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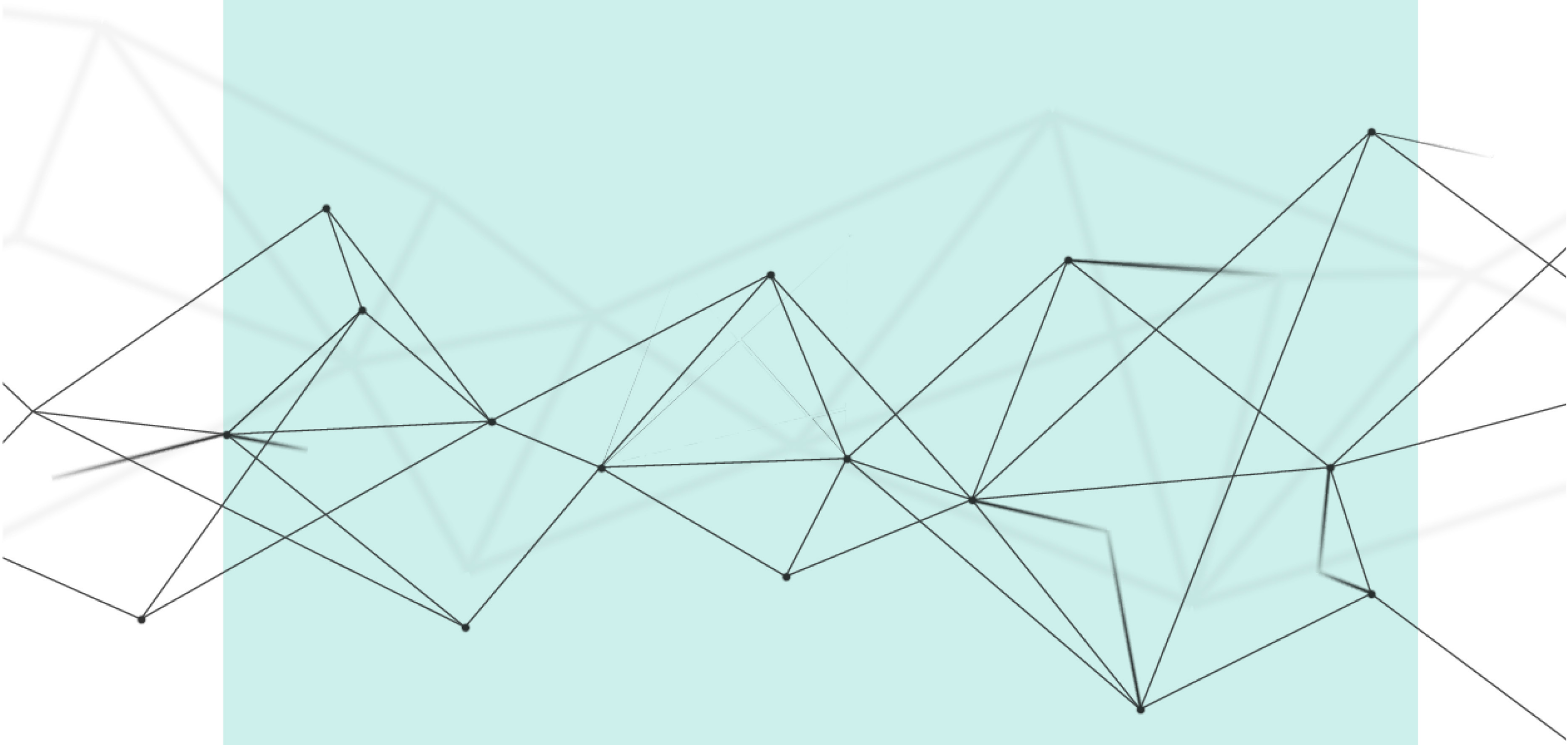
Potential output estimates for the Swiss economy: Model selection and sensitivity analysis



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Anmerkungen
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Schätzungen des Produktionspotenzials für die Schweizer Wirtschaft: Modellauswahl und Sensitivitätsanalyse

Zusammenfassung

In dieser Studie werden die jährlichen und vierteljährlichen Schätzungen des Potenzialwachstums und der Produktionslücke für die Schweiz mit Hilfe der Produktionsfunktionsmethode der Europäischen Kommission aktualisiert. Im Gegensatz zu univariaten Zeitreihenfiltern beinhaltet diese Methode einen strukturellen Ansatz und erlaubt somit, die Determinanten des Wirtschaftswachstums zu identifizieren.

Die Aktualisierung ist aufgrund der jüngsten Krisen (Covid-19 und Energiekrise 2021/2022) gerechtfertigt. Wir aktualisieren die Auswahl der Modelle anhand der aktuellen vierteljährlichen und jährlichen Stichproben (1980-2024), überprüfen die Konsistenz der Ergebnisse im Vergleich zu einer Stichprobe vor der Pandemie (1980-2019) und testen die Sensitivität der optimalen Modelle gegenüber Änderungen (i) der wichtigsten Inputreihen und (ii) eines Strukturparameters (Outputelastizität in Bezug auf die Arbeit in der Produktionsfunktion).

Die Modellauswahl basiert auf vorgegebenen Kriterien, die sich auf die Volatilität und Prozyklizität des Potenzialwachstums und die Persistenz des TFP-Wachstums beziehen. Das neue optimale vierteljährliche Modell führt zu Schätzungen, die dem derzeit vom SECO verwendeten Modell nahekommen. Die besten vierteljährlichen und jährlichen Modelle liefern weitgehend vergleichbare Schätzungen, die über die Zeit stabil sind.

Unter Verwendung des neuen optimalen Modells untersuchen wir seine Sensitivität gegenüber Änderungen der Inputreihen (BIP, Investitionen, geleistete Arbeitsstunden usw.) und der Arbeitselastizität in der Produktionsfunktion. Der Grund dafür ist, dass wiederkehrende Datenrevisionen und Prognoserevisionen der Inputreihen die Schätzungen des Produktionspotenzials und der Produktionslücke beeinflussen können. Die Sensitivitätsanalyse auf Basis einzelner Schocks zeigt, dass Revisionen der wichtigsten Inputvariablen zu erheblichen Revisionen der Schätzungen in der nahen und fernen Vergangenheit führen können. Die grössten Auswirkungen haben Revisionen des realen BIP-Wachstums, der Bevölkerung im erwerbsfähigen Alter und der geleisteten Arbeitsstunden. Revisionen der Investitionen und der Arbeitslosenquote haben nur geringe Auswirkungen.

Wir erweitern die obige Analyse um ein multivariates Szenario, das die typische Anpassung zyklischer Variablen wie Beschäftigung, durchschnittliche Arbeitsstunden, Investitionen oder Arbeitslosenquote an eine Revision des realen BIP beinhaltet, die durch Impulsantworten aus einem vierteljährlichen VAR-Modell bestimmt wird. Die Ergebnisse zeigen, dass ein Schock von einem Prozent im realen BIP-Wachstum das Produktionspotenzial im selben Jahr um 0,03 Prozentpunkte und die Produktionslücke um 0,57 Prozentpunkte erhöht. Die entsprechenden jährlichen Werte sind höher, nämlich 0,09 Prozentpunkte Erhöhung des Potenzialwachstums und 0,63 Prozentpunkte Erhöhung der Produktionslücke.

Das Quartalsmodell führt zu geringeren Revisionen der Produktionslücke in den beiden Prognosejahren als das Jahresmodell, aber zu höheren Revisionen in der historischen Perspektive. Auf Basis eines Vergleichs der relativen Vorteile von Quartals- und Jahresmodell empfehlen wir, das bestehende Quartalsmodell durch ein Jahresmodell zu ergänzen und beide Modelle gleichzeitig in der Prognosepraxis zu evaluieren.

Estimations de la production potentielle de l'économie suisse : Sélection de modèles et analyse de sensibilité

Résumé

Cette étude met à jour les estimations annuelles et trimestrielles de la croissance potentielle et de l'écart de production pour la Suisse en utilisant la méthodologie de la fonction de production de la Commission européenne et fournit une analyse de sensibilité des estimations par rapport à des données centrales. Contrairement aux filtres de séries temporelles univariées, cette approche structurelle permet d'identifier les sources de la croissance potentielle de la production.

Cette mise à jour est justifiée par les crises récentes (Covid-19 et la crise énergétique de 2021/2022). Nous actualisons la sélection des modèles en utilisant les échantillons trimestriels et annuels actuels (1980-2024), vérifions la cohérence des résultats par rap- port a` un échantillon prépandémique (1980-2019) et testons la sensibilité des modèles optimaux aux changements (i) des séries d'intrants clés et (ii) d'un paramètre structurel (élasticité de la production par rapport au travail dans la fonction de production).

La sélection du modèle est basée sur des critères pré-spécifiés impliquant la volatilité et la procyclicité de la croissance de la production potentielle et la persistance de la croissance de la productivité globale des facteurs (TFP). Le nouveau meilleur modèle trimestriel produit des estimations proches de celles du modèle actuel utilisé par le SECO. Le meilleur modèle trimestriel et le meilleur modèle annuel produisent des estimations largement similaires qui sont stables a` travers différents sous-échantillons.

En utilisant le nouveau modèle optimal, nous examinons sa sensibilité aux changements des séries d'intrants (PIB, investissement, nombre total d'heures travaillées, etc.) et à l'élasticité du travail dans la fonction de production. Ceci est motivé par les révisions récurrentes des données et des prévisions des séries d'intrants, qui sont susceptibles d'affecter les estimations de la production potentielle et de l'écart de production.

L'analyse de sensibilité basée sur des chocs isolés montre que les révisions des données clés peuvent entraîner des révisions significatives des estimations de la croissance de la production potentielle et de l'écart de production dans un passé proche et lointain. Les révisions de la croissance du PIB réel, de la population en âge de travailler et des heures travaillées ont l'effet le plus important. Les révisions de l'investissement et du taux de chômage ont de faibles effets.

Nous étendons l'analyse ci-dessus avec un scénario multivarié qui englobe l'ajustement typique des variables cycliques telles que l'emploi, le nombre moyen d'heures travaillées, l'investissement ou le taux de chômage `a une révision du PIB réel déterminée par les impulse responses d'un modèle VAR trimestriel. Les résultats indiquent qu'un choc de 1% sur la croissance du PIB réel augmente la production potentielle au cours de la même année de 0,03 point de pourcentage et l'écart de production de 0,57 point de pourcentage. Les chiffres annuels correspondants sont plus élevés : 0,09 point de pourcentage d'augmentation de la croissance de la production potentielle et 0,63 point de pourcentage d'augmentation de l'écart de production. Le modèle trimestriel produit des révisions de l'écart de production moins importantes pour les deux années de prévision que le modèle annuel, mais des révisions plus importantes dans la perspective historique. Sur la base d'une comparaison des avantages relatifs des modèles trimestriels et annuels, nous recommandons de compléter le modèle trimestriel actuel par un modèle annuel et d'évaluer les deux modèles simultanément dans la pratique de prévision.

Stime del prodotto potenziale per l'economia svizzera: Selezione del modello e analisi di sensibilità

Riassunto

Questo studio aggiorna le stime annuali e trimestrali della crescita del prodotto potenziale e dell'output gap per la Svizzera utilizzando la metodologia della funzione di produzione della Commissione europea e fornisce un'analisi di sensibilità delle stime rispetto a input centrali. A differenza dei filtri univariati delle serie temporali, questo approccio strutturale consente di identificare le fonti della crescita del prodotto potenziale.

L'aggiornamento è giustificato dalle recenti crisi (Covid-19 e crisi energetica del 2021/2022). Aggiorniamo la selezione dei modelli utilizzando gli attuali campioni trimestrali e annuali (1980-2024), verifichiamo la coerenza dei risultati rispetto a un campione pre-pandemia (1980-2019) e testiamo la sensibilità dei modelli ottimali alle variazioni (i) delle serie di input chiave e (ii) di un parametro strutturale (elasticità della produzione rispetto al lavoro nella funzione di produzione).

La selezione del modello si basa su criteri prestabiliti che riguardano la volatilità e la prociclicità della crescita del prodotto potenziale e la persistenza della crescita della TFP. Il nuovo miglior modello trimestrale produce stime vicine a quelle dell'attuale modello utilizzato dal SECO. Il miglior modello trimestrale e quello annuale producono stime sostanzialmente simili, stabili su diversi sottocampioni.

Utilizzando il nuovo modello ottimale, esaminiamo la sua sensibilità alle variazioni delle serie di input (PIL, investimenti, ore lavorate totali, ecc.) e all'elasticità del lavoro nella funzione di produzione. Ciò è motivato dalle revisioni ricorrenti dei dati e delle previsioni delle serie di input, che probabilmente influenzano le stime del prodotto potenziale e dell'output gap.

L'analisi di sensibilità basata su shock isolati mostra che le revisioni dei principali input possono portare a revisioni significative delle stime sulla crescita del prodotto potenziale e sull'output gap nel passato prossimo e remoto. Le revisioni della crescita del PIL reale, della popolazione in età lavorativa e delle ore lavorate hanno l'effetto maggiore. Le revisioni degli investimenti e del tasso di disoccupazione hanno effetti modesti.

Estendiamo l'analisi precedente con uno scenario multivariato che comprende il tipico aggiustamento di variabili cicliche come l'occupazione, le ore medie lavorate, gli investi- menti o il tasso di disoccupazione a una revisione del PIL reale determinata dalle impulse responses di un modello VAR trimestrale. I risultati indicano che uno shock dell'1% alla crescita del PIL reale aumenta il prodotto potenziale nello stesso anno di 0,03 punti percentuali e l'output gap di 0,57 punti percentuali. Le cifre annuali corrispondenti sono più alte, con un aumento di 0,09 punti percentuali della crescita del prodotto potenziale e di 0,63 punti percentuali dell'output gap. Il modello trimestrale produce revisioni dell'output gap minori nei due anni di previsione rispetto al modello annuale, ma revisioni più elevate in prospettiva storica. Sulla base di un confronto dei vantaggi relativi dei modelli trimestrali e annuali, raccomandiamo di integrare l'attuale modello trimestrale con un modello annuale e di valutare entrambi i modelli contemporaneamente nella pratica delle previsioni.

Potential output estimates for the Swiss economy: Model selection and sensitivity analysis

Summary

This study updates annual and quarterly estimates of potential output growth and the output gap for Switzerland using the production function methodology of the European Commission and provides a sensitivity analysis of the estimates with respect to key inputs. Unlike univariate time series filters, this structural approach allows to identify the sources of potential output growth.

The update is warranted by the recent crises (Covid-19 and the 2021/2022 energy crisis). We update the model selection using the current quarterly and annual samples (1980-2024), check the consistency of the results against a pre-pandemic sample (1980- 2019), and test the sensitivity of the optimal models to changes (i) in the key input series and (ii) in a structural parameter (output elasticity with respect to labor in the production function).

The model selection is based on pre-specified criteria involving the volatility and pro- cyclicality of potential output growth and the persistence of TFP growth. The new best quarterly model produces estimates that are close to those of the current model used by SECO. The best quarterly and annual model produce broadly similar estimates that are stable across different sub-samples.

