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# Weekly economic activity: Measurement and informational content

Philipp Wegmüller[a,*], Christian Glocker[b], Valentino Guggia[c]

[a] Swiss State Secretariat For Economic Affairs SECO Bern, BE, Switzerland
[b] Austrian Institute of Economic Research, Austria
[c] Swiss State Secretariat for Economic Affairs, Switzerland

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ABSTRACT

We construct a composite index to measure the real activity of the Swiss economy on a weekly frequency. The index is based on a novel high-frequency data set capturing economic activity across distinct dimensions over a long time horizon. We propose a six-step procedure for extracting precise business cycle signals from the raw data. By means of a real-time evaluation, we highlight the importance of our proposed adjustment procedure: (i) our weekly index significantly outperforms a comparable index without adjusted input variables; and (ii) the weekly index outperforms established monthly indicators in nowcasting GDP growth. These insights should help improve other recently developed high-frequency indicators.



## 1. Introduction

Fluctuations in real economic activity are generally characterized by a high degree of inertia. In normal times, monthly or even quarterly economic data thus provide sufficient information for macroeconomic forecasting, surveillance, and policymaking. However, in times of economic distress, the timeliness of economic data becomes a valuable asset for policymakers. In the wake of the Covid-19 pandemic, abrupt decisions with far-reaching social and economic consequences had to be made. As a consequence, both private and public actors expressed an immediate need for information on the stance of the economy, which caused an unprecedented surge in so-called *high-frequency* data.

An extension of macroeconomic surveillance to a higher frequency than monthly or quarterly seems straightforward at first sight. As a major drawback, however, weekly or daily data often contain considerable noise. This obscures the information contained in these data relevant for assessing the stance of the real economy. In this context, Proietti et al. (2018) mention the challenges that arise from weekly data: compared to lower-frequency data, they generally exhibit substantial volatility and feature more outliers and breaks. Against this background, Proietti et al. (2018) stress the need for adjustment steps, as weekly data might contain various idiosyncrasies, and recommend the use of annual growth rates. This paper investigates how an appropriate adjustment of the input data helps to improve the performance of a weekly coincident indicator.

We develop a weekly economic activity (WEA) index for Switzerland. Switzerland is well suited for such a study: first, a large number of data series are available on a weekly frequency; second, the majority of these series are updated regularly and often; third, the series are available for a long time horizon (some begin in the early 2000s); and fourth, trade data on goods imports and exports are available on a weekly basis, which offers unique coverage of real economic activity. Many other countries lack at least one of these features.

* Corresponding author.
*E-mail addresses:* philipp.wegmueller@seco.admin.ch (P. Wegmüller), christian.glocker@wifo.ac.at (C. Glocker), valentino.guggia@bak-economics.com (V. Guggia).

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To the best of our knowledge, there are no results in the literature regarding how an appropriate adjustment of the data used to construct a weekly index affects its nowcasting performance. We particularly focus on an adequate adjustment of our input series. We clean the data for seasonal patterns and for calendar, holiday, and temperature effects. Moreover, we remove outliers and establish homogeneous periodicity by addressing the problem of the surplus week (53rd week). We evaluate the nowcasting and forecasting performance of our proposed index with adjusted input variables in an ex post out-of-sample exercise. We compare its predictive power relative to both a weekly index without adjusted input series and established monthly business cycle indicators.

Our final weekly measure for real activity, the WEA index, is based on nine carefully selected weekly data series. The input data cover the economy along distinct dimensions: private household consumption, production activity, the labor market, and domestic and international trade. The WEA index has a high correlation with GDP and captures the different phases of the Swiss business cycle well. Importantly, in the spring of 2020, the index quickly provided an accurate signal for the fall in economic activity due to the imposed containment measures to impair the spread of Covid-19. The WEA index is robust to many specification changes, including the estimation method and the inclusion or omission of constituent series.

We report five main findings regarding the informational content of our index: First, weekly data in the form of our WEA index with adjusted input series contain relevant information for nowcasting and forecasting GDP growth. Second, our results strongly suggest that carefully accounting for calendar and seasonal effects and removing outliers is crucial to extract the relevant business cycle signals. Third, weekly data are superior to monthly data, especially for nowcasting. The WEA index significantly outperforms established monthly indices for the Swiss economy. Fourth, the WEA index not only serves as a tool in times of crisis but has also proven to deliver useful signals and accurate predictions in tranquil times as well. Fifth, the scaled index itself covers economic activity well and does not necessarily need to be accompanied by a more sophisticated econometric model such as a bridge equation for forecasting.

Our paper contributes to the growing literature on measuring business cycle fluctuations at high frequency. Recently, weekly or even daily indices for tracking real economic activity have been brought forward for various countries (see Eraslan & Goetz, 2020; Fenz & Stix, 2021; Rua & Lourenço, 2020, among others). Most prominently, Lewis et al. (2021) established a weekly economic index (WEI) for the US early on in 2020. Following the recommendations of Proietti et al. (2018), they derived the 52-week log differences of their input variables. Yet, they neglected the fact that some years have 53 weeks and that holidays such as Easter move from year to year. Contrary to them and other related work, we take great care in cleaning the data for such effects. In addition, we adjust our series for intra-monthly seasonal patterns and outliers. Rua and Lourenço (2020) address similar issues using daily data for the Portuguese economy. Our paper complements their analysis by studying a broader set of indicators and focusing on weekly data instead.

For Switzerland, Eckert et al. (2020) and Burri and Kaufmann (2020) provide alternative weekly economic activity measures. While both studies demonstrate the usefulness and importance of high-frequency information to capture the downturn in the wake of the Covid-19 recession, they lack the use of data on real economic activity spanning over a long time horizon. Eckert et al. (2020) use mixed frequency data to derive a long time series for their weekly real activity measure by also including monthly and quarterly data. Our index is instead purely based on daily or weekly information. This has the advantage that it is less prone to revisions (from GDP, for instance). Further, we do not aim at constructing a weekly GDP measure. Rather, the objective is to provide a weekly coincident index for the Swiss economy.

Apart from establishing a novel weekly economic indicator, we also add to the discussion on the usefulness of high-frequency data for predicting GDP growth. The literature has so far been divided about the nowcasting ability of weekly series relative to monthly series. According to Carriero et al. (2020), the accuracy of nowcasts for GDP growth typically improves as time moves forward within a quarter, making additional data available, with monthly data more important to accuracy than weekly data. Similarly, Bańbura et al. (2013) demonstrate that higher-frequency information does not contribute to the nowcasting accuracy of GDP growth. In contrast to these contributions, Aastveit et al. (2020), Fenz and Stix (2021), Lewis et al. (2021), Monteforte and Raponi (2019) highlight the strong predictive power of high-frequency information for providing an accurate nowcast of GDP growth or the components thereof. Our findings add to this discussion by highlighting how an appropriate data adjustment can substantially increment the informational content in weekly data.

In Section 2, we describe the data and outline the adjustment procedure and method used to construct the WEA index. We present its in-sample properties in Section 3, followed by an out-of-sample evaluation in Section 4. Finally, Section 5 concludes.

## 2. Data and methodology

This section presents the high-frequency input series used to construct the weekly economic activity index. We pay particular attention to data adjustments, and we highlight the consequences of each transformation step on the characteristics of the data series. In a second step, we outline the methodological approach used to construct the WEA index.

### 2.1. Data

We gathered daily and weekly data both from private and public sources covering a broad range of economic activity, such as the labor market, consumption, mobility, foreign trade, and industrial production. These data come with the same challenges as any other economic indicator. For instance, some series are only available once per month, even though they are collected on a daily basis (e.g., air freight). Moreover, as the collection of high-frequency data is rather novel, its history is often limited (e.g., parcel mail). Further, some series show substantial volatility unrelated to business cycle fluctuations (e.g., government financial flows). On the positive side, high-frequency data are often less prone to revisions than typical monthly and quarterly indicators, since they are generally directly measured at points of sales (e.g., credit card transactions) or official registries (e.g., construction permits).

