \\ CU_t &= \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \beta_1 c_t\end{aligned}\right\} \quad \text{cycle}\,, \tag{41}$$

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

The unobserved cycle c_t in the annual model follows a more flexible $AR(2)$ process and the annual model features a simpler lag-structure in the second measurement equation.

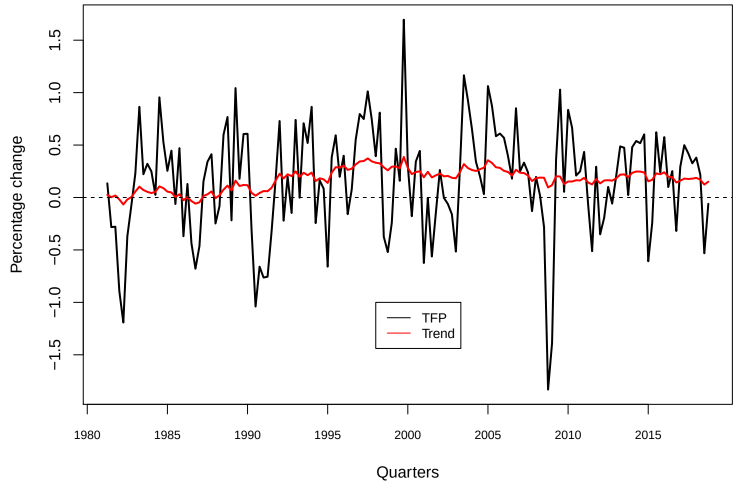
Table 2: Best annual models 1980-2018 (HP)

No	Trend	Cycle Lag	Error AR	Error MA	PC Lags	**TFP R^2**	**Range PO**	**Sd. PO**	**Cyclic. PO**
107	2nd order RW	2	0	1	0-1	0.44	0.30	0.31	0.33
108	2nd order RW	2	0	1	0-2	0.45	0.29	0.30	0.33
109	2nd order RW	2	0	1	0-3	0.45	0.29	0.30	0.32
110	2nd order RW	2	0	1	0-4	0.45	0.29	0.30	0.33
113	2nd order RW	2	1	0	0-2	0.48	0.33	0.31	0.42
114	2nd order RW	2	1	0	0-3	0.48	0.33	0.31	0.42
116	2nd order RW	2	1	1	0	0.43	0.30	0.31	0.33
117	2nd order RW	2	1	1	0-1	0.44	0.30	0.31	0.33
118	2nd order RW	2	1	1	0-2	0.45	0.30	0.31	0.32
119	2nd order RW	2	1	1	0-3	0.45	0.29	0.31	0.32
120	2nd order RW	2	1	1	0-4	0.45	0.29	0.30	0.33
121	2nd order RW	2	2	1	0	0.44	0.29	0.30	0.33
122	2nd order RW	2	2	1	0-1	0.44	0.29	0.30	0.33
123	2nd order RW	2	2	1	0-2	0.45	0.29	0.31	0.32
124	2nd order RW	2	2	1	0-3	0.45	0.29	0.31	0.32
125	2nd order RW	2	2	1	0-4	0.45	0.29	0.30	0.33
134	Damped	2	0	1	0-3	0.46	0.30	0.30	0.38
135	Damped	2	0	1	0-4	0.45	0.32	0.31	0.45
141	Damped	2	1	1	0	0.44	0.30	0.31	0.36
143	Damped	2	1	1	0-2	0.46	0.30	0.30	0.35
144	Damped	2	1	1	0-3	0.46	0.30	0.30	0.35
145	Damped	2	1	1	0-4	0.46	0.30	0.29	0.37
146	Damped	2	2	1	0	0.45	0.29	0.30	0.35
147	Damped	2	2	1	0-1	0.45	0.30	0.30	0.36
148	Damped	2	2	1	0-2	0.45	0.30	0.30	0.35
150	Damped	2	2	1	0-4	0.45	0.29	0.29	0.37
171	**2nd order RW**	**2**	**2**	**0**	**0**	**0.47**	**0.30**	**0.29**	**0.37**
172	2nd order RW	2	2	0	0-1	0.46	0.29	0.30	0.33
173	2nd order RW	2	2	0	0-2	0.45	0.29	0.30	0.33
174	2nd order RW	2	2	0	0-3	0.44	0.29	0.30	0.32
175	2nd order RW	2	2	0	0-4	0.45	0.29	0.30	0.33
177	Damped	2	2	0	0-1	0.46	0.29	0.29	0.36
178	Damped	2	2	0	0-2	0.46	0.29	0.29	0.36
Med						0.43	0.47	0.42	0.48

Table 3: Best quarterly models Q1:1981-Q4:2018 (HP)

No	Trend	Cycle Lag	Error AR	Error MA	PC Lags	**TFP R^2**	**Range PO**	**Sd. PO**	**Cyclic. PO**
90	RW drift	2	1	0	0-4	0.92	0.43	0.47	0.62
95	RW drift	2	1	1	0-4	0.92	0.42	0.45	0.62
98	RW drift	2	2	1	0-2	0.92	0.43	0.47	0.62
99	RW drift	2	2	1	0-3	0.92	0.42	0.46	0.62
100	RW drift	2	2	1	0-4	0.92	0.41	0.45	0.62
115	2nd order RW	2	1	0	0-4	0.92	0.40	0.44	0.61
120	2nd order RW	2	1	1	0-4	0.92	0.38	0.41	0.61
121	2nd order RW	2	2	1	0	0.92	0.42	0.47	0.64
123	2nd order RW	2	2	1	0-2	0.92	0.37	0.40	0.62
124	2nd order RW	2	2	1	0-3	0.92	0.35	0.39	0.61
125	2nd order RW	2	2	1	0-4	0.92	0.34	0.38	0.60
140	Damped	2	1	0	0-4	0.92	0.40	0.43	0.61
145	Damped	2	1	1	0-4	0.92	0.38	0.41	0.61
146	Damped	2	2	1	0	0.92	0.40	0.43	0.61
147	Damped	2	2	1	0-1	0.92	0.43	0.46	0.61
148	Damped	2	2	1	0-2	0.92	0.38	0.42	0.62
149	Damped	2	2	1	0-3	0.92	0.36	0.39	0.61
150	Damped	2	2	1	0-4	0.92	0.34	0.38	0.60
160	**2nd order RW**	**1**	**2**	**0**	**0-4**	**0.92**	**0.15**	**0.22**	**0.42**
170	RW drift	2	2	0	0-4	0.92	0.41	0.45	0.62
171	2nd order RW	2	2	0	0	0.92	0.39	0.46	0.67
175	2nd order RW	2	2	0	0-4	0.92	0.36	0.40	0.61
180	Damped	2	2	0	0-4	0.92	0.36	0.40	0.60
Med						0.92	0.46	0.54	0.70

Figure 7: Growth of observed TFP and TFP trend



The trend of the logarithm of total factor productivity f_t is estimated using model 160. The figure shows the quarterly growth rate of TFP ($\exp(F_t)$, black) and its trend ($\exp(f_t)$, red).

4.2 Potential output

Figure 7 compares the (quarter-on-quarter) growth rates of the TFP trend $\exp(f_t)$ with the growth rates of the observed TFP (Solow Residual). The next step is to insert the estimates for the trends of productivity $\exp(f_t)$, working-age population POP_t, participation rate $\overline{PRT}_t$, unemployment rate ν_t and average working hours in the production function to yield a time series for potential output:

$$\bar{Y}_t = \exp(f_t) \cdot (POP_t \cdot \overline{PRT}_t \cdot (1 - \nu_t) \cdot \bar{H}_t)^{\alpha} \cdot K_t^{1-\alpha}. \tag{42}$$

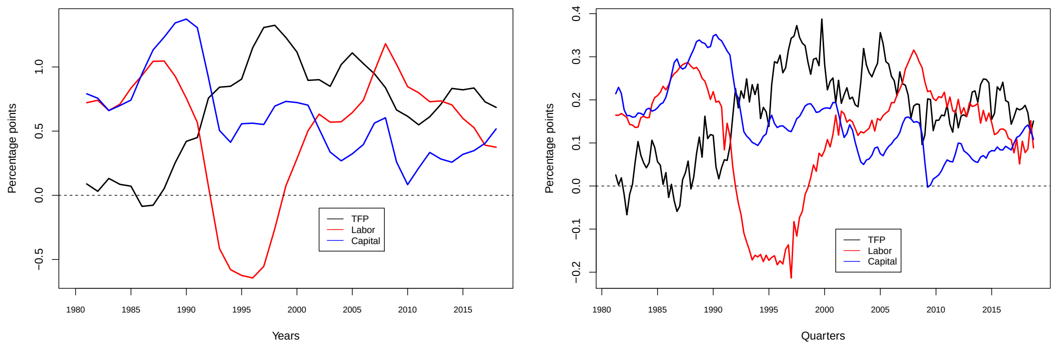
The right panel of Figure 8 shows the quarterly series of potential output growth estimated using the optimal quarterly model 160. The potential growth series estimated using the optimal annual model 171 shown in the left panel is significantly less volatile.

The decomposition of quarterly potential growth shows a negligible TFP contribution prior to 1992 (Figure 9). The labor contribution shows a plausible variation, becoming negative during the economic recession in the 1990s. A similar decomposition based on the annual estimates paints the same picture more clearly (left panel).

Figure 8: Growth of real GDP and potential output

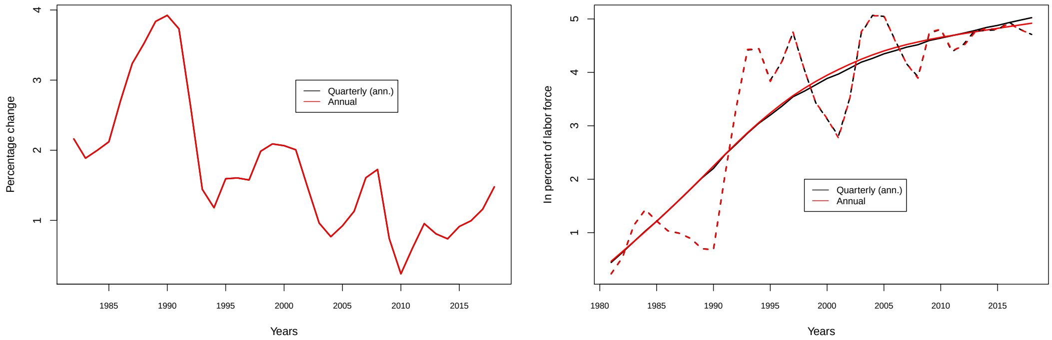
The left panel shows the annual growth of potential output estimated using model 171. The result of the quarterly application of model 160 is shown in the right panel.

Figure 9: Contributions to potential output growth



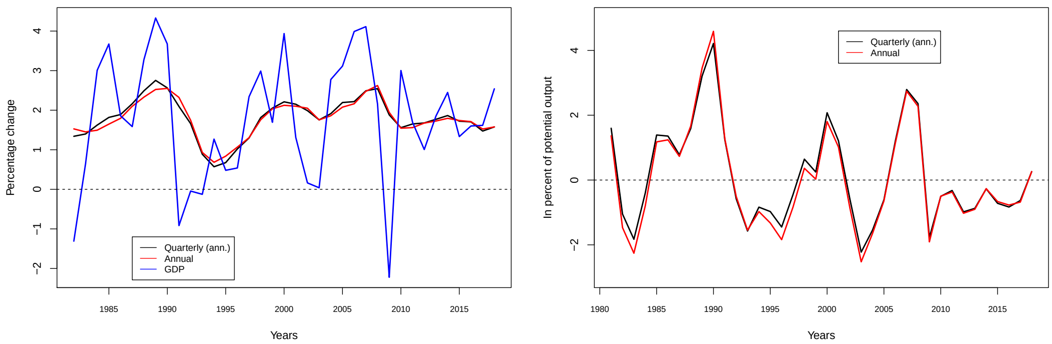
The figure shows the contributions of TFP (f_t, black), labor (l_t, red) and capital (k_t, blue) to the growth of potential output. The contributions are defined by equations (6), (7) and (8). The three contributions add to the growth of potential output g_t. The series in the left panel are based on the annual data, those in the right panel on the quarterly data.

Figure 10: Growth of capital stock and NAWRU



The left panel shows the annualized quarterly growth rate of the capital stock, which is identical to the annual growth rate. The right panel compares the annual unemployment rate and the annual NAWRU with the annualized quarterly unemployment rate and the annualized quarterly NAWRU. The annual NAWRU estimate was obtained using model 102, whereas the quarterly estimate is generated by model 120.

Figure 11: Potential output growth and output gap



The series were estimated using the pair of models (annual 171, quarterly 160) for the TFP-trend and (annual 102, quarterly 120) for the NAWRU.

