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A High-Frequency GDP Indicator for Switzerland*

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Abstract

This paper presents a weekly GDP indicator for Switzerland, which addresses the limitations of existing economic activity indicators by using alternative high-frequency data created in response to the COVID-19 pandemic. The indicator is derived from a Bayesian mixed-frequency dynamic factor model, which integrates both conventional macroeconomic and alternative high-frequency data at weekly, monthly, and quarterly frequencies. The model extracts business cycle information from a wide range of data frequencies and captures the large and sudden fluctuations during the pandemic by estimating missing observations as latent states through data augmentation, incorporating stochastic volatility in the state equation, and accounting for serial correlation in the measurement errors. An empirical application shows that the indicator accurately approximates weekly GDP growth for Switzerland and provides valuable information on the trajectory of GDP at high frequency, particularly during crisis periods. A pseudo real-time analysis demonstrates high forecast accuracy at short leads and improvements over other GDP indicators for Switzerland.

JEL Classification: C11, C32, C38, C53, E32, E37

Keywords: Dynamic Factor Model, Business Cycle Index, High-Frequency Data, Economic Activity Indicator, Covid-19

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1 Introduction

During the COVID-19 pandemic, the trajectory of economic activity experienced unprecedented volatility due to the implementation of containment measures, including social distancing, industry shutdowns, and lockdowns. Conventional econometric models failed to accurately capture these strong and sudden movements in economic activity for several reasons. Macroeconomic indicators are typically collected monthly and published with a lag of one month or more. Consequently, they fail to provide timely information on high-frequency economic developments. Additionally, as such large swings have never been recorded in the history of the data, econometric models have not been able to adequately capture these movements, and model estimation has often been heavily biased by these highly influential observations. However, reliable up-to-date assessment of the current economic situation is particularly important for policy making in such situations.

In response to the challenges posed by the COVID-19 pandemic, various methods have been developed to produce accurate forecasts of economic activity under the changed conditions. One approach is to use alternative high-frequency data to approximate economic activity at a higher frequency. Alternative data includes all types of data that do not come from traditional sources such as official statistics offices, government departments, or financial market data but contain useful information to reveal shifts in consumer behavior, mobility patterns, or transaction volumes.

This paper presents a weekly GDP indicator for Switzerland constructed from a mixed-frequency dynamic factor model that integrates weekly, monthly, and quarterly data from both conventional macroeconomic indicators and alternative high-frequency sources. This model facilitates the near real-time monitoring of GDP by extracting business cycle information from a wide range of data frequencies, thereby enhancing the timeliness and accuracy of economic assessments.

The construction of high-frequency GDP indicators became popular due to the seminal work of Lewis et al. (2021) who introduced the Weekly Economic Indicator (WEI) for the US, which uses the first principal component of a set of ten high-frequency series to produce a weekly GDP indicator representing the 52-week growth rate of economic activity. This methodology inspired subsequent developments, including regional economic activity indicators for the US by Baumeister et al. (2024), weekly GDP indicator for Switzerland by Wegmüller et al. (2023), Austria by Fenz and Stix (2021), and Italy by Delle Monache et al. (2021). Alternatively, Woloszko (2020) utilize Google Trends, while Aprigliano et al. (2023) rely on text-based newspaper data. Wegmüller and Glocker (2023) show how preprocessing steps for alternative high-frequency data before applying PCA can improve the extracted WEI of Lewis et al. (2021). Eraslan and Götz (2021) propose a weekly economic activity indicator for Germany using a mixed-frequency data set that includes, along with weekly high-frequency indicators, industrial production and GDP. Their approach employs temporal aggregation, as proposed by Mariano and Murasawa (2003), and an expectation maximization (EM) algorithm to interpolate the low frequency indicators. Adam et al. (2021) followed this approach for the Czech Republic. In contrast to the before mentioned unsupervised approaches, the latest contributions address the issue of missing observations in a supervised mixed-frequency set-up. Eckert et al. (2025) as well as Eraslan and Reif (2023) propose a mixed-frequency dynamic factor model to produce weekly forecasts of quarter-on-quarter GDP growth rates by employing data augmentation and temporal aggregation constraints to ensure the summation of weekly GDP growth rates aligning with actual quarterly growth rates.

This paper builds on the model proposed by Eckert et al. (2025), a Bayesian mixed-frequency dynamic factor model estimated using three independent state-space blocks applying the precision sampler from Chan and Jeliazkov (2009). These blocks encompass the estimation of missing observations as latent states through data augmentation, the

extraction of dynamic factors, and the estimation of stochastic volatility in the factor state equation. The model estimates the factors conditional on the augmented data, thus enabling the incorporation of alternative high-frequency data despite inherent limitations such as short historical records, high volatility, irregular missing data patterns, publication lags, and varying correlations with actual economic activity. Additionally, the model addresses serial correlation in the measurement errors through quasi-differencing following Chib and Greenberg (1994) to allow the factor to deviate stronger for certain periods. By imposing straightforward identification restrictions on the factor, it is forced to fit the target series, GDP, resulting in a straightforward interpretable high-frequency GDP indicator.

The methodology stands out from existing methods in that it expands the mixed-frequency setup, including high-frequency data, in a way that the model can deal with missing observations and the extreme observations of the COVID-19 pandemic. Eraslan and Reif (2023) also create a high-frequency GDP indicator by applying a similar precision sampling approach to estimate missing observations in a mixed-frequency dynamic factor model. However, including several model extensions as in Eckert et al. (2025), who focus on nowcasting with multiple factors, can significantly improve the extraction of the indicator. In contrast to Eraslan and Reif (2023), the stochastic volatility in the state equation of the factor allows the variance of common shocks to the factor to vary, as shocks to the economy tend to be larger and more volatile during periods of crisis than during calm periods. Failing to account for this would lead to an underestimation of risk in turbulent periods and an overestimation in calm periods. Additionally, thanks to quasi-differencing, the model can account for serial correlation in the measurement errors arising from persistence in the idiosyncratic noise of individual variables that are irrelevant to the common factor. This may be relevant for high-frequency variables prone to reporting or processing errors that are sometimes loosely related to economic activity and

that may exhibit behavioral persistence. Failing to account for this could misattribute idiosyncratic persistence to the common factor and overstate factor persistence.

The presented indicator is the first for Switzerland that can be directly interpreted as a measure of GDP growth in high frequency thanks to its straightforward identification and the use of alternative high frequency data in a supervised mixed-frequency estimation approach. There exist several GDP indicators for Switzerland related to the indicator presented. The Swiss National Bank (SNB) Business Cycle Index (SNB-BCI) by Galli (2018) is a supervised approach based on a dynamic factor model using approximately 650 indicators, including official statistics, business and household surveys, and foreign and financial variables.¹ The Swiss Economic Confidence Indicator (SECO-SEC) of the State Secretariat for Economic Affairs (SECO) by Glocker and Kaniovski (2019) follows an unsupervised approach, as it is a monthly composite indicator that consists of a weighted average of 30 indicators, selected from more than 200 monthly and quarterly soft sentiment indicators with the highest information content for GDP prediction. The Economic Barometer (KOF-BARO) from the KOF Swiss Economic Institute (KOF) by Abberger et al. (2014) and extended by Abberger et al. (2018) uses a supervised two-step procedure where more than 200 from a set of 476 indicators (number growing) indicators are selected and then used in a static factor model to extract a monthly business cycle indicator. All of the models mentioned above are based on traditional monthly and quarterly macroeconomic indicators. In contrast, the SECO Weekly Economic Activity Indicator (SECO-WEA) by Wegmüller et al. (2023) was created during the COVID-19 pandemic to provide faster information on the current economic situation in Switzerland. It follows the example of Lewis et al. (2021) and uses only alternative high-frequency data in an unsupervised approach. All series are aggregated to weekly frequency and adjusted

¹In Galli et al. (2019) the model is compared with other models for forecasting Swiss GDP, where it shows precision gains over other methods. Glocker and Wegmueller (2019) build on this and show the benefits of introducing a Markov-switching process for the factor in their small-scale DFM to quickly assess the business cycle and identify recessionary periods.

for seasonality and outliers. A common factor is constructed from the growth rates of the data using the first principal component. Another high-frequency indicator, constructed with an unsupervised approach, is the fever curve (F-CURVE) by Burri and Kaufmann (2020), which provides a timely assessment of the economic health of the Swiss economy. It represents a high-frequency sentiment, as it is constructed from a factor using principal component analysis on daily financial and news data, providing an early warning signal, especially during crisis periods.²

In an empirical application, the characteristics of the weekly GDP indicator for Switzerland are analyzed. An in-sample analysis demonstrates that the indicator accurately captures Swiss GDP dynamics and offers additional insights due to its weekly frequency. An examination of the five most recent economic crises in Switzerland illustrates that the indicator provides valuable information on the trajectory of GDP, especially during periods of abrupt and substantial economic change. A comparison with other high-frequency indicators for Switzerland highlights the distinctive and practical utility of this indicator due to its straightforward interpretability as weekly GDP growth. Additionally, a real-time analysis indicates that the indicator identifies business cycle turning points relatively early and provides good forecast accuracy relative to existing business cycle indicators for Switzerland.

The remainder of this paper is structured as follows. Section 2 presents the model including the three state-space blocks, the identification of the factor, and the estimation procedure. Section 3 presents an empirical application for Swiss GDP, including a description of the data, the in-sample characteristics, out-of-sample forecast performance, and a discussion of the real-time properties of the indicator. Finally, Section 4 concludes.

²Other studies that applied alternative high-frequency data for Switzerland include Eckert and Mikosch (2020), who created a mobility tracker that proved effective in indicating sales activity during the COVID-19 pandemic, and Felber and Beyeler (2023), who use transaction payment data to nowcast GDP with machine learning methods.

2 Model

This paper adopts the methodology from Eckert et al. (2025), but in contrast, the model is constrained to a single factor to develop a high-frequency GDP indicator, aiming for an optimal in-sample fit and reliable real-time performance that depicts weekly GDP growth. This factor is determined by minimizing the error term of the measurement equation for the GDP series, thereby ensuring that the factor is closely aligned with the GDP series. As a result, the factor can be interpreted as a high-frequency indicator of GDP. The following chapter presents the model structure, which is based on the approach of Eckert et al. (2025), but tailored to the use of a single factor and its specific identification.

2.1 Data Augmentation

The model utilizes a collection of n time series with varying frequencies, where t represents the time index of the highest frequency in the data set. Lower-frequency observations are recorded in the last high-frequency period of the corresponding low-frequency interval, with all other entries set to zero to standardize all time series to the highest frequency. For example, when integrating weekly, monthly, and quarterly data, monthly (quarterly) observations are recorded in the last week of each month (quarter) and set to zero elsewhere. If an observation is missing due to publication delays or insufficient historical observations, the time series is also assigned a zero value for that period. Consequently, the n -dimensional vector \mathbf{y}_t generally contains a few actual observations among many zeros. \mathbf{x}_t is an n -dimensional vector that includes real observations and estimated latent observations for variables that are not observed. The relationship between the sparse vector \mathbf{y}_t and the dense vector \mathbf{x}_t is captured by the following identity:

$$\mathbf{y}_t = \mathbf{S}_t \mathbf{x}_t, \tag{1}$$

where \mathbf{S}_t is a diagonal selection matrix of size $n \times n$, with ones on the diagonal where the corresponding value in \mathbf{y}_t is observed, and zeros otherwise. Data augmentation refers to converting the sparse vector \mathbf{y}_t into the dense vector \mathbf{x}_t . Thus, Equation (1) is termed the *data augmentation equation*.

2.2 Dynamic Factor

The dynamic factor is defined at a weekly frequency. The *measurement equation for the dynamic factor* f_t is defined as

$$\mathbf{x}_t = \mathbf{L}_0 \boldsymbol{\lambda} f_t + \mathbf{L}_1 \boldsymbol{\lambda} f_{t-1} + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s} + \mathbf{e}_t. \quad (2)$$

s denotes the number of factor lags. The n -dimensional vector $\boldsymbol{\lambda}$ holds the time-invariant factor loadings. The diagonal distributed lag matrices $\mathbf{L}_0, \dots, \mathbf{L}_s$ contain predefined weights that ensure proper temporal aggregation of the high-frequency factor to the lower-frequency variables in \mathbf{x}_t according to the geometric mean approximation method initially proposed by Mariano and Murasawa (2003).³ The model is constrained to a single dynamic factor, which is later identified as the high-frequency growth rate of GDP (see Section 2.5). All time series are stationary and normalized to have a mean of zero and a unit variance.

The measurement errors in Equation (2) follow a first-order autoregressive process

$$\mathbf{e}_t = \boldsymbol{\rho} \mathbf{e}_{t-1} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}), \quad (3)$$

where the autoregressive coefficient matrix $\boldsymbol{\rho}$ and the error covariance matrix $\boldsymbol{\Sigma}$ are both assumed to be diagonal and constant over time to maintain a parsimonious model parametrization. Doz et al. (2012) show that modeling autoregression helps capture serial correlation in the idiosyncratic components, preventing bias in the factor estimates, and

³See for details Appendix A.1.

improving prediction intervals. It has become standard in the literature to account for one lag, as it should capture most of the serial correlation. Since the dynamic factor model is estimated at weekly frequency, allowing for stochastic volatility in the measurement errors would increase the number of estimated parameters immensely, leading potentially to overparameterization, increasing estimation risk, and numerical fragility.

To estimate the dynamic factor while accounting for serial correlation in the measurement errors, Chib and Greenberg (1994) suggest applying quasi-differencing to the measurement equation. To do this, the quasi-differenced augmented data vector is defined as

$$\tilde{\mathbf{x}}_t = \mathbf{x}_t - \boldsymbol{\rho}\mathbf{x}_{t-1}. \quad (4)$$

Substituting Equation (2) into Equation (4) results in the *quasi-differenced measurement equation for the dynamic factor*:

$$\tilde{\mathbf{x}}_t = \left(\mathbf{L}_0 \boldsymbol{\lambda} f_t + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s} \right) - \boldsymbol{\rho} \left(\mathbf{L}_0 \boldsymbol{\lambda} f_{t-1} + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s-1} \right) + \mathbf{u}_t, \quad (5)$$

where \mathbf{u}_t is defined in Equation (3) and is serially uncorrelated.⁴ The ability to eliminate serially correlated measurement errors through quasi-differencing is feasible because the original measurement equation in Equation (2) uses the dense augmented data vector \mathbf{x}_t . This approach allows for managing serial correlation despite the presence of mixed frequencies, missing observations, varying release lags, and differing lengths of the original data set. By eliminating serial correlation, the common factor can strongly explain the mixed-frequency series during certain periods while being less explanatory during others. This is particularly useful when the data set includes alternative high-frequency series that fluctuate significantly and are often weakly related to actual economic activity.

⁴It is straightforward to rearrange terms in Equation (5) to simplify the estimation of the factor.

The *state equation for the dynamic factor* is given by the autoregressive process

$$f_t = \phi_1 f_{t-1} + \dots + \phi_p f_{t-p} + e^{h_t} \eta_t, \quad \eta_t \sim \mathcal{N}(0, 1). \quad (6)$$

The autoregressive coefficients are denoted by the scalars ϕ_1, \dots, ϕ_p , with p indicating the number of lags.⁵ The composite error term $e^{h_t} \eta_t$ comprises the time-varying stochastic volatility factor e^{h_t} and the error term η_t following a standard normal distribution.

2.3 Stochastic Volatility

The variance of the error term in Equation (6) varies over time to enhance the ability of the model to capture periods of increased volatility, especially during crises. Therefore, the *state equation of the stochastic volatility factor* is represented by the logarithmized stochastic volatility factor which follows a random walk

$$h_t = h_{t-1} + v_t, \quad v_t \sim \mathcal{N}(0, \omega), \quad (7)$$

Due to the nonlinearities arising from directly solving Equation (6) for h_t , Primiceri (2005) suggest to transform the equation into a linear system through squaring and logarithmic operations. This transformation leads to the subsequent *measurement equation for the stochastic volatility factor*:

$$\log \left((f_t - \phi_1 f_{t-1} - \dots - \phi_p f_{t-p})^2 + c \right) = 2h_t + \log \left(\eta_t^2 \right). \quad (8)$$

An offset constant $c = 0.001$ is introduced to enhance the robustness of the estimation. Since η_t adheres to a standard normal distribution, the error term $\log(\eta_t^2)$ follows a log chi-squared distribution with one degree of freedom, denoted as $\log \chi^2(1)$. To further transform the system into a Gaussian state-space model, the $\chi^2(1)$ -distribution is approximated using a mixture of normals, following the methodology outlined in Kim et al.

⁵To handle unit roots, non-stationary draws of ϕ_1, \dots, ϕ_p are excluded, and distant lags of the autoregressive coefficients are shrunk towards zero.

(1998).⁶

2.4 Latent Data

The *measurement equation for the latent dense data vector* \mathbf{x}_t is defined by

$$\mathbf{y}_t = \mathbf{S}_t \mathbf{x}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(0, \epsilon \mathbf{I}_n). \quad (9)$$

The value of ϵ is chosen as a very small value (10^{-9}), relative to the observed data in \mathbf{y}_t , in order to closely approximate the relationship between observed and augmented data established by Equation (1). As the covariance matrix needs to be invertible in the precision sampling algorithm in the estimation, imposing an exact identity is not feasible. The *state equation for the latent dense data vector* \mathbf{x}_t is obtained by combining Equation (5) and Equation (4) to

$$\mathbf{x}_t = \left(\mathbf{L}_0 \boldsymbol{\lambda} f_t + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s} \right) - \boldsymbol{\rho} \left(\mathbf{L}_0 \boldsymbol{\lambda} f_{t-1} + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s-1} \right) + \boldsymbol{\rho} \mathbf{x}_{t-1} + \mathbf{u}_t \quad (10)$$

with $\mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma})$. The computational complexity remains feasible, as the components involving the distributed lag matrices $\mathbf{L}_0, \dots, \mathbf{L}_s$ can be pre-assigned outside the sampling algorithm.

2.5 Factor Identification and Interpretation

Because the dynamic factor and the factor loadings are unknown, there are infinite ways to interpret the data, a situation known as observational equivalence. To address this issue and identify the factor, certain constraints must be imposed on the parameter space. As outlined by Bai and Wang (2015), the factor loading on GDP, represented as λ_{gdp} , is fixed at unity by using informative priors. This approach resolves the scale and sign indeterminacy typically associated with dynamic factor models. Additionally, rotational

⁶See for details Appendix A.9.

indeterminacy is not an issue in the single-factor case. As a result, the dynamic factor is uniquely identified.

One advantage of this methodology is that it provides a clear and intuitive interpretation of the dynamic factor. This is accomplished by applying informative priors to the measurement error for GDP, such that the high-frequency dynamic factor closely approximates the week-on-week growth rate of GDP. Specifically, the autoregressive coefficient ρ_{gdp} is strongly shrunk towards zero, and the error term σ_{gdp} on GDP growth is constrained to a small value. This value determines the extent to which the temporally aggregated high-frequency factor can deviate from the observed GDP growth rates.