Overall, we collected a set of 22 different high-frequency indicators.[1] While each indicator provides itself a partial picture of economic activity, our objective was to provide a high-frequency measure of aggregate economic activity. Depending on their individual characteristics, not all of the available data are equally useful for calculating the WEA index. Thus, we first selected a subset of adequate indicators based on a few simple criteria. First, the data should be available in a timely manner. If data were available on a weekly frequency but published with a substantial delay or only once per month, their usefulness for monitoring activity on a weekly frequency is limited. Second, the series should span over at least four years in order to properly address issues regarding seasonality and calendar effects. According to the US Census Bureau (2017), a time series should have at least 60 observations on a monthly frequency to estimate seasonal and calendar effects with reasonable success. Currently, there are no official guidelines on seasonal adjustment methods tailored to deal with higher than monthly frequency. We find that series with at least four years of observations can be reasonably adjusted. Third, once aggregated to a quarterly frequency, the series should be correlated significantly with GDP or the components thereof. We calculated correlations based on the robust $\tilde{t}$-statistic following Dalla et al. (2020) and used the 10% significance level as a threshold. We also tested a more elaborate approach, such as that used in Camacho and Perez-Quiros (2010), Glocker and Wegmüller (2020), but while more time and resource intensive, we ended up with the same final set of data.

Given these few criteria, we dropped several variables from our initial list of data, namely, electricity production, construction permits, job seekers, bankruptcy announcements, passengers at the Zurich airport (excluding transit passengers), road traffic (private vehicles and trucks), and financial market data. Each of these weekly series comes with its specific problems. For instance, electricity production is unrelated to business cycle dynamics and mostly driven by particular movements in the energy market and weather conditions. Construction permits–apart from being highly volatile–generally perform well for forecasting, though worse for nowcasting due to the time span between the receipt of the building permit and the actual commencement of construction. Similarly, data on insolvency are traditionally a lagging indicator. Moreover, in the spring of 2020, filing for insolvency by public authorities (tax offices, etc.) had been temporarily suspended, rendering the series less suitable.[2] Finally, the inclusion of financial variables might blur the picture of real economic activity, as the development in interest rates and stock markets can be heavily influenced by monetary policy and the expectations of financial actors.

Our final data set comprised nine input series listed and described in Table 1. While the number of series used is comparably small, the data capture real economic activity across various dimensions and are readily available. In fact, every indicator is obtained with a delay of no more than five days after the end of the corresponding week. Four indicators start before 2010, and some of them span back as far as 2002.

The input series can broadly be divided into five categories. First, data on card transactions and cash withdrawals capture the consumption activity of private households. Transactions with domestic and foreign credit and debit cards are acquirer data, i.e., from the point of view of the merchant's bank. They span a wide range of goods and economic sectors and cover about 60% of the total transaction volume.[3] Data on cash withdrawals are collected from the point of view of the card-issuing bank. They contain cash withdrawals done at an ATM with debit cards issued by a domestic institution. Second, we use data on foreign trade in goods. Exports are an indicator of both foreign demand and industrial production, whereas imports are a measure of domestic demand. For goods imports, the data cover the period 2002 to present, while goods exports are available from February 2013 onward.[4] Trade data are deflated using the monthly Import Price Index (IPI) and the Producer Price Index (PPI) for imports and for exports, respectively. Third, we include electricity consumption, air pollution, and net tonne-kilometers (railroad traffic) to capture the production activity of the manufacturing sector. Fourth, registered unemployment indicates the stance of the labor market. Fifth, we use weekly data on the sight deposits of private banks held at the Swiss National Bank (SNB) to capture financial market pressures and economic uncertainty, in particular, appreciation pressures regarding the Swiss franc.

### 2.2. Data adjustment

One of the main challenges when working with high-frequency data concerns their adjustment. Weekly data

1 The full set of indicators is provided in Tables 1 and A.1.

2 We also have indicators for the tourism industry. However, these show a very sharp contraction in the wake of the Covid-19 pandemic, which overstates the overall economic slump. Given that the tourism industry accounts for less than 2% of Swiss GDP, an inclusion of these indicators would result in an overly pessimistic course for the overall weekly activity indicator.

3 We observe presence transactions only. Data on e-commerce are highly volatile and result in worse model outcomes, and their correlation with GDP growth is low.

4 The Federal Customs Administration has reported weekly data for exports since 2002. However, we were told that these data are not usable before 2013 because of their poor quality. Prior to 2013, the dispatch date for exports was used to determine the due customs. As the exact export date of a specific good was often unknown, it was attributed to the first week of the month. The resulting series thus show a huge peak at the beginning of each month. As of February 2013, all transactions are recorded electronically with exact export dates. Note that monthly data of Swiss foreign trade in goods are available starting from 1988.

**Table 1**
Final set of indicators.

| Series | Source[a] | Start and frequency | Notes |
|---|---|---|---|
| Air pollution | EEA | 2015 Jan., daily | Average concentration of $NO_2$ (in $\mu g/m^3$) in 9 Swiss cities |
| Card transactions | Worldline | 2012 Apr, daily | Total credit and debit card transactions, presence |
| Cash withdrawals | SIX | 2016 Aug, daily | Total ATM cash withdrawal using debit cards[b] |
| Electricity consumption | Swissgrid, ENTSOE[c] | 2009 Jan., daily | End-user consumption of energy in GWh[d] |
| Goods exports | FCA | 2013 Feb., weekly | Total real goods exports without valuables and non-monetary gold[e] |
| Goods imports | FCA | 2002 Jan., weekly | Total real goods imports without valuables and non-monetary gold[e] |
| Net tonne kilometers | SFR | 2001 Jan., daily | Unit of measurement for rail freight transport[f] |
| Sight deposits | SNB | 2011 Aug., weekly | Weekly average of the sight deposits held at the SNB |
| Registered unemployment | SECO | 2004 Jan., daily | Number of registered unemployed persons at regional employment centers |

[a]*Abbreviations.* EEA – European Environment Agency, ENTSOE – European Network of Transmission System Operators for Electricity, FCA – Federal Customs Administration, SFR – Swiss Federal Railways, SNB – Swiss National Bank, SECO – State Secretariat for Economic Affairs
[b]Own-bank cash withdrawals executed using an ATM of type *Futura* or *Bancomat 5* are registered only partially and gradually since 2018. Therefore, these values are removed from the series in order to avoid movements that are not indicators of changes in the business cycle but rather due to an increase of registered cash withdrawal.
[c]ENTSOE data are used to extend the Swissgrid data, which are delayed (once a month). These data have been tested and found to be an highly correlated proxy for Swissgrid data.
[d]Grid losses and own use in power plants are excluded.
[e]Valuables include precious metals (mainly gold), precious stones and gems, works of art, and antiques. These goods are excluded from the analysis because they are highly volatile, quantitatively large, and contain no information on the business cycle stance of an economy.
[f]A net tonne-kilometer (ntkm) corresponds to the transportation of one net tonne of freight over a distance of one kilometer.

pose special problems because–contrary to annual, quarterly, and monthly data–they are not exactly periodic. The number of any given weekday within a year can be either 52 or 53, and its position varies from year to year. Further, the seasonal patterns vary from series to series and show potentially large calendar effects. For instance, cash withdrawals are high at the end of a month when salaries are paid out and bills are due; electricity consumption is high when it is cold in winter, but low in the summer; card transactions rise at the end of the year for Christmas shopping; and rail freight is low around national holidays. Not least, weekly data are more prone to excessive volatility than lower-frequency data. For example, imports might be extraordinarily high in a specific week due to the purchase of a new passenger plane, while in the following week no plane passes the customs.

Therefore, Proietti et al. (2018) recommend properly cleaning high-frequency data from any periodic, calendar, and outlier effects prior to estimating any econometric model.[5] In the following we describe six steps of data adjustment. All weekly time series were subjected to this procedure. In case a (raw) series is available on a daily frequency, we aggregate it to the weekly frequency prior to any adjustment. Table 2 provides an overview of how each series is adjusted. Notably, sight deposits do not show any seasonality, and hence no adjustment is made.[6]

1. **Surplus week adjustments.** According to international standard ISO 8601, most years have 52 weeks. However, every 5 to 6 years there is a year with 53 weeks, for example, the years 2004, 2009, 2015, and 2020. Moreover there are no "half" weeks, which implies that some days in the calendar week belong to a year other than the usual date. We correct all those years that have 53 weeks by the excess week so that all years in our data set end up having exactly 52 weeks. We enforce this by distributing the value of the 53rd week evenly to the other weeks of the year. While this changes the distribution of the weekly values we, however, make sure that this does not induce a change in the annual values. The primary purpose of removing the 53rd calendar week is to render feasible the calculation of growth rates with respect to the same week of the previous year.