5 Benchmarking

5.1 Comparison with the SNB estimate

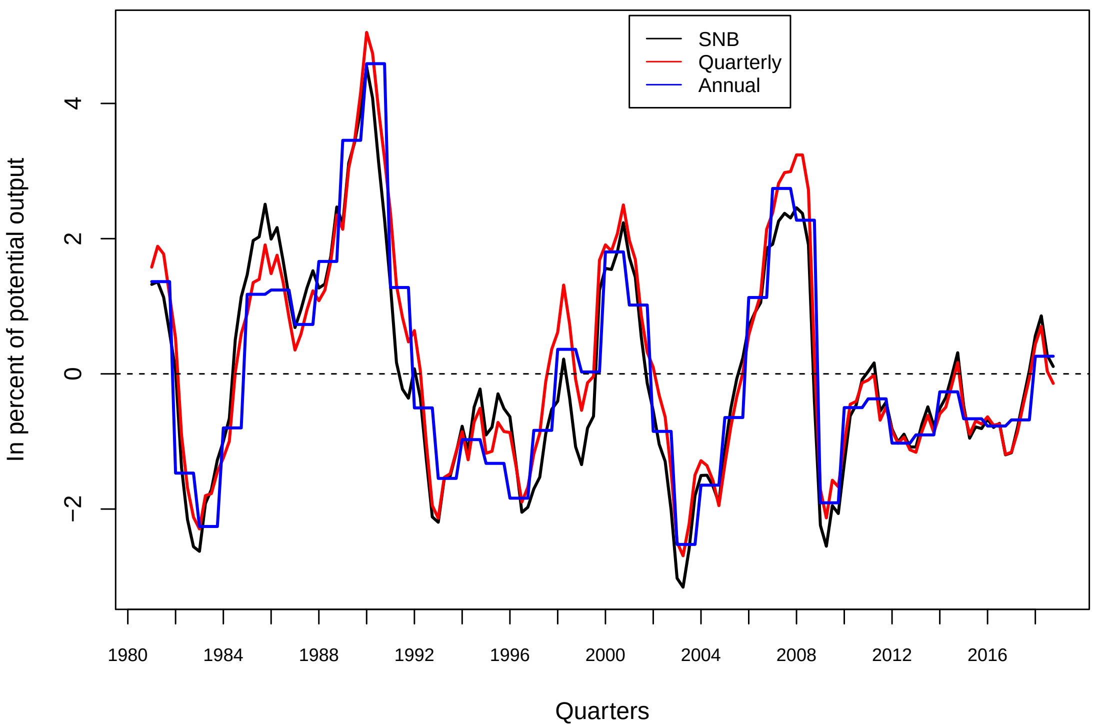
Figure 12 compares the quarterly output gap with the quarterly estimate published by the Swiss National Bank (SNB). The SNB publishes three estimates of potential output. Two of them are based on filters, whereas the third one, shown in the figure, is based on a production function approach. The figure shows that our annual estimate is very close to that of the SNB. Our quarterly estimate tends to indicate the turning points of the business cycle, especially at the peaks, more pronouncedly than the SNB estimate. The largest differences between all three estimates can be seen during the period of economic recession in the 1990s, where the SNB series shows the smallest negative output gap of all three estimates.

5.2 Comparison with EC estimates

Tables 4 and 5 compare the annual estimates for Switzerland obtained using the best annual model with the annual estimates of the EC for the EU15. The comparison is performed in terms of excessive volatility and excessive procyclicality. The excessive volatility is expressed by the ratio of the standard deviation of the growth rates of potential output to the standard deviation of the growth rates of actual output (real GDP), rather than the ratio of the spreads of growth rates used in the model selection. This is done to increase the variety in the presentation, as the conclusions drawn from the comparison apply equally to both volatility measures. The excessive procyclicality is measured by the correlation between the annual growth rates of potential output and the annual growth rates of real GDP. It is sufficient to compare the annual estimates, since the inclusion of a congruence criterion in the process of model selection considerably narrowed the discrepancy between the annualized estimates of the best quarterly model and the estimate of the best annual model. The comparison is presented by decade, with the overall figure provided in the last row of each table. Two figures are provided for Switzerland. The first figure (**CH HP**) refers to the estimate that uses an HP-filter to smooth the participation rate and the average hours worked. The second figure (**CH LOESS**) refers to the estimate relying on the optimal smoothing of these input series. The analysis in Appendix B has shown that the LOESS smoothing produces more volatile estimates.

The overall conclusion from the figures presented in both tables for the main variant

Figure 12: A comparison of output gaps



The quarterly output gap is compared to the gap published by the SNB, which is also based on a production function methodology. The step line shows the annual estimate uniformly 'stretched' across the four quarters of a year.

based on the application of the HP-filter to the exogenous input series is that the estimates for Switzerland are neither excessively volatile, nor excessively procyclical. This follows from a comparison of the Swiss figures to the corresponding medians of the EC estimates for the EU15 member states. The period 1991-2000 is the only decade in which the growth rates of Swiss potential output were (relatively to the GDP) more volatile than those of at least half of the EU15 member states. This finding is not surprising, given the fact that Switzerland has experienced a recession during this decade and the potential output estimate is still moderately procyclical. This recession was unique to Switzerland. In all other periods, including the decade of the global financial and economic crisis, the estimated growth rates of potential output show smaller volatility relative to the growth rates of real GDP than in the majority of the EU15 member states. The estimates are also not excessively procyclical, as evidenced by the comparison of the correlation between the two growth rates for Switzerland and the median correlations for the EU15 member states reported in the last column. The estimates based on LOESS, on the other hand, are markedly more volatile, with Swiss figures being larger than the respective medians in three of the four time periods under consideration. The overall volatility of the estimates based on LOESS is still lower than the median value for the EC member states. The alternative estimates do not appear to be excessively procyclical.

Table 4: Volatility of annual estimates of potential output growth (HP)

	BE	DE	DK	EL	ES	FR	IE	IT	LU	NL	AT	PT	FI	SE	UK	CH HP	CH LOESS	Med EU15
1980-1990	0.41	0.27	0.16	0.22	0.63	0.30	0.19	0.12	0.44	0.40	0.34	0.26	0.36	0.11	0.31	0.25	0.31	0.29
1991-2000	0.14	0.43	0.24	0.58	0.27	0.14	0.55	0.26	0.32	0.17	0.35	0.30	0.40	0.30	0.35	0.39	0.52	0.31
2001-2010	0.21	0.07	0.17	0.49	0.45	0.19	0.69	0.27	0.31	0.32	0.29	0.55	0.35	0.20	0.37	0.16	0.24	0.30
2011-2018	0.37	0.35	0.59	0.19	0.28	0.15	0.94	0.28	0.17	0.41	0.33	0.45	0.30	0.26	0.50	0.19	0.71	0.31
1980-2018	0.38	0.33	0.31	0.60	0.61	0.39	0.81	0.54	0.48	0.55	0.44	0.60	0.45	0.26	0.45	0.29	0.38	0.45

Table 5: Procyclicality of annual estimates of potential output growth (HP)

	BE	DE	DK	EL	ES	FR	IE	IT	LU	NL	AT	PT	FI	SE	UK	CH HP	CH LOESS	Med EU15
1980-1990	0.89	0.82	0.79	0.08	0.88	0.84	0.59	0.64	0.79	0.81	0.67	0.92	0.12	0.68	0.77	0.62	0.68	0.78
1991-2000	0.63	0.23	0.46	0.78	0.63	-0.07	0.92	-0.02	0.77	0.89	0.33	0.71	0.84	0.91	0.68	0.20	0.23	0.65
2001-2010	0.38	0.73	0.34	0.92	0.94	0.65	0.76	0.57	0.35	0.31	0.62	0.35	0.51	0.40	0.75	0.28	0.39	0.54
2011-2018	0.81	-0.16	0.71	0.72	0.78	0.60	0.95	0.77	0.03	0.87	0.60	0.92	0.77	0.63	0.17	0.02	-0.05	0.72
1980-2018	0.61	0.43	0.53	0.75	0.71	0.56	0.88	0.62	0.64	0.65	0.58	0.78	0.66	0.60	0.66	0.37	0.41	0.63

The tables compare the annual estimates for Switzerland obtained using the best annual model to the current annual estimates of the EC for the EU15 (Spring 2019). The comparison is performed in terms of excessive volatility and excessive procyclicality. The excessive volatility is expressed by the ratio of the standard deviation of the growth rates of potential output to the standard deviation of the growth rates of actual output (real GDP). The excessive procyclicality is measured by the correlation between the annual growth rates of potential output and the annual growth rates of real GDP.

6 Restricting the sample to 1991-2018

This section presents quarterly estimates for a sub-sample starting in Q1:1991. The main reason for narrowing the sample is the comprehensive change in the scope and methodology of collecting labor market statistics starting in 1991. Comparing the estimates based on a sub-sample to those based on the full sample provides a natural robustness check. Due to the loss of observations associated with the computation of lagged values of the exogenous variable in the Phillips curve, the actual estimation sample starts in Q1:1992.

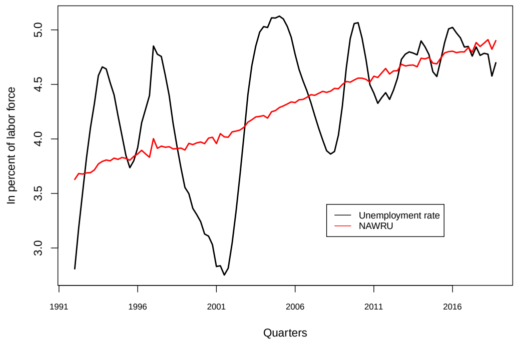
The model selection procedure is the same as the one performed for the full sample, except that we do not impose the average congruence criterion between the annualized quarterly and the annual estimates of potential output growth rates and the output gap. The reason for this is the absence of reliable annual estimates for the short sample: 28 annual observations between 1991 and 2018 are not enough to reliably estimate unobserved component models for the NAWRU and the TFP trend. To summarize the model selection procedure for the sample starting in 1991, as in the full sample, we first select a plausible NAWRU model, then we apply the selection criteria (29)-(31) for the candidate models for the TFP trend, while keeping the NAWRU model fixed. When selecting the candidate models among the full set of 180 models, we first remove the models that produce constant growth rates for the TFP trend. The final model is based on a combination of the three criteria used to pick the candidate models.

The NAWRU estimates for 36 sample models now fall into two categories. The first category comprising 19 models returns a nearly linear trend,[6] the second category returns the actual unemployment rate. We therefore proceed with the model 120, which is the model used in the full-sample quarterly estimation. This estimate is shown in Figure 13. Turning to the models for the TFP trend, we first remove the 19 models that produce constant growth rates for the TFP trend.[7] The candidate models are selected from the remaining 161 models by applying the model selection criteria (29)-(31). Note that the median comparison values are computed for the set of 161 models, i.e. excluding the constant growth models. Table 6 reports the values of the selection criteria for the candidate models. In a final step, we select the model that maximizes the unweighted sum of the three criteria:

$$\mathbf{TFP}R^2 - \textbf{Range PO} - \textbf{Cyclic. PO}. \tag{43}$$

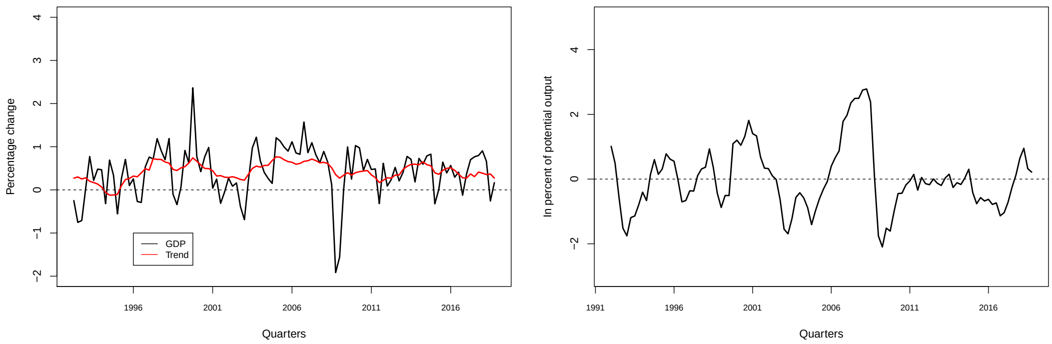
[6]This set is: 78, 84, 88, 94, 100, 102, 108, 114, 120, 123, 129, 133, 137, 145, 149, 153, 168, 174, 180.
[7]These models are: 23, 24, 48, 49, 50, 73, 74, 75, 99, 100, 153, 154, 155, 158, 159, 160, 169, 170, 180.

Figure 13: The NAWRU Q1:1992-Q4:2018



The figure shows the nearly linear quarterly estimate of the NAWRU obtained using the shorter sample from Q1:1992-Q4:2018. The estimated specification 120 is the same as that used for the quarterly models estimated using the full sample.

