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REPLICATION

US weekly economic index: Replication and extension

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Summary

We revisit the US weekly economic index (WEI) put forth by Lewis, Mertens, Stock and Trivedi (2021). In a narrow sense, we replicate their main results with data gathered from its original sources. In a wide sense, we apply the methodology established in Wegmüller, Glocker and Guggia (2023) to adjust the weekly input series for seasonal patterns, calendar day effects, and excess volatility. In a long sense, we show that our proposed data adjustment significantly improves the nowcasting performance of the WEI.

KEYWORDS

business cycle index, Covid-19, dynamic factor model, forecast evaluation, high-frequency data, nowcasting, seasonal adjustment

1 | INTRODUCTION

Lewis et al. (2021) propose a weekly economic index (henceforth WEI) to track the economic developments of the US economy on a weekly frequency. Their composite index consists of ten series, of which eight are timely available and two with some delay. The authors highlight the WEI's high nowcasting accuracy of the current-quarter's GDP growth rate especially in the first half of 2020, with weaker performance in the second half. They also document the WEI's ability to track key events in the course of the Covid-19 pandemic.

We replicate the results of Lewis et al. (2021) in a narrow, wide and long sense. In a first step, we collected all input series from their original sources and achieved an exact narrow replication of the main results in Lewis et al. (2021). This underscores the authors' accurate, careful, and high-quality work.[1]

In a second step, the wide replication extends the work of Lewis et al. (2021) by implementing an adjustment procedure of the raw data for the purpose of improving upon the nowcasting accuracy of the WEI. The idea is motivated by the results put forth in Wegmüller et al. (2023). They propose a 6-step adjustment procedure for extracting precise business cycle signals from the high-frequency raw data and highlight the significant gain in nowcasting accuracy of their weekly index by means of a real-time evaluation.[2]

Although Lewis et al. (2021) stress the high nowcasting accuracy of the WEI, they, however, refrain from applying an adjustment procedure of the raw data. In their work, "[w]eekly seasonal adjustment is implemented by taking 52-week dif-

[1]Lewis et al. (2021) provide a partial set of publicly available input series along with well documented replication material for the software Matlab on https://qed.econ.queensu.ca/jae/datasets/lewis002/. We obtained data for this project from the American Staffing Association, Rasmussen Reports, Edison Electric Institute, Redbook Consumer Research, and Booth Financial Consulting LLC. For the replication analysis, we use the software R. Some data providers only made data available through the end of 2020. In order to mimic as closely as possible the data availability in the first week of 2021, we obtained real-time vintages from ALFRED where available as published on January 7, 2021.

[2]Based on the recommendation of a referee, we also studied the STL-decomposition as an alternative filter procedure (Cleveland et al., 1990). Although the loadings are comparable to the other specifications, the variance explained by the factor is considerably lower. Further, our proposed wide extension of the index outperforms alternatives based on STL in the out-of-sample exercise.

ferences or log-differences, depending on the series (for two series, the native units are already 52-week percent changes)." Although this procedure might be sufficient to remove intra-monthly seasonal patterns in some cases, daily and weekly data generally exhibit substantial volatility and feature more outliers and breaks. According to Proietti et al. (2018), a proper adjustment of the raw data for seasonal, holiday, and calendar effects is indispensable in order to extract precise signals of the high-frequency data.[3]

We report qualitatively similar factor loadings resulting from the estimation of the same model specification as in Lewis et al. (2021) based on adjusted input series. When looking at the individual series, the 6-step adjustment procedure results in modified series that are markedly distinct from their raw counterparts. The total variance explained by the factor increases notably, and the variance of the factor itself is substantially reduced. This highlights the importance of a proper adjustment of the raw data to identify precise business cycle signals.

Finally, in a long sense, we extend the work of Lewis et al. (2021) by performing an extensive real-time out-of-sample analysis. We evaluate the nowcasting performance of the unadjusted WEI of Lewis et al. (2021) against the adjusted WEI (adjusted input series), going week by week from 2008:W1 to 2020:W52. We find evidence that weekly information clearly outperforms the standard univariate quarterly benchmark model. Moreover, we find a significant improvement in the nowcasting accuracy of the WEI based on adjusted input series.

