Revisions in Concurrent Seasonal Adjustments of Daily Air Pollution and Weekly Google Searches for Unemployment in Germany

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Abstract
Shortly after the COVID-19 outbreak in Germany in March 2020, the Bundesbank has introduced a weekly activity index for the timely tracking of pandemic-related economic turmoils. Besides monthly industrial production and quarterly GDP, this PCA-based index utilises information from several daily and weekly economic time series whose complex seasonal dynamics are currently being removed with an experimental in-house seasonal adjustment approach based upon the STL method. In May 2023, however, a new version of the official JDemetra+ program has been released that contains several pretreatment and seasonal adjustment methods tailored to the specifics of infra-monthly time series. Therefore, the Bundesbank now plans to migrate the seasonal adjustment of the daily and weekly index components to one of the official methods. To assist the underlying decision-making process, we provide an empirical comparison between the real-time revisions in various concurrent signal estimates obtained with the aforementioned seasonal adjustment methods. Our main findings are that the JDemetra+ methods tend to outperform the experimental in-house method in terms of computational speed and that an extension of the famous ARIMA model-based seasonal adjustment approach generates the smallest and least volatile revisions on average.

Key Words: extended ARIMA model-based approach, extended X-11 approach, real-time analysis, signal extraction, stability analysis, STL approach

1. Motivation

The Bundesbank has launched a new weekly activity index (WAI) shortly after the COVID-19 outbreak in Germany in March 2020 in order to monitor pandemic-related economic disruptions in a timely manner. In essence, this index is the outcome of a principal component analysis that utilises several daily and weekly economic time series as well as monthly industrial production and quarterly GDP as input variables, see Eraslan and Götz (2021) for more details. Most of these input series display a fair amount of seasonality that needs to be removed prior to the WAI calculation. Whereas the monthly and quarterly inputs are routinely seasonally adjusted with the JDemetra+ (JD+) implementation of the famous X-11 method (Shiskin et al.; 1967), the more complex forms of infra-yearly repetitive dynamics present in the daily and weekly inputs are currently being removed with an experimental in-house STL-based method implemented in the {`dsa`} package (Ollech; 2021). In May 2023, however, a new version of JD+ has been released that contains various seasonal adjustment methods tailored to the specifics of infra-monthly data, such as the coexistence of multiple seasonal patterns with potentially fractional periodicities, see Webel (2022) and Webel and Smyk (2024) for detailed descriptions of these methods. In particular, the new JD+ version implements a TRAMO-like linear regression model for data pretreatment as well as extensions of the ARIMA model-based (AMB) and X-11 seasonal adjustment approaches alongside the classic STL method and structural time series models.

Given these recent additions to JD+ and an aspiration for a harmonised production of official seasonally adjusted figures, the Bundesbank now intends migrating the seasonal adjustment of the daily and weekly WAI component series from the experimental in-house

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method to one of the official JD+ methods. The aim of this paper is to assist this migration process by comparing the real-time revision profiles of various signal estimates obtained from concurrent seasonal adjustments with the aforementioned methods and, if possible, by identifying those JD+ methods that generate the lowest and least volatile revisions on average. To the best of our knowledge, such a real-time revision analysis for daily and weekly economic data constitutes an entirely new field of empirical research. So far, revisions in signal estimates have been studied exclusively for monthly and quarterly time series; for example, Dagum (1982a,b), Huot et al. (1986), McKenzie (1984), Pierce and McKenzie (1987) and Wallis (1982) analyse revisions in classic X-11 seasonal adjustments while Maravall (1986), McElroy and Gagnon (2008) and Planas and Depoutot (2002), amongst others, conduct similar research for the classic AMB approach.

We start with a brief data description in Section 2. Afterwards, we introduce some basic notations and revision measures in Section 3. The results of our real-time revision analysis are reported in Section 4, including an assessment of computation times and a visual inspection of the stability of estimated pretreatment effects across data vintages. We conclude with a summary and some final remarks for future research in Section 5.

2. Real-Time Data

We consider two out of the six infra-monthly WAI component series as available in the 2022 W01 through 2024 W01 vintages processed by the Bundesbank during the experimental seasonal adjustments: daily air pollution as of 1 January 2016 and weekly Google searches for "Arbeitslosigkeit"—the German translation of unemployment—as of 2004 W02.

Air pollution (AP) is defined as the concentration of nitrogen dioxide in units of micrograms per cubic metre averaged across all available measurement stations in Germany. Measurements are currently taken at more than 500 stations in diverse urban, suburban and rural areas; the data is published by the German Environment Agency. The Google trends (GT) series covers weekly search activity for unemployment from Sunday through Saturday. Owing to Google's download restrictions regarding sample size, non-overlapping 5-year sequences of observations are downloaded first, with the maximum observations being normalised to 100 within each sequence. Those sequences are then padded and rescaled to form a break-free GT series with values ranging between 100 and 200.

The two series are displayed in Figure 1 along with autoregressive estimates of their spectral densities. In a nutshell, both the time series and spectral plots indicate presence of strong day-of-the-week (DOW) and day-of-the-year (DOY) dynamics in the AP series as well as presence of non-ignorable week-of-the-year (WOY) movements in the GT series.