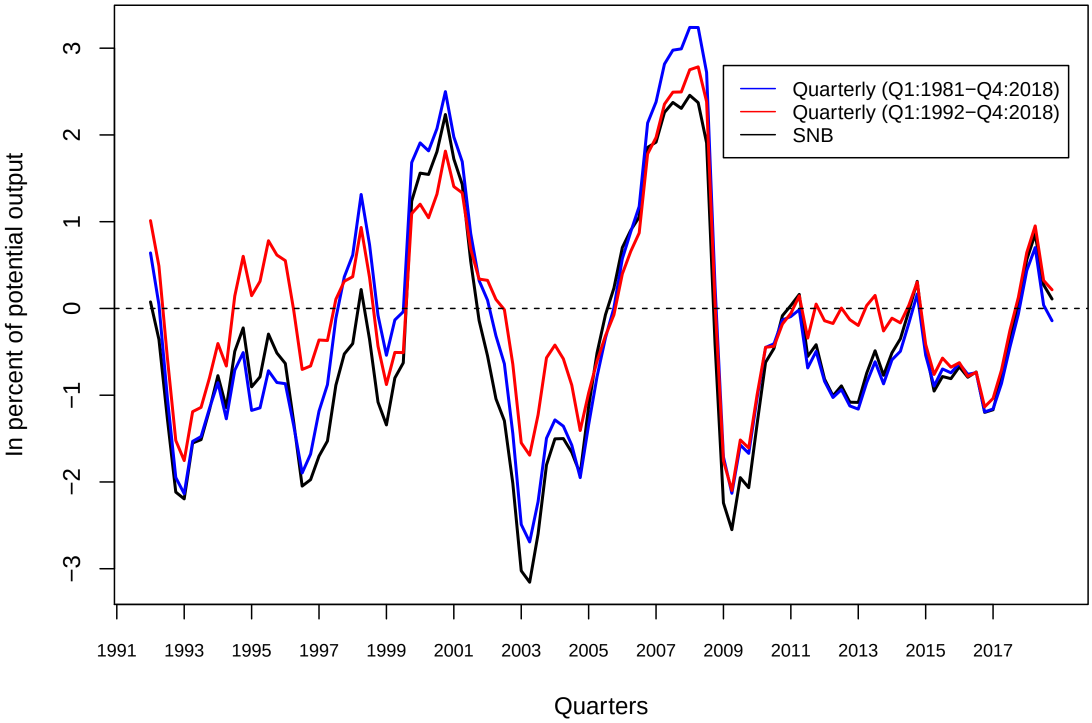
Figure 14: Potential output growth and output gap Q1:1992-Q4:2018



The estimates were generated using the quarterly models 165 for the TFP-trend and 120 for the NAWRU.

The above approach penalizes excess volatility and excess procyclicality, while promoting a good fit in the second measurement equation modeling the capacity utilization. The result of the above procedure identifies model 165 as the best model. The results shown in Figure 14 and the comparison with the SNB estimate in Figure 15 are obtained using model 165 as the quarterly model for the TFP trend and the model 120 as the quarterly model for the NAWRU.

Figure 15: A comparison of output gaps for different samples



The quarterly output gap is compared to the gap published by the SNB, which is also based on a production function methodology, and the analogous estimate based on the full quarterly sample. The figure shows substantial differences between the output gaps estimated using the full sample Q1:1981-Q4:2018 and the shorter sample Q1:1992-Q4:2018.

Table 6: Best quarterly models Q1:1992-Q4:2018

No	Trend	Cycle Lag	Error AR	Error MA	PC Lags	**TFP R^2**	**Range PO**	**Sd. PO**	**Cyclic. PO**
71	Damped	1	2	1	0	0.91	0.21	0.33	0.55
72	Damped	1	2	1	0-1	0.91	0.24	0.36	0.60
90	RW drift	2	1	0	0-4	0.92	0.49	0.51	0.60
96	RW drift	2	2	1	0	0.92	0.41	0.49	0.64
97	RW drift	2	2	1	0-1	0.92	0.47	0.54	0.64
98	RW drift	2	2	1	0-2	0.92	0.45	0.48	0.58
115	2nd order RW	2	1	0	0-4	0.91	0.50	0.52	0.60
121	2nd order RW	2	2	1	0	0.92	0.41	0.49	0.64
122	2nd order RW	2	2	1	0-1	0.91	0.47	0.54	0.64
123	2nd order RW	2	2	1	0-2	0.91	0.47	0.50	0.59
124	2nd order RW	2	2	1	0-3	0.92	0.45	0.48	0.59
125	2nd order RW	2	2	1	0-4	0.92	0.46	0.49	0.59
140	Damped	2	1	0	0-4	0.92	0.49	0.51	0.60
146	Damped	2	2	1	0	0.92	0.32	0.41	0.60
147	Damped	2	2	1	0-1	0.92	0.44	0.51	0.63
148	Damped	2	2	1	0-2	0.92	0.44	0.48	0.58
149	Damped	2	2	1	0-3	0.92	0.41	0.44	0.57
150	Damped	2	2	1	0-4	0.92	0.41	0.44	0.57
165	**Damped**	**1**	**2**	**0**	**0-4**	**0.91**	**0.19**	**0.25**	**0.59**
Med						0.91	0.50	0.60	0.67

7 Projections

The aim of the EC methodology is to put fiscal planning and surveillance in the EU member states on a firm theoretical and empirical footing. The planning extends to a ten-year horizon, with detailed plans covering the medium term of up to four years. Long-term projections are discussed in the EC Ageing Reports. This section discusses some of the assumptions used by the EC when making projections, as well as their adequacy in the context of quarterly estimates for Switzerland.[8]

The EC methodology views potential output as a trend around which the actual output fluctuates over the course of a business cycle. This trend describes the output trajectory of an economy in the medium and long term. A typical forecasting cycle of the EC commences with the publication of short-term forecasts twice a year. The spring forecast covers the current and 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-term forecast by three more years ($t + 3$ through $t + 5$, currently until 2023). It essentially describes the transition from short-term business cycle fluctuations to a long-term steady-state growth driven independently by demographic developments and exogenous technical progress. The output gap is assumed to close at the end of the medium-term horizon $t + 5$, and the unemployment rate converges to an equilibrium unemployment rate, which is determined by labor market institutions, as well as several non-structural factors and persistent cyclical factors. Further extensions up to $t + 10$ assess the dynamics of certain types of public expenditures. Finally, the long-term projections underlying the EC Ageing Reports study the implications of the current demographic projections on economic growth and public finances till 2070. The long-term projections typically assume a gradual convergence of country-specific trend estimates towards common values.

Demographic trends are the starting point of a potential output projection. The working age population is sourced directly from a baseline population scenario. The EC projects participation rates for individual sex-age cohorts using a dynamic activity model and combines the results with the shares of the cohorts in the working-age population to yield the future total labor supply. The aggregate participation rate then equals the ratio of labor supply to working age population. The aggregate participation rate thus depends on the dynamics of individual activity rates and the composition of the working-age population. The labor supply combined with an estimate of the NAWRU yields the

[8] For a detailed description of the methodology, see European Commission (2017).

number of persons employed. Because the NAWRU is an aggregate concept, changes in the composition of employment follow the changes in the composition of the labor force. Projections of the average hours worked assume static cohort-specific preferences with respect to working time. Fixing the working hours at the cohort level leaves the composition of employment as the sole determinant of the change in hours worked.

7.1 NAWRU anchor

The NAWRU represents an equilibrium rate of unemployment – the rate that would prevail on an equilibrium growth path described by potential output. The EC methodology thus assumes the convergence of the actual unemployment rate to the NAWRU over the medium term ($t+5$), which in turn converges to an anchor value in the long term, so that the NAWRU represents the actual unemployment rate starting from $t+5$. However, the NAWRU is not constant beyond $t+5$ but is assumed to converge to a long-term value, called the NAWRU anchor, determined by structural determinants of unemployment and labor market institutions.

The theoretical underpinnings of the NAWRU anchor estimates have been discussed in the precursor project and can be found in Orlandi (2012) and Hristov et al. (2017). Orlandi's approach is based on two assumptions. The first assumption is that the empirical determinants of actual unemployment can also explain the trend of the actual unemployment represented by the NAWRU. The structural factors are related to the reservation wage and other determinants of the probability of a match between a job seeker and a firm, such as active labor market policies. The non-structural factors that are likely to affect the equilibrium unemployment rate include the TFP growth, the real interest rate and the size of the construction sector as a persistent cyclical factor. The second assumption is that structural determinants are time-invariant, whereas non-structural variables vary over the business cycle. The invariance of the structural determinants is consistent with a general application of a no-policy-change rule in developing projections.

Table 7 shows an updated set of fixed-effects estimates for the old EU member states based on an annual sample for 1991-2017 and the current estimates of the TFP growth (one of the independent variables) and the NAWRU (the dependent variable). The choice of the starting year has been motivated by a structural break in the Swiss labor market data in 1991. This structural break is particularly apparent in the time series of the unemployment rate. Two regressions have been run in order to check the sensitivity of the estimates to the inclusion of Swiss data. The regression model reads:

$$NAWRU_{it} = \alpha_i + \beta_1 cons_{it} + \beta_2 r_{it} + \beta_3 tfp_{it} + \beta_4 almp_{it} + \beta_5 ud_{it} + \beta_6 tw_{it} + \beta_7 rr_{it} + \epsilon_{it}. \quad (44)$$

The dependent variable is the annual NAWRU estimate according to the production function methodology. The independent variables comprise non-structural variables, such as the annual growth rate of the TFP, tfp_{it}, the share of the construction sector in total employment, $cons_{it}$, and the real interest rate, r_{it}. The structural variables include the unemployment benefit replacement rates, rr_{it}, expenditure on active labor market policies, $almp_{it}$, the degree of trade union density, ud_{it} and the tax wedge, tw_{it}. The index i refers to a country, where $i = 1, 2, \ldots, 14$ when the sample includes Switzerland. The time index $t = 1, 2, \ldots, 27$ refers to the years between 1991 and 2017. Both models explain roughly sixty percent of the variation in the NAWRU rates, with the value of the Hausman test statistic validating the choice of the estimator.

Table 7: 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	-0.579	0.055	-10.432	***	-0.613	0.054	-11.421	***
r	0.206	0.033	6.173	***	0.202	0.033	6.214	***
tfp	-0.072	0.029	-2.470	*	-0.069	0.028	-2.449	*
almp	-0.054	0.007	-7.846	***	-0.051	0.006	-7.897	***
ud	0.001	0.016	0.093		-0.003	0.016	-0.176	
tw	0.164	0.023	7.142	***	0.160	0.022	7.109	***
rr	0.067	0.011	6.276	***	0.063	0.01	6.063	***
n	13				14			
T	27				27			
N	351				378			
Adj. R^2	0.61				0.60			
F-stat:	80.41			***	82.35			***
Hausman-stat:	28.63			***	23.84			***

The sample covers the period 1985-2017 for Switzerland and Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden and United Kingdom. Statistical significance: *** $<$ 0.001; * 0.01.

The anchor values for each country are based on the estimated coefficients of the panel models. To derive a country-specific anchor, the nonstructural variables are averaged over the sample to remove any cyclical variation, whereas the structural variable are held at their current values. The third quantity to enter the anchor calculations are the panel-fixed effects, which capture the country-specific, time-invariant factors. Table 8 compares the country estimates for the anchor. The anchor estimate for Switzerland equals 3.929.

Table 8: NAWRU anchors

	13 EU member states	13 EU member states and Switzerland
Austria (AT)	4.75	4.77
Belgium (BL)	7.49	7.50
Switzerland (CH)	-	3.93
Germany (DE)	6.29	6.37
Denmark (DK)	4.06	4.12
Spain (ES)	14.98	15.01
Finland (FI)	8.27	8.32
France (FR)	8.85	8.85
Ireland (IE)	10.41	10.41
Italy (IT)	10.34	10.26
Netherlands (NL)	4.91	4.89
Portugal (PT)	9.32	9.32
Sweden (SE)	5.74	5.80
United Kingdom (UK)	6.08	6.11

7.2 Closure rules

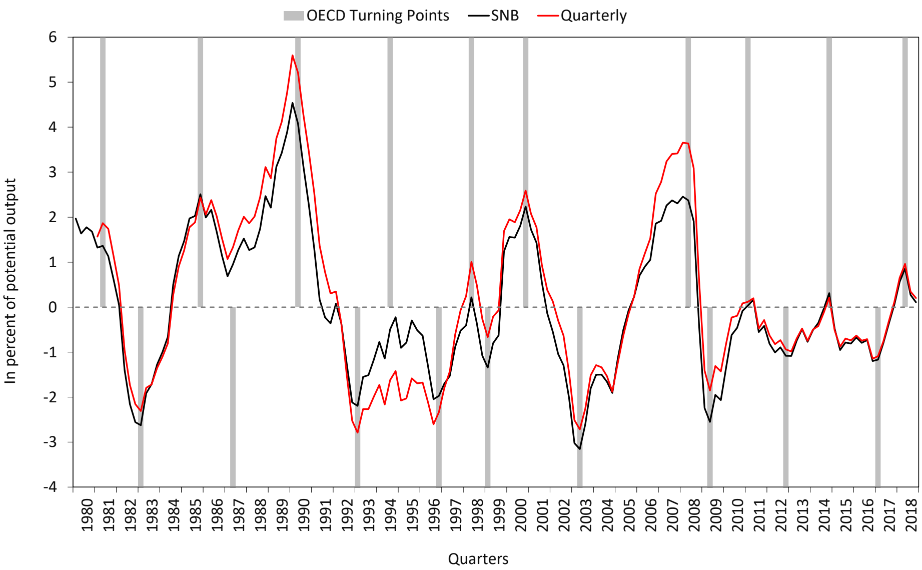
When developing projections, the EC implements several closure rules that specify the transition between short-term business cycle fluctuations and long-term potential growth. The first rule applies to the output gap as the difference between the actual real GDP and the potential output. The second rule applies to the employment gap as the difference between the actual unemployment rate and the NAWRU. This rule is essentially the same as that for the output gap, whereby both gaps are assumed to vanish at the end of the medium-term horizon $t + 5$. Since the unobserved component model used to estimate the NAWRU does not ensure that the forecast takes values between zero and one, as is appropriate for an unemployment rate, some sort of adjustment over the medium and long term is inevitable. The third rule specifies the convergence of the NAWRU to its anchor value. In general, Hristov et al. (2017) recommend $t + 10$ as a convergence horizon for the NAWRU to its anchor. This rule is perhaps the most problematic of all closure rules, because it retroactively affects the estimates of potential output and the output gap in the past. The following discussion focuses on the output gap and the anchor. Further rules pertain to capital. One such rule involves the use of univariate time-series models of the ratio of real investment expenditure to potential output to forecast the capital stock according to the perpetual inventory method, and another rule is used to pinpoint the capital-to-output ratio (capital deepening) in the very long term.[9]

Turning to the closure rule for the output gap, recall that the estimation sample for models involved in the EC methodology includes the short-term forecast as data. The rule requires the gap to vanish between $t + 3$ and $t + 5$, regardless of the cyclical position at the end of the short-term forecast horizon in $t + 2$. The adjustment path between $t + 3$ and $t + 5$ is linear. When combined with a projection for the level of potential output, the assumption about the evolution of the output gap determines the level of actual output (real GDP) during the transition period, at the end of which both output concepts become equivalent. This observation is important because it shows that unreasonable closure rules for the gap can produce unreasonable output projections during the transition period.