2 | NARROW REPLICATION

Lewis et al. (2021) establish a weekly index of economic activity as the first principal component of ten weekly measures of real economic activity. Table 1 lists the series used to construct the WEI, which can be divided into three categories: (1) consumer-focused series (Redbook Research same-store retail sales and the Rasmussen Consumer Index); (2) labor market series (initial and continuing claims for unemployment insurance, the American Staffing Association Staffing Index, and a measure of federal withholding tax collections); and (3) four industrial series (raw steel production, US fuel sales to end users, US railroad traffic, and electric utility output). All series enter the index as standardized 52-week log-differences. The WEI hence measures the change in the overall economic activity during the reference week relative to the corresponding week one year earlier. For interpretability, the index is scaled to the mean and standard deviation of the four-quarter GDP growth rate.

The first (numeric) column in Table 1 provides the weights of the first principal component, as well as the total variance explained based on the ten weekly series as put forth in Table 2 in Lewis et al. (2021). The estimates are based on the full sample between the first week of January 2008 and the last week of February 2020. The second column ("Narrow") in Table 1 provides the weights from our replication using the same series, the same transformations, and the same sample size. As only some of the input series are publicly available, we contacted the original sources to obtain series for electricity output, Rasmussen consumer confidence, Redbook same-store retail sales, the ASA Staffing Index as well as withholding tax collections. We used the open-source software R for replication.[4] The narrow replication finds no differences in the results compared with those in Lewis et al. (2021), underscoring the authors' accurate, careful, and high-quality work.

2.1 | Wide replication: Weekly seasonal adjustment

In the wide replication, we take the 10 input series from the narrow replication and—where necessary—apply the 6-step adjustment procedure proposed by Wegmüller et al. (2023) to clean the series for intra-monthly seasonal patterns, calendar day and holiday effects, and excess volatility. Lewis et al. (2021) consider 52-week percentage changes of the constituent series and argue that "[t]his transformation has the added benefit of eliminating most seasonality in the data, which is otherwise a challenging problem for weekly data." They hence refrain from using any additional data adjustment procedure. However, the 52-week difference filter has several important implications: First, although it can potentially reduce or eliminate the annual cycle, this is not true for the monthly cycle observed in some weekly time series, such as US unemployment reports (initial claims). Second, the 52-week difference filter can lead in turn to over-adjusting the high seasonal frequencies. For these and related issues, see the evidence documented in Proietti and Pedregal (2022). Against this back-

[3]To provide a practical example, it is not clear from the work of Lewis et al. (2021), how the surplus week in 2020 was handled. Was this piece of data omitted, or was the growth rate taken with respect to the first week of 2020? Either way, the non-integer periodicity of weekly data (most years have 52 weeks, some, however, have 53 weeks) poses a practical problem which should be properly addressed.

[4]In particular, we use the function `prcomp()` from the `stats-Package` of Rbase for the computations.

TABLE 1 Factor loadings of different models.

Indicator	Lewis et al. (2021)	Narrow	Wide
Initial claims	−0.37	−0.37	−0.38
Continued claims	−0.41	−0.41	−0.40
Steel production	0.36	0.36	0.36
Railroad traffic	0.34	0.34	0.36
Fuel sales	0.22	0.22	0.18
Staffing index	0.40	0.40	0.40
Electricity output	0.12	0.12	0.14
Consumer confidence	0.23	0.23	0.23
Same-store retail sales	0.28	0.28	0.28
Withholding tax	0.30	0.30	0.30
Total variance explained	55.4	55.4	57.2

TABLE 2 Seasonal and calendar adjustment.

	Native unit	Transformation	ARIMA	Further regressors
Initial claims	No. of persons	log	$(3{,}1{,}2)\,(1{,}1{,}0)_{52}$	bd
Continued claims	No. of persons	log	$(3{,}1{,}0)\,(1{,}1{,}0)_{52}$	bd
Steel production	Net tons	-	$(2{,}1{,}2)\,(1{,}0{,}0)_{52}$	bd
Railroad traffic	Car loads	log	$(3{,}1{,}1)\,(1{,}1{,}0)_{52}$	bd
Fuel sales	Barrels	-	$(0{,}1{,}3)\,(1{,}0{,}0)_{52}$	bd
Staffing index	Index	log	$(3{,}1{,}0)\,(1{,}1{,}0)_{52}$	bd
Electricity output	Gigawatt hours	log	$(1{,}1{,}1)\,(1{,}1{,}0)_{52}$	bd
Consumer confidence	Index	(no weekly seasonal adjustment)		
Same-store retail sales	52-week change	-	$(1{,}1{,}1)\,(0{,}0{,}1)_{52}$	bd
Tax withholding	52-week change	-	$(0{,}1{,}0)\,(1{,}0{,}1)_{52}$	bd

