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Weekly economic activity: Measurement and informational content[*]

Philipp Wegmüller[**] Christian Glocker[***] Valentino Guggia[§]

Abstract

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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 provides sufficient information for macroeconomic forecasting, surveillance and policy making. However, in times of economic distress, timeliness of economic data becomes a valuable asset for policy makers. In the wake of the COVID-19 pandemic, abrupt decisions with far-reaching social and economic consequences have been made across the globe. In the following, both private and public actors expressed an immediate need for information on the stance of the economy, which caused an unprecedented surge for 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 contains considerable noise. This obscures the information contained in the 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, it generally exhibits substantial volatility, features more outliers and breaks. They therefor recommend the use of annual growth rates. Nevertheless, they stress the need for further adjustment steps as weekly data might contain various idiosyncrasies. This paper investigates how an appropriate adjustment of the input data helps to improve the performance of a weekly coincident indicator.

To shed light on this issue, we develop a weekly economic activity (short: WEA) index for Switzerland. The country is well suited for a such study: first, a large number of data-series are available on a weekly frequency; second, the majority of these series are regularly and timely updated; 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 a unique coverage of real economic activity. Many other countries lack at least one of these features.

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. For this purpose, we particularly focus on an adequate adjustment of our input variables prior to estimating the common factor. We clean the data for seasonal patters, calendar and holiday effects. Moreover, we remove outliers and impose periodicity by addressing the problem of the surplus week. We evaluate the now- and forecasting performance of our proposed index with adjusted input variables in an ex-post out-of-sample exercise starting in 2007. We compare its predictive power relative to both a weekly index without adjusted inputs as well as relative to established monthly business cycle indicators.

Our final index is based on nine carefully selected weekly data series. The input data covers the economy along distinct dimensions: private household consumption, production activity, labor market, domestic and international trade. The WEA index shows an high correlation with GDP and captures the different phases of the Swiss business cycle well. Importantly, in spring 2020, the index quickly provided an accurate signal for the fall in economic activity due to the imposed containment measures to slowdown the spread of Coronavirus. The WEA index is robust to many specification changes including the estimation method and the inclusion and/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 contains relevant information for nowcasting and forecasting GDP growth. *Second*, our evidence strongly suggests that carefully accounting for calendar and seasonal effects and removing outliers is crucial to derive a precise business cycle signal. *Third*, weekly data is superior to monthly, especially for nowcasting. The WEA index significantly outperforms established monthly indices for the Swiss economy. *Fourth*, the index itself contains sufficient informational content for predicting GDP growth. The index covers economic activity well and need not necessarily be accompanied by a more sophisticated econometric model like a Bridge-equation for forecasting. *Fifth* the WEA index not only serves as a tool in times of crisis. It has proven to deliver useful signals and accurate predictions also in calm times.

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 Fenz and Stix, 2021, Eraslan and Goetz, 2020, Rua and Lourenço, 2020, among others]. Most prominently, Lewis et al. [2020] established early on in 2020 a weekly economic index (WEI) for the US. Following the recommendations of Proietti et al. [2018], they derive the 52-week log-differences of their input variables. Yet, they neglect the facts that some years have 53 weeks and that holidays like Easter or Christmas are moving from year to year. Contrary to them and other related work, we specifically clean the data for such kind of 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 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] mix frequencies to derive a long time series by including monthly and quarterly data. Our index instead is purely based on daily or weekly information. This has the advantage that it is less prone to revisions (for instance from GDP). Further, we do not aim at constructing a weekly GDP, rather, the objective is to provide a weekly coincident index for the Swiss economy. Burri and Kaufmann [2020] calculate an index based on financial markets data and news paper articles. We omit such data as we find it to be of lesser importance to derive a measurement for real economic activity.

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] report evidence that higher frequency information does not contribute to the nowcasting accuracy of GDP growth. In recent work, Aastveit et al. [2020], Fenz and Stix [2021], Lewis et al. [2020], Monteforte and Raponi [2019] highlight the strong predictive power of high frequency information for providing an accurate nowcast of GDP growth. Our findings add to this discussion by highlighting how an appropriate data adjustment can increment substantially 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 the data adjustment and highlight the consequence of each transformation step on the characteristics of the data series. In a second step, we outline the methodological approach 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 or industrial production. These data come with its challenges as any other economic indicator: For instance, some series are only available once per month, although collected on a daily basis (e.g., air freight). Apart, 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., flows of government finances). On the positive side, high-frequency data is often less prone to revisions as typical monthly and quarterly indicators, since it is 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 16 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 is equally useful for calculating the weekly business cycle index. Thus, we first selected a subset of adequate indicators based on a few simple criteria: (*i*) We dropped series which are not published timely, i.e., the data should be available at most one week after the reference period; (*ii*) the series should span over at least four years in order to properly address issues regarding seasonality and calendar effects; (*iii*) the indicator should be characterized by some degree of persistence and not be too volatile; (*iv*) the data – once aggregated to a quarterly frequency – should be correlated significantly with GDP or components thereof.[2]

Given these few criteria, we dropped several variables such as 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 from our initial list of 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 its high volatility – is a series that generally performs 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. Data on insolvency instead are traditionally a lagging indicator. Moreover, in Spring 2020 the filing for insolvency by public authorities (tax offices, etc.) had temporarily been suspended, making the series less suitable. What concerns financial variables, their inclusion might spur the picture as the development in interest rates and stock markets can be heavily influenced by monetary policy and expectations of financial actors. Other indicators measuring particular aspects of economic activity may be too short or sector specific. While that may be of separate interest, we find that including some of these variables results in an overly pessimistic assessment of the business cycle stance as they would attach too much weight to the service sector relative to the one implied by National Account data.