All other prior distributions are uninformative. Nevertheless, stationarity constraints are enforced on the autoregressive coefficients of the dynamic factor. This approach improves the robustness of convergence during sampling, particularly near turning points⁷

2.6 Estimation

The estimation process involves estimating the dynamic factor f_t , the stochastic volatility factor h_t , the dense latent data vector \mathbf{x}_t , as well as the parameters $\boldsymbol{\lambda}, \phi_1, \dots, \phi_p, \boldsymbol{\rho}, \omega$, and $\boldsymbol{\Sigma}$. The joint posterior distribution is simulated using Gibbs sampling. Separate Gibbs sampling blocks are used to estimate f_t , h_t , \mathbf{x}_t , and the aforementioned parameters, conditional on observed data \mathbf{y}_t , the selection matrix \mathbf{S}_t , and distributed lag matrices $\mathbf{L}_0, \dots, \mathbf{L}_s$. To enhance computational efficiency, sparse matrix pre-allocation and sparse matrix algorithms are employed. The initial values are randomly generated from uniform distributions to ensure robust convergence of the sampler. The convergence of the Gibbs sampling algorithm is evaluated using trace plots and by examining differences in the recursive means of selected parameters. Due to parsimonious parameterization, a burn-

⁷A detailed explanation of the conditional distributions is provided in Appendix A.

in of 10,000 iterations is sufficient for convergence. Once convergence is achieved, every fifth draw is saved until a sample of 5,000 draws is obtained.

Estimation of f_t , h_t , and \mathbf{x}_t follows the procedure of Chan and Jeliazkov (2009) in the separate Gibbs sampling blocks. The algorithm is extended to handle mixed-frequency data by incorporating the temporal aggregation scheme of Mariano and Murasawa (2003). Thanks to the parsimonious setup of the model and the efficient estimation using the precision sampler by Chan and Jeliazkov (2009) with sparse matrix preallocation, the model can be estimated much faster than in other mixed-frequency setups. Appendix A provides the estimation methods for f_t , h_t , \mathbf{x}_t and the remaining parameters $\boldsymbol{\lambda}$, ϕ_1, \dots, ϕ_p , ω , $\boldsymbol{\rho}$ and $\boldsymbol{\Sigma}$ respectively.

3 Empirical Analysis

3.1 Data

The data set is compiled to cover a wide range of economic activity in Switzerland. The data cover a period from January 1990 to September 2021. The data set consists of 53 variables, one sampled quarterly, 26 monthly, one weekly, and 25 daily. Table C.3 in the Appendix provides an overview of all the series used in this study, together with meta-information such as frequency, starting date, unit, transformation, and source. The table also categorizes the series into alternative high-frequency data, financial variables, production, labor market variables, retail sales, and business surveys.

The data set includes 22 daily and one weekly alternative high-frequency series. The aim was to cover a broad range of the economy. Consumer spending is captured by debit and credit card transaction volumes in retail trade, the volume of cash withdrawals at ATMs, passenger frequency in public and private transport, Google mobility data, and

Google search hits related to economic conditions and consumer goods purchases. Manufacturing is measured by truck frequency, truck toll from Germany, energy production and consumption volumes, and the frequency of motor vehicles passing through key monitoring stations. Google searches about the perceived labor market situation capture the labor market. The international activity is captured with the number of flight arrivals and departures at the main national airport

In addition to the alternative high-frequency series, the data set includes three daily and two monthly financial series and 24 monthly macroeconomic series, including business tendency surveys, purchasing manager indices, imports and exports, retail sales, consumer and producer prices, short- and long-term interest rates, and stock market indices. These financial and macroeconomic variables are commonly used in the GDP nowcasting literature and cover the most important aspects of the economy. Note that because many of the real indicators in Switzerland, such as industrial production, construction output, or service turnover, are published with a longer delay, survey data is favored in order to obtain better real-time performance of the indicator.

A major challenge for the use of alternative high-frequency data is the limited historical record and missing values. The series are often short, and many only begin in the outbreak of the COVID-19 pandemic and sometimes have missing values. However, the model can handle data sets with series starting at different or later dates. This capability results from the treatment of each series as a latent process, regardless of its observation status. Furthermore, thanks to explicit modeling of measurement errors including serial correlation as well as the estimation of a time-varying stochastic volatility factor, the model better filters out noise coming from idiosyncratic movements, outliers, or persistence in single indicators that are not relevant for the estimation of the common component. Additionally, as alternative high-frequency series may be suspect of structural breaks due to changes in the definition, scope, or coverage of the series, thorough checks have been

made.⁸ All time series are made stationary and standardized to have a mean of zero and a unit variance.

The daily series in the data set are aggregated to the weekly frequency. This approach simplifies the analysis by avoiding weekly seasonality patterns in the daily series and results in a regular frequency that provides four weekly observations for each of the 12 months, giving a total of 48 weekly observations per year. Temporal aggregation is performed by dividing each month into four approximately equal intervals: days 1 to 7, 8 to 14, 15 to 21, and 22 to the last day. The arithmetic mean of all daily observations within the same interval is then calculated. The same regularization procedure can be applied to the weekly variables in the data set, as they are linked to specific publication days. This frequency regularization ensures that the observations are equally spaced and have a consistent frequency.

Since 2005, the Swiss economy has experienced five distinct periods of economic crisis or shocks colored gray: the Great Recession during 2008Q4–2009Q3, the European sovereign debt crisis within 2011Q3–2013Q1, the Swiss franc shock during 2015Q1–2015Q2, the German car production shock during 2018Q3–2018Q4, and the COVID-19 pandemic during 2020Q1–2021Q2. The start and end dates of these crises correspond to periods of quarterly GDP declines or strong recovery. The crisis periods do not necessarily align with recession periods, which are technically defined as two consecutive quarters of negative GDP growth. During the European sovereign debt crisis, Switzerland experienced two non-consecutive quarters of negative growth within a single year. Similarly, during the Swiss franc shock and the German car production shock, Swiss GDP growth turned negative for only one quarter. Figure B.1 in the Appendix illustrates the annualized quarter-on-quarter growth rate of Swiss real GDP, adjusted for financial inflows and outflows related to international sporting events, which serves as the target variable.⁹

⁸The notes to table C.3 in the Appendix indicate which series have been adjusted.

⁹Note that the European Football Association (Uefa) and the International Olympic Committee (IOC)

3.2 The Weekly GDP Indicator

The weekly indicator resulting from the mixed-frequency dynamic factor model is constructed in such a way that it approximates the annualized week-on-week growth rate of GDP (see Section 2). For this reason, the dynamic factor is henceforth referred to as *weekly economic activity indicator* (WAI). This section studies the in-sample characteristics of the WAI.

The top panel of Figure 1 shows the WAI and its 95%-confidence interval resulting from an ex-post estimation (data available until December 31, 2021). The WAI is shown together with the actual quarter-on-quarter growth rate of GDP, indicated by horizontal red bars.¹⁰ The indicator and the quarter-on-quarter growth rate of GDP match well for the entire history.

The mid-panel presents the WAI as an index. It helps to see how certain periods have permanently weakened the growth path of GDP and helps to put the dimensions of the various crises into perspective. For example, the Great Recession led to a long-term loss of income, while GDP has largely recovered from the COVID-19 crisis and it has been possible to resume the old growth path.

The lower panel shows the stochastic volatility of the errors in the state equation for the dynamic factor. Time-varying errors allow the factor to account for the higher volatility of economic activity during crisis periods. The model uses this flexibility during periods of sudden and strong economic fluctuations, where the volatility of the error term increases.

The alternative high-frequency data presented above are especially useful in times of sharp and strong downturns and rebounds, as they should capture the increased volatility faster

are based in Switzerland. This results in large idiosyncratic movements of GDP. As a result, it is common practice for forecasting to adjust Swiss GDP for financial inflows and outflows related to international sporting events.

¹⁰The vertical axis of the figure is cropped to allow for an inspection of the fluctuations during normal times. The period of the COVID-19 pandemic will be discussed in greater detail later on.

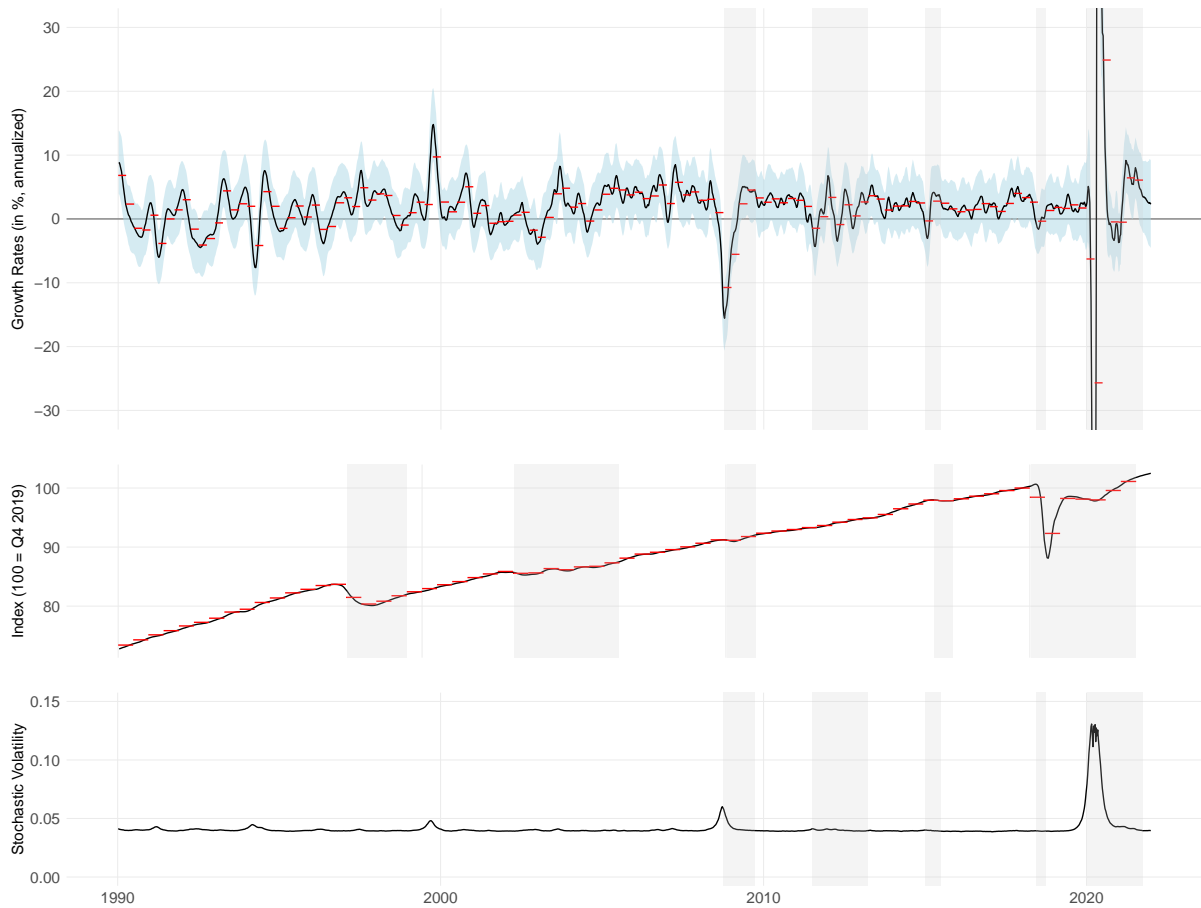


Figure 1: History of Weekly GDP and Stochastic Volatility. The upper panel shows the dynamic factor, representing the annualized week-on-week growth rate of Swiss real GDP, together with a 95%-confidence interval in blue. The estimation is conducted ex post, i.e. based on all data available until December 31, 2021. The red bars indicate the official annualized quarter-on-quarter growth rates of real GDP. The mid panel shows the WAI as an index, normalized by its value in Q4 2019. The red bars indicate the official real GDP observations. The lower panel shows the estimated stochastic volatility. Periods classified as economic crisis are indicated by vertical grey bars. The vertical axis of the upper panel is truncated to allow for an appropriate assessment of the entire history.

and to a greater extent than conventional macroeconomic data. To study this, a special emphasis is put on the five economic crises in Switzerland since the year 2005.

Figure 2 presents a more detailed view of the WAI during the before mentioned crisis periods. Again, the annualized weekly growth rates with 95%-confidence intervals in blue are illustrated together with the realized annualized quarter-on-quarter growth rate of GDP in red. The crisis quarters are indicated with vertical gray bars.

During the Great Recession, the indicator showed negative growth rates from the last week of July 2008 onward, reaching a low in mid-October of about -15%. From March 2009, weekly growth rates returned to positive territory. Overall, GDP experienced 30

consecutive weeks of negative growth. The evolution of these weekly growth rates shows that both the downturn and the subsequent recovery were stronger than the quarterly GDP observations would suggest.

During the European sovereign debt crisis, Switzerland experienced a significant degree of economic volatility over several quarters, including several negative or almost stagnating quarterly GDP growth rates. This was driven by several factors, including the appreciation of the Swiss franc, increased uncertainty, and highly volatile transit trade. The WAI indicates that weekly GDP experienced negative growth in the third quarter of 2012, which would have been missed by quarterly observations.

On 15 January 2015, the Swiss National Bank (SNB) unexpectedly abandoned the minimum exchange rate of 1.20 Swiss francs per euro. This resulted in a swift appreciation of the Swiss franc, which has been referred to as the "Swiss franc shock". This event led to a 0.7% decline in GDP during the first quarter of 2015, followed by a robust growth of 2.7% in the subsequent quarter. The WAI indicates that the economic downturn following the shock was pronounced reaching -3%, but a sharp recovery commenced at the end of February, mitigating a more severe contraction for the first quarter of 2015 in quarterly numbers.

In the third quarter of 2018, Switzerland experienced a decline in GDP growth, followed by a period of relatively weak GDP growth. This was in part due to the introduction of the new emission testing standard WLTP ("Worldwide Harmonized Light Vehicles Test Procedure") in the EU in September 2018. As a consequence of the fact that a significant number of vehicle types had not yet been certified by the deadline, inventories were increased to a considerable extent, and production was temporarily halted. Consequently, German GDP declined by 0.8%. The postponement of the approval of new German automobile models had an impact on Swiss suppliers of vehicle parts and metals, as well as on the sale of new vehicles. The new standard in the automotive industry had long-

term effects on the entire sector, resulting in rather weak growth in the next quarters. Furthermore, chemical and pharmaceutical exports experienced a pronounced decline in the third quarter, which was offset in the first month of the fourth quarter. This suggests a temporal shift in foreign deliveries.

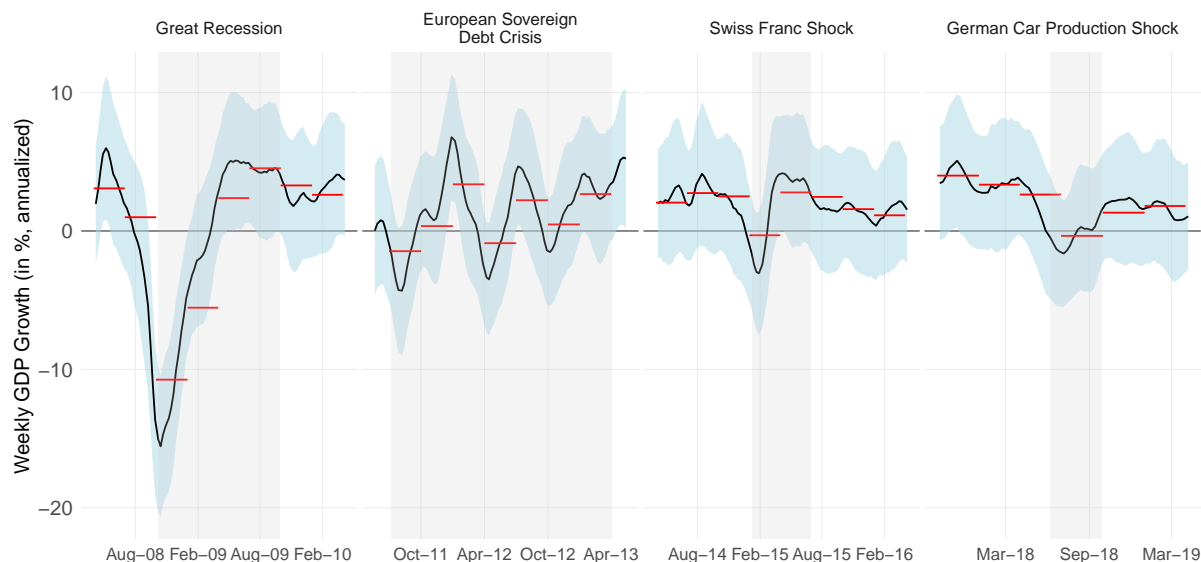


Figure 2: Weekly GDP Growth During Crisis Periods. Notes: See Figure 1.

Figure 3 focuses on the period of the COVID-19 pandemic, which represented a profound and abrupt shock to the Swiss economy. The figure illustrates the WAI along with a 95% confidence interval and the actual quarter-on-quarter GDP growth rate. Important policy decisions during the pandemic are marked by vertical dotted lines. Table C.2 in the Appendix details the timing and presents a list of measures implemented by the Swiss federal government. The first COVID-19 infection in Switzerland was reported on February 25, 2020. Restrictions on events and gatherings gradually intensified from late February through early March. On March 16, the government imposed a nationwide lockdown in response to the widespread transmission of the virus. The WAI shows a significant decline in economic activity even before the lockdown, which can according to Eckert and Mikosch (2020) be attributed to a reduction in mobility and consumption by the population from late February onward in reaction to the spread of the pandemic.

Companies cut back on production, as evidenced by a marked increase in claims for short-

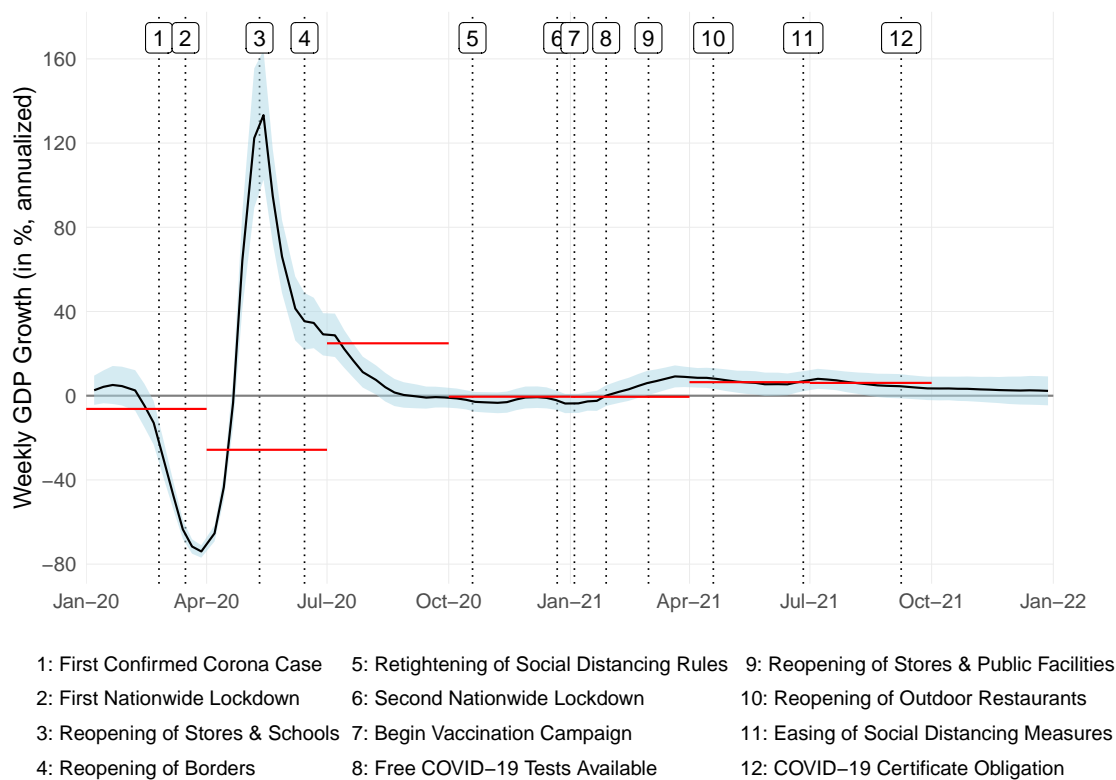


Figure 3: Weekly GDP Growth During the COVID-19 Pandemic. Notes: See Figure 1.

term work. The lockdown intensified the economic downturn, which reached its lowest point at the end of March. As infection rates fell rapidly in April, public life resumed and businesses and schools reopened on 29 April, leading to a rapid economic recovery. From May, weekly GDP growth declined again and briefly turned negative in early October due to a resurgence of COVID-19 cases. On 19 October, the government reintroduced stricter social distancing measures. In December and January, partial closures were reimposed. However, the economic impact of these measures was minimal compared to the lockdown in spring 2020. With the acceleration of the vaccination campaign and the free availability of COVID-19 tests, economic activity returned to positive growth rates in early 2021. Despite a resurgence of COVID-19 infections in the winter of 2021, driven by the rapid spread of the Omicron variant, economic activity remained largely unaffected and continued to normalize throughout the rest of 2021.