3. Notations and Definitions

Model Let $\{y_t\}$ denote an infra-monthly time series and assume that it can be decomposed additively into unobservable components (UC) according to

$$f(y_t) = t_t + s_t + h_t + i_t, \tag{1}$$

where $f(\cdot)$ is a potentially non-linear transformation, $\{t_t\}$ is the trend-cyclical component, $\{s_t\}$ is the seasonal component, $\{h_t\}$ is the holiday component and $\{i_t\}$ is the irregular component. Throughout this paper, $f(\cdot)$ will be either the identity or the log transformation. The former model will be referred to as the additive UC model, whereas the latter model will be referred to as the multiplicative UC model. The seasonal component in (1) is further

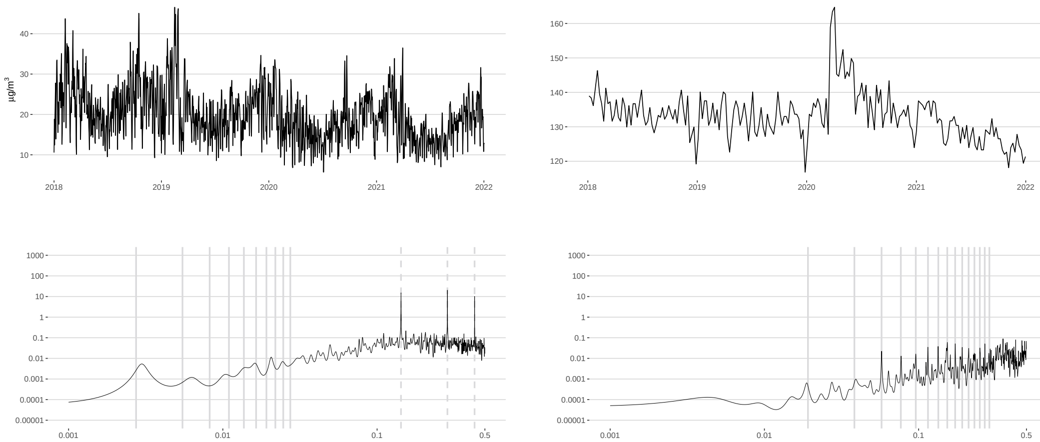

Figure 1: Time series plot (*top*, 2022 W01 vintage) and autoregressive spectral density estimate (*bottom*, differenced logged data) for the daily AP series (*left*) and the weekly GT series (*right*). Gray verticals in the spectral plots mark selected day/week-of-the-year frequencies (*solid*) and the three day-of-the-week frequencies (*dashed*).

assumed to be an additive superimposition of multiple seasonal patterns, that is

$$s_t = \sum_{\tau \in \mathbb{S}} s_t^{(\tau)}, \tag{2}$$

where $\mathbb{S} = \{\tau_1, \tau_2, \ldots\}$ is a finite set of seasonal periodicities with $\tau_i \in [2, \infty)$ for all i and $\{s_t^{(\tau)}\}$ denotes the seasonal pattern associated with periodicity τ.

In JD+, pretreatment of $\{y_t\}$ will utilise a linear regression model in which the disturbances are driven by what is called the extended Airline model (EAM). The entire pretreatment model can be written compactly as

$$(1-B)\prod_{\tau \in \mathbb{S}} (1 - B^{\tau}) \left[f(y_t) - \mathbf{x}_t^{\top} \boldsymbol{\beta} \right] = (1 - \theta_1 B) \prod_{\tau \in \mathbb{S}} (1 - \theta_\tau B^{\tau})\, \varepsilon_t, \tag{3}$$

where B is the backshift operator, i.e. $By_t = y_{t-1}$, $\mathbf{x}_t$ is a k-dimensional vector of exogenous variables related to holidays and outliers at time t, $\boldsymbol{\beta}$ is a k-dimensional vector of unknown regression effects and $\{\varepsilon_t\}$ is zero-mean white noise with finite variance $\sigma_\varepsilon^2 > 0$. If $\mathbb{S}$ contains fractional seasonal periodicities in (2), then the corresponding powers of the backshift operator in (3) are defined through the first-order Taylor approximation at unity, that is

$$B^{\tau} \approx (1 - \alpha_\tau) B^{\lfloor \tau \rfloor} + \alpha_\tau B^{\lfloor \tau \rfloor + 1}, \tag{4}$$

where $\lfloor x \rfloor$ is the largest integer not exceeding x and $\alpha_\tau = \tau - \lfloor \tau \rfloor \in [0, 1)$ is the fractional remainder of τ. Since each $(1 - B^{\tau})$ factor naturally carries a $(1 - B)$ factor, model (3) is prone to over-differencing. Therefore, we will consider the generalised version

$$(1-B)^d \prod_{\tau \in \mathbb{S}} S_\tau(B) \left[f(y_t) - \mathbf{x}_t^{\top} \boldsymbol{\beta} \right] = (1 - \theta_1 B) \prod_{\tau \in \mathbb{S}} (1 - \theta_\tau B^{\tau})\, \varepsilon_t, \tag{5}$$

where $d \in \{1, \ldots, 1 + |\mathbb{S}|\}$ is the order of non-seasonal differencing and

$$S_\tau(B) = (1 - B^{\tau})(1 - B)^{-1} = 1 + B + \cdots + B^{\lfloor \tau \rfloor - 1} + \alpha_\tau B^{\lfloor \tau \rfloor} \tag{6}$$

is the seasonal summation operator associated with periodicity τ. Some theoretical properties of model (5) are discussed in Webel (2022) and Webel and Smyk (2024); the corresponding linearisation step of the experimental in-house STL-based method, which is run on the DOW-adjusted data, is described in Ollech (2021).