Our final data set comprises nine input series listed and described in Table 1. While the

[1] The full set of indicators is provided in Table 6.

[2] We have also tested a more elaborate approach such as used in [Camacho and Perez-Quiros, 2010, Glocker and Wegmüller, 2020], however, while more time and resource intensive, we ended up with the same final set of data.

number of series used is comparably small, the data captures real economic activity across various dimensions and is readily available. In fact, every indicator is obtained with a delay of not more than five days after the end of the corresponding week. Four indicators start before 2010, 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 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 both an indicator for foreign demand and industrial production, imports in turn are a measure for domestic demand. For (goods) imports, the data covers 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 production activity of the manufacturing sector. *Fourth*, registered unemployment indicates the stance of the labor market. *Fifth*, we use weekly data on sight deposits 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 is its adequate adjustment. Weekly data pose special problems because – contrary to annual, quarterly or 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

[3] We observe presence transactions only. Data on E-commerce are highly volatile which results in worse model outcomes, and its correlation with the monthly data from SNB is low.

[4] The Federal Customs Administration disposes of weekly data for exports since 2002. However, we have been told that these data are not usable until 2013 because of their poor quality. Prior to 2013, for exports the dispatch date 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 shows thus 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 is 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[f]
Net tonne kilometres	SFR	2001 Jan, daily	Unit of measurement for rail freight transport[g]
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 available (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] See *e*.

[g] A net tonne-kilometre (ntkm) corresponds to the transportation of one net tonne of freight over a distance of one kilometre.

transactions rise at the end of the year for Christmas shopping; 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 incoming of a new passenger plane, while in the following week no plane passes the customs.

Therefore, Proietti et al. [2018] recommends to properly clean 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, hence no adjustment is made.[6]

1. **Surplus week adjustment.** According to international standard ISO 8601, most years have 52 weeks. However, the yearly surplus day and leap years imply that every 5 to 6 years there is a year with 53 weeks, for example, the years 2004, 2009, 2015, 2020. Since there are no "half" weeks, some days in their 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 53^{rd} 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 53^{rd} calendar week, if present, is to render feasible the calculation of growth rates with respect to the same week of the previous year.

2. **Calendar day and holiday adjustment.** The problem of adjusting data for calendar effects due to changing month length (surplus day), day-of-the-week effects, and public holidays is well established in the context of monthly or 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]

[5] See also Harvey et al. [1997a], Cleveland and Scott [2007].

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

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

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

Besides correcting for the amount 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 either corresponds to the 52^{nd}, 53^{rd} or 1^{st} week depending on the year. Moreover, if the week with Christmas Eve has many business days before the festivities, economic activity will be high, whereas it is low if Christmas Eve is early in the week. We check separately for these end-of-year effects using dummy variables. We use a parametric Reg-Arima Model to perform the calendar day and holiday adjustments.[9] Where necessary, we also correct the data for temperature effects by including additional regressors: for instance, average concentration of nitrogen dioxide (NO_2) is higher when temperatures are low.

3. **Seasonal adjustment.** 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 Hillmer and Tiao [1982], Koopman et al. [2007], Ollech [2018].[10]

4. **Excessive volatility adjustment.** 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 series, i.e., the rate of growth of an indicator for a given week to the same week in the previous year. By doing so, any remaining part of seasonal elements in the data not captured previously should be eliminated.

[9] We follow the lines of TRAMO-SEATS proposed by Gomez and Maravall [2001]. More details can be found in 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 AIC information criteria.

[10] For series with a low number of observations such as cash withdrawals we estimate seasonal factors only up until Mid-March. We thus avoid that the first shutdown during the COVID-19 has an effect on the seasonal factors and hence influences 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.

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]

We now present graphical evidence on how the data adjustment improves the business cycle signals of the indicators. Figure 1 illustrates the 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 subfigures in the right column show the year-over-year growth rate of both the raw series and the final adjusted series as they enter the model (*adjusted*). For imports, for instance, the effect of calendar days around the 53^{rd} calendar week (2015 and 2020) is clearly visible and underscores the importance of proper adjustment.

2.3 Econometric methodology

Next, we describe the details of the econometric approach taken to establish the index of weekly economic activity. 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 called latent factors, denoted by f_t, which capture the co-movements among the observed variables in X_t, and an idiosyncratic component, $u_{t,i}$, $\forall\, i = 1, ..., n$. The idiosyncratic disturbances arise from measurement

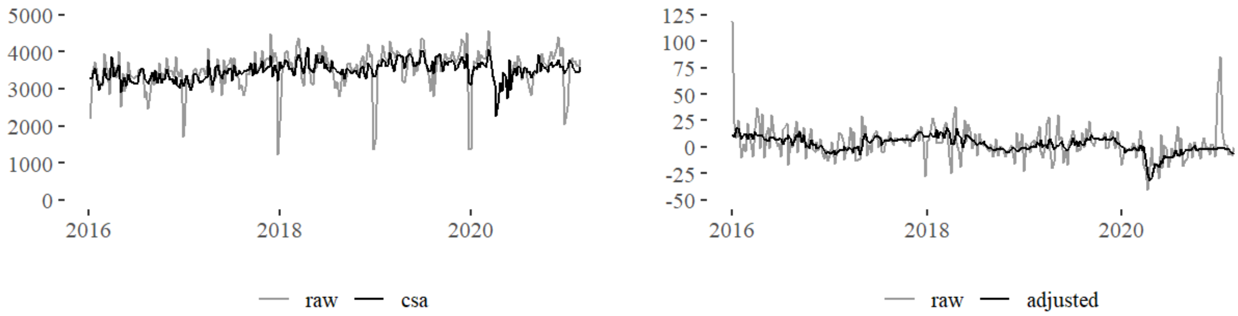
[12] For instance, in any given week Switzerland exports a shipment of an expensive cancer treatment, rising exports by several 100 Mio. CHF. In the next week, however, no such shipment happens. This leads to sudden jumps in the growth rates which are observed twice, once in the week of the shipment 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 then classified as an outlier if lies far enough from the median. Outliers are replaced by the median value of the specified window.