Note: The transformation of raw data to estimate seasonal factors (log-transformation for multiplicative model or no transformation for additive model) is based on the AIC-criteria (Sax & Eddelbuettel, 2018). Abbreviation: bd, business days of the week approximated by working days at New York stock exchange.

ground, Wegmüller et al. (2023), using high-frequency data for the Swiss economy, apply a 6-step adjustment procedure prior to calculating the 52-week growth rates. This procedure addresses the aforementioned problems in a coherent form, providing thereby a suitable starting point for any subsequent analysis. In what follows, we outline the procedure and apply it to the constituent series of the WEI.

The Wegmüller et al. (2023) 6-step adjustment procedure involves the following:

1. Surplus week adjustment[5]: We correct all those years that have 53 weeks 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. This approach aligns with the suggestions put forth in Pierce et al. (1984).
2. Calendar day and holiday adjustments: Weekly data exhibit problems of changing lengths of months (surplus days), day-of-the-week effects, and public holidays. In the United States, for instance the Memorial Day, Labor Day and Thanksgiving are moving holidays. To properly adjust for working day and holiday effects, we take as proxy for the US working day volume the opening days of the New York Stock Exchange. We separately check for end-of-year effects using dummy variables. We use a parametric Reg-Arima Model (consider Findley & Soukup, 2000) to perform the calendar day and holiday adjustments.
3. Seasonal adjustment: Seasonal patterns in weekly data can appear due to recurrent fluctuations within a month or within a year. We estimate seasonal factors using a generalized (fractional) airline decomposition model[6] (see Aston & Koopman, 2006; Hillmer & Tiao, 1982, for further details) which is a seasonal ARIMA $(p, d, q)(P, D, Q)_s$

[5]According to international standard ISO 8601, most years have 52 weeks. However, every 5 to 6 years, there is a year with 53 weeks, for example, the years 2009, 2015, and 2020. Moreover, there are no "half" weeks, which implies that some days in the calendar week belong to a year other than the usual date.

[6]Our baseline approach uses un-transformed data (native units) for the seasonal and calendar adjustment procedure. However, when the residuals of these regressions display heteroskedastic patterns, we then use the log-transformation of a series, see Findley et al. (1998) and Table 2.

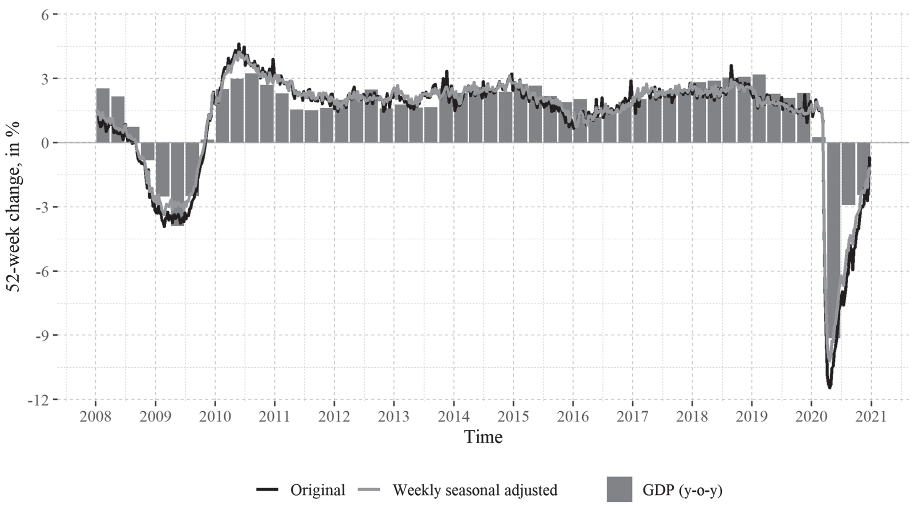

FIGURE 1 Comparing US weekly indices: adjusted versus original.

model.[7] The s is the periodicity of the series, and it is in general non-integer (hence *fractional*) for daily and weekly data. However, in our case $s = 52$ because we adjusted for the surplus week (i.e., the 53rd week) in step 1. As a consequence, our setup comprises the *airline* model which is one of the most commonly applied seasonal models.[8]