Types of Revisions The AP and GT series are recorded each Monday, yielding a triangular-type data array $\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_T)$ for each of them, where the column vector $\mathbf{v}_i$ is the data vintage that contains the observations released in the i-th week. Each new data vintage will thus contain one additional observation for the GT series and seven additional observations (on average) for the AP series. Therefore, some slight changes to the standard notations used in the literature on data revisions seem inevitable.

Let $\hat{S}_{t|\mathbf{v}_i}$ be the estimated signal of interest at time t using raw data up to the last observation available in vintage $\mathbf{v}_i$. Typical signals of interest are the seasonal patterns in (2) and the seasonally adjusted data. In analogy to standard notations, the concurrent and final signal estimates are denoted by $\hat{S}_{t|\mathbf{v}_{i(t)}}$ and $\hat{S}_{t|\mathbf{v}_T}$, respectively, where $i(t)$ is a function of time that picks the week of the inaugural release of y_t. In general, we consider two types of revisions. The first type measures changes in later signal estimates as a percentage of the concurrent estimates (PCE). More precisely, we define the final and lag-k PCE revisions as the sequences $\{r_t\}$ and $\{r_t(k)\}$ with

$$r_t = 100 \times \frac{\hat{S}_{t|\mathbf{v}_T} - \hat{S}_{t|\mathbf{v}_{i(t)}}}{\hat{S}_{t|\mathbf{v}_{i(t)}}} \quad \text{and} \quad r_t(k) = 100 \times \frac{\hat{S}_{t|\mathbf{v}_{i(t)+k}} - \hat{S}_{t|\mathbf{v}_{i(t)}}}{\hat{S}_{t|\mathbf{v}_{i(t)}}}, \tag{7}$$

respectively. The second revision type measures changes in the period-to-period (P2P) percentage changes between later and concurrent signal estimates. More specifically, the final and lag-k P2P revisions are given by the sequences $\{r_t^{\%}\}$ and $\{r_t^{\%}(k)\}$ with

$$r_t^{\%} = \Delta^{\%}\hat{S}_{t|\mathbf{v}_T} - \Delta^{\%}\hat{S}_{t|\mathbf{v}_{i(t)}} \quad \text{and} \quad r_t^{\%}(k) = \Delta^{\%}\hat{S}_{t|\mathbf{v}_{i(t)+k}} - \Delta^{\%}\hat{S}_{t|\mathbf{v}_{i(t)}}, \tag{8}$$

where

$$\Delta^{\%}\hat{S}_{t|\mathbf{v}_i} = 100 \times \frac{\hat{S}_{t|\mathbf{v}_i} - \hat{S}_{t-1|\mathbf{v}_i}}{\hat{S}_{t-1|\mathbf{v}_i}}.$$

Revision Measures For the sake of brevity, we use the final PCE revisions $\{r_t\}$ to define the majority of revision measures, bearing in mind that the measures for the other revision types in (7) and (8) can be defined analogously.

Let n be the number of observations in the span chosen for the revision analysis. To quantify size and volatility of revisions, we consider three descriptive statistics: the mean revision (MR), the mean absolute revision (MAR) and the standard deviation (SD) of revisions. These measures are given by:

$$\begin{aligned}
\text{MR} &= n^{-1}\sum_{t=1}^{n} r_t, \\
\text{MAR} &= n^{-1}\sum_{t=1}^{n} |r_t|, \\
\text{SD} &= \sqrt{n^{-1}\sum_{t=1}^{n} (r_t - \text{MR})^2}.
\end{aligned}$$

To assess the speed at which preliminary revisions converge to final ones, we consider the rate of convergence (RC), which is defined as the SD ratio between the lag-k and final PCE revisions in (7), i.e.

$$\mathrm{RC}(k) = \frac{\mathrm{SD}\left[r_t(k)\right]}{\mathrm{SD}\left[r_t\right]}, \quad k \in \{1, 2, \ldots\}. \tag{9}$$

Fast (slow) convergence of PCE revisions is indicated by (9) if $\mathrm{RC}(k) \to 1$ for small (large) values of k. Usually, there will be a trade-off between size and speed of convergence of revisions, that is smaller (larger) preliminary PCE revisions typically go along with slower (faster) convergence.

4. Results

Seasonal Adjustment Specifications Each vintage of the AP and GT series is seasonally adjusted with the extended AMB, STL and X-11 approaches implemented in JD+, including re-estimation of pretreatment model (5). The AP series is also seasonally adjusted with the experimental in-house STL-based method implemented in the {`dsa`} package. For either series, calibration of the seasonal adjustment specification is carried out using the raw data released in the 2022 W01 vintage; once completed, the chosen specification is held fixed over all subsequent vintages.

The choice regarding the decomposition type of UC model (1) is based upon a set of commonly accepted model selection criteria calculated from pretreatment model (5) as specified below. The results reported in Table 1 indicate that the multiplicative model is favoured over the additive model for either series.