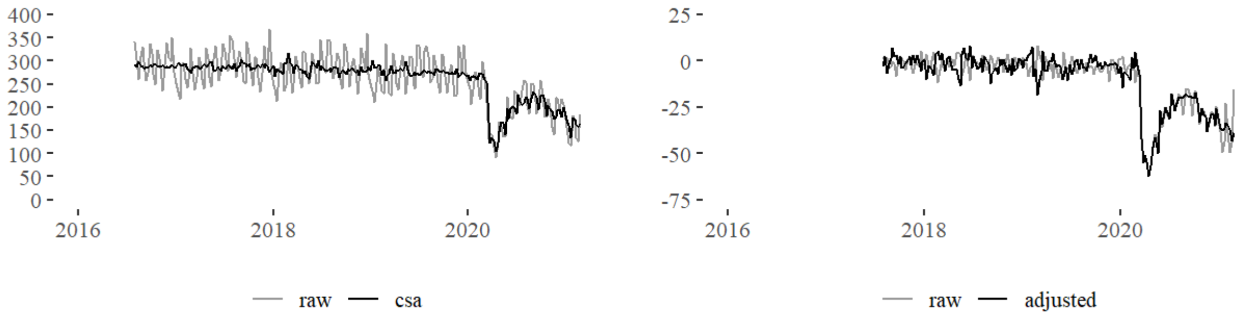
[14] See also Chernis and Sekkel [2017], Camacho and Perez-Quiros [2010], Camacho and Perez Quiros [2011], Camacho et al. [2015], Rusnák [2016] for applications of such linear models to countries as for instance Argentina, Canada, Czech Republic, Spain, Switzerland with monthly and quarterly data.

Figure 1: Data adjustment
Left column: level; right column: growth rates

(a) Goods imports



(b) Cash withdrawals



(c) Registered unemployed persons

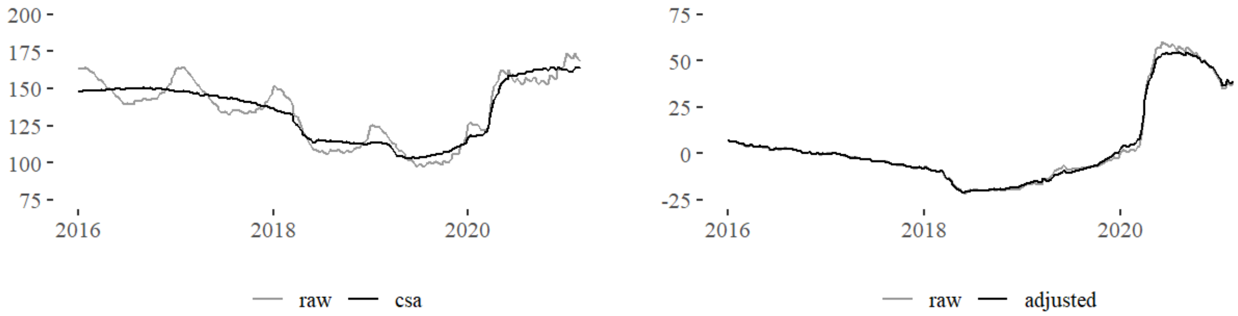


Table 2: Overview of the adjustments

(a) Seasonal and calendar adjustment

	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 kilometres	Level	(0,1,2) $(1,1,0)_{52}$	bd
Sight deposits	-	-	-
Registered unemployment	Log	(0,1,1) $(0,1,1)_{52}$	bd

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.

(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

errors and features specific to an individual series. The latent factors follow a stochastic process. In what follows 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 described in Table 1. All individual series in X_t are given by year-on-year growth rates and are standardized. The

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

DFM is specified $\forall\, t = 1, ..., T$ by the following system of equations:

$$\begin{aligned} X_t &= \gamma \cdot f_t + \boldsymbol{u}_t, & (2.1)\\ (1-\phi_f(L)) \cdot f_t &= \nu_t^f, & (2.2)\\ (1-\phi_{u,i}(L)) \cdot u_{t,i} &= \nu_{t,i} \quad \forall\, i = 1, ..., n & (2.3)\\ \begin{pmatrix} \nu_t^f \\ \boldsymbol{\nu}_t \end{pmatrix} &\sim NID\left(\mathbf{0}, \begin{bmatrix} \sigma_f^2 & \mathbf{0} \\ \mathbf{0} & \Sigma_\nu \end{bmatrix}\right). & (2.4) \end{aligned}$$

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

Equations (2.2) and (2.3) are the transition equations, where $\boldsymbol{\nu}_t = (\nu_{t,1}, ..., \nu_{t,n})'$. $\phi_f(L)$ and $\phi_{u,i}(L)$ are lag-polynomials. 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 — γ, $\phi_f(L)$, $\phi_{u,i}(L)$ and Σ_ν, respectively — are necessary to complete the model. We assume that Σ_ν is diagonal, implying that all co-variances are zero by construction. For identification reasons we impose that σ_f^2 is unity.