4. Excessive volatility adjustment: Some series might still exhibit excessive volatility even after the previous adjustment steps; if this is the case, one could then apply a one-sided moving average smoother.[9] For the present US data, the previous adjustment steps are sufficient.
5. Compute weekly annual growth rates, $\Delta y_t = \log(Y_t) - \log(Y_{t-52})$: Although this transformation might eliminate any remaining part of seasonal elements in the data not captured previously, the main intention of this step is to implement the same transformation across all series to construct a synthetic (composite) indicator.
6. Outlier adjustment: As the data might still show certain anomalies unrelated to business cycle movements, we correct for such outliers in the growth rates by applying generalized Hampel filters following (Pearson, 1999; Pearson et al., 2016; Proietti & Pedregal, 2022).

Table 2 provides details on the adjustment specifications of the different series.[10] Importantly, we estimate the seasonal factors only with data until the end of 2019. By doing so, the sharp decline in economic activity in spring 2020 along with the pandemic crisis period throughout 2020 is considered as outlier in the seasonal adjustment procedure.[11] We adjust the data of the crisis period for seasonal and calendar effects with the estimated factors. Notably, no series has to be adjusted for end-of-year dummies. Concerning the outlier adjustment, we set a window of 6 weeks and a threshold of 2 standard deviations for all series, except for the series on electricity output, for which the threshold is set to 1 standard deviation.[12]

Once having transformed the data, we re-estimate the principal components model of the narrow estimation with the adjusted input series. The third column of Table 1 reports the resulting factor loadings. Notably, the differences of the loadings to the original work are small. Electricity output, railroad traffic, and initial claims get a somewhat higher weight, whereas fuel sales and continued claims a slightly smaller one. Overall, the total variance explained by the factor increases by roughly 2 percentage points. Further, the WEI based on the adjusted input series has a notably lower variance.[13]

[7]This model can be written as $\Phi(L)\delta(L)y_t = \theta(L)e_t$ where $\delta(L) = (1-L)^d(1-L^s)^D$, $\Phi(L) = (1+\phi_1 L + \ldots + \phi_p L^p)(1+\Phi_1 L^s + \ldots + \Phi_P L^{Ps})$, and $\theta(L) = (1+\theta_1 L + \ldots + \theta_q L^q)(1+\theta_1 L^s + \ldots + \theta_Q L^{Qs})$; L denotes the lag-operator and $e_t \sim N(0,\sigma^2)$ is the error term. In general, for a weekly series, the periodicity is $s = 52.1775$ (Proietti et al., 2018) and the seasonal AR-filter would change to $1 - 0.82L^{52} - 0.18L^{53}$ in case of weekly data (similar change in the seasonal MA-filter). See Appendix A.1 for details.

[8]We utilize the *rjdhighfreq* R-package (see Sax & Eddelbuettel, 2018, for further details).

[9]In the Swiss case, this applies for instance to weekly imports and exports of goods or air pollution.

[10]See Section A.2 in the Appendix for an illustration of how the weekly seasonal adjustment affects different constituent series.

[11]Although most series start earlier, for reasons of comparability and computation, we estimate the seasonal factors where possible based on data starting in 2000:M1. The Rasmussen consumer index starts in 2004:M10, data on withholding tax in 2005:M1, and the Staffing index in 2006:M6.

[12]Following Pearson (1999), we use the median absolute deviation (MAD) outlier approach.

[13]The WEI based on adjusted data could in principle be criticized in terms of its real-time information content as its constituent series arise from the application of two-sided filters, using also future observations. However, this is common practice because most dynamic factor models use (monthly or quarterly) seasonally adjusted data.

TABLE 3 Forecasting performance of WEI index.