The choice of a five-year horizon is motivated by the average duration between successive business cycle turning points observed in the past. Since 1960, the average duration between successive business cycle peaks or troughs (i.e. one full cycle) in most of the old EC member states was between four and five years. The assumption of a linear adjust-

[9] Detailed descriptions of these rules can be found in Havik et al. (2014), Hristov et al. (2017) and the European Commission (2017).

Figure 16: The output gap vs. the Swiss business cycle



The figure plots the turning points of the Swiss business cycle according to the OECD with the quarterly estimates of the output gap. The vertical lines mark the business cycle peaks (positive half-axis) and troughs (negative half-axis). The figure shows good agreement between the turning points and the local extrema of the gap series, confirming the ability of the quarterly estimate to trace the main phases of the Swiss business cycle.

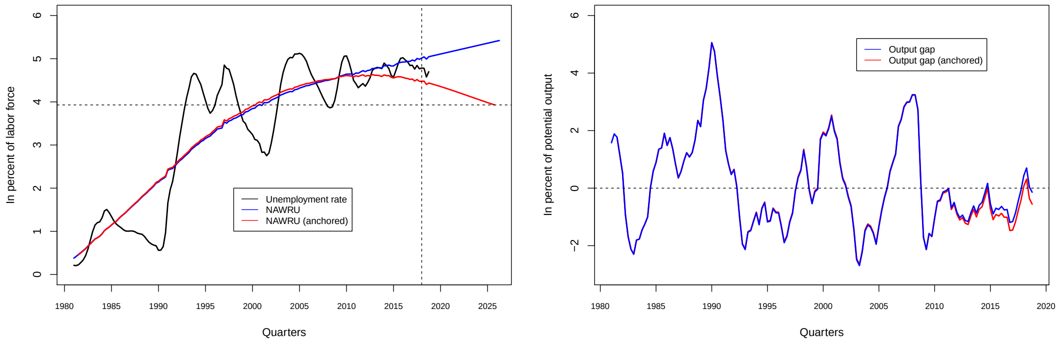
ment is, of course, purely arbitrary. The above reasoning equally applies to the Swiss business cycle. Figure 16 compares the turning points of the Swiss business cycle according to the OECD with the quarterly estimates of the output gap. The gray vertical stripes show the business cycle peaks (positive half-axis) and troughs (negative half-axis). The figure shows excellent agreement between the turning points and the local extrema of the gap series, confirming the ability of the quarterly estimate to trace the main phases of the Swiss business cycle. According to the OECD, the average number of quarters between successive Swiss business cycle peaks or troughs since 1980 is 18, or 4.5 years. This observation validates the five-year closure rule, or the assumption that, regardless of the current position in the business cycle, the output gap can be expected to close in the following five years. Note that the number of quarters between successive intersections of the zero line by the output gap series is smaller than 18 quarters. This is because the gap tends to frequently cross the zero line when the aggregate capacity utilization remains close to normal during a prolonged period. Staying close to zero for a sustained period of time entails frequent crossings, but they reflect noise in the estimates of the output gap rather than of tangible changes in the business cycle. The above discussion shows that the output gap closure rule is relatively innocuous, despite being overly simplistic.[10]

The choice of the rate of convergence of the NAWRU to its anchor and the time to convergence appears to be a more nuanced issue, strongly influenced by the method used to compute the transition path by the GAP50 – the estimation software used by the EC and here. First, imposing the constraint changes 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 in-sample, where in-sample refers to the historical period plus the current short-term forecast, i.e. till $t + 2$. Second, the convergence horizon is limited to 30 periods. This can either be 30 years in the case of annual data, or 30 quarters (7.5 years) in the case of quarterly data. For most of the older EU member states, the EC set the convergence date to 8 years after $t+2$. This assumption is consistent with the $t+10$ horizon implicit in the EU framework, whose current practice amounts to assuming that the NAWRU should be anchored at the end of this horizon.

Figure 17 shows the magnitude of in-sample distortions in the estimate of the output gap due to setting the anchor value of 3.929 in 28 quarters, or 7 years. In view of

[10]The output gap closing rule ignores the fact that cyclical output fluctuations induce auto-correlation in the output gap, and that the closeness of economic ties in a globalized economy renders the output gaps of trading partners positively correlated.

Figure 17: Quarterly projection of NAWRU (anchored)



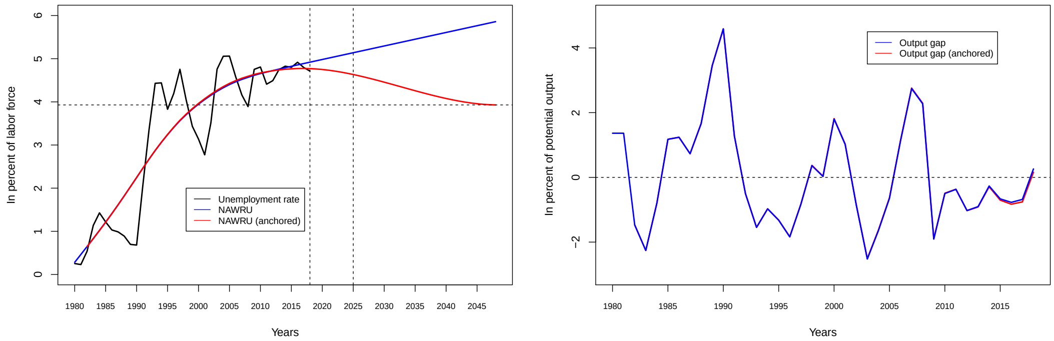
The left panel shows the quarterly NAWRU anchored on the panel-econometric estimate of 3.929 in 28 quarters (7 years). The value of the anchor is indicated by a horizontal dashed line. The vertical dashed line marks the end of the estimation sample in 2018. Limiting the horizon to 7 years causes sizable in-sample distortions. The magnitude of the distortions in the output gap is illustrated in the right panel.

the magnitude of these distortions and the fact that the estimate of the anchor has been obtained using annual data, it appears reasonable to set the anchor at the annual frequency, and at the latest possible date. The result of setting the anchor in 30 years (i.e. in 2048) is shown in Figure 18. This approach minimizes the in-sample distortions at the corresponding frequency. The consistency between the quarterly and the annual transition path can be ensured by choosing the correct annual intermediate value as the quarterly anchor. For example, setting the anchor value of 3.929 in 30 years implies that the NAWRU should attain the value of 4.634 in the seventh year (i.e. in 2025), which should then be imposed as the anchor value on the quarterly basis. Setting the anchor value of 4.634 in 28 quarters instead of 3.929 in 28 quarters leads to more plausible quarterly projections that remain consistent with the annual version. Clearly, the above translation of the annual-to-quarterly convergence horizon can be applied regardless of the year in which the convergence to the anchor is complete but choosing the latest possible year will minimize the in-sample distortions.

8 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

Figure 18: Annual projection of NAWRU (anchored)



The left panel shows the annual projection of NAWRU anchored on 3.929 at the maximum admissible horizon of 30 years (2048). The horizontal dashed line marks the value of the anchor. The vertical dashed lines mark the end of the estimation sample in 2018 and the 7-year horizon (28 quarters) appropriate for anchoring a quarterly projection. Postponing the convergence point increases the smoothness of the transition to the anchor and decreases the in-sample distortions due to anchoring, as is evident from the difference in the output gaps in the right panel.

cycle dating and the contributions of capital, labor and productivity to economic growth. Knowing the current cyclical position is relevant to forecasting and guiding economic policy.

Building on a previous project "Estimating the Potential Output Using the Methodology of the European Commission", this project estimates potential output for Switzerland on a quarterly basis. Using a quarterly frequency yields a timely estimate of the cyclical position and expands the scope of econometric techniques that can be effectively applied. The annual model has been updated to ensure consistency with the quarterly model. Both models use the same set of macroeconomic data covering the period from 1980 to 2018. Together, they can be used to develop mutually consistent projections of potential output for Switzerland in the short, medium and long term.

The analysis applies a transparent set of criteria for model selection to a large set of potential specifications. The optimal model should have reasonable predictive power for an observed cyclical quantity, which is either capacity utilization in the case of the TFP trend or the change in wage-inflation in the case of a Phillips curve (NAWRU). The resulting growth rates of potential output should not be too volatile or too pro-cyclical. Further optimization maximizes congruence between an annual and a quarterly estimate, as we would like the two estimates to be mutually consistent.

We test a variety of alternative detrending methods for the participation rate and the average hours worked, which enter the model as exogenous variables. Alternative methods tend to produce more volatile trends. We check the robustness using a sample starting in 1991, which is a natural starting point due to a structural break in the data. The NAWRU estimates based on the shorter sample are, however, less plausible than those based on the full sample.

The annual and annualized quarterly estimates for Switzerland are comparable to the estimates by the European Commission for the EU15 in terms of their volatility and cyclicality. The quarterly estimate of the output gap closely traces the business cycle turning points published by the OECD for Switzerland; in the recent past, it closely agrees with the output gap published by the Swiss National Bank.

References

Baxter, M. and R. G. King (1995), “Measuring business cycles: approximate bandpass filters”, *The Review of Economics and Statistics*, 81(4), pp. 575-593.

Christiano, L. and T. J. Fitzgerald (2003), “The bandpass filter”, *International Economic Review*, 44(2), pp. 435-465.

Cotis, J., J. Elmeskov and A. Mourougane (2005), “Estimates of potential output: Benefits and pitfalls from a policy perspective”, in L. Reichlin (ed.), Euro Area Business Cycle: Stylised Facts and Measurement Issues, CEPR, London.

De Jong, R. M. and N. Sakarya (2016), “The econometrics of the Hodrick-Prescott filter”, *The Review of Economics and Statistics*, 98(2), pp. 310–317.

Dovern, J. and C. Zuber (2019). “Revisions of potential output estimates in the EU after the Great Recession”, CESifo Working Paper Series 7681, CESifo Group Munich.

EU IFIs (2018), “A practicioner’s guide to potential output and the output gap”, EU Independent Fiscal Institutions.

European Commission (2017), “The 2018 ageing report. Underlying assumptions & projection methodologies”, Institutional Paper 065, European Commission, Brussels.

Fatás, A. (2018), “Fiscal policy, potential output and the shifting goalposts”, CEPR Discussion Papers, No. 13149, Centre for Economic Policy Research.

Fatás, A. and L. H. Summers (2018), “The permanent effects of fiscal consolidations”, *Journal of International Economics*, 112, pp. 238–250.

Galí, J. and M. Gertler (1999), “Inflation dynamics: A structural econometric analysis”, *Journal of Monetary Economics*, 44(2), pp. 195-222.

Glocker, C. and S. Kaniovski (2019), “Estimating the potential output for Switzerland using the methodology of the European Commission”, Report. Commissioned by State Secretariat for Economic Affairs SECO, Bern, Switzerland.

Golyandina, N., V. Nekrutkin and A. Zhigljavsky (2001), Analysis of time series structure: SSA and related techniques. Monographs on Statistics and Applied Probabilty 90. Chapman and Hall/CRC

Hamilton, J. D. (2017), “Why you should never use the Hodrick-Prescott filter”, NBER Working Paper, No. 23429, National Bureau of Economic Research.