5 See also Cleveland and Scott (2007), Harvey et al. (1997a).

6 We tested the robustness of our adjustment for data available on a daily frequency, for instance, data on cash withdrawals. We ran the routines of Ollech (2018) to seasonally adjust the daily data first and then aggregate it up to the weekly frequency. We found that the volatility was higher and not all seasonality was properly removed when following this approach.

**Table 2**
Overview of the adjustments.

(a) Seasonal and calendar adjustments

| | Specification | ARIMA | Further regressors |
|---|---|---|---|
| Air pollution | Log | $(0,1,1)\ (0,1,1)_{52}$ | bd, temp |
| Card transactions | Log | $(0,1,1)\ (0,1,1)_{52}$ | bd |
| Cash withdrawals | Log | $(0,1,1)\ (0,1,1)_{52}$ | bd |
| Electricity consumption | Level | $(0,1,1)\ (0,1,1)_{52}$ | bd, $cv_1$, $cv_{52}$, temp |
| Goods exports | Level | $(2,1,0)\ (1,1,0)_{52}$ | bd, $cv_1$, $cv_{52}$ |
| Goods imports | Level | $(3,1,1)\ (0,0,1)_{52}$ | bd, $cv_1$, $cv_{52}$ |
| Net tonne kilometers | Level | $(0,1,2)\ (1,1,0)_{52}$ | bd |
| Sight deposits | – | – | – |
| Registered unemployment | Log | $(0,1,1)\ (0,1,1)_{52}$ | bd |

(b) Outlier adjustment

| | Simple moving average | | Hampel filter | |
|---|---|---|---|---|
| | Window | Alignment | Window | Threshold |
| Air pollution | 3 | Backward | 6 | 1 |
| Card transactions | – | – | 6 | 1.5 |
| Cash withdrawals | – | – | 6 | 2 |
| Electricity consumption | 3 | Backward | 6 | 0.75 |
| Goods exports | 3 | Backward | 6 | 2 |
| Goods imports | 3 | Backward | 6 | 1.25 |
| Net tonne kilometers | 3 | Backward | 6 | 0.75 |
| Sight deposits | – | – | 6 | 2 |
| Registered unemployment | – | – | 6 | 2 |

*Abbreviations* bd: business days of the week; $cv_1$: dummy for the calendar week 1 of the year that follows a year with 53 weeks; $cv_{52}$: dummy for the calendar week 52 of a year with 53 weeks; temp: weekly average temperature in Switzerland.

2. **Calendar day, holiday, and temperature adjustments.** The problem of adjusting data for calendar effects due to the changing lengths of months (surplus days), day-of-the-week effects, and public holidays is well established in the context of monthly and quarterly data.[7] This problem equivalently applies to weekly data. The key problem concerns public holidays that move over the calendar weeks (for example, Easter) in comparison to those that are fixed (for example, New Year's Day). Correcting weekly data for public holidays is more complex than for lower-frequency data, because weeks may be subject to irregularities related to a different amount of working days. To properly adjust for working day and holiday effects, we take the working day volume of the canton of Zurich.[8] Besides correcting for the number of business days per week, one particular issue concerns the treatment of the weeks around the change of the year. Most people are on vacation between Christmas and New Year's day–the last week of the year–and this week corresponds to the 52nd, 53rd, or 1st week, depending on the year. Moreover, if Christmas Eve is later in the week, economic activity will be high, whereas it is low if Christmas Eve is early in the week. We separately check for these end-of-year effects using dummy variables. Where necessary, we also correct the data for temperature effects by including additional regressors. For instance, the average concentration of nitrogen dioxide ($NO_2$) is higher when temperatures are low. We use a parametric Reg-Arima Model following Findley and Soukup (2000) to perform the calendar day, holiday, and temperature adjustments.[9]
3. **Seasonal adjustments.** Seasonal patterns in weekly data can appear due to recurrent fluctuations within a month (e.g., unemployment registrations rise in the last week of the month as contracts end) or because of recurring fluctuations within the year (e.g., energy consumption is low in summer and high in winter). Such seasonal fluctuations mask the underlying business cycle development. We estimate seasonal factors using a generalized fractional airline decomposition model following

7 See for instance Cleveland and Devlin (1982) on monthly data and Rodrigues and Esteves (2010) on daily data.

8 Given that public holidays in Switzerland vary across cantons, we used public holidays in the canton of Zurich as a proxy for the whole country.

9 We follow the lines of TRAMO-SEATS proposed by Gómez and Maravall (2001). An outline of the procedure is given in Appendix A.1. More details can be found in Findley and Soukup (2000), Proietti et al. (2018). Depending on the characteristics of the series, we estimate the model either in Levels (additive model) or in Logs (multiplicative model). The order of the model is determined automatically via the Akaike information criterion.

Hillmer and Tiao (1982), Koopman and Aston (2006), Koopman et al. (2007), Ollech (2018).[10]

4. **Excessive volatility adjustments.** For most indicators, the previous adjustment steps are sufficient to establish an informative indicator. Four series, however, display excessive volatility even after calendar and seasonal adjustment: exports, imports, air pollution, and net tonne-kilometers. We smooth these series by applying a one-sided three-week moving average.[11]
5. **Computing weekly annual growth rates.** After implementing steps 1 to 4, we compute the annual growth rates of the adjusted series, i.e., the rate of growth of an indicator for a given week to the same week in the previous year, given by $\Delta y_t = \log(Y_t) - \log(Y_{t-52})$. By doing so, any remaining part of seasonal elements in the data not captured previously should be eliminated.
6. **Outlier adjustment.** Even after cleaning the data and deriving growth rates, the data might show certain anomalies unrelated to business cycle movements.[12] We correct for such outliers in the growth rates by applying generalized Hampel filters (Pearson et al., 2016).[13]

Fig. 1 illustrates the six-step procedure for goods imports (top row), cash withdrawals (middle row), and registered unemployed persons (bottom row). The left column shows the respective levels of the weekly data (*raw*) and after adjustment steps 1 to 4 (*csa*). Imports are noisy and plagued by numerous outliers, cash withdrawals display a more regular seasonal pattern and are less volatile, and unemployment figures are dominated by low-frequency seasonality. Evidently, as soon as seasonal and calendar effects are removed, business cycle movements become apparent in the series. The sub-figures in the right column show the year-over-year (y-o-y) growth rate of both the raw series and the final adjusted series (*adjusted*). For imports, for instance, the effect of calendar days around the 53rd calendar week (2015 and 2020) is clearly visible and underscores the importance of a proper adjustment.

### 2.3. Econometric methodology

Next, we describe the details of the econometric approach taken to establish the WEA index. We aim at summarizing the information contained in a set of high-frequency indicators in one overall index. The leading technical concept in this context is the linear dynamic factor model (DFM) developed by Geweke (1977) and Sargent and Sims (1977).[14] The basic idea of this class of models is to explain the information contained in a vector of observable time series by a small number of unobserved (latent) series.

The premise of DFMs is to decompose a vector of observed time series $X_t$ of dimension $n$ into two orthogonal components: common components, also referred to as latent factors, denoted by $f_t$, which capture the co-movements among the observed variables in $X_t$; and idiosyncratic components, $u_{t,i},\ \forall\, i = 1, \dots, n$. Idiosyncratic components arise from measurement errors and features specific to an individual series. The common components are assumed to follow a stochastic process. We proceed by considering a one-factor structure, implying that $f_t$ is a scalar.[15]

The vector of time series $X_t$ consists of the nine weekly series $x_{i,t} \forall\, i = 1, \dots, 9$ described in Table 1. All individual series are given by the year-over-year growth rates and are standardized. The DFM is specified as $\forall\ t = 1, \dots, T$ by the following system of equations:

$$X_t = \boldsymbol{\gamma} \cdot f_t + \boldsymbol{u}_t, \tag{2.1}$$

$$\left(1 - \phi_f(L)\right) \cdot f_t = \nu_t^f, \tag{2.2}$$

$$\left(1 - \phi_{u,i}(L)\right) \cdot u_{t,i} = \nu_{t,i} \quad \forall\, i = 1, \dots, n \tag{2.3}$$

$$\begin{pmatrix} \nu_t^f \\ \boldsymbol{\nu}_t \end{pmatrix} \sim NID\left(\mathbf{0}, \begin{bmatrix} \sigma_f^2 & \mathbf{0} \\ \mathbf{0} & \Sigma_\nu \end{bmatrix}\right). \tag{2.4}$$

In the observation Eq. (2.1), the idiosyncratic component is given by $\boldsymbol{u}_t = \left(u_{t,1}, \dots, u_{t,n}\right)'$. The vector of factor loadings $\boldsymbol{\gamma}$ captures the relation between the common component $f_t$–our object of interest in what follows–and the observed variables in $X_t$.