Using the new optimal model, we examine its sensitivity to changes of the input series (GDP, investment, total hours worked, etc.), and the labor elasticity in the production function. This is motivated by the recurrent data-revisions and forecast revisions of the input series, which is likely to affect the estimates of potential output and the output gap. The sensitivity analysis based on isolated shocks shows that revisions to key inputs can lead to significant revisions of estimates for potential output growth and the output gap in the near and distant past. Revisions to real GDP growth, the working-age population and hours worked have the largest effects. Revisions to investment and the unemployment rate have small effects.

We extend the above analysis with a multivariate scenario that encompasses the typical adjustment of cyclical variables such as employment, average hours worked, investment, or the unemployment rate to a revision in real GDP determined by impulse responses from a quarterly VAR model. The results imply that a one percent shock to real GDP growth increases potential output in the same year by 0.03 percentage points and the output gap by 0.57 percentage points. The corresponding annual figures are higher at 0.09 percentage points increase in potential output growth and 0.63 percentage points increase of the output gap. The quarterly model produces smaller output gap revisions in the two forecast years than the annual model, but higher revisions in the historical perspective. Based on a comparison of the relative advantages of quarterly and annual models, we recommend supplementing the current quarterly model with an annual model and evaluating both models simultaneously in forecasting practice.

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1 Introduction

The output gap is an important economic concept for assessing the cyclical position of an economy in the business cycle. It is therefore of crucial importance to policymakers when deciding on cyclical stabilisation measures for the macroeconomy. While this measure has long been a mainstay of monetary policy decisions (Boschen et al., 1990), it has recently gained additional importance with the adoption of the cyclically-adjusted budget balance for fiscal policy (Duarte Lledo et al., 2019). This concept is based on the output gap. The crucial input for the output gap is, in turn, the *potential output* (PO). The usefulness of the output gap for policy making depends on the accuracy with which potential output is measured.

A common misconception is that the potential output is the maximum output the economy could produce if everyone were employed and all capital was used. Instead, potential output is what can be produced if the economy operates at maximum *sustainable* level of employment, where unemployment is at its natural rate. It is also commonly referred to the medium-term trend output of an economy. Therefore, actual output can be either above or below potential output.

Although potential output is an important economic concept, it is not directly observable (nor is the output gap). It must therefore be estimated. As with any application of statistical methods, the estimate is subject to inaccuracies arising from parameter and model uncertainty. However, there is an additional source of uncertainty related to revisions in the data used to estimate potential output in the first place.

This study examines the role of model uncertainty in the process of estimating the potential output for the Swiss economy. The focus is on analyzing the sensitivity of estimates for the potential output to revisions in historical data and revisions in the projected future paths of the gross domestic product (GDP), investment, the unemployment rate, and labour supply (total hours worked). The work is decomposed into two parts. The first one identifies an optimal model for estimating and measuring the potential output. The selection of an optimal model among a broad set of alternatives hinges on a set of statistical criteria. The second part utilizes the optimal model of the first part to carry out an extensive sensitivity analysis for the potential output.

The central issues of this study include the following:

1. What are the best models at quarterly and annual frequencies for the period 1980 to 2024 for estimating non-accelerating wage-inflation rate of unemployment (NAWRU)

and the trend of total factor productivity (TFP)?

2. How sensitive is the best model or the model currently used by SECO to marginal adjustments?

3. Which sample frequency should be used based on a comparison of the best models at quarterly and annual frequencies?

As regards the first bullet point, previous studies have already examined optimal models in this context, however, in the meantime, the Covid-19 pandemic and the 2021/2022 energy crisis have changed the economic time series data significantly so that a reassessment of optimal model selection is warranted. This is of particular importance since the output gap comprises an important input for the Swiss Federal Finance Administration (Eidgenössische Finanzverwaltung, EFV) for fiscal policy. The Swiss State Secretariat for Economic Affairs (SECO) publishes time series of potential output and the output gap for Switzerland since December 2019. These time series cover a period from 1980 to 2031, are currently calculated on a quarterly frequency, and are based on a production function approach developed by the European Commission (EC) and used in EU member states. They are included in the government accounts, budget, and financial planning of the Swiss Federal Finance Administration (EFV) since March 2022.

One of the aims of updating the optimal model is to assess the consistency of the model selection. In particular, the model selected on the sample 1980-2024 is examined relative to a model selected on the sub-sample 1980-2019, which excludes the two recent crises. The model selection is based upon criteria which are based on prior experience and insights from the recent literature that will be reviewed in this study. We compare the results of the model selection to the current quarterly model used by SECO and use common criteria to assess its overall plausibility.

The second bullet point makes up the major part of this study. It provides a sensitivity analysis for the optimal model with respect to changes in the input time series and the output elasticity of labor as a key structural parameter. It considers changes to the main input series (GDP, investment, total hours worked, working-age population, and unemployment) to examine the sensitivity of the estimates of potential output and the output gap. In each case these changes can be interpreted as data revisions or forecast revisions. In this context we perform a sensitivity analysis based on both (i) isolated changes of one input series, and (ii) a multivariate sensitivity analysis in which a change to one input series also causes changes in other input series.

Following this introduction, we review the recent literature on the estimation of potential output and discuss the challenges of obtaining plausible and reliable estimates (Section 2). In Sections 3 and 3.1 we present the production function methodology and a rich set of the unobserved component models for estimating the productivity trend and the equilibrium unemployment rate. Section 3.2 explains the model selection criteria and discusses the optimal quarterly and annual models. Section 4 investigates the stability of the optimal model using two types of sensitivity analyses. Section 5 discussed the relative advantages of the quarterly and annual versions of the model and provides an overview of current ideas of extensions as examined by the Output Gap Working Group (OGWG) Members of the EC. The final section offers concluding remarks. The Appendices A-G contain supplementary tables and figures, as well as additional technical details.

2 Literature review

The estimation of potential output holds a critical role in guiding fiscal policy decisions based on structural balances. Difficulties in accurately estimating the potential output can lead to misguided policy stances, consequently impacting the medium/long-term economic growth path. Hence for accurate policy-making and credibility, it is important that revisions between real time and ex-post estimates for the potential output (and in turn the output gap) are not too large. Unfortunately, however, as they are not observable, they hence need to be estimated from the data. In this context, parameter and model uncertainty can give rise to revisions. As regards the latter, Casey et al. (2021) argue that in terms of the stability of vintages of potential output growth estimates, there appears to be a clear winner, with the production function approach having the best stability characteristics for potential output growth across all countries studied. Against this background, it has become common practice to use a production function-based method to estimate the level or growth rate of potential output (D'Auria et al., 2010). It is important to note that the production function approach typically encompasses various trend-cycle decomposition methods. While short-term forecasts are typically incorporated into the estimation process (in this context, forecasts are treated as already observed outcomes), it is common for potential output (or output gap) estimates to undergo revisions over time, particularly during turning points in the business cycle. Data revisions (actual data or forecasts) comprise hence another important source of revisions to the estimates of potential output.

In this regard, Tereanu et al. (2014) examine historical data concerning revisions to actual and potential output growth within the countries of the European Union, as well as the implications of these revisions for the cyclically adjusted primary balance (CAPB). The study reveals significant revisions in output gap estimates, averaging nearly 1.5 percent of potential GDP. Moreover, revisions to potential output contribute significantly to revisions in the estimated CAPB, particularly during crisis years. Based on these findings and historical correlations, the study proposes a rule of thumb to minimize errors in measuring the CAPB, suggesting that *significant* data revisions in actual GDP growth rates give rise to revisions in potential output growth rates (our subsequent analysis will examine this issue for the Swiss economy). These findings underscore the importance of accurately estimating the potential output to ensure sound fiscal policy decisions that promote sustainable economic growth.

As the CAPB is calculated from the output gap, much attention has been paid to the estimates of the output gap and its revisions relative to potential output. Orphanides and van Norden (2002) highlight that ex-post revisions of output gap measures have been shown to predominantly relate to changes in potential as opposed to actual output. Another study in this context is the one of Tóth (2021). He emphasizes that real-time output gap estimates for the euro area from international institutions (IMF, OECD, EC) consistently exhibited lower values between 1999 and 2013 compared to more recent estimates. The discrepancy is most pronounced in the period leading up to the 2008/2009 global financial crisis (GFC). In particular, it was the period from the mid-2000s to 2007, where real-time estimates indicated a certain degree of slack or a nearly neutral cyclical position. However, more recent estimates demonstrate significantly positive output gaps during this period. If the more recent estimates are considered better approximations of the true cyclical position during that period, it suggests that these methods and the forecast errors made during the same time-frame contributed to overly pessimistic assessments of the state of the euro area economy at a critical juncture. The author concludes that this highlights the importance of continuously improving and refining estimation methods to enhance the accuracy and reliability of potential output and output gap estimates, particularly during pivotal economic periods.

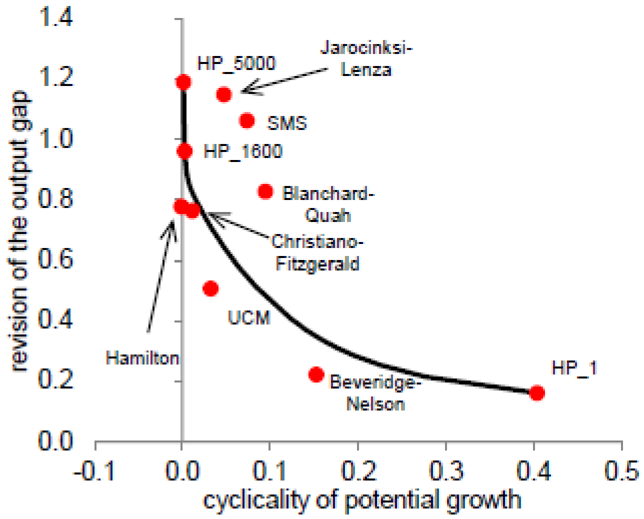
In a similar vein, Maidorn and Reiss (2017) and Fatás (2019) examine the potential problems that can arise from imprecise estimates of potential output. Fatás (2019) investigates the adverse feedback loop resulting from the interplay between imprecise (pessimistic) assessments of potential output and the impact of fiscal policy during the period of 2008-2014 in the countries of the European Union. The financial crisis of 2008 fostered an excessively pessimistic outlook on potential output among policymakers, prompting significant adjustments in fiscal policy. The implementation of contractionary fiscal measures, coupled with hysteresis effects, led to a decline in potential output. This not only validated the initial pessimistic forecasts but also triggered a subsequent round of fiscal consolidation. The sequence of contractionary fiscal policies likely proved counterproductive for many European Union countries. The negative impact on GDP inflicted more harm on debt sustainability than the benefits derived from budgetary adjustments. The author concludes by discussing alternative frameworks for fiscal policy that have the potential to circumvent such detrimental loops in future crises. By exploring alternative approaches, policymakers can strive to mitigate the adverse effects of imprecise potential output estimates and to avoid exacerbating economic downturns. Maidorn and Reiss (2017) argue that ex-post revisions in the level of structural balances primarily stem from output gap revisions, while forecast errors are influenced to a significant extent by other factors. When considering the change in the structural balance, a crucial indicator for fiscal consolidation efforts in the EU, the contribution of potential output revisions to forecast errors appears to be relatively minor. Unlike our study, they do not delve into identifying the specific sources responsible for potential output revisions.

A recent observation made by Coibion et al. (2018) highlights that revisions to potential output estimates by certain institutions tend to be procyclical. In other words, when actual GDP growth rates are high, potential output growth is often revised upwards, whereas it is revised downwards during periods of perceived weak growth. It is crucial, as noted by Deroose et al. (2019), to distinguish between the procyclicality of the "true" measure of potential output and the procyclicality of revisions to potential output estimates. While the actual level of potential output or its growth rate may legitimately exhibit some procyclicality, due to labor market hysteresis as explored by Blanchard and Summers (1987) and its potential reversal as suggested by Yellen (2016), the procyclicality observed in revisions to potential output estimates may indicate that the estimation method employed is influenced by the end-point problem. Recognizing this disparity is essential for understanding the limitations and potential biases in estimating the potential output, allowing for more accurate assessments and informed policy decisions. The aforementioned *end-point problem* has been at the focus of the analysis when attempting to identify an optimal model for estimating the potential output. Several things are worth being mentioned in this regard. The end-point problem is a common issue encountered in two-sided filters that employ future data to estimate the present level of potential output. As the sample approaches its end, the reliability of trend-cycle decomposition diminishes due to the reduced availability of information concerning the persistence of shocks. However, purely backward oriented methods like the Beveridge-Nelson decomposition, structural VARs, and production function approaches do not suffer from this problem since they do not rely on future data for estimation (Giorno et al., 1995). In the context of implementing the production-function approach (D'Auria et al., 2010), two-sided filters are not directly used to determine the potential output. That is to say, two-sided filters are not applied directly to the GDP. However, these filters are used for numerous variables that are employed in determining the potential output. As a consequence, the current methodology for measuring the potential output and the output gap is susceptible to the end-point problem. It is important to note that the production function approach is not an independent method but rather encompasses various trend-cycle decomposition methods.

More closer related to our contribution is part of the analysis put forth in Havik et al. (2014). The authors focus their examination of revisions in the potential output that stem from revisions of the non-accelerating wage-inflation rate of unemployment (NAWRU). Since the NAWRU is a crucial component of the production function approach used to compute the potential output (and in turn the output gap), any revisions to the NAWRU directly impacts the estimates of the potential output (and the output gap). Their findings reveal that, on average, a 1.0 percentage point change in the NAWRU leads to a 0.65 percentage point change in the output gap. In their conclusion, the authors emphasize that revisions to potential output growth and the output gap are inevitable due to forecast uncertainties (and revisions thereof) and revisions of historical data.

In a similar vein, Seco Justo and Szörfi (2021) conducted a study on output gap estimates provided by the EC and the OECD, revealing that the estimates of the EC undergo the least revisions, while those of the OECD experience the most significant changes. To gain a deeper understanding of these revisions, the authors further analyzed their drivers. Contrary to previous beliefs and existing studies, they show that statistical revisions of the underlying GDP data play a crucial role in explaining output gap and potential output growth revisions. Although, on average, the impact of data revisions may seem small over time, this average masks substantial revisions occurring in opposing directions, leading to cancellations of their effects. Another noteworthy factor in explaining output gap revisions are the revisions made to potential output growth. The study reveals that po-

Figure 1: The trade-off between revisions and procyclicality



The figure–taken from Seco Justo and Szörfi (2021)–highlights the trade-off between the revision of the output gap and the procyclicality of potential growth.

tential output growth is partly revised due to GDP forecast errors. If an overly optimistic economic outlook is put forth, and if then GDP growth falls short of the expectations, potential output is then often revised downwards, even for historical periods. Additionally, even if GDP remains unchanged in historical data, revisions to potential output can still cause adjustments to the output gap. Based on these findings, Seco Justo and Szörfi (2021) emphasize the importance of considering the trade-off between the reliability of output gap estimates and the cyclicality of potential output growth.[1] This is shown in Figure 1: a high level of output gap revisions contrasts with a low procyclicality of potential output growth. The difficulty here concerns the particular choice of the desired position on the line: while one would prefer to choose a low output gap revision together with a low procyclicality of potential output growth, the trade-off emphasizes that it is not possible to enjoy both at the same time. As a result, they recommend that estimates of potential output and the output gap be analyzed together, while also examining their properties. Moreover, to deal effectively with model uncertainty, they suggest looking at a range of estimates rather than relying on a single method.