3.3 In-sample Evaluation

The following analysis compares the WAI with the most important and frequently used business cycle indicators for the Swiss economy. These include two indicators developed during the COVID-19 pandemic using high-frequency data, which are the weekly economic activity indicator (WEA) from SECO by Wegmüller et al. (2023) and the standardized and inverted daily "fever curve" (F-CURVE) by Burri and Kaufmann (2020). Both follow an unsupervised approach by extracting the indicator from the first principal component. Other indicators were already in place prior to the pandemic and are based on traditional monthly and quarterly macroeconomic indicators. Specifically, there is the monthly Swiss Economic Confidence Indicator from SECO (SECO-SEC) by Glocker and Kaniovski (2019) which follows an unsupervised approach by taking the arithmetic mean of soft indicators, and two supervised approaches using factor models such as the monthly Business Cycle Index from SNB (SNB-BCI) by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018).

Figure 4 shows the history of the WAI, transformed into annual growth rates for easier comparison in red, the black bars indicate the official quarterly growth rates of Swiss real GDP (adjusted for international sporting events), while the blue lines are the benchmark indicators. Depending on the indicator either year-over-year or quarter-over-quarter growth rates are shown.

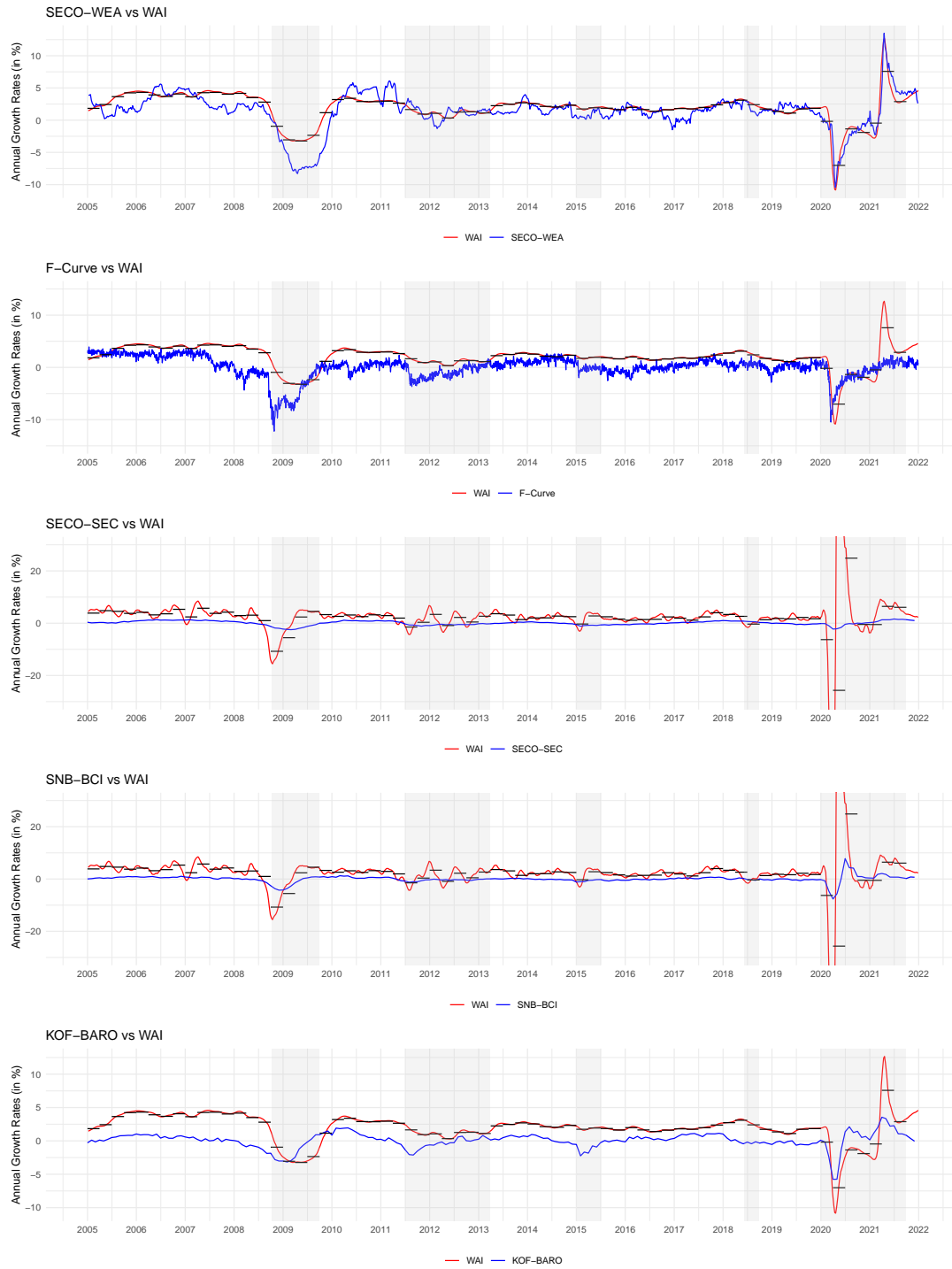


Figure 4: Comparison with Other Benchmark Indicators. Each panel shows in red the weekly GDP indicator, transformed into annual growth rates and as black bars the official quarterly rates of Swiss real GDP. Depending on the indicator, either the year-over-year or the quarter-over-quarter growth is shown. In blue in each panel a benchmark indicator is shown from top to bottom: The weekly economic activity indicator (SECO-WEA) from SECO by Wegmüller et al. (2023) in year-on-year growth rates, the standardized and inverted daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly Business Cycle Index (SNB-BCI) from SNB by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018).

The upper panel of Figure 4 shows the weekly economic activity indicator (WEA) from

SECO by Wegmüller et al. (2023) transformed to year-on-year growth rates in blue. Despite its simple unsupervised approach and the limited amount of data it uses, the WEA shows a relatively good fit, especially during the COVID-19 pandemic. However, the indicator is rather short, as it starts in 2005. Also it is quite volatile and can sometimes produce misleading signals, showing substantial deviations, particularly during the great financial crisis, as it does not necessarily need to sum up to quarterly GDP growth rates. The second panel of Figure 4 shows the inverted standardized "fever curve" (F-CURVE) by Burri and Kaufmann (2020) in daily growth rates in blue, which was also created during the COVID-19 pandemic as a high-frequency indicator. The figure shows that the indicator deviates strongly from GDP growth, which is particularly evident during the COVID-19 pandemic when the indicator does not capture the subsequent recovery. Therefore, it serves less as a GDP measures but rather provides a broader economic sentiment.

The following three panels in Figure 4 show other business cycle indicators created by SECO, SNB, and KOF. All of these indicators use a mixed-frequency setup with traditional quarterly and monthly data. All three indicators measure a broader definition of the business cycle. While the SECO-SEC and the KOF-BARO are sentiment indicators similar to the F-CURVE and rather loosely follow GDP growth, the SNB-BCI, in contrast, follows rather closely the year-on-year GDP growth with a lead. However, this lead appears to vary over time.

Figure B.5 in the Appendix shows the cross-correlation for each indicator with Swiss real GDP (adjusted for international sporting events). The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. As the SECO-WEA and the WAI directly track GDP growth, they can be calculated in YoY and QoQ, while the other indicators cannot be transformed, and thus are left the same for the two measures. To show the lead of the indicators, the cross-correlation is shown for different lags from

four to zero quarters ahead of GDP realization. Three different measures are tested; "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as the reference value. The analysis uses a sample starting in 1990 or as soon as data is available until the end of 2021.

As the WAI is designed to provide an accurate estimate of current GDP growth, it exhibits the highest correlation with GDP at one- and zero-lead.¹¹ Using the last value or the last month improves performance over the mean of the entire quarter. Further, as it tracks GDP itself, it performs well in YoY and QoQ comparison, as it can be transformed into both measures. In contrast, the other indicators show a lower overall correlation with GDP and a more diffuse lead, as well as displaying different leading characteristics than the WAI. While the SECO-WEA shows the highest correlation with YoY GDP growth with zero lead, the F-CURVE shows the highest correlation with a one- or two-quarter lead, the SECO-SEC shows the highest correlation with a zero- or one-quarter lead, and the SNB-BCI and KOF-BARO show the highest correlation with a zero- to three-quarter lead, depending on the measure. For QoQ, except for the SNB-BCI mean, the benchmark measures show a low correlation with GDP for all leads and measures. Similar results can be shown with the R^2 -statistic in the Appendix C.6.

Similarly, Table 1 presents the in-sample predictive content of the indicators by showing the relative root mean squared errors (RMSE) against the WAI for predicting GDP growth rates in a linear regressions. The analysis is again run for both year-on-year (YoY) and quarter-on-quarter (QoQ) GDP growth, as well as for different leads and measures. For year-on-year (YoY) GDP growth, the WAI significantly outperforms almost all benchmark indicators for all measures for one and zero leads. For quarter-on-quarter GDP growth,

¹¹The lead is relatively short. However, due to the indicator's fast reaction to the downturn in the first quarter of 2020 and its recovery starting in the second quarter, it is able to capture movements that are only reflected in subsequent GDP publications. This results in a higher lead.

the WAI significantly outperforms all benchmark indicators for a one-quarter lead. The results are robust when using the mean squared error (see Appendix C.7).¹² The in-sample analysis shows that the WAI outperforms the benchmark indicators in similarity to GDP growth and in consistency of its lead structure, providing a reliable measure of a high-frequency GDP indicator.

Table 1. In-sample GDP Forecast Evaluation: Relative RMSE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
SECO-WEA	1.10	1.16*	1.19**	1.31**	21.83***	1.26*	1.26*	1.29*	2.41**	1.22*
F-CURVE	1.04	0.97	0.96	1.07*	32.10***	1.13	1.12	1.15	2.14*	0.98
SECO-SEC	1.01	0.96	0.91	0.97*	24.99***	1.05*	1.04*	1.07	2.01**	0.92
SNB-BCI	1.00	0.86	0.96	1.22	35.30***	1.00	1.00	1.03	1.93**	0.55
KOF-BARO	0.99	0.87	0.90	1.17**	34.00***	1.01	1.00	1.02	1.95**	0.77
Last										
SECO-WEA	1.13*	1.19*	1.19**	2.56***	1.13***	1.26*	1.26*	1.36*	2.90**	1.17*
F-CURVE	1.06	1.03	0.68	2.49***	1.63***	1.19*	1.02	1.02	2.52**	1.11
SECO-SEC	1.00	0.97	0.91	2.11***	1.11***	1.05*	1.04*	1.12	2.37**	0.92
SNB-BCI	0.97	0.86	1.00	2.65***	1.61***	1.00	1.00	1.08	2.01***	0.80
KOF-BARO	0.96	0.88	0.95	2.66***	1.56***	1.01	1.00	1.08	2.22**	0.87
Last Month										
SECO-WEA	1.12*	1.18*	1.21**	1.92**	1.57***	1.26*	1.26*	1.35*	3.24**	1.18*
F-CURVE	1.02	0.95	0.98	1.60***	2.26***	1.13	1.12	1.21	2.70**	1.00
SECO-SEC	1.00	0.96	0.91	1.45**	1.70***	1.05*	1.04*	1.12	2.66**	0.92
SNB-BCI	0.96	0.85	1.00	1.82***	2.47***	1.00	1.00	1.07	2.25**	0.80
KOF-BARO	0.96	0.87	0.95	1.83***	2.40***	1.01	1.00	1.08	2.49**	0.87

Notes: This table shows the relative root mean squared error (RMSE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on the sample starting in 1990 or as soon as data is available until the end of 2021 and is then used for predicting each quarter of GDP growth. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the weekly economic activity indicator (WAI), the weekly economic activity indicator (SECO-WEA) from SECO by Wegmüller et al. (2023), the daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot directly be transformed and thus are left the same for the two measures. To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value. Significance levels indicate differences in forecast performance according to the one-sided Diebold-Mariano test against the WAI and are denoted by asterisks: *** (1% level), ** (5% level), and * (10% level).

¹²As robustness check, the whole analysis was also performed using only data starting 2005, as the shortest indicator starts at this time, and the results are very similar.

A similar analysis is performed using different specifications of the weekly economic activity indicator (WAI) to see how relevant certain characteristics are. The performance of the indicator is tested against a version without stochastic volatility (WAI-SV), without high-frequency data, and without stochastic volatility (WAI-(SV+HF)), and without high-frequency data (WAI-HF). Figure B.4, B.6 and Table in the Appendix show the history, the in-sample correlation, and the factor loadings for different specifications of the WAI, while the tables C.8, C.9, and C.10 show the in-sample relative RMSE, MAE and R^2 with GDP.

The comparison shows that, although the in-sample fit of the model using no stochastic volatility looks similar, it performs significantly worse at capturing short-term movements when predicting quarter-on-quarter GDP growth. This can be explained with the lower factor loadings on high-frequency variables in the model without stochastic volatility. As a result, the factor relies more on information from slower monthly data. When excluding high-frequency variables, the indicator is not flexible enough to capture strong GDP growth movements. Factor loadings are mainly related to price data, imports, exports, and survey data, while the relevance of retail sales decreases. Stochastic volatility seems to be irrelevant in the specification without high-frequency data. The factor loadings are therefore similar.

As a robustness check, two additional versions with a slightly different data set are tested, namely excluding financial high-frequency data (WAI-HF) and excluding retail sales subcomponents (WAI-Retail). Excluding the three financial and longest available high-frequency variables has little impact on the indicator's performance; however, factor loadings on other high-frequency indicators also decrease. Excluding all six retail sales indicators except total retail sales does affect the indicator, particularly during crisis periods. The retail sales variables seem important to extract a meaningful factor, as many of the high-frequency variables are consumption-related indicators. As a result, the factor

loadings are higher for survey data and many of the high-frequency variables.

3.4 Pseudo Real-time Properties

The previous analysis showed that the WAI effectively captures ex-post fluctuations in economic activity. However, its real-time performance may differ as it is subject to revisions caused by new information from subsequent data releases. The pseudo real-time properties of the indicator were assessed by recursively estimating the model from January 2005 until December 2021 at weekly intervals. Data availability is reconstructed according to the publication dates described in Table C.3 in the Appendix. Potential data revisions are not taken into account in order to abstract this effect.

Figure 5 illustrates the WAI from its initial release to its 30th version, covering the period 2005 to 2021. The initial release for any given week t serves as the real-time estimate for that week, incorporating only the data available up to week t . In contrast, the 30th release version for any given week t incorporates data published up to the 29th week after week t .

Earlier releases, indicated in yellow, exhibit more pronounced fluctuations and often lag behind relative to later releases shown in red and blue, particularly during periods of crisis. This suggests that earlier releases tend to respond more slowly to macroeconomic fluctuations than later releases. Initial estimates are primarily based on alternative and financial high-frequency series, as these are the most immediately available data in the data set. In contrast, later releases incorporate monthly series and actual quarterly GDP figures. The macroeconomic variables published later help to correct any potentially misleading or overstated signals from the high-frequency alternative and financial data. However, only a few revisions are necessary for the indicator to align closely with the stable state depicted in subsequent releases.

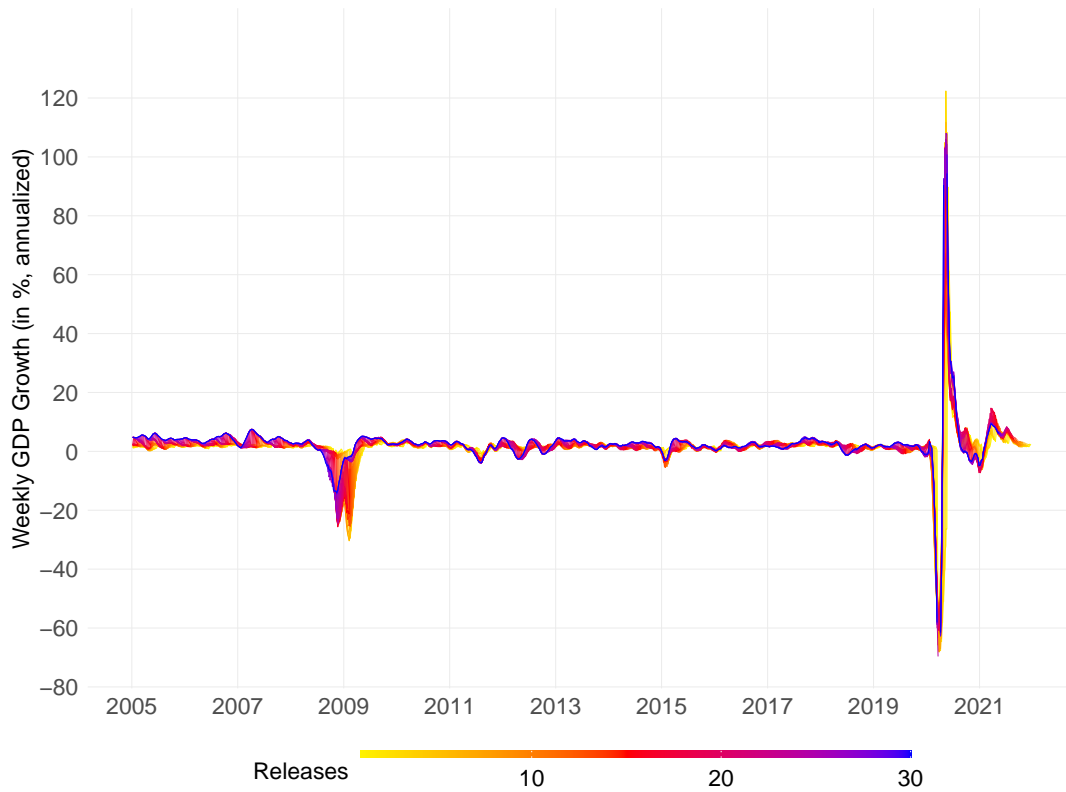


Figure 5: Revisions of the WAI. The figure compares the WAI for different releases. The color bar goes from the first release in yellow over the 15th release in red to the 30th release in blue.