Eqs. (2.2) and (2.3) govern the dynamics of the model. $\phi_f(L)$ and $\phi_{u,i}(L)$ are lag-polynomials and $\boldsymbol{\nu}_t = (\nu_{t,1}, \dots, \nu_{t,n})'$. The common component $f_t$ is thus identified based on both the historical cross-correlations of the vector of variables $X_t$ and its own historical auto-correlations. Identification is achieved only up to scale, as initial conditions for the parameters–$\gamma$, $\phi_f(L)$, $\phi_{u,i}(L)$, and $\Sigma_\nu$, respectively–are necessary to complete the model. We assume that $\Sigma_\nu$ is diagonal, implying that all co-variances are zero by construction. For identification reasons we impose that $\sigma_f^2$ is unity.

10 For series with a low number of observations such as cash withdrawals, we estimate seasonal factors only up until mid-March 2020. We thus prevent the effects of the first shutdown during the Covid-19 pandemic from influencing the series prior to 2020. The estimated parameter values are then used for the seasonal adjustment of the whole time series.

11 Avoiding this intermediate adjustment step renders model estimation unstable and leads to meaningless results.

12 For instance, in any given week, Switzerland exports a shipment of an expensive cancer treatment, raising exports by several hundred million Swiss francs. In the next week, however, no such shipment happens. This leads to sudden jumps in the growth rates that are observed twice: once in the week of the shipment with an extraordinary increase, and once a year later with an extraordinary decrease.

13 We relate a particular data point with the median of preceding and succeeding values according to a window length to be chosen. A data point is classified as an outlier if it lies far enough (for instance, two standard deviations) from the median. Outliers are replaced by the median value of the specified window.

14 See also Camacho et al. (2015), Camacho and Perez-Quiros (2010), Camacho and Perez Quiros (2011), Chernis and Sekkel (2017), Rusnák (2016) for applications of linear models to countries such as Argentina, Canada, Czech Republic, Spain, and Switzerland with monthly and quarterly data.

15 We tested the robustness of our model to choosing more factors. Increasing the number of factors substantially reduces the information contained in the business cycle factor and makes it more volatile.

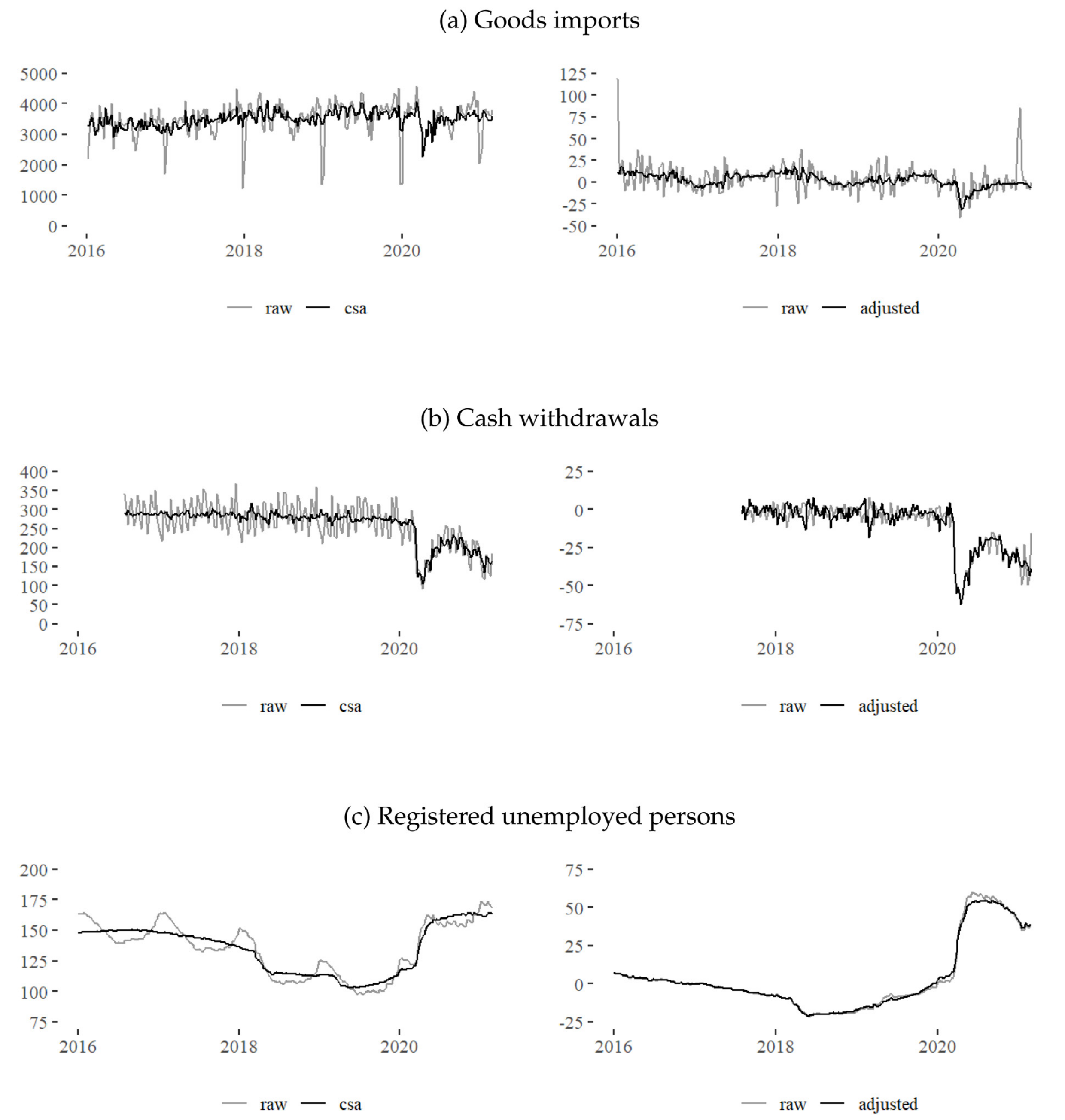


**Fig. 1.** Data adjustments. *Left column: level; right column: growth rates.*

The two primary methods for estimating the model, i.e., Eqs. (2.1)–(2.4) and hence the common component $f_t$, are principal components and state space methods, where within the latter, the common component (and the model's parameters $\gamma$, $\phi_f(L)$, $\phi_{u,i}(L)$, and $\Sigma_\nu$) is estimated by running the Kalman filter (Durbin & Koopman, 2002). We adopt the state space approach[16] to estimate the model, as the weekly series in $X_t$ are subject to missing observations as some series start earlier than others (see Table 1). Moreover, ragged edges at the end of the sample are an additional problem related to missing observations.[17] We consider the filtered state estimate for the common component denoted by $f_{t|t}$.[18]

16 We refer the reader to the Online Appendix of Glocker and Wegmüller (2020) for details concerning the state space representation of the model of Eqs. (2.1)–(2.4).

17 We also estimated the model using simple principal components methods. As data must be square and complete, this comes at the expense of having an index starting as late as August 2016.

18 An alternative would be the smoothed ($f_{t|T}$) or predictive ($f_{t|t-1}$) state estimates. The filtered and smoothed state estimates are equal

We start the estimation in the first week of 2005. In our preferred specification, Eq. (2.2) has an AR(3) structure and the idiosyncratic components (Eq. (2.3)) are specified as white noise. We assess the sensitivity of our results with respect to the specification of the transition equation (2.2) in Section 3.2.2.

The estimation of the common component $f_t$ relies solely on weekly data. The model could in principle be extended with lower-frequency time series.[19] However, this would impair the assessment of the informational content of the weekly data.

## 3. Measurement

In the following we present the weekly economic activity index. We describe its in-sample characteristics, discuss its robustness and assess the contributions of the indicators for the overall index.

### 3.1. Index of weekly economic activity (WEA)

The model is estimated based on the standardized annual growth rates of the nine indicators outlined in Table 1 contained in $X_t$. Our index of weekly economic activity is derived from the common component $f_t$. As the common component is not anchored to any measure of economic activity, its values are not directly interpretable. To convert the common component into meaningful units, we follow Lewis et al. (2021) and re-scale $f_t$ to the quarterly year-over-year GDP growth rates. This scaling implies that the index average over 13 weeks—-which corresponds roughly to one quarter—-gives an indication of the real, seasonal, calendar, and sport event adjusted GDP growth during the period, compared with the same period in the previous year.[20] We chose GDP growth as anchor and target because of its particular interest for macroeconomic policymakers. The choice of quarterly year-over-year growth rates aligns with the 52-week growth rates used for the weekly series.

