Estimating a Weighted Output Gap for Switzerland: Methodology and Application*

Christian Glocker** Serguei Kaniovski*** Philipp Wegmüller§

July 28, 2026

Abstract

This paper introduces a novel weighted output gap measure for Switzerland, combining estimates from univariate filters, multivariate filters, and production function approaches. Published quarterly by SECO since 2019:Q4, the weighted output gap measure demonstrates significant advantages, including robustness, historical consistency, and superior predictive power for future inflation. Using a rigorous inflation forecasting framework, we show that the weighted output gap outperforms alternative methodologies in terms of Granger causality and achieves competitive mean absolute error (MAE) values. These findings emphasize the practical utility of the weighted output gap for business cycle analysis and forecasting, making it a valuable tool for researchers and policymakers alike.

JEL class: E24, E32, E37

Keywords: Output gap, Inflation, Business cycle, Switzerland, Revisions, Forecasting

*We wish to thank Felicitas Kemeny for support. Thanks also go to Sarah Fischer, Caroline Schmidt, Stefan Neuwirth and Samuel Schmassmann for valuable discussions and comments. We are grateful for fruitful inputs and discussions with colleagues at the SNB, KOF, FDF and FSO as well as with participants at the 6th Workshop of the Swiss Network on Public Economics (SNoPE) meeting. The views, opinions, findings, and conclusions or recommendations expressed in this paper are strictly those of the authors. They do not necessarily reflect the views of the State Secretariat for Economic Affairs (SECO). SECO does not take responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper.

**Austrian Institute of Research, Arsenal Objekt 20, 1030 Vienna, Austria. christian.glocker@wifo.ac.at

***Austrian Institute of Research, Arsenal, Object 20, 1030 Vienna, Austria. serguei.kaniovski@wifo.ac.at

§Corresponding author: State Secretariat for Economic Affairs, Short Term Economic Analyses, Holzikofenweg 36, 3003 Bern, Switzerland. philipp.wegmueller@seco.admin.ch

1 Introduction

Is the Swiss economy expanding or contracting? Does overall economic activity correspond to normal utilization of production capacities, or are these over- or underutilized? The answers to these questions are crucial for economic policymakers, guiding both the assessment of current conditions and the direction of economic policy. Key insights can be derived from potential output estimates and the corresponding output gap, which provide a basis for analyzing economic performance and business cycle dynamics.

Understanding an economy's position in the business cycle is vital for informed policy decisions, as it reflects the use of available production capacities. The output gap is a critical indicator for monetary policy and helps to assess and forecast inflationary pressures. It is also integral to fiscal policy, particularly in calculating structural annual budget balances. For instance, a negative output gap suggests underutilized resources, warranting above-average growth to improve capacity utilization, while a significantly positive gap signals potential overheating, risking inflationary pressures. Thus, potential output and the output gap are central to economic analysis and policy formulation.

Since December 2019, the Swiss State Secretariat for Economic Affairs (SECO) has been publishing quarterly time series on potential growth and the output gap of the Swiss economy from 1980 onward.[1] In this paper, we describe the data and methodology behind SECO's weighted output gap measure and demonstrate its applications in economic analysis and forecasting through two use cases.

Methodology. Estimating the output gap of an economy presents significant challenges. Unlike actual output, potential output cannot be observed or measured directly and must be inferred through estimation. Consequently, a wide range of methodologies has been developed in the academic literature to estimate potential output.[2] These methods aim to decompose aggregate output into a trend component, representing potential output, and a cyclical component, representing the output gap.

Two broad classes of methods dominate this field: purely statistical approaches and those based on economic theory. Statistical methods include simple linear trends, the Hodrick-

[1]See https://www.seco.admin.ch/potenzialwachstum Additionally, SECO publishes separately data produced using the methodology of the European Commission, allowing comparisons and consistency with broader European economic analyses. See https://www.seco.admin.ch/dam/seco/de/dokumente/Wirtschaft/Wirtschaftspolitik/Wachstum/mfs_inputs.xlsx.download.xlsx/mfs_inputs.xlsx for the inputs and https://www.seco.admin.ch/dam/seco/de/dokumente/Wirtschaft/Wirtschaftspolitik/Wachstum/mfs.xlsx.download.xlsx/mfs.xlsx for the estimated medium-term development of the potential output and the output gap according to the methodology of the European Commission. Contrary to the in-sample weighted output gap presented here, the one following the methodology of the European Commission aims to predict potential output growth in the medium term and thus includes economic forecasts.

[2]See for instance Álvarez and Gómez-Loscos (2018), Kiley (2013), Ladiray et al. (2003), Dupasquier et al. (1999) or Giorno et al. (1995) for surveys on methodologies for estimating potential output and the output gap.

Prescott filter, and various unobservable component techniques that rely on time series properties to separate long-term trends from short-term fluctuations. In contrast, theory-based approaches, such as the production function method, estimate potential output by explicitly modeling relationships between labor, capital, and productivity.

Given that potential output cannot be directly measured, even retrospectively, comparing the accuracy of different methods is inherently challenging. SECO addresses this issue by employing a comprehensive strategy that integrates 13 different methodologies: seven univariate filters, four multivariate unobserved components models, and two production functions. Each approach is designed to produce plausible quarterly series for potential growth and the output gap, satisfying key statistical properties. These individual results are then weighted and averaged to form a consolidated time series for potential growth and the output gap. All calculations are based on officially available real GDP data starting from 1980, measured at quarterly frequency.

Several other institutions also publish output gap estimates for Switzerland. For instance, the Swiss National Bank (SNB) provides quarterly estimates using the Hodrick-Prescott filter, a multivariate unobserved components model, and a production function approach. These estimates are released approximately 75 days after the reference quarter, alongside the monetary policy assessment.[3] Similarly, the Organization for Economic Co-operation and Development (OECD) releases twice-yearly estimates based on a production function approach, available at annual frequency.[4] The KOF Swiss Economic Institute at ETH Zurich also applies the European Commission's production function methodology to estimate annual output gap values, updated quarterly.[5]

Despite the contributions of these institutions, SECO's estimate stands out for its comprehensiveness and timeliness. By integrating a broad range of methodologies, the weighted output measure reduces dependency on any single model, enhancing robustness and reliability. Furthermore, SECO publishes its estimates approximately 60 to 75 days after the reference quarter. This makes it the only timely and regularly available quarterly measure of economic slack for Switzerland, offering policymakers and analysts a unique tool for monitoring the business cycle.

We examine the revision properties of the Swiss output gap measure in real time. Estimating potential output and the output gap is inherently challenging due to the reliance on revised GDP data and the sensitivity of estimation techniques to updated information. The weighted output gap, by aggregating multiple methods, is hypothesized to be less prone to substantial revisions compared to individual methods. To investigate this, we analyze the

[3]See https://data.snb.ch/de/topics/snb/chart/snbprodluch.

[4]See https://www.oecd.org/en/topics/economic-outlook.html.

[5]See https://kof.ethz.ch/en/forecasts-and-indicators/forecasts/kof-economic-forecast.html.

revision properties of each methodology using both real-time GDP data and final vintage data. This allows us to evaluate how well the weighted output gap performs in terms of stability and reliability under practical conditions.

We find that the weighted output gap demonstrates remarkable stability and robustness in real-time settings. Compared to individual methodologies, the weighted measure has a higher correlation with ex-post estimates and exhibits lower mean absolute revisions. Additionally, the weighted measure is less prone to sign changes in real-time estimates, with only 6% of simulated quarters showing a deviation in sign compared to the final estimate. This is a key advantage for policymakers, as it ensures consistency in the assessment of economic slack. While individual methods, such as the Beveridge-Nelson decomposition, excel in specific metrics like low mean absolute revisions, the weighted output gap balances these strengths by construction, offering a more comprehensive and reliable measure. The weighted measure's lower sensitivity to data revisions underscores its robustness, making it a superior tool for economic policy planning.

Related Literature. The estimation of the output gap in Switzerland has been the focus of several studies. Fischer et al. (2024) present a quarterly estimation of the Swiss potential output, utilizing the production function methodology developed by the European Commission. Their approach estimates the trend of total factor productivity and the natural rate of unemployment using unobserved component models. This study is closely aligned with the present analysis, as its methodology forms the basis of one of the two production functions incorporated into SECO's weighted output gap measure.

In addition to this, SECO has contributed significantly to the field with numerous discussion papers exploring various aspects of the output gap and its policy implications. For instance, Glocker and Kaniovski (2020a) provide a comprehensive estimation of a quarterly potential output series for Switzerland. Stalder (2020a) compare production function approaches and filtering techniques, offering a critical evaluation of their performance in the Swiss context. Stalder (2020c) delve into the theoretical foundations and applications of univariate and multivariate filter methods, while Stalder (2020b) present an estimation and forecasting framework for potential output based on a production function approach. Further, Glocker and Kaniovski (2020b) apply the European Commission's methodology to Switzerland, offering a harmonized perspective on potential output estimation. Finally, Glocker and Kaniovski (2024) contribute a detailed sensitivity analysis and comparison of methods for estimating potential output, emphasizing the robustness of the results.

Beyond these contributions, additional studies have examined the broader dynamics of Switzerland's output gap. Leist (2013) identify the primary drivers of the Swiss output gap, employing a New Keynesian small open economy model to emphasize the role of foreign shocks in cyclical fluctuations. Similarly, Leist and Neusser (2010) use a DSGE model and Bayesian econometrics to estimate Switzerland's natural output level, comparing their findings with alternative measures of the output gap. In a related study, Bignasca and Rossi (2007) apply a multivariate filter to Swiss data, estimating potential output and investigating the effects of exchange rate pass-through on inflation. Together, these works enhance the understanding of Switzerland's cyclical dynamics and provide a rich foundation for the present analysis.

Use case. The applications of the output gap are diverse and significant. One primary application is in economic policy analysis. Policymakers use the output gap to gauge the overall health of the economy and to decide on appropriate economic policies. For instance, a large negative output gap might prompt expansionary policies to stimulate growth, while a positive gap could lead to contractionary measures to cool down the economy. Another crucial application is in economic forecasting. The output gap is a vital input in forecasting models that predict future economic performance. By understanding the current state of the economy relative to its potential, analysts can make more accurate predictions about future growth, inflation, and unemployment.

In this use case, we focus on the predictive capabilities of the proposed weighted output gap measure, particularly its relationship to future inflation in Switzerland. Using the theoretical framework of the New Keynesian Phillips curve, we assess whether inflation forecasts improve when incorporating the weighted output gap compared to its individual components.[6] This analysis sheds light on the practical relevance of the weighted output gap for economic policy, particularly for inflation-targeting central banks.

The objective is not to conduct a comprehensive comparison or "horse race" of inflation forecasting models, but to assess the relative predictive power of the output gap estimates. By focusing on their explanatory power, the analysis provides insights into how well the weighted measure captures inflationary pressures relative to its individual components.

The results reveal that the weighted output gap shows a decent forecasting ability, particularly over longer horizons and for specific inflation measures, as for instance, the producer price index (PPI). These findings highlight the importance of considering both statistical and theoretical perspectives when selecting output gap measures for inflation forecasting.