A more detailed examination of certain periods (see figure B.2 for a close-up of subperiods) shows that the model requires a relatively long adjustment period for the Great Recession. One possible explanation for this is that it was the first significant economic crisis in the sample and that the model lacked comparable data at the time. Another explanation is that at this time only a limited number of high-frequency indicators were available for use in the model, most of which were financial variables. Consequently, the model was only able to utilize these in its early vintages. Subsequently, in the period after the Great Recession, the indicator shows a rather quick adjustment and lower errors compared to the last vintage. During the COVID-19 pandemic, the model demonstrated markedly accelerated adjustment because it had already acquired the capacity to learn from previous crisis periods and because the data set encompassed a substantial number of high-frequency indicators that captured fluctuations during this period. Examining different vintages during the COVID-19 pandemic (see figure B.3 in the Appendix), the

first (real-time) vintage captures the crisis generally well but lags behind in capturing the movements in 2020 and 2021. However, already the vintage four weeks after the reference period, which includes no monthly and only weekly indicators yet, shows a rather fast reaction similar to the last vintage.

Changes in the factor loadings can explain the different real-time behavior (see table C.4 in the Appendix). The factor loadings for the estimate using a vintage up to just before the Great Recession show high loadings on purchasing manager indices (PMI), prices, retail sales, imports, exports, and the high-frequency financial series, while most other high-frequency variables are not yet available. After the Great Recession, the loadings on the financial variables, as well as the Google searches for labor market information increase further, while manufacturing data become more important. Until the onset of the COVID-19 pandemic, the loadings remain similar, while new high frequency data became available. After the COVID-19 pandemic, financial and manufacturing data lose importance, while retail sales, imports, exports, and high-frequency mobility data such as truck, flight, public transport, and consumption data gain importance. It shows that the factor loadings of the high-frequency series seem to be relevant and contribute to the extraction of the factor.

3.5 Out-of-sample Performance

To evaluate the real-time performance of the indicator, an out-of-sample forecast exercise is performed using real-time vintages to predict quarterly GDP. This exercise uses real-time GDP vintages from Indergand and Leist (2014).¹³ The exercise incorporates 67 GDP publications that span from 2005Q1 to 2021Q3. Forecasts of the year-on-year and quarter-on-quarter growth rates of GDP are made using a linear regression that

¹³Real-time GDP vintages adjusted for international sporting events date back to Q3 2018; prior to this, unadjusted GDP measures were used because the former did not exist.

includes a constant. Forecast errors are illustrated as root mean squared errors (RMSE) relative to WAI errors. To demonstrate the lead of the indicators, the cross-correlation is displayed for various lags ranging from four to zero quarters ahead of GDP realization. Three different measures are tested: 'Mean' shows aggregation of all observations over the quarter; 'Last' uses the final observation; and 'Last Month' uses aggregation over the final month as the reference value. For the WAI, weekly real-time vintages are estimated. Real-time vintages exist for the KOF-BARO from 2014m4 onward, before pseudo-vintages were created. For the other benchmark indicators, pseudo-vintages were created.

Table 2 shows that the indicator highly outperforms the AR(1) model and all benchmark indicators for the year-on-year (YoY) measure at zero lag, and for the quarter-on-quarter (QoQ) measure at leads of one and zero quarters. The only exception is the SNB-BCI at zero lag and the mean measures at one lead. However, only the WAI and partly the KOF-BARO use real-time vintages. The other indicators rely on ex-post vintages, benefiting from future information. This advantage is likely negligible for unsupervised methods (SECO-WEA, F-CURVE, SECO-SEC) but may affect the supervised SNB-BCI. Improvements against the three monthly indicators are generally higher when using the 'Last' observation of the WAI rather than the average over the 'Last Month' which proves the benefit of the high-frequency updates of the indicator. As a robustness check, the mean absolute error gives similar results (see table C.11). Therefore, the superior forecast performance at short leads provides evidence that the indicator gives relatively accurate real-time signals of the current economic condition.

The same analysis has also been performed using a pseudo-real-time analysis, where the last vintage of GDP of the analysis (26.11.2021), as well as the last vintage in 2021 for WAI and KOF-BARO is used, while for the other benchmark indicators pseudo-vintages are created. Table C.12 and C.13 in the Appendix show the relative RMSEs and MAEs. The analysis gives similar conclusions, however, the results became more significant.

Table 2. Real-time Out-of-sample GDP Forecast Evaluation: RMSE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
AR	0.97	1.01	1.04	1.12	1.91**	1.00	1.00	0.97	0.89	2.35
SECO-WEA	1.07	1.11	1.08	1.08	1.30	1.04	1.05	1.02	0.94*	2.04
F-CURVE	1.06	0.99	0.96	0.96	1.72**	1.02	1.01	0.98	0.91	1.78
SECO-SEC	0.99	0.94	0.89	0.94	1.56**	1.00	1.00	0.97	0.90	1.74
SNB-BCI	1.00	0.82	1.11	1.30	2.45*	1.01	0.99	0.97	0.98	0.85
KOF-BARO	0.97	0.86	0.87	1.11	1.78***	1.00	0.99	0.95	0.94	1.69
Last										
AR	0.97	1.02	1.03	1.05	2.03**	1.00	1.00	0.94	1.08	1.57
SECO-WEA	1.06	1.11	1.07	1.02	1.40*	1.04	1.04	0.99	1.14	1.34
F-CURVE	1.06	1.01	0.96	0.96	1.91**	1.02*	1.01	0.97	1.10	1.20
SECO-SEC	1.00	0.95	0.89	0.88	1.69**	1.00	1.00	0.94	1.09	1.16
SNB-BCI	0.99	0.85	1.03	1.11	2.33**	1.01*	0.99	0.96	1.11	0.75
KOF-BARO	0.97	0.86	0.86	1.03	1.95***	1.01	0.99	0.93	1.13	1.10
Last Month										
AR	0.97	1.01	1.02	1.06	1.99**	0.99	1.00	0.93	1.08	1.55
SECO-WEA	1.06	1.11	1.08	1.05	1.40	1.04	1.04	0.98	1.14	1.32
F-CURVE	1.06	1.01	0.95	0.98	1.82**	1.02	1.01	0.94	1.11	1.18
SECO-SEC	0.99	0.94	0.88	0.89	1.66**	1.00	1.00	0.93	1.09	1.14
SNB-BCI	0.99	0.84	1.02	1.12	2.28**	1.00	0.99	0.94	1.11	0.73
KOF-BARO	0.97	0.86	0.86	1.04	1.91***	1.00	0.99	0.91	1.13	1.08

Notes: This table shows the relative root mean squared error (RMSE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The AR-model uses one period lag GDP growth as indicator. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on a sample starting 1990 or as soon as data is available with prediction starting 2005 with an expanding window until end of 2021. Real-time GDP vintages are used from Indergand and Leist (2014). Real-time vintages of GDP adjusted for international sporting events exist from 2018Q3 onward. Before non-adjusted GDP vintages are used. For the KOF-BARO exist real-time vintages from 2014m4 onward. The WAI uses weekly real-time vintages. For the SECO-WEA, F-CURVE, SECO-SEC, and SNB-BCI pseudo real-time vintages are created as no official real-time vintages exist. See Table 1 for a description of the Table labels.

4 Conclusion

This paper introduces a novel weekly GDP indicator for Switzerland, which addresses the limitations of existing economic activity indicators using alternative high-frequency data to capture the fast and sharp economic changes observed during crisis periods such as the COVID-19 pandemic. The Bayesian mixed-frequency dynamic factor model, which integrates weekly, monthly, and quarterly data from conventional macroeconomic indicators and alternative high-frequency sources, enables near real-time monitoring of GDP.

This paper extends the Bayesian mixed-frequency dynamic factor model proposed by Eckert et al. (2025) to develop a high frequency indicator that, thanks to its straightforward identification, can be directly interpreted as the weekly GDP growth. The model incorporates three independent state-space blocks: estimating missing observations as latent states via data augmentation, extracting dynamic factors, and estimating stochastic volatility in the factor state equation. Additionally, the model addresses serial correlation in the measurement errors by applying quasi-differencing. As a result, the model can extract business cycle information from a wide range of data frequencies and capture large and sudden fluctuations.

The empirical application demonstrates that the indicator provides an accurate and timely reflection of Swiss GDP dynamics, providing valuable insights, particularly during periods of significant economic crisis. The performance of the indicator during periods of economic crisis in Switzerland, including the COVID-19 pandemic, illustrates its effectiveness in tracking abrupt economic changes and providing a credible depiction of these events.

A pseudo-real-time assessment of the WAI shows how the indicator has performed differently in different periods. Although the indicator needed several releases to capture the Great Recession, when almost no high-frequency data was available, it was able to identify turning points at an early stage and quickly converged to its final version during the COVID-19 pandemic, when it was able to exploit the high-frequency information in the data. In this way, it could be used to provide up-to-date information about state of the economy during crisis periods to inform policy decisions.

A comparative analysis with other high-frequency indicators for Switzerland highlights the unique characteristics of this indicator, showing superior in-sample fit with GDP and out-of-sample predictive accuracy for GDP for short leads.

The indicator’s direct interpretation as weekly GDP growth, its high-frequency updates,

and its superior nowcast performance relative to benchmark indicators using traditional methods provide valuable benefits to business cycle observers. The methodology can be adopted for other countries, where similar high-frequency data exist, while taking into account the specific characteristics of that particular country. Therefore, the methodology could help make better informed policy decisions than compared to using traditional indicators.

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A Model Derivation and Estimation

A.1 Temporal Aggregation

Aggregating the high-frequency factor f_t to a lower frequency factor \bar{f}_t is straightforward for stock variables. In such scenarios, temporal aggregation is done by simple averaging:

$$\bar{f}_t = \sum_{i=0}^{k-1} \lambda_i f_{t-i}, \quad \text{where} \quad \lambda_i = \frac{1}{k}$$

The variable k indicates how many high frequency intervals fit into a single low frequency interval (e.g., $k = 3$ for aggregating monthly data into quarterly periods). The aggregation becomes more complex for flow variables. These variables are typically used in forecasting models as growth rates, introducing nonlinearities when aggregated over time. Mariano and Murasawa (2003) proposed an approximation using geometric means instead of arithmetic means, which has since become widely adopted:

$$\bar{f}_t = \sum_{i=0}^s \lambda_i f_{t-i}, \quad \text{where} \quad \lambda_i = \frac{k - |1 + i - k|}{k}$$

The number of distributed lags is determined by $s = 2(k - 1)$. Geometric mean aggregation involves a triangular weighting scheme that addresses the statistical effects observed during the aggregation of growth rates. To illustrate this, consider a flow variable X :

$$\log X_{Q1} = \frac{1}{3} (\log X_{Jan} + \log X_{Feb} + \log X_{Mar})$$

The growth rate for the second quarter is determined as:

$$\begin{aligned} \log X_{Q2} - \log X_{Q1} &= \\ &= \frac{1}{3} \left(\log (X_{Jun} + \log X_{May} + \log X_{Apr}) - \frac{1}{3} (\log X_{Mar} + \log X_{Feb} + \log X_{Jan}) \right) \\ &= \frac{1}{3} (\log X_{Jun} - \log X_{Mar}) + \frac{1}{3} (\log X_{May} - \log X_{Feb}) + \frac{1}{3} (\log X_{Apr} - \log X_{Jan}). \end{aligned}$$

Next, incorporate additional terms into the equation:

$$\begin{aligned}
\log X_{Q2} - \log X_{Q1} = & \\
& \frac{1}{3} (\log X_{Jun} - \log X_{May} + \log X_{May} - \log X_{Apr} + \log X_{April} - \log X_{Mar}) + \\
& \frac{1}{3} (\log X_{May} - \log X_{Apr} + \log X_{Apr} - \log X_{Mar} + \log X_{Mar} - \log X_{Feb}) + \\
& \frac{1}{3} (\log X_{Apr} - \log X_{Mar} + \log X_{Mar} - \log X_{Feb} + \log X_{Feb} - \log X_{Jan})
\end{aligned}$$

By defining growth rates as $x_t = \log X_t - \log X_{t-1}$, the previous equation simplifies to

$$\begin{aligned}
x_{Q2} = & \frac{1}{3} (x_{Jun} + x_{May} + x_{April}) + \frac{1}{3} (x_{May} + x_{April} + x_{March}) \\
& + \frac{1}{3} (x_{April} + x_{March} + x_{Feb}) \\
= & \frac{1}{3} x_{Jun} + \frac{2}{3} x_{May} + \frac{3}{3} x_{April} + \frac{2}{3} x_{March} + \frac{1}{3} x_{Feb}
\end{aligned}$$

This triangular weighting structure is inserted in the distributed lag matrices $\mathbf{L}_0, \dots, \mathbf{L}_s$ in Equation (2).

A.2 Latent Data Estimation

To group the parameters in appropriate blocks, the measurement equation for \mathbf{x}_t given in Equation (9) is stacked over all periods $t = 1, \dots, T$. This results in

$$\mathbf{y} = \mathbf{S}\mathbf{x} + \boldsymbol{\epsilon}, \quad \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_T \otimes \boldsymbol{\epsilon}_n), \quad (11)$$

where $\mathbf{y} = [\mathbf{y}'_1, \dots, \mathbf{y}'_T]'$, $\mathbf{x} = [\mathbf{x}'_1, \dots, \mathbf{x}'_T]'$ and $\mathbf{S} = \text{diag}(\mathbf{S}_1, \dots, \mathbf{S}_T)$. The state equation for \mathbf{x}_t , as depicted in Equation (10), is similarly stacked :

$$\mathbf{K}\mathbf{x} = \mathbf{G}\mathbf{f} + \mathbf{u}, \quad \mathbf{u} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_T \otimes \boldsymbol{\Sigma}), \quad (12)$$

with \mathbf{G} defined in Equation (14) and

$$\mathbf{K}_{nT \times nT} = \begin{bmatrix} \mathbf{I}_n & & & \\ -\mathbf{P} & \mathbf{I}_n & & \\ & \ddots & \ddots & \\ & & -\mathbf{P} & \mathbf{I}_n \end{bmatrix}.$$

The precision matrix \mathbf{P}_0 is then given by $\mathbf{K}'(\mathbf{I}_T \otimes \boldsymbol{\Sigma})^{-1}\mathbf{K}$ and the conditional posterior of \mathbf{x} follows a normal distribution according to

$$(\mathbf{x}|\mathbf{y}, \mathbf{f}, \mathbf{h}, \boldsymbol{\Theta}) \sim \mathcal{N}(\mathbf{p}_1, \mathbf{P}_1), \quad (13)$$

with

$$\begin{aligned} \mathbf{P}_1 &= \left(\mathbf{P}_0 + \mathbf{S}'(\mathbf{I}_T \otimes \epsilon \mathbf{I}_n)^{-1} \mathbf{S} \right)^{-1}, \\ \mathbf{p}_1 &= \mathbf{P}_1 \left(\mathbf{K}'_{-1} (\mathbf{I}_{T-1} \otimes \boldsymbol{\Sigma})^{-1} \mathbf{G}\mathbf{f} + \mathbf{S}'(\mathbf{I}_T \otimes \epsilon \mathbf{I}_n)^{-1} \mathbf{y} \right), \end{aligned}$$

where \mathbf{K}_{-1} denotes \mathbf{K} with its first n rows removed. The conditional posterior distribution of \mathbf{x} is thus a weighted average of \mathbf{y} and a projection using $\mathbf{G}\mathbf{f}$. These weights are determined by \mathbf{S} , taking values of zero or one. Specifically, when a variable is observed and its corresponding entry in \mathbf{y}_t is non-zero, its weight is one, and the corresponding entry in \mathbf{x}_t approximates this observed value. In contrast, when a variable is not observed and its corresponding entry in \mathbf{y}_t is zero, its weight is zero, and the corresponding entry in \mathbf{x}_t is equal to the projection estimate.

A.3 Dynamic Factor

To estimate f_t , the measurement equation for the factor, as presented in Equation (5), is stacked over all time periods $t = 1, \dots, T$, resulting in

$$\tilde{\mathbf{x}} = \mathbf{G}\mathbf{f} + \mathbf{u}, \quad \mathbf{u} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_T \otimes \boldsymbol{\Sigma}), \quad (14)$$

where

$$\begin{aligned} \underset{n(T-1) \times 1}{\tilde{\mathbf{x}}} &= \begin{bmatrix} \tilde{\mathbf{x}}_2 \\ \vdots \\ \tilde{\mathbf{x}}_T \end{bmatrix}, \quad \underset{n(T-1) \times (T+s)}{\mathbf{G}} = \\ &\begin{bmatrix} -\boldsymbol{\rho}\mathbf{L}_s\boldsymbol{\lambda} & (\mathbf{L}_s - \boldsymbol{\rho}\mathbf{L}_{s-1})\boldsymbol{\lambda} & \dots & (\mathbf{L}_1 - \boldsymbol{\rho}\mathbf{L}_0)\boldsymbol{\lambda} & \mathbf{L}_0\boldsymbol{\lambda} \\ & \ddots & & \ddots & \\ & -\boldsymbol{\rho}\mathbf{L}_s\boldsymbol{\lambda} & (\mathbf{L}_s - \boldsymbol{\rho}\mathbf{L}_{s-1})\boldsymbol{\lambda} & \dots & (\mathbf{L}_1 - \boldsymbol{\rho}\mathbf{L}_0)\boldsymbol{\lambda} & \mathbf{L}_0\boldsymbol{\lambda} \end{bmatrix}. \end{aligned}$$

It should be noted that G incorporates the temporal aggregation scheme of Mariano (2003) into the procedure established by Chan (2009). The state equation for the factor, as presented in Equation (6), is similarly stacked:

$$\mathbf{H}\mathbf{f} = \mathbf{v}, \quad \mathbf{v} \sim \mathcal{N}(\mathbf{0}, \mathbf{V}), \quad (15)$$

where

$$\underset{(T+s) \times (T+s)}{\mathbf{H}} = \begin{bmatrix} 1 & & & & & \\ -\phi_1 & 1 & & & & \\ \vdots & \ddots & \ddots & & & \\ -\phi_p & \dots & -\phi_1 & 1 & & \\ & \ddots & \ddots & \ddots & \ddots & \\ & & -\phi_p & \dots & -\phi_1 & 1 \end{bmatrix}, \quad \underset{(T+s) \times 1}{\mathbf{f}} = \begin{bmatrix} f_{1-s} \\ f_{2-s} \\ \vdots \\ f_1 \\ \vdots \\ f_T \end{bmatrix},$$

where \mathbf{V} is a diagonal matrix containing the time-varying variances $e^{2h_{1-s}}, \dots, e^{2h_T}$. The precision matrix \mathbf{F}_0 is defined as $\mathbf{H}'\mathbf{V}^{-1}\mathbf{H}$. Consequently, the conditional posterior distribution of the factors follows a normal distribution given by

$$\begin{aligned} \mathbf{f} &\sim \mathcal{N}(\mathbf{f}_1, \mathbf{F}_1), \quad \text{where} \quad \mathbf{f}_1 = \mathbf{F}_1 \left(\mathbf{G}'(\mathbf{I}_{T-1} \otimes \boldsymbol{\Sigma}^{-1})\tilde{\mathbf{x}} \right), \\ \mathbf{F}_1 &= \left(\mathbf{F}_0 + \mathbf{G}'(\mathbf{I}_{T-1} \otimes \boldsymbol{\Sigma}^{-1})\mathbf{G} \right)^{-1}. \end{aligned}$$

Rather than inverting \mathbf{F}_1 , it is more efficient to compute the banded Cholesky factor of \mathbf{F}_1 and solve for \mathbf{f}_1 using forward and backward substitution. Overall, employing block-banded matrix algorithms significantly enhances the computational efficiency of estimating the latent states f_t , h_t , and \mathbf{x}_t , as well as the remaining parameters.