[1]See, also Maidorn (2018).

Finally, Hristov et al. (2017) examine the issue of revision of the NAWRU (and in turn the potential output and the output gap) from the point of view of the observed procyclicality of the NAWRU estimates. Procyclicality refers to a situation where the estimate of the NAWRU closely aligns with the current unemployment rate at the end of the data sample (end-point problem). Such procyclical NAWRU estimates are deemed undesirable since they diminish the significance of considering the business cycle in concurrent analyses. Consequently, this becomes crucial in the estimation of potential output, the output gap, and, in turn, the cyclically adjusted primary balance (CAPB). Importantly, the authors' motivation for this study stems from the 2008/2009 global financial crisis and the subsequent significant revisions of the NAWRU estimates for EU countries for the years preceding the GFC. Hristov et al. (2017) argue that procyclicality serves as one source of revisions. As new observations become available, a concurrent trend estimate gravitates towards the local mean of the series, necessitating a larger deviation to reach that mean for more procyclical concurrent trend estimates. Hence, reducing procyclicality is expected to lead to a reduction in the extent of revisions of the potential output. They demonstrate that anchoring noticeably mitigates real-time revisions to the one- and two-step-ahead NAWRU forecasts in twenty-two EU countries.

In summary, the literature highlights the challenges of estimating potential output and the implications for fiscal policy decisions. Key findings include: First, the production function approach is generally stable for estimating potential output growth but has limitations. Second, there is a trade-off between the size of output gap revisions and the procyclicality of potential output. Third, output gap revisions are usually associated with changes in potential output rather than revisions in actual GDP data, especially during economic crises.

3 Overview of the production function methodology

The production function describes the transformation of the quantities of factor inputs (labor and capital) of an economy to the output measured by the real GDP. The same specification is then used to compute the level of potential output by removing cyclical fluctuations in the labor market and aggregate capacity utilization (Havik et al., 2014). The EC estimates potential output using a production function methodology which is continuously developed (a discussion on that is provided in Section 5.2) by the representatives of all EU member states in the Output Gap Working Group (OGWG).

The aggregate production function models the current level of actual GDP (chain-linked volumes at 2015 reference levels), Y_t, using a Cobb-Douglas specification, with capital stock (K_t) and total hours worked (L_t) as factor inputs:[2]

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

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 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 implies the equivalence of the Hicks-neutral and factor-augmenting technological 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 derived from business 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).

Definition of potential output

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 potential output describes the

[2]The presentation of the EU production function methodology follows Glocker and Kaniovski (2020).

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 74 (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 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. The output gap, as the relative deviation of real GDP from potential output ($\bar{Y}_t$), reflects the cyclical position of the economy:

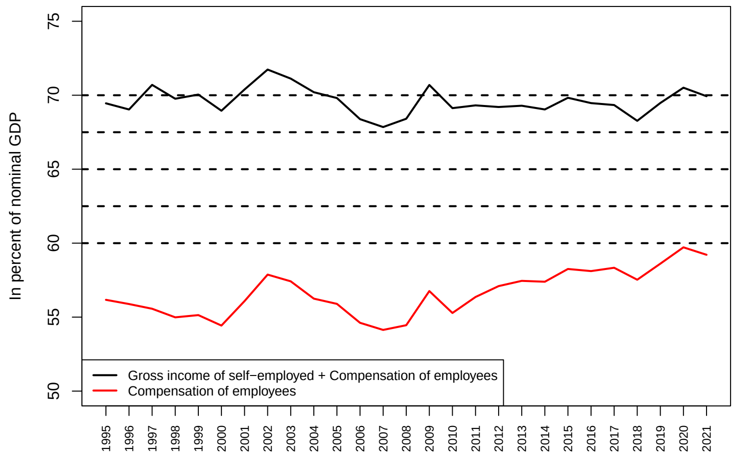
$$GAP_t = 100 \cdot \frac{Y_t - \bar{Y}_t}{\bar{Y}_t}. \tag{5}$$

A positive output gap indicates above-average capacity utilization. The output gap as an indicator of rising inflationary pressure is of central importance for monetary policy. A comparison of the output gap with the change in the primary budget balance shows whether fiscal policy is pro-cyclical or counter-cyclical. The output gap can thus be used to benchmark fiscal policy that seeks to mitigate the impact of cyclical fluctuations on private incomes while ensuring sustainability of public finances over the medium term.

The output elasticity of labor

The parameter α is the output elasticity of labor, or the percentage change in output caused by a one percent increase in labor input. If all factor inputs are compensated based on their marginal products, α should be well approximated by the share of labor income in nominal GDP (the income side of the Systems of National Accounts (SNA)). The EC imposes $\alpha = 0.65$ as an estimate obtained using a panel regression for the EU

Figure 2: The labor share



Plausible range for the share of labor income in nominal GDP.

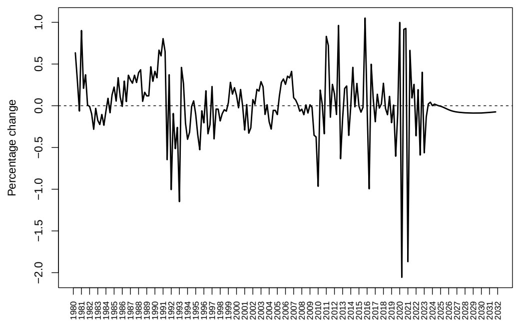
member states (D'Auria et al., 2010). This is also the value used in the current SECO model.

A plausible range for a labor coefficient is therefore between the share of compensation of employees in nominal GDP and the sum of the shares of self-employment income and compensation of employees (Figure 2). The income of the self-employed is included in gross operating surplus, which is a mixed income component. In Section 4 we test the sensitivity of the estimates of potential output growth and the output gap to the assumption on α for a range of values between 0.6 and 0.7.

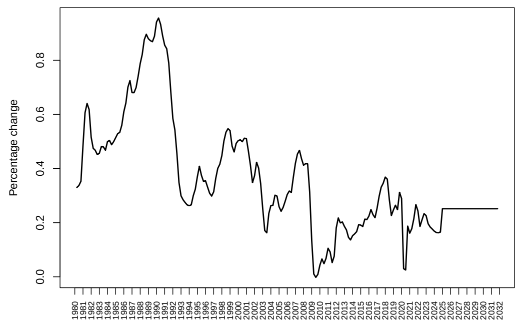
Trend in participation rate and average hours worked

The EC applies the Hodrick-Prescott filter (HP) to annual series of the participation rate and the average working hours (Figure 3 (c) and (d)). The EC recommends smoothing the annual series with $\lambda = 10$. This value is somewhat higher than the value of $\lambda = 6.25$ recommended by Ravn and Uhlig (2002), but is within the range of values commonly used. In the case of the quarterly model, these two input series must be smoothed using a higher parameter value. The quarterly series are smoothed using $\lambda = 1600$, the value typically recommended for quarterly data.

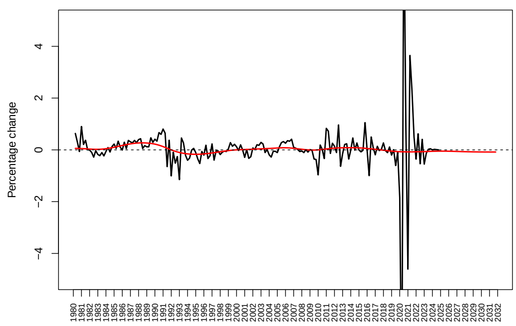
Figure 3: Growth rates of auxiliary inputs (quarterly)



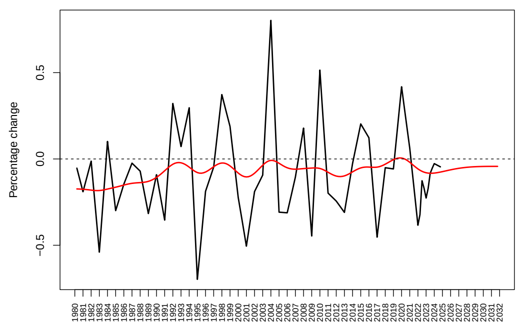
(a) Working-age population



(b) Capital stock



(c) Trend of participation rate



(d) Trend of average hours worked

The figure shows the expected decline in the working-age population and the labor force participation rate, as well as the long-term trends towards lower average total hours worked and slower capital accumulation.

3.1 The unobserved component model

The trend in total factor productivity and the natural rate of unemployment are estimated using unobserved component models (Planas and Rossi, 2020). The following example of a simple unobserved component model splits the main observable variable into a trend and a cycle. The cycle is assumed to be influenced by another observable variable, which adds a second measurement equation to the system. The model can include exogenous variables.

The natural rate of unemployment is measured by means of the Non-Accelerating Wage Inflation Rate of Unemployment (NAWRU), for which the current setup relies on a standard Phillips curve relation. The Phillips curve postulates a negative relationship between wage inflation and the unemployment gap. There is a downward pressure on nominal wage growth when the actual unemployment rate exceeds the NAWRU. The Phillips curve is the second measurement equation of the model, with the change in wage inflation as the dependent variable. A typical Phillips curve may include changes in terms of trade, labor productivity and the labor share as exogenous variables. 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.

Consider a simple unobserved component model:

$$X_t = f_t + c_t\,, \quad \text{first measurement} \tag{6}$$

$$\Delta f_t \sim N(\mu, \sigma^2_{a^p}) \qquad \text{trend}\,, \tag{7}$$

$$\left.\begin{aligned} &c_t = \varphi_1 c_{t-1} + a^c_t \sim N(0, \sigma^2_{a^c}) \\ &Z_t = \mu_z + \beta c_t + a^z_t \sim N(0, \sigma^2_{a^z}) \quad \text{second measurement} \end{aligned}\right\} \quad \text{cycle.} \tag{8}$$

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 Z_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 $Z_t = CU_t$ (rate of capacity utilization). In the case of the NAWRU, $X_t = U_t$ (actual unemployment rate) and $Z_t = \Delta^2 W_t$ (change in wage inflation – Phillips curve). The difference between the actual rate of unemployment and the NAWRU (unemployment gap) reflects the cyclical variation in the labor market. Since the cycle feeds into an observable variable Z_t, the above system has two measurement equations and two state equations. The models are estimated using the Kalman filter described in Koopman (1997), with the likelihood function maximised by a sequential quadratic programming method and the standard errors computed using the information matrix.

3.1.1 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 second-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

$$\left.\begin{aligned} \Delta f_t &= \eta_{t-1} + a_t^f \\ \Delta \eta_t &= a_t^\eta \end{aligned}\right\} \qquad \text{trend } (2^{nd} \text{ order RW}), \tag{9}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\ a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{10}$$

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,

$$\left.\begin{aligned} \Delta f_t &= \eta_{t-1} + a_t^f \\ \eta_t &= \mu_p(1-\rho) + \rho\eta_{t-1} + a_t^\eta \end{aligned}\right\} \qquad \text{trend (Damped)}, \tag{11}$$

$$a_t^f \sim N(0, \sigma^2_{a^p}),\ a_t^\eta \sim N(0, \sigma^2_{a^\eta}) \qquad \text{error terms.} \tag{12}$$

The parameter ρ influences the long-run (gain) value of Δf_t as a result of a random shock a_t^η. The second-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 fit of the second measurement equation depends on the lag structure and the error process. We include up to two lags of the dependent variable and up to four lags of the cycle for a total of 15 distinct lag structures for this equation. In the order of increasing complexity,

$$CU_t = \beta_1 c_t + a_t^{cu} \,, \tag{13}$$

$$CU_t = \alpha_1 CU_{t-1} + \beta_1 c_t + a_t^{cu} \,, \tag{14}$$

$$\ldots$$

$$\begin{aligned} CU_t = \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} + \\ + \beta_1 c_t + \beta_2 c_{t-1} + \beta_3 c_{t-2} + \beta_4 c_{t-3} + \beta_5 c_{t-4} + a_t^{cu} \,. \end{aligned} \tag{15}$$

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

- Three **Trend**(s).
- Two lag structures for the dependent variable in the cycle equation (**AR Cyc**).
- Two lag structures for the dependent variable in the second measurement equation (**AR CU**).
- Two models for the error term in the second measurement equation (**Error MA**).
- Five lag structures for the cycle in the second measurement equation (**Cyc Lags CU**).

The model universe consists of combinations of unobserved component models for the NAWRU and the TFP trend from which the estimates of potential output and output gap are derived. The models differ in how they parameterize the trend (simple or nested random walk, or a damped trend, and the structure of lags in the cyclical equation).

The model universe comprises all combinations of 36 NAWRU and 180 TFP trend specifications (6480 in total) listed in Appendix A and B.[3] In the above taxonomy, the

[3]The first column of those tables shows the number we use when referring to a specific NAWRU or TFP model. The columns in bold refer to the code in a model file with the extension `*.nml`), which is a text file containing the specification of an unobserved component model, the data used for the estimation

quarterly models currently in use by SECO carry the numbers 102 (NAWRU) and 158 (TFP-trend). The figure in Appendix A shows the types of estimates that can be obtained for the NAWRU using the current quarterly sample. NAWRU estimates of the ragged and smooth types deserves further consideration (for naming notation, see the footnote in Figure A). The current quarterly NAWRU model No. 102 is smooth, and the NAWRU model No. 120 chosen in the previous study by Glocker and Kaniovski (2020) belong to this type.

3.2 Model selection

The criteria for model selection build on our prior experience with the quarterly and annual data for Switzerland and the recent literature discussed in Section 2. The commonly used evaluation criteria include measures of volatility and procyclicality of potential output and the output gap. Estimates of potential output should not be excessively volatile, procyclical, and unstable. Stability means that output gap estimates should not be prone to significant and unexpected revisions.

There is a common conception among practitioners and policy makers that long-term growth trends determined by fundamentals such as technological progress and population growth should not change too much from one period to another, i.e. it should be rather smooth. This mirrors the idea that the output gap should reflect frequent but irregular business cycle fluctuations caused by demand shocks. Though inherently subjective and vague as a formal criterion, our experience and our interpretation of the literature show that high volatility of potential output estimates is undesirable. Whereas excessive volatility muddles the decision-making process by adding noise, excessive procyclicality can bias the output gap. By reducing the amplitude of output gap fluctuations, procyclicality renders the measurement of the current state of the economy less accurate and its assessment more biased. The EU Independent Fiscal Institutions (IFIs) identify procyclicality as the most important issue common to all potential output estimation techniques (Casey et al., 2021).

Excessively volatile and procyclical estimates of potential output can arise when fluctuations in capacity utilization are not properly separated from the long-term productivity trend. Since estimates of the unobserved component models can be excessively volatile

and the control parameters for the GAP software such as the frequency of the data or the horizon and the value of the NAWRU anchor. The GAP software parses this model file, solves the model, and returns the estimates with the associated diagnostics.

depending on the estimates of the standard deviations of several disturbance terms, also the NAWRU estimates can be excessively volatile. The NAWRU estimates can also contribute to the procyclicality if they follow the actual unemployment rate too closely.