Havik, K., K. Mc Morrow, F. Orlandi, C. Planas, R. Raciborski, W. Roeger, A. Rossi, A. Thum-Thysen and V. Vandermeulen (2014), “The production function methodology for calculating potential growth rates & output gaps”, European Economy, Economic Paper, No. 535, European Commission.

Hodrick, R. J. and E. C. Prescott (1997), “Postwar US business cycles: an empirical investigation”, *Journal of Money, Credit, and Banking*, 29(1), pp. 1-16.

Hristov, A., C. Planas, W. Roeger and A. Rossi (2017), “NAWRU estimation using structural labour market indicators”, European Economy, Discussion Papers, No. 69, European Commission.

Hurvich, C. M., J. S. Simonoff and C. L. Tsai (1998), “Smoothing parameter selection in nonparametric regression using an improved Akaike Information Criterion”, Journal of the Royal Statistical Society B 60: 271–293.

Hyndman, R. J., A. B. Koehler, J. K. Ord and R. D. Snyder (2008), Forecasting with exponential smoothing: The state space approach, Springer-Verlag.

King, R. and S. Rebelo (1993), “Low frequency filtering and real business cycles”, *Journal of Economic Dynamics and Control*, 17(1-2), pp. 207–231.

Orlandi, F. (2012), “Structural unemployment and its determinants in the EU countries”, European Economy, Economic Paper, No. 455, European Commission.

Planas, C. and A. Rossi (2018), "Program GAP. Technical description and user-manual", European Commission, Joint Research Centre.

Ravn, M. O. and H. Uhlig (2002), "On adjusting the Hodrick-Prescott filter for the frequency of observations", *The Review of Economics and Statistics*, 84(2), pp. 371-376.

Schüler, Y. S. (2018), "On the cyclical properties of Hamilton's regression filter", Discussion Paper, Deutsche Bundesbank, No. 3.

Turner, D., M. C. Cavalleri, Y. Guillemette, A. Kopoin, P. Ollivaud and E. Rusticelli (2016), "An investigation into improving the real-time reliability of OECD output gap estimates", OECD Economics Department, Working Papers, No. 1294, OECD Publishing.

A List of Model Specifications

Table 9: Subset of NAWRU models

No	Trend	*.nml	AR Cyc	AR $\Delta^2 W_t$	Error MA	*.nml	Cyc Lags $\Delta^2 W_t$	*.nml
3	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0-2	**lagvar = 4**
9	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0-3	**lagvar = 5**
13	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0-2	**lagvar = 4**
19	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0-3	**lagvar = 5**
25	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0-4	**lagvar = 6**
27	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0-1	**lagvar = 3**
33	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0-2	**lagvar = 4**
39	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0-3	**lagvar = 5**
45	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0-4	**lagvar = 6**
48	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-2	**lagvar = 4**
54	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-3	**lagvar = 5**
58	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0-2	**lagvar = 4**
62	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-1	**lagvar = 3**
70	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0-4	**lagvar = 6**
74	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0-3	**lagvar = 5**
78	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0-2	**lagvar = 4**
84	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0-3	**lagvar = 5**
88	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0-2	**lagvar = 4**
94	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0-3	**lagvar = 5**
100	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0-4	**lagvar = 6**
102	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0-1	**lagvar = 3**
108	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0-2	**lagvar = 4**
114	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0-3	**lagvar = 5**
120	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0-4	**lagvar = 6**
123	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0-2	**lagvar = 4**
129	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0-3	**lagvar = 5**
133	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0-2	**lagvar = 4**
137	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0-1	**lagvar = 3**
145	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0-4	**lagvar = 6**
149	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0-3	**lagvar = 5**
153	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0-2	**lagvar = 4**
159	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0-3	**lagvar = 5**
165	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0-4	**lagvar = 6**
168	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0-2	**lagvar = 4**
174	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0-3	**lagvar = 5**
180	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0-4	**lagvar = 6**

Table 10: Complete list of models

No	Trend	*.nml	AR Cyc	AR CU	Error MA	*.nml	Cyc Lags CU	*.nml
1	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0	**lagvar = 2**
2	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0-1	**lagvar = 3**
3	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0-2	**lagvar = 4**
4	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0-3	**lagvar = 5**
5	RW drift	**label = 1**	1	0	0	**ARord = 1 0 MAord = 0**	0-4	**lagvar = 6**
6	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0	**lagvar = 2**
7	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0-1	**lagvar = 3**
8	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0-2	**lagvar = 4**
9	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0-3	**lagvar = 5**
10	RW drift	**label = 1**	1	0	1	**ARord = 1 0 MAord = 1**	0-4	**lagvar = 6**
11	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0	**lagvar = 2**
12	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0-1	**lagvar = 3**
13	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0-2	**lagvar = 4**
14	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0-3	**lagvar = 5**
15	RW drift	**label = 1**	1	1	0	**ARord = 1 1 MAord = 0**	0-4	**lagvar = 6**
16	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0	**lagvar = 2**
17	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0-1	**lagvar = 3**
18	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0-2	**lagvar = 4**
19	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0-3	**lagvar = 5**
20	RW drift	**label = 1**	1	1	1	**ARord = 1 1 MAord = 1**	0-4	**lagvar = 6**
21	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0	**lagvar = 2**
22	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0-1	**lagvar = 3**
23	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0-2	**lagvar = 4**
24	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0-3	**lagvar = 5**
25	RW drift	**label = 1**	1	2	1	**ARord = 1 2 MAord = 1**	0-4	**lagvar = 6**
26	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0	**lagvar = 2**
27	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0-1	**lagvar = 3**
28	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0-2	**lagvar = 4**
29	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0-3	**lagvar = 5**
30	2nd order RW	**label = 2**	1	0	0	**ARord = 1 0 MAord = 0**	0-4	**lagvar = 6**
31	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0	**lagvar = 2**
32	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0-1	**lagvar = 3**
33	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0-2	**lagvar = 4**
34	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0-3	**lagvar = 5**
35	2nd order RW	**label = 2**	1	0	1	**ARord = 1 0 MAord = 1**	0-4	**lagvar = 6**
36	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0	**lagvar = 2**
37	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0-1	**lagvar = 3**
38	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0-2	**lagvar = 4**
39	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0-3	**lagvar = 5**
40	2nd order RW	**label = 2**	1	1	0	**ARord = 1 1 MAord = 0**	0-4	**lagvar = 6**
41	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0	**lagvar = 2**
42	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0-1	**lagvar = 3**
43	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0-2	**lagvar = 4**
44	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0-3	**lagvar = 5**
45	2nd order RW	**label = 2**	1	1	1	**ARord = 1 1 MAord = 1**	0-4	**lagvar = 6**
46	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0	**lagvar = 2**
47	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-1	**lagvar = 3**
48	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-2	**lagvar = 4**
49	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-3	**lagvar = 5**
50	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-4	**lagvar = 6**
51	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0	**lagvar = 2**
52	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-1	**lagvar = 3**
53	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-2	**lagvar = 4**
54	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-3	**lagvar = 5**
55	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-4	**lagvar = 6**
56	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0	**lagvar = 2**
57	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0-1	**lagvar = 3**
58	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0-2	**lagvar = 4**
59	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0-3	**lagvar = 5**
60	Damped	**label = 3**	1	0	1	**ARord = 1 0 MAord = 1**	0-4	**lagvar = 6**
61	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0	**lagvar = 2**
62	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-1	**lagvar = 3**
63	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-2	**lagvar = 4**
64	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-3	**lagvar = 5**
65	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-4	**lagvar = 6**
66	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0	**lagvar = 2**
67	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0-1	**lagvar = 3**

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Table10– *Continued from previous page*

No	Trend	*.nml	AR Cyc	AR CU	Error MA	*.nml	Cyc Lags CU	*.nml
68	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0-2	**lagvar = 4**
69	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0-3	**lagvar = 5**
70	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0-4	**lagvar = 6**
71	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0	**lagvar = 2**
72	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0-1	**lagvar = 3**
73	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0-2	**lagvar = 4**
74	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0-3	**lagvar = 5**
75	Damped	**label = 3**	1	2	1	**ARord = 1 2 MAord = 1**	0-4	**lagvar = 6**
76	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0	**lagvar = 2**
77	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0-1	**lagvar = 3**
78	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0-2	**lagvar = 4**
79	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0-3	**lagvar = 5**
80	RW drift	**label = 1**	2	0	0	**ARord = 2 0 MAord = 0**	0-4	**lagvar = 6**
81	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0	**lagvar = 2**
82	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0-1	**lagvar = 3**
83	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0-2	**lagvar = 4**
84	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0-3	**lagvar = 5**
85	RW drift	**label = 1**	2	0	1	**ARord = 2 0 MAord = 1**	0-4	**lagvar = 6**
86	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0	**lagvar = 2**
87	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0-1	**lagvar = 3**
88	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0-2	**lagvar = 4**
89	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0-3	**lagvar = 5**
90	RW drift	**label = 1**	2	1	0	**ARord = 2 1 MAord = 0**	0-4	**lagvar = 6**
91	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0	**lagvar = 2**
92	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0-1	**lagvar = 3**
93	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0-2	**lagvar = 4**
94	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0-3	**lagvar = 5**
95	RW drift	**label = 1**	2	1	1	**ARord = 2 1 MAord = 1**	0-4	**lagvar = 6**
96	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0	**lagvar = 2**
97	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0-1	**lagvar = 3**
98	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0-2	**lagvar = 4**
99	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0-3	**lagvar = 5**
100	RW drift	**label = 1**	2	2	1	**ARord = 2 2 MAord = 1**	0-4	**lagvar = 6**
101	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0	**lagvar = 2**
102	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0-1	**lagvar = 3**
103	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0-2	**lagvar = 4**
104	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0-3	**lagvar = 5**
105	2nd order RW	**label = 2**	2	0	0	**ARord = 2 0 MAord = 0**	0-4	**lagvar = 6**
106	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0	**lagvar = 2**
107	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0-1	**lagvar = 3**
108	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0-2	**lagvar = 4**
109	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0-3	**lagvar = 5**
110	2nd order RW	**label = 2**	2	0	1	**ARord = 2 0 MAord = 1**	0-4	**lagvar = 6**
111	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0	**lagvar = 2**
112	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0-1	**lagvar = 3**
113	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0-2	**lagvar = 4**
114	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0-3	**lagvar = 5**
115	2nd order RW	**label = 2**	2	1	0	**ARord = 2 1 MAord = 0**	0-4	**lagvar = 6**
116	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0	**lagvar = 2**
117	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0-1	**lagvar = 3**
118	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0-2	**lagvar = 4**
119	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0-3	**lagvar = 5**
120	2nd order RW	**label = 2**	2	1	1	**ARord = 2 1 MAord = 1**	0-4	**lagvar = 6**
121	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0	**lagvar = 2**
122	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0-1	**lagvar = 3**
123	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0-2	**lagvar = 4**
124	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0-3	**lagvar = 5**
125	2nd order RW	**label = 2**	2	2	1	**ARord = 2 2 MAord = 1**	0-4	**lagvar = 6**
126	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0	**lagvar = 2**
127	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0-1	**lagvar = 3**
128	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0-2	**lagvar = 4**
129	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0-3	**lagvar = 5**
130	Damped	**label = 3**	2	0	0	**ARord = 2 0 MAord = 0**	0-4	**lagvar = 6**
131	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0	**lagvar = 2**
132	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0-1	**lagvar = 3**
133	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0-2	**lagvar = 4**
134	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0-3	**lagvar = 5**
135	Damped	**label = 3**	2	0	1	**ARord = 2 0 MAord = 1**	0-4	**lagvar = 6**

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Table10– *Continued from previous page*

No	Trend	*.nml	AR Cyc	AR CU	Error MA	*.nml	Cyc Lags CU	*.nml
136	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0	**lagvar = 2**
137	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0-1	**lagvar = 3**
138	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0-2	**lagvar = 4**
139	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0-3	**lagvar = 5**
140	Damped	**label = 3**	2	1	0	**ARord = 2 1 MAord = 0**	0-4	**lagvar = 6**
141	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0	**lagvar = 2**
142	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0-1	**lagvar = 3**
143	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0-2	**lagvar = 4**
144	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0-3	**lagvar = 5**
145	Damped	**label = 3**	2	1	1	**ARord = 2 1 MAord = 1**	0-4	**lagvar = 6**
146	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0	**lagvar = 2**
147	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0-1	**lagvar = 3**
148	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0-2	**lagvar = 4**
149	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0-3	**lagvar = 5**
150	Damped	**label = 3**	2	2	1	**ARord = 2 2 MAord = 1**	0-4	**lagvar = 6**
151	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0	**lagvar = 2**
152	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0-1	**lagvar = 3**
153	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0-2	**lagvar = 4**
154	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0-3	**lagvar = 5**
155	RW drift	**label = 1**	1	2	0	**ARord = 1 2 MAord = 0**	0-4	**lagvar = 6**
156	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0	**lagvar = 2**
157	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0-1	**lagvar = 3**
158	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0-2	**lagvar = 4**
159	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0-3	**lagvar = 5**
160	2nd order RW	**label = 2**	1	2	0	**ARord = 1 2 MAord = 0**	0-4	**lagvar = 6**
161	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0	**lagvar = 2**
162	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0-1	**lagvar = 3**
163	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0-2	**lagvar = 4**
164	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0-3	**lagvar = 5**
165	Damped	**label = 3**	1	2	0	**ARord = 1 2 MAord = 0**	0-4	**lagvar = 6**
166	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0	**lagvar = 2**
167	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0-1	**lagvar = 3**
168	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0-2	**lagvar = 4**
169	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0-3	**lagvar = 5**
170	RW drift	**label = 1**	2	2	0	**ARord = 2 2 MAord = 0**	0-4	**lagvar = 6**
171	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0	**lagvar = 2**
172	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0-1	**lagvar = 3**
173	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0-2	**lagvar = 4**
174	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0-3	**lagvar = 5**
175	2nd order RW	**label = 2**	2	2	0	**ARord = 2 2 MAord = 0**	0-4	**lagvar = 6**
176	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0	**lagvar = 2**
177	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0-1	**lagvar = 3**
178	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0-2	**lagvar = 4**
179	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0-3	**lagvar = 5**
180	Damped	**label = 3**	2	2	0	**ARord = 2 2 MAord = 0**	0-4	**lagvar = 6**