A.4 Factor Loadings

The factor loadings $\boldsymbol{\lambda}$ are estimated by stacking the quasi-differenced measurement equation (5) over all periods $t = 1, \dots, T$. This results in:

$$\tilde{\mathbf{x}} = \mathbf{Z}\boldsymbol{\lambda} + \mathbf{u}, \quad \mathbf{u} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_T \otimes \boldsymbol{\Sigma}), \quad (16)$$

where

$$\mathbf{Z}_{n(T-1) \times n} = \sum_{i=0}^s \begin{bmatrix} \mathbf{f}_{2-i} \mathbf{D}_i \\ \vdots \\ \mathbf{f}_{T-i} \mathbf{D}_i \end{bmatrix}, \quad \mathbf{D}_i = \begin{cases} \mathbf{L}_0, & \text{if } i = 0, \\ -\mathbf{P}\mathbf{L}_s, & \text{if } i = s, \\ \mathbf{L}_{i-1} - \mathbf{P}\mathbf{L}_i, & \text{otherwise.} \end{cases}$$

This results in the following conditional posterior distribution of the factor loadings:

$$(\boldsymbol{\lambda} | \mathbf{x}, \mathbf{f}, \mathbf{h}, \boldsymbol{\Theta} \setminus \boldsymbol{\lambda}) \sim \mathcal{N}(\mathbf{b}_1, \mathbf{B}_1) \quad \text{with } \mathbf{B}_1 = (\mathbf{B}_0^{-1} + \mathbf{Z}'(\mathbf{I}_{T-1} \otimes \boldsymbol{\Sigma}^{-1})\mathbf{Z})^{-1}, \quad (17)$$

$$\mathbf{b}_1 = \mathbf{B}_1 (\mathbf{B}_0^{-1}\mathbf{b}_0 + \mathbf{Z}'(\mathbf{I}_{T-1} \otimes \boldsymbol{\Sigma}^{-1})\tilde{\mathbf{x}}).$$

The prior mean vector \mathbf{b}_0 is a vector of ones. Choosing very large values for the prior variances in \mathbf{B}_0 results in an uninformative prior.

A.5 Error Covariance in Factor Measurement Equation

To estimate the covariance matrix $\boldsymbol{\Sigma}$ of the serially uncorrelated measurement errors in the quasi-differenced measurement equation (5), the measurement errors are computed

from $\tilde{\mathbf{x}} - \mathbf{Z}\boldsymbol{\lambda}$ are stacked. The matrix $\boldsymbol{\Sigma}$ is assumed to be diagonal, reflecting the belief that the dynamic factor captures most of the cross-correlation in the data. Additionally, the variances of the measurement errors are considered to be constant over time to maintain a simple model structure. Consequently, the error variances σ_i^2 are drawn from an inverse Gamma distribution for each equation.¹

$$\sigma_i^2 \sim \mathcal{IG}(c_{1,i}/2, d_{1,i}/2), \quad \text{where} \quad c_{1,i} = c_{0,i} + T, \quad (18)$$

$$d_{1,i} = d_{0,i} + \mathbf{u}_i \mathbf{u}_i'.$$

The priors are chosen to be uninformative with $c_{0,i} = 3$ and $d_{0,i} = 10^{-9}$.

A.6 Autoregressive Coefficients of Factor Measurement Errors

The autoregressive coefficients in matrix \mathbf{P} of Equation (3) in the main text are estimated from the serially correlated measurement errors of Equation (2) in the main text. These measurement errors are obtained from $\mathbf{x}_t - \mathbf{L}_0 \boldsymbol{\lambda} f_t + \mathbf{L}_1 \boldsymbol{\lambda} f_{t-1} + \dots + \mathbf{L}_s \boldsymbol{\lambda} f_{t-s}$ for $t = 1, \dots, T$. The diagonal elements of \mathbf{P} are drawn individually for each equation, based on the vector \mathbf{e}_i , which contains the serially correlated errors for the i th variable. The conditional posterior distribution for these diagonal elements, P_i, \dots, P_n , is given by

$$(P_i | \mathbf{x}, \mathbf{f}, \mathbf{h}, \boldsymbol{\Theta} \setminus P_i) \sim \mathcal{N}(r_{1,i}, R_{1,i}) \quad \text{with} \quad R_{1,i} = \left(R_{0,i}^{-1} + \sigma_i^{-2} \mathbf{e}_{i,-T}' \mathbf{e}_{i,-T} \right)^{-1}, \quad (19)$$

$$r_{1,i} = R_{1,i} \left(R_{0,i}^{-1} r_{0,i} + \sigma_i^{-2} \mathbf{e}_{i,-T}' \mathbf{e}_{i,-1} \right).$$

The prior mean $r_{0,i}$ for all variables i is set to 0. The prior variances $R_{0,i}$ are set to $1/T$.

This choice is weakly informative and pulls the autoregressive coefficients towards zero.

¹An alternative model incorporating stochastic volatility in the measurement equation was tested. However, this led to significant numerical instabilities during sampling due to the high frequency of estimation and the inclusion of numerous time series.

A.7 Autoregressive Coefficients of Factor State Equation

The autoregressive coefficients Φ_1, \dots, Φ_p are derived according to the method described by Chan et al. (2018). The state equation for the factor in Equation (6) is combined over all periods from $t = p + 1$ to T to obtain

$$\mathbf{m} = \mathbf{M}\Phi + \mathbf{v}, \quad \mathbf{v} \sim \mathcal{N}(\mathbf{0}, \mathbf{V}), \quad (20)$$

where

$$\mathbf{m} = \begin{bmatrix} f_{p+1} \\ \vdots \\ f_T \end{bmatrix}, \quad \mathbf{M} = \begin{bmatrix} f_p & \dots & f_1 \\ \vdots & \ddots & \vdots \\ f_{T-1} & \dots & f_{T-p} \end{bmatrix}, \quad \Phi = \begin{bmatrix} \Phi_1 \\ \vdots \\ \Phi_p \end{bmatrix}$$

with \mathbf{V} being a diagonal matrix containing the time-varying variances of the state equation $e^{2h_{p+1}}, \dots, e^{2h_T}$. The conditional posterior is given by

$$(\Phi | \mathbf{x}, \mathbf{f}, \mathbf{h}, \Theta \setminus \Phi) \sim \mathcal{N}(\mathbf{a}_1, \mathbf{A}_1) \text{ with } \mathbf{A}_1 = (\mathbf{A}_0^{-1} + \mathbf{M}'\mathbf{V}^{-1}\mathbf{M})^{-1}, \quad (21)$$

$$\mathbf{a}_1 = \mathbf{A}_1 (\mathbf{A}_0^{-1}\mathbf{a}_0 + \mathbf{M}'\mathbf{V}^{-1}\mathbf{m}).$$

For the chosen parameterization of $p = 1$, priors can be set as uninformative with a mean of zero and a variance of one.² Stationarity is enforced by discarding draws where the largest absolute eigenvalue of the companion matrix exceeds a specific threshold. Following the approach in Antolin-Diaz et al. (2024), setting this threshold to 0.8 has been found to ensure robust convergence, thereby promoting stationarity. This threshold enhances the numerical stability of the Gibbs sampling process. After convergence, the draws of Φ_1, \dots, Φ_p generally remain well below this threshold.

²Higher-order autoregressive processes likely require constraints on the parameter space, such as a prior that forces distant lag parameters towards zero more strongly. In such cases, \mathbf{a}_0 would be a vector of zeros, and \mathbf{A}_0 would be a diagonal matrix with values of $1/p^2$.

A.8 Error Variance in Stochastic Volatility State Equation

The variance ω of the errors in the state equation for the stochastic volatility factor, as shown in Equation (7), is sampled from an inverse gamma distribution as follows:

$$\omega \sim \mathcal{IG}(k_1/2, l_1/2), \quad \text{where} \quad k_1 = k_0 + T + s, \quad (22)$$

$$l_1 = l_0 + \mathbf{v}\mathbf{v}'.$$

The vector \mathbf{v} holds the residuals from the stochastic volatility state equation. Uninformative priors are used, with $k_0 = 3$ and $l_0 = 0.01$.

A.9 Stochastic Volatility

The error term in the measurement equation for the stochastic volatility factor from Equation (8) follows a $\log \chi^2(1)$ -distribution. To approximate this within a linear Gaussian state space model, the moments of the distribution are estimated using a mixture of normal distributions, as detailed by Kim et al. (1998) and Primiceri (2005). This approach uses a combination of seven normal distributions. Each distribution $j = 1, \dots, 7$ has a specific mean μ_j , variance ξ_j , and is selected based on a probability q_j . The parameters and selection probabilities are taken directly from Kim et al. (1998) and are summarized in Table A.1.

Table A.1. Parameters and Selection Probabilities of Mixing Distribution

j	q_j	μ_j	ξ_j
1	0.00730	-11.40039	5.79596
2	0.10556	-5.24321	2.61369
3	0.00002	-9.83726	5.17950
4	0.04395	1.50746	0.16735
5	0.34001	-0.65098	0.64009
6	0.24566	0.52478	0.34023
7	0.25750	-2.35859	1.26261

Notes: $\mu_j + 1.2704$ equals m_i from Table 4 of Kim et al. (1998). .

For simplicity in notation, define $w_t = \log \left((f_t - \phi_1 f_{t-1} + \dots + \phi_p f_{t-p})^2 + c \right)$. To estimate the stochastic volatility factor h_t , the measurement equation for h_t from Equation (8) is stacked over all periods $t = 1, \dots, T$ to get³

$$\mathbf{w} = \mathbf{W}\mathbf{h} - \boldsymbol{\mu} + \varepsilon, \quad \varepsilon \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Xi})$$

where

$$\mathbf{W}_{(T+s) \times 1} = \begin{bmatrix} w_{1-s} \\ \vdots \\ w_1 \\ \vdots \\ w_T \end{bmatrix}, \quad \mathbf{W}_{(T+s) \times (T+s)} = \begin{bmatrix} 2 & & & \\ & 2 & & \\ & & \ddots & \\ & & & 2 \\ & & & & 2 \end{bmatrix}, \quad \mathbf{h}_{(T+s) \times 1} = \begin{bmatrix} h_{1-s} \\ \vdots \\ h_1 \\ \vdots \\ h_T \end{bmatrix}$$

Each element of the vector $\boldsymbol{\mu}$ is assigned a specific μ_j from the set $[\mu_1, \dots, \mu_7]$, according to the probabilities listed in Table A.1. Similarly, each element of the diagonal matrix $\boldsymbol{\Xi}$ is filled with the corresponding ξ_j values from the set $[\xi_1, \dots, \xi_7]$ as specified in the table.

There is no prior knowledge about the initial state of the stochastic volatility. Therefore, the approach of Chan and Jeliazkov (2009) is followed, imposing a diffuse prior by stacking the stochastic volatility state equation from Equation (7) accordingly:

$$\mathbf{N}\mathbf{h} = \mathbf{u}, \quad \mathbf{u} \sim \mathcal{N}(\mathbf{0}, \omega \mathbf{I}_{T+s})$$

where \mathbf{N} is of reduced rank and is given by

$$\mathbf{N}_{(T+s-1) \times (T+s)} = \begin{bmatrix} -1 & 1 & & \\ & & \ddots & \ddots \\ & & & -1 & 1 \end{bmatrix}$$

The precision matrix \mathbf{Q}_0 is defined as $\mathbf{N}'(\omega \mathbf{I}_{T+s})^{-1} \mathbf{N}$ and the conditional posterior of

³Note that no values exist for $w_{1-s}, \dots, w_{1-s+p-1}$ since f_{1-s} is the first estimated factor. Values for w_t are assumed to be zero.

the stochastic volatility is normally distributed:

$$\mathbf{h} \sim \mathcal{N}(\mathbf{q}_1, \mathbf{Q}_1) \quad \text{where} \quad \mathbf{Q}_1 = (\mathbf{Q}_0 + \mathbf{W}'\mathbf{\Xi}^{-1}\mathbf{W})^{-1}$$

$$\mathbf{q}_1 = \mathbf{Q}_1 (\mathbf{W}'\mathbf{\Xi}^{-1}(\mathbf{w} + \boldsymbol{\mu}))$$

Similarly to the dynamic factor, this algorithm becomes computationally highly efficient when utilizing block-banded matrix algorithms and preallocating sparse matrices.

B Additional Figures

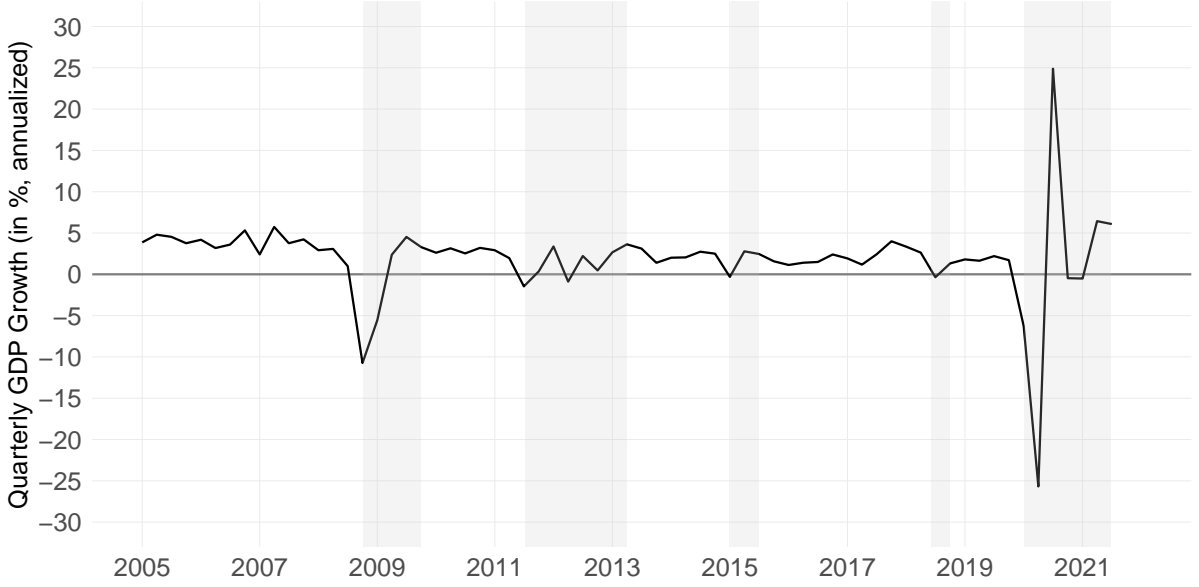


Figure B.1: History of Swiss GDP Growth. The figure illustrates the annualized quarter-on-quarter growth rate of Swiss real GDP, adjusted for financial inflows and outflows related to international sporting events, in percent from 2005Q1 to 2021Q3. The crisis periods are indicated by vertical gray bars.



Figure B.2: Revisions of the Weekly GDP Indicator for Subperiods. The figure compares the weekly GDP indicator for different releases and different subperiods. Shown are the period from 2005-2009, 2010-2019, 2020-2022. The color bar goes from the first release in yellow over the 15th release in red to the 30th release in blue. The sample ranges from beginning of 2005 to end of 2021.

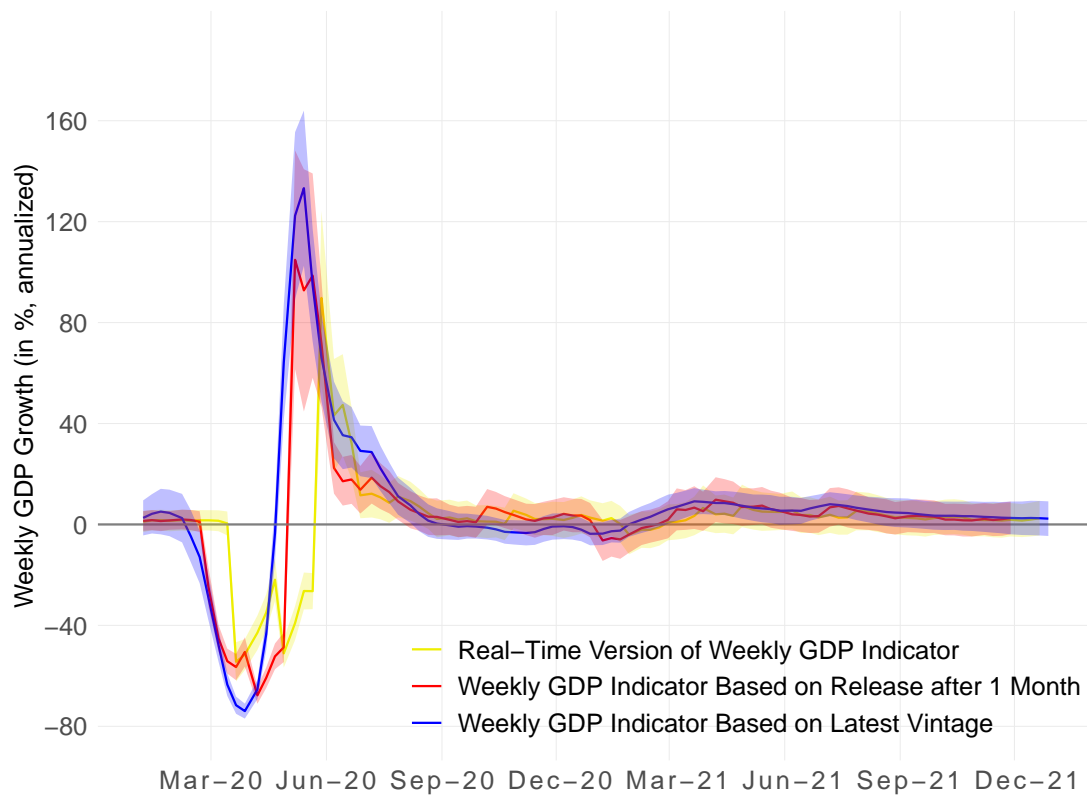


Figure B.3: Different Releases of the Weekly GDP Indicator During the COVID-19 Pandemic. The figure compares the weekly GDP indicator as recorded by its first release (“real-time indicator”) with the indicator as recorded by its release one month after the first release and with the indicator based on the last available data vintage (December 31, 2021). All indicator versions are displayed with 95%-confidence intervals.

