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FvS Real Economy Index:

Technical Note

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Abstract

The FvS Real Economy Index is a weekly common factor estimated using an approximate dynamic factor model from a set of real-time economy indicators, GDP growth and industrial production growth. The aim of this project is to track the post Covid-19 economic recovery. The real-time economy indicators include mainly internet data. This note presents the technical specificities as well as the list and sources of the variables used for the construction of the index.

Zusammenfassung

Der FvS-Realwirtschaftsindex ist ein wöchentlich ermittelter gemeinsamer Faktor, der mit Hilfe eines „approximate dynamic factor model“ aus einer Reihe von Echtzeit-Wirtschaftsindikatoren, dem BIP-Wachstum und dem Wachstum der Industrieproduktion geschätzt wird. Ziel dieses Projekts ist es, die wirtschaftliche Erholung nach dem Einbruch der Covid-19-Pandemie zu verfolgen. Die Echtzeit-Wirtschaftsindikatoren umfassen hauptsächlich Internet-Daten. In dieser Notiz werden die technischen Besonderheiten sowie die Liste und Quellen der für die Konstruktion des Index verwendeten Variablen vorgestellt.

Introduction

To track real economic activity after the Covid-19 pandemic, we compute a common factor from a set of variables based on the quarter-on- quarter growth rate of GDP and industrial production as well as various weekly and daily indicators which are related to GDP and reflect current economic activity. We use an approximate dynamic factor model as presented by Duarte and Süßmuth (2018) to estimate the common factor. In this note we present the model and its estimation procedure as well the variable selection and transformation process to construct the index for Germany.

The Model

The starting point is that each series (y_t^i) can be expressed as the sum of two components: a factor (f_t) which is common to a set of variables (GDP growth and the indicators) and an idiosyncratic component (u_t^i) which captures the unique characteristics of each series. In general, the model can be expressed as:

$$Y_t^i \quad = Lf_t + u_t^i, \qquad (1)$$

where Y_t^i is a matrix of dimensions $M \times 1$ (M is the total number of variables); L is an $M \times 1$ matrix with the coefficients of the common factor in the equation for each series (factor loadings); since we work with one single factor, f_t has a 1×1 dimension and u_t^i is a $M \times 1$ matrix.

Additionally, since it is unlikely that past values do not explain present values for the common factor f_t and the idiosyncratic factors u_t^i, we allow for serial correlation such that:

$$\begin{aligned} f_t \quad &= A_1 f_{t-1} + \cdots A_p f_{t-p} + \eta_t \qquad (2) \\ u_t^i \quad &= C_1 u_{t-1}^i + \cdots C_q u_{t-q}^i + \varepsilon_t, \qquad (3) \end{aligned}$$

where η_t and ε_t are white noise processes. To be estimated are the matrices L, A_i, and C_j for $i = 1, \dots, p$ and $j = 1, \dots, q$ plus the unobserved common factor $\hat{f}_t$.

We use an approximate dynamic factor model as presented by Duarte and Süßmuth (2018). The idea is that we can have a parametric state-space representation – where equation (1) is the observation equation, and equations (2) and (3) are the *state* equations – from which the likelihood can be estimated using the Kalman filter and the unobserved factor can be computed from the Kalman smoother (Stock and Watson, 1991; 2016). The main advantage of this method for our goal is that it can efficiently handle missing data and mixed frequencies.

The implementation of our model is done in three steps. First, we select a set of relevant daily and weekly indicators, second, we transform the indicators accordingly and third we estimate the model and compute the estimated values of $\hat{f}_t$.

Variable Selection: Germany

For the selection of the variables we rely on economic analysis on the very specific situation we are currently aiming to track, namely the post Covid-19 economic recovery.

Our starting point are official GDP and industrial production. GDP is available every quarter and industrial production every month, both since 1991.

We only use two additional "hard" indicators: electricity consumption (source: ENTSO-E) and mobility of large trucks. Electricity consumption is available in hourly frequency and we include it because it is a necessary input for most of economic activity.