The most important criteria are the volatility and procyclicality of potential output growth and have been applied in the previous study to select optimal quarterly and annual models (Glocker and Kaniovski, 2020). In this study we add the persistence of the TFP trend as a third model criterion. This criterion is motivated by macroeconomic theory, in which technological progress follows a highly persistent but stationary autoregressive process. Persistence refers to the magnitude of (first order) autocorrelation of the estimated TFP trend. This criterion ensures that the empirical estimates of potential output growth align with values commonly estimated and used in the literature, for instance, in the context of real-business cycle models (see Kydland and Prescott, 1982; King and Rebelo, 1999, among others), while also avoiding estimates for potential output that are too volatile.

3.2.1 Practical implementation of model selection

The search for an optimal pair of NAWRU and TFP trend models is carried out in three steps. First, we discard models that fail to extract a reasonable trend or fail regression diagnostics. These include TFP trend models that fit the cycle perfectly so that the trend matches the actual variable, or models with significant autocorrelation in the residuals of the trend and cycle equations, as indicated by a Ljung-Box test statistic at the 5 percent level of statistical significance. We also discard NAWRU models with a perfect fit on the actual unemployment rate or models that return a linear trend, i.e. the type a) and b) in the taxonomy of Appendix A. Perfect fits to the cycle indicate the inability to extract a meaningful trend, while linear trends are implausible and usually arise from problems with disturbance terms in the stochastic trend specification of the unobserved component model. Here we also check for parameter estimates hitting their boundary values.

This preliminary regression diagnostics retain about ten percent of the models to which we then apply the model selection criteria. The second step improves the application of the main criteria: volatility and procyclicality of potential output growth and the persistence of the TFP trend. Following the above discussion, low volatility and procyclicality are standard requirements mentioned in the literature, whereas the persistence of the TFP trend is inspired by models of economic growth in which technological progress is modeled as a persistent AR(1) process.

Let tfp_t^*, y_t^*, y_t be the growth rates of the TFP trend, potential output, and real GDP:

1. **Volatility** of potential output growth: $\sigma_{y_t^*}$,[4]

2. **Procyclicality** of potential output growth: $\rho(y_t^*, y_t)$,

3. **Persistence** of the TFP trend: $\rho(tfp_t^*, tfp_{t-1}^*)$,

where $\rho(\cdot, \cdot)$ is the conventional (Pearson's product moment) coefficient of correlation. We thus search for combinations of NAWRU and TFP models that produce stable, not overly procyclical potential output growth estimates and highly persistent TFP trends.

In a final step in the model selection procedure we check the (pseudo) R^2 as a conventional measure of fit for an unobserved component model, which reflects the one-step-ahead forecast error of the model on the observed cycle, and test the overall plausibility of the resulting estimates of potential output growth and the output gap. The above model selection procedure is applied separately to the current quarterly and annual samples, and their shorter prepandemic counterparts. When viewing the results, we compare the similarity of the quarterly and annual estimates or the similarity of the new quarterly estimates and the current quarterly estimates. Note that we do not impose similarity criteria when selecting the optimal pair of models, for example by minimizing the deviations between them, but note that some congruence of estimates at different frequencies may be a desirable feature when both models are used in parallel.

Many additional criteria that have been suggested in the literature, for example, the symmetry of the output gap estimate over a complete cycle, its stability around turning points or robustness to data revisions. We do not impose the symmetry of the output gap estimate or minimize the deviation of the output gap series from zero. Doing so would be problematic in view of the profound dent in potential output series caused by severe economic crisis such as the Covid-19 pandemic, which could shift the entire output gap series.

As a final remark, since we do not have vintages of macroeconomic data required to estimate (historical) potential outputs in real time, we hence refrain from considering data revision in the process of model selection. However, the data revisions are at the core of the analysis of the sensitivity of our selected model, which is being carried out in Section

[4]In the previous study Glocker and Kaniovski (2020), we used the ratio of the range of variation between the maximum and minimum values of potential growth and the range of variation between the maximum and minimum values of actual output growth. The results of the model selection procedure are similar, so we use the standard deviation as a simple measure.

4. In this context, our stability analysis relies on the estimates of typical revisions in the input data rather than the actual revisions recorded in the past. The advantage of this approach is that it can be applied to both data and forecast revisions. The sensitivity analysis is based on isolated shocks to the main input series and a multivariate scenario that more accurately reflects the joint dynamics of the series over the business cycle. In each case the shock can be interpreted as a data revision or a forecast revision.

3.2.2 Model groups

To get a broad picture of the estimates, we take a closer look at those models that pass the preliminary regression diagnostics by clustering the estimates using the main model selection criteria.[5] Table 1 summarizes the averages (centroids) of the groups. These group statistics should be interpreted with caution, as groups may still contain considerable heterogeneity.

The first group (Cluster No. 1) of models appears to be a clear winner among the quarterly models in both samples. This group contains 78 pairs of models for the current sample and 11 pairs of models in the sample 1980-2019. Estimates belonging to this group combine low volatility and procyclicality with persistent TFP trends. The current quarterly model (NAWRU model No. 102, TFP model No. 158) belongs to this group. Estimates in the next best group (Cluster No. 2) tend to either have much lower persistence of the TFP trends (Quarterly 2022) or have a much higher procyclicality (Quarterly 2019).

The picture is less clear-cut among the annual models. Here we see two groups featuring persistent TFP trends, of which one group is clearly superior in terms of the volatility and procyclicality of potential output growth. The number of models in the top groups at annual frequency is generally larger than at the quarterly frequency. The annual implementations appear to offer a larger model variety, as the number of candidate models in the best group tends to be larger than in the case of quarterly implementations.

[5] The number of groups (clusters) is loosely based on the elbow heuristic. This practical heuristic recommends the smallest number of clusters that results in a substantial reduction in the total sum of squares within clusters.

Table 1: Model clusters

Cluster		Potential output growth		TFP trend growth
No.	Size	Volatility	Procyclicality	Persistence
Quarterly 2022				
1 (current model)	78	0.150	0.246	0.927
2	91	0.177	0.287	0.317
3	377	0.502	0.533	0.177
4	377	0.553	0.469	0.010
5	208	0.473	0.467	-0.124
Annual 2022				
1	96	0.547	0.512	0.931
2	144	0.463	0.307	0.931
3	171	0.518	0.425	0.326
4	114	0.599	0.600	0.326
5	375	0.880	0.449	0.320
Quarterly 2019				
1 (current model)	11	0.136	0.151	0.990
2	55	0.195	0.381	0.7525
3	88	0.446	0.514	0.344
4	297	0.497	0.466	0.107
5	198	0.396	0.453	-0.038
Annual 2019				
1	120	0.454	0.304	0.951
2	108	0.521	0.484	0.942
3	96	0.527	0.466	0.398
4	137	0.884	0.483	0.390
5	115	0.828	0.382	0.327

3.2.3 Selected NAWRU models

The specification of the preferred quarterly model No. 174 is given by

$$U_t = \nu_t + z_t \,,$$

$$\left.\begin{aligned} \Delta\nu_t &= \eta_{t-1} + a_t^{\nu} \\ \Delta\eta_t &= a_t^{\eta} \end{aligned}\right\} \qquad \text{trend}\,,$$

$$\left.\begin{aligned} &z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t^{z} \\ &\Delta^2 W_t = \mu_w + \alpha_1 \Delta^2 W_{t-1} + \alpha_2 \Delta^2 W_{t-2} \\ &+\beta_1 z_t + \beta_2 z_{t-1} + \beta_3 z_{t-2} + \beta_4 z_{t-3} \\ &+\gamma_1 \Delta^2 tot_t + \gamma_2 \Delta^2 prod_t + \gamma_3 \Delta^2 ls_t + a_t^{w} \end{aligned}\right\} \qquad \text{cycle}\,,$$

$$a_t^{\nu} \sim N(0, \sigma^2_{a^{\nu}}),\ a_t^{\eta} \sim N(0, \sigma^2_{a^{\eta}}),\ a_t^{z} \sim N(0, \sigma^2_{a^{z}}),\ a_t^{w} \sim N(0, \sigma^2_{a^{w}}) \qquad \text{errors.}$$

The trend ν_t is a nested (second order) 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, and the labor share is the compensation of employees divided by the nominal GDP.

The specification of the selected annual model No. 114 is given by

$$
\begin{aligned}
& U_t = \nu_t + z_t \,, \\
& \left.\begin{aligned} \Delta\nu_t &= \eta_{t-1} + a_t^{\nu} \\ \Delta\eta_t &= a_t^{\eta} \end{aligned}\right\} && \text{trend}\,, \\
& \left.\begin{aligned} & z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + a_t^{z} \\ & \Delta^2 W_t = \mu_w + \alpha_1 \Delta^2 W_{t-1} \\ & +\beta_1 z_t + \beta_2 z_{t-1} + \beta_3 z_{t-2} + \beta_4 z_{t-3} \\ & +\gamma_1 \Delta^2 tot_t + \gamma_2 \Delta^2 prod_t + \gamma_3 \Delta^2 ls_t + a_t^{w} \end{aligned}\right\} && \text{cycle}\,, \\
& a_t^{\nu} \sim N(0, \sigma^2_{a^{\nu}}),\ a_t^{\eta} \sim N(0, \sigma^2_{a^{\eta}}),\ a_t^{z} \sim N(0, \sigma^2_{a^{z}}),\ a_t^{w} \sim N(0, \sigma^2_{a^{w}}) && \text{errors.}
\end{aligned}
$$

We consider the quarterly NAWRU model No. 180 that appeared in the model selection table (see, Appendix D). This model is not stable as its shape changes considerable with the choice of the sample. In other words, the estimate that would have been obtained using the pre-pandemic sample looks remarkable different from the estimate obtained using the same specification in the current sample. We therefore discard this NAWRU specification at both frequencies in favor of the NAWRU model No. 114, which is essentially identical to NAWRU model No. 174 and the current NAWRU model No. 102, both of which are of the smooth type. This has the added advantage that the resulting potential output and output gap series are similar at the quarterly and annual frequencies, which improves the overall consistency of the estimates.

Table 2: NAWRU estimates (1980-2024)

NAWRU 174	Quarterly (180 observations)		
	Coefficient	S.E.	t-stat
φ_1	1.8633	0.0281	66.3527
φ_2	-0.9134	0.0279	-32.7388
α_1	-0.0671	0.0277	-2.4190
α_2	-0.0398	0.0229	-1.7353
γ_1	-0.5743	0.0424	-13.5411
γ_2	0.9293	0.0253	36.7147
γ_3	0.8707	0.0249	34.9415
β_1	-0.0019	0.0049	-0.3938
β_2	0.0020	0.0127	0.1557
β_3	0.0003	0.0127	0.0251
β_4	-0.0006	0.0049	-0.1225
R^2 (one-step-ahead predictions): 0.9634			
NAWRU 114	Annual (45 observations)		
	Coefficient	S.E.	t-stat
φ_1	1.1185	0.1251	8.9380
φ_2	-0.5636	0.1197	-4.7077
α_1	-0.0555	0.1121	-0.4949
γ_1	-0.3699	0.1621	-2.2821
γ_2	0.6495	0.1101	5.8990
γ_3	0.4720	0.1023	4.6132
β_1	-0.0056	0.0038	-1.4792
β_2	-0.0035	0.0062	-0.5690
β_3	0.0061	0.0067	0.9067
β_4	-0.0002	0.0044	-0.0357
R^2 (one-step-ahead predictions): 0.5019			

3.2.4 Selected TFP models

The specification of the optimal quarterly TFP model No. 159 is given by:

$$
\begin{aligned}
&F_t = f_t + c_t\,, && \\
&\left.\begin{aligned} &\Delta f_t = \eta_{t-1} + a_t^f \\ &\Delta \eta_t = a_t^\eta \end{aligned}\right\} && \text{trend}\,, \\
&\left.\begin{aligned} &c_t = \varphi_1 c_{t-1} + a_t^c \\ &CU_t = \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} \\ &+\beta_1 c_t + \beta_2 c_{t-1} + \beta_3 c_{t-2} + \beta_4 c_{t-3} + a_t^{cu} \end{aligned}\right\} && \text{cycle}\,, \\
&a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}),\; a_t^c \sim N(0, \sigma^2_{a^c}),\; a_t^{cu} \sim N(0, \sigma^2_{a^{cu}}) && \text{errors.}
\end{aligned}
$$

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 second order random walk. The cycle c_t also follows an $AR(1)$ process. The measurement equation featuring the series for capacity utilization CU_t includes three lagged values of the cycle c_t.

The specification of the optimal annual model No. 172 is:

$$
\begin{aligned}
&F_t = f_t + c_t\,, && \\
&\left.\begin{aligned} &\Delta f_t = \eta_{t-1} + a_t^f \\ &\Delta \eta_t = a_t^\eta \end{aligned}\right\} && \text{trend}\,, \\
&\left.\begin{aligned} &c_t = \varphi_1 c_{t-1} + \varphi_1 c_{t-2} + a_t^c \\ &CU_t = \mu_{cu} + \alpha_1 CU_{t-1} + \alpha_2 CU_{t-2} \\ &+\beta_1 c_t + \beta_2 c_{t-1} + a_t^{cu} \end{aligned}\right\} && \text{cycle}\,, \\
&a_t^f \sim N(0, \sigma^2_{a^p}),\; a_t^\eta \sim N(0, \sigma^2_{a^\eta}),\; a_t^c \sim N(0, \sigma^2_{a^c}),\; a_t^{cu} \sim N(0, \sigma^2_{a^{cu}}) && \text{errors.}
\end{aligned}
$$

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

The final step inserts 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:

$$\bar{Y}_t = \exp(f_t) \cdot (POP_t \cdot \overline{PRT}_t \cdot (1 - \nu_t) \cdot \bar{H}_t)^\alpha \cdot K_t^{1-\alpha}. \tag{16}$$

Figure 4 compares the estimates of the optimal models to the estimates of the current

Table 3: TFP trend estimates (1980-2024)

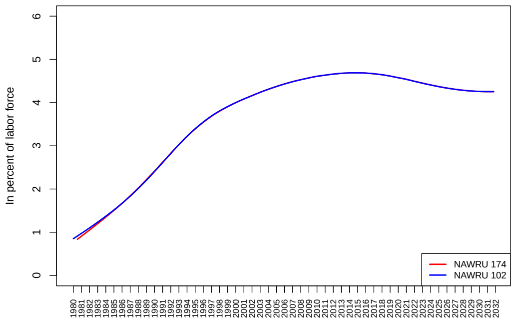
TFP 159	Quarterly (180 observations)		
	Coefficient	S.E.	t-stat
φ_1	0.9276	0.0391	23.7184
α_1	1.1772	0.0722	16.2992
α_2	-0.2833	0.0716	-3.9566
β_1	0.4539	0.0955	4.7542
β_2	-0.0686	0.1407	-0.4877
β_3	-0.2222	0.1396	-1.5911
β_4	-0.1515	0.1021	-1.4837
R^2 (one-step-ahead predictions): 0.8995			
TFP 172	Annual (45 observations)		
	Coefficient	S.E.	t-stat
φ_1	0.7663	0.1617	4.7397
φ_2	-0.3742	0.1505	-2.4855
α_1	0.6361	0.1418	4.4855
α_2	-0.1804	0.1024	-1.7615
β_1	1.3924	0.2149	6.4783
β_2	-1.0703	0.2888	-3.7055
R^2 (one-step-ahead predictions): 0.3381			

model (TFP model No. 158, NAWRU model No. 102). The first thing to note is how similar the estimates listed are to each other. We pick the NAWRU model No. 174 and TFP model No. 159 as the optimal pair at the quarterly frequency and the NAWRU model No. 114 and TFP model No. 172 at the annual frequency. These pairs have the highest persistence of the TFP trend coupled with low volatility and low procyclicality of potential output growth. The quarterly NAWRU model No. 180 specification appears in some of the candidate estimates, but it is not stable over the two samples (see below).

