WIFO Weekly Economic Index (WWWI) for GDP and its Sub-Indicators

Methodological Description

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The following note describes the procedure for obtaining historical estimates and nowcasts of the **weekly GDP indicator (WWWI)** and its sub-components. The set of indicators covers ten items on the production side and eight on the demand side of the Quarterly National Accounts (Q-NA), supplemented by the monthly time series of foreign and domestic overnight stays and retail sales. All nominal time series are price-adjusted using short-term inflation forecasts with a time horizon of up to two months.

In the WWWI-system the weekly indicator of GDP growth is estimated as the sum of the growth contributions of the complete system of components on the production side. The demand side has a residual that reflects the contribution of changes in inventories and the trade balance in non-tourism services.

The **temporal disaggregation** of monthly and quarterly data provided by Statistics Austria or OeNB[1] to weekly frequency (historical estimates) relies on a modern version of Chow – Lin's (1971) regression model and its extension by Litterman (1983). The estimated disaggregation models are formulated as **dynamic factor models in a state-space representation**, as explained in Proietti (2006). The basic idea is to transform the problem of temporal disaggregation of quarterly or monthly time series into a forecasting problem of **unobserved weekly observations** by treating them as missing data. For the **nowcasting** the same set of models are applied.

The state space model is estimated using the **Kalman filter**, which is the standard for modelling the common movement of time series with different lengths and frequencies that may feature missing observations. The temporal disaggregation is achieved by extending the state space of the model to include partial average of weekly growth rates. For a quarterly series, these averages are observed at the end of a quarter only, i.e., every 13th week, where they correspond to the realized quarterly year-on-year growth rate (Harvey, 1989, chap. 6.3; Proietti, 2006). For the remaining weeks in between, the partial averages are estimated and imputed using the Kalman filter.

Both models, Chow – Lin and Litterman, tend to produce similar historical estimates but differ in out-of-sample forecasts. The Litterman model tends to produce smoother estimates due to a richer specification of the error term. This model is preferred for historical decomposition but

[1] Monthly frequency: overnight stays, retail sales, production indices, external trade in goods and VAT notifications. Quarterly frequency: NAQ sub-aggregates, travel exports and imports according to the balance of payments as reported by the OeNB.

can lead to excessive smoothing of lockdown periods. Forecasts made using the Chow – Lin model tend to display stronger mean reversion. The nowcast consists of a combination of the forecasts using both models. In most cases, temporal disaggregation is informative because it uses weekly indicator variables as input. However, for some public sector variables, such as subsidies, noninformative temporal disaggregation leads to more plausible estimates.

The temporal disaggregation models rely on a single weekly indicator. In case multiple weekly indicator series are available, their joint dynamics are captured by the largest principal component. The principal component, which is first centred and then rescaled by the mean and standard deviation of the quarterly series, enters a temporal disaggregation model as a synthetic composite weekly indicator.

In addition, the temporal disaggregation models also feature an autocorrelation coefficient that controls the persistence of the dynamic factor over time and thus the degree of smoothness of a weekly series[2]. The state-space structure of temporal disaggregation models ensures that the average growth rate of all weeks in a quarter is consistent with quarterly (monthly) year-on-year growth.

Since all models are updated both after Statistics Austria publishes a new Q-NA and after WIFO's flash estimate of the Q-NA for the most recent quarter, the **WWWI and its components remain consistent with the current quarterly data**. In addition, all models are updated upon release of relevant monthly data (see footnote 1), which can also lead to a revision of the WWWI.

The temporal disaggregation is based on **the growth rates in relation to the previous year's week** (52 weeks, difference in percent)[3]. The 13-week average of the weekly rates of change from the previous year corresponds to the year-on-year rate of change in the corresponding quarterly time series from the National Accounts. Time disaggregation proceeds in two steps: quarterly to monthly and monthly to weekly. Each step involves an out-of-sample nowcast of the disaggregated quarterly series using the leading high frequency data. In the first step, the quarterly growth rates are disaggregated to monthly frequency using a suitable set of monthly indicators. In the second step, the weekly growth rates of the GDP components are obtained by a weekly disaggregation of the monthly series from the first step. The weekly disaggregation is based on observed weekly indicator time series. Examples of weekly indicator series are cashless transactions by several providers, freight and passenger transportation activity, Google mobility data, persons registered as unemployed with the Public Employment Service Austria, electricity consumption and pollutant emissions by industry, stringency indices related to COVID-19 policies, international weekly indicators of economic activity (Table 1).

[2] The autocorrelation coefficient must be chosen carefully to avoid over-smoothing the structural breaks following the introduction and removal of officially imposed restrictions (e.g., lockdowns).

[3] The fact that the year 2020 had 53 calendar weeks was taken into account in the weekly calculations: Calendar week 53 was distributed evenly among the 13 weeks of the fourth quarter of 2020.

Table 1: **Determinants for the sub-components of the National Accounts**

Demand side

	Weekly indicators	Monthly indicators
Private consumption	Credit card data• mobility retail	
Public consumption		Employment O_Q
Gross fixed capital formation	Sub-indicator goods producing sector • mileage • rail freight • cargo flights arrival	Import of equipment • construction sales • firm vehicle registration
Exports of goods	Weekly economic activity world (export-weighted) • mileage • rail freight • cargo flights departure	Export of goods (foreign trade statistics)
Imports of goods	Mileage • rail freight • cargo flights arrival • sub-indicator exports of goods • sub-indicator private consumption • sub-indicator gross fixed capital formation	Import of goods (foreign trade statistics)
Tourism exports	Credit card data• bookings • passenger flights arrival • stringency index	Credit card data
Tourism imports	Passenger flights departure • credit card data• stringency index	Credit card data

Production side

Goods producing sector – NACE A_E	Unemployment A_E • energy consumption • NO_2-emissions	Production index B_E
Construction – NACE F	Unemployment F	Production index F
Wholesale and retail trade, repair of motor vehicles – NACE G	Unemployment G • credit card data • mobility retail • stringency index	Retail sales index
Retail sales excluding motor vehicles	Credit card data • mobility retail • stringency index	
Transportation – NACE H	Mileage • rail freight • cargo and passenger flights	VAT notifications
Accommodation and food service activities – NACE I	Credit card data • overnight stays • stringency index	VAT notifications, overnight stays
Other market-related services – NACE J_N	Sub-indicator goods producing sector	VAT notifications
Public administration in broad sense – NACE O_Q		Employment O_Q
Other services – NACE R_T	Unemployment R_T • credit card data • stringency index	VAT notifications
Taxes on products – ESA D21	Sub-indicator private consumption	VAT notifications

Credit card data: The weekly data on cashless transactions is obtained from three providers and is used according to its relevance for forecasting a specific weekly sub-indicator. If multiple weekly sources are available, they are aggregated into a single indicator using principal components.

The weekly indicator series are adjusted for outliers before being converted into year-on-year growth rates and before a sub-indicator is estimated (Bilek-Steindl et al., 2020, chap. 2). However, they are not seasonally adjusted because a reliable seasonal adjustment is not feasible given the short sample size. A large part of the weekly time series starts with calendar week 1 in 2019, so there is a maximum of four observations per respective week. This is not sufficient for a reliable econometric estimate of a weekly seasonal pattern. Therefore, the reference of the growth rates of the weekly sub-indicators to the previous year's week was chosen, thereby reducing the impact of seasonality in the existing weekly indicators on the estimation.

Literature

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