The two primary methods for estimating the model, i.e., equations (2.1)–(2.4) and hence the common factor f_t are by principal components and state space methods, where within the latter, the common factor (and the model's parameters γ, $\phi_f(L)$, $\phi_{u,i}(L)$ and Σ_ν) is estimated by running the Kalman filter [Durbin and Koopman, 2002]. We adopt the state space approach 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).[16]

We start the estimation in the first week of 2005. In our preferred specification, equation (2.2) has an AR(3) structure and the idiosyncratic components (equation (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.

3 Measurement

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

[16] We have 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.

3.1 The 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 factor f_t. As the common factor is not anchored to any measure of economic activity, its values are not directly interpretable. To convert the common factor into meaningful units, we follow Lewis et al. [2020] and re-scale f_t to the quarterly year-on-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, seasonally, calendar and sport event adjusted GDP growth during the period, compared with the same period in the previous year.[17] We chose GDP growth as anchor and target because of its particular interest for macroeconomic policy makers. The choice of quarterly year-on-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,

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

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

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

The resulting weekly economic activity index starting in 2005 is displayed in Figure 2. The WEA 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 the GDP growth rate 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.[18]

3.2 Properties of the latent factor

We now turn to discuss the properties of the common factor 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 equation (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 (γ) associated with the common factor f_t on the weekly series. The table provides an overview of the estimated factor loadings

[17] Quarterly GDP for Switzerland starts in 1980 and is published on `https://www.seco.admin.ch/gdp`.
[18] See for instance Glocker and Kaniovski [2019].

Figure 2: Swiss weekly economic activity (WEA) index

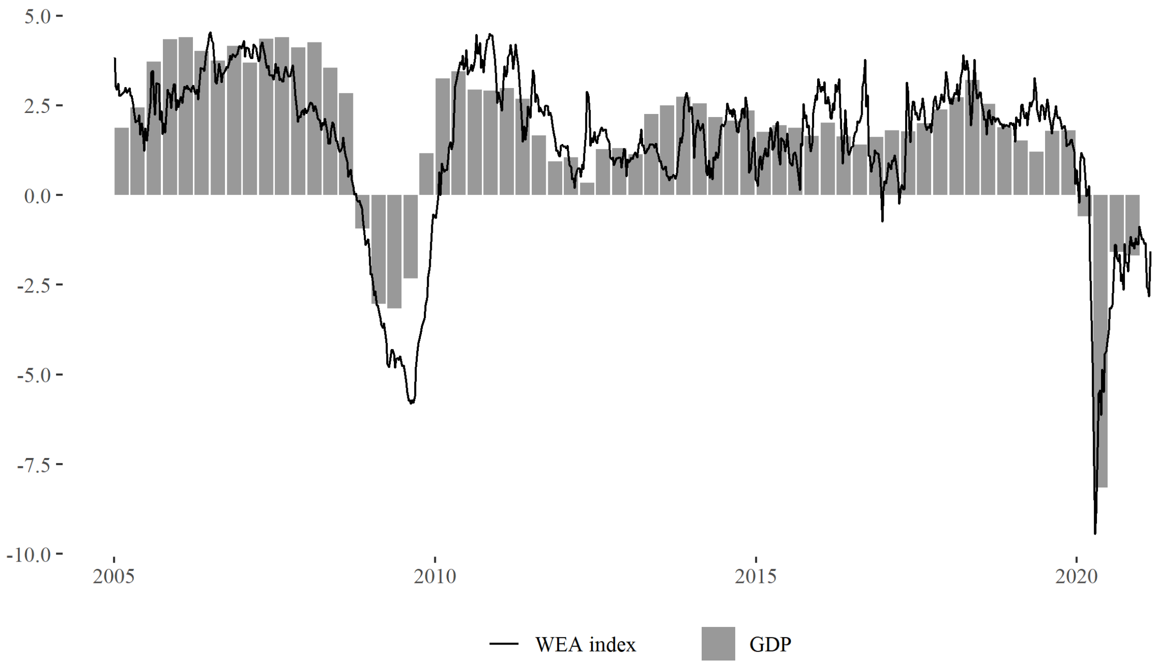


Table 3: Factor loadings of different models

Indicator	Base	Hard data	Financial data
Air pollution	0.21	0.37	0.36
Card transactions	0.21	0.02	0.01
Cash withdrawal	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-kilometer	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	-
Trucks traffic	-	-0.00	-
Term spread	-	-	-0.01
Volatility SMI	-	-	0.04
Contemp. Correlation	0.89	0.80	0.83

across different series comprised 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 factor f_t. These two variables are counter-cyclical: an increase in sight deposits held by the national bank generally imply heightened appreciation pressures of the Swiss Franc, which usually happens at times of financial distress or high economic uncertainty.[19] As regards, unemployment, the negative sign essentially confirms the role 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.

While the sign of the factor loadings is important, the same applies to their size. Since all variables used in the model enter in standardized form, the factor loadings allow for a direct assessment of a variable's contribution to the common factor f_t. As can be seen, imports, exports and net tonne-kilometers have the largest factor loadings (in absolute terms) highlighting their dominant role. Since these three variables capture the underlying dynamics of the manufacturing sector, the model hence confirms the dominant role of the manufacturing sector for shaping the aggregate fluctuations of the Swiss economy.