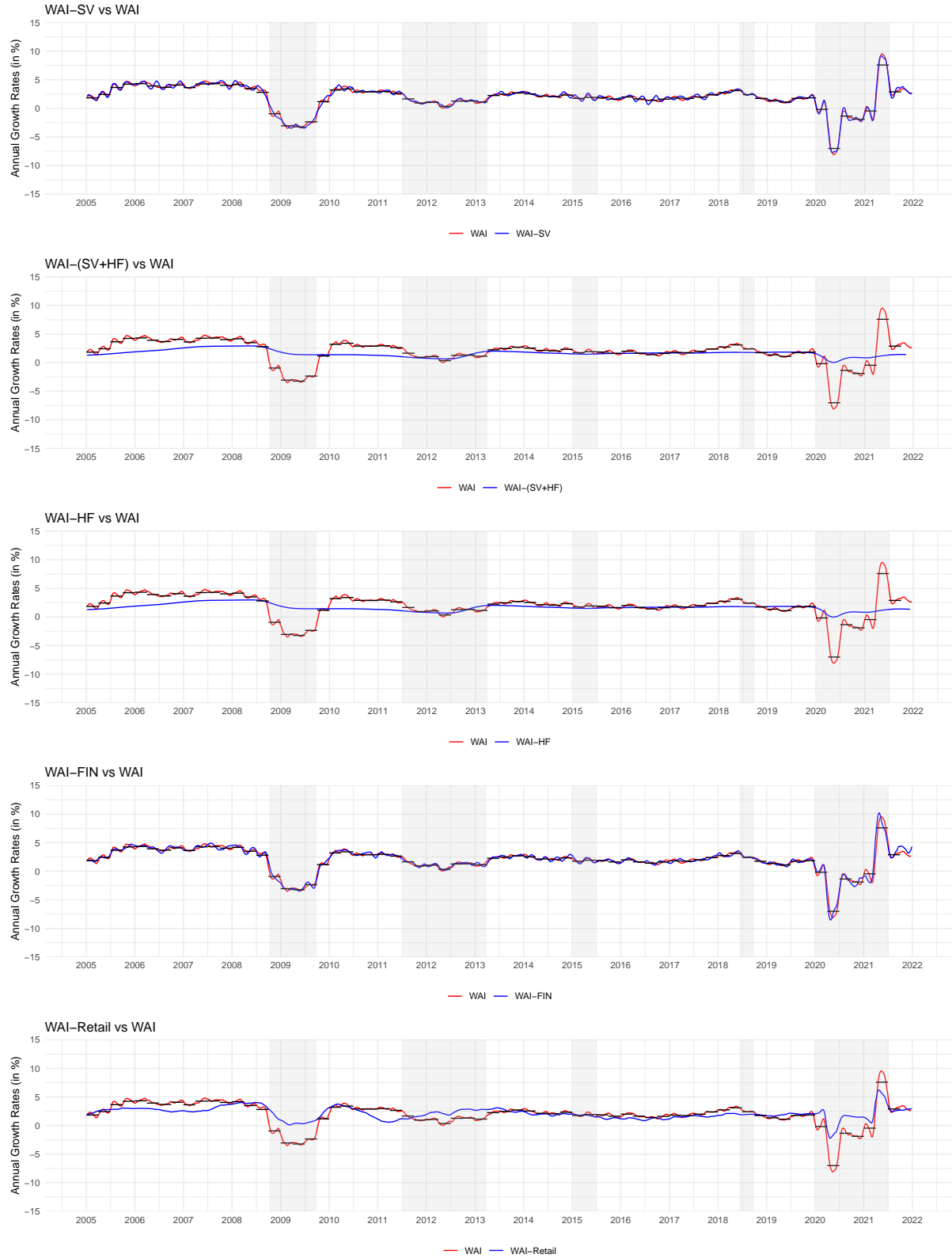


Figure B.4: Comparison with Other Specifications. Each panel shows in red the weekly GDP indicator, transformed into annual growth rates and as black bars the official quarterly year-over-year growth rates of Swiss real GDP. In blue in each panel another specification of the weekly GDP indicator is shown from top to bottom: Without stochastic volatility (WAI-SV), without stochastic volatility and without high-frequency indicators (WAI-(SV+HF)), without high-frequency indicators (WAI-HF), without financial variables (WAI-FIN), and without retail sales indicators except total retail sales (WAI-Retail).

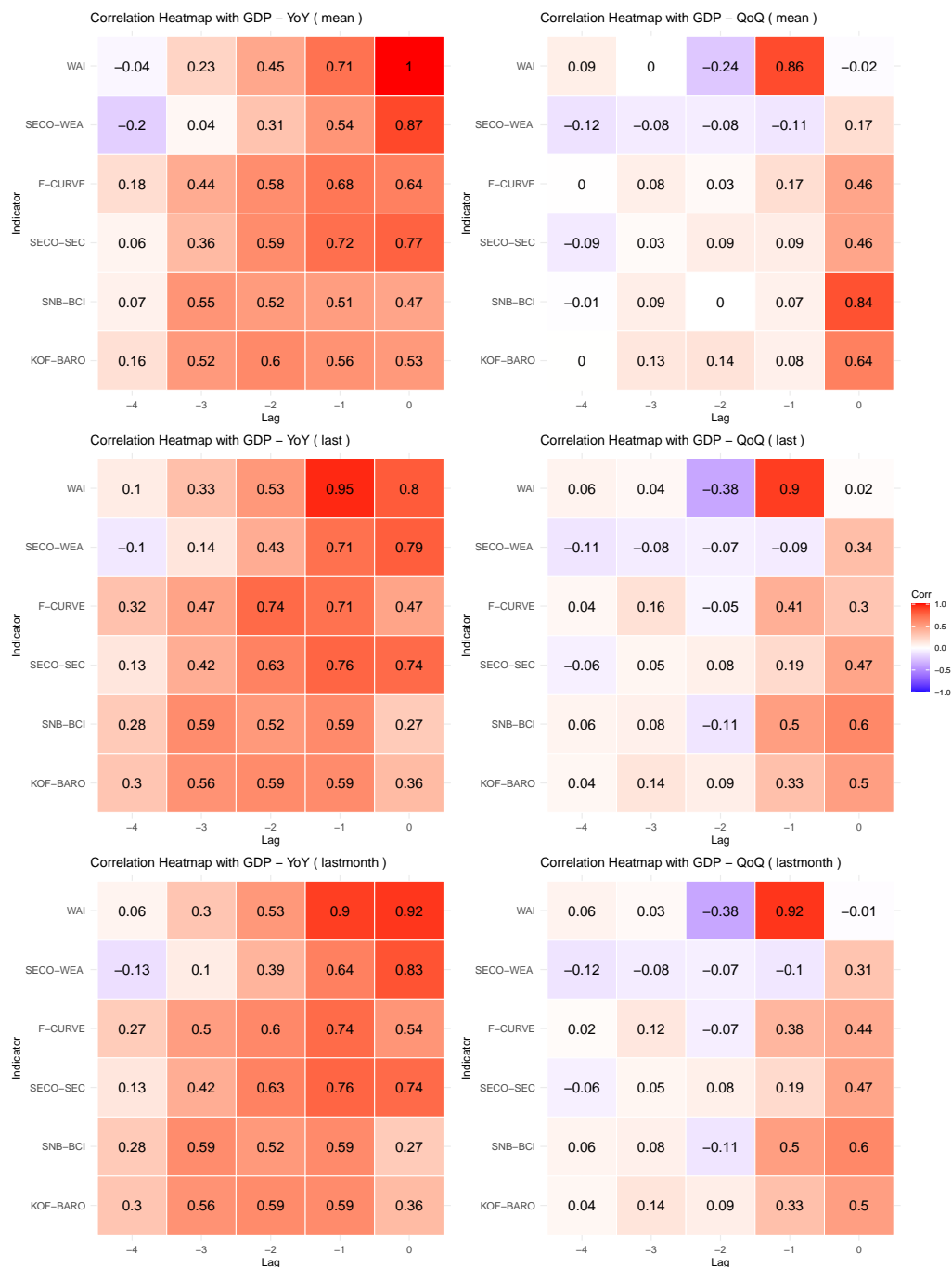


Figure B.5: Cross-correlation with GDP for Different Indicators. Notes: This figure shows the cross-correlation for each indicator with Swiss real GDP (adjusted for international sporting events) starting in 1990 or as soon as data is available until the end of 2021. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the WAI (WAI), the weekly economic activity indicator (WEA) from SECO by Wegmüller et al. (2023), the standardized and inverted daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly Business Cycle Index from SNB (SNB-BCI) by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot be transformed and thus are left the same for the two measures. To show the lead of the indicators, the cross-correlation is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

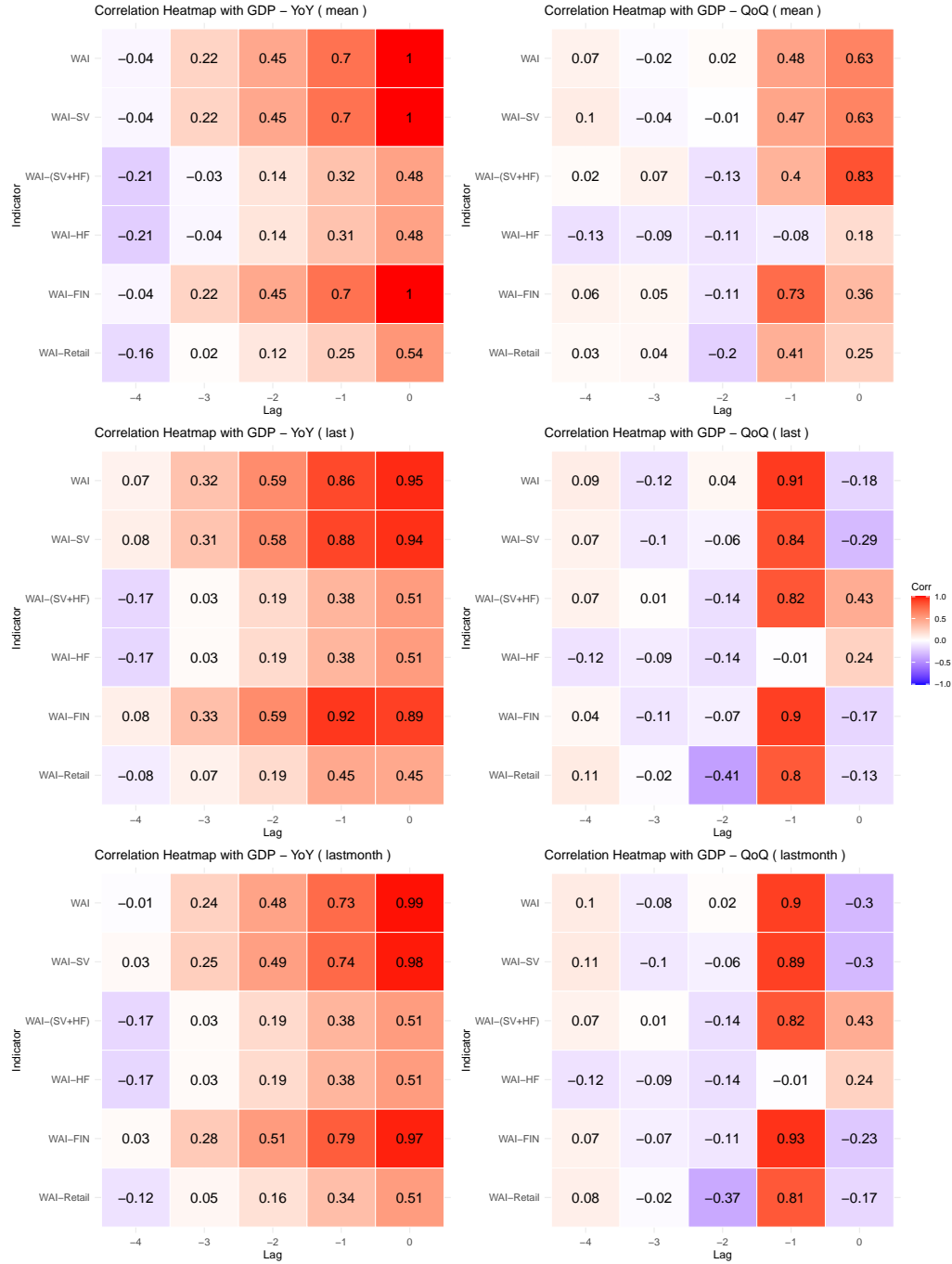


Figure B.6: Cross-correlation of Different Specifications with GDP. This figure shows the cross-correlation for each specification with Swiss real GDP (adjusted for international sporting events) starting 1990 until end of 2021. The target is either the year-over-year (YoY) or the quarter-over-quarter (QoQ) growth rates of real GDP. The indicators are the weekly GDP indicator (WAI), without stochastic volatility (WAI-SV), without stochastic volatility and without high-frequency indicators (WAI-(SV+HF)), without financial variables (WAI-FIN), and without retail sales indicators except total retail sales (WAI-Retail). To show the lead of the indicators, the cross-correlation is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

C Additional Tables

Table C.2. Chronology of COVID-19 containment measures in Switzerland

Date	Description
28 February 2020	Declaration of "Special Situation" and prohibition of mass events over 1000 people
13 March 2020	Prohibition of events over 100 people, restrictions of maximum occupancy in restaurants, bars, and clubs. End of classroom teaching.
16 March 2020	Declaration of "Extraordinary Situation": Lockdown and border closures.
20 March 2020	Prohibition of meetings with more than 5 people.
29 April 2020	Shutdown Easing Phase 1: Relaxation of lockdown, opening of shops, restaurants, markets, museums, and gyms. Classroom teaching for children up to the age of 15.
30 May 2020	Meetings with up to 30 people allowed.
06 June 2020	Shutdown Easing Phase 3: Events of up to 300 people allowed. Opening of most leisure and tourism businesses, classroom teaching for all ages.
15 June 2020	Reopening of all borders.
22 June 2020	End of "Extraordinary Situation": Abolition of most containment measures and repealing of home office recommendation.
06 July 2020	Mandatory mask wearing in public transport, quarantine for travelers from high-risk areas.
19 October 2020	Reintroduction of restrictions on meetings with more than 15 people, general mask requirement in public spaces. Home office again recommended.
28 October 2020	Further tightening of restrictions: closure of nightclubs, extension of mandatory mask wearing. Restrictions in restaurants and bars: max. 4 people per group, curfew from 11 PM to 6 AM.
02 November 2020	Ban on in-person events at higher education institutions.
09 December 2020	Ski resorts require approval from the canton and must present strict protection plans.
12 December 2020	Restricted opening hours for hospitality establishments, public businesses and facilities. Ban on events. Restricted number of people for leisure activities of no more than 5 people.
22 December 2020	Closure of most leisure facilities. Further restriction on the number of people in stores. Expanded use of rapid tests also for asymptomatic individuals.
18 January 2021	Closure of shops selling non-daily necessities. Employers are required to implement home office wherever possible: Masks are mandatory in all indoor work areas.
28 January 2021	The federal government also assumes the costs for tests of asymptomatic individuals.
01 February 2021	Offenses against measures to combat the epidemic are explicitly listed as punishable offenses.
08 February 2021	Possibility of shortening quarantine. Collection of contact details by entering the country. A negative PCR test must be shown upon entering the country.
01 March 2021	Opening of outdoor areas of leisure and sports facilities, shops, museums, and libraries. Private gatherings and events are allowed outdoors with a maximum of 15 people.
15 March 2021	The federal government will cover the costs for all rapid tests
22 March 2021	Private gatherings and events indoors are allowed with a maximum of 10 people.
19 April 2021	Exception from contact quarantine in businesses where testing is conducted. Permitted teaching in-person up to 50 people, and cultural and sporting activities for up to 15 people. Opening of publicly accessible leisure and entertainment facilities. Events are permitted again with restrictions.
31 May 2021	No quarantine for vaccinated and recovered individuals. No mandatory home office for businesses. Relaxation of a maximum number of people for cultural and sports events up to 50 people, private gatherings up to 30 indoors and 50 outdoors, and public events up to 100 and 300. Reopening of indoor areas of restaurants and wellness facilities.
26 June 2021	mask requirement outdoors, home office requirement, attendance limit for in-person events in education facilities and restaurants is lifted. Reopening of nightclubs and dance venues. No restrictions for events where access is limited to individuals with a COVID certificate.
13 September 2021	Certificate requirements for indoor facilities, events, and restaurants, optional at universities and offices.
20 December 2021	Mandatory home office requirement. Cultural and sports activities, indoor events, restaurants, bars, and clubs are restricted to those vaccinated or recovered (2G).

Notes: All information is collected and summarized from official documents from the Swiss Federal Department of Home Affairs FDHA, Federal Office of Public Health FOPH, December 31, 2021.

Table C.3. Data Overview

Name	Category	Frequency	Release Lag	Start Date	Unit	Transformation	Type	Source
Passenger Car Frequency, Counting Stations on Major Swiss Motorways	Alternative	Daily	1W	2005W2	Actual	Log Difference	Flow	ASTRA
Truck Frequency, Counting Stations on Major Swiss Motorways	Alternative	Daily	1W	2005W2	Actual	Log Difference	Flow	ASTRA
Google Search Index, Perceived Economic Situation	Alternative	Daily	1W	2006W1	Index	None	Stock	trendEcon
Google Search Index, Perceived Labour Market Situation	Alternative	Daily	1W	2006W1	Index	None	Stock	KOF
Truck-Toll Mileage Index, Germany	Alternative	Daily	1W	2008W2	Actual	Log Difference	Flow	Destatis
Energy Consumed by Swiss End Users	Alternative	Daily	1W	2009W2	kWh	Log Difference	Flow	Swissgrid
Energy Production in Switzerland	Alternative	Daily	1W	2009W2	kWh	Log Difference	Flow	Swissgrid
Total Flight Arrivals, Zurich Airport	Alternative	Daily	1W	2011W2	Actual	Log Difference	Flow	Zurich Airport
Total Flight Departures, Zurich Airport	Alternative	Daily	1W	2011W2	Actual	Log Difference	Flow	Zurich Airport
Cash Withdrawals, Swiss-Wide Volume in CHF	Alternative	Daily	1W	2018W2	CHF, in Millions	Log Difference	Flow	SIX Group
Non-Online Retail Sales, Swiss-Wide Volume in CHF	Alternative	Daily	1W	2018W2	CHF, in Millions	Log Difference	Flow	SIX Group
Swiss Debit Card Transactions Abroad, Volume in CHF	Alternative	Daily	1W	2018W2	CHF, in Millions	Log Difference	Flow	SIX Group
Public Transport Passenger Frequency, Zurich Hardbruecke	Alternative	Daily	1W	2019W30	Actual	Log Difference	Flow	SBB
Credit Card Transactions, Swiss-Wide Frequency	Alternative	Weekly	1W	2020W2	Actual, in Thousands	Log Difference	Flow	SPA
Google COVID-19 Community Mobility Reports, Grocery and Pharmacy	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Google COVID-19 Community Mobility Reports, Parks	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Google COVID-19 Community Mobility Reports, Residential	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Google COVID-19 Community Mobility Reports, Retail and Recreation	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Google COVID-19 Community Mobility Reports, Transit Stations	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Google COVID-19 Community Mobility Reports, Workplaces	Alternative	Daily	1W	2020W2	Percentage	Log Difference	Flow	Google
Median Day Distance of Representative Swiss Population Sample	Alternative	Daily	1W	2020W2	km	Log Difference	Flow	intervista
Private Transport Frequency, Important Counting Stations, Zurich	Alternative	Daily	1W	2020W2	Actual	Log Difference	Flow	StatistikZH
Public Transport Passenger Frequency, Zurich Main Station	Alternative	Daily	1W	2020W2	Actual	Log Difference	Flow	SBB
10-Year Confederation Bond Yield	Financial	Monthly	5W	1990M1	Percentage	Detrended	Stock	SECO
Swiss Market Index (SMI)	Financial	Daily	1W	1990W1	CHF	Log Difference	Flow	SIX Group
Swiss Stock Market Index, Financials	Financial	Daily	1W	1990W1	CHF	Log Difference	Flow	Datastream
Swiss Stock Market Index, Industrials	Financial	Daily	1W	1990W1	CHF	Log Difference	Flow	Datastream
3-Month CHF LIBOR	Financial	Monthly	5W	1991M12	Percentage	Detrended	Stock	SNB
Consumer Price Index, Total	Prices	Monthly	5W	1990M1	Index, 2015M12=100	Log Difference	Flow	SECO
Producer Prices Index	Prices	Monthly	5W	1990M1	Index, 2015M12=100	Log Difference	Flow	SECO
Consumer Price Index, Excl. Energy, Fresh & Seasonal Products	Prices	Monthly	5W	2000M6	Index, 2015M12=100	Log Difference	Flow	SECO
Gross Domestic Product, Adjusted for International Sport Events	Production	Quarterly	9W	1990Q1	CHF, Real Prices	Log Difference	Flow	SECO

(Continued on next page)