Table 11: Model selection criteria (full sample)

No	TFP R^2	Range PO	Sd. PO	Cyclic. PO	TFP R^2	Range PO	Sd. PO	Cyclic. PO
	Annual (1980:2018)				*Quarterly (Q1:1981-Q4:2018)*			
1	0.28	0.53	0.46	0.32	0.85	0.82	0.91	0.44
2	0.41	0.56	0.49	0.42	0.90	0.55	0.67	0.70
3	0.42	0.54	0.48	0.40	0.91	0.53	0.61	0.76
4	0.43	0.54	0.47	0.39	0.92	0.48	0.56	0.78
5	0.43	0.54	0.46	0.40	0.92	0.48	0.57	0.79
6	0.31	0.44	0.37	0.52	0.84	0.55	0.63	0.59
7	0.38	0.48	0.43	0.44	0.90	0.54	0.65	0.70
8	0.39	0.49	0.43	0.43	0.91	0.51	0.59	0.76
9	0.41	0.49	0.42	0.43	0.92	0.44	0.52	0.78
10	0.41	0.48	0.42	0.43	0.92	0.44	0.53	0.79
11	0.34	0.50	0.45	0.43	0.90	0.46	0.60	0.82
12	0.41	0.56	0.50	0.39	0.92	0.46	0.55	0.79
13	0.43	0.52	0.45	0.42	0.92	0.45	0.53	0.79
14	0.43	0.52	0.45	0.43	0.92	0.45	0.54	0.79
15	0.43	0.52	0.45	0.43	0.92	0.38	0.42	0.76
16	0.33	0.45	0.41	0.49	0.90	0.45	0.59	0.82
17	0.39	0.48	0.44	0.43	0.92	0.46	0.55	0.79
18	0.42	0.50	0.43	0.43	0.92	0.45	0.53	0.79
19	0.44	0.53	0.46	0.42	0.92	0.44	0.52	0.78
20	0.41	0.48	0.42	0.43	0.92	0.38	0.43	0.76
21	0.39	0.47	0.42	0.43	0.92	0.40	0.47	0.78
22	0.40	0.48	0.43	0.43	0.92	0.43	0.49	0.78
23	0.42	0.50	0.43	0.43	0.92	0.43	0.48	0.77
24	0.48	0.54	0.47	0.47	0.92	0.42	0.48	0.77
25	0.43	0.52	0.44	0.42	0.92	0.44	0.53	0.79
26	0.29	0.48	0.41	0.39	0.85	0.82	0.91	0.44
27	0.41	0.54	0.47	0.46	0.90	0.55	0.67	0.70
28	0.42	0.52	0.46	0.43	0.91	0.52	0.60	0.76
29	0.43	0.52	0.45	0.42	0.92	0.47	0.55	0.77
30	0.43	0.51	0.44	0.43	0.92	0.47	0.56	0.78
31	0.27	0.29	0.31	0.32	0.84	0.55	0.63	0.59
32	0.37	0.41	0.38	0.49	0.90	0.54	0.65	0.70
33	0.38	0.42	0.37	0.48	0.91	0.50	0.58	0.75
34	0.40	0.42	0.37	0.49	0.92	0.43	0.51	0.77
35	0.40	0.40	0.36	0.49	0.92	0.43	0.51	0.77
36	0.35	0.45	0.42	0.49	0.90	0.43	0.57	0.82
37	0.42	0.55	0.48	0.42	0.92	0.44	0.52	0.78
38	0.43	0.50	0.42	0.46	0.92	0.43	0.51	0.78
39	0.43	0.50	0.42	0.46	0.92	0.44	0.52	0.78
40	0.43	0.49	0.42	0.46	0.92	0.33	0.37	0.73
41	0.32	0.31	0.31	0.38	0.90	0.39	0.53	0.82
42	0.37	0.42	0.38	0.49	0.92	0.43	0.50	0.78
43	0.39	0.42	0.37	0.48	0.92	0.42	0.49	0.77
44	0.40	0.42	0.37	0.49	0.92	0.42	0.50	0.77
45	0.40	0.40	0.36	0.49	0.92	0.28	0.32	0.70
46	0.38	0.40	0.36	0.50	0.91	0.26	0.33	0.55
47	0.39	0.41	0.37	0.49	0.92	0.40	0.46	0.76
48	0.39	0.41	0.36	0.49	0.92	0.38	0.43	0.75
49	0.47	0.51	0.46	0.44	0.92	0.38	0.44	0.75
50	0.39	0.38	0.35	0.48	0.92	0.34	0.38	0.74
51	0.29	0.49	0.42	0.37	0.84	0.69	0.76	0.45
52	0.41	0.50	0.45	0.51	0.89	0.52	0.65	0.73
53	0.42	0.52	0.45	0.46	0.91	0.47	0.57	0.78
54	0.43	0.51	0.44	0.45	0.91	0.40	0.52	0.78
55	0.43	0.50	0.43	0.47	0.92	0.40	0.52	0.79
56	0.27	0.29	0.29	0.34	0.83	0.49	0.58	0.59
57	0.39	0.42	0.38	0.55	0.90	0.49	0.61	0.73
58	0.40	0.42	0.38	0.54	0.91	0.43	0.54	0.77
59	0.41	0.42	0.37	0.54	0.92	0.36	0.47	0.76
60	0.41	0.39	0.36	0.55	0.92	0.36	0.46	0.76
61	0.35	0.43	0.41	0.52	0.90	0.34	0.48	0.82
62	0.42	0.52	0.47	0.47	0.92	0.34	0.45	0.78
63	0.44	0.48	0.41	0.50	0.92	0.34	0.45	0.77
64	0.44	0.48	0.41	0.50	0.92	0.35	0.46	0.77
65	0.43	0.46	0.40	0.52	0.92	0.35	0.46	0.77
66	0.33	0.39	0.37	0.56	0.90	0.30	0.43	0.80

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Table11– *Continued from previous page*

No	TFP R^2	Range PO	Sd. PO	Cyclic. PO	TFP R^2	Range PO	Sd. PO	Cyclic. PO
		Annual (1980:2018)				*Quarterly (Q1:1981-Q4:2018)*		
67	0.40	0.42	0.39	0.54	0.92	0.32	0.43	0.77
68	0.40	0.42	0.39	0.54	0.92	0.33	0.44	0.76
69	0.41	0.43	0.38	0.54	0.92	0.34	0.44	0.75
70	0.41	0.39	0.36	0.55	0.92	0.35	0.45	0.76
71	0.39	0.40	0.36	0.55	0.92	0.29	0.37	0.67
72	0.40	0.42	0.38	0.54	0.92	0.31	0.40	0.70
73	0.41	0.43	0.39	0.53	0.92	0.31	0.39	0.70
74	0.45	0.47	0.40	0.52	0.92	0.30	0.38	0.73
75	0.42	0.44	0.42	0.51	0.92	0.31	0.41	0.73
76	0.43	0.52	0.47	0.35	0.91	0.72	0.80	0.48
77	0.44	0.53	0.47	0.46	0.92	0.56	0.65	0.58
78	0.45	0.52	0.47	0.45	0.92	0.57	0.64	0.67
79	0.45	0.53	0.46	0.45	0.92	0.57	0.64	0.67
80	0.44	0.52	0.46	0.45	0.92	0.58	0.64	0.66
81	0.43	0.42	0.37	0.49	0.91	0.62	0.70	0.56
82	0.43	0.44	0.40	0.48	0.92	0.55	0.62	0.57
83	0.43	0.44	0.40	0.48	0.92	0.55	0.61	0.66
84	0.43	0.44	0.39	0.48	0.92	0.52	0.58	0.66
85	0.43	0.43	0.39	0.48	0.92	0.52	0.58	0.66
86	0.43	0.47	0.44	0.47	0.92	0.45	0.56	0.70
87	0.44	0.54	0.48	0.44	0.92	0.53	0.60	0.67
88	0.45	0.50	0.43	0.48	0.92	0.53	0.59	0.67
89	0.45	0.50	0.43	0.47	0.92	0.50	0.54	0.63
90	0.45	0.49	0.43	0.48	0.92	0.43	0.47	0.62
91	0.42	0.42	0.39	0.47	0.92	0.43	0.53	0.69
92	0.43	0.44	0.40	0.48	0.92	0.51	0.58	0.66
93	0.43	0.44	0.39	0.48	0.92	0.52	0.58	0.66
94	0.43	0.43	0.39	0.48	0.92	0.51	0.55	0.63
95	0.43	0.43	0.38	0.48	0.92	0.42	0.45	0.62
96	0.42	0.42	0.38	0.48	0.92	0.45	0.51	0.65
97	0.43	0.44	0.39	0.48	0.92	0.50	0.56	0.65
98	0.43	0.44	0.39	0.48	0.92	0.43	0.47	0.62
99	0.48	0.54	0.46	0.48	0.92	0.42	0.46	0.62
100	0.45	0.49	0.42	0.47	0.92	0.41	0.45	0.62
101	0.44	0.48	0.43	0.39	0.91	0.72	0.80	0.48
102	0.46	0.50	0.45	0.49	0.92	0.56	0.65	0.58
103	0.46	0.51	0.45	0.47	0.92	0.57	0.63	0.67
104	0.46	0.51	0.45	0.47	0.92	0.57	0.64	0.66
105	0.46	0.49	0.44	0.48	0.92	0.58	0.64	0.66
106	0.39	0.29	0.31	0.31	0.91	0.62	0.70	0.56
107	0.44	0.30	0.31	0.33	0.92	0.54	0.61	0.57
108	0.45	0.29	0.30	0.33	0.92	0.54	0.61	0.66
109	0.45	0.29	0.30	0.32	0.92	0.50	0.56	0.66
110	0.45	0.29	0.30	0.33	0.92	0.50	0.57	0.65
111	0.45	0.43	0.41	0.51	0.92	0.44	0.54	0.69
112	0.45	0.53	0.47	0.46	0.92	0.52	0.58	0.66
113	0.48	0.33	0.31	0.42	0.92	0.52	0.58	0.66
114	0.48	0.33	0.31	0.42	0.92	0.49	0.53	0.63
115	0.46	0.44	0.40	0.51	0.92	0.40	0.44	0.61
116	0.43	0.30	0.31	0.33	0.92	0.42	0.52	0.69
117	0.44	0.30	0.31	0.33	0.92	0.50	0.56	0.66
118	0.45	0.30	0.31	0.32	0.92	0.50	0.56	0.66
119	0.45	0.29	0.31	0.32	0.92	0.50	0.54	0.63
120	0.45	0.29	0.30	0.33	0.92	0.38	0.41	0.61
121	0.44	0.29	0.30	0.33	0.92	0.42	0.47	0.64
122	0.44	0.29	0.30	0.33	0.92	0.48	0.53	0.64
123	0.45	0.29	0.31	0.32	0.92	0.37	0.40	0.62
124	0.45	0.29	0.31	0.32	0.92	0.35	0.39	0.61
125	0.45	0.29	0.30	0.33	0.92	0.34	0.38	0.60
126	0.44	0.50	0.44	0.36	0.90	0.71	0.79	0.47
127	0.45	0.47	0.44	0.52	0.92	0.55	0.64	0.58
128	0.45	0.50	0.44	0.49	0.92	0.56	0.63	0.67
129	0.46	0.50	0.45	0.50	0.92	0.56	0.63	0.67
130	0.45	0.47	0.44	0.50	0.92	0.56	0.62	0.66
131	0.41	0.29	0.30	0.32	0.91	0.65	0.72	0.53
132	0.45	0.36	0.35	0.50	0.92	0.54	0.62	0.57
133	0.45	0.36	0.35	0.50	0.92	0.53	0.60	0.66