3.2.1 Augmenting the set of variables

Next, we discuss the robustness of our preferred specification to changes in the variable composition in X_t. 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 factor'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 factor's correlation with the y-o-y growth rate of GDP as another aspect within the model/variable selection process.[20]

The second column of Table 3 therefor provides the factor loadings for an extended model in which we add further hard 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 though 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 wrong sign. The extension of our preferred specification with additional hard data also leads to heightened

[19] See for instance Jordan [2016] for a description on recent monetary policy adjustments by the Swiss National Bank.

[20] We calculate the correlation using quarterly data for the common factor (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 within 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 latent factor's quality to timely track economic activity.

volatility in the factor 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 step. Yet, financial data might also contain relevant business cycle information.[21] 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.[22] The loadings of both variables are negligibly small and of 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.

Summarized, in the context of weekly data it is not necessarily the case that more data is always better. 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 factor of our preferred specification to variations in the model set-up. We consider two extensions in this context involving different specifications of the transition equation (2.2) in each case.[23]

Our baseline model uses an AR(3) specification for the transition equation (2.2). While an auto-regressive specification is common in this context [compare Camacho and Perez-Quiros, 2010, Carriero et al., 2020, among others], there are though 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 equation (2.2).[24]

Our baseline specification can be changed to a multivariate local-level set-up when changing equation (2.2) to a random walk: $f_t = f_{t-1} + v_t^f$. 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 equation (2.2) as further alternatives. In both cases, the path of the common factor is similar to that of the baseline specification, yet

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

[22] We also tested the model's robustness with stock indices SMI and SPI as well as with the nominal CHF/EUR-exchange rate. Here we only report the best model with financial data. Further results are available upon request.

[23] We have run 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 equation (2.3) reduces the volatility of the latent factor. Typically, the idiosyncratic terms follow an AR(2) process. In our case, this renders the factor unstable and leads to implausible results.

[24] 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.

we prefer the model with three lags as the coefficients for the first three lags are statistically significantly different from zero, while in-significant from the fourth lag onward.

Finally, we assess the size of revisions to the index. Overall, they are very limited. A comparison of the published first indicator release with the last available vintage reveals only very small quantitative changes in the path of the WEA index.[25] The real-time publication of the WEA index already provides a good estimate of the prevailing economic situation. The results underscore the stability of our model within an excessively volatile economic episode. This contrasts the findings of Eckert et al. [2020] and shows the usefulness of a purely weekly data set.

3.3 Contribution of the variables to the WEA index

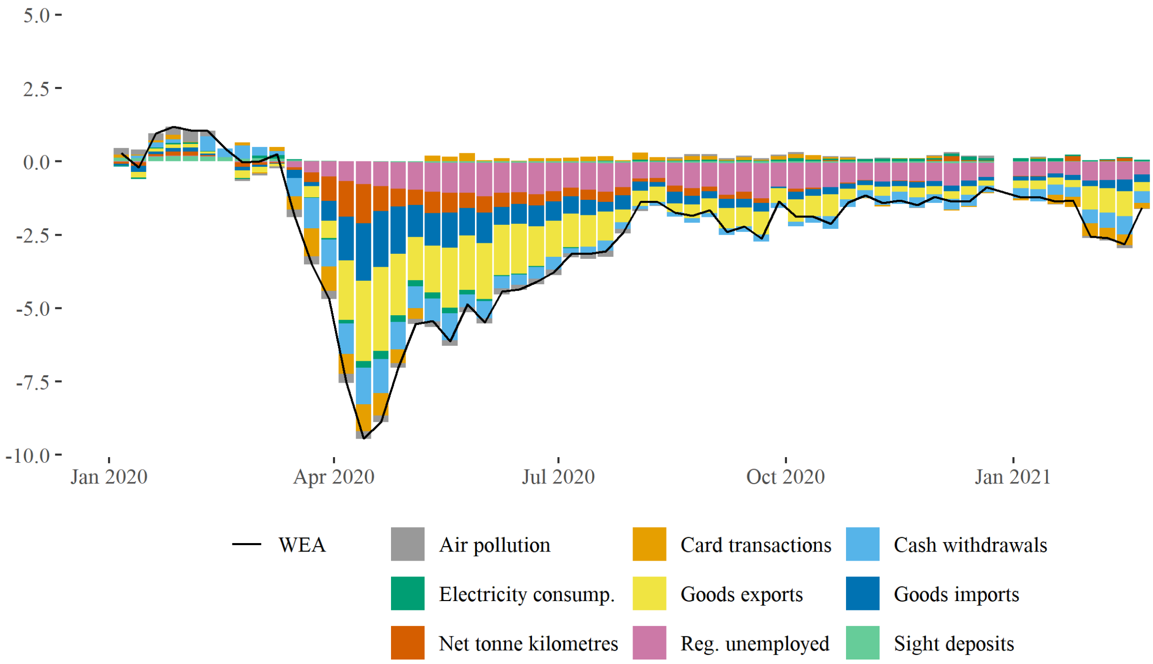
An important aspect in the context of business cycle surveillance concerns the identification of sector-specific developments in shaping aggregate fluctuations. Since our set-up involves variables that proxy for the developments arising from different sectors, we can use the WEA index to assess the extent to which different sectors and/or markets shape the overall dynamics. We do so by considering the contribution of each variable in the vector X_t of the observation equation (2.1) for the path of the WEA index. To this purpose, we use equation (2.1) and consider the change in the WEA index relative to the change in the variables in X_t. Considering equation (2.1), while the marginal contribution of variable $x_{i,t} \in X_t$ to the factor f_t is given by $\Delta f_t / \Delta x_{i,t} = \gamma_i$, the contribution of variable $x_{i,t}$ for the change in the factor can then be computed by $\Delta f_t = \gamma_i \Delta x_{i,t}$, i.e., we assess the change in the common factor f_t that arises from a change in some variable $x_{i,t}$ [Rosen and Saunders, 2010]. We do so for each of the nine variables in X_t. Once having identified the contribution of a particular variable to the common factor f_t, we then use equation (3.2) the assess its contribution for the WEA index. The results of this exercise are depicted in Figure 3.