Name	Category	Frequency	Release Lag	Start Date	Unit	Transformation	Type	Source
Retail Sales, Culture and Recreation Goods, Constant Prices	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Food, Beverage and Tobacco	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Household Equipment	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Information and Communication Equipment	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Non-Food	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Other Goods	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Retail Sales, Total	Retail	Monthly	9W	2000M2	Index, 2015=100	Log Difference	Flow	FSO
Purchasing Managers Index, Manufacturing Sector	Survey	Monthly	5W	1995M1	Index (Diffusion)	None	Stock	procure.ch & UBS
Purchasing Managers Index, Manufacturing Sector, Backlog of Orders	Survey	Monthly	5W	1995M1	Index (Diffusion)	None	Stock	procure.ch & UBS
Purchasing Managers Index, Manufacturing Sector, Output	Survey	Monthly	5W	1995M1	Index (Diffusion)	None	Stock	procure.ch & UBS
Business Situation Assessment, Manufacturing	Survey	Monthly	5W	2004M2	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Manufacturing Consumption Goods	Survey	Monthly	5W	2004M2	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Manufacturing Durable Goods	Survey	Monthly	5W	2004M2	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Manufacturing Intermediate Goods,	Survey	Monthly	5W	2004M2	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Manufacturing Investment Goods	Survey	Monthly	5W	2004M2	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, All Industries	Survey	Monthly	5W	2009M5	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Finance & Insurance	Survey	Monthly	5W	2010M8	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Construction	Survey	Monthly	5W	2011M5	Net Balance	Log Difference	Flow	KOF
Business Situation Assessment, Project Engineering	Survey	Monthly	5W	2011M5	Net Balance	Log Difference	Flow	KOF
Switzerland, Export: Total, Real, SA, Index (1997=100)	Trade	Monthly	5W	1997M2	Index	Log Difference	Flow	BAZG
Switzerland, Import: Total, Real, SA, Index (1997=100)	Trade	Monthly	5W	1997M2	Index	Log Difference	Flow	BAZG

Notes: "W" stands for week, "M" for month, and "Q" for quarter. Unless otherwise indicated, all series apply to Switzerland. All monthly series are seasonally adjusted. The release lag for each variable is based on 2020 release schedules. Detrending of a variable is performed by subtracting the rolling in-sample moving average of three times the frequency of the respective variable. During data collection, the following series were adjusted to eliminate structural breaks due to changes in definition, scope, or coverage: Energy Consumed by Swiss End Users, Energy Production in Switzerland, Passenger Car Frequency, and Truck Frequency. Eichenauer et al. (2020) details the methods used for constructing the trendEcon Google search index on perceived economic conditions, which can be found www.trendecon.org. The same trendEcon methodology is employed for compiling the Google search index on the perceived labor market situation. *Abbreviations of sources:* ASTRA: Swiss Federal Roads Office, Destatis: German Federal Statistical Office, BAZG: Federal Office for Customs and Border Security, KOF: KOF Swiss Economic Institute, SBB: Swiss federal railways, SECO: Swiss State Secretariat for Economic Affairs, SNB: Swiss National Bank, SPA: Swiss Payment Association, StatistikZH: Statistical Office of the Canton of Zurich, FSO: Swiss Federal Statistical Office.

Table C.4. Estimated Lambdas for Different Samples

Variable Name	Frequency	Lag	Start	λ_{-GR}	λ_{+GR}	λ_{-CO}	λ_{+CO}
Swiss Stock Market Index, Financials	Daily	1W	1990W1	0.4	0.62	0.62	0.19
Swiss Stock Market Index, Industrials	Daily	1W	1990W1	0.53	0.72	0.71	0.23
Swiss Market Index (SMI)	Daily	1W	1990W1	0.41	0.59	0.59	0.18
Consumer Price Index, Total	Monthly	5W	1990M1	-0.2	0.09	0.11	0.16
Producer Prices Index	Monthly	5W	1990M1	0.29	0.39	0.32	0.16
10-Year Confederation Bond Yield	Monthly	5W	1990M1	0.26	0.32	0.3	0.06
Gross Domestic Product, Adjusted for International Sport Events	Quarterly	9W	1990Q1	1	1	1	1
3-Month CHF LIBOR	Monthly	5W	1991M12	0.19	0.31	0.3	0.08
Purchasing Managers Index, Manufacturing Sector	Monthly	5W	1995M1	0.29	0.47	0.45	0.29
Purchasing Managers Index, Manufacturing Sector, Backlog of Orders	Monthly	5W	1995M1	0.37	0.55	0.53	0.37
Purchasing Managers Index, Manufacturing Sector, Output	Monthly	5W	1995M1	0.49	0.68	0.65	0.57
Switzerland, Export: Total, Real, SA, Index (1997=100)	Monthly	5W	1997M2	0.17	0.37	0.31	0.42
Switzerland, Import: Total, Real, SA, Index (1997=100)	Monthly	5W	1997M2	0.12	0.15	0.13	0.49
Consumer Price Index, Excl. Energy, Fresh and Seasonal Products	Monthly	5W	2000M6	0.13	0.03	0.06	0.02
Retail Sales, Total	Monthly	9W	2000M2	0.19	0.24	0.24	0.56
Retail Sales, Food, Beverage and Tobacco	Monthly	9W	2000M2	0.05	0.07	0.11	0.14
Retail Sales, Non-Food	Monthly	9W	2000M2	0.22	0.27	0.25	0.67
Retail Sales, Information and Communication Equipment	Monthly	9W	2000M2	0.22	0.24	0.09	0.14
Retail Sales, Household Equipment	Monthly	9W	2000M2	0.22	0.29	0.23	0.51
Retail Sales, Culture and Recreation Goods, Constant Prices	Monthly	9W	2000M2	0.23	0.24	0.23	0.54
Retail Sales, Other Goods	Monthly	9W	2000M2	0.22	0.21	0.19	0.75
Business Situation Assessment, Manufacturing	Monthly	5W	2004M2	0.01	0.34	0.54	0.22
Business Situation Assessment, Manufacturing Investment Goods	Monthly	5W	2004M2	0	0.34	0.5	0.3
Business Situation Assessment, Manufacturing Durable Goods	Monthly	5W	2004M2	-0.06	0.25	0.29	0.16
Business Situation Assessment, Manufacturing Consumption Goods	Monthly	5W	2004M2	0.01	0.18	0.29	0.2
Business Situation Assessment, Manufacturing Intermediate Goods	Monthly	5W	2004M2	0.08	0.46	0.57	0.23
Passenger Car Frequency, Counting Stations on Major Swiss Motorways	Daily	1W	2005W2	0.05	0.05	0.12	0.76
Truck Frequency, Counting Stations Major Swiss Motorways	Daily	1W	2005W2	0.04	0.07	0.12	0.23
Google Search Index, Perceived Economic Situation	Daily	1W	2006W1	0.11	0.06	0.05	0.09
Google Search Index, Perceived Labour Market Situation	Daily	1W	2006W1	-0.03	0.04	0.03	0.4
Truck-Toll Mileage Index, Germany	Daily	1W	2008W2	0.01	0.18	0.17	0.37
Energy Consumed by Swiss End Users	Daily	1W	2009W2	0	0.02	0.02	0.09
Energy Production in Switzerland	Daily	1W	2009W2	0	0.03	0	0.02
Business Situation Assessment, All Industries	Monthly	5W	2009M5	0	0	0.31	0.63
Business Situation Assessment, Finance and Insurance	Monthly	5W	2010M8	0	0	0.22	0.33
Total Flight Departures, Zurich Airport	Daily	1W	2011W2	0	0	0.03	0.71
Total Flight Arrivals, Zurich Airport	Daily	1W	2011W2	0	0	0.04	0.72
Business Situation Assessment, Construction	Monthly	5W	2011M5	0	0	-0.01	0.57
Business Situation Assessment, Project Engineering	Monthly	5W	2011M5	0	0	-0.03	0.53
Swiss Debit Card Transactions Abroad, Volume in CHF	Daily	1W	2018W2	0	0	-0.01	0.24
Cash Withdrawals, Swiss-Wide Volume in CHF	Daily	1W	2018W2	0	0	0.01	0.08
Non-Online Retail Sales, Swiss-Wide Volume in CHF	Daily	1W	2018W2	0	0	0.01	0.22
Public Transport Passenger Frequency, Zurich Hardbruecke	Daily	1W	2019W30	0	0	0	0.41
Public Transport Passenger Frequency, Zurich Main Station	Daily	1W	2020W2	0	0	0	0.24
Median Day Distance of Representative Swiss Population Sample	Daily	1W	2020W2	0	0	0	0.24
Private Transport Frequency, Important Counting Stations, Zurich	Daily	1W	2020W2	0	0	0	0.24
Google COVID-19 Community Mobility Reports, Retail & Recreation	Daily	1W	2020W2	0	0	0	0.1
Google COVID-19 Community Mobility Reports, Grocery & Pharmacy	Daily	1W	2020W2	0	0	0	0.17
Google COVID-19 Community Mobility Reports, Parks	Daily	1W	2020W2	0	0	0	-0.01
Google COVID-19 Community Mobility Reports, Transit Stations	Daily	1W	2020W2	0	0	0	0.13
Google COVID-19 Community Mobility Reports, Workplaces	Daily	1W	2020W2	0	0	0	0.14
Google COVID-19 Community Mobility Reports, Residential	Daily	1W	2020W2	0	0	0	-0.12
Credit Card Transactions, Swiss-Wide Frequency	Weekly	1W	2020W2	0	0	0	0.22

Notes: This table shows the factor loadings (λ) for each variable from the weekly GDP indicator (WAI) estimated using different samples together with the variable names, frequency, lags in weeks, and the start date of the series. The samples are: until before the start of the Great Recession (λ_{-GR}), after the Great Recession (λ_{+GR}), before the COVID-19 pandemic (λ_{-CO}), and after the COVID-19 pandemic (λ_{+CO}).

Table C.5. Estimated Lambdas for Different Specifications

Variable Name	Frequency	Lag	Start Date	λ_{BL}	λ_{-SV}	$\lambda_{-(SV+HF)}$	λ_{-HF}	λ_{-FIN}	$\lambda_{-Retail}$
Gross Domestic Product, Adjusted for International Sport Events	Quarterly	9W	1990Q1	1	1	1	1	1	1
Consumer Price Index, Total	Monthly	5W	1990M1	0.16	0.03	0.25	0.23	0.12	0.09
Producer Prices Index	Monthly	5W	1990M1	0.16	0.07	0.47	0.44	0.05	0.26
Consumer Price Index, Excl. Energy, Fresh & Seasonal Products	Monthly	5W	2000M6	0.02	0.05	0	0	0.04	0.14
Retail Sales, Total	Monthly	9W	2000M2	0.56	0.04	0.12	0.13	0.33	0.7
Retail Sales, Food, Beverage and Tobacco	Monthly	9W	2000M2	0.14	0.05	-0.38	-0.36	0.13	0
Retail Sales, Non-Food	Monthly	9W	2000M2	0.67	0.08	0.23	0.23	0.36	0
Retail Sales, Information and Communication Equipment	Monthly	9W	2000M2	0.14	-0.09	-0.19	-0.18	0.03	0
Retail Sales, Household Equipment	Monthly	9W	2000M2	0.51	-0.09	0.02	0.03	0.22	0
Retail Sales, Culture and Recreation Goods, Constant Prices	Monthly	9W	2000M2	0.54	-0.02	0.16	0.15	0.25	0
Retail Sales, Other Goods	Monthly	9W	2000M2	0.75	0.24	0.4	0.41	0.51	0
Business Situation Assessment, Manufacturing	Monthly	5W	2004M2	0.22	0.26	0.76	0.73	0.33	1.47
Business Situation Assessment, Construction	Monthly	5W	2011M5	0.57	0.48	0.71	0.74	0.54	1.38
Business Situation Assessment, Finance & Insurance	Monthly	5W	2010M8	0.33	0.18	0.28	0.29	0.25	0.49
Business Situation Assessment, Project Engineering	Monthly	5W	2011M5	0.53	0.56	0.82	0.85	0.61	0.94
Business Situation Assessment, All Industries	Monthly	5W	2009M5	0.63	0.59	0.89	0.92	0.68	0.66
Business Situation Assessment, Manufacturing Investment Goods	Monthly	5W	2004M2	0.3	0.1	0.62	0.6	0.17	0.29
Business Situation Assessment, Manufacturing Durable Goods	Monthly	5W	2004M2	0.16	0.28	0.5	0.48	0.31	0.42
Business Situation Assessment, Manufacturing Consumption Goods	Monthly	5W	2004M2	0.2	0.26	0.5	0.49	0.26	0.4
Business Situation Assessment, Manufacturing Intermediate Goods	Monthly	5W	2004M2	0.23	0.3	0.73	0.68	0.26	0.38
Switzerland, Export: Total, Real, SA, Index (1997=100)	Monthly	5W	1997M2	0.42	0.34	0.79	0.76	0.39	0.61
Switzerland, Import: Total, Real, SA, Index (1997=100)	Monthly	5W	1997M2	0.49	0.25	0.52	0.51	0.33	0.23
10-Year Confederation Bond Yield	Monthly	5W	1990M1	0.06	0.14	0.05	0.05	0.06	0.48
Purchasing Managers Index, Manufacturing Sector	Monthly	5W	1995M1	0.29	0.25	0.21	0.2	0.29	0.53
Purchasing Managers Index, Manufacturing Sector, Backlog of Orders	Monthly	5W	1995M1	0.37	0.27	0.27	0.26	0.34	0.63
Purchasing Managers Index, Manufacturing Sector, Output	Monthly	5W	1995M1	0.57	0.46	0.38	0.36	0.48	0.93
3-Month CHF LIBOR	Monthly	5W	1991M12	0.08	0.1	0.08	0.08	0.05	0.76
Credit Card Transactions, Swiss-Wide Frequency	Weekly	1W	2020W2	0.22	0.02	0	0	0.09	0.52
Swiss Stock Market Index, Financials	Daily	1W	1990W1	0.19	0.05	0	0	0	0.21
Swiss Stock Market Index, Industrials	Daily	1W	1990W1	0.23	0.08	0	0	0	0.24
Swiss Market Index (SMI)	Daily	1W	1990W1	0.18	0	0	0	0	0.13
Public Transport Passenger Frequency, Zurich Main Station	Daily	1W	2020W2	0.24	0.01	0	0	0.08	0.43
Public Transport Passenger Frequency, Zurich Hardbruecke	Daily	1W	2019W30	0.41	0.22	0	0	0.29	1.05
Median Day Distance of Representative Swiss Population Sample	Daily	1W	2020W2	0.24	0.02	0	0	0.09	0.51
Swiss Debit Card Transactions Abroad, Volume in CHF	Daily	1W	2018W2	0.24	0.14	0	0	0.19	0.59
Cash Withdrawals, Swiss-Wide Volume in CHF	Daily	1W	2018W2	0.08	0.06	0	0	0.07	0.15
Non-Online Retail Sales, Swiss-Wide Volume in CHF	Daily	1W	2018W2	0.22	0.1	0	0	0.17	0.55
Private Transport Frequency, Important Counting Stations, Zurich	Daily	1W	2020W2	0.24	-0.01	0	0	0.08	0.55
Passenger Car Frequency, Counting Stations on Major Swiss Motorways	Daily	1W	2005W2	0.76	0.22	0	0	0.36	0.78
Truck Frequency, Counting Stations on Major Swiss Motorways	Daily	1W	2005W2	0.23	0.11	0	0	0.16	0.35
Truck-Toll Mileage Index, Germany	Daily	1W	2008W2	0.37	0.19	0	0	0.3	0.29
Energy Consumed by Swiss End Users	Daily	1W	2009W2	0.09	0.07	0	0	0.08	0.16
Energy Production in Switzerland	Daily	1W	2009W2	0.02	-0.02	0	0	0.02	0
Total Flight Departures, Zurich Airport	Daily	1W	2011W2	0.71	0.45	0	0	0.6	1.42
Total Flight Arrivals, Zurich Airport	Daily	1W	2011W2	0.72	0.45	0	0	0.61	1.06
Google COVID-19 Community Mobility Reports, Retail and Recreation	Daily	1W	2020W2	0.1	-0.05	0	0	-0.02	0.45
Google COVID-19 Community Mobility Reports, Grocery and Pharmacy	Daily	1W	2020W2	0.17	0.01	0	0	0.06	0.3
Google COVID-19 Community Mobility Reports, Parks	Daily	1W	2020W2	-0.01	0.04	0	0	0.01	0.11
Google COVID-19 Community Mobility Reports, Transit Stations	Daily	1W	2020W2	0.13	-0.04	0	0	-0.01	0.18
Google COVID-19 Community Mobility Reports, Workplaces	Daily	1W	2020W2	0.14	-0.03	0	0	0.01	-0.21
Google COVID-19 Community Mobility Reports, Residential	Daily	1W	2020W2	-0.12	0.04	0	0	0.01	-0.12
Google Search Index, Perceived Economic Situation	Daily	1W	2006W1	0.09	0.03	0	0	0.04	0.14
Google Search Index, Perceived Labour Market Situation	Daily	1W	2006W1	0.4	0.16	0	0	0.21	0.56

Notes: This table shows the factor loadings (λ) for each variable from the weekly GDP indicator (WAI) estimated using different specifications together with the variable names, frequency, lags in weeks, and the start date of the series. The specifications are: The baseline model (λ_{BL}), the model excluding stochastic volatility (λ_{-SV}), excluding high-frequency variables and stochastic volatility ($\lambda_{-(SV+HF)}$), excluding high-frequency variables (λ_{-HF}), excluding financial variables (λ_{-FIN}), and excluding the retail sales subcomponents but only keeping the total retail sales ($\lambda_{-Retail}$).