Moreover, the weighted output gap demonstrates greater robustness and stability compared to individual methods. Many estimation approaches are prone to endpoint instability due to their reliance on two-sided filters, and frequent GDP revisions in Switzerland can further complicate forecast evaluations.[7] The weighted output gap mitigates these issues by

[6] Jarociński and Lenza (2018) perform a similar analysis for the Euro area, focusing on unobserved components models akin to the multivariate filter suggested by the IMF (Blagrave et al., 2015).

[7] For evidence on GDP revision effects in the US, see **?** and Orphanides (2001). For Swiss-specific evidence,

combining diverse methodologies, reducing sensitivity to model-specific weaknesses and data revisions. This makes it a more reliable tool for policymakers who rely on real-time estimates for decision-making.

The rest of the paper is structured as follows: In Section 2 we present the methodology applied and the data used to estimate potential output and the weighted output gap. Section 3 presents the weighted output gap measure along with a discussion on its sensitivity. In Section 4, we illustrate a use case for the new metric. Section 5 concludes.

2 Data and Methodology

The estimation of potential growth and the output gap is central to macroeconomic analysis and policy formulation. These variables are latent and cannot be observed directly, necessitating the use of econometric methods for their estimation. The Swiss State Secretariat for Economic Affairs (SECO) applies a multi-method approach to produce robust quarterly series of the output gap and potential growth, starting from 1980. This section outlines the data used for estimation, the methodologies employed, as well as the consolidation process.

2.1 Data

Swiss quarterly GDP is available since 1980. In order to provide estimates for potential output and the output gaps since 1980, we need to construct the input series. Where available, quarterly data are drawn directly from their original sources such as GDP from SECO or employment from FSO.[8] Nevertheless, in their original sources both the labor input and the capital stock are only available at an annual frequency, in both cases starting later than 1980. Moreover, prior to 1990 the availability of quarterly data with respect to the labor market is rather scarce in the case of Switzerland. Therefore, we have put particular emphasis in constructing proper quarterly series for capital and labor spanning as far back as possible. Additional data, e.g. the measure of aggregate capacity utilization (KOF) or CPI inflation (FSO), are drawn from national sources. The appendix provides a list of variables required for estimating the potential output (see Appendix A.1).[9]

see Indergand and Leist (2014).

[8] FSO: Federal statistics office. If not stated otherwise, we use the real, seasonally, calendar and sport event adjusted GDP as of 2023:Q3. For more information on the importance of sport related events in GDP and their adjustment consider https://www.seco.admin.ch/gdp.

[9] For more information on the specific details how the data is constructed see Fischer et al. (2024).

2.2 Methodological Framework

The output gap, y_t, is defined as the percentage deviation of actual output (Y_t) from potential output (Y_t^*):

$$y_t = \frac{Y_t - Y_t^*}{Y_t^*} \times 100. \tag{2.1}$$

Various classes of empirical methods have been developed to determine production potential and the output gap. These differ mainly in their econometric and structural complexity.

A brief survey

Univariate methods rely solely on information contained in real GDP. The simplest approach in this category is a deterministic linear trend, which was widely used until the early 1970s. Over time, increasingly sophisticated empirical methods were developed. Following the influential work of Nelson and Plosser (1982), many methods have been proposed to decompose real GDP into a stochastic permanent component and a transitory component, thereby accounting for variations in potential growth over time.

A prominent example is the widely used Hodrick-Prescott filter, which estimates potential growth more flexibly than a linear trend but remains a highly mechanical approach.[10] One drawback of these two-sided filters is their pronounced instability at the sample edges (Stalder, 2020c). Additional time-series econometric methods, such as unobserved components models proposed by Watson (1986), Harvey and Stock (1989), and Clark (1989), or the Beveridge-Nelson decomposition (Miller, 1988), have since been developed. Modern techniques like spectral analysis (Golyandina et al., 2001) have further enhanced the sophistication of these methods.[11]

A major limitation of univariate filter methods is their lack of substantive economic interpretation for the dynamics of permanent and transitory components (Stalder, 2020a). Additionally, they lack structural connections to key economic variables such as inflation and employment, which are essential for defining potential output.

In response to these criticisms, multivariate extensions of unobserved components models (Watson, 1986) have been proposed. These methods allow for a degree of structural interpretation by incorporating relationships between observable variables. For example, they utilize empirical relationships like Okun's Law (linking output and unemployment) or the Phillips Curve (linking unemployment and inflation). Adding observable variables not only enriches the structural foundation of the models but also stabilizes the estimates. An

[10] A technical description is given in Appendix A.2.2. Other mechanical filters similar to the Hodrick-Prescott filter include the Hamilton filter (Hamilton, 2018), the Baxter-King bandpass filter (Baxter and King, 1999), and the Christiano-Fitzgerald filter (Christiano and Fitzgerald, 2003).

[11] See also the modern version of the Beveridge-Nelson decomposition by Kamber et al. (2018).

overview of such methods is provided in Stalder (2020c). The technical description can be found in the Appendix A.2.8.

A third class of methods relies on structural approaches based on theoretical models. One prominent example is the production function, which links GDP to inputs such as labor, capital, and productivity. In its simplest form, this approach employs a Cobb-Douglas production function, which is defined as:

$$Y_t = TFP_t \times L_t^{\alpha} \times K_t^{1-\alpha}, \tag{2.2}$$

where Y_t is GDP, TFP_t is the Solow residual, L_t is the labor input, and K_t is the capital input. Potential output is estimated by applying this function to potential paths for the input factors. For labor, the potential path assumes no inflationary or wage pressures, while for capital, it assumes an average utilization rate.

A more advanced version of the production function approach was developed by the European Commission and is applied across all EU member states. This methodology emerged from the Stability and Growth Pact and has become central to fiscal oversight and evaluating structural reforms in the European Union. In its core, this methodology features estimates of the trend in total factor productivity (TFP) and the natural rate of unemployment (NAWRU) obtained by applying the Kalman filter to unobserved component models. Fischer et al. (2024) applied this approach to Switzerland, adapting it to quarterly frequency.[12]

Beyond the scope of this work, but also worth mentioning are other approaches like the Blanchard-Quah decomposition based on a VAR-specification (Blanchard and Quah, 1989), dynamic stochastic general equilibrium (DSGE) models or macroeconomic structural models. These alternative approaches are often prone to uncertainties in parameter estimation and data quality (Basu and Fernald, 2009). While they feature specific advantages based on the use case, e.g., shock decomposition, data calibration, micro-foundations, for the present case they are not particularly well suited due to their complexity and use of timely resources.

Methods applied

As potential growth cannot be directly measured, even retrospectively, it is challenging to definitively evaluate the results of one estimation method over another. To address this, SECO employs a broad range of approaches that produce plausible quarterly series for potential growth and the output gap, starting in 1980. These approaches are selected to ensure acceptable statistical properties. The results of all methods are averaged to construct consolidated time series for potential output and the output gap.

[12] Glocker and Kaniovski (2020b,a) provide further evidence on the working and robustness of the output gap derived by the method of the European commission.

Table 1: Estimation Methods Used

Method	Specification	Source
Univariate filters		
Linear Trend		
HP Filter	$\lambda = 1600$	Cogley and Nason (1995)
Modified HP Filter	$\lambda = 1600$	Bruchez (2003)
Christiano-Fitzgerald Filter	Oscillation between 2 and 40 quarters	Christiano and Fitzgerald (2003)
Advanced Beveridge-Nelson	Automatic window selection	Kamber et al. (2018)
Hamilton Filter	$h = 8$ and $p = 4$	Hamilton (2018)
Singular Spectral Analysis	5-year window	Golyandina et al. (2001)
Multivariate filters		
SSD	Capacity utilization (KOF)	Alichi (2015)
SSU	Smoothed ILO unemployment rate	
SSP	Inflation (GDP deflator)	
SSDUP	All three variables	
Production function approaches		
Classical Approach	Least-squares estimation	Proietti et al. (2007)
EC Methodology	Unobserved Components	Havik et al. (2014)

Currently, 13 methods are employed: seven univariate filters, four multivariate filters, and two production function approaches (see Table 1). The univariate filters include a linear trend, an HP filter, a modified HP filter, the Christiano-Fitzgerald filter, the advanced Beveridge-Nelson decomposition, the Hamilton filter, and a spectral analysis filter. Some comments on the different methods are in order: The sole smoothing parameter of the HP-filter is set at $\lambda = 1600$ as it is standard in the literature. The CF-filter is a bandpass filter. It can suppress both the low frequency trend components and the high frequency cycle components. The parameters of the CF-filter are set at their recommended values for quarterly data: $p_l = 2$ and $p_h = 40$. Hamilton (2018) advocates the use of regression analysis instead of the HP-filter. The HAM-filter is specified by a linear model on a univariate time series shifted ahead by h periods, regressed against a series of variables constructed from varying lags of the series by some number of periods, p. We follow the recommendations and set $h = 8$ and $p = 4$. The specifications of the multivariate filters and the classical production function approach follow Stalder (2020b,c). The production function approach of the European Commission is described at length in Fischer et al. (2024). All methods are explained further in the Appendix A.2.

The selection of methods is based on a wide range of descriptive statistics and statistical tests. This enables retrospective evaluation of the methods using various statistical metrics (Marcellino and Musso, 2011). Alternatively, the forecast accuracy of the output gap concerning a target variable, such as inflation, can be analyzed. Detailed analyses of the revision properties and forecast accuracy of the filter methods and production function approaches can be found in Stalder (2020a,b,c) and Glocker and Kaniovski (2020a,b). Finally, the resulting output gap is evaluated in its historical context and validated against other data sources. The range of methods is regularly reviewed and, if necessary, expanded or adapted.[13]

Table 2: Descriptive Statistics
Calculations based on quarterly data from 1980Q1 to 2024Q3.

	Potential Growth						Output Gap				
	Mean	Min	Max	Std	Pers	Corr	Mean	Min	Max	Std	Pers
Weighted average	1.80	0.56	2.73	0.48	0.98	0.41	0.04	-7.94	4.60	1.51	0.80
Univariate filters											
Linear trend	1.79	1.79	1.79	0.00	-0.01	-0.08	0.00	-7.98	6.73	2.18	0.90
HP-filter	1.80	0.49	2.79	0.53	0.99	0.50	0.03	-7.93	3.48	1.37	0.76
Modified HP-filter	1.81	0.49	2.79	0.53	0.99	0.50	0.02	-7.92	3.48	1.37	0.76
Christiano-Fitzgerald-filter	1.80	0.48	2.82	0.55	0.98	0.31	0.06	-8.48	3.92	1.60	0.81
Advanced Beveridge-Nelson	1.79	-1.46	4.66	1.33	0.92	0.79	0.05	-5.55	2.21	0.94	0.72
Hamilton-Filter	1.84	-4.50	6.75	1.70	0.79	-0.28	0.04	-9.29	7.42	2.72	0.88
Singular spectral analysis	1.79	0.70	2.66	0.44	0.98	0.47	0.04	-8.03	4.05	1.47	0.79
Multivariate filters											
SSD	1.84	-0.09	3.34	0.81	0.98	0.41	0.05	-8.32	4.80	1.60	0.81
SSU	1.75	0.69	2.80	0.49	0.98	0.41	0.09	-7.38	4.74	1.66	0.84
SSP	1.80	0.51	2.82	0.54	0.99	0.50	-0.03	-7.60	3.47	1.39	0.76
SSDUP	1.80	0.38	2.86	0.53	0.98	0.44	0.06	-7.85	4.90	1.53	0.80
Production function approaches											
Classic PF	1.78	0.64	2.61	0.48	0.98	0.39	-0.02	-8.33	4.19	1.51	0.81
EC method PF	1.83	0.47	3.13	0.55	0.98	0.25	0.08	-7.99	6.04	1.83	0.86

MW: Mean, MIN: Minimum, MAX: Maximum, STD: Standard Deviation, PERS: Persistence (AR(1) Coefficient), Corr: Correlation of potential output growth and GDP growth. Potential growth is given by the quarterly year-on-year growth rate.