	Full sample					2009 Q3 to 2019 Q4				
Horizon1	**1**	**7**	**13**	**19**	**25**	**1**	**7**	**13**	**19**	**25**
RMSFE Benchmark	15.96**	16.18**	14.44**	16.77**	16.77**	3.34**	6.02**	6.02**	7.67**	7.67**
Relative RMSFE to benchmark										
original										
MEAN[2]	**0.32**	**0.39**	0.89	0.95	0.90	0.95	**0.55**	0.77	0.73	1.00
LAST[3]	**0.39**	**0.35**	0.59	0.96	1.00	1.24	**0.55**	0.66	0.66	0.85
adjusted										
MEAN	**0.26**	**0.35***	**0.89**	**0.94**	0.91	0.93	**0.53**	**0.70***	**0.66**	0.90
LAST	**0.38**	**0.30****	0.50*	0.89	0.92	1.19*	**0.56**	**0.53****	0.60*	0.73*

Note: Benchmark is ARMA(1,1)-model for yearly GDP growth. Forecast evaluation is based on the modified Diebold-Mariano test (Harvey et al., 1997) with the Null-hypothesis that two forecasts have the same accuracy. Asterisks denote rejection of the null of equal predictive accuracy against the alternative of superior predictive accuracy of the adjusted WEI methods against its unadjusted counterpart at 1 % (***), 5 % (**) and 10 % (*) significance levels, whereas in bold denotes rejection of the null of equal predictive accuracy against the benchmark model (up to 10 % (*) significance levels). Forecasting horizon in weeks. h is the GDP forecast considering the WEI for all weeks in the quarter less one (i.e., $13 - 1 = 12$). *MEAN*: average value of the WEI index in the corresponding quarter. *LAST*: last value of the WEI index in the corresponding quarter.Abbreviation : RMSFE, root mean squared forecast errors.

Figure 1 displays both US weekly economic indices along with the real-time, yearly GDP growth rate. The resulting index with seasonally adjusted indicators clearly exhibits a smoother pattern. During both downturns, the fall in economic activity was lower for the adjusted series relative to the original WEI. Summarized, we find strong in-sample evidence that a proper adjustment of the data prior to estimating the common factor is important to derive precise business cycle signals.

3 | LONG REPLICATION: OUT-OF-SAMPLE PERFORMANCE

Finally, we extend the work of Lewis et al. (2021) in a long sense by studying in more depth the out-of-sample properties of the WEI. In their work, the WEI is aggregated to the quarterly frequency by taking the mean over the respective quarter, and then the root mean squared forecast error (RMSFE) with respect to the last available vintage of the year-over-year GDP growth rates is computed. They report a RMSFE of 0.7 for the WEI for the period 2010:Q1 to 2019:Q4.[14]

We in turn take a different approach for evaluating the nowcasting accuracy of the WEI: We carry out a recursive out-of-sample evaluation using real-time quarterly US GDP data. Our evaluation period spans from 2009:Q1 to 2020:Q4. We establish one nowcast/forecast per week for both the current and the following quarter. For the purpose of a robustness check, we define a subsample based on the period between the two recent recessions (2009:Q3 to 2019:Q4). As benchmark, we use an univariate ARMA(1,1)-specification, estimated recursively on the real, seasonally adjusted, year-over-year GDP growth rate starting in 1995:Q1.[15] We use both the average value of the WEI (with as much data as available at that point in time) and the last weekly value for nowcasting quarterly values. The forecast errors are evaluated by means of the first available GDP vintage.

We provide the results of this exercise in Table 3. In the first row, we report the resulting RMSFE for the ARMA(1,1) benchmark. Below, we display the relative RMSFE of the original WEI from Lewis et al. (2021) based on unadjusted input series, followed by the adjusted WEI based on input series from our wide replication. The relative RMSFEs are shown together with significance levels from the modified Diebold-Mariano test,[16] where we test the hypothesis that (1) nowcasts from the WEI are more accurate than the univariate benchmark (in bold), and (2) the adjusted WEI has a superior predictive accuracy for GDP than its unadjusted counterpart (marked by asterisks).[17]

[14]This is based on the GDP vintage published in 2021:Q1. Our adjusted WEI has an insample RMSFE of 0.67.

[15]We tested the robustness of our results against different univariate benchmark models, for instance an AR(2)-specification. The results are quantitatively and qualitatively robust.

[16]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. (1997).

[17]As an example, the relative RMSFE of the adjusted MEAN WEI with 7 weeks horizon is 0.35, the forecast errors are significantly lower than the benchmark model (indicated in bold), and also significantly outperform the original MEAN WEI at the 10 % level (indicated by the asterisk).

