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Estimation of a coincident indicator for international trade and global economic activity

Abstract

World economic aggregates are compiled infrequently and released after considerable lags. There are, however, many potentially relevant series released in a timely manner and at a higher frequency that could provide significant information about the evolution of global aggregates. The challenge is then to extract the relevant information from this multitude of indicators and combine it to track the real-time evolution of the target variables. We develop a methodology based on dynamic factor models adapted to accommodate for variables with heterogeneous frequencies, ragged ends and missing data. We apply this nowcast methodologies to three variables of interest: global trade in goods, global trade in services and world GDP in real terms. In addition to monitoring these variables in real time, this method can also be used to obtain short-term forecasts based on the most up-to-date values of the underlying indicators.

Keywords: Coincident indicators, nowcasting methodologies, short-term forecasts, international trade, economic activity

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1 Introduction

On a global scale, there is a constant stream of economic information released by official and private sources. National statistical authorities publish national accounts, balance of payments, government finances, monetary statistics, data from the banking sector and a multitude of other socio-economic indicators. International actors also compile and publish diverse statistical series. To this, one can add the data produced by commercial statistical providers, with products such as public opinion polls or surveys of business confidence. Lately, there has been an important addition to this list: private actors that collect statistical information as part of their activities and that bundle them as standalone products. This includes, to name just a few examples, stock exchanges, financial actors, port operators, retailers, and social media and social networking companies.

All these series provide a piece of information either on overall economy activity or on specific sectors. Although this means that we can keep track of the state of the economy in real time, it also introduces the challenge of sorting out the information that is relevant from that which is not. This problematic is exacerbated by a long list of statistical complications: missing data, measurement errors, undercoverage, low signal-to-noise ratio, heterogeneous frequencies, different starting and ending dates, asynchronous update schedule, constant revisions, and others.

Assessing the real-time evaluation of macroeconomic variables based on a series of timely, high-frequency indicators (a process that has come to be called “nowcasting”) is not new. The classical literature on coincident and leading indicators (see, for example, Conference Board (2001) and OECD (2012)) is well established and it has been applied in many areas. Bridge models, linking high frequency variables to a target variable of lower frequency, are standard tools in statistical analysis (see Baffigi et al. (2004), Barhoumi et al. (2008) and Rossiter (2010) for recent examples of their application to forecast economic activity). Progress in this area accelerated with the development of more sophisticated techniques of data selection and processing, particularly after the application of dynamic factor models by Stock and Watson (2002a,b), Forni et al. (2005) and Giannone et al. (2008).

Dynamic factor models introduce the assumption that the observed indicators can be divided into two components: one that can be attributed to one or a few (unobserved) factors that are common to all series, and another that is specific or idiosyncratic to each component. The factor model serves to establish a mapping between the common factors and the indicators. It is a dynamic model, so the factors are assumed to change through time according to an autoregressive process. This model can be summarized through a statespace representation, in which the mapping between indicators and factors becomes the measurement equation, and the dynamics of the unobserved factors become the transition equation. The likelihood of this model can then be calculated via the Kalman filter and the maximum likelihood estimators (MLE) obtained via standard optimization techniques.

The simplicity of the dynamic factor model and its good empirical performance explain its positive reception as a tool to nowcast or forecast economic variables based on many heterogeneous indicators. This solution was later extended and applied to many contexts. For example, Mariano and Murasawa (2003) modified the model to allow indicators of mixed frequencies and Camacho and Perez-Quiros (2010) developed this further by taken into consideration variable reporting lags and the availability of early or “flash” estimates. Schumacher and Breitung (2006) implemented some modifications to improve the forecasting performance of the model. Aruoba et al. (2009) and Aruoba and Diebold (2010) constructed a similar model to incorporate very high frequency indicators and a dynamic factor model that does not require the use of approximations. Matheson (2011) applies the basic methodology but extends the application to simultaneously track economic growth in 32 economies by using country-specific and global indicators. The constant stream of economic indicators is called “big data” by Bok et al. (2017) and in their paper they describe the nowcasting methodology of the Federal Reserve Bank of New York, which closely follows some of the research cited above.
However, dynamic factor models are not the only methodologies used to tackle this problem. For example, Clements and Galvão (2008) use the mixed-frequency model (MIDAS) proposed by Ghysels et al. (2006a,b) to

track output growth in the United States. This method allows to incorporate data sampled at different frequencies in a flexible way. Marcellino and Schumacher (2010) and Ferrara and Marsilli (2014) also employ this methodology to nowcast German and global economic activity, respectively. This paper will not explore this approach since, as it will be explained later, recent developments in dynamic factor models also allow to efficiently incorporate variables of mixed frequencies, in addition to overcoming other statistical complications of empirical data.