Table 2 presents descriptive statistics for the resulting potential growth and output gap derived from all employed methodologies. Calculations are based on quarterly data from 1980Q1 to 2024Q3. The methods exhibit notable differences in the variability of their results. For potential growth, the mean and persistence are relatively consistent across methodologies. However, the dispersion varies significantly. The linear trend, by construction, shows no variance, while other methods reveal a considerable range. Of all univariate filters, the Hamilton-filter shows the least favorable properties with the largest variance in least persistence. Among the multivariate filters, the one with capacity utilization (SSD) as an additional explanatory variable exhibits the largest variance. Minimum values range from -0.10% to 1.43%, while maximum values range from 2.12% to 4.66% for potential growth in individual quarters. The multivariate filters yield rather smooth potential growth series, driven by the statistical constraints of these methods, such as the imposed relationship between the variance of the cycle and the trend. By contrast, production function approaches exhibit greater variability, reflecting fluctuations in underlying variables like capital stock and labor input. Across all methods except the linear trend and the Hamilton filter, potential output growth aligns procyclically with the business cycle. Periods of economic expan-

[13]Other methods, such as the Blanchard-Quah decomposition (Blanchard and Quah, 1989), structural models, or dynamic stochastic general equilibrium (DSGE) models, are not yet included. Incorporating these methods and testing their performance relative to existing approaches remains a task for future research.

sion correspond to increased investments and labor utilization, raising production potential, while recessions result in subdued potential growth. The 1980s exemplified strong potential growth and overutilization, while the post-financial crisis era has been marked by subdued dynamics, consistent across methods.

For the output gap, the mean and persistence are similarly consistent across methods, reflecting the expectation that, in the long term, the output gap converges to zero as the economy operates at normal capacity. However, certain estimation methods yield output gap means that deviate from zero, a result influenced by parameter estimation uncertainty in specific models. Additionally, the availability and extension of data—especially for production functions that rely on statistical backcasting to 1980—also contribute to these deviations. As with potential growth, the dispersion in output gap estimates varies considerably, mirroring the variability of potential growth estimates. Despite methodological differences, the historical development of the output gap reveals a qualitatively consistent picture across all estimation approaches. Divergences between the three methodological groups are rare and largely confined to specific time periods. Since the late 1990s, the differences have become minimal, with all methods identifying the same turning points. This robustness highlights the ability of the various estimation techniques to provide a reliable assessment of the Swiss economy's cyclical position.

Consolidation of Estimates

The methodologies outlined above generally produce plausible results, even if certain phases exhibit notable differences between approaches. Since neither potential growth nor the output gap can be directly observed, it remains unclear which method provides the most accurate representation of reality. Consequently, incorporating all plausible approaches offers a robust solution, reducing sensitivity to model-specific characteristics (Armstrong, 2001).

Armstrong (2001) suggest that consolidating multiple time series can benefit from weighting the various methods based on established criteria.[14] In this study, we group the methods into three categories: univariate filters, multivariate filters, and production functions. Hence, each model group gets a weight of 1/3, the weight is constant over time. Within each group, we calculate an unweighted average, and these group averages are then aggregated into consolidated time series for the output gap and potential growth.

This approach allows for differential weighting of estimation methods. For instance, simpler statistical methods like univariate filters are assigned smaller weights due to their

[14] An alternative approach could involve a simple arithmetic mean, treating each method equally. However, there is no reason to assume that all methods are equally reliable. Advanced techniques, such as Bayesian model averaging or weighting based on predictive performance, such as the output gap's explanatory power for inflation, could also be considered.

purely statistical nature and lower implementation complexity. By contrast, more sophisticated structural approaches, such as production function methodologies, are given greater weight. However, the inclusion of simple methods, like the linear trend, ensures that the measure remains comprehensive and does not overlook fundamental signals.

The resulting weighted output gap measure balances the strengths and weaknesses of individual methods while minimizing model-specific biases. It provides a consolidated assessment that is both robust and interpretable, offering valuable insights into the cyclical position and potential growth of the Swiss economy.

3 Results

In this section, we present the resulting weighted output gap for Switzerland and evaluate its sensitivity to revisions arising from changes in the dataset. The analysis demonstrates why the weighted output gap is a superior measure compared to individual methodologies, emphasizing its robustness and practical utility.

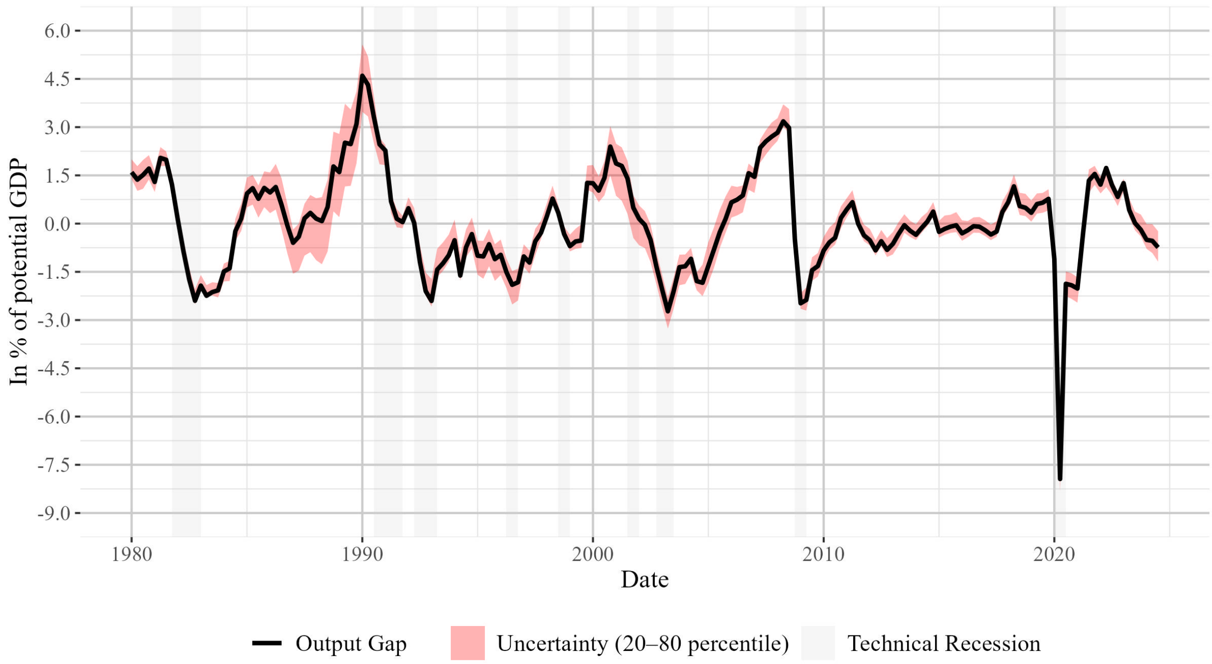
3.1 The weighted Swiss output gap

The consolidated output gap for Switzerland is presented in Figure 1. The weighted output gap effectively captures three distinct phases of significant overutilization of the Swiss economy: 1988–1990, 1999–2000, and 2006–2008. Similarly, substantial underutilization is evident during the mid-1980s, mid-1990s, the Dotcom crisis of 2003/04, and the global financial crisis of 2008/09. Since 2010, the output gap has hovered close to zero, reflecting a balanced economy with neither pronounced overutilization nor underutilization.

The shaded areas in Figure 1 denote periods of technical recession. These coincide with large deviations in the output gap, highlighting its capacity to diagnose economic slack during downturns. The dotted lines show a range of one standard deviation around the weighted output gap across the different output gap estimates at each point in time, reflecting the inherent uncertainty in the estimation process. This uncertainty narrows during stable periods and widens during times of economic volatility, such as the global financial crisis, further showcasing the weighted output gap's ability to adapt to varying conditions.

Unlike individual methodologies, the weighted output gap consolidates information from 13 different approaches, reducing reliance on any single method. This aggregation ensures that the resulting measure is less sensitive to idiosyncratic assumptions or parameter instability inherent to specific methods. For example, univariate filters tend to generate smoother estimates but may lack structural economic interpretations. Conversely, production function approaches offer theoretical rigor but are susceptible to revisions due to chang-

Figure 1: Weighted output gap for Switzerland since 1980:Q1

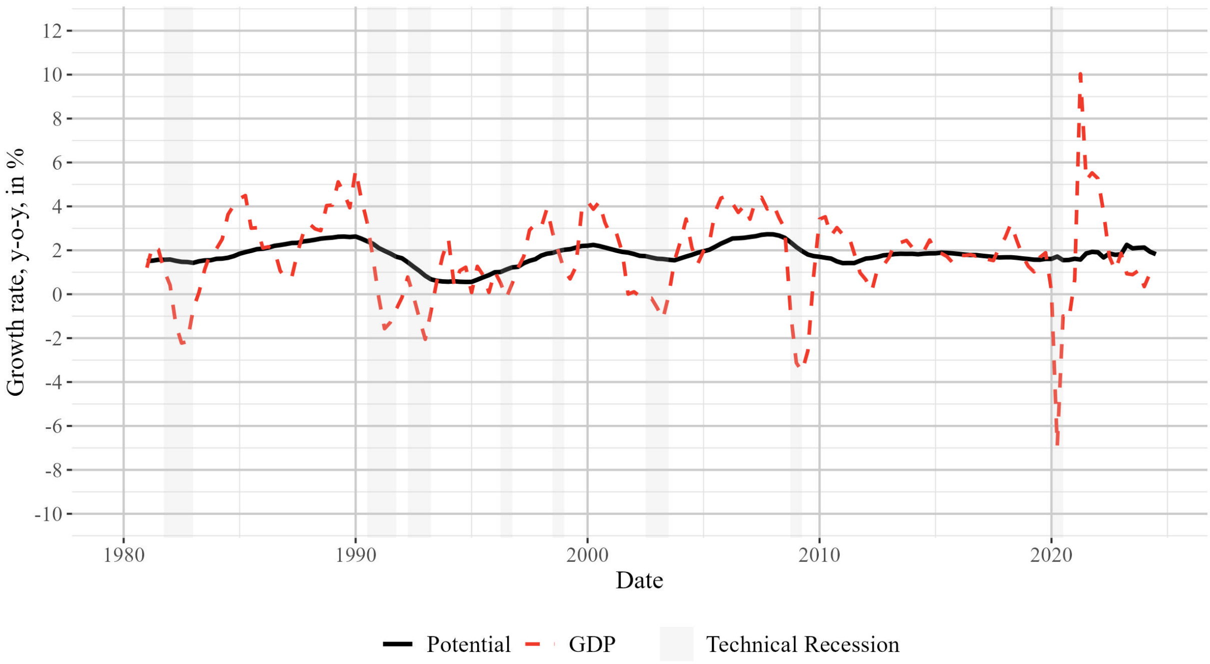


ing input assumptions and also changing structural relations; e.g., steepening of the Phillips Curve. By combining these diverse methods, the weighted measure balances statistical robustness with economic interpretability.