Two key results emerge from the analysis: First, we find strong evidence that weekly information contributes significantly to the predictive accuracy relative to the quarterly benchmark. For the full sample, the relative RMSEs are substantially lower at most horizons. Forecast accuracy improves significantly at least up to 7 weeks ahead. For the adjusted MEAN WEI, they are significantly lower even up to 19 weeks ahead. Second, the WEI based on adjusted input series is more accurate in nowcasting GDP than the WEI based on unadjusted input series. The RMSFE is lower in most cases. This finding applies both to the sample with the Covid-19 crisis and the period which captures fluctuations as of "normal times." The gain in predictive accuracy is statistically significantly different from zero at the 5% level and applies to a horizon of up to 19 weeks.[18]

4 | CONCLUSION

We performed a replication of Lewis et al. (2021) in a narrow sense gathering the input data from their original providers and using the open-source program R. We managed to fully replicate the results of the original paper. In a wide sense, we extended the existing work by applying the 6-step adjustment procedure outlined in Wegmüller et al. (2023) to clean the weekly input series. We showed that the qualitative nature of the input series remains the same, whereas the volatility of the resulting weekly composite index is substantially reduced. In a long sense, we showed that the weekly composite index based on adjusted input series has a superior predictive accuracy than its counterpart based on unadjusted input series.

We conclude that high-frequency data should be handled with the same care as lower frequency data in order to obtain precise business cycle signals.

AUTHOR CONTRIBUTIONS

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

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at DOI: 10.15456/jae.2023075.0909504723.

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[18]See Section A.3 in the Appendix for more details on how the nowcasting performed during the Covid-19 pandemic in 2020.

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APPENDIX A

A.1 | Details on the data adjustment

This section provides more detailed information on specific aspects of the adjustment of the weekly data.

We consider a Reg-Arima model to perform the calendar and holiday adjustment, following the lines of Findley and Soukup (2000). The Reg-Arima model comprises a commonly used approach to this purpose, where each effect (outliers, calendar effects, etc.) is associated to a specific regression and where the residuals of the model are supposed to follow a general Arima model. In particular, such a model reads

$$y_t = \beta' \mathbf{X}_t + z_t \tag{A1}$$

in which y_t is a given time series, $\mathbf{X}_t$ denotes the mean function's regressor containing the holiday/calendar/temperature effects, and z_t denotes a mean zero Arima process.

The algorithm proposed by Gómez and Maravall (2001), which is implemented in the software TRAMO-SEATS, is probably the most popular and the most efficient way to estimate Equation (A1). This algorithm performs an automatic detection of the decomposition model (additive and multiplicative), an automatic detection and correction of outliers (additive outlier, level shifts, transitory changes, ramps, and seasonal outliers), an automatic detection and correction of usual trading-day effects, an automatic adjustment of the Arima model, and produces forecasts and backcasts of the series. The routine is commonly used by statistical agencies and recommended by Mazzi et al. (2018).

TRAMO fits a seasonal Arima model $(p, d, q)(P, D, Q)_s$ to a series y_t. This model can be written as

$$\Phi(L)\delta(L)y_t = \theta(L)e_t \tag{A2}$$

where $\delta(L) = (1 - L)^d(1 - L^s)^D$, $\Phi(L) = (1 + \phi_1 L + \ldots + \phi_p L^p)(1 + \Phi_1 L^s + \ldots + \Phi_P L^{Ps})$, and $\theta(L) = (1 + \theta_1 L + \ldots + \theta_q L^q)(1 + \theta_1 L^s + \ldots + \theta_Q L^{Qs})$; L denotes the lag-operator and $e_t \sim N(0, \sigma^2)$ is the error term. In these equations, s is the integer periodicity of the series. For daily and weekly data, s is not any more a single and constant integer. In general, for