To capture mobility and trade, the "truck toll mileage index" (source: German statistical office) provides a daily measure of traffic of large trucks in German roads.

We use internet data to capture further economic activity. The main motivation is that the internet is almost omnipresent in modern life and a simple search query often precedes many economic activities. As Choi and Varian (2011) show, using the search intensity of keywords in Google (collected in "Google Trends") can be an accurate predictor of real economy variables such as unemployment, sales and trips. The Google Trends statistics offers categories which compile the search intensity of keywords in related terms. The category "Welfare and Unemployment", for example, stores the search intensity of keywords such as "unemployment office", "unemployment support", "jobs", etc. The data is available in a weekly frequency.

The categories we use for the German index are the following:

- Welfare & Unemployment.
- Job Listings.
- Shopping.
- Travel.
- Restaurants.

Finally, to track individual mobility as lockdown measures are slowly lifted, we use the Google mobility reports for the categories "workplaces" and "transit stations".

Data Transformation

The goal of this second step is to assure that our data is stationary, seasonally adjusted and comparable. For GDP and industrial production, we use the seasonally adjusted data as provided by the source and calculate the quarter on quarter percentage change.

For electricity consumption we take the total consumption during the hour between 11 a.m. and 12 a.m. to get daily data. Since our goal is to have a weekly index, we take weekly averages. Because of the strong seasonal component of the series, we calculate rolling averages over 52 weeks. Finally, we get a weekly series starting in 2016, week 14. For the daily truck-mileage index, we take weekly averages and then quarterly rolling averages to smooth out the seasonality in the series. Afterwards we have a weekly series starting in 2008, week 23.

For the Google trends indicators, we calculate rolling averages of the weekly data over 52 weeks to smooth seasonal pattern of the series. At the end we get weekly series starting in 2016, week 36.

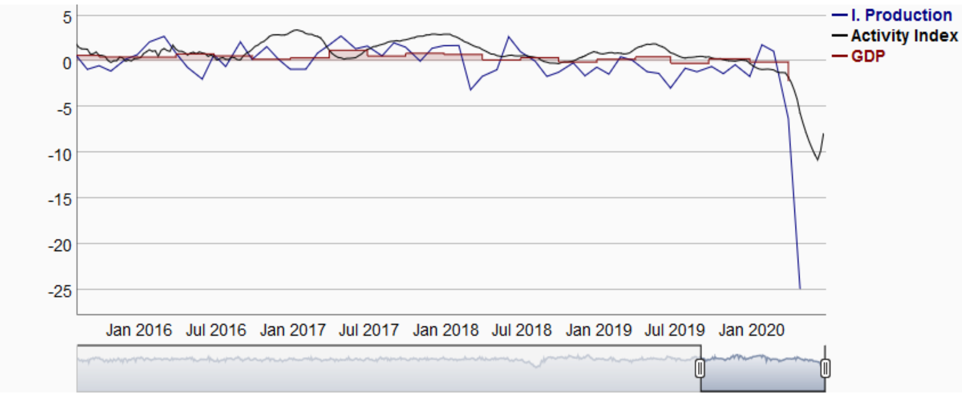
We do not transform the mobility indicators because they are too short, starting in 2020w6. We still include them because they can provide useful information on the economic recovery while lockdown measures are lifted and, as explained above, our estimation procedure can handle efficiently this kind of differences in data availability.

Finally, we calculate the quarter on quarter percentage changes (the difference over the last 12 weeks) as most series are I(1) and because our goal is to approximate quarterly GDP growth.

Model Estimation

With our 9 weekly indicators, industrial production and GDP growth, we estimate the approximate dynamic factor model described above. The results are 3 matrices of coefficients and the estimated common factor $\hat{f}_t$. Since we aim to track GDP growth, it is necessary to rescale $\hat{f}_t$ to match the mean and standard deviation of GDP growth. Figure 1 shows the resulting time series of our index together with GDP growth and industrial production.

Figure 1: Real Economic Index, Germany



Source: Flossbach von Storch Research Institute, German Statistical Office

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