Figure 2 displays the consolidated potential growth series together with the realized GPD growth rate. The impact of the real estate crisis in the mid-1990s is clearly visible. Similarly, the financial crisis, through its negative effect on investment and capital stock accumulation, dampened potential growth. Additionally, the influx of migrants starting in the early 2000s positively contributed to potential growth. On average, potential growth between 1980 and 2023 was approximately 1.8%. Remarkably, the sharp recession caused by the pandemic of the Coronavirus in 2020 has not left a deep scar in the growth potential of the Swiss economy.

The consolidated potential growth series is fairly over time, reflecting the underlying structural capacity of the Swiss economy. Beyond migration, potential growth has been influenced by advancements in technology, shifts in labor force participation, and fluctuations in investment levels. These factors collectively determine the productive capacity of the economy over time. More on the determinants of Swiss potential growth is discussed in Fischer et al. (2024), who focus solely on the production function approach and the supply side determinants. The consolidated potential growth measure instead does not allow for a more structural interpretation. The weighted output gap also exhibits desirable statistical properties, as shown in the first row of Table 2. Apart from its mean being close to zero, it has in particular a relatively low volatility and high persistence compared to individual

Figure 2: Potential output growth for Switzerland since 1980:Q1



methods.

However, the in-sample characteristics presented in Table 2 cannot simply be extrapolated to out-of-sample performance. When studying the properties of trend-cycle decompositions, a key challenge arises from the fact that different filtering techniques share a common limitation: they are susceptible to revisions when new data becomes available and when the economy experiences turning points. The issue of endpoint bias and the resulting instability of trend estimates has been widely documented (see, e.g., **?**Hamilton (2018)). This problem is especially critical for real-time policy analysis, where filtering-based estimates of potential output or the output gap can lead to significant revisions as new data arrives (see Cogley and Nason (1995); **?**). To address that issue, in the next section we present a detailed analysis of the revision properties inherent to the different output gap estimates.

3.2 Sensitivity to revisions

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

In this section, we investigate the revision patterns in the weighted output gap and the individual output gap estimates. By doing so we want to provide insight into the question on how reliable the output gap estimates are over time. To do so, we simulate in a *pseudo* real-time exercise the different estimation approaches described previously. We therefor follow closely the procedure of Marcellino and Musso (2011). Our exercise spans over 98 quarters, starting in 2000:Q2 until 2024:Q3. Given that the data set has been recently established, no true real-time vintages are available for the capital stock nor the labor input.[15] In order to mimic – at least partially – the exercise of the practitioner in real-time, we perform two different simulations: (i) we rely on the available real-time vintages of GDP. By doing so, we are able to capture some of the potential revisions in the raw data.[16] For the univariate filters, this corresponds to a precise real-time exercise. For the other approaches, the revisions in the remaining variables such as the CPI or capacity utilization should be minimal compared to those inherent in GDP, while the revisions in labor and capital input in the production functions are expected to be similarly large as those in GDP. To obtain the estimates of the TFP trend and the NAWRU in the production functions, we re-estimate the corresponding unobserved component models for each vintage of the sample.[17] (ii) we use *final* vintage data (i.e., the last available GDP vintage as of 2024:Q3) and perform the recursive simulations. This corresponds to a purely pseudo real-time analysis.

Table 3 presents the results. Those in the upper part are based on the 'true' real-time GDP vintages, i.e. the simulated information set available at that point in time. In the lower part, the results are based on the recursive output gap estimations carried out with data from the latest available GDP vintage as of 2024:Q3. The weighted output demonstrates remarkable stability in the pseudo real-time exercises. The correlation (CORR) between the pseudo real-time and ex-post estimates for the weighted output gap exceeds 0.95, outperforming most individual methods. Moreover, the weighted output gap shows a sign switch (SIGN-lev) in only 6% of all quarters, underscoring its robustness in dynamic economic environments.

Recursive estimations using the latest GDP vintage reaffirm these findings. While in-

[15] For a further robustness analysis, we were able to obtain the *true* real-time vintages of the weighted output gap presented here from SECO. The sample only starts in 2019:Q4 and covers mostly the volatile crisis period of 2020-2022. Still, we compare the revisions of the true real-time estimates as they were published with the recursive estimates presented here. The MAE of the true real-time estimates (0.19) is slightly higher than of the pseudo real-time estimates (0.14 with real-time GDP; 0.15 final vintage data). Figure A.1 illustrates the different vintages of the published series since 2019:Q4.

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

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

Table 3: Summary reliability indicators of Swiss output gap estimates

	CORR[1]	NS[2]	NSR[3]	SIGN-lev[4]	SIGN-ch[5]	MAR[6]
Based on real-time GDP vintages						
Weighted average	0.968	0.239	0.315	94.0	82.3	0.280
Univariate filters						
Linear trend	0.972	0.223	0.296	90.0	82.9	0.481
HP-filter	0.955	0.279	0.391	93.4	80.6	0.271
Modified HP-filter	0.953	0.282	0.399	93.4	80.5	0.273
Christiano-Fitzgerald-filter	0.959	0.266	0.361	94.2	80.5	0.306
Advanced Beveridge-Nelson	0.954	0.289	0.384	91.6	80.0	0.195
Hamilton filter	0.974	0.221	0.290	93.9	82.7	0.500
Singular spectral analysis	0.963	0.258	0.362	93.8	81.3	0.277
Multivariate filters						
SSD	0.970	0.232	0.357	88.9	81.0	0.332
SSU	0.955	0.286	0.390	91.5	79.6	0.376
SSP	0.957	0.271	0.369	92.2	80.7	0.277
SSDUP	0.905	0.402	0.511	87.2	81.1	0.510
Production function approaches						
Classic PF	0.936	0.308	0.419	92.8	80.9	0.348
EC method PF	0.965	0.250	0.316	94.0	81.3	0.405
Based on latest GDP vintage						
Weighted average	0.993	0.0961	0.143	96.2	99.1	0.116
Univariate filters						
Linear trend	0.990	0.108	0.142	95.2	98.3	0.271
HP-filter	0.990	0.107	0.225	98.6	99.3	0.049
Modified HP-filter	0.988	0.119	0.250	98.6	99.2	0.056
Christiano-Fitzgerald-filter	0.986	0.149	0.257	94.1	98.0	0.146
Advanced Beveridge-Nelson	0.999	0.073	0.099	98.2	98.2	0.057
Hamilton filter	0.990	0.130	0.175	96.8	94.2	0.309
Singular spectral analysis	0.993	0.094	0.183	98.4	99.5	0.048
Multivariate filters						
SSD	0.992	0.121	0.227	93.2	97.4	0.250
SSU	0.974	0.208	0.301	94.2	98.4	0.268
SSP	0.990	0.122	0.228	97.6	99.0	0.096
SSDUP	0.957	0.270	0.314	91.6	96.5	0.364
Production function approaches						
Classic PF	0.961	0.202	0.290	96.0	97.9	0.217
EC method PF	0.981	0.179	0.226	95.0	98.7	0.320

Notes: Estimation sample: 2000:Q2 to 2024:Q3 (98 observations); Data starts in 1980:Q1.

[1] CORR: Correlation between (pseudo) real-time estimate and ex post estimate.

[2] NS: Ratio of the standard deviation of the revision to that of the ex post estimate.

[3] NSR: Ratio of the root mean square of the revision to the standard deviation of the ex post estimate.

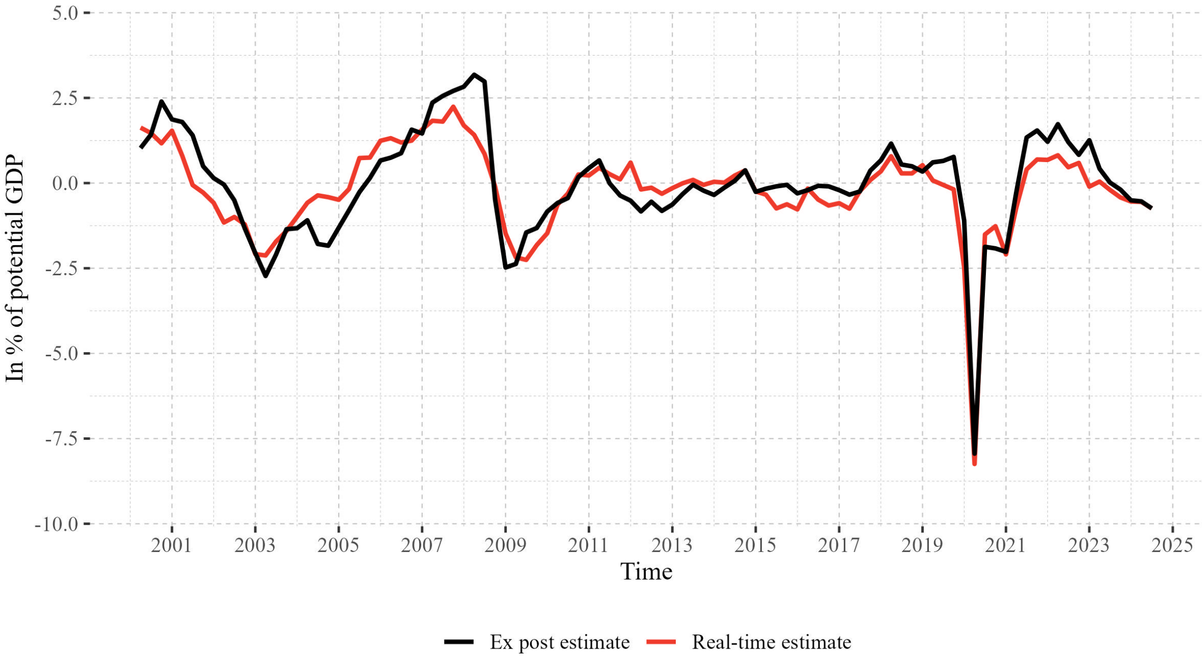
[4] SIGN-lev: Percentage of times the level of the (pseudo) real-time estimate has the same sign as the level of the ex post estimate.

[5] SIGN-ch: Percentage of times the change in the (pseudo) real-time estimate has the same sign as the change in the ex post estimate.

[6] MAR: Mean absolute revision (ex post minus (pseudo) real-time) error.

dividual methods like the Hamilton filter achieve high correlations, they are prone to significant revisions (MAR), making them less reliable in real-time applications. The lowest correlation corresponds to the SSDUP model. This should not be surprising, as this model features many parameters to be estimated. This result aligns well with the evidence reported

Figure 3: Pseudo-Real-Time and Ex Post Swiss Output Gap Estimates



in Marcellino and Musso (2011). By contrast, the weighted output gap mitigates these issues by integrating information across methodologies. For instance, it balances the low revision sensitivity of the Beveridge-Nelson decomposition with the high interpretability of production function approaches.