Using model (5), the AP series is corrected for the deterministic effects of selected fixed and moving holidays. The fixed holidays are New Year's Day (1 January), Epiphany (6 January), Labour Day (1 May), German Unification Day (3 October), the 500-th Reformation Day (31 October 2017), All Saints' Day (1 November), Christmas Eve (24 December), Christmas Day (25 December), Boxing Day (26 December) and New Year's Eve (31 December); thereby, fixed holidays that fall onto a Sunday are treated as regular Sundays. The moving holidays are Good Friday, Easter Monday, Ascension, Ascension Friday, Pentecost Monday, Corpus Christi and Corpus Christi Friday. The corresponding dummy regression variables have been corrected for their long-term means, which are calculated from 1 January 1950 to 31 December 2030. In addition, automatic detection of additive outliers and level shifts with length-adjusted critical t-values based upon the U.S. Census Bureau's modifications to the original formula derived in Ljung (1993) is run. Drawing on the visual

Table 1: Model selection criteria for AP and GT series

Series	UC model (1)	AIC	AICC	BIC	HQ
AP	Additive	12,109.54	12,109.97	12,229.03	12,153.22
	Multiplicative	9,574.50	9,575.06	9,695.66	9,619.20
GT	Additive	6,503.52	6,503.85	6,561.63	6,525.67
	Multiplicative	5,866.09	5,866.51	5,928.32	5,889.88

Notes: **1** The considered criteria are Akaike's information criterion (AIC), the corrected AIC (AICC), the Bayesian information criterion (BIC) and the Hannan-Quinn criterion (HQ). **2** For multiplicative UC models, the criteria are defined in terms of the untransformed data, that is, the maximised log likelihood obtained from the differenced logged data is corrected using the Jacobian log transformation adjustment.

evidence provided in Figure 1, we set $\mathbb{S} = \{7, 365.2425\}$ and $d = 2$ in (5). The same setup for data linearisation is used in the $\{$`dsa`$\}$ approach; the only exception is that the stochastic EAM-type seasonality that drives the regression residuals is replaced with a set of 20 Fourier terms plus a (011) specification for the orders of the non-seasonal ARIMA model. No forecasts of the raw data are generated from either pretreatment model. The sequential extraction of the DOW and DOY patterns from the linearised AP series is carried out with the following specifications:

- The extended AMB approach is run in full default mode without calculating back- and forecasts of any estimated signal.
- The extended X-11 approach is run with trend-cycle filters constructed from a cubic Henderson kernel. The length of the symmetric filter is set to the smallest odd integer larger than the seasonal periodicity of current interest, that is, the length is 9 for DOW extraction and 367 for DOY extraction. Asymmetric variants are obtained through the cut-and-normalise approach (Gasser and Müller; 1979). The 3×9 and 3×3 seasonal filters are chosen for DOW and DOY extraction, respectively, the maximum length of which is essentially dictated by the number of observations available in the 2022 W01 vintage. It should also be noted that the extended X-11 method does not generate naive forecasts of any seasonal pattern at the moment; as a result, fully asymmetric trend-cycle and seasonal extraction filters are used at the beginning and end of the series. Finally, the default σ-limits of $(1.5, 2.5)$ are specified for the automatic detection of extreme values in the detrended data.
- The STL method utilises trend-cycle and seasonal LOESS smoothers whose lengths match the lengths of their X-11 counterparts, regardless of whether the non-robust or robust STL variant is applied.
- $\{$`dsa`$\}$ is run with the same trend-cycle and seasonal LOESS smoothers specified in the JD+ implementation of STL. In addition, the "combined factors" option is selected to interpolate the seasonally adjusted values on 29 Februaries.

As for the GT series, two types of weekly user-defined holiday regression variables are considered for data linearisation via (5): first, dummy variables are used to capture the effects related to Carnival, Good Friday, Easter Monday, Pentecost and Corpus Christi; second, weekly shares of k-day periods are used to capture the effects of those holidays that are spread across k consecutive days and may hence be distributed across two adjacent weeks in some years. In particular, we have $k = 3$ for the Christmas period and $k = 2$ for the New Year period, whereby holidays that fall onto a Sunday are always counted as holidays. Long-term averages are removed from all weekly regression variables, noting that even holidays with a fixed datum can be moving on the weekly scale. For example, each fixed holiday of the 3-day Christmas period can fall in either week 51 or 52. In addition, automatic outlier detection is run in the exact same way as for the AP series. Based upon spectral evidence (Figure 1), we set $\mathbb{S} = \{52.18\}$ and again $d = 2$ in (5). For each JD+ method, the extraction of the WOY pattern from the linearised GT series is based upon the same setup described above. The only slight exception is the length of the symmetric X-11 trend-cycle filter, which is set to 55 in place of 53 alongside the 3×5 seasonal filter.

Computation Times Table 2 reports the average computation times required for linearisation of and signal extraction from the AP and GT series. Averages are taken over all data vintages, using 25 replications within each vintage. All calculations have been carried out on a 64-bit Windows OS with an Intel Xeon Gold 6338T CPU @ 2.10 GHz and 32.00 GB

Table 2: Average computation times in seconds for various seasonal adjustments

		AP series				GT series		
Program	Method	EAM (5)	DOW	DOY	Total	EAM (5)	WOY	Total
JD+ 3.0	AMB	12.719	0.039	9.955	22.713	0.227	0.054	0.281
	X-11	12.719	0.011	0.140	12.870	0.227	0.021	0.248
	STL	12.719	0.004	0.151	12.874	0.227	0.010	0.237
	STL-R	12.719	0.048	1.525	14.292	0.227	0.076	0.303
{dsa}	STL				33.635			
	STL-R				49.726			

Note: The suffix "-R" indicates usage of robustness weights in STL.

RAM. As for the JD+ methods, a large portion of the average total computation time is typically needed for data pretreatment whereas DOW and DOY extraction from the linearised AP series as well as WOY extraction from the linearised GT series is quite fast, especially for the non-parametric X-11 and STL methods. Seasonal adjustment of the AP series with the experimental in-house STL-based method is noticeably slower.

Stability of Parameter Estimates from Pretreatment Model (5) To assess the relative constancy of estimated holiday effects and MA parameters when model (5) is re-estimated with new data, we plot the parameter estimates and their standard errors against the 2022 W01 through 2024 W01 vintages.