We show the temporal trajectory of the contributions only for the year 2020. The graph gives an 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. The decline in exports reflects the contraction in international demand. Due to the high import content of exports, this is also reflected in imports. Moreover, trade in goods was impaired by the abrupt interruption of global value chains.[26] 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 shutdown was put in place by March 16, 2020. Ac-

[25]See 4 in the Appendix.

[26]See Büchel et al. [2020] for a description of the COVID-19 related Swiss trade collapse.

Figure 3: Contribution of the variables to the weekly index



cordingly, both variables show a strong negative contribution to the WEA index. In contrast to the indicators for foreign trade and consumption, those 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.

The figure also identifies the variables that shaped the economic recovery once the containment measures were lifted step by step from mid-May onward. The rapid rebound in international demand led to a swift disappearance of the negative contributions of exports to the WEA index. Besides, the opening of the retail sector boosted consumption activities, mirrored by a swiftly declining negative contribution of card transactions. The contribution of cash withdrawal remains negative throughout 2020, as people shifted their preferences towards card payments.

The indicator for unemployment has a somewhat contrary trend as shown in Figure 3. While unemployment had only a small negative contribution to the WEA index in the phases of the most pronounced containment measures, the negative contributions increased in the wake of the economic recovery. The reason for this delayed course could be the extensive public support measures in the form of, for example, short-time work policies, which stretched the overall adjustment in the labor market.

4 Assessing the informational content of the WEA index

In this section we illustrate the usefulness of weekly data – in our case in form of the WEA index – for predicting GDP growth. In a first step, we asses 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 revised ex post. What concerns 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 corresponding week is released with a time lag of one week. GDP is published with a delay of 60 days, i.e., 26 weeks. The assessment considers therefor the prediction of current quarter GDP (*"Nowcast"*) for horizons 1 to 13 weeks and of the following quarter (*"Forecast"*), corresponding to weeks 14 to 25. Our estimation sample spans from 2007:W1 to 2020:W52, which amounts to 683 weeks, or 52 quarters. We define the period between the financial crisis of 2008 and the beginning of the coronavirus recession of 2020 as subsample without economic recession in Switzerland. In particular, following the recession dating of the ECRI-Institute[27], the subsample spans from 2009:M5 to 2019:M11. 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.[28] Forecast errors are calculated relative to the final GDP vintage.[29]

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

[28]Our results are qualitatively robust to other benchmarks such as random walk or an AR(p)-model with lags determined by by the BIC. Results are reported separately in the Appendix (See Tables 7 and 9).

[29]The results are qualitatively robust to calculating forecast errors relative to the first release of GDP (see Tables 8 and 10 in the Appendix).

4.2 The role of data adjustment

The adjustment of weekly data prior to estimating a weekly composite index comprises 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. [2020]. We refer to these two weekly activity measures as *adjusted* and *unadjusted* WEA indices.[30] In a first step, we do not specify any econometric structure to derive the forecasts. Rather, we test for the following direct relationship:

$$y_{t_q} = WEA_{i,t}, \tag{4.1}$$

in which y_{t_q} is our target variable GDP growth, and i either stands for *Mean* or *Last*. The former corresponds to the average WEA index of the published weeks corresponding to the quarter to predict (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 either extend 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 relative RMSE together with significance levels from modified Diebold-Mariano tests,[31] where we test the hypothesis whether the adjusted WEA index outperforms the unadjusted index.

Table 4: Forecasting performance of WEA index

	Full sample					2009 Q2 - 2019 Q4				
Horizon	1	7	13	19	25	1	7	13	19	25
adjusted										
MEAN	0.59***	0.59**	0.70*	0.94**	0.99***	0.83***	0.75	0.90	0.94	1.02
LAST	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 model AR(1). 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 level: *p-value*: *** < 0.01, ** < 0.05, * < 0.1.

Several results emerge. First, both adjusted WEA indices exhibit at any horizon a lower RMSE relative to the benchmark. Second, the unadjusted indices also exhibit a better per-

[30] Figure 5 in the Appendix illustrates the difference over time in the two series.

[31] 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].

formance, but only for a short horizon. Third, the forecasting accuracy improves with a decreasing horizon in all cases. For instance, with only 7 weeks left (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 performs significantly better than its unadjusted counterpart. This applies across any horizon considered (1 week to 25 weeks). We interpret this result as 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, results are not significant anymore for the forecasting period.