Recursive estimations based on the final GDP vintage give insights into parameter instability and uncertainty. As each model is estimated every quarter, model parameters are prone to substantial uncertainty. Overall, the findings with the real-time data vintages are confirmed: (1) the correlation between real-time and final estimate are above 90%; (2) the SSDUP approach exhibits the highest noise-to-signal ratio; (3) the CF-filter has the best performance concerning the percentage of times, in which the level of the real-time estimate has the same sign as the final estimate; (4) the linear trend performs best when considering the change in the real-time estimate; (5) the Beveridge-Nelson decomposition has the lowest mean absolute revision. Summarized, data revisions in GDP worsen somewhat the reliability of real-time output gap estimates, albeit not drastically.

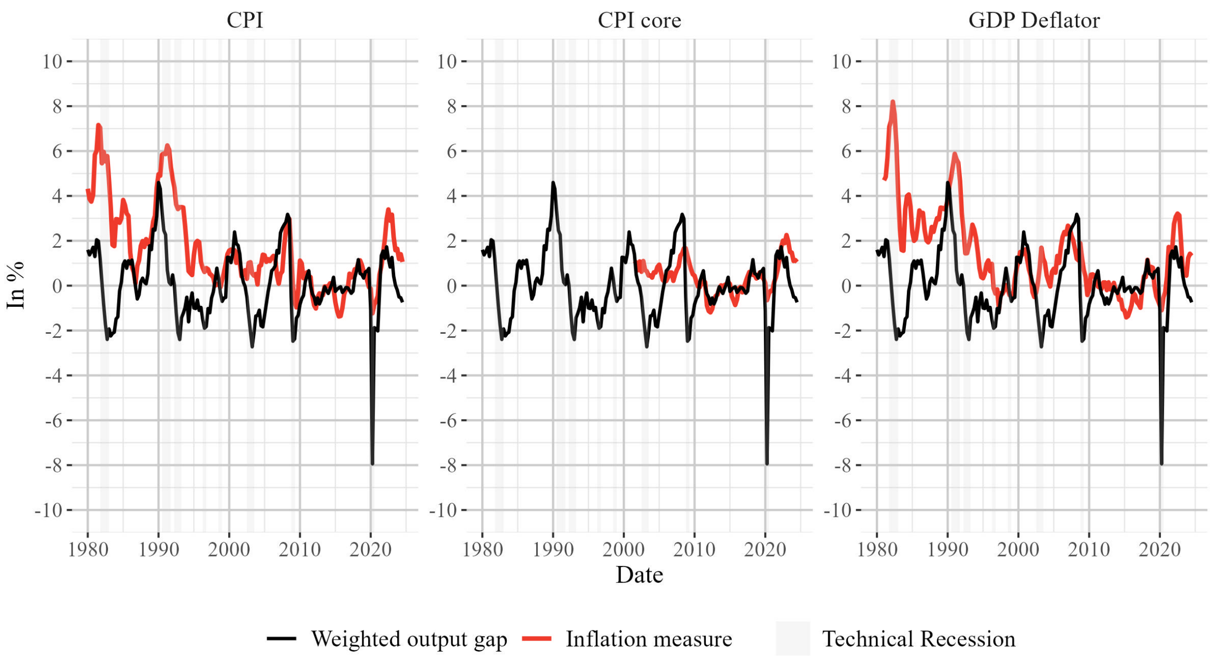
Figure 3 further illustrates the stability of the weighted output gap.[18] The close alignment between the pseudo real-time and ex-post estimates highlights its resilience to data revisions and parameter uncertainties. This property is critical for policymakers who rely on real-time estimates for timely economic decisions.

[18] In the appendix we also illustrate the same figure for the three distinct methodological groups, see Figure A.2.

4 Use case: inflation forecasting

We consider inflation forecasting as a particular use case to illustrate a possible application of the weighted output gap measure. This is an appealing application because it allows us to examine the contribution of the output gap to inflation forecasting based on the theoretical framework of the New Keynesian Phillips curve. The latter posits a positive relationship between inflation and the output gap. Most importantly, this theoretical building block suggests that inflation forecasts can be improved by taking the output gap into account. As figure 4 illustrates, the positive relationship can also be found in Swiss data: a positive output gap (black line) is frequently associated with an increase in the price level (grey lines, measured by the y-o-y change in different inflation metrics). In addition, Table 4 reports the contemporaneous regression coefficients of a simple linear regression of the distinct inflation measure on the output gap. Although the correlation coefficients vary between 0.16 for the CPI core metric and 1.27 for the import price index (IPI), they are all significantly positive, indicating a clear relationship between the output gap and price development.

Figure 4: Weighted output gap for Switzerland since 1980:Q1 and selected inflation metrics



To this end, we focus on various inflation measures involving the GDP deflator, the consumer price index (CPI), the producer price index (PPI) and several subcomponents thereof. To match the inflation series with the frequency of the different output gap measures, we convert monthly inflation series (CPI, PPI, etc.) to a quarterly frequency by considering the monthly average for the corresponding quarter.

Table 4: Correlation of the output gap with different inflation metrics

Metric	GDP Deflator	CPI	CPI core	CPI ultra core	CPI domestic	CPI foreign	PPI	PPI core	IPI	IPI core
correlation	0.40	0.41	0.16	0.23	0.31	0.91	0.61	0.48	1.27	0.85
std.error	0.09	0.09	0.05	0.06	0.08	0.13	0.09	0.10	0.20	0.16
t-statistic	4.44	4.68	3.25	3.71	3.74	7.15	7.15	4.68	6.24	5.31
p.value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

We consider the following ARMAX model

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{4} \beta_k x_{t-k} + \epsilon_t \tag{4.1}$$

where, y_t is the inflation rate (endogenous variable), x_t is the output gap (exogenous variable), ϵ_t is the error term, ϕ_i are the autoregressive coefficients (lags for the endogenous variable), θ_j are the coefficients for the moving average terms (lags for the error term), and β_k are the coefficients for the exogenous variable (lags for the output gap).

The lag-polynomials for the autoregressive (AR) and moving average (MA) terms in equation (4.1) capture the dependence of inflation on its own past values and past forecast errors, respectively. The inclusion of the output gap as an exogenous variable with lags from $t-1$ to $t-4$ allows us to account for the role of the output gap at different time horizons in forecasting inflation.

We estimate equation (4.1) based on an optimal ARMA structure, for which we select the order of the autoregressive (p) and moving average (q) polynomials of the model by using the Schwartz Information Criterion (SIC/BIC). The sample period spans from the first quarter 1980 to the third quarter of 2023. For the purpose of forecasting assessment, we consider data vintages from the second quarter of 2000 until the third quarter of 2023. This results in a total of 94 vintages, one for each quarter during this time span. For each data vintage, we estimate the ARMAX model starting from 1980:Q1 up to the particular point in time, say T_0.

The parameter estimates obtained from this estimation are then used to forecast inflation for the following quarter(s), $T_0 + h$, where h is the forecast horizon. The forecast for the h-step ahead quarter is then compared with the realization. This process is repeated for all 94 data points, resulting in a series of h-step ahead forecasts, each associated with one of the 94 quarters.

To assess the accuracy of the model's predictions, we consider both in-sample and out-of-sample test statistics. Specifically, we use the Granger causality test to evaluate in-sample forecasting performance, while the mean absolute error (MAE) is employed to gauge out-of-sample prediction accuracy. For each output gap measure, a separate ARMAX model is estimated, incorporating the specific output gap measure as the exogenous variable (x_t, listed in the first column of Table 5), and is applied to three inflation measures (listed in the first row of Table 5). The results of these analyses are summarized in Table 5.

The Granger causality test is used to assess the contribution of each output gap measure in improving the accuracy of inflation forecasts. This test is conducted sequentially for each output gap measure across all 94 data vintages. The values reported in the corresponding columns, labeled "GC" in the first, third, and fifth numeric columns of Table 5, indicate the number of instances in which the Granger causality test supports the inclusion of a specific output gap measure for forecasting inflation. The remaining numeric columns provide the MAE for each output gap measure. The results reveal that the weighted average output gap measure is selected by the Granger causality test in 98 out of 94 cases, offering compelling evidence of its effectiveness in enhancing inflation forecasts.

Among the univariate filters, which rely solely on historical data from a single variable, the Hamilton filter stands out as the most effective in forecasting inflation, particularly in relation to the GDP deflator. This filter not only exhibits a high Granger causality (GC = 93), indicating a robust relationship between the output gap and inflation, but it also generates a relatively low MAE of 0.36, suggesting a precise inflation forecast. Furthermore, the Advanced-Beveridge-Nelson filter, another univariate approach, performs similarly well, particularly for forecasting the GDP deflator, with a GC of 94 and a slightly higher MAE of 0.37. Other univariate filters, such as the Linear trend and the HP-filter, exhibit moderate performance, with GC values ranging from 66 to 83 for the GDP deflator and CPI, and slightly higher MAE values. Nonetheless, these filters remain competitive in terms of forecasting accuracy.

Turning to the multivariate filters, which incorporate additional economic variables beyond the output gap to capture more complex relationships, the results are more nuanced. The SSDU filter, for instance, shows a high GC for the GDP deflator (93), but it is associated with a slightly higher MAE (0.38) than the simpler univariate filters. Other multivariate filters, such as the SSP and SSU, also demonstrate decent performance in terms of Granger causality but exhibit slightly higher MAE values (ranging from 0.24 to 0.25). These findings suggest that while multivariate filters can provide valuable insights by incorporating more information, they do not consistently outperform the simpler univariate filters in terms of forecasting accuracy.

The results underscore the relative superiority of the univariate Hamilton filter in forecasting inflation, particularly for the GDP deflator, due to its high Granger causality and low mean absolute error. While more complex multivariate filters offer additional forecasting capacity, their performance does not consistently surpass that of the simpler univariate

Table 5: Output gap estimates and inflation forecasting

Target	GDP-Deflator		CPI		CPI Core	
Method	GC	MAE	GC	MAE	GC	MAE
Weighted average	89	0.37	41	0.41	33	0.24
Univariate filters						
Linear trend	83	0.36	34	0.41	33	0.24
HP-filter	66	0.38	13	0.40	32	0.24
modified HP-filter	67	0.38	13	0.40	32	0.24
Hamilton-filter	93	0.36	46	0.39	67	0.22
Christiano-Fitzgerald-filter	70	0.36	12	0.40	32	0.23
Advanced-Beveridge-Nelson	94	0.37	46	0.41	76	0.24
Singular spectral analysis	70	0.37	18	0.40	33	0.24
Multivariate filters						
SSD	87	0.38	27	0.41	38	0.25
SSU	83	0.38	33	0.41	38	0.24
SSP	77	0.37	20	0.40	33	0.24
SSDUP	93	0.38	41	0.43	52	0.25
Production function approaches						
classic PF	78	0.36	21	0.40	32	0.24
EC method PF	90	0.38	40	0.42	39	0.24

Notes: Forecast sample: 2000:Q2 to 2023:Q3 (94 observations); Data starts in 1980:Q1. The column GC shows the number of vintages with significant Granger causality tests at the 5 percent level.

methods, particularly in terms of forecast accuracy.