The scaling and shift coefficients are estimated using the regression,

$$\Delta^4\text{GDP}_{t_q} = \beta_1 + \beta_2 \cdot f_{t_q} + e_{t_q}, \tag{3.1}$$

where $\Delta^4\text{GDP}_{t_q}$ is the quarterly year-over-year growth rate of GDP, and $f_{t_q}$ is the common component on a quarterly frequency $t_q$. We compute the WEA index as follows:

$$\text{WEA}_{t_q} = \hat{\beta}_1 + \hat{\beta}_2 \cdot f_{t_q}. \tag{3.2}$$

This transformation extends the common component $f_t$ to an interpretable measure. The WEA index measures the change in overall macroeconomic activity during a particular week, relative to the corresponding week of the previous year. It is displayed in Fig. 2. As can be seen, the index adequately captures the economic development indicated by GDP growth over a long period of time. Despite a relatively high level of volatility at a weekly frequency, the index has a correlation of 0.9 with GDP growth rates at a quarterly level. For the period between the major crises in 2009 and 2020, the correlation is almost 0.6 and is therefore comparable with that of widely used monthly economic indicators.[21]

### 3.2. Properties of the common component

We now turn to discuss the properties of the common component in detail and assess its sensitivity. In this context, we first check the robustness with respect to adding further variables to the model and, second, to alternative specifications of the dynamic elements in Eq. (2.2).

We start by discussing the factor loadings of our preferred specification to assess the model's in-sample fit. Table 3 lists the factor loadings ($\boldsymbol{\gamma}$) associated with the common component $f_t$ on the weekly series. The table provides an overview of the estimated factor loadings across different series in $X_t$. Our preferred model is composed of nine indicators. The results thereof are depicted in the first column of Table 3. All estimated factor loadings are different from zero, at least at the five percent level of statistical significance. Moreover, all factor loadings have the expected sign. In particular, registered unemployment and sight deposits have a negative effect on the common component $f_t$. These two variables are counter-cyclical: an increase in sight deposits held at the national bank generally implies heightened appreciation pressures of the Swiss franc, which usually happens at times of financial distress or high economic uncertainty (see Jordan, 2016). Regarding unemployment, the negative sign essentially confirms the validity of Okun's law for the Swiss economy. Concerning the positive factor loading of imports, contrary to the standard view in national accounting, imports are interpreted within the model as an indicator of final demand, and therefore have a pro-cyclical behavior.

#### 3.2.1. Augmenting the set of variables

So far, we have presented an index of weekly economic activity based on nine indicators. As mentioned in Section 2.1, there are several other possible weekly indicators which could be considered. Besides studying the robustness of factor loadings, we judge the overall model fit by comparing the common component's contemporaneous correlation with GDP across different model specifications (bottom row of Table 3). Since we intend to identify a measure for weekly economic activity that co-moves strongly with GDP, we hence consider the common component's correlation with the y-o-y growth

at the end of the sample where $t = T$. Most important for us is the fact that the filtered state estimate is less sensitive to revisions when adding new data, which is not the case for the smoothed state estimate (see Section 3.2.3 for further details).

[19] In Bilek-Steindl et al. (2020), Chernis et al. (2020), Monteforte and Raponi (2019), among others, a dynamic factor model is used that includes time series of three different frequencies: weekly/bi-weekly time series (credit card sales, truck mileage, rail freight transport, and electricity consumption), monthly time series (business surveys, industrial production, retail sales, etc.), and quarterly time series (GDP growth rates).

[20] Quarterly GDP for Switzerland starts in 1980 and is published on https://www.seco.admin.ch/gdp.

[21] See, for instance, Glocker and Kaniovski (2019).

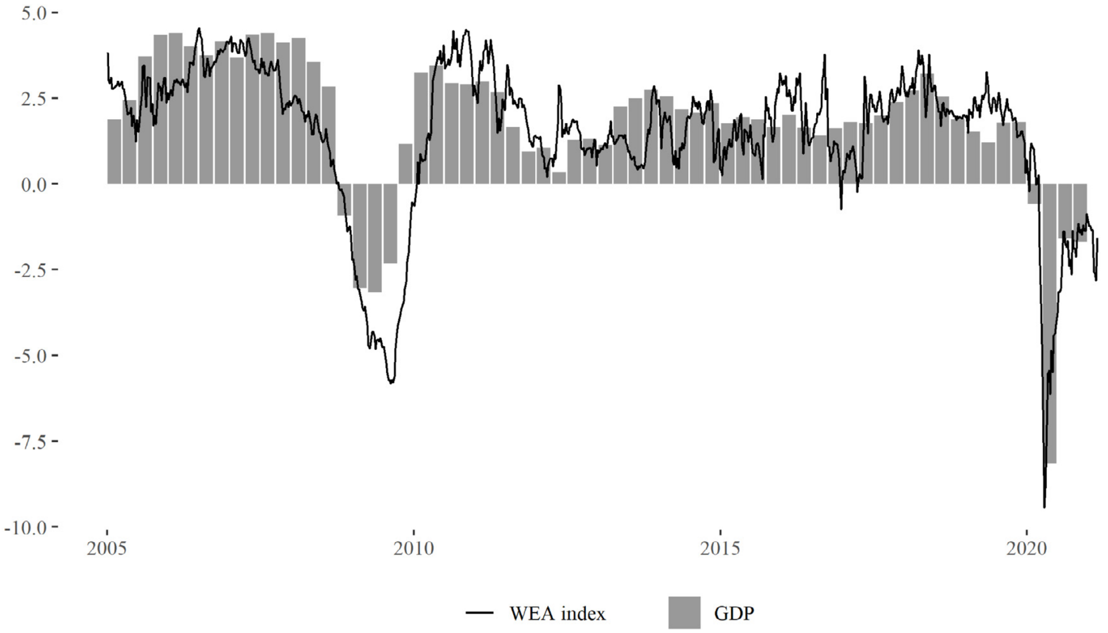


**Fig. 2.** Swiss weekly economic activity (WEA) index.

**Table 3**
Factor loadings of different models.

| Indicator | Base | Extended | Financial data |
|---|---|---|---|
| Air pollution | 0.21 | 0.37 | 0.36 |
| Card transactions | 0.21 | 0.02 | 0.01 |
| Cash withdrawals | 0.38 | 0.03 | 0.02 |
| Electricity consumption | 0.30 | 0.55 | 0.57 |
| Goods exports | 0.57 | 0.11 | 0.11 |
| Goods imports | 0.44 | 0.63 | 0.66 |
| Net tonne-kilometers | 0.43 | 0.05 | 0.05 |
| Registered unemployment | −0.37 | −0.03 | −0.03 |
| Sight deposits | −0.03 | −0.02 | −0.02 |
| Bankruptcies | – | 0.12 | – |
| Flight passengers | – | 0.01 | – |
| Truck traffic | – | −0.00 | – |
| Term spread | – | – | −0.01 |
| Volatility SMI | – | – | 0.04 |
| Contemp. Correlation | 0.89 | 0.80 | 0.83 |

rate of GDP as another aspect within the model/variable selection process.[22]

The second column of Table 3 therefore provides the factor loadings for an extended model in which we add further indicators. The indicators still fulfill the criteria of timely availability, reasonable volatility, and economic content. As it turns out, the series for bankruptcies has a positive factor loading which is at odds with theoretical considerations. While the estimated size of the factor loading is large compared to the one of other variables, it is not statistically different from zero. The factor loadings of flight passengers and truck traffic are negligibly small, with the loading of the latter also being of the wrong sign. The extension of our preferred specification with additional indicators also leads to heightened volatility in the common component $f_t$ and a lower correlation with GDP.

As the aim of the weekly index is to capture real economic activity, we omitted any financial data in a first

[22] We calculate the correlation using quarterly data for the common component ($f_t$, done by considering the average across the corresponding weeks) and the y-o-y growth rate of GDP. We compute the correlation for both the entire time span and a sub-sample: the period between the recession that occurred in the wake of the global financial crisis and the Covid-19 recession. This is important in order to identify possible sub-sample instabilities, which then allows for a better overall assessment of the common component's quality to track economic activity in a timely manner.

step. Yet, financial data might also contain relevant business cycle information.[23] The third column thus provides the factor loadings for yet another extended model in which we add two financial variables–the term spread and the implied volatility of the Swiss stock market index (VSMI)–to the baseline specification.[24] The loadings of both variables are negligibly small and of the wrong sign in each case. Moreover, they are not statistically different from zero at the five percent level of significance, and the model's in-sample performance worsens substantially.