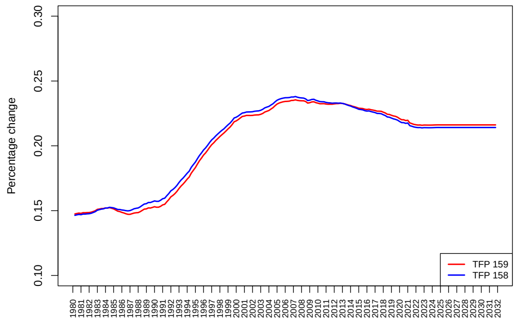
It turns out that the optimal quarterly model produces estimates that are practically identical to the current ones. We see minimal difference in the growth rate of the TFP trend and essentially identical estimates for the potential output growth and the output gap. We can thus confirm the goodness of the current quarterly implementation.

To compare the best quarterly and annual models, we aggregate the quarterly estimates to the annual frequency. The best annual model produces slightly lower growth rates for the TFP trend and potential output for the current years and the extension, and the correspondingly smaller negative output gap. The results of the best quarterly and annual models are quite similar, with the estimates of the best quarterly model being practically identical to the current estimates.

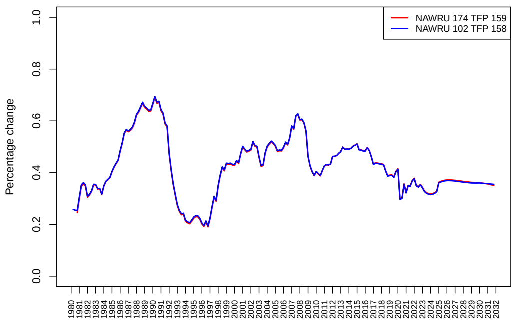
Figure 4: Estimates based on optimal specifications (quarterly)



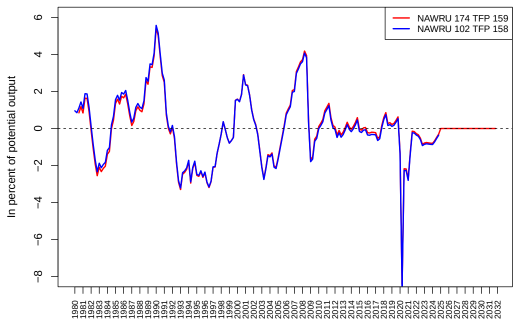
(a) NAWRU 174



(b) TFP trend growth 159



(c) Potential output growth



(d) Output gap

The optimal quarterly pair (NAWRU model No. 174, TFP model No. 159) leads to estimates that are very close to the current estimates (NAWRU model No. 102, TFP model No. 158). Minimal differences in the TFP trend growth lead to nearly identical estimates for potential output growth and the output gap.

Table 4: Model selection

	NAWRU No.	TFP No.	Potential output Vol.	Procycl.	TFP trend Persis.	NAWRU R^2	TFP R^2
			Quarterly 2022				
Current	102	158	0.120	0.088	0.991	0.962	0.898
Most persistent							
– Least volatile	174	159	0.120	0.088	0.992	0.963	0.899
– Least procyclical	102	159	0.120	0.088	0.992	0.962	0.899
Least volatile	174	159	0.120	0.088	0.992	0.963	0.899
Least procyclical	102	152	0.123	0.078	0.149	0.962	0.890
			Annual 2022				
Current	102	158	0.469	0.250	0.963	0.490	0.245
Most persistent							
– Least volatile	180	172	0.439	0.317	0.978	0.577	0.338
– Least procyclical	114	172	0.459	0.253	0.978	0.502	0.338
Least volatile	180	172	0.439	0.317	0.978	0.577	0.338
Least procyclical	114	115	0.465	0.247	0.976	0.502	0.357
			Quarterly 2019				
Current	102	158	0.119	0.088	0.990	0.917	0.905
Most persistent							
– Least volatile	180	158	0.118	0.094	0.990	0.923	0.905
– Least procyclical	174	158	0.119	0.088	0.990	0.922	0.905
Least volatile	180	158	0.118	0.094	0.990	0.923	0.905
Least procyclical	174	158	0.119	0.088	0.990	0.922	0.905
			Annual 2019				
Current	102	158	0.450	0.247	0.959	0.420	0.236
Most persistent							
– Least volatile	129	113	0.445	0.265	0.974	0.464	0.346
– Least procyclical	114	113	0.448	0.250	0.974	0.427	0.346
Least volatile	114	179	0.438	0.282	0.962	0.427	0.309
Least procyclical	114	115	0.453	0.244	0.970	0.427	0.348

4 Sensitivity analysis

Estimates of potential output and the output gap are revised on a regular basis. Revisions can be caused by revisions to current economic data (revisions of quarterly and annual SNA) or by revisions to the current economic outlook (forecast revisions), or both. Practical economic forecasting is often confronted with the need to anticipate revisions to current estimates of potential output and the output gap as an important part of the overall interpretation of the forecast. The literature on potential output estimation highlights the trade-off between procyclicality and stability of the estimates, which renders sensitivity analysis of the estimates to the input time series essential for validating the model.

In the first part of the analysis, we consider isolated shocks to key inputs to get an overall sense of the sensitivity of potential output growth and the output gap. We introduce a shock (unexpected change) to one of the following variables: GDP, investment, total hours worked, working-age population and unemployment and check how this shock changes the estimates. The shocks occur at a specific point in time, t, and have zero autocorrelation. We examine their immediate effects at time t, and their effects in a five-year period before and after time t, for which we report the average annual effects.

The above simulation design helps us to determine when the shocks have their most significant impact and whether there are asymmetries in their pre- and post-impact. In addition, we investigate whether shocks of the same absolute magnitude, but with opposite sign, cause symmetric or asymmetric changes in potential output growth and the output gap. This investigation is motivated by the non-linear nature of the equations and one-sided univariate filters used in the construction and estimation of potential output, both of which may lead to asymmetries. We conduct this analysis for both the quarterly version of the potential output model and the annual one.

To compare the estimates at quarterly and annual frequencies, we first shock the growth rate of an input in the annual model and then shock the year-over-year growth rate of that input in each quarter in the quarterly model. Assuming the same magnitude and timing of the shock, the average of the four quarterly shocks equals to the magnitude of the annual shock, allowing us to compare the stability of the estimates at different frequencies. It should be noted that more complex quarterly shock patterns are likely to occur in practice; the simple shock design proposed here is chosen to allow easy comparison between estimates at different frequencies.

4.1 Univariate shock analysis

Tables 5 and 6 and Figures 9-14 in the Appendix F show the results of the sensitivity analysis of the best quarterly and annual models when the input series are shocked individually. The panels in Figures 9-14 have been scaled similarly to give a better sense of how the shocks change the current forecast and the past assessment. Note that the tables omit the average effect on the output gap for 2025-2031 because the closure rule ensures that the gap disappears in the medium term by construction (Appendix E).

The sensitivity analysis shows that changes in the input series, which are subsequently smoothed by applying the HP filter, generally cause large revisions that extend far into the past. The application of a HP filter twists the trend estimate in such a way that higher growth in the current period is associated with lower growth in the past. Such input time series are the working-age population (HP-filtered labor force participation rate) and the total number of hours worked (HP-filtered average hours worked). Revisions to real GDP tend to have the largest effect, followed by revisions to population and hours worked. The effects of revisions in investment are moderate due to the small size of investment relative to the capital stock. Revisions to the unemployment rate have only a minor effect due to the robustness of the smooth NAWRU estimates, which we generally consider to be superior to the estimates of the ragged type, and the fact that the quarterly unemployment rate is smoothed using the HP-filter prior to the estimation (Appendix C).

Revisions at the top of the current sample such as the typical forecast revisions can lead to significant revisions for the immediate and distant past, leading to a reassessment of the cyclical position of the economy in the past. However, caution is needed regarding the magnitude of the effect of a shock to the total number of hours worked, as an increase in the total number of hours worked that is not offset by a corresponding increase in employment leads to an implausibly large increase in average hours worked. Revisions to the unemployment rate have little effect due to the overall stability of the chosen NAWRU specification. The effects of positive shocks differ from the effects of negative shocks, and the effects of a persistent shock over two consecutive years are not additive.

The quarterly models tend to produce smaller revisions in the current forecast period 2023-2024 than the annual models, but larger revisions of the past, including quite distant past. This recommends a quarterly implementation over the annual one. In practice, the revisions in the current forecast period will be even smaller, because not every quarter of a given year will necessarily be revised. Recall that we assumed the same shock (revision) for the year-over-year growth rates at each quarter of a year. The quarterly model is overall less sensitive than the annual model but is more sensitive to the choice of the output elasticity of labor (labor coefficient).

The example of an isolated shock to total hours worked suggests that such shocks may be implausible. Typical data and forecast revisions jointly change all the input time series. Forecasts prepared by expert groups often start with a draft GDP revision, which

Table 5: Sensitivity to an isolated shock (quarterly)

Shock		Potential output growth				Output gap		
Size in ppt	Year	2016-2022	2023	2024	2025-2031	2016-2022	2023	2024
		GDP (yoy)						
+1	2023	0.01	0.02	0.02	0.02	-0.32	0.46	0.40
−1	2023	-0.01	-0.01	-0.01	-0.01	0.35	-0.44	-0.39
+1	2024	0.01	0.01	0.01	0.01	-0.26	-0.44	0.48
−1	2024	-0.01	-0.01	-0.01	-0.01	0.27	0.45	-0.47
+1	2023-2024	0.02	0.03	0.03	0.03	-0.56	0.02	0.88
−1	2023-2024	-0.02	-0.03	-0.03	-0.03	0.65	0.03	-0.84
		Total hours worked (yoy)						
+1	2023	0	0.03	0.02	-0.01	0.17	-0.04	-0.12
−1	2023	0	-0.03	-0.02	0.01	-0.16	0.04	0.13
+1	2024	0	0.02	0.03	0	0.16	0.04	-0.06
−1	2024	0	-0.02	-0.03	0	-0.16	-0.04	0.06
+1	2023-2024	0	0.05	0.04	-0.01	0.34	0.01	-0.17
−1	2023-2024	0	-0.05	-0.04	0.01	-0.31	0	0.19
		Investment (yoy)						
+1	2023	0	0.01	0.01	0	0.03	0.01	-0.03
−1	2023	0	-0.01	-0.01	0	-0.03	-0.01	0.03
+1	2024	0	0	0.01	0	0.01	0.02	-0.01
−1	2024	0	0	-0.01	0	-0.01	-0.02	0.01
+1	2023-2024	0	0.01	0.02	0	0.04	0.03	-0.04
−1	2023-2024	0	-0.01	-0.02	0	-0.04	-0.03	0.04
		Working-age population (yoy)						
+1	2023	-0.01	0.13	-0.03	0	0.05	-0.25	-0.13
−1	2023	0.01	-0.13	0.03	0	-0.05	0.25	0.13
+1	2024	-0.01	-0.03	0.13	-0.01	0.02	0.25	-0.25
−1	2024	0.01	0.03	-0.13	0.01	-0.02	-0.25	0.25
+1	2023-2024	-0.02	0.09	0.10	-0.01	0.07	0	-0.38
−1	2023-2024	0.02	-0.09	-0.10	0.01	-0.07	0	0.38
		Unemployment rate						
+0.5	2023	0	0	0	0	0.01	0.02	0.02
−0.5	2023	0	0	0	0	-0.02	-0.02	-0.02
+0.5	2024	0	0	0	0	0.02	0.03	0.03
−0.5	2024	0	0	0	0	-0.02	-0.03	-0.03
+0.5	2023-2024	0	0	0	0	0.03	0.05	0.04
−0.5	2023-2024	0	0	0	0	-0.04	-0.06	-0.05

Table 6: Sensitivity to an isolated shock (annual)

Shock		Potential output growth				Output gap		
Size in ppt	Year	2016-2022	2023	2024	2025-2031	2016-2022	2023	2024
		GDP (yoy)						
+1	2023	0.05	0.07	0.07	0.07	-0.19	0.56	0.49
−1	2023	-0.05	-0.08	-0.08	-0.08	0.18	-0.54	-0.46
+1	2024	0.04	0.07	0.08	0.08	-0.14	-0.37	0.53
−1	2024	-0.05	-0.09	-0.09	-0.09	0.13	0.39	-0.50
+1	2023-2024	0.08	0.13	0.14	0.14	-0.33	0.22	1.06
−1	2023-2024	-0.10	-0.19	-0.20	-0.20	0.31	-0.12	-0.91
		Total hours worked (yoy)						
+1	2023	0.01	0.08	0.06	-0.03	0.06	-0.10	-0.16
−1	2023	-0.01	-0.09	-0.07	0.03	-0.06	0.11	0.18
+1	2024	-0.01	0.06	0.08	-0.02	0.07	0	-0.08
−1	2024	0.01	-0.07	-0.08	0.01	-0.07	0.01	0.09
+1	2023-2024	0	0.13	0.13	-0.06	0.12	-0.09	-0.22
−1	2023-2024	0	-0.16	-0.16	0.03	-0.13	0.13	0.29
		Investment (yoy)						
+1	2023	0	0.03	0.04	-0.01	0.01	0	-0.04
−1	2023	0	-0.03	-0.04	0.01	-0.01	0	0.04
+1	2024	0	0	0.03	0	0	0.01	-0.02
−1	2024	0	0	-0.03	0	0	-0.01	0.02
+1	2023-2024	-0.01	0.02	0.07	-0.01	0.02	0.01	-0.06
−1	2023-2024	0.01	-0.02	-0.07	0.01	-0.02	-0.01	0.06
		Working-age population (yoy)						
+1	2023	-0.04	0.52	-0.11	-0.02	0.06	-0.25	-0.14
−1	2023	0.04	-0.52	0.12	0.02	-0.06	0.26	0.14
+1	2024	-0.02	-0.11	0.52	-0.04	0.02	0.25	-0.26
−1	2024	0.02	0.12	-0.52	0.04	-0.02	-0.25	0.26
+1	2023-2024	-0.06	0.40	0.40	-0.06	0.08	0	-0.4
−1	2023-2024	0.06	-0.40	-0.40	0.06	−0.08	0	0.4
		Unemployment rate						
+1	2023	0	0	0	0	0	0	0
−1	2023	0	0	0	0	−0.01	−0.01	0
+1	2024	0	0	0	0	0.02	0.02	0.02
−1	2024	0	0	0	0	−0.02	−0.03	−0.03
+1	2023-2024	0	0	0	0	0.02	0.03	0.02
−1	2023-2024	0	0	0	0	−0.03	−0.03	−0.03

is subsequently adjusted by forecasts of the GDP components and other macroeconomic variables. We therefore extend the sensitivity analysis to include a multivariate scenario that mimics the revisions in a typical short-term forecast.