Figure 2 shows the results for the AP series. In general, the parameter estimates and their point-wise standard errors are reasonably stable over time, although the estimated holiday effects occasionally undergo minor jumps when there is a new observation for the underlying event. Being even slightly more stable over time, the behaviour of the {dsa} estimates is quite similar despite some (time-constant) moderate differences in the size of some estimated effects. Unsurprisingly, the automatic outlier detection routines also produce very similar results: ranging between 1 and 2 with a standard deviation of 0.23 across all vintages, an average of 1.06 outliers, or 0.04% of the average sample size, is automatically detected in model (5); almost the same average of 1.08 outliers is detected during data linearisation in the robust STL method in {dsa} (standard deviation is 0.27) whereas no outliers are automatically found by the non-robust STL method.

Figure 3 shows the stability results for the GT series. The estimated holiday effects are as stable as the ones for the AP series although the finer scale of the vertical axis in Figure 3 makes them appear much more volatile across data vintages (see especially their marked changes across the first 10 vintages). However, the estimated MA parameters fluctuate somewhat stronger than those of the AP series. The same goes for the outcome of the automatic outlier detection routine in model (5): ranging between 0 and 7, the average number of automatically detected outliers is 2.51, or 0.25% of the average sample size, with a standard deviation of 1.41. On the flip side, the point-wise standard errors of the parameter estimates tend to be visibly smaller than those for the AP series.

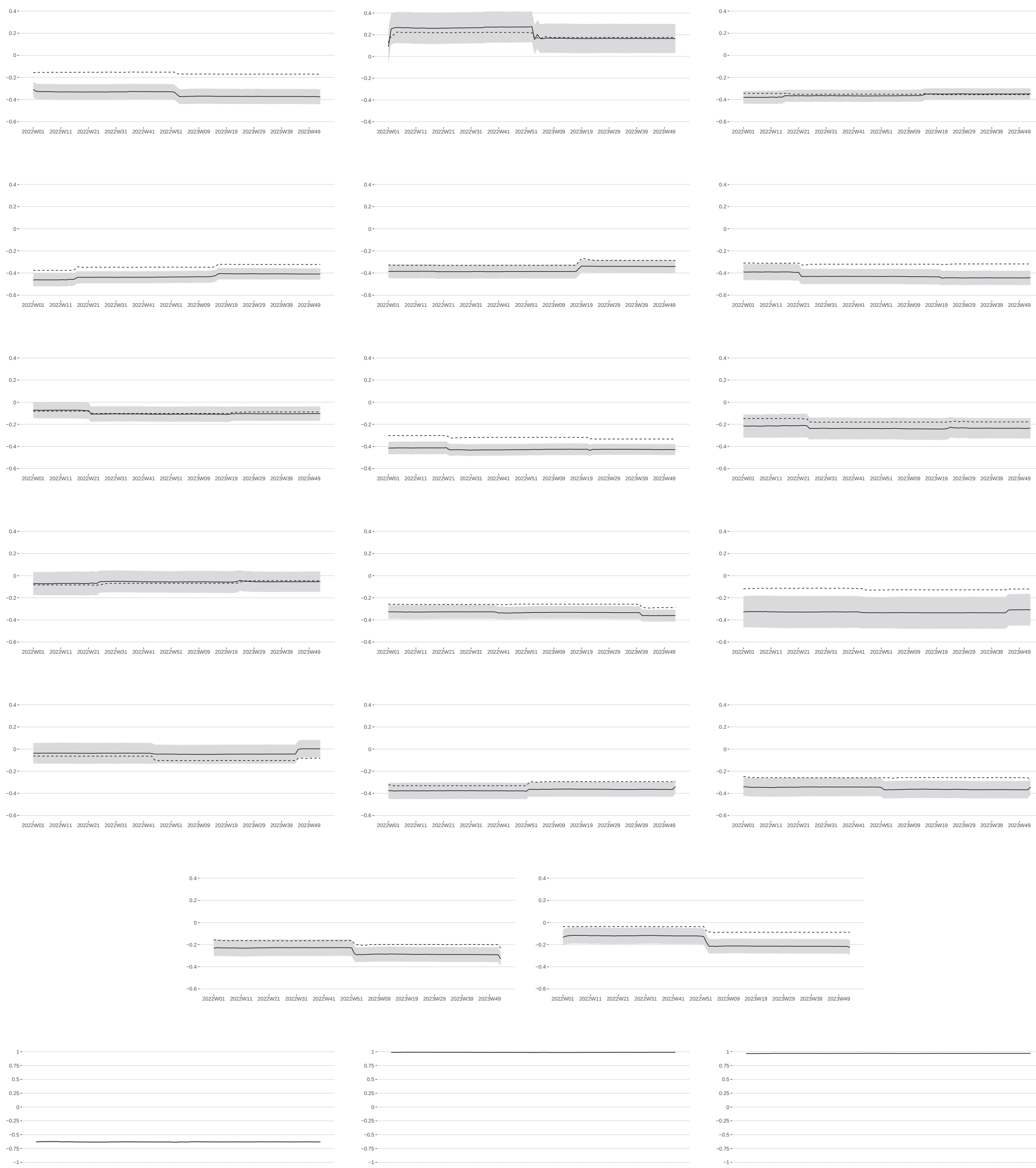

Figure 2: Estimated holiday effects and MA parameters from (5) for the AP series (solid lines). Shaded areas mark point-wise ± 1 SE intervals. Dashed lines correspond to estimated holiday effects from the linearisation step of the non-robust $\{\texttt{dsa}\}$ approach. The ordering is (*left to right*): New Year's Day, Epiphany, Good Friday (*row 1*); Easter Monday, Labour Day, Ascension (*row 2*); Ascension Friday, Pentecost Monday, Corpus Christi (*row 3*); Corpus Christi Friday, German Unification Day, 500-th Reformation Day (*row 4*); All Saints' Day, Christmas Eve, Christmas Day (*row 5*); Boxing Day, New Year's Eve (*row 6*); $\hat{\theta}_1$, $\hat{\theta}_7$, $\hat{\theta}_{365.2425}$ (*row 7*).