In summary, in the context of weekly data it is not necessarily the case that more data are always better. This aligns with the evidence put forward in Camacho and Perez-Quiros (2010), among others, regarding the use of monthly indicators. The nine variables selected in our preferred specification are sufficient to establish a weekly index that provides a robust and coherent picture of Swiss economic activity.

#### 3.2.2. Sensitivity to changes in the specification

We now evaluate the robustness of the estimated common component of our preferred specification to variations in the model setup. We consider two extensions in this context involving different specifications of the transition Eq. (2.2) in each case.[25]

Our baseline model uses an AR(3) specification for the transition Eq. (2.2). While an auto-regressive specification is common in this context (compare Camacho & Perez-Quiros, 2010; Carriero et al., 2020, among others), there are various alternatives. We assess the sensitivity of the results of the baseline model with respect to extensions involving (i) a multivariate local-level model, and (ii) different lag-lengths for Eq. (2.2).[26]

Our baseline specification can be changed to a multivariate local-level setup when changing Eq. (2.2) to a random walk: $f_t = f_{t-1} + \nu_t^f$. As a consequence of this change, the corresponding factor $f_t$ turns out to be slightly more volatile, though still very much in line with the AR(3) specification. The same also applies to the second extension where we consider either an AR(1) or an AR(2) specification for Eq. (2.2) as further alternatives. In both cases, the path of the common component is similar to that of the baseline specification, yet we prefer the model with three lags because the coefficients for the first three lags are statistically significantly different from zero, while in-significant from the fourth lag onward.

[23] See for instance Burri and Kaufmann (2020). Further, Stuart (2020) provides evidence that the term structure contains information useful for predicting recessions in Switzerland.

[24] We also tested the model's robustness with the stock indices SMI and SPI, as well as with the nominal Swiss franc–euro exchange rate. Here we only report the best model with financial data. Further results are available upon request.

[25] We ran several different robustness exercises. Apart from estimating the model with more than one factor or with principal components instead of maximum likelihood, we also tested whether imposing a lag structure in Eq. (2.3) reduces the volatility of the common component. Typically, the idiosyncratic terms follow an AR(2) process. In our case, this renders the factor unstable and leads to implausible results.

[26] We refrain from considering non-linear extensions, as done for instance in Camacho et al. (2018) by using a Markov-switching process, given that it is not the aim of the paper to identify different regimes over time.

#### 3.2.3. Revisions to the WEA index

A stable course, and thus a low susceptibility to revisions of the WEA index are important properties for its suitability for assessing the current economic stance and providing reliable forecasts. To this purpose, we evaluate the scope of its in-sample revisions. Given our methodology, revisions can arise from the following four sources:

1. Changes in the raw data. Among our nine weekly constituent series, only goods exports and imports are revised.
2. Revisions in the wake of the data pre-adjustment. With every new observation, the six-step adjustment procedure outlined in Section 2.2 may affect the measurement of weekly economic activity ex post. As an example, once the value of the 53rd calendar week is known, it is distributed across the remaining 52 weeks of the year. Also, the coefficients from the seasonal adjustment procedure are estimated every week, potentially leading to some revisions in the past.
3. Changes in the parameter estimates of the DFM. This may apply at times when the constituent series exhibit particularly volatile patterns, rendering the parameter estimates potentially unstable over time.
4. Revisions due to the re-scaling with GDP. Once a new quarter of GDP data is released, the common component $f_t$ is rescaled. The GDP growth rates may induce revisions in the WEA index once excessively volatile GDP growth rates affect the parameters estimates of Eqs. (3.1) and (3.2).

We assessed the temporal path of the WEA index and its sensitivity to revisions within a real-time evaluation. The results are provided in Figure A.1. Overall, we find that the WEA index is only subject to minor revisions. The real-time publication of the WEA index already provides a good estimate of the prevailing economic situation. A crucial element in this respect pertains to the long sample that we consider for estimation. This promotes the stability (i) of the estimated parameters of the models used to pre-adjust the data, (ii) of the estimated factor loadings of the DFM, and (iii) of the parameter estimates when re-scaling the common component $f_t$ with GDP growth (Eqs. (3.1) and (3.2)). The results corroborate the stability of our model within an excessively volatile economic episode as was the case in the wake of the Covid-19 pandemic. This highlights the usefulness of a purely weekly data set.

### 3.3. Contribution of the variables to the WEA index

An important aspect in the context of business cycle surveillance concerns the identification of sector-specific developments in shaping aggregate fluctuations. Our framework allows for assessing the contribution of each variable in the vector $X_t$ of the observation Eq. (2.1) to the path of the WEA index. For this purpose, we use the approach proposed by Koopman and Harvey (2003). They show how the Kalman filter enables the computation of the contribution of each constituent series $x_{i,t} \in X_t$ to the

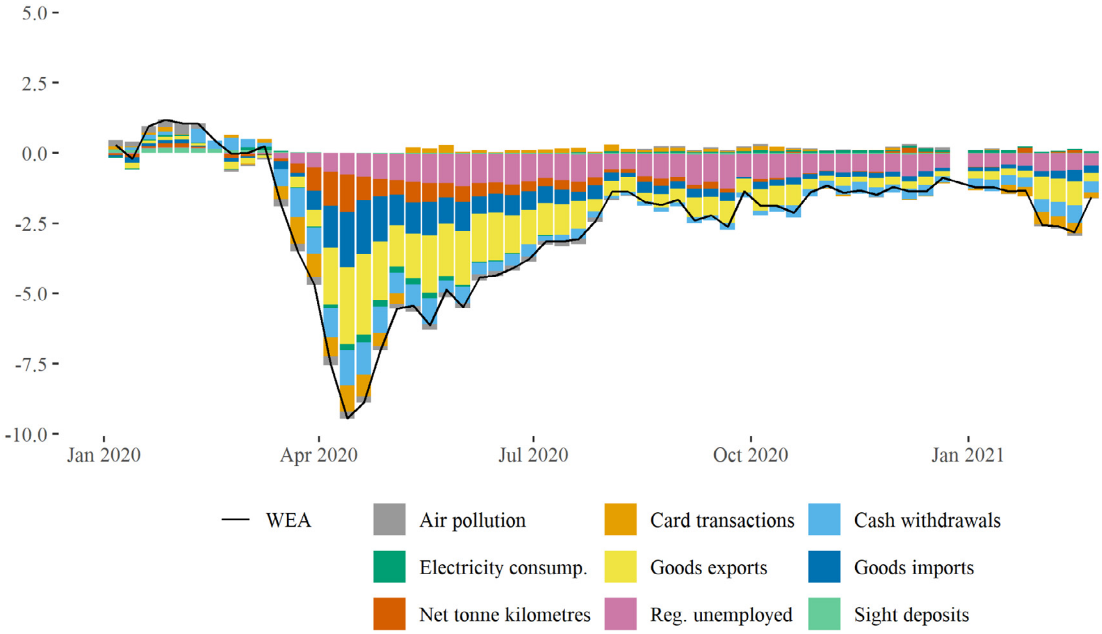


**Fig. 3.** Contribution of the variables to the WEA index.

common component $f_t$ and its forecasts.[27] Let $a_{t|t}$ denote the state vector as implied by the state space representation of the model (see Glocker & Wegmüller, 2020). As our estimate for the common component is based on the filtered state estimate $a_{t|t}$, the weight matrices $w_i(a_{t|t})\ \forall\ i \in \{1, \ldots, n\}$ can then be computed after the Kalman filter has been applied.

Fig. 3 displays the results for $w_i(a_{t|t})$ for the year 2020. The graph provides insight into the driving forces behind the economic slump in the wake of the Covid-19 pandemic. From mid-March onward, both exports and imports contributed most to the decline in economic activity. Trade in goods was impaired by the abrupt interruption of global value chains.[28] Indicators which proxy private household consumption also display a strong decline and hence a pronounced negative contribution to the WEA index. Both cash withdrawals and card transactions fell immediately once the first shutdown was put in place by March 16, 2020. Accordingly, both variables show a strong negative contribution to the WEA index. In contrast, the indicators that capture activity in the manufacturing sector reveal a smaller contribution to the overall economic downturn. Electricity consumption, air pollution, and the transportation of goods by railways (net tonne-kilometers) all contribute negatively, albeit only moderately. While their individual contribution is small, their joint contribution compares well to those of foreign trade and consumption. The model hence confirms the important role of the manufacturing sector for shaping the aggregate fluctuations of the Swiss economy.