4.3 Is weekly information superior to monthly?

As we have shown in the previous section, the WEA index with adjusted inputs contains valuable information for now- and forecasting. We now challenge its performance against two established monthly business cycle indicators for the Swiss economy:[32] (i) KOF Economic Barometer,[33] and (ii) the SECO-SEC indicator.[34] We assign to each indicator a typical release or availability week based on its usual publication schedule. Specifically, we 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 yet no new information from the monthly indicators, though 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 model. 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, α and potentially an autoregressive term, γy_{t_q-1}. The lag polynomial is given by $\beta\left(L\right) = \sum_{i=0}^{p} \beta_{i+1} L^i$, with $L x_{t_q} = x_{t_q-1}$. The predictor x_{t_q} is the monthly or weekly indicator $x_{t_{m,w}}$ aggregated to the quarterly frequency via the function $x_{t_q} = \sum_{j=0}^{r} \omega_j L^{j/3,13} x_{t_{m,w}}$. This is an indirect forecasting procedure as it involves two steps: (1) forecasting the monthly or weekly

[32] 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.

[33] 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 sub-set is used which, though changes over time Graff et al. [2014].

[34] This indicator (Swiss economic confidence indicator) is provided by SECO and comprises thirty survey indicators for the Swiss economy. See `https://www.seco.admin.ch/kss` for the data.

indicator; (2) time aggregation to obtain the quarterly prediction.[35]

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 estimate Bridge equations also for the WEA. This allows not only for a fair assessment across the monthly and weekly indicators, it also renders the possibility to test whether additional econometric structure on top of the weekly index improves its nowcasting performance further. We use the real-time vintages for GDP growth.

Table 5: Forecasting performance of WEA index versus monthly indicators

	Full sample					2009 Q2 - 2019 Q4				
Horizon	1	7	13	19	25	1	7	13	19	25
WEA adjusted										
MEAN	0.59**	0.59*	0.70	0.94*	0.99	0.83*	0.75	0.90	0.94	1.02
LAST	0.68**	0.62*	0.66	0.89*	0.98	0.88	0.78	0.85	0.91	1.03
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 data										
KOF AR-BRI.	**0.74****	**0.84***	0.93**	0.94*	0.94	0.82*	0.76	0.75	0.70	0.68
KOF BRI.	**0.98**	**0.84**	0.93	0.87	0.85	1.06	0.85	0.80	0.58	0.53
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

RMSE relative to the benchmark model AR(1). 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.
Test for monthly data: WEA MEAN (adj.) is more accurate than the model. Figures in boldface indicate significance at least at the 10% level.

We report evidence of this exercise in Table 5. Again, the RMSE for different forecasting horizons in weeks is relative to the AR(1) benchmark model. Significance levels are based on the modified Diebold-Mariano test with the null-hypothesis that the tested model outperforms the benchmark. 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. (ii) Regarding the forecasting period (13 weeks and more horizon), the monthly indicators perform somewhat better than the predictions with the WEA index. The statistical support for this is, however, limited. (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

[35] 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.

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 exhibits similarly low RRMSE as its monthly counterpart, though its performance is not significantly better. What concerns the forecasting period (horizon of 13 and more weeks), the monthly data even outperforms our weekly index.

To summarize, we find clear evidence that weekly data can have superior informational content for GDP now- 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, albeit only composed by nine indicators. Given the subsample stability of our results, the WEA proves not only a useful tool during recessions, but also serves for nowcasting in calm economic times.

5 Conclusion

The COVID-19 pandemic has boosted the need for quickly available tools to assess the current stance of the business cycle. While in calm times monthly or even quarterly data is sufficient for analysts and policy makers, the speed and severity of the current crisis requires tools at an higher frequency.

We have developed a coincident business cycle indicator based on nine weekly time series, which we carefully adjust for seasonal patterns, calendar effects, outliers, and the surplus week. The resulting high-frequency index has a high correlation with GDP and accurately captures movements in the Swiss business cycle since 2005.

Its early availability compared to other business cycle indicators makes it a great tool for macroeconomic surveillance, not only in crisis times. A real-time evaluation highlights the superior informational content of the index relative to commonly used monthly indicators for nowcasting GDP growth.

Our results should not only be regarded as particular to the case of the Swiss economy. We show that an appropriate adjustment of weekly data is essential to obtain good predictions of GDP growth. This finding supports the construction and refinement of similar weekly indices in other countries.

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A Additional Tables

Table 6: Other weekly indicators tested for WEA index

Series	Source	Start and frequency
Financial markets data		
Nominal exchange rate CHF-EUR	Macrobond Financials AB	2000 Jan, daily
Term spread	Macrobond Financials AB	2000 Jan, daily
Volatility SMI	Macrobond Financials AB	2000 Jan, daily
Hard data		
Bankrupcies	SOGC	2002 Jan, daily
Constuction permits	Wüest Partner	2008 Jan, daily
Energy production	Swissgrid, ENTSOE	2009 Jan, daily
Federal tax flows	FTA	2016 Jan, daily
Flight passengers	Airport Zurich, FOCA	1998 Jan, weekly
Mailed letters	Swiss Post	2019 Jan, weekly
Parcels shipment	Swiss Post	2019 Jan, weekly
Retail sales paid by debit card	SIX	2016 Aug, daily
Truck traffic	FEDRO	2005 Jan, weekly
Value Added Tax	FTA	2019 Jan, weekly

Abbreviations FOCA: Federal Office of Civil Aviation; FEDRO: Federal Roads Office; SOGC: Swiss Official Gazzette of Commerce
Note Construction permits are available since 2000 but we were warned from the source about their poor quality until 2008.

Table 7: Forecasting performance of WEA index w.r.t. another benchmark model

	Full sample				
Horizon	1	7	13	19	25
adjusted					
WEA LAST	0.492*	0.541**	0.729**	0.996**	1.093***
WEA MEAN	0.429***	0.516**	0.774*	1.047**	1.100***
unadjusted					
WEA LAST	0.597	0.793	1.087	1.266	1.362
WEA MEAN	0.600	0.748	1.228	1.296	1.333

RMSE relative to the benchmark model Auto Arima. 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 level: *p-value*: *** < 0.01, ** < 0.05, * < 0.1.