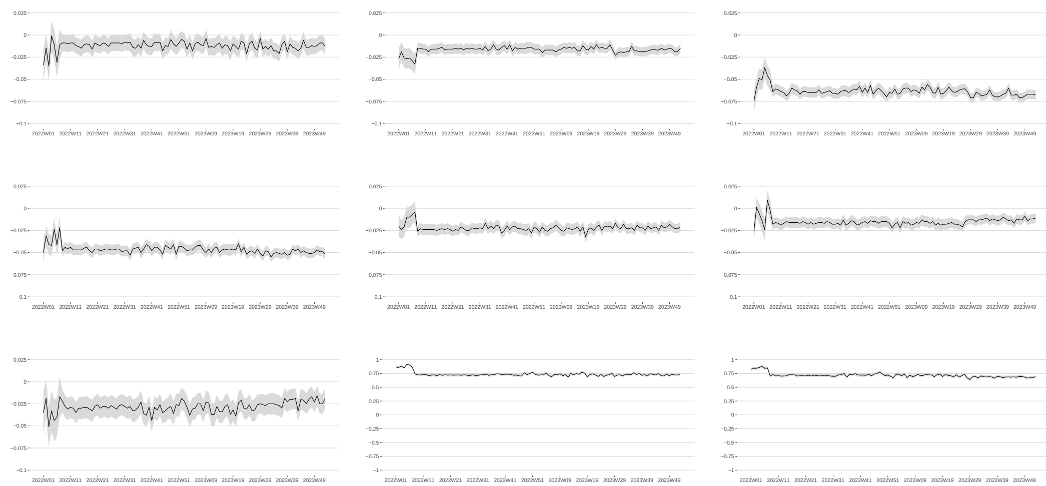

Figure 3: Estimated holiday effects and MA parameters from (5) for the GT series. Shaded areas mark point-wise ± 1 SE intervals. The ordering is (*left to right*): New Year, Carnival, Good Friday (*row 1*); Easter Monday, Pentecost, Corpus Christi (*row 2*); Christmas, $\hat{\theta}_1$, $\hat{\theta}_{52.18}$ (*row 3*).

Revisions in Signal Estimates We now calculate the final and lag-1 PCE revisions (7) and P2P revisions (8) over the 2022 W01 to 2022 W52 vintages for both the raw AP and GT data and various signal estimates, using the 2024 W01 vintage as the final vintage $\mathbf{v}_T$.

Table 3 reports the results for the AP series. The raw series displays moderate PCE and P2P revisions. As for the signal estimates, the extended AMB method produces the smallest revisions by far. The revision measures for the X-11 and STL estimates are quite similar although the STL method tends to produce somewhat smaller revisions in the longer DOY and SA signals. Unsurprisingly, the revisions obtained from the $\{\texttt{dsa}\}$ estimates are very similar to those of the STL estimates in JD+. Nevertheless, the lag-1 revisions in the longer DOY and SA signals have sizes that are close to the range of those for the AMB estimates. The rate of convergence for the DOW estimates obtained from the extended AMB and X-11 methods in JD+ and the non-robust STL method in $\{\texttt{dsa}\}$ is shown in Figure 4. It confirms the classic trade-off between the size of revisions and the speed of convergence: the AMB estimates have the smallest revisions on average but the slowest convergence whereas the other two methods generate larger average revisions that converge significantly faster to their final values.

Table 4 reports the revision measures for the GT series. In contrast to the AP series, the entire history of the GT series may be revised with each release of a new vintage. Therefore, the fact that the revisions of the raw data are noticeably larger comes as no surprise; this is especially true for the lag-1 PCE and P2P revisions (see also Table 3). In contrast, the revision measures for the concurrent estimates of the WOY signal are generally low and very similar across the JD+ methods. Nevertheless, the lowest and least volatile ones are often produced by the extended AMB approach yet again, followed by the extended X-11 method. Somewhat mixed results are obtained for the SA signal. The extended AMB and X-11 approaches are still competitive; however, the non-robust STL method produces the smallest measures for the lag-1 PCE revisions whereas the robust STL method gains a slight advantage in terms of low lag-1 P2P revisions. Overall, the average size and volatility of the revisions in the concurrent estimates of the seasonally adjusted GT series are very similar to those of the unadjusted GT series.