## 4. Assessing the informational content of the WEA index

In this section we illustrate the usefulness of weekly data–in our case in the form of the WEA index–for predicting GDP growth. In a first step, we assess the role of data adjustment as outlined in Section 2.2. We then continue with evaluating the informational content of weekly data relative to the one contained in commonly used monthly business cycle indicators for the Swiss economy. Finally, we provide some robustness checks for our findings.

### 4.1. Out-of-sample setup

We conduct the forecast exercise in *pseudo*-real time; i.e., we mimic the regular forecasting routine, but abstract from potential data revisions in the weekly input series. As mentioned previously, most of the weekly indicators contained in the WEA index are not ex post revised. Concerning the target variable, GDP, we draw real-time vintages from Indergand and Leist (2014).

We consider a weekly calendar of data releases and forecast origins similar to Carriero et al. (2020). Our forecast calendar includes 13 weeks for each quarter, reflecting approximately four weeks per month of the quarter. The WEA index of a given week is released with a time lag of one week. GDP is published with a delay of 60 days, i.e., 8.6 weeks. The assessment therefore considers the prediction of current quarter GDP (*"Nowcast"*) for horizons of 1 to 13 weeks and of the following quarter (*"Forecast"*), corresponding to weeks 14 to 26. Our estimation sample spans from 2007:W1 to 2020:W52, which

[27] This approach is commonly used in the context of small-scale dynamic factor models for the purpose of forecasting GDP growth (see Bańbura & Rünstler, 2011; Camacho & Perez-Quiros, 2010; Camacho & Perez Quiros, 2011; Camacho et al., 2018, for instance) under mixed frequencies (monthly and quarterly data being used jointly in the DFM).

[28] See Büchel et al. (2020) for a description of the Covid-19-related Swiss trade collapse.

amounts to 728 weeks, or 56 quarters. We define the period between the financial crisis of 2008 and the beginning of the Covid-19 recession of 2020 as a subsample without economic recession in Switzerland. In particular, following the recession dating of the ECRI Institute,[29] the subsample spans from 2009:M5 to 2019:M12. The estimation sample is recursively expanded over time.

We calculate the relative root-mean-squared error (RRMSE) to measure the predictive accuracy. As a benchmark, we estimate an AR(1) model on the real-time vintages of GDP growth.[30] Forecast errors are calculated relative to the final GDP vintage.[31]

### 4.2. Role of data adjustments

The adjustment of weekly data prior to estimating a weekly composite index is a central part of this work. We now assess the gains of this procedure for the predictive accuracy of the WEA index. For this purpose, we compute an alternative WEA index based on the same nine input series, though without any adjustment of the data, as outlined in Section 2.2. This approach is analogous to the one of Lewis et al. (2021). We refer to these two weekly activity measures as the *adjusted* and *unadjusted* WEA indices.[32] In a first step, we do not specify any econometric structure to derive the forecasts. Rather, we test for the following direct relationship:

$$y_{t_q} = \mathrm{WEA}_{i,t} \tag{4.1}$$

in which $y_{t_q}$ is our target variable GDP growth, and $i$ stands for either the *Mean* or *Last*. The former corresponds to the average WEA index of the published weeks corresponding to the quarter of the prediction (henceforth *WEA MEAN*); the latter corresponds to the last observed value of the WEA index in the corresponding quarter (henceforth *WEA LAST*). For the quarter one period ahead, we extend either the mean or last value to the end of the prediction period.

We provide evidence of this first exercise in Table 4. The table reports the relative RMSE together with significance levels from the modified Diebold–Mariano test,[33] where we test the hypothesis that the adjusted WEA index outperforms the unadjusted index.

Several results emerge for the full sample. First, both adjusted WEA indices exhibit at any horizon a lower RMSE relative to the benchmark. Second, the unadjusted indices also exhibit a better performance, but only for a short horizon. Third, the forecasting accuracy improves with a decreasing horizon in all cases. For instance, with only seven weeks left (the middle of the nowcasting quarter), the *WEA MEAN* index is 40% better than the AR benchmark. Fourth, the difference between *WEA LAST* and *WEA MEAN* is negligible. Fifth, both *WEA MEAN* and *WEA LAST* with adjusted inputs perform significantly better than their unadjusted counterpart. This applies across any horizon considered (1 week to 25 weeks). We interpret this result as a strong indication for our proposed data adjustment procedure outlined in Section 2.2. Finally, the results are robust also for the subsample without crisis periods. However, the results are not significant anymore for the forecasting period.

### 4.3. Is weekly information superior to monthly information?

As shown in the previous section, the WEA index with adjusted inputs contains valuable information for nowcasting and forecasting. We now challenge its performance against two established monthly business cycle indicators for the Swiss economy:[34] (i) KOF Economic Barometer,[35] and (ii) the SECO-SEC indicator.[36] We assign to each indicator a typical release or availability week based on its usual publication schedule and allocate the monthly data to the first, fifth, and ninth week of any given quarter. For instance, at the end of week 2, a forecaster has no new information from the monthly indicators, but one additional week of the WEA index. The key question is whether this additional weekly information improves the predictive accuracy for GDP growth.

Contrary to the WEA index, the levels of the monthly indicators cannot be directly interpreted as growth rates of GDP, and we need to specify some econometric models. To keep it simple, we consider single indicator bridge equations following Baffigi et al. (2004):

$$y_{t_q} = \alpha + \gamma y_{t_q-1} + \beta\left(L\right) x_{t_q} + u_{t_q}, \tag{4.2}$$

in which $y_{t_q}$ is again quarterly GDP growth. The bridge equation contains a constant, $\alpha$, and potentially an autoregressive term, $\gamma y_{t_q-1}$. The lag polynomial is given by $\beta\left(L\right) = \sum_{i=0}^{p} \beta_{i+1} L^i$, with $Lx_{t_q} = x_{t_q-1}$. The predictor $x_{t_q}$ is the monthly or weekly indicator $x_{t_{\{m,w\}}}$ aggregated to the quarterly frequency via the function $x_{t_q} =$

[29] See ECRI Business Cycle Peak and Trough Dates.

[30] Our results are qualitatively robust to other benchmarks such as random walks or an AR(p) model with lags determined by the BIC. The results are reported separately in the Appendix (See Tables A.2 and A.4).

[31] The results are qualitatively robust to calculating forecast errors relative to the first release of GDP (see Tables A.3 and A.5 in the Appendix).

[32] Figure A.2 in the Appendix illustrates the difference over time in the two series.

[33] Diebold and Mariano (1995) provide a pairwise test to analyze whether the differences between two or more competing models are statistically significant. As there is potentially a short-sample problem, we apply the modified version of the Diebold–Mariano test according to Harvey et al. (1997b). We assessed the robustness of these results using the fixed-*b* test of Coroneo and Iacone (2020), in order to control for the presence of serially correlated errors and the small sample size. In the majority of pairwise comparisons, the results of the Coroneo and Iacone (2020) test confirm those of the modified Diebold–Mariano. The results are available upon request.

[34] There are other possible alternatives. For instance, we also perform the tests with respect to the manufacturing PMI, to an export-weighted manufacturing PMI, and to the business cycle index of the Swiss National Bank (SNB-BCI). Our findings are qualitatively robust and shown in the appendix.

[35] The KOF Economic Barometer is a leading composite indicator that shows how the Swiss economy is likely to develop. The database consists of over 500 indicators, of which only a subset is used, which changes over time (Graff et al., 2014).

[36] The Swiss Economic Confidence indicator is provided by SECO and comprises 30 survey indicators for the Swiss economy. See https://www.seco.admin.ch/kss for the data.