With regard to production function approaches, both the classic production function (PF) and its variant introduced by the EC method yield reasonable results. The EC method, for instance, produces a Granger causality (GC) of 90 for the GDP deflator, although it is associated with a higher mean absolute error (MAE) of 0.38. In contrast, the classic PF exhibits a lower GC of 78 for the GDP deflator but demonstrates an MAE similar to that of the univariate filters (0.36). These results suggest that while production function approaches provide a more structural perspective on the economy, they do not consistently offer a substantial advantage in forecasting inflation when compared to alternative methods.

It is important to note that the two evaluation metrics – Granger causality and MAE – occasionally provide conflicting assessments of the output gap measures. For example, although the Granger causality test supports the use of the output gap derived from the EC method as an effective measure for improving inflation forecasts in 90 out of 94 cases, its MAE is generally among the highest when compared to other output gap measures. This discrepancy underscores the relative inadequacy of the EC method for producing out-of-sample forecasts, despite its strong in-sample performance. Such inconsistencies emphasize the importance of considering multiple evaluation criteria when assessing the suitability of output gap measures for inflation forecasting. While Granger causality highlights the potential theoretical relevance of a measure, the MAE provides a more direct empirical assessment of its forecasting accuracy.

Table 6: Forecasting performance of the weighted average output gap

	GC	2015:1 - 2019:4 $h=1$	$h=2$	$h=3$	$h=4$	2022:1 - 2024:4 $h=1$	$h=2$	$h=3$	$h=4$
GDP-Deflator	0.209	0.21	0.09	0.80	1.19	0.16	-2.18	-2.62	3.81
CPI	0.679	-0.07	-0.04	0.77	-1.28***	-0.57	-6.01*	-8.63***	4.00
Core CPI	0.252	0.03	0.20	1.20	0.04	-0.92	-1.93*	-10.43**	-0.36**
Ultra core CPI	0.091	-0.20	0.11	1.44	0.05	-0.79	-1.77*	-11.76**	-0.59**
Domestic CPI	0.005	-0.09	-0.74	-1.19	1.33	-0.10	-4.02*	-11.98**	-9.19**
Foreign CPI	0.546	0.40	0.27	0.03	-2.12**	-0.64	-4.23**	-0.15**	9.55
PPI	0.063	-2.01	-0.13	-0.50	-2.75***	-3.24	-6.77**	-5.77***	4.63
Core PPI	0.143	-2.07*	-0.34	0.48	-0.01*	-5.10**	-3.11**	-6.12***	0.07
IPI	0.071	-0.52	-0.07	-0.66*	-3.53***	0.67	-2.71**	-0.10	2.80
Core IPI	0.312	-0.92	-0.01	0.35	-0.56*	-4.97	-2.15**	-2.37**	3.44

The column GC reports the p-value of the Granger causality test over the entire sample, where H_0 maintains that the output gap does not Granger-cause inflation. The remaining columns show the percentage deviation in the RMSE of the ARMAX(1,1) model with the Weighted Average compared to the univariate ARMA(1,1).
*** 1 percent; ** 5 percent; * 10 percent level of statistical significance refer to the one-sided Diebold-Mariano test with a small sample correction.
CPI: Consumer Price Index; PPI: Producer Price Index; IPI: Import Price Index

To further explore the contribution of the weighted average output gap measure, we provide detailed statistics in Table 6. This table includes the Granger causality test results for an extended set of inflation measures, encompassing ten distinct series, along with out-of-sample forecast accuracy statistics. These statistics, presented in the second through ninth columns, report the root mean squared error (RMSE) of using the weighted average output gap in the ARMAX model specified in equation (4.1), relative to an ARMA model for inflation alone. The RMSE values are expressed as percentages, with negative entries indicating improved forecasting ability when the weighted average output gap is employed.

The Granger causality test statistics (first numeric column in Table 6) suggest that the weighted average output gap notably improves the forecast of inflation based on the domestic CPI (at the 1 percent significance level), as well as for inflation measures such as the ultra core CPI, PPI, and IPI, which are significant at the 10 percent level.

Regarding the RMSE statistics, we observe that the contribution of the weighted average output gap to forecasting inflation tends to increase with the forecast horizon. While its effect on forecast accuracy is marginal at the one-quarter horizon ($h = 1$), it generally improves as the forecast horizon extends beyond the second quarter. Notably, the weighted average output gap measure demonstrates the greatest improvement in forecasting for the IPI, PPI, foreign CPI, and CPI during the 2015:1–2019:4 forecast evaluation period. The limited out-of-sample forecasting ability for the domestic CPI underscores a common finding in forecasting: a variable that fits well in-sample does not necessarily provide strong out-of-sample forecasts.

The results for the second forecasting sample (2022:1 to 2024:4) yield similar findings.

However, on average, the weighted average output gap measure exhibits superior forecasting ability across most inflation indicators compared to the pre-COVID-19 forecasting period. These results reinforce the necessity of adopting a balanced approach when selecting an output gap measure for practical applications, one that incorporates both statistical performance and theoretical considerations.

5 Conclusions

The estimation of the output gap is fraught with three primary sources of uncertainty: (1) model uncertainty, arising from the lack of a definitive approach to measure unobservable potential output; (2) parameter uncertainty and instability, reflecting the sensitivity of model parameters to changing economic conditions; and (3) data revisions, particularly for key inputs such as GDP. The proposed multi-method approach mitigates these challenges by aggregating insights from diverse methodologies, thereby reducing reliance on any single model and improving the robustness of estimates.

The consolidated output gap series published by SECO on a quarterly basis has several desirable characteristics. It offers greater stability and reliability than individual methods, as evidenced by its good performance in real-time forecasting exercises and its resilience to data revisions. The weighted output gap captures the main cyclical dynamics of the Swiss economy, closely following major economic events such as recessions and recoveries, while maintaining a low mean absolute error and a high degree of forecasting accuracy for inflation. As a use case, we evaluate its forecasting accuracy for different measures of inflation. The results show that the weighted average output gap has a reasonable forecasting ability, especially over longer horizons and for specific measures of inflation, such as the PPI. This makes it a valuable tool for policymakers tasked with assessing the economy's position in the cycle and designing timely fiscal and monetary responses.

These findings align with insights from the international literature, such as Marcellino and Musso (2011), where weighted approaches have consistently outperformed individual methods in terms of stability and reliability. The weighted output gap thus represents a best-practice model for countries with similar economic characteristics, offering a compelling blueprint for other statistical agencies and research institutions. Moreover, its proven ability to enhance inflation forecasting underscores its broader relevance for economic modeling and policy analysis.

By providing a consolidated, timely, and robust measure of economic slack, the weighted output gap bridges the gap between theoretical rigor and practical application. It not only offers researchers a reliable metric for empirical analysis but also equips policymakers with a versatile tool for navigating complex economic conditions.

References

Alichi, Ali (2015) *A new methodology for estimating the output gap in the United States* number 15-144 (International Monetary Fund)

Álvarez, Luis J, and Ana Gómez-Loscos (2018) 'A menu on output gap estimation methods.' *Journal of Policy Modeling* 40(4), 827–850

Armstrong, J Scott (2001) 'Combining forecasts.' In 'Principles of forecasting' (Springer) pp. 417–439

Basu, Susanto, and John G Fernald (2009) 'What do we know (and not know) about potential output?' *Federal Reserve Bank of St. Louis Review*

Baxter, Marianne, and Robert G King (1999) 'Measuring business cycles: approximate band-pass filters for economic time series.' *Review of economics and statistics* 81(4), 575–593

Bignasca, Franziska, and Enzo Rossi (2007) 'Applying the Hirose-Kamada filter to Swiss data: Output gap and exchange rate pass-through estimates.' Working Papers 2007-10, Swiss National Bank, 10

Blagrave, Patrick, Mr Roberto Garcia-Saltos, Mr Douglas Laxton, and Fan Zhang (2015) *A simple multivariate filter for estimating potential output* (International Monetary Fund)

Blanchard, Olivier, and Danny Quah (1989) 'The dynamic effects of aggregate demand and supply disturbances.' *American Economic Review* 79, 655–673

Bruchez, Pierre-Alain (2003) 'A modification of the HP filter aiming at reducing the end-point bias.' *Swiss Financial Administration, Working Paper*

Christiano, Lawrence J, and Terry J Fitzgerald (2003) 'The band pass filter.' *International Economic Review* 44(2), 435–465

Clark, Peter K (1989) 'Trend reversion in real output and unemployment.' *Journal of Econometrics* 40(1), 15–32

Cogley, Timothy, and James M Nason (1995) 'Effects of the hodrick-prescott filter on trend and difference stationary time series implications for business cycle research.' *Journal of Economic Dynamics and control* 19(1-2), 253–278

Coibion, Olivier, Yuriy Gorodnichenko, and Mauricio Ulate (2018) 'The cyclical sensitivity in estimates of potential output.' *Brookings Papers on Economic Activity* 49(2 (Fall)), 343–441

Cotis, Jean-Philippe, Jørgen Elmeskov, and Annabelle Mourougane (2004) 'Estimates of potential output: benefits and pitfalls from a policy perspective.' *The Euro area business cycle: stylized facts and measurement issues. Centre for Economic Policy Research, London* pp. 35–60

Dupasquier, Chantal, Alain Guay, and Pierre St-Amant (1999) 'A survey of alternative methodologies for estimating potential output and the output gap.' *Journal of Macroeconomics* 21(3), 577–595

Fischer, Sarah, Christian Glocker, Serguei Kaniovski, and Philipp Wegmüller (2024) 'Assessing the potential output for switzerland: Determinants, trends and drivers.' *Journal of Business Cycle Research* pp. 1–42

Giorno, Claude, Pete Richardson, Deborah Roseveare, and Paul van den Noord (1995) 'Estimating potential output, output gaps and structural budget balances.' *OECD Economics Department Working Papers*

Glocker, Christian, and Serguei Kaniovski (2020a) 'Estimating a quarterly potential output series for switzerland.' Technical Report 12, Staatssekretariat für Wirtschaft SECO, Bern

— (2020b) 'Estimating the potential output for switzerland using the methodology of the european commission.' Technical Report 8, Staatssekretariat für Wirtschaft SECO, Bern

— (2024) 'Potential output estimates for the swiss economy: Model selection and sensitivity analysis.' Technical Report 44, Staatssekretariat für Wirtschaft SECO, Bern, Schweiz

Golyandina, Nina, Vladimir Nekrutkin, and Anatoly A Zhigljavsky (2001) *Analysis of time series structure: SSA and related techniques* (Chapman and Hall/CRC)

Hamilton, James D (2018) 'Why you should never use the hodrick-prescott filter.' *Review of Economics and Statistics* 100(5), 831–843

Harvey, Andrew C, and James H Stock (1989) 'Estimating integrated higher-order continuous time autoregressions with an application to money-income causality.' *Journal of Econometrics* 42(3), 319–336