Table 3: Revision measures for the AP series

		PCE revisions (7)					
		$\{r_t\}$			$\{r_t(1)\}$		
Signal	Method	MR	MAR	SD	MR	MAR	SD
Raw		-0.7419	0.8406	0.9903	-0.0703	0.1877	0.8604
DOW	AMB	$\mathbf{0.0077}$	$\mathbf{0.8187}$	$\mathbf{1.0029}$	$\mathbf{0.0019}$	$\mathbf{0.1459}$	$\mathbf{0.1894}$
	X-11	0.0947	3.2296	4.0237	0.0642	2.1925	2.9115
	STL	0.1136	3.3301	4.2544	0.0579	1.9308	2.5343
	STL-R	0.2066	4.6625	5.9298	0.0617	2.1882	2.9752
	{dsa}	0.1206	3.3975	4.1627	0.0536	1.9284	2.4579
	{dsa}-R	0.2160	4.8799	6.2020	0.0367	1.9032	2.6260
DOY	AMB	$\mathbf{-0.0132}$	$\mathbf{0.8456}$	$\mathbf{1.1096}$	-0.0793	$\mathbf{0.7061}$	$\mathbf{0.9139}$
	X-11	-0.0232	5.3735	7.5876	-0.0558	2.1325	3.9708
	STL	-0.3656	5.7863	7.6786	-0.2545	1.4108	2.8576
	STL-R	0.1163	6.8879	10.7423	-0.7297	1.9900	5.3682
	{dsa}	0.6746	5.9582	7.5285	$\mathbf{0.0073}$	0.7901	1.0274
	{dsa}-R	0.8875	7.4585	11.7053	-0.0299	1.2967	3.5762
SA	AMB	-0.6678	$\mathbf{1.5122}$	$\mathbf{1.9236}$	$\mathbf{0.0118}$	$\mathbf{0.8220}$	$\mathbf{1.1735}$
	X-11	$\mathbf{-0.0406}$	5.9149	8.8292	0.1483	2.6104	4.8069
	STL	0.3084	6.5963	8.8378	0.2601	2.0231	3.7133
	STL-R	0.6161	8.3938	14.5393	1.0596	3.1208	7.6671
	{dsa}	-0.8544	6.5810	8.0764	-0.0890	1.3638	1.7137
	{dsa}-R	-8.9126	14.6443	22.8953	-1.0741	2.7335	8.0703

		P2P revisions (8)					
		$\{r_t^{\%}\}$			$\{r_t^{\%}(1)\}$		
Signal	Method	MR	MAR	SD	MR	MAR	SD
Raw		0.0303	0.5272	1.3706	-0.0017	0.2578	1.1952
DOW	AMB	-0.1751	$\mathbf{1.1862}$	$\mathbf{1.5416}$	-0.0029	$\mathbf{0.1758}$	$\mathbf{0.2283}$
	X-11	-0.1365	4.0301	5.1402	-0.0186	3.0074	3.9611
	STL	$\mathbf{0.0064}$	4.0019	5.1876	0.0042	2.4194	3.1644
	STL-R	-0.0578	5.7015	7.3397	$\mathbf{0.0027}$	2.8928	3.9714
	{dsa}	0.0214	4.0966	5.1951	0.0081	2.4260	3.1740
	{dsa}-R	-0.1184	6.2918	7.9927	-0.0071	2.6954	3.5270
DOY	AMB	$\mathbf{-0.0024}$	$\mathbf{0.2072}$	$\mathbf{0.3205}$	$\mathbf{0.0001}$	$\mathbf{0.2271}$	$\mathbf{0.5777}$
	X-11	-0.1084	5.5730	8.5015	-0.0653	2.5848	4.9588
	STL	-0.0153	4.7719	6.3195	-0.0026	1.0453	1.8696
	STL-R	-0.1170	8.1432	14.8023	-0.1650	2.6683	7.8864
	{dsa}	-0.0592	4.6972	6.0406	0.0071	0.8494	1.0994
	{dsa}-R	-0.3764	8.7518	15.6825	0.0746	2.0070	7.2289
SA	AMB	0.0112	$\mathbf{1.4986}$	$\mathbf{2.2317}$	$\mathbf{-0.0024}$	$\mathbf{0.4959}$	$\mathbf{1.1611}$
	X-11	$\mathbf{-0.0001}$	6.2611	9.9308	-0.0827	3.5358	6.8499
	STL	0.0507	5.4985	7.4936	-0.0720	1.7862	3.0337
	STL-R	0.2087	10.0203	17.7484	-0.1955	4.0311	9.6669
	{dsa}	0.1339	5.4249	6.9779	-0.0061	1.6214	2.0946
	{dsa}-R	0.5364	10.5313	19.4393	0.2499	3.3197	8.6444

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions. **2** The suffix "-R" indicates usage of robustness weights in the STL-based methods. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

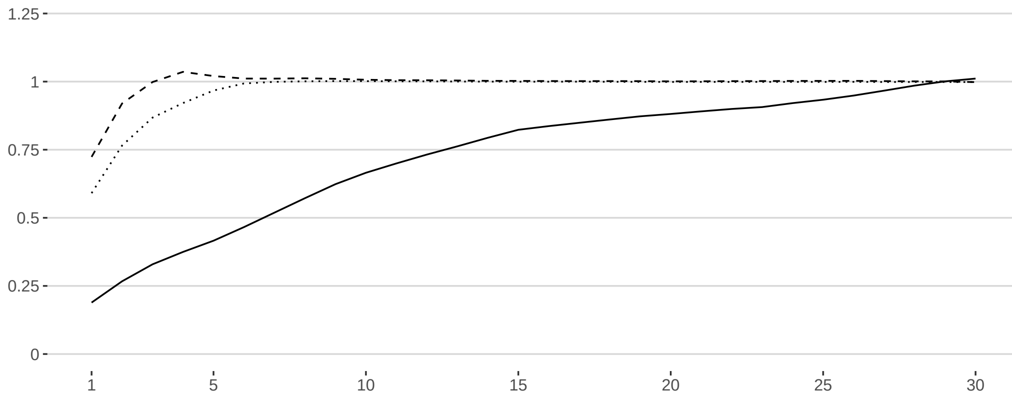

Figure 4: Rate of convergence (9) with $k \in \{1, \ldots, 30\}$ for the DOW estimates of the AP series obtained from the extended AMB (*solid line*), extended X-11 (*dashed line*) and non-robust $\{\texttt{dsa}\}$ (*dotted line*) methods.