**Table 4**
Forecasting performance of WEA index.

| Horizon | Full sample | | | | | 2009 Q2 – 2019 Q4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 7 | 13 | 19 | 25 | 1 | 7 | 13 | 19 | 25 |
| *adjusted* | | | | | | | | | | |
| MEAN[a] | 0.59*** | 0.59** | 0.70* | 0.94** | 0.99*** | 0.83*** | 0.75 | 0.90 | 0.94 | 1.02 |
| LAST[b] | 0.68** | 0.62** | 0.66** | 0.89** | 0.98*** | 0.88** | 0.78* | 0.85 | 0.91 | 1.03 |
| *unadjusted* | | | | | | | | | | |
| MEAN | 0.83 | 0.86 | 1.11 | 1.16 | 1.20 | 1.26 | 1.27 | 1.44 | 1.46 | 1.49 |
| LAST | 0.83 | 0.91 | 0.98 | 1.14 | 1.22 | 1.16 | 1.34 | 1.46 | 1.42 | 1.57 |

RMSE relative to the benchmark AR(1)-model. Forecasting horizon in weeks.
Modified Diebold–Mariano test: the alternative hypothesis states that the adjusted WEA method is more accurate than the unadjusted method.
Significance levels: *p-value*: *** < 0.01, ** < 0.05, * < 0.1 of the modified Diebold–Mariano test (Harvey et al., 1997b).
[a]*MEAN*: average value of the WEA index in the corresponding quarter.
[b]*LAST*: last value of the WEA index in the corresponding quarter.

$\sum_{j=0}^{r} \omega_j L^{j/\{3,13\}} x_{t_{\{m,w\}}}$. This is an indirect forecasting procedure as it involves two steps: (1) forecasting the monthly or weekly indicator, and (2) time aggregation to obtain the quarterly prediction.[37]

We consider two distinct econometric models for the assessment: (i) bridge equations, and (ii) bridge equations with autoregressive elements (AR-bridge), where the lag order is determined by BIC. Analogous to the monthly indicators, we also estimate bridge equations for the WEA. This allows not for a fair assessment across the monthly and weekly indicators, and it offers the possibility of testing whether additional econometric structure on top of the weekly index improves its nowcasting performance further. We use the real-time vintages for GDP growth.

We report evidence of this exercise in Table 5. For comparison purposes, in the first row we repeat the results for the preferred *WEA MEAN* specification of Table 4. In rows 2 and 3, we show the RMSE relative to the AR(1)-benchmark model for different forecasting horizons in weeks for estimating AR-bridge equations based on the adjusted *WEA MEAN* index. Next, we display the resulting RMSE for monthly indicators based on AR-bridge equations. We test the model performances both with respect to the AR(1)-benchmark and against the benchmark of the weekly adjusted *WEA MEAN* specification. Significance levels are based on the modified Diebold–Mariano test with the hypothesis that the tested model outperforms the benchmark.[38]

The results highlight the following: (i) For nowcasting, i.e., up to a horizon of 13 weeks, the WEA index clearly outperforms the monthly indicators. The difference is significantly different from zero at the 1% level in the case of the nowcast from the KOF Barometer estimated by a bridge equation. (ii) Regarding the forecasting period (13 weeks and more), the monthly indicators perform somewhat better than the predictions with the WEA index. The statistical support for this is limited, however. (iii) The nowcasts with weekly data do not improve when adding econometric structure via bridge equations and accounting for the autoregressive structure in GDP. Predictions based on *WEA MEAN* are at least as good as when using a bridge equation. (iv) Forecasts with weekly data improve when estimating a bridge equation including an autoregressive component for GDP growth. (v) The results are also encouraging for the period between the two great recessions of 2008 and 2020: weekly data exhibit similarly low RMSE as their monthly counterparts, though the performance is not significantly better. Regarding the forecasting period (horizon of 13 and more weeks), the monthly data even outperform our weekly index.

To summarize, we find clear evidence that weekly data can have superior informational content for GDP nowcasting and forecasting relative to commonly used monthly business cycle indicators. Moreover, the performance of the WEA cannot be further improved by adding information on GDP via a bridge equation. This implies in turn that our weekly index provides a very adequate picture of real economic activity, even though it only has nine indicators. Given the subsample stability of our results, the WEA is useful during recessions and also for nowcasting in tranquil economic times.[39]

## 5. Conclusion

We developed a coincident business cycle indicator based on nine weekly time series, which we carefully adjusted for seasonal patterns, calendar effects, outliers,

37 For brevity and simplicity, we do not compare a vast amount of different modeling approaches. As an extension for future work, one could study the performance of mixed-data sampling (MIDAS) models, following Ghysels et al. (2006), with weekly data (see Galvão (2013) for an application to weekly data) as a direct forecasting approach and compare the results to simple bridge equations.

38 Again, we assessed the robustness of these results using the fixed-*b* test of Coroneo and Iacone (2020). The findings are qualitatively robust and available upon request from the authors.

39 It should be kept in mind that the information from weekly indicators is suitable mainly for nowcasting and short-term forecasting, but not for longer horizons (more than two quarters). It follows that the WEA index is only conditionally suitable for creating an annual forecast: at the beginning of the year, the contribution to predictive accuracy is small, but it increases steadily over the course of the year.

**Table 5**
Forecasting performance of WEA index versus monthly indicators.

| Horizon | Full sample | | | | | 2009 Q2 – 2019 Q4 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 7 | 13 | 19 | 25 | 1 | 7 | 13 | 19 | 25 |
| MEAN adj. | 0.59*** | 0.59** | 0.70* | 0.94** | 0.99*** | 0.83*** | 0.75 | 0.90 | 0.94 | 1.02 |
| *MEAN WEA adjusted* – Benchmark: AR(1)-model | | | | | | | | | | |
| AR-BRIDGE | 0.69** | 0.72* | 0.77* | 0.83 | 0.89 | 0.76* | 0.69 | 0.79 | 0.85 | 1.01 |
| BRIDGE | 0.59** | 0.61* | 0.75 | 0.94 | 1.00 | 0.82* | 0.75 | 0.90 | 1.03 | 1.14 |
| *Monthly indictors* – Benchmark: AR(1)-model | | | | | | | | | | |
| KOF AR-BRI. | 0.74** | 0.84* | 0.93** | 0.94* | 0.94 | 0.82* | 0.76 | 0.75 | 0.70 | 0.68 |
| SEC AR-BRI. | 0.69** | 0.74* | 0.85 | 0.83 | 0.84 | 0.80* | 0.71 | 0.69 | 0.62 | 0.61 |
| SEC BRI. | 0.74** | 0.63* | 0.77 | 0.73 | 0.74 | 0.84 | 0.65 | 0.64 | 0.43 | 0.46 |
| *Monthly indicators* – Benchmark: MEAN WEA adjusted | | | | | | | | | | |
| KOF AR-BRI. | 1.25** | 1.42* | 1.33 | 1.00 | 0.95 | 0.99 | 1.01 | 0.83 | 0.74 | 0.67 |
| KOF BRI. | 1.66*** | 1.42* | 1.33 | 0.93 | 0.86 | 1.28 | 1.13 | 0.89 | 0.62 | 0.52 |
| SEC AR-BRI. | 1.17 | 1.25 | 1.21 | 0.88 | 0.85 | 0.96 | 0.95 | 0.77 | 0.66 | 0.60 |
| SEC BRI. | 1.25* | 1.07 | 1.10 | 0.78 | 0.75 | 1.01 | 0.87 | 0.71 | 0.46 | 0.45 |

RMSE relative to the respective benchmark models. Forecasting horizon in weeks.
Modified Diebold–Mariano test: the alternative hypothesis states that the tested method is more accurate than the benchmark.
Significance level: *p-value*: *** < 0.01, ** < 0.05, * < 0.1.

and the surplus week. The resulting weekly economic activity (WEA) index has a high correlation with GDP and accurately captures movements in the Swiss business cycle since 2005.

A real-time evaluation highlighted the superior informational content of the index relative to commonly used monthly indicators for nowcasting GDP growth. Our results demonstrate, however, that the use of weekly data necessitates a careful pre-treatment procedure of the raw data. We conclude that weekly data can comprise an appealing complement to traditionally used monthly indicators.

Our results should not be viewed as specific to the Swiss economy solely. We demonstrated that appropriate adjustments to the weekly data are essential. This finding supports the construction and refinement of similar weekly indices for other countries.

## CRediT authorship contribution statement

**Philipp Wegmüller:** Developed the idea, Conducted data analysis, Interpreted the results, Major contributors in writing the manuscript. **Christian Glocker:** Developed the idea, Conducted data analysis, Interpreted the results, Major contributors in writing the manuscript. **Valentino Guggia:** Developed the idea, Conducted data analysis, Interpreted the results, Major contributors in writing the manuscript.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Availability of data and materials

The weekly economic index is published regularly on www.seco.admin.ch/wwa.

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## Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2021.10.010.

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