Havik, Karel, Kieran Mc Morrow, Fabrice Orlandi, Christophe Planas, Rafal Raciborski, Werner Roeger, Alessandro Rossi, Anna Thum Thysen, and Valerie Vandermeulen (2014) 'The production function methodology for calculating potential growth rates & output gaps.' *Economic papers* 1(535), 1–120

Hodrick, Robert, and Edward Prescott (1997) 'Postwar U.S. business cycles: An empirical investigation.' *Journal of Money, Credit and Banking* 29(1), 1–16

Indergand, Ronald, and Stefan Leist (2014) 'A real-time data set for switzerland.' *Swiss Journal of Economics and Statistics* 150, 331–352

Jarociński, Marek, and Michele Lenza (2018) 'An inflation-predicting measure of the output gap in the euro area.' *Journal of Money, Credit and Banking* 50(6), 1189–1224

Kamber, Güneş, James Morley, and Benjamin Wong (2018) 'Intuitive and reliable estimates of the output gap from a beveridge-nelson filter.' *Review of Economics and Statistics* 100(3), 550–566

Kiley, Michael T (2013) 'Output gaps.' *Journal of Macroeconomics* 37, 1–18

Ladiray, Dominique, Gian Luigi Mazzi, and Fabio Sartori (2003) 'Statistical methods for potential output estimation and cycle extraction.' *Office for Official Publications of the European Communities*

Leist, Stefan (2013) 'Driving forces of the swiss output gap.' *Swiss Journal of Economics and Statistics* 149, 493–531

Leist, Stefan, and Klaus Neusser (2010) 'Measuring the natural output level by dsge models: An empirical investigation for switzerland.' *Swiss Journal of Economics and Statistics* 146, 275–300

Marcellino, Massimiliano, and Alberto Musso (2011) 'The reliability of real-time estimates of the euro area output gap.' *Economic Modelling* 28(4), 1842–1856

Miller, Stephen M (1988) 'The beveridge-nelson decomposition of economic time series: Another economical computational method.' *Journal of Monetary Economics* 21(1), 141–142

Nelson, Charles R, and Charles R Plosser (1982) 'Trends and random walks in macroeconomic time series: some evidence and implications.' *Journal of Monetary Economics* 10(2), 139–162

Orphanides, Athanasios (2001) 'Monetary policy rules based on real-time data.' *American Economic Review* 91(4), 964–985

Orphanides, Athanasios, and Simon van Norden (2002) 'The unreliability of output-gap estimates in real time.' *The Review of Economics and Statistics* 84(4), 569–583

Proietti, Tommaso, Alberto Musso, and Thomas Westermann (2007) 'Estimating potential output and the output gap for the euro area: a model-based production function approach.' *Empirical Economics* 33(1), 85–113

Ravn, Morten O., and Harald Uhlig (2002) 'On adjusting the Hodrick-Prescott filter for the frequency of observations.' *The Review of Economics and Statistics* 84(2), 371–376

Stalder, Peter (2020a) 'Methoden der potentialschätzung: Produktionsfunktion oder filterverfahren? eine vergleichende beurteilung in der anwendung auf die schweiz.' Technical Report 11, Staatssekretariat für Wirtschaft SECO, Bern

__ (2020b) 'Schätzung und prognose des potentialoutput auf basis einer produktionsfunktion – theorie und anwendung auf die schweiz.' Technical Report 9, Staatssekretariat für Wirtschaft SECO, Bern

__ (2020c) 'Univariate und multivariate filter zur schätzung des potentialoutput: Theorie und anwendungen auf die schweiz.' Technical Report 10, Staatssekretariat für Wirtschaft SECO, Bern

Watson, Mark W (1986) 'Univariate detrending methods with stochastic trends.' *Journal of Monetary Economics* 18(1), 49–75

A Appendix

A.1 Data Sources

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

Table A.1: Data sources to construct labor input

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

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

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

Table A.2: Data sources to construct capital stock

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

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

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

Table A.3: Further data sources

Series	Source	Frequency	Start
Capacity utilization manufacturing	KOF	Q	1980
Consumer price index CPI	FSO	Q	1980
GDP Deflator	SECO	Q	1980

A.2 Models

A.2.1 Linear Detrending

Linear detrending assumes that the trend component of a time series is a simple linear function of time, $T_t = \alpha + \beta t$. The cyclical component is obtained by subtracting the linear trend from the original series:

$$C_t = Y_t - T_t \tag{A.1}$$

A.2.2 The HP-filter

The state-space representation of the HP-filter is given by

$$\begin{aligned} Y_t &= \mu_t + \xi_t, \quad \xi_t \sim N(0, \sigma_\xi^2) && \text{(A.2)} \\ \mu_t &= \mu_{t-1} + \eta_{t-1} && \text{(A.3)} \\ \eta_t &= \eta_{t-1} + \nu_{\eta,t}, \quad \nu_{\eta,t} \sim N(0, \sigma_\eta^2) && \text{(A.4)} \end{aligned}$$

where μ_t is the stochastic trend of Y_t and ξ_t is the cyclical component of Y_t which is assumed to be independently and identically distributed (iid). The key element in the context of the HP filter is the smoothing parameter $\lambda \geq 0$, which with respect to the equations (A.2)-(A.4) is given by the ratio of two variances

$$\lambda = \frac{\sigma_\xi^2}{\sigma_\eta^2} \tag{A.5}$$

To see how the smoothing parameter λ affects the system, consider $\lambda = 0$; in this case $\sigma_\xi^2 \to 0$, and hence $\mu_t = Y_t$, in other words, no smoothing takes place. A high value of λ in turn results in a relatively large variance of the cyclical component (σ_ξ^2) compared to the trend component (σ_η^2). Consequently, ξ_t will capture a significant portion of the high-frequency fluctuations in Y_t, while μ_t will account for the remaining, smoother component of Y_t. Therefore, when λ is large, μ_t will exhibit a smooth trajectory, as the variation attributed to η_t and μ_t is small relative to that captured by ξ_t. For quarterly data, a commonly used value is $\lambda = 1,600$ (Hodrick and Prescott, 1997; Ravn and Uhlig, 2002). This choice implies that $\sigma_\xi^2 = 1,600\sigma_\eta^2$, meaning that the variance of the cyclical component is permitted to be 1,600 times greater than the variance of the trend component (σ_η^2).

A.2.3 The Modified HP-filter

The modified HP-filter (mHP) builds on the standard HP-filter by addressing the endpoint bias that often distorts the trend estimation at the boundaries of the series. The mHP modifies the penalty structure for the first and last few observations, ensuring that the trend does not disproportionately "pull" towards the final observed values.

The mathematical implementation can be summarized as follows:

- The smoothed trend z_t is derived by solving $\mathbf{A} \cdot \mathbf{z} = \mathbf{x}$, where $\mathbf{A}$ is an $n \times n$ smoothing matrix, $\mathbf{x}$ is the observed series, and $\mathbf{z}$ is the trend.
- Near the boundaries (e.g., for $t = 1$ and $t = n$), the matrix $\mathbf{A}$ includes specific adjustments to reduce the weight of differences between observations, improving the robustness of the trend.
- For intermediate observations ($3 \leq t \leq n - 2$), the structure follows the standard HP-filter with a penalty term proportional to λ.

The result is a decomposition of the input series x_t into a smooth trend z_t and a cyclical component $x_t - z_t$. This approach is particularly useful for reducing biases at the edges of the time series, making it suitable for real-time economic analysis.

A.2.4 The Christiano-Fitzgerald Filter

The Christiano-Fitzgerald (CF) filter is a band-pass filter designed to isolate cyclical components of a time series within a specific frequency range. The filter operates by approximating an ideal band-pass filter using a finite lag structure. The filtered series $\tilde{Y}t$ is obtained by:

$$\tilde{Y}t = \sum k = -K^K w_k Yt - k \tag{A.6}$$

where w_k are the weights determined by the desired frequency range, and K is the number of lags. The weights are computed to emphasize cycles within a chosen periodicity (e.g., 2 to 8 years for business cycles). The CF filter assumes the series is stationary and symmetric, and it allows for flexibility in defining the desired frequency bands.

A.2.5 The Advanced Beveridge-Nelson Decomposition

The Beveridge-Nelson (BN) decomposition separates a time series into a stochastic trend and a stationary component. For a time series modeled as an ARIMA process:

$$\phi(L)(Y_t - \mu) = \theta(L)\epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2) \tag{A.7}$$

the trend component τ_t is defined as the long-term forecast of the series:

$$\tau_t = \mu + \sum_{j=0}^{\infty} \psi_j \epsilon_{t-j}, \tag{A.8}$$

where ψ_j are derived from the moving-average representation of the ARIMA process. The cyclical component is then:

$$\zeta_t = Y_t - \tau_t. \tag{A.9}$$

The advanced BN decomposition enhances the original methodology by using state-space models and Kalman filtering to estimate the components more accurately.

A.2.6 The Hamilton Filter

The Hamilton filter, proposed by Hamilton (2018), avoids the use of the HP-filter by modeling the trend as a function of lagged values of the series. For a series Y_t, the trend is estimated using a regression of the form:

$$Y_t = \beta_0 + \beta_1 Y_{t-h} + \cdots + \beta_p Y_{t-h-p} + \epsilon_t \tag{A.10}$$

where h is the forecast horizon, and p is the number of lags. This approach avoids endpoint biases and is robust to model misspecifications, making it a flexible alternative to traditional filtering techniques.

A.2.7 Singular Spectral Analysis (SSA)

Singular Spectral Analysis (SSA) is a non-parametric technique that decomposes a time series into a sum of interpretable components, such as trends, oscillatory patterns, and noise. SSA relies on the singular value decomposition (SVD) of a trajectory matrix constructed from the time series. The process involves:

- Embedding the time series into a trajectory matrix.
- Performing SVD to extract eigenvectors and eigenvalues.
- Grouping components to reconstruct the trend and cycle.

SSA is highly flexible and can be applied to both linear and nonlinear time series, making it a versatile tool for analyzing complex dynamics.

A.2.8 The multivariate filter

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

$$Y_t = \bar{Y}_t + \epsilon_t^y \tag{A.11}$$

$$\bar{Y}_t = \bar{Y}_{t-1} + g_t \qquad \epsilon_t^y \sim \mathcal{N}(0, \sigma_y^2) \qquad \sigma_y^2 = \lambda \sigma_g^2 \tag{A.12}$$

$$g_t = g_{t-1} + \epsilon_t^g \qquad \epsilon_t^g \sim \mathcal{N}(0, \sigma_g^2) \qquad \sigma_g^2 = e^{\theta_1} \tag{A.13}$$

$$duc_t = \beta_1 + \beta_2 \epsilon_t^y + \epsilon_t^{duc} \qquad \epsilon_t^{duc} \sim \mathcal{N}(0, \sigma_{duc}^2) \qquad \sigma_{duc}^2 = e^{\theta_2} \tag{A.14}$$

$$\pi_t = \beta_3 + \beta_4 \epsilon_t^y + \epsilon_t^{\pi} \qquad \epsilon_t^{\pi} \sim \mathcal{N}(0, \sigma_{\pi}^2) \qquad \sigma_{\pi}^2 = e^{\theta_3} \tag{A.15}$$

$$ur_t = \beta_5 + \beta_6 \epsilon_t^y + \epsilon_t^{ur} \qquad \epsilon_t^{ur} \sim \mathcal{N}(0, \sigma_{ur}^2) \qquad \sigma_{ur}^2 = e^{\theta_4} \tag{A.16}$$

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

A.2.9 Classic production function

The estimation of the potential output follows a Cobb-Douglas production function framework. The production function is specified as:

$$Y = A \cdot L^{\alpha} \cdot K^{(1-\alpha)},$$

where Y is the real GDP, L represents labor input, K denotes capital stock, and A is Total Factor Productivity (TFP). The parameter α captures the elasticity of output with respect to labor.