Table 8: Forecasting performance w.r.t. the first release of GDP

	Full sample				
Horizon	1	7	13	19	25
adjusted					
WEA LAST	0.797*	0.665**	0.66***	0.925**	0.999**
WEA MEAN	0.669***	0.605**	0.708*	0.962**	1.006**
unadjusted					
WEA LAST	0.960	0.990	1.072	1.184	1.262
WEA MEAN	0.950	0.919	1.170	1.204	1.236

RMSE relative to the benchmark model AR(1). 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 level: *p-value*: *** < 0.01, ** < 0.05, * < 0.1.

Table 9: Forecasting performance of WEA index versus monthly indicators w.r.t. another benchmark model

	Full sample				
Horizon	1	7	13	19	25
WEA adjusted					
AR-BRIDGE	0.494*	0.629	0.850	0.919	0.987
BRIDGE	0.427*	0.529	0.833	1.049	1.111
LAST	0.492*	0.541	0.729	0.996	1.093
MEAN	0.429*	0.516	0.774	1.047	1.100
monthly data					
KOF AR-BRIDGE	**0.536***	*0.732*	1.031	1.045	1.044
KOF BRIDGE	**0.708**	*0.732*	1.030	0.968**	0.944**
SEC AR-BRIDGE	0.495*	0.643	0.938	0.921	0.940
SEC BRIDGE	*0.536**	0.546	0.850*	0.808	0.823

RMSE relative to the benchmark model Auto Arima. 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.
Test for monthly data: WEA MEAN (adj.) is more accurate than the model.
Significance level: *p-value*: **bold** < 0.05, *italic* < 0.1.

Table 10: Forecasting performance of WEA index versus monthly indicators w.r.t. the first release of GDP

	Full sample				
Horizon	1	7	13	19	25
WEA adjsuted					
AR-BRIDGE	0.697**	0.800*	0.843	0.872	0.917*
BRIDGE	0.668*	0.643	0.804	0.976	1.018
LAST	0.797	0.665	0.660	0.925	0.999
MEAN	0.669*	0.605	0.708	0.962	1.006
monthly data					
KOF AR-BRIDGE	0.689**	0.809	0.925**	0.949	0.953
KOF BRIDGE	**1.045**	0.877	0.993	0.917	0.906
SEC AR-BRIDGE	0.640**	0.737*	0.880*	0.869	0.887
SEC BRIDGE	*0.840**	0.704	0.870*	0.808	0.811

RMSE relative to the benchmark model AR(1). 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.
Test for monthly data: WEA MEAN (adj.) is more accurate than the model.
Significance level: *p-value*: **bold** < 0.05, *italic* < 0.1.

B Additional Figures

Figure 4: Real-time path of the WEA index from 2020

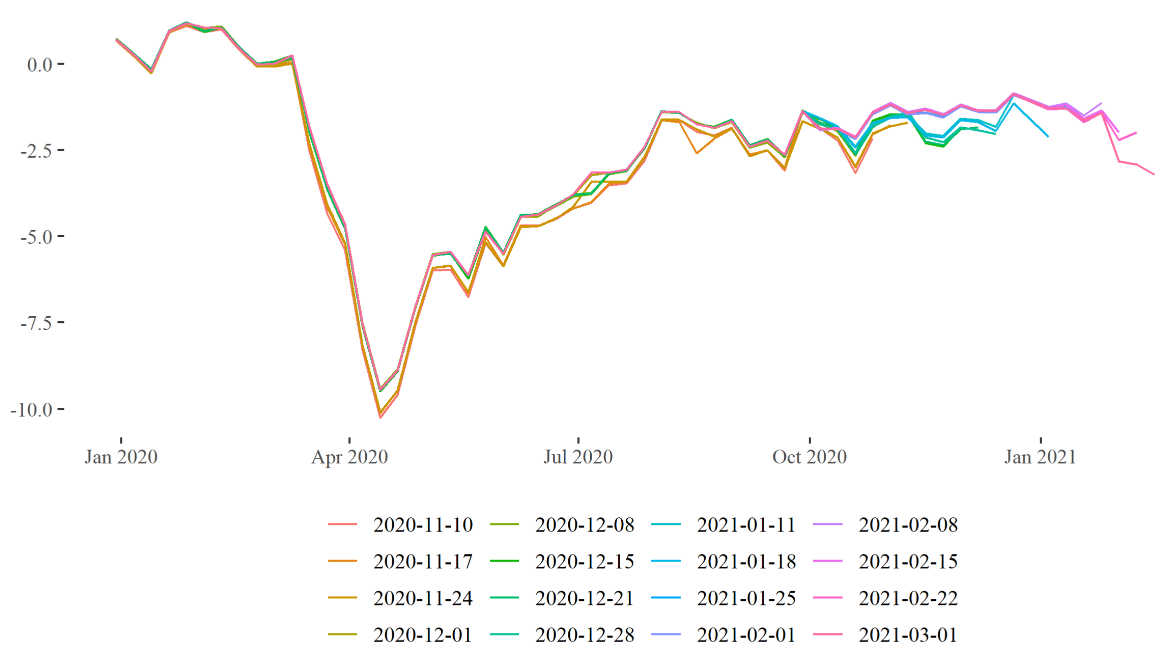

Figure 5: Adjusted and unadjusted WEA