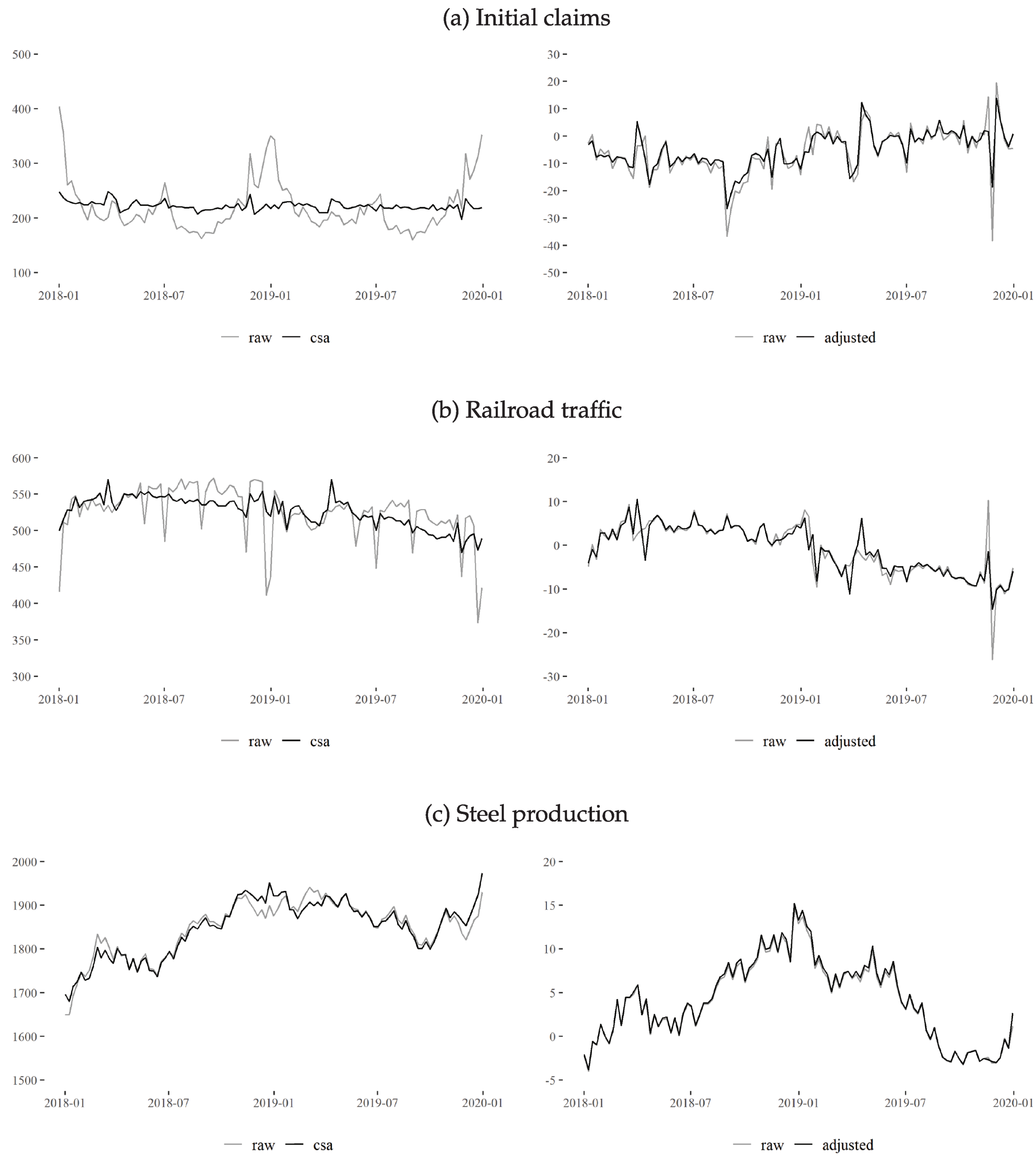

FIGURE A.1 Data adjustment. Left column: level (in Thousand); right column: growth rates

a weekly series, the average yearly periodicity is $s = 52.1775$ (see Proietti et al., 2018, for instance). However, in our case $s = 52$ because we adjusted for the surplus week (i.e., the 53rd week) in step 1 of the data pre-adjustment.

Seasonal adjustment by means of econometric models relies on the principle that a series can be decomposed into different unobserved components. The seasonal component is removed from the data to obtain seasonally adjusted data. The seasonal component is not observed and hence has to be inferred from the data itself through the use of an econometric model. Given Equation (A2), the aim is to decompose time series y_t into components for seasonality S_t, trend T_t and irregularity I_t, under the assumption that $y_t = S_t + T_t + I_t$ is modeled by Equation (A2). Details on the specifications of the three components (S_t, T_t and I_t) can be found in (Aston & Koopman, 2006; Koopman et al., 2007), among others. This set up comprises the *airline* model $ARIMA(011)(011)_s$ which is one of the most commonly applied seasonal models. It was introduced by Box and Jenkins (1976) who used it to study a time series of the monthly number of US airline passengers.