Continued on next page

Table11– *Continued from previous page*

No	TFP R^2	Range PO	Sd. PO	Cyclic. PO	TFP R^2	Range PO	Sd. PO	Cyclic. PO
		Annual (1980:2018)				*Quarterly (Q1:1981-Q4:2018)*		
134	0.46	0.30	0.30	0.38	0.92	0.48	0.52	0.65
135	0.45	0.32	0.31	0.45	0.92	0.48	0.53	0.65
136	0.45	0.42	0.41	0.52	0.92	0.44	0.54	0.71
137	0.45	0.45	0.43	0.53	0.92	0.49	0.55	0.67
138	0.45	0.45	0.40	0.53	0.92	0.50	0.56	0.66
139	0.45	0.45	0.40	0.53	0.92	0.50	0.55	0.64
140	0.46	0.43	0.39	0.55	0.92	0.40	0.43	0.61
141	0.44	0.30	0.31	0.36	0.92	0.42	0.52	0.70
142	0.45	0.36	0.35	0.50	0.92	0.47	0.53	0.66
143	0.46	0.30	0.30	0.35	0.92	0.47	0.52	0.65
144	0.46	0.30	0.30	0.35	0.92	0.53	0.57	0.64
145	0.46	0.30	0.29	0.37	0.92	0.38	0.41	0.61
146	0.45	0.29	0.30	0.35	0.92	0.40	0.43	0.61
147	0.45	0.30	0.30	0.36	0.92	0.43	0.46	0.61
148	0.45	0.30	0.30	0.35	0.92	0.38	0.42	0.62
149	0.48	0.45	0.43	0.50	0.92	0.36	0.39	0.61
150	0.45	0.29	0.29	0.37	0.92	0.34	0.38	0.60
151	0.40	0.50	0.43	0.44	0.91	0.37	0.46	0.82
152	0.42	0.53	0.47	0.42	0.92	0.43	0.50	0.78
153	0.43	0.52	0.44	0.42	0.92	0.44	0.51	0.79
154	0.47	0.55	0.52	0.32	0.92	0.44	0.52	0.78
155	0.41	0.54	0.50	0.26	0.92	0.35	0.39	0.76
156	0.41	0.45	0.39	0.50	0.91	0.18	0.28	0.46
157	0.40	0.42	0.36	0.51	0.92	0.25	0.33	0.61
158	0.43	0.48	0.41	0.47	0.92	0.41	0.48	0.77
159	0.41	0.45	0.39	0.48	0.92	0.43	0.50	0.77
160	0.40	0.40	0.37	0.46	0.92	0.15	0.22	0.42
161	0.41	0.43	0.38	0.54	0.91	0.26	0.36	0.75
162	0.41	0.43	0.38	0.54	0.92	0.30	0.39	0.73
163	0.43	0.47	0.40	0.52	0.92	0.32	0.42	0.75
164	0.43	0.46	0.39	0.52	0.92	0.34	0.44	0.75
165	0.41	0.44	0.42	0.51	0.92	0.34	0.44	0.75
166	0.43	0.47	0.41	0.48	0.92	0.42	0.50	0.68
167	0.45	0.52	0.45	0.46	0.92	0.51	0.57	0.66
168	0.45	0.50	0.43	0.48	0.92	0.51	0.57	0.66
169	0.45	0.48	0.42	0.48	0.92	0.48	0.52	0.63
170	0.45	0.54	0.50	0.26	0.92	0.41	0.45	0.62
171	0.47	0.30	0.29	0.37	0.92	0.39	0.46	0.67
172	0.46	0.29	0.30	0.33	0.92	0.49	0.55	0.66
173	0.45	0.29	0.30	0.33	0.92	0.49	0.55	0.66
174	0.44	0.29	0.30	0.32	0.92	0.45	0.49	0.63
175	0.45	0.29	0.30	0.33	0.92	0.36	0.40	0.61
176	0.45	0.36	0.35	0.51	0.92	0.38	0.45	0.67
177	0.46	0.29	0.29	0.36	0.92	0.46	0.51	0.65
178	0.46	0.29	0.29	0.36	0.92	0.46	0.50	0.65
179	0.48	0.45	0.43	0.50	0.92	0.45	0.49	0.63
180	0.48	0.46	0.43	0.51	0.92	0.36	0.40	0.60

B Alternative Smoothing of Exogenous Inputs

Economic theory and empirical evidence suggest that both the aggregate participation rate and, especially, the average working hours are subject to cyclical fluctuations. The EC uses the HP-filter with the smoothing parameter $\lambda = 10$ for detrending these series at the annual frequency. The value of the smoothing parameter corresponds to a certain ratio of the variance of the cyclical component to the variance of the second difference of the trend component. Setting $\lambda = 1600$ for a quarterly series has been suggested by Hodrick and Prescott (1997). The EC choice for an annual series is fairly close to the optimal value of 6.25 suggested by Ravn and Uhlig (2002).

The choice use the HP-filter is motivated by desire to ensure comparability with the EC estimates (Section 5). The second reason for using the HP-filter at both frequencies is that choosing $\lambda = 10$ and $\lambda = 1600$ yields essentially the same trend, thus minimizing the discrepancy between the quarterly and the annual estimates of the output gap. Indeed, Figure 3 shows that quarterly HP-trends computed with $\lambda = 1600$ aggregate to the annual HP-trends computed with $\lambda = 10$. This consistency has been demonstrated in Ravn and Uhlig (2002) and De Jong and Sakarya (2016).

While our choice is entirely conventional, the HP-filter was criticized immediately after its initial publication, and more recently by Hamilton (2017). The early critics emphasizes the end-of-sample problem of the standard two-sided version of the filter. Hamilton (2017) argues, however, that even the one-sided version is problematic. The filter produces a spurious dynamic relationship and is difficult to reconcile with a plausible data-generating process.[11] Hamilton's third point pertains to the ad hoc nature of the assumption regarding the smoothing parameter. To date, however, the question whether the alternative suggested by Hamilton (2017) can resolve all the shortcomings of the HP-filter is not entirely settled (Schüler 2018).

B.1 Locally Estimated Scatterplot Smoothing (LOESS)

The LOESS performs a local quadratic WLS regression around each observation, with the weights diminishing as we move the current focal point further from the observation. The degree of locality of the regression is controlled by the span parameter. A span of unity means that the window around each observation encompasses the entire sample, whereas

[11] King and Rebelo (1993) demonstrate that the HP-filter yields a stationary detrended series, provided that the fourth differences of the original series are stationary.

a span of 1/3 means that the window covers one third of the sample. Note that, even if the window covers the entire sample, the weights change as we move from one focal point to another. We use the procedure based on an improved AIC, called AICC, to identify the optimal span (Hurvich et al., 1998). The lower the AICC, the better the fit.

To initialize the search for an optimal span value, we first estimate a baseline LOESS regression with a span of unity. This span indicates that all 156 quarterly observations between Q1:1980 and Q4:2018 should be included in the window.[12] For the quarterly participation rate, the baseline model with the span of unity has a residual standard error of 1.28 and an AICC value of 1.54. The optimal model for the participation rate has a residual standard error of only 0.15 and a significantly lower AICC value of -2.52. The optimal span equals 0.12, indicating that 12 percent of the sample or 19 observations should be encompassed by the window. The application of the same procedure to the quarterly series of average hours worked reduces the residual standard error from 4.67 in the baseline model to 0.99, and the AICC value from 4.12 to 1.23. The optimal span for this time series also equals 0.12.

B.2 Singular Spectrum Analysis (SSA)

The SSA reconstructs a smoothed version of a time series from its spectral decomposition by discarding the contribution of less informative principle components of the covariance matrix.[13] The covariance matrix is based on time-shifted series at different lags. The SSA performs a principle component analysis of the input series, such that the principle components are contemporaneously uncorrelated and ordered according to their variance, or the eigenvalues of the covariance matrix. Being projections, the principal components cannot be directly compared to the time series. But they can be projected back onto the eigenvectors to yield a time series in the original coordinates, each one corresponding to one of the components. A reconstruction based on a few dominant components leads to a smoothed time series, whereas the series based on less informative components are discarded as noise.

The SSA requires setting a windows width parameter that bounds the captured periodicity. The standard window for SSA equals half of the observations. We found that choosing a window of 4 observations roughly replicates the optimal LOESS smoothing,

[12] Note that the estimation sample for the full model begins in Q1:1981, because up to four quarters are lost when computing lags of the exogenous variables of the Phillips curve.

[13] For a comprehensive discussion of the SSA, see Golyandina et al. (2001).

as is shown in Figure 19, whereas a windows of length 15 closely replicates the HP trend with the smoothing parameter of $\lambda = 1600$. The standard window of $n/2$, where n is the number of observations ($n = 156$) produces a trend that is almost linear. In all cases, the series for the SSA trend has been reconstructed using the first principle component. Including further components typically leads to more variation in the trend.

Less smoothing of the exogenous inputs foreshadows a more procyclical potential output. Such a significant change in the input series warrants a new specification search. Next, we therefore repeat the two-step specification search for an optimal pair of models, keeping the pairs of optimal NAWRU models (102,120). Figures 20 and 21 provide the usual annual vs. annualized quarterly comparison for the input series. The alternative specification search is based on LOESS smoothing of the input series.

The application of the three criteria to the set of annual models returns a subset of 33 candidate models listed in Table 12. The same criteria applied to the quarterly models yield the 26 candidate models listed in Table 13. The number of candidate models is thus the same as in the main variant based on the HP-filter. But in the case of LOESS smoothing, the pair of models that minimizes the two discrepancies according to the composite *average criterion* in the second step of the two-step model selection procedure is given by:

$$\textbf{125 (quarterly), label} = \textbf{2 ARord} = \textbf{2 2 MAord} = \textbf{1 lagvar} = \textbf{6},$$
$$\textbf{135 (annual), label} = \textbf{3 ARord} = \textbf{2 0 MAord} = \textbf{1 lagvar} = \textbf{6}.$$

Figure 22 compares the growth rates of potential output with the series obtained using the HP-filter. It is clearly seen that the HP-filter with the smoothing parameter $\lambda = 1600$ achieves a stronger smoothing that translates into less volatile and considerably less procyclical growth rates of potential output. The comparison of output gaps in Figure 23, however, shows that the output gaps are not very sensitive to the choice of the smoothing technique.

Table 12: Best annual models 1980-2018 (LOESS)

No	Trend	Cycle Lag	Error AR	Error MA	PC Lags	**TFP R^2**	**Range PO**	**Sd. PO**	**Cyclic. PO**
107	2nd order RW	2	0	1	0-1	0.44	0.36	0.37	0.31
108	2nd order RW	2	0	1	0-2	0.45	0.35	0.37	0.31
109	2nd order RW	2	0	1	0-3	0.45	0.35	0.36	0.30
110	2nd order RW	2	0	1	0-4	0.45	0.35	0.36	0.31
113	2nd order RW	2	1	0	0-2	0.48	0.39	0.38	0.38
114	2nd order RW	2	1	0	0-3	0.48	0.39	0.38	0.38
116	2nd order RW	2	1	1	0	0.43	0.36	0.37	0.31
117	2nd order RW	2	1	1	0-1	0.44	0.36	0.37	0.31
118	2nd order RW	2	1	1	0-2	0.45	0.36	0.37	0.31
119	2nd order RW	2	1	1	0-3	0.45	0.35	0.37	0.31
120	2nd order RW	2	1	1	0-4	0.45	0.35	0.37	0.31
121	2nd order RW	2	2	1	0	0.44	0.35	0.37	0.31
122	2nd order RW	2	2	1	0-1	0.44	0.35	0.37	0.31
123	2nd order RW	2	2	1	0-2	0.45	0.35	0.37	0.31
124	2nd order RW	2	2	1	0-3	0.45	0.35	0.37	0.31
125	2nd order RW	2	2	1	0-4	0.45	0.35	0.36	0.31
134	Damped	2	0	1	0-3	0.46	0.36	0.36	0.34
135	**Damped**	**2**	**0**	**1**	**0-4**	**0.45**	**0.38**	**0.38**	**0.41**
141	Damped	2	1	1	0	0.44	0.36	0.37	0.34
143	Damped	2	1	1	0-2	0.46	0.36	0.36	0.33
144	Damped	2	1	1	0-3	0.46	0.36	0.36	0.33
145	Damped	2	1	1	0-4	0.46	0.35	0.36	0.34
146	Damped	2	2	1	0	0.45	0.35	0.36	0.33
147	Damped	2	2	1	0-1	0.45	0.36	0.36	0.33
148	Damped	2	2	1	0-2	0.45	0.36	0.36	0.32
150	Damped	2	2	1	0-4	0.45	0.35	0.36	0.34
171	2nd order RW	2	2	0	0	0.47	0.36	0.36	0.34
172	2nd order RW	2	2	0	0-1	0.46	0.35	0.36	0.31
173	2nd order RW	2	2	0	0-2	0.45	0.35	0.36	0.31
174	2nd order RW	2	2	0	0-3	0.44	0.35	0.36	0.30
175	2nd order RW	2	2	0	0-4	0.45	0.35	0.36	0.31
177	Damped	2	2	0	0-1	0.46	0.35	0.35	0.33
178	Damped	2	2	0	0-2	0.46	0.35	0.35	0.33
Med						0.43	0.51	0.48	0.44

Table 13: Best quarterly models Q1:1981-Q4:2018 (LOESS)