4.2 Multivariate shock analysis

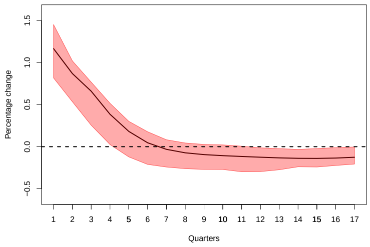
The multivariate scenario shows the typical joint adjustment of cyclical variables such as employment, average hours worked, investment, or the unemployment rate to a change in real GDP determined by the impulse responses of a quarterly VAR(2) model that includes the above variables (Figure 5). With the exception of the unemployment rate, the VAR is specified in terms of year-over-year growth rates. The lag structure is selected to minimize the BIC statistic, which balances the goodness of fit of a model against model complexity expressed by the number of parameters. The model is stable, and structural shocks are identified using the conventional Cholesky decomposition.

The shapes of the impulse responses have the expected signs. The bands around the impulse responses correspond to the 95 percent confidence level computed using a bootstrap method. Employment and investment growth increase by about 1 to 1.5 percentage points in the short run, while the effects on the average hours worked, and the unemployment rate are more moderate, so that the latter variables remain stable. All effects except that of the average hours worked are statistically significant at the 5 percent level. The results based on the shocks derived from the impulse responses imply that a one percent shock to real GDP growth increases potential output in the year of the shock (2023) by about 0.03 and the output gap by 0.57 percentage points. The corresponding annual figures are higher at 0.09 percentage points increase in potential output growth and 0.63 percentage points increase of the output gap. When averaged over the forecast horizon (2023-2024), the output gap widens by 0.88 percentage point in the case of the quarterly model and by 0.94 in the case of the annual model. The quarterly model implies smaller revisions to the output gap in the forecast sample (2023-2024) than the annual model, but larger revisions in the historical sample (2016-2022).

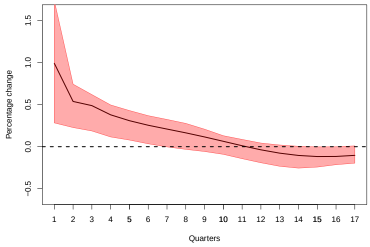
5 Discussion

In what follows we discuss the results from the point of view of a practitioner. The focus is on whether using the quarterly, the annual or rather both models in parallel. Furthermore, we discuss current (as of the time of writing this study) work on extensions

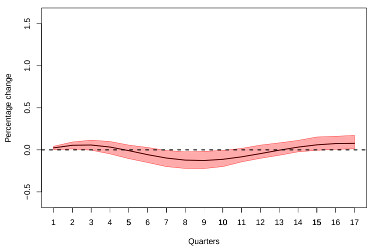
Figure 5: Impulse response of a VAR to a GDP shock (quarterly)



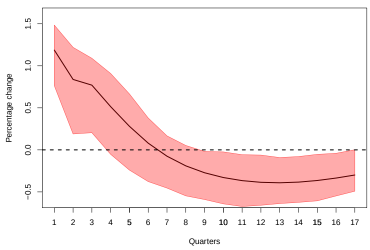
(a) Real GDP growth



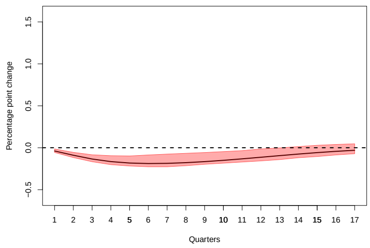
(b) Employment growth



(c) Average hours worked growth



(d) Investment growth



(e) Unemployment rate

The figure shows the impulse response of a quarterly VAR(2) to a 1 percentage point shock to real GDP growth. The bands correspond to a 95 percent confidence interval computed using a bootstrap.

Table 7: Multivarite sensitivity to a 1 ppt GDP shock

	2016-2022	2023	2024	2025-2031
GDP	0	1	0.74	0.13
Employment	0	0.85	0.46	0.23
Average hours worked	0	0.02	0.04	-0.04
Investment	0	1.02	0.72	0.14
Unemployment rate	0	-0.03	-0.08	-0.15
Potential output growth				
– Quarterly	0.01	0.03	0.03	0.01
– Annual	0.03	0.09	0.14	0.06
Output gap				
– Quarterly	-0.21	0.57	1.19	0
– Annual	-0.13	0.63	1.24	0

on the methodology put forth by the European Commission for computing the potential output and the output gap.

5.1 Using the annual or quarterly model? A contrasting juxtaposition

In the previous examination, both the quarterly and the annual models were found to be adequate for the purpose of producing plausible estimates of potential output and, hence, the output gap. Nevertheless, the results differ and the practical application of the two models varies. With this in mind, we will now take a closer look at this complex comparison. When deciding whether to use a quarterly or annual version of the model, there are compelling arguments on both sides:

Relative advantages of the quarterly version:

- More data and better precision: The quarterly data-set provides a greater volume of data, resulting in a more robust and therefore qualitatively better statistical estimation with greater precision of the parameters.
- Intra-year analysis: The quarterly version allows the examination of intra-year developments for key variables such as potential output and the output gap. This is particularly valuable when analysing episodes such as the Covid-19 outbreak, which are associated with significant intra-year fluctuations (especially in the second and

third quarters of 2020). Unlike the annual version of the model, the quarterly version allows these developments to be examined.

- Stability of estimates over time: Based on our sensitivity analysis, the estimates of the quarterly version of the model tend to be more stable towards the end of the forecast sample than the annual version.

Relative advantages of the annual version:

- Simplified input series: The annual version does not require separate quarterly forecasts for several input variables. This is particularly relevant for the forecast period for which the annual (growth rate) values (which are determined outside the model and are used as an exogenous input) have to be disaggregated to a quarterly path. The fact that different quarterly paths can produce the same annual growth rate is a common problem in this respect. In the context of an annual forecast, where all input series are available only at the annual frequency, this means that all input series, including population, capital stock, and hours worked, must be disaggregated to the quarterly frequency up to the end of the forecast horizon.

- Avoidance of seasonal adjustments: The annual version does not require a seasonal adjustment of the input series, thereby streamlining the modelling process. This is of particular advantage when correcting for "moving holidays" (for instance Easter holidays, etc.).

- Wider choice of models: Given our results from the model-selection exercise, the annual version offers a broader set of plausible models. This in turn increases the flexibility as regards the choice of the final model to be used.

- Simplicity of smoothing: There is no need for separate smoothing of the actual unemployment rate in the annual version, which however, is important when using the quarterly version of the model.

- Data stability: Results in the annual version tend to be more stable, as the annual System of National Accounts (SNA) data and the annual growth forecasts are subject to fewer revisions, both in terms of volume and frequency, than their quarterly counterparts.

- Comparison advantage: The EC predominantly uses the annual version, rendering it advantageous for comparison purposes and alignment with existing practices and the results from other countries.

The range of advantages and disadvantages associated with both the quarterly and annual versions of the model suggests that a practitioner faces trade-offs. Given the balance of advantages and disadvantages of each model relative to the other, it is therefore important to gain a better understanding and insight into the operation of each model. In this context, it is advisable to use both models in parallel. This approach allows to benefit from the strengths of each model and to gain a more rounded perspective on the data. It allows for a wider range of experiences and insights to be gathered, ultimately increasing the depth of analysis and decision making.

5.2 Current extensions of the model framework

There are, of course, many extensions possible and reasonable for improving the methodology for estimating the potential output. Given the plethora of possibilities in this context, the following will be confined to ideas, topics and existing extensions as discussed within the Output Gap Working Group (OGWG) Members of the European Commission.

5.2.1 The energy-environment nexus

The current methodology for estimating the potential output ignores the impact of the energy-environment nexus on the economy. Accounting for the impact of the energy transition on long-run output means considering two main impact channels. The first is the direct impact of decarbonising an economy's energy sources on the output trajectory, which, as pointed out by Pisani-Ferry (2021), is akin to a negative supply shock. The second is the positive impact of avoiding environmental damages on the economy. Many models that consider the economic impact of the energy transition use a production function with energy as an explicit factor of production. Hence, the current methodology by the European Commission for estimating the potential output can be readily extended in this respect. This is done, for instance in Guillemette (2022). In his set-up, carbon mitigation is assumed to impact potential output via the trend labour efficiency channel.

Conceptually, trend employment is unaffected as it measures the number of persons. Even if there are frictional employment losses due to sectoral reallocation and other economic dislocations, structurally the same number of people remain available for work.

Trend labour efficiency is negatively affected, because a higher relative price for energy (via carbon pricing or other means) leads firms to substitute labour and conventional capital for energy, reducing overall allocative efficiency. The impact on the economy's capital stock is ambiguous. On the one hand, the scrapping rate increases, at least temporarily, because capital goods that are still functional (power plants, petrol cars, etc.) must be retired before their natural end-of-life. On the other hand, rapid decarbonisation necessitates substantial investment in new (greener) capital, offsetting to some extent the higher scrapping rate for old (brown) capital. A successful transition could conceivably lead to little reduction in the aggregate capital stock.

The model proposed in Guillemette (2022) finds, in line with most other studies, that impacts on (potential) output from environmental damages are modest at best. The reason for this is that the cost of environmental degradation is derived from smooth (linear) damage functions relating global temperatures to economic output. In reality, these relationships are almost certainly not smooth. There are likely climate "tipping points" and where along the global average temperature continuum these discontinuities might occur remains highly uncertain (Lenton et al., 2019).

Other extensions in this context concern, for instance the modification of TFP by climate/environmental specific variables which affect economic activity adversely. This is considered, for instance in Hassler et al. (2016, 2018) and also elaborated on within the OGWG Members. The key idea is that the use of fossil energy causes carbon emissions (which can mathematically be described by a convex function). The extent of carbon emissions in turn cause global (mean) temperatures to rise (for which a concave relationship tends to prevail). Global (mean) temperatures are then modelled to enter TFP with a negative relationship, that is, higher global (mean) temperatures cause TFP to decline.

5.2.2 Stabilizing the TFP decomposition via asymmetric cycles

Upon examination by the European Commission (interim results of an on-going internal project), a consistent pattern of asymmetry emerges within the TFP cycle of nearly each EU member country. This observation prompts a thought-provoking research inquiry: Can the integration of this identified asymmetry within the TFP cycle effectively temper the need for substantial revisions during the TFP decomposition process? In this context, the asymmetry signifies situations where economic crises manifest as more pronounced troughs in the TFP cycle, outweighing the magnitude of the peaks.

To tackle this challenge, a cycle-asymmetric model is considered, which supplements the traditional economic cycle with a specialized mechanism engineered to capture these conspicuous troughs. The transitions between troughs and peaks adhere to a Markov-switching process, governing their dynamics. The methodology draws inspiration from the Kim and Nelson (1999) decomposition, with a notable innovation, that is, a secondary equation accounting for capacity utilization.

The analysis yields a noteworthy finding: The inclusion of the cycle-asymmetric model, as per the Kim and Nelson (1999) proposal, shows promise in bolstering the stability of the TFP decomposition during concurrent time periods for specific European Union countries. It is important to note, however, that this effect does not exhibit uniformity across all countries.

5.2.3 Fossil energy supply disruptions

The energy crisis of 2021/2022 has spurred the Output Gap Working Group (OGWG) to assess the credibility of potential output and output gap estimates in the aftermath of significant adverse supply-side shocks, especially adverse terms-of-trade shocks.

The OGWG employed an adapted version of the EC's methodology for potential output estimation, incorporating an energy component, next to the standard set-up. The inherent estimation challenges are notably heightened due to substantial downside risks. These risks stem from the macroeconomic repercussions of energy price surges, contingent on factors like substitution possibilities, storage conditions, and other variables related to unexpected demand fluctuations, all of which introduce considerable estimation uncertainty.

Nevertheless, the stylized model, when extended by energy considerations, generates plausible results. As regards, the modelling approaches for incorporating an energy component in the potential output methodology, the reader is referred to the references put forth in Section 5.2.1. Sensitivity analysis reveals that the adverse impact could be even more pronounced if substitution proves to be less feasible.

In light of these findings, the OGWG reached the conclusion that the current iteration of the EC's potential output estimation methodology yields reasonable results for both potential output and the output gap and the same applies for the extended model with energy. Consequently, there is no compelling need for further extensions beyond the incorporation of energy to being able to adequately account for of sudden spikes in fossil energy prices.

5.2.4 Labor supply, labor hoarding and further trends

During the Covid-19 period, a noteworthy observation emerged: in certain EU member states, as many as 45 percent of employees participated in short-term work schemes. This phenomenon led to a significant divergence between GDP fluctuations and employment dynamics, thereby weakening the applicability of Okun's law. Consequently, there were cascading repercussions on labor productivity and the hours worked per employee, both of which play pivotal roles in potential output estimation. This disconnection bears considerable implications for the assessment of potential output and the output gap.

Addressing this challenge necessitates the establishment of a dependable metric for labor hoarding (European Commission, Directorate - General for Economic and Financial Affairs, 2023), reflecting the degree of workforce utilization. The complexity arises from the fact that labor hoarding is inherently unobservable. To address this, the European Commission has introduced a labor hoarding index, derived from existing survey data sourced from the Joint Harmonised European Union Programme of Business and Consumer Surveys.

Preliminary findings (see Hristov, 2021, for instance) indicate that incorporating labor effort into the Phillips curve effectively compensates for labor effort fluctuations. Furthermore, the existing capacity utilization and the indirect labor hoarding (as examined) demonstrate similar information content and exert comparable effects on potential output and output gap estimates.

6 Summary and conclusions

In this study, we update the model selection put forward in Glocker and Kaniovski (2020) using the current quarterly and annual samples (1980-2024), check the consistency of the results with an estimation based on the pre-pandemic samples (1980-2019), and test the sensitivity of the optimal models to changes in the input time series and the output elasticity of labor (labor share) as an essential structural parameter.

The criteria for model selection build on prior experience and the recent literature. The most important criteria are the volatility and procyclicality of potential output growth and the persistence of trend TFP growth. The latter criterion is motivated by macroeconomic theory, in which technological progress follows a highly persistent but stationary autoregressive process. The model selection procedure looks for pairs of NAWRU and TFP trend models that produce stable and not overly procyclical estimates of potential growth and a highly consistent TFP trend. Further criteria include various regression diagnostics such as goodness-of-fit statistics. The similarity of the quarterly and annual estimates or the similarity of the new estimates and the current estimates is not relevant for model selection.

The optimal quarterly model produces estimates that are virtually identical to the estimates of the currently used model by SECO. We see minimal differences in the growth rate of the TFP trend and essentially identical estimates for potential output growth and the output gap. We can therefore confirm the current quarterly model. The estimates of the optimal quarterly model are stable under the shorter sample.

The best annual model produces slightly lower growth rates for the TFP trend and the potential output, as well as a smaller negative gap at the top of the (current) sample. The results of the best quarterly and annual models are quite similar. Even though more annual models from the set of all models pass the preliminary regression diagnosis, the best quarterly model produces less volatile and less procyclical estimates of the growth rate of potential output.

To assess the stability of the optimal models, we perform a sensitivity analysis of the estimates of potential output growth and the output gap with respect to revisions in economic data and outlook. Revisions in real GDP growth, the working-age population, and hours worked have the largest effects, whereas the effects of revisions in investment and unemployment rate are small. Quarterly estimates are less sensitive in the short term but more sensitive in the distant past, compared to their annual counterparts. In a multivariate scenario simulating typical data or forecast revisions obtained using the impulse-response of a quarterly VAR model, a one percent shock to real GDP growth increases potential output in the same year by 0.03 percentage points and the output gap by 0.57 percentage points. The corresponding annual figures are higher at 0.09 percentage points increase in potential output growth and 0.63 percentage points increase of the output gap.