Table 4: Revision measures for the GT series

		PCE revisions (7)					
		$\{r_t\}$			$\{r_t(1)\}$		
Signal	Method	MR	MAR	SD	MR	MAR	SD
Raw		3.5653	3.5723	2.5882	-1.3321	1.8892	1.8984
WOY	AMB	-0.4388	0.7823	$\mathbf{0.8190}$	-0.3734	$\mathbf{0.4663}$	$\mathbf{0.3966}$
	X-11	$\mathbf{-0.2073}$	$\mathbf{0.6962}$	0.8483	$\mathbf{-0.1986}$	0.5044	0.6820
	STL	-0.3952	0.7884	0.9457	-0.3865	0.4811	0.4545
	STL-R	-0.4069	0.7913	0.9542	-0.2981	0.4709	0.5337
SA	AMB	4.0205	4.0205	$\mathbf{2.1533}$	-0.9727	1.5745	1.8987
	X-11	$\mathbf{3.7805}$	$\mathbf{3.7882}$	2.1955	-1.1409	1.7636	2.0919
	STL	3.9765	3.9814	2.1702	$\mathbf{-0.9600}$	$\mathbf{1.5540}$	$\mathbf{1.8705}$
	STL-R	3.9927	4.0106	2.3508	-1.0461	1.6680	1.9377
		P2P revisions (8)					
		$\{r_t^{\%}\}$			$\{r_t^{\%}(1)\}$		
Signal	Method	MR	MAR	SD	MR	MAR	SD
Raw		0.0126	2.2190	3.0619	0.0859	1.9792	3.0325
WOY	AMB	$\mathbf{0.0007}$	$\mathbf{0.7418}$	$\mathbf{0.9550}$	-0.0152	$\mathbf{0.3379}$	$\mathbf{0.5093}$
	X-11	0.0231	0.7838	0.9976	-0.0091	0.7385	0.9593
	STL	0.0683	0.9033	1.2708	0.0037	0.4159	0.6043
	STL-R	0.0711	0.9718	1.4162	$\mathbf{0.0005}$	0.5674	0.7580
SA	AMB	$\mathbf{0.0116}$	$\mathbf{1.9282}$	2.7060	0.1104	$\mathbf{1.8977}$	3.0305
	X-11	-0.0170	1.9686	2.7270	0.1060	2.1551	3.3152
	STL	-0.0487	1.9948	$\mathbf{2.6436}$	0.0992	1.9093	3.0325
	STL-R	-0.0652	2.0199	2.6779	$\mathbf{0.0936}$	1.9553	$\mathbf{3.0241}$

Notes: **1** Revision measures are mean revision (MR), mean absolute revision (MAR) and standard deviation (SD) of revisions. **2** The suffix "-R" indicates usage of robustness weights in STL. **3** Bold figures indicate the smallest absolute value of the revision measure for the considered signal.

5. Summary

The Bundesbank has launched a new weekly activity index (WAI) for a more timely monitoring of economic developments in Germany in the post-COVID-19 era. Several daily and weekly time series with pronounced seasonality enter the WAI; prior to its calculation, these seasonal dynamics are currently being removed with an experimental in-house STL-based method implemented in the {`dsa`} package. Given the recent release of a new JDemetra+ (JD+) version that implements several other signal extraction methods for infra-monthly time series, the Bundesbank now plans to migrate from its experimental in-house solution to one of the official JD+ approaches. To assist this migration process, this study provides an empirical real-time comparison between the involved methods, using the 2022 W01 to 2024 W01 vintages of two infra-monthly WAI input series: daily air pollution (AP) and weekly Google trends (GT) for unemployment. The main findings are threefold. First, computational speed is generally high for the JD+ methods thanks to the underlying fast Java routines, especially those for data pretreatment, including automatic outlier detection, and non-parametric seasonal adjustment. The example of the AP series highlights that 33%–60% of computation time can be saved when using the JD+ methods in place of the experimental in-house non-robust STL variant. Second, the models used for data linearisation are reasonably stable across data vintages in both JD+ and {`dsa`}. Third, amongst all competitors, the extended ARIMA model-based approach implemented in JD+ tends to generate the smallest and least volatile real-time revisions on average in various concurrent signal estimates obtained from the AP and GT series. On the flip side, however, convergence of preliminary to final revisions may take significantly longer for this method, as seen for the concurrent estimates of the day-of-the-week pattern in the AP series.

The stability and revision analyses described here are currently being conducted for the other four daily WAI component series not covered in this report. Once completed, future research could consider more nuanced, or individual, set of regression variables for data linearisation as well as non-standard specifications for seasonal adjustment. For example, the extended X-11 approach alone implements a wide range of options for kernel-based trend-cycle extraction (Proietti and Luati; 2008) and selection of $3 \times k$ seasonal filters. Comparing the revision profiles of concurrent estimates of seasonally adjusted infra-monthly time series with those of estimates utilising projected seasonal factors obtained from earlier seasonal adjustments of forecast-extended time series would be another interesting strand of empirical research. Any of these studies could also include (basic) structural time series models or other seasonal adjustment methods currently not implemented in JD+, such as atomic seasonals or CAMPLET (see Webel; 2022, for an overview).

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