No	Trend	Cycle Lag	Error AR	Error MA	PC Lags	**TFP R^2**	**Range PO**	**Sd. PO**	**Cyclic. PO**
90	RW drift	2	1	0	0-4	0.92	0.46	0.52	0.68
95	RW drift	2	1	1	0-4	0.92	0.45	0.50	0.68
98	RW drift	2	2	1	0-2	0.92	0.46	0.52	0.68
99	RW drift	2	2	1	0-3	0.92	0.45	0.51	0.68
100	RW drift	2	2	1	0-4	0.92	0.44	0.50	0.68
115	2nd order RW	2	1	0	0-4	0.92	0.43	0.49	0.67
120	2nd order RW	2	1	1	0-4	0.92	0.41	0.47	0.66
121	2nd order RW	2	2	1	0	0.92	0.44	0.52	0.70
123	2nd order RW	2	2	1	0-2	0.92	0.39	0.47	0.66
124	2nd order RW	2	2	1	0-3	0.92	0.38	0.45	0.66
125	**2nd order RW**	**2**	**2**	**1**	**0-4**	**0.92**	**0.37**	**0.44**	**0.65**
140	Damped	2	1	0	0-4	0.92	0.43	0.49	0.67
143	Damped	2	1	1	0-2	0.92	0.48	0.57	0.70
145	Damped	2	1	1	0-4	0.92	0.41	0.47	0.66
146	Damped	2	2	1	0	0.92	0.40	0.48	0.67
147	Damped	2	2	1	0-1	0.92	0.43	0.51	0.66
148	Damped	2	2	1	0-2	0.92	0.40	0.47	0.67
149	Damped	2	2	1	0-3	0.92	0.39	0.45	0.66
150	Damped	2	2	1	0-4	0.92	0.37	0.44	0.66
160	2nd order RW	1	2	0	0-4	0.92	0.22	0.33	0.46
170	RW drift	2	2	0	0-4	0.92	0.44	0.50	0.68
171	2nd order RW	2	2	0	0	0.92	0.43	0.53	0.70
175	2nd order RW	2	2	0	0-4	0.92	0.39	0.46	0.66
177	Damped	2	2	0	0-1	0.92	0.46	0.57	0.69
178	Damped	2	2	0	0-2	0.92	0.47	0.56	0.69
180	Damped	2	2	0	0-4	0.92	0.39	0.46	0.66
Med						0.92	0.48	0.59	0.74

B.3 Exponential smoothing state space model (ETS)

Exponential smoothing state space models (ETS) can be used for smoothing historical data and for forecasting (Hyndman, et al. 2008). The inclusion of a damping trend in a ETS model ensures that projections stabilize at a certain level rather than increasing or decreasing indefinitely. This leveling off is desirable, given that the participation rate is already quite high (Figure 1), and the average hours worked follow a steep downward trend that is unlikely to persist over the long term (Figure 2). We should therefore expect a nearly constant participation rate, with the dynamics of the average hours worked petering out in the long run. The only question is at what level and how soon each of the series will level off. The following specification ensures convergence to a level. This level and the convergence rate are determined endogenously by the parameter estimates.

The exponential smoothing state space model of a time series X_t with additive errors generated by a single disturbance term $\epsilon_t \sim N(0, \sigma^2)$ can be written as:

$$X_t = l_{t-1} + \phi b_{t-1} + \epsilon_t \, , \tag{45}$$

$$l_t = \alpha l_{t-1} + \alpha \phi b_{t-1} + \alpha \epsilon_t \, , \tag{46}$$

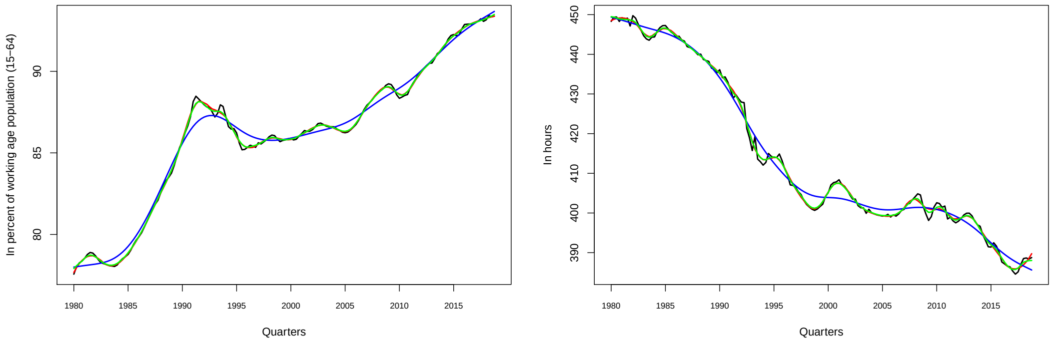
$$b_t = \phi b_{t-1} + \alpha \beta \epsilon_t . \tag{47}$$

Here $\alpha \in (0, 1)$ and $\beta \in (0, 1)$ are the smoothing parameters. The damping parameter $\phi \in (0, 1)$ controls the rate of change of the trend. Equation (46) describes the level and equation (47) the change in the level. This interpretation of the two equations follows from the fact that an h-step ahead forecast of X_t tends to l_t in the absence of damping ($\phi = 0$). In the presence of damping ($\phi > 0$) this limit equals $l_t + \frac{\phi}{1-\phi} b_t$. To see this, observe that an h-step ahead forecast of X_t at time t is given by

$$\begin{aligned} \hat{X}_{t+h|t} &= l_t + b_t \sum_{i=1}^{h} \phi^i \, , \\ l_t &= \alpha Y_t + \alpha(1-\alpha)(l_{t-1} + \phi b_{t-1}) \, , \\ b_t &= \beta \Delta l_t + (1-\beta)\phi b_{t-1} . \end{aligned}$$

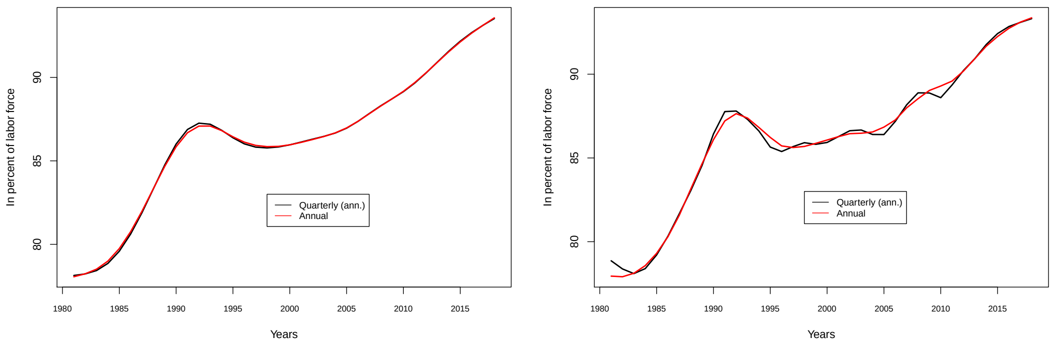
The forecast tends to $l_t + \frac{\phi}{1-\phi} b_t$ when $h \to \infty$. The output of such a model comprises the estimates of α, β, ϕ and σ, as well as paths of the unobserved components l_t and b_t. The results of the application of an ETS model are shown in Figure 24.

Figure 19: Participation rate and average hours worked (HP, LOESS, SSA)



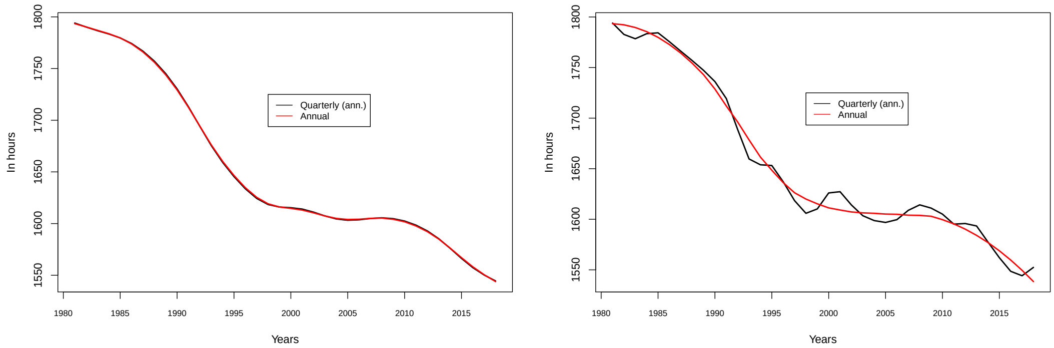
The left panel shows the result of the application of different smoothing techniques to the aggregate participation rate, and the right panel does the same with the average hours worked. All series are quarterly series. Black lines denote the level of the actual series. Blue lines show the result of the application of the HP-filter with the smoothing parameter $\lambda = 1600$. Red lines show the result of the optimal LOESS smoothing. Green lines show the result of the SSA. The LOESS and the SSA return very similar trends that are considerably less smooth than the trend produced by the HP-filter.

Figure 20: Participation rates (HP vs. LOESS)



The left panel shows the annualized quarterly series and the annual series computed using the HP-filter with the smoothing parameters of $\lambda = 1600$ and $\lambda = 10$, respectively. The right panel shows an analogous series obtained by the application of optimal LOESS smoothing at each frequency. The HP-filter achieves a markedly stronger smoothing at each frequency.

Figure 21: Average hours worked (HP vs. LOESS)

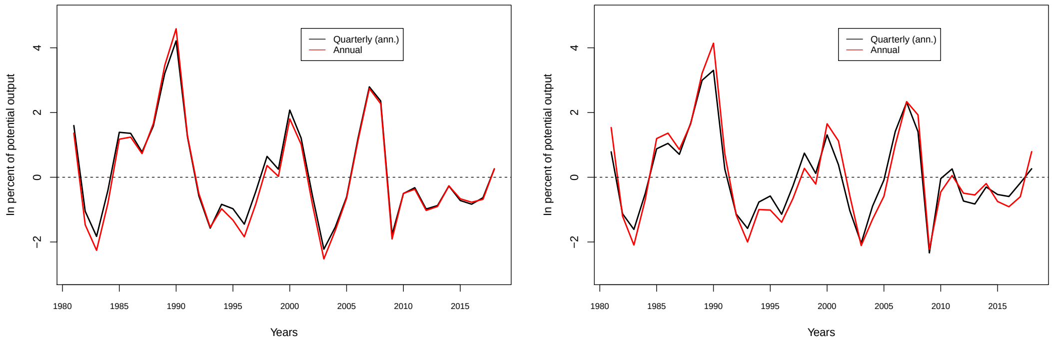


The left panel shows the annualized quarterly series and the annual series computed using the HP-filter with the smoothing parameters of $\lambda = 1600$ and $\lambda = 10$, respectively. The right panel shows a variant based on the application of optimal LOESS smoothing at each frequency. The HP-filter achieves a markedly stronger smoothing at each frequency.

Figure 22: Growth of potential output (HP vs. LOESS)

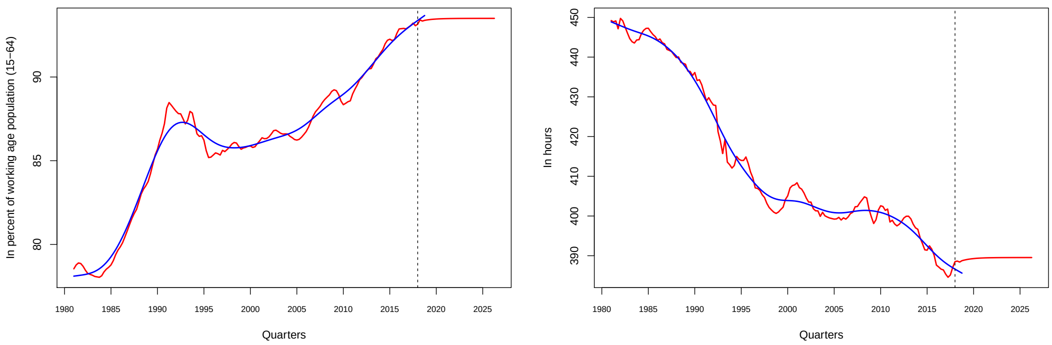
The figure compares the growth rates of potential output computed using the HP-filter (left panel) with the growth rates of potential output computed using the optimal LOESS smoothing (right panel). The HP-filter achieves a stronger smoothing, producing less volatile and procyclical growth rates of potential output.

Figure 23: Output gaps (HP vs. LOESS)



The figure compares the output gaps computed using the HP-filter (left panel) with the output gaps computed using the optimal LOESS smoothing (right panel). Despite markedly stronger smoothing by the HP-filter, evidenced by the growth rates of potential output, the resulting gaps are not too different when compared at an annual frequency. Since the output gaps depend on cumulative growth rates of potential output, more noise in the growth rates does not necessarily imply more volatile output gaps if the subsequent perturbations in the growth rates cancel out.

Figure 24: Participation rates and average hours worked (HP vs. ETS)



The quarterly trend series of the aggregate participation rate and the average working hours are extracted using the HP-filter with the smoothing parameter $\lambda = 1600$ (blue) and (additive) exponential smoothing state space models (red). The trends estimated using ETS models include 30-quarters-ahead forecasts.