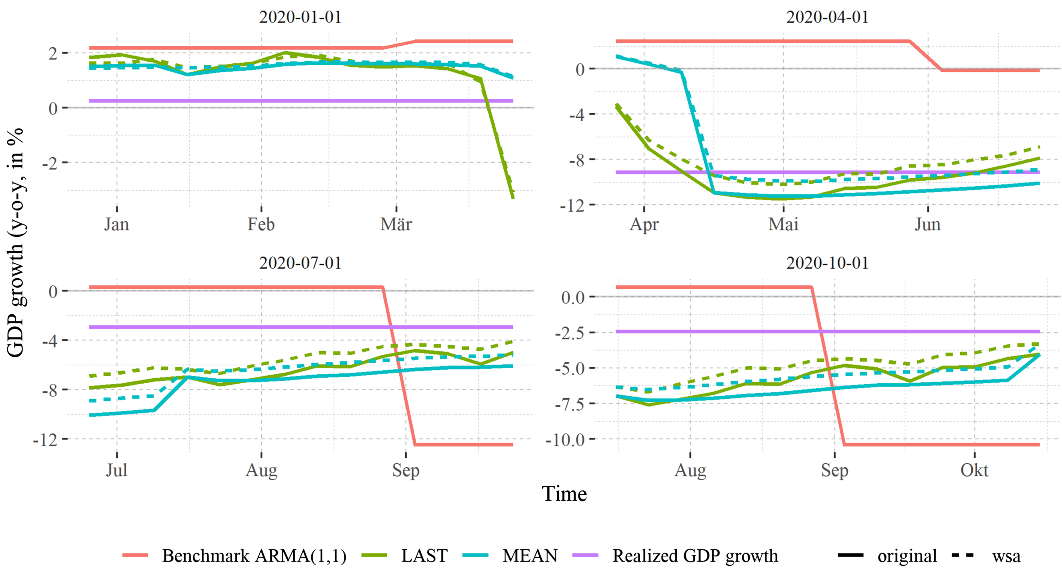

FIGURE A.2 Nowcasting GDP during the pandemic

A.2 | Illustration of selected adjusted variables

Figure A.1 highlights the changes due to the 6-step adjustment procedure for some selected variables[19]: (i) initial claims, (ii) railroad traffic, and (iii) steel production. In each case, the sub-figures on the left hand side display the level of the series whereas those on the right the annual growth rates; both for the unadjusted (gray lines) and adjusted data (black lines). For initial claims and railroad traffic, the adjustment procedure causes noteworthy changes of the series, whereas for steel production, however, the changes are negligibly small. We acknowledge the fact that for the input series of the WEI, indeed the 52-week percentage change is able to eliminate a substantial part of the seasonal patterns in the data. Yet, a priori this might not always be the case, as the evidence of Wegmüller et al. (2023) shows for the Swiss case.

A.3 | Nowcasting during Covid-19 in 2020

A central application of weekly economic indicators was to provide a guidance in the wake of the Covid-19 crisis. An accurate nowcasting performance is key in this respect.

We show the path of the two weekly indicators in Figure A.2 and compare their paths for this time period with the benchmark model (ARMA(1,1)-specification). We do so for the four quarters of 2020; the purple line displays the realized GDP growth rate, the red one the nowcast of the benchmark model, and the green and turquoise colors show *LAST* and *MEAN* (see Table 3 for further information) values of the weekly indicators, of which the solid lines refer to the original WEI and the dashed lines to its seasonally adjusted version.

The paths of the two WEIs (adjusted and unadjusted) show a remarkably high overlap in the weeks of the first quarter (MEAN and LAST). Their significant drop from mid-March onwards (especially LAST-WEIs) stands in contrast to the rise in the benchmark model's nowcast. The path of the adjusted and unadjusted WEIs already diverges noticeably in the second quarter. This applies to both the LAST and MEAN version. On average, the seasonally adjusted WEI tends to be closer to the realized GDP growth rate. The overall trajectory of the WEIs is though not crucially affected by the seasonal adjustment. A similar pattern emerges for the third and fourth quarter. For both the MEAN and LAST version of the WEI, the seasonally adjusted indicator is closer to the realization of the GDP growth rate.

The values of the WEIs at the end of a quarter are in each case already rather close to the realized GDP growth rate for the same quarter. This is one of the most important advantages of weekly indicators, especially in view of the fact that the publication of the realized GDP growth rates takes place with a considerable delay (one month for the GDP-Flash).

[19]Although the series start in 2008 for estimation of the principal component, we only show a short time segment to facilitate the comparison of the adjusted and unadjusted series.