To account for structural breaks and time trends, two trend variables (t_1 and t_2) are constructed, corresponding to different time periods:

$$t_1 = \begin{cases} 0 & \text{if } t < 1980 \\ t - 1980 & \text{otherwise,} \end{cases} \quad t_2 = \begin{cases} 0 & \text{if } t < 1995 \\ t - 1995 & \text{otherwise.} \end{cases}$$

The log-linearized model is estimated as:

$$\ln\left(\frac{Y}{K}\right) = \beta_0 + \alpha \ln\left(\frac{L}{K}\right) + \beta_1 t_1 + \beta_2 t_2 + \epsilon,$$

where ϵ is the error term. The estimated parameters are used to compute α and the structural contributions of t_1 and t_2.

TFP (A) is calculated as the residual from the production function:

$$\ln(A) = \ln(Y) - \alpha \ln(L) - (1-\alpha)\ln(cu * K),$$

where cu is the demeaned capacity utilization in manufacturing.

The trend component of TFP is extracted using the Hodrick-Prescott (HP) filter with a smoothing parameter (λ) of 1600. The potential output (Y^*) is then derived as:

$$Y^* = \exp\left(\text{TFP}_{\text{trend}}\right) \cdot L^*\alpha \cdot K^{(1-\alpha)}.$$

$L*$ is given by the product of population, smoothed participation rate, nawru estimate and smoothed hours worked per worker (see Fischer et al. (2024) for details).

A.3 Further results

Figure A.1: Vintages of published output gap

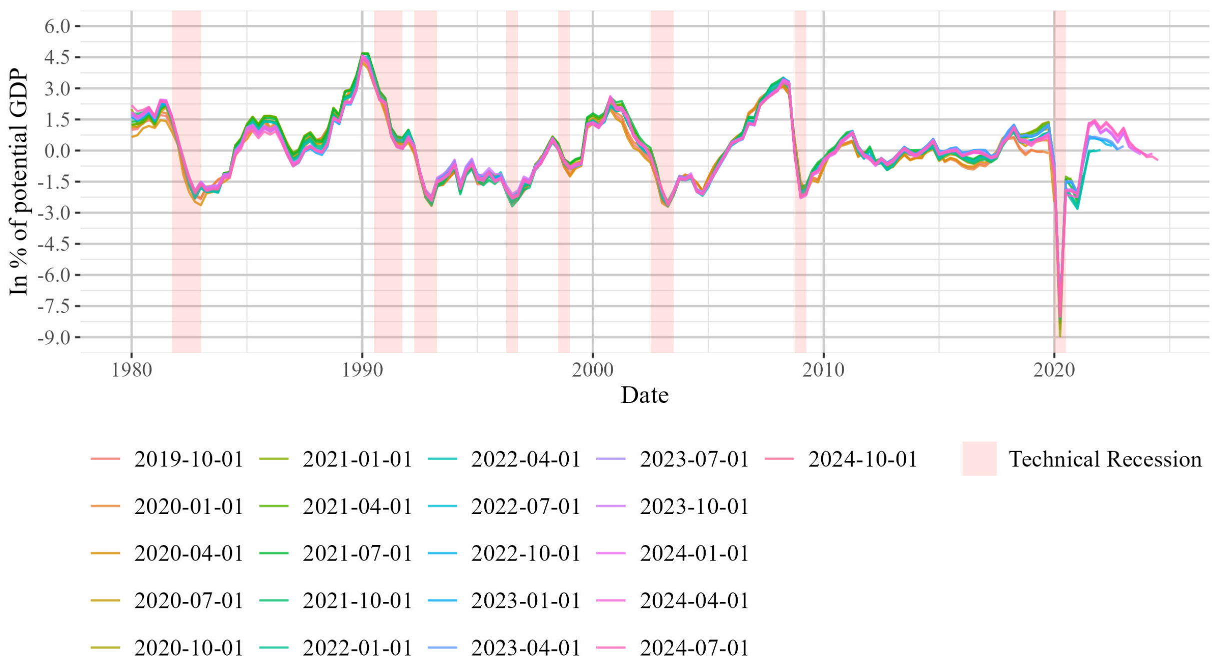
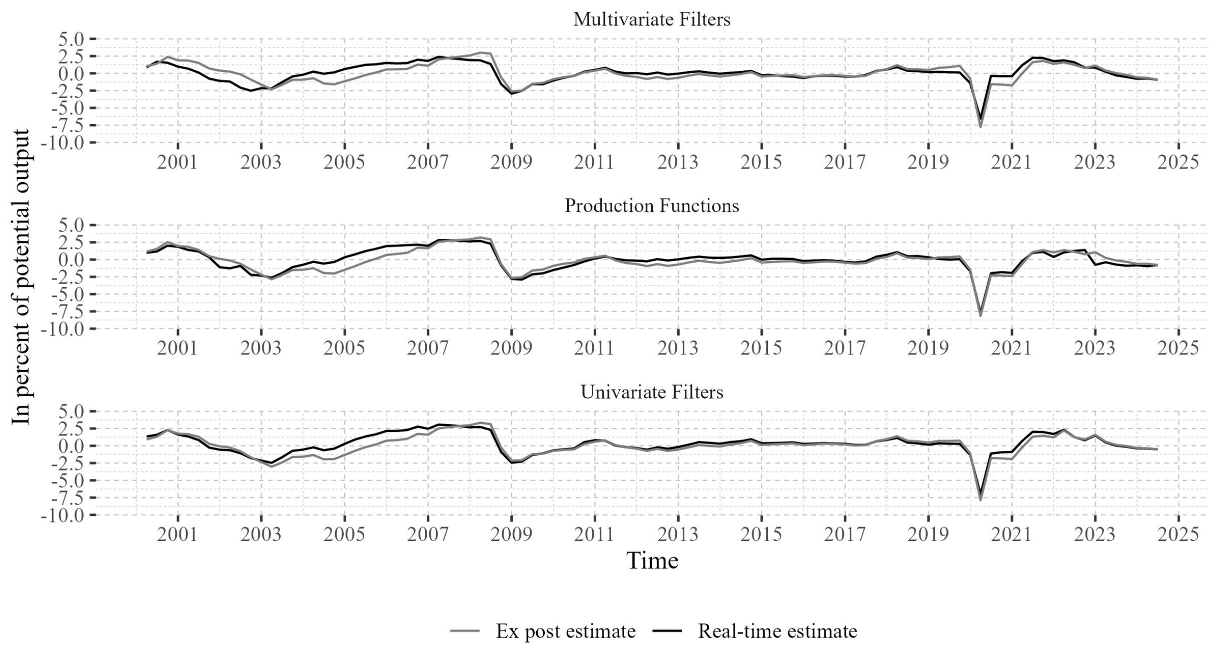


Figure A.2: Pseudo-Real-Time and Ex Post Swiss Output Gap Estimates for different Methods



A.4 Forecasting performance of the SDUP-filter and the classic Production Function

Table A.4: Forecasting performance of the SSDUP-filter and the classic Production Function

		2015:1 2019:4				2022:1 2024:4			
	GC	$h=1$	$h=2$	$h=3$	$h=4$	$h=1$	$h=2$	$h=3$	$h=4$
					Multivariate filters: SSDUP				
GDP-Deflator	0.173	0.27	0.21	0.89	1.17	0.10	-2.20	-3.40	3.76
Consumer Price Index (CPI)	0.643	-0.03	-0.04	0.59	-1.16***	-0.11	-6.07*	-8.46***	4.14
Core CPI	0.296	-0.01	0.15	0.67	0.02	-0.40	-1.91*	-9.90**	-0.41**
Ultra core CPI	0.117	-0.27	0.04	0.78	0.01	-0.32	-1.73*	-11.22**	-0.62**
Domestic CPI	0.001	-0.08	-0.74	-1.57	0.79	0.22	-3.68	-10.38**	-8.68**
Foreign CPI	0.641	0.35	0.17	0.02	-1.64**	-0.50	-4.45**	-0.17**	10.27
Producer Price Index (PPI)	0.134	-1.95	-0.12	-0.58	-2.53***	-3.43	-7.17**	-6.01***	5.35
Core PPI	0.161	-2.08*	-0.39	0.29	-0.01	-4.27*	-3.17**	-6.22***	0.20
Import Price Index (IPI)	0.146	-0.48	-0.06	-0.63*	-3.19***	0.37	-3.02**	0.01	4.33
Core IPI	0.356	-0.86	-0.01	0.32	-0.49**	-4.65	-2.19**	-2.55**	4.02
					Classic Production Function: classic PF				
GDP-Deflator	0.221	0.16	0.01	0.81	1.17	0.09	-1.74	-2.08	3.89
Consumer Price Index (CPI)	0.640	-0.25	-0.13	0.73	-1.36***	-0.22	-6.15*	-8.02**	3.85
Core CPI	0.227	0.05	0.29	1.50	0.08	-0.84	-2.41*	-10.29**	-0.53**
Ultra core CPI	0.077	-0.14	0.21	1.98	0.11	-0.73	-2.24*	-11.60**	-0.72**
Domestic CPI	0.035	-0.28	-1.09	-1.57	1.27	-0.23	-5.40*	-12.72**	-9.89**
Foreign CPI	0.372	0.30	0.35	-0.10*	-3.04***	-0.23	-3.63*	0.39	8.26
Producer Price Index (PPI)	0.020	-2.16	-0.09	-0.46	-3.09***	-2.40	-6.39*	-4.92***	3.72
Core PPI	0.115	-2.10*	-0.30	0.71	-0.09**	-4.39**	-3.23**	-5.32**	0.42
Import Price Index (IPI)	0.027	-0.60	-0.04	-0.82*	-4.27***	0.85	-2.21*	-0.02	0.98
Core IPI	0.212	-0.93	0.04	0.43	-0.94***	-4.29	-2.03*	-1.73**	2.45

Notes: The column GC reports the p-value of the Granger causality test over the entire sample, where $H0$ maintains that output gap does not Granger cause inflation. The remaining columns show the percentage deviation in the RMSE of the ARMAX(1,1) model with an output gap compared to the univariate ARMA(1,1). *** 1 percent; ** 5 percent; * 10 percent level of statistical significance refer to the one-sided Diebold-Mariano test with a small sample correction.

Declarations

Competing Interests

The authors declare that they have no competing interests.

Funding

This research was not supported by any external funding.

Authors' Contributions

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

Availability of data and material

The data are made available to the public on the website https://www.seco.admin.ch/potenzialwachstum. The data is updated quarterly with a delay of around 60 days. Codes for replication are available from the authors upon request.