Table C.6. In-sample GDP Forecast Evaluation: R^2

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
WAI	0.00	0.05	0.21	0.50	1.00	0.01	0.00	0.06	0.73	0.00
SECO-WEA	0.04	0.00	0.10	0.29	0.75	0.02	0.01	0.01	0.01	0.03
F-CURVE	0.03	0.19	0.34	0.47	0.41	0.00	0.01	0.00	0.03	0.21
SECO-SEC	0.00	0.13	0.34	0.51	0.60	0.01	0.00	0.01	0.01	0.22
SNB-BCI	0.01	0.30	0.27	0.26	0.22	0.00	0.01	0.00	0.01	0.70
KOF-BARO	0.03	0.27	0.36	0.31	0.28	0.00	0.02	0.02	0.01	0.41
Last										
WAI	0.01	0.11	0.28	0.91	0.64	0.00	0.00	0.15	0.81	0.00
SECO-WEA	0.01	0.02	0.18	0.51	0.62	0.01	0.01	0.00	0.01	0.12
F-CURVE	0.10	0.23	0.55	0.50	0.22	0.00	0.03	0.00	0.17	0.09
SECO-SEC	0.02	0.18	0.40	0.58	0.55	0.00	0.00	0.01	0.04	0.22
SNB-BCI	0.08	0.34	0.28	0.35	0.07	0.00	0.01	0.01	0.25	0.36
KOF-BARO	0.09	0.31	0.35	0.35	0.13	0.00	0.02	0.01	0.11	0.25
Last Month										
WAI	0.00	0.09	0.28	0.81	0.85	0.00	0.00	0.15	0.85	0.00
SECO-WEA	0.02	0.01	0.15	0.41	0.69	0.01	0.01	0.00	0.01	0.10
F-CURVE	0.07	0.25	0.36	0.54	0.30	0.00	0.02	0.01	0.14	0.19
SECO-SEC	0.02	0.18	0.40	0.58	0.55	0.00	0.00	0.01	0.04	0.22
SNB-BCI	0.08	0.34	0.28	0.35	0.07	0.00	0.01	0.01	0.25	0.36
KOF-BARO	0.09	0.31	0.35	0.35	0.13	0.00	0.02	0.01	0.11	0.25

Notes: This table shows the coefficient of determination (R^2) between each indicator and quarterly Swiss real GDP (adjusted for international sporting events) starting in 1990 or as soon as data is available until the end of 2021. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the weekly economic activity indicator (WAI), the weekly economic activity indicator (SECO-WEA) from SECO by Wegmüller et al. (2023), the daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot directly be transformed and thus are left the same for the two measures. To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

Table C.7. In-sample GDP Forecast Evaluation: Relative MAE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
SECO-WEA	0.97	1.08	1.19	1.35**	30.47***	1.09	1.08	1.02	1.71**	1.02
F-CURVE	0.96	0.90	0.91	1.14	41.01***	1.05	1.01	0.96	1.48*	0.84
SECO-SEC	0.97	0.94	0.92	1.06*	33.46***	0.99	0.97	0.91	1.45**	0.85
SNB-BCI	0.98	0.86	0.98	1.38***	47.69***	1.02	0.99	0.96	1.54***	0.71
KOF-BARO	0.95	0.88	0.95	1.42***	48.68***	1.01	0.95	0.89	1.51**	0.92
Last										
SECO-WEA	1.03	1.13	1.19	2.43***	1.53***	1.10	1.08	1.02	2.39***	1.01
F-CURVE	0.97	1.00	0.86	2.53***	2.24***	1.06	0.99	0.91	2.11***	0.94
SECO-SEC	0.98	0.97	0.93	2.09***	1.53***	0.99	0.97	0.90	1.98***	0.85
SNB-BCI	0.97	0.89	1.07	2.71***	2.34***	1.01	0.99	0.99	1.96***	0.75
KOF-BARO	0.93	0.91	1.05	2.95***	2.34***	1.00	0.95	0.90	2.07***	0.92
Last Month										
SECO-WEA	1.01	1.11	1.26*	1.83***	2.53***	1.09	1.08	1.02	2.58***	1.00
F-CURVE	0.94	0.88	0.99	1.73***	3.49***	1.04	0.99	1.00	2.12***	0.81
SECO-SEC	0.97	0.95	0.96	1.53***	2.61***	0.99	0.97	0.90	2.13***	0.84
SNB-BCI	0.96	0.87	1.10	1.99***	3.98***	1.01	0.99	0.98	2.11***	0.75
KOF-BARO	0.92	0.89	1.08	2.16***	3.98***	1.00	0.95	0.90	2.22***	0.92

Notes: This table shows the relative mean absolute error (MAE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on the sample starting in 1990 or as soon as data is available until the end of 2021 and is then used for predicting each quarter of GDP growth. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the weekly economic activity indicator (WAI), the weekly economic activity indicator (SECO-WEA) from SECO by Wegmüller et al. (2023), the daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), and the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot directly be transformed and thus are left the same for the two measures. To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

Table C.8. In-sample GDP Forecast Evaluation for Different Specifications: Relative RMSE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
WAI-SV	1.00	1.00	1.00*	1.00	0.83	0.99	1.00	1.04	1.91**	0.82
WAI-(SV+HF)	0.97	1.00	1.07*	1.23***	29.44***	1.01	1.00	1.03	2.01*	0.53
WAI-FIN	1.01	1.01	1.08*	1.26***	31.94***	1.00	1.00	1.05	2.12*	1.00
WAI-Retail	0.98	1.01	1.05	1.18**	22.33***	1.01	1.00	1.04	1.73**	0.98
Last										
WAI-SV	1.00	1.00	0.95	1.84*	0.53	1.00	1.00	1.13	0.99	0.91
WAI-(SV+HF)	0.97	1.04	1.10**	3.14***	1.19	1.00	1.00	1.09*	1.39	0.91
WAI-FIN	0.99	1.04	1.11**	3.27***	1.34**	1.00	1.00	1.07	1.94***	0.98
WAI-Retail	0.99	1.02	1.05	2.47***	1.14	1.00	1.00	1.01	1.11	0.99
Last Month										
WAI-SV	0.99	1.01	1.02	1.61**	0.39	1.00	1.00	1.12	1.15	0.91
WAI-(SV+HF)	0.97	1.03	1.10*	2.00***	1.79***	1.00	1.00	1.08*	1.58	0.91
WAI-FIN	0.99	1.03	1.11*	2.11***	2.00***	1.00	1.00	1.12	2.38**	0.99
WAI-Retail	0.98	1.02	1.06	1.85***	1.51***	1.00	1.00	1.04	1.19*	0.98

Notes: This table shows the relative root mean squared error (RMSE) for each specification resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on the sample starting in 1990 or as soon as data is available until the end of 2021 and is then used for predicting each quarter of GDP growth. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The specifications are the weekly GDP indicator (WAI), without stochastic volatility (WAI-SV), without stochastic volatility and without high-frequency indicators (WAI-(SV+HF)), without financial variables (WAI-FIN), and without retail sales indicators except total retail sales (WAI-Retail). To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

Table C.9. In-sample GDP Forecast Evaluation for Different Specifications: Relative MAE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
WAI-SV	1.00	1.00	1.00*	1.00	0.85	1.02	0.99	0.98	1.48**	0.60
WAI-(SV+HF)	1.03	1.06*	1.15***	1.34***	32.08***	1.03	0.97	1.03	1.42**	0.52
WAI-FIN	1.02	1.04*	1.19***	1.46***	36.36***	1.03	1.01	0.96	1.60**	0.90
WAI-Retail	1.06**	1.02	1.08*	1.34***	31.78***	1.04*	1.00	1.01	1.77***	0.86
Last										
WAI-SV	1.00	1.00	0.89	1.62**	0.63	0.98	1.02	1.00	1.24*	1.04
WAI-(SV+HF)	1.02	1.10**	1.17***	3.05***	1.54***	1.00	1.01	1.05	1.26	0.82
WAI-FIN	1.01	1.10**	1.22***	3.38***	1.79***	1.02*	1.01	1.14*	2.47***	1.04
WAI-Retail	1.04*	1.02	1.11**	2.97***	1.70***	1.00	1.01	1.01	1.46***	1.03
Last Month										
WAI-SV	0.99	1.02	1.07*	1.44***	0.68	0.99	1.00	0.99	1.29*	1.07
WAI-(SV+HF)	1.02	1.08**	1.23***	2.05***	2.75***	1.00	1.00	1.04	1.34*	0.81
WAI-FIN	1.01	1.08**	1.29***	2.27***	3.18***	1.02*	1.01	1.02	2.64***	1.02
WAI-Retail	1.04*	1.02	1.18***	2.09***	2.91***	0.99	1.00	1.03	1.55***	1.02

Notes: This table shows the relative mean absolute error (MAE) for each specification resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on the sample starting in 1990 or as soon as data is available until the end of 2021 and is then used for predicting each quarter of GDP growth. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The specifications are the weekly GDP indicator (WAI), without stochastic volatility (WAI-SV), without stochastic volatility and without high-frequency indicators (WAI-(SV+HF)), without financial variables (WAI-FIN), and without retail sales indicators except total retail sales (WAI-Retail). To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

Table C.10. In-sample GDP Forecast Evaluation for Different Specifications: R^2

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
WAI	0.04	0.02	0.14	0.40	1.00	0.01	0.00	0.09	0.78	0.04
WAI-SV	0.04	0.02	0.14	0.40	1.00	0.03	0.00	0.01	0.20	0.36
WAI-(SV+HF)	0.09	0.01	0.01	0.10	0.29	0.00	0.00	0.04	0.11	0.73
WAI-FIN	0.02	0.00	0.00	0.04	0.16	0.00	0.00	0.00	0.01	0.03
WAI-Retail	0.07	0.00	0.06	0.16	0.59	0.00	0.00	0.03	0.34	0.07
Last										
WAI	0.00	0.07	0.20	0.91	0.52	0.00	0.00	0.22	0.82	0.00
WAI-SV	0.00	0.06	0.27	0.71	0.87	0.01	0.01	0.00	0.82	0.17
WAI-(SV+HF)	0.06	0.00	0.03	0.16	0.32	0.00	0.00	0.07	0.65	0.17
WAI-FIN	0.01	0.00	0.02	0.09	0.14	0.00	0.01	0.10	0.32	0.03
WAI-Retail	0.01	0.02	0.13	0.48	0.38	0.01	0.00	0.20	0.78	0.02
Last Month										
WAI	0.00	0.05	0.20	0.79	0.79	0.01	0.00	0.21	0.86	0.00
WAI-SV	0.02	0.03	0.16	0.46	0.97	0.01	0.01	0.00	0.82	0.18
WAI-(SV+HF)	0.06	0.00	0.03	0.16	0.32	0.00	0.00	0.07	0.65	0.17
WAI-FIN	0.02	0.00	0.01	0.07	0.15	0.00	0.00	0.01	0.22	0.03
WAI-Retail	0.04	0.01	0.10	0.28	0.52	0.00	0.00	0.15	0.80	0.05

Notes: This table shows the coefficient of determination (R^2) between each specification and quarterly Swiss real GDP (adjusted for international sporting events) on the sample starting in 1990 or as soon as data is available until the end of 2021 and is then used for predicting each quarter of GDP growth. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The specifications are the weekly GDP indicator (WAI), without stochastic volatility (WAI-SV), without stochastic volatility and without high-frequency indicators (WAI-(SV+HF)), without financial variables (WAI-FIN), and without retail sales indicators except total retail sales (WAI-Retail). To show the lead of the indicators, the RMSE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value.

Table C.11. Real-time Out-of-sample GDP Forecast Evaluation: MAE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
AR	0.98	1.05	1.12**	1.22**	1.62***	0.97	1.00	1.04	0.93	1.13
SECO-WEA	1.04	1.13	1.17*	1.21**	1.47**	1.05	1.06	1.16	1.06*	1.12
F-CURVE	0.99	0.94	0.96	1.06	1.82***	1.07	1.01	1.02	0.89	0.94
SECO-SEC	0.98	0.93	0.91	0.99	1.66***	0.99	0.98	1.03	0.89	0.89
SNB-BCI	0.96	0.77	0.93	1.25	2.04***	1.03*	0.98	1.01	0.89	0.66
KOF-BARO	0.93	0.82	0.89	1.33**	2.08***	1.00	0.95	0.96	0.88	0.95
Last										
AR	0.98	1.05	1.11**	1.18**	1.66***	0.98	1.02	0.98	1.06	1.14
SECO-WEA	1.02	1.12	1.13*	1.17*	1.50**	1.06	1.08	1.09	1.19	1.11
F-CURVE	1.02	0.98	0.96	1.09	1.92***	1.08*	1.04	0.98	1.02	0.93
SECO-SEC	0.98	0.92	0.89	0.95	1.71***	1.00	1.00	0.97	1.01	0.88
SNB-BCI	0.96	0.80	0.89	1.14	2.09***	1.03**	1.00	0.96	0.96	0.73
KOF-BARO	0.92	0.81	0.87	1.26**	2.18***	1.01	0.97	0.91	1.00	0.95
Last Month										
AR	0.98	1.05	1.09**	1.18**	1.67***	0.97	1.03*	1.00	1.03	1.18
SECO-WEA	1.02	1.12	1.13*	1.19*	1.53**	1.04	1.08	1.10	1.16	1.16
F-CURVE	1.01	0.96	0.94	1.06	1.89***	1.07	1.05	0.99	1.00	0.98
SECO-SEC	0.98	0.92	0.87	0.95	1.72***	0.99	1.01	0.99	0.99	0.92
SNB-BCI	0.96	0.80	0.88	1.14	2.10***	1.02*	1.01	0.98	0.93	0.76
KOF-BARO	0.92	0.80	0.86	1.26**	2.19***	1.00	0.98	0.92	0.97	0.99

Notes: This table shows the relative mean absolute error (MAE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The AR-model uses one period lag GDP growth as indicator. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on a sample starting 1990 or as soon as data is available with prediction starting 2005 with an expanding window until end of 2021. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the WAI (WAI), the weekly economic activity indicator (WEA) from SECO by Wegmüller et al. (2023), the standardized and inverted daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniovski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot be transformed and thus are left the same for the two measures. To show the lead of the indicators, the MAE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value. Real-time GDP vintages are used from Indergand and Leist (2014). Real-time vintages of GDP adjusted for international sporting events exist from 2018Q3 onward. Before non-adjusted GDP vintages are used. For the KOF-BARO exist real-time vintages from 2014m4 onward. The WAI uses weekly real-time vintages. For the SECO-WEA, F-CURVE, SECO-SEC, and SNB-BCI pseudo real-time vintages are created as no official real-time vintages exist.

Table C.12. Pseudo-real-time Out-of-sample GDP Forecast Evaluation: RMSE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
AR	0.99	1.03	1.08*	1.19**	2.41**	1.00	1.00	0.92	2.17**	1.39
SECO-WEA	1.04	1.10	1.12	1.16*	1.72***	1.05	1.05	0.97	2.30**	1.31
F-CURVE	1.05	0.95	0.89	0.92	2.17***	1.02	1.02	0.94	2.18*	1.07*
SECO-SEC	0.97	0.93	0.87	0.90	1.86***	0.99	0.99	0.91	2.17*	1.06*
SNB-BCI	1.03	0.85	1.06	1.31	3.11**	1.01	1.00	0.94	2.35*	0.48
KOF-BARO	1.02	0.87	0.88	1.09	2.48***	1.00	0.99	0.92	2.29*	0.90
Last										
AR	0.99	1.03	1.08*	1.12**	4.07**	0.99	1.00	0.91	2.04**	0.96
SECO-WEA	1.03	1.09	1.11	1.09*	2.85***	1.04	1.05	0.96	2.17*	0.89
F-CURVE	1.05	0.97	0.91	0.93	3.90***	1.01	1.02	0.95	2.05*	0.74
SECO-SEC	0.97	0.93	0.87	0.84	3.23***	0.99	1.00	0.91	2.03*	0.73
SNB-BCI	1.02	0.87	1.00	1.12	4.79**	1.00	1.00	0.94	2.08*	0.42
KOF-BARO	1.01	0.88	0.87	1.01	4.31***	1.00	0.99	0.91	2.11*	0.64
Last Month										
AR	0.99	1.02	1.07*	1.07	3.57**	0.99	1.00	0.91	1.50*	0.85
SECO-WEA	1.03	1.09	1.11	1.06	2.59***	1.04	1.05	0.96	1.59	0.80
F-CURVE	1.05	0.96	0.89	0.89	3.29***	1.01	1.02	0.94	1.52*	0.66
SECO-SEC	0.97	0.92	0.86	0.80	2.83***	0.99	0.99	0.91	1.50*	0.65
SNB-BCI	1.01	0.87	0.98	1.07	4.20**	1.00	1.00	0.94	1.53	0.38
KOF-BARO	1.01	0.88	0.86	0.97	3.78***	0.99	0.99	0.91	1.55	0.57

Notes: This table shows the relative root mean squared error (RMSE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The AR-model uses one period lag GDP growth as indicator. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on a sample starting in 1990 or as soon as data is available until the end of 2021 with prediction starting 2005 until end of 2021. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the WAI (WAI), the weekly economic activity indicator (WEA) from SECO by Wegmüller et al. (2023), the standardized and inverted daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniowski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot be transformed and thus are left the same for the two measures. To show the lead of the indicators, the MAE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value. Pseudo real-time vintages of GDP are created according to the publication dates in Indergand and Leist (2014). For all other indicators, pseudo real-time vintages are created using the last vintage of 2021.

Table C.13. Pseudo real-time Out-of-sample GDP Forecast Evaluation: MAE

Lags	YoY					QoQ				
	-4	-3	-2	-1	0	-4	-3	-2	-1	0
Mean										
AR	1.04*	1.10**	1.22***	1.37***	2.78***	0.99	1.00	0.94	1.79***	1.63***
SECO-WEA	0.93	1.01	1.15*	1.35**	2.65***	1.01	1.01	0.92	1.81**	1.72**
F-CURVE	0.97	0.91	0.94	1.08	3.15***	1.00	0.98	0.90	1.65**	1.45***
SECO-SEC	0.96	0.92	0.90	1.08	2.91***	0.93	0.93	0.87	1.62**	1.40***
SNB-BCI	1.07	0.91	1.05	1.42**	3.85***	1.01	1.00	0.94	1.70**	0.97
KOF-BARO	1.01	0.92	1.01	1.45***	4.03***	0.99	0.95	0.89	1.74**	1.44***
Last										
AR	1.04*	1.10**	1.22***	1.34***	4.79***	0.98	1.01	0.94	1.84***	1.30
SECO-WEA	0.92	1.01	1.13	1.29**	4.36***	0.99	1.01	0.92	1.84**	1.34
F-CURVE	0.99	0.96	0.97	1.14	5.71***	0.99	0.99	0.92	1.69**	1.15
SECO-SEC	0.96	0.92	0.89	1.04	5.01***	0.91	0.94	0.87	1.66**	1.09
SNB-BCI	1.07*	0.94	1.01	1.34*	6.72***	0.99	1.01	0.95	1.67**	0.80
KOF-BARO	1.01	0.93	0.98	1.39**	7.07***	0.98	0.95	0.89	1.75**	1.13
Last Month										
AR	1.04*	1.09**	1.17***	1.26***	4.00***	0.97	1.00	0.92	1.48***	1.40
SECO-WEA	0.91	1.00	1.10	1.24**	3.78***	0.98	1.00	0.90	1.47*	1.46
F-CURVE	0.99	0.93	0.92	1.03	4.59***	0.99	0.98	0.89	1.37**	1.24
SECO-SEC	0.96	0.91	0.86	0.98	4.17***	0.91	0.93	0.85	1.33**	1.17
SNB-BCI	1.07*	0.93	0.98	1.25	5.61***	0.99	1.00	0.93	1.35*	0.87
KOF-BARO	1.01	0.92	0.95	1.30**	5.89***	0.98	0.95	0.87	1.41**	1.22

Notes: This table shows the relative mean absolute error (MAE) for each indicator resulting from a linear regression on quarterly Swiss real GDP (adjusted for international sporting events) against the WAI. The AR-model uses one period lag GDP growth as indicator. The regression is estimated with OLS according to $Y_t = \alpha + \beta X_t + \varepsilon_t$ on a sample starting in 1990 or as soon as data is available until the end of 2021 with prediction starting 2005 until end of 2021. The target is either the year-on-year (YoY) or the quarter-on-quarter (QoQ) growth rates of real GDP. The indicators are the WAI (WAI), the weekly economic activity indicator (WEA) from SECO by Wegmüller et al. (2023), the standardized and inverted daily fever curve by Burri and Kaufmann (2020), the monthly Swiss Economic Confidence Indicator (SECO-SEC) by Glocker and Kaniowski (2019), the monthly SNB Business Cycle Index (SNB-BCI) by Galli (2018), the monthly Economic Barometer (KOF-BARO) from KOF by Abberger et al. (2018). As the SECO-WEA and the WAI are directly tracking GDP growth, they are transformed from YoY to QoQ and vice versa, while the other indicators cannot be transformed and thus are left the same for the two measures. To show the lead of the indicators, the MAE is shown for different lags from 4 to zero quarters ahead of GDP realization. Three different measures are tested, "Mean" shows the aggregation of all observations over the quarter, "Last" uses the last observation of the quarter, and "Last Month" uses the last month of the quarter as reference value. Pseudo real-time vintages of GDP are created according to the publication dates in Indergand and Leist (2014). For all other indicators, pseudo real-time vintages are created using the last vintage of 2021.