The sensitivity analysis shows that the quarterly model is less sensitive in the current period (top of the sample) than the annual model, but more sensitive in a historical perspective. In other words, quarterly estimates are less prone to large revisions in the present and the near future, but more prone to large revisions in the more distant past. Estimates from the best quarterly model appear to be more stable than the best annual estimates in the more plausible multivariate scenario. Combined with the lower volatility and procyclicality of quarterly estimates relative to annual estimates, the higher stability of quarterly estimates in the current period, which is more relevant for business cycle forecasting and policy guidance than the distant past, suggest quarterly implementation over an annual one.

The assortment of benefits and drawbacks connected to both the quarterly and annual model versions implies that practitioners face trade-offs. Considering the interplay of pros and cons for each model in relation to the other, it is advantageous at this point to gain a deeper understanding of their functioning. In this regard, employing both models in parallel is recommended. This approach enables to leverage the strengths of each model and obtain a more comprehensive perspective on the results.

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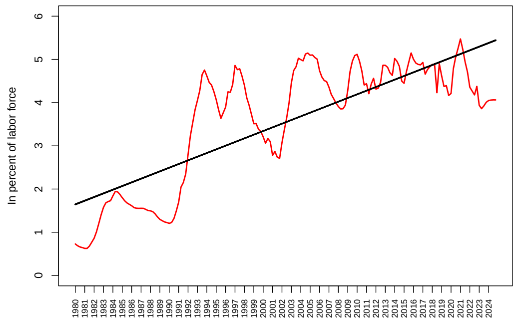
A List of NAWRU models

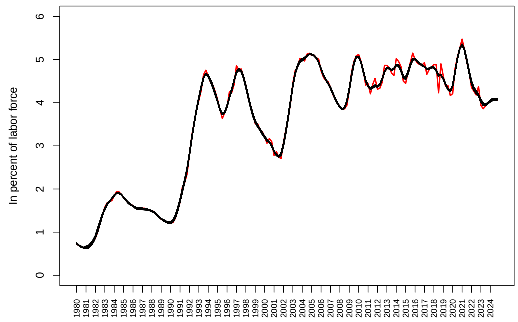
Table 8: List of NAWRU models

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**

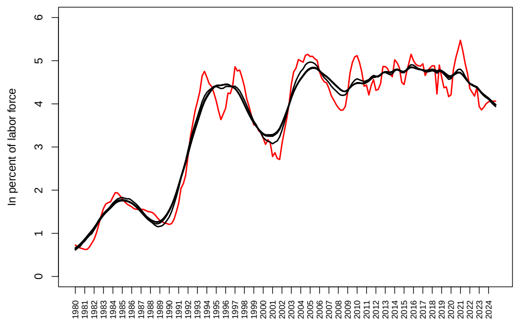
Figure 6: Taxonomy of NAWRU estimates (quarterly)



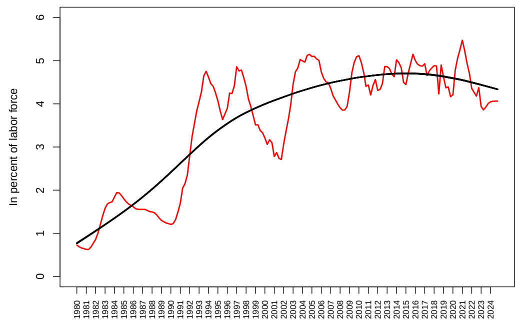
(a) Linear (78, 84, 88, 94, 100, 168)



(b) Actual (18 models)



(c) Ragged (129, 133, 137, 145, 149, 180)



(d) Smooth (102, 108, 114, 120, 123, 174)

The figure shows the types of quarterly NAWRU estimates. Linear trends and estimates close to the actual unemployment rate can be rejected a priori. Smooth estimates, such as those of the current quarterly NAWRU model No. 102, tend to be the most stable.

B List of TFP trend models

Table 9: List of TFP trend 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**
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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**
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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**
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47	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-1	**lagvar = 3**
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49	2nd order RW	**label = 2**	1	2	1	**ARord = 1 2 MAord = 1**	0-3	**lagvar = 5**
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54	Damped	**label = 3**	1	0	0	**ARord = 1 0 MAord = 0**	0-3	**lagvar = 5**
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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**
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63	Damped	**label = 3**	1	1	0	**ARord = 1 1 MAord = 0**	0-2	**lagvar = 4**

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Table9– *Continued from previous page*

No	Trend	*.nml	AR Cyc	AR CU	Error MA	*.nml	Cyc Lags CU	*.nml
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66	Damped	**label = 3**	1	1	1	**ARord = 1 1 MAord = 1**	0	**lagvar = 2**
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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**
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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**

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Table9– *Continued from previous page*

No	Trend	*.nml	AR Cyc	AR CU	Error MA	*.nml	Cyc Lags CU	*.nml
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**
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**
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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**

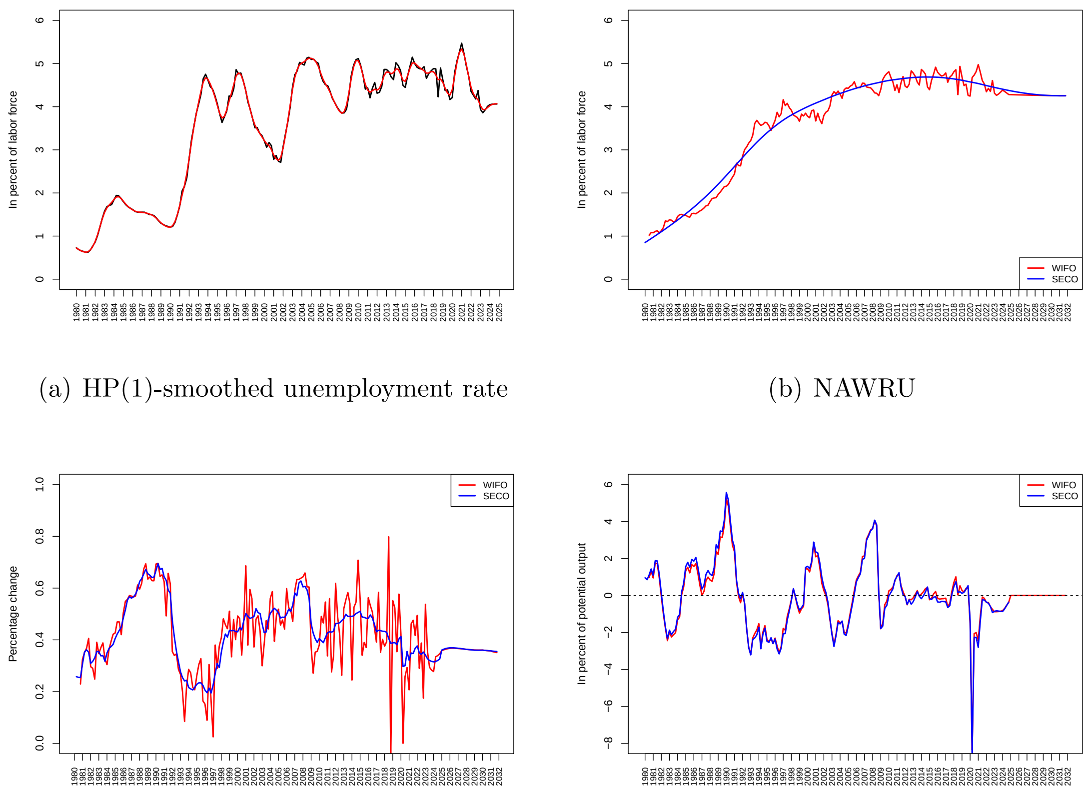
C Smoothing of quarterly unemployment rate

The current quarterly implementation uses a HP-filter with the parameter $\lambda = 1$ to smooth the quarterly time series for the unemployment rate as an input to the unobserved component model for the NAWRU. This low value of lambda smooths out the fluctuations in the unemployment rate, most pronounced between 2010 and 2020 (panel a) in Figure 7). Table 10 compares the optimal estimates according to the model selection criteria with the actual and smoothed unemployment rate. Using the actual unemployment rate produces excessively volatile and procyclical estimates of potential output growth and the output gap, as can be seen from panels c) and d) of Figure 7. While the fluctuations in the NAWRU (panel b) may not appear excessive they lead to implausibly noisy estimates of potential output growth. We therefore retain the smoothing of the quarterly unemployment rate in this study.

Table 10: Model selection with smoothed unemployment rate

	NAWRU	TFP	Potential output growth		NAWRU
	No.	No.	Volatility	Procyclicality	R^2
			Actual unemployment rate		
Most persistent					
– Least volatile	180	159	0.153	0.170	0.967
– Least procyclical	114	159	0.158	0.155	0.965
Least volatile	180	159	0.153	0.170	0.967
Least procyclical	114	152	0.161	0.146	0.965
			Smoothed unemployment rate		
Current	102	158	0.120	0.088	0.962
Most persistent					
– Least volatile	174	159	0.120	0.088	0.963
– Least procyclical	102	159	0.120	0.088	0.962
Least volatile	174	159	0.120	0.088	0.963
Least procyclical	102	152	0.123	0.078	0.962

Figure 7: Estimates based on unsmoothed unemployment rate



(a) HP(1)-smoothed unemployment rate

(b) NAWRU

(c) Potential output growth

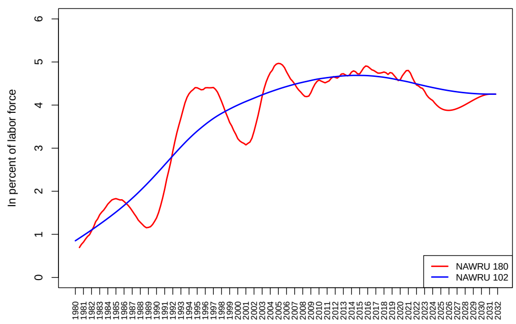
(d) Output gap

The current practice of smoothing the quarterly unemployment rate with an HP(1) filter before entering it into the unobserved component model for the NAWRU results in less volatile and less procyclical estimates of potential output growth.

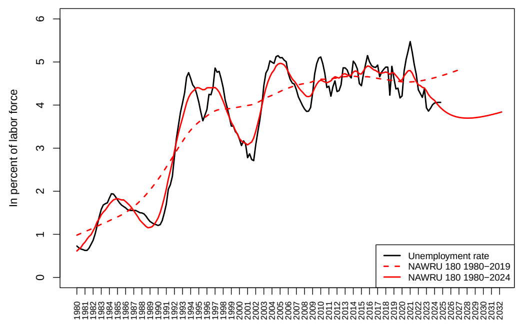
D The case of NAWRU model No. 180

The NAWRU 180 is not stable as its shape changes considerable with the choice of the sample. In other words, the estimate that would have been obtained using the pre-pandemic sample looks remarkable different from the estimate obtained using the same specification in the current sample. We therefore discard this NAWRU specification at both frequencies in favor of the NAWRU 114.

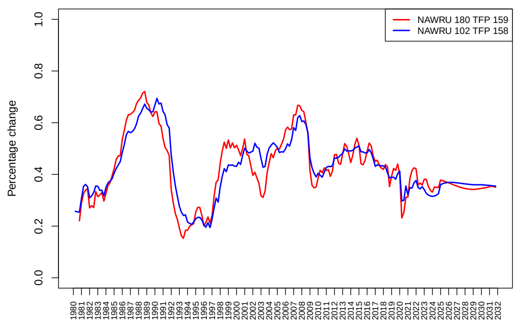
Figure 8: Example of an unstable NAWRU



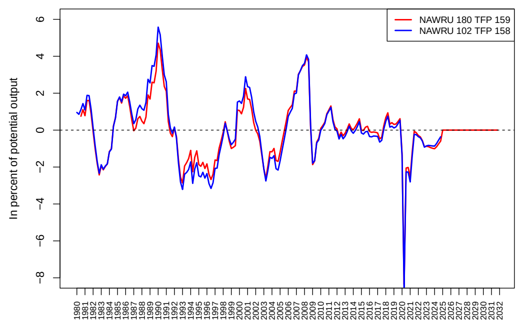
(a) NAWRU 180



(b) Unanchored NAWRU 180 is unstable



(c) Potential output growth



(d) Output gap

NAWRU 180 appears adequate in the 1980-2019 sample, but changes significantly when the 1980-2024 sample is used.

E Extension till 2031

In this section, we summarize the medium-term extension of the potential output estimate. The production function combines the estimates of the TFP trend and the NAWRU with the working-age population, the capital stock and the trends in the participation rate and average hours worked. The estimation sample includes the current short-term forecast for the years 2023 and 2024. The short-term forecast includes all the additional variables necessary to compute potential output. It uses a population scenario and features the participation rate and average working hours to be smoothed using univariate filters. It also includes investment to update the capital stock using the perpetual inventory method. Extending the estimates beyond the estimation sample requires assumptions on the TFP and the quantities of factor inputs. This section provides a brief overview of how potential output estimates are extended beyond the estimation sample.

The unobserved components models provide an out-of-sample forecast of the TFP trend and the NAWRU. The forecast of the TFP trend is unconstrained. The forecast of the NAWRU as equilibrium unemployment rate assumes convergence to a certain value (anchor) in 2031. This long-term anchor is determined by structural and non-structural factors and labor market institutions (Orlandi, 2012). The structural factors are related to the determinants of the reservation wage and labor market frictions. These include unemployment benefit rates, the tax wage and spending on active labor market policies to reduce search costs. Institutional determinants include trade-union density as an indicator of collective bargaining power. These structural and institutional factors influence the matching probability or the chances of the unemployed to find a job. Non-structural factors that may affect the equilibrium unemployment rate include TFP growth, the real interest rate, and the weight of the construction sector in total employment as a persistent cyclical factor.

The anchor value is derived from the coefficients of a panel regression model, whereby the nonstructural variables are averaged over the sample to remove their cyclical variation and the structural and institutional variables are held at their current values (no policy-change assumption). The current anchor estimate for Switzerland equals 4.254, which is slightly below the current unemployment rate of 4.3 but above the value of 4.1 for 2024 in the current short-term forecast. A detailed discussion of the anchor estimate for Switzerland can be found in Glocker and Kaniovski (2020).

The medium-term extension assumes that both the output gap (the difference between the actual output and the potential output) and the employment gap (the difference between the actual unemployment rate and the NAWRU) close between $t = 3$ and $t = 5$ (i.e., currently in 2027). In the following years, the unemployment rate converges to an anchor. Hristov et al. (2017) recommend $t + 10$ as a convergence horizon for the NAWRU to its anchor. The convergence path is smooth but nonlinear (Planas and Rossi, 2020). It retroactively affects the estimates of potential output and the output gap in the past (Glocker and Kaniovski, 2020). This feature makes it impossible to compare anchored NAWRU estimates between two distant samples, e.g., between the pre-pandemic sample ending in 2019 and the current sample ending in 2024. The estimated anchor values can differ and their magnitude relative to the current actual unemployment rates has a considerable effect on the out-of-sample convergence path as well as the historic path. Therefore, we use unanchored NAWRU in model selection.

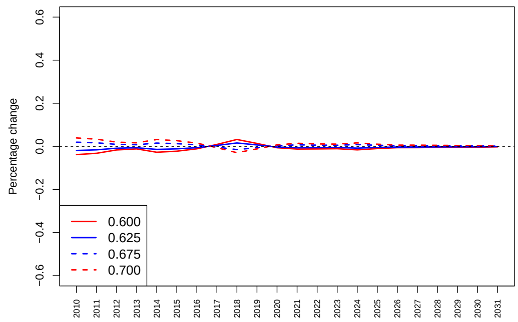
Extensions of the potential output estimates require extensions of the capital stock. Here we may assume a ratio of real investment expenditure to potential output to forecast the capital stock according to the perpetual inventory method, or alternative fix capital-to-output ratio.[6] The current extension assumes a linear convergence of the capital to potential output ratio to the long-term value of 1.56.

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. In conjunction with a forecast for the level of potential output, the assumption about the closure of the output gap determines the level of actual output (real GDP) during the transition period.

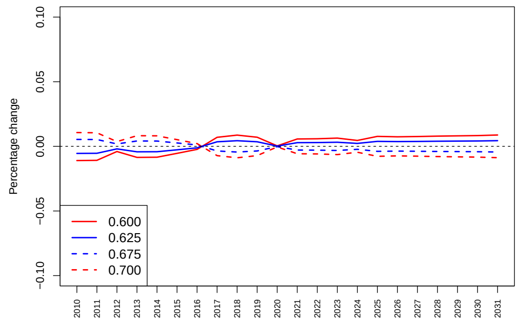
[6] Detailed descriptions of these rules can be found in Havik et al. (2014) and Hristov et al. (2017).

F Sensitivity of potential output growth

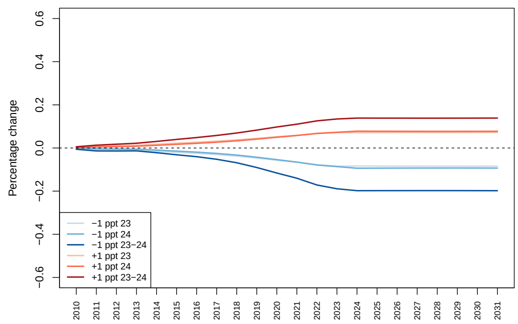
Figure 9: Sensitivity of potential output growth (output elasticity of labor, GDP)



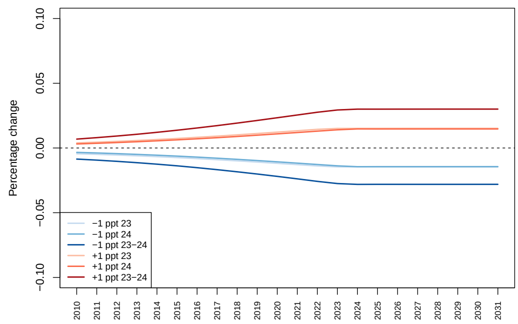
(a) Output elasticity α (annual)



(b) Output elasticity α (quarterly)

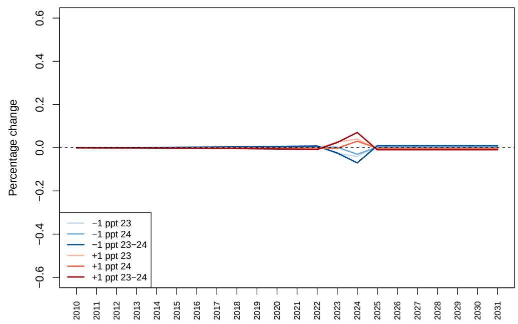


(c) GDP (annual)

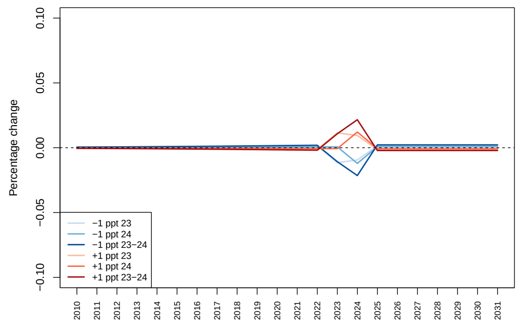


(d) GDP (quarterly)

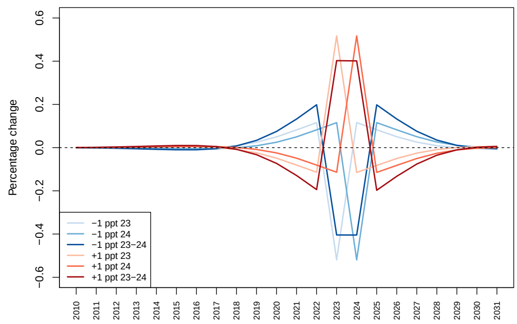
Figure 10: Sensitivity of potential output growth (investment, population)



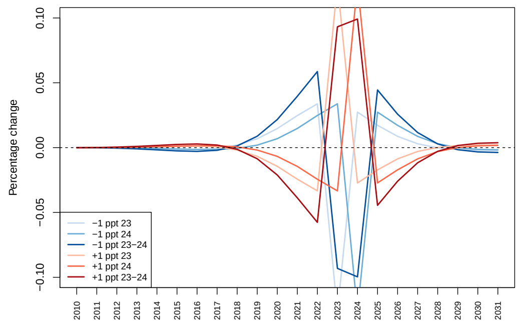
(a) Investment (annual)



(b) Investment (quarterly)

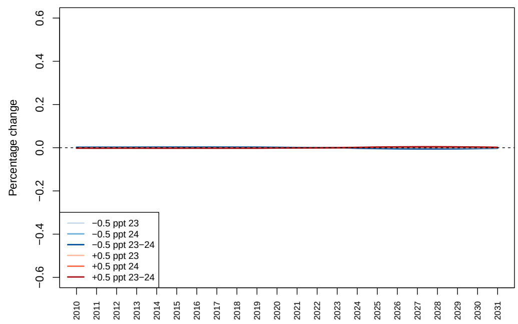


(c) Population (annual)

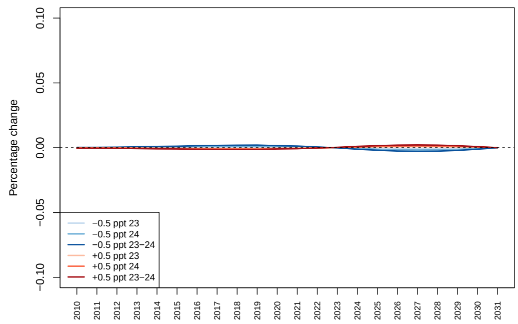


(d) Population (quarterly)

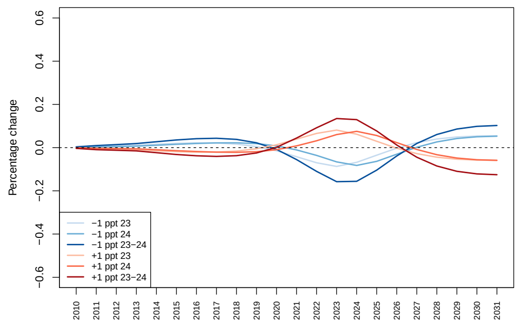
Figure 11: Sensitivity of potential output growth (unemployment, hours worked)



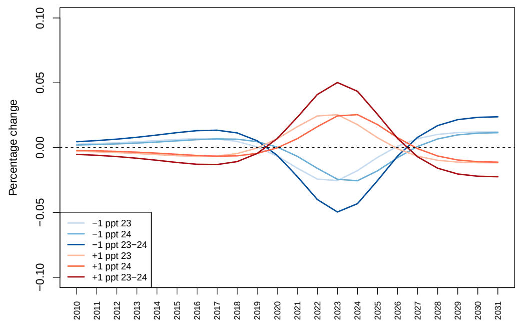
(a) Unemployment (annual)



(b) Unemployment (quarterly)



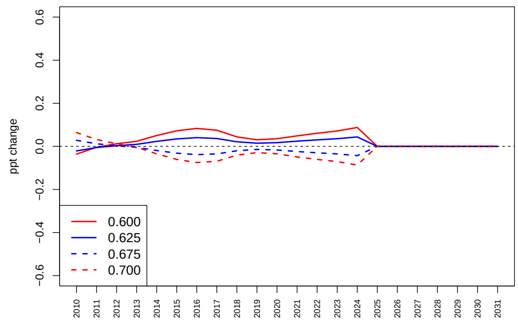
(c) Hours worked (annual)



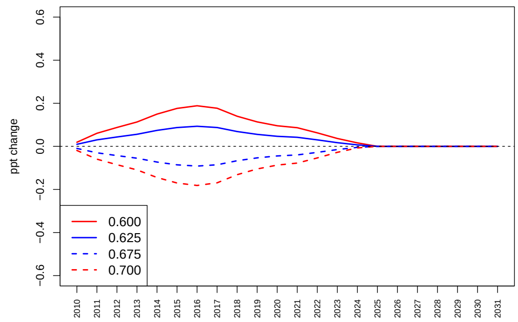
(d) Hours worked (quarterly)

G Sensitivity of output gap

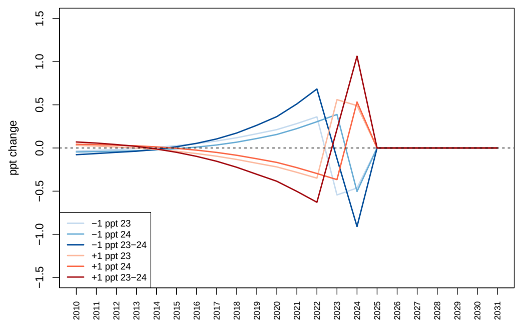
Figure 12: Sensitivity of output gap (output elasticity of labor, GDP)



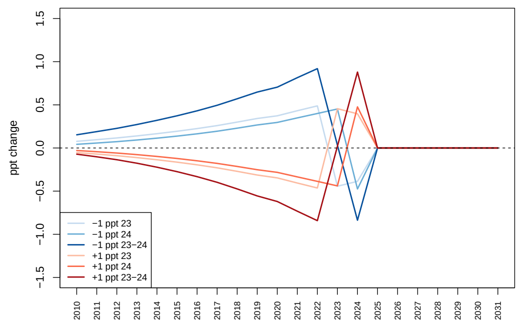
(a) Output elasticity of labor α (annual)



(b) Output elasticity of labor α (quarterly)

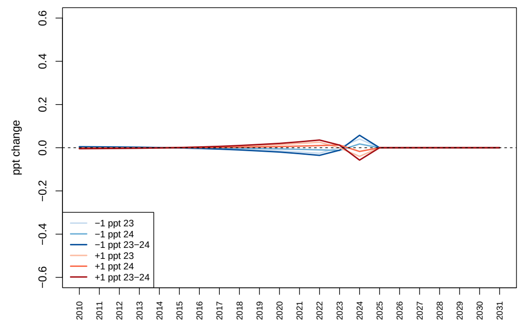


(c) GDP (annual)

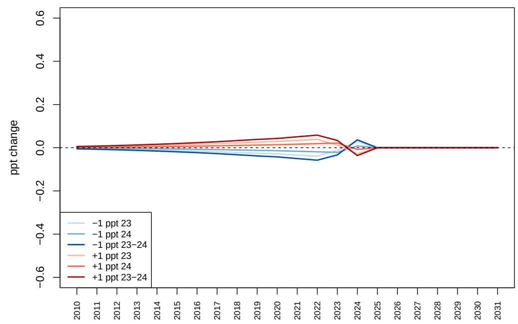


(d) GDP (quarterly)

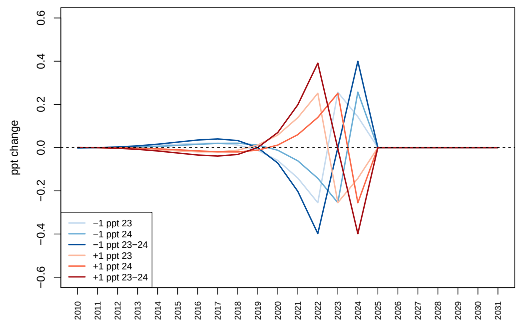
Figure 13: Sensitivity of output gap (investment, population)



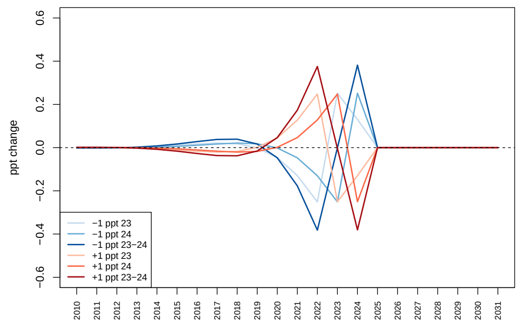
(a) Investment (annual)



(b) Investment (quarterly)

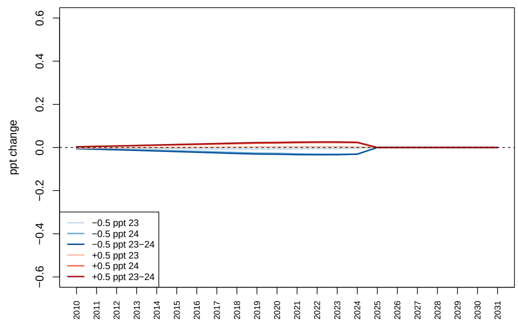


(c) Population (annual)

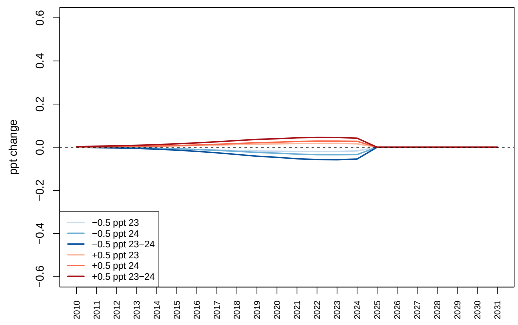


(d) Population (quarterly)

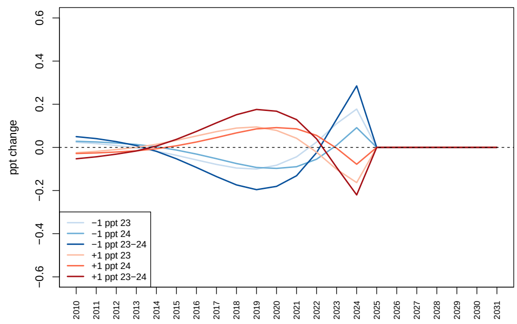
Figure 14: Sensitivity of output gap (unemployment, hours worked)



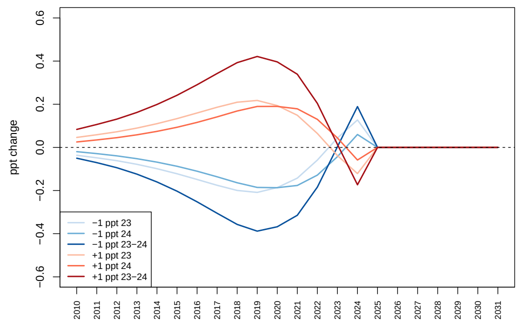
(a) Unemployment (annual)



(b) Unemployment (quarterly)



(c) Hours worked (annual)



(d) Hours worked (quarterly)