The main objective of this paper is the development of a nowcasting methodology for world trade. The methods will also be used to nowcast global economic activity to demonstrate how they can be applied to other target variables. The standard dynamic factor model will be adapted to accommodate the characteristics of trade variables, and it will incorporate the information available in an extensive list of indicators. The nowcasts will be published in future releases of UNCTAD's Handbook of Statistics.[1]

The rest of the paper is organized as follows. The next section will introduce the concept of nowcasting as specifically applied to global trade variables. After that, Section 3 will describe the dynamic factor model and the data transformations required. Section 4 will then present the application of this methodology to our variables of interest and the results obtained. A final section will conclude and introduce some possible areas of future work.

2 Nowcasting global trade variables

Most of the literature described above employs a nowcasting methodology to assess the evolution of global economic activity. Only a handful of recent articles have applied this approach to international trade. Guichard and Rusticelli (2011) develop a dynamic factor model for world trade relying on a set of monthly indicators. Golinelli and Parigi (2014) uses an augmented bridge model based on theoretical-level relationships to jointly assess world trade and economic activity. Finally, Barhoumi and Ferrara (2015) construct two leading indicators for global trade: one relying on the traditional methodology of the Conference Board cited above, and another based on dynamic factor models with single-frequency indicators.

Assessing the evolution of world trade is crucial for a comprehensive evaluation and forecasting of the economy. Many countries rely on international trade as an important component of their economy and demand shocks or episodes of price volatility can bring about severe periods of instability. It is therefore essential to identify shifting trends and sudden changes of direction in these variables immediately or as soon as possible after they occur. International trade is also a variable that can affect the entire national economy, creating imbalances or influencing the effectiveness of economic policy. National authorities are therefore interested to closely monitor this variable so that they can adapt their policies in a timely manner.

Figures on world trade are reliably published by international actors. However, they are only available after a considerable lag and with a low frequency (annual or quarterly). Some providers release variables with a higher frequency (monthly), but at the cost of lower coverage and greater variability. At the same time, there are many variables from a multitude of sources that can potentially provide information on international trade. The challenge of any nowcasting exercise is to extract the relevant information from a heterogeneous set of variables affected, to a greater or lesser degree, with different statistical problems, and organize it into a coherent statistical model.

Two approaches could be followed to monitor international trade. One is to target total figures of global trade directly. The other is to monitor trade variables for the main trading countries or the most important sectors, and then aggregate them into an overall estimate of trade. We prefer the former approach. This because trade variables are influenced by global developments that cross national and regional boundaries: globalization and the internationalization of production, growing importance of global value chains, emergence of large multinationals and their reliance on intra-firm industrial processes spread all over the world, generalized

[1] For the latest release of this annual publication, see UNCTAD (2017).

influence of exchange rate dynamics, rise of protectionism, extended effect of new technologies on production, etc. All this may lead to the existence of business cycles that are specific to global trade, but different from those at the country level. In fact, Burgert and Dées (2008) find evidence that this approach leads to improved forecasts in comparison to the other ("bottom-up") approach.

In this paper, we will rely on the dynamic factor models to nowcast global (aggregate) trade variables. We will adapt the existing solutions to the specific characteristics of trade variables and the indicators that can potentially be used to track them. However, it must be noted that this is not a macroeconometric model that selects explanatory variables based on their causal linkages with international trade or by following a structural model of the world economy. Instead, this is a statistical exercise where indicators are selected because of their correlation with the target variable and their availability in a reliable and timely manner. The following section will describe the methodology and the procedures followed to overcome the different data issues.

3 The nowcasting model

The goal of the exercise is to nowcast a target variable observed with low frequency (quarterly or annual) or after a considerable lag based on a set of indicators that are available more frequently or after a shorter publication lag. However these indicators are not necessarily available as a rectangular, balanced dataset. Instead, they are affected with different statistical issues: mixed frequencies, different start and end dates (i.e., ragged ends), asynchronous timing of data publication, and missing data. The methodology employed to calculate the nowcast should take into account these features of the data. This paper takes the methodologies described in Mariano and Murasawa (2003) and Camacho and Perez-Quiros (2010) as starting points, and extends them to incorporate additional types of variables relevant for nowcasting trade variables.

3.1 Mixed frequencies

The approach to overcome this issue is to express all variables in terms of the highest frequency available in the dataset (in this case, monthly). This requires transforming the variables, through approximations if necessary, so that they are all expressed in terms of monthly growth rates.

3.1.1 Annual variables

Let X_t^A be a variable observable once per year. This variable can be written as an aggregation of the last 12 observations of its corresponding (unobservable) monthly time series, in the following way.

$$X_t^A = X_t^m + X_{t-1}^m + \cdots + X_{t-11}^m$$

Note that the t index refers to time in months and that the target variable is available only once every 12 months, with the rest of the observations missing. It is possible to represent this sum as 12 times the average of the last 12 monthly observations.

$$X_t^A = 12\left(\frac{X_t^m + X_{t-1}^m + \cdots + X_{t-11}^m}{12}\right)$$

In order to facilitate the construction of the model, the arithmetic mean will be approximated by the geometric mean.[2]

[2] This approximation is not expected to have a significant effect in the estimation, especially in cases where the rate of growth of the variables are small, leading to a very small difference between the two means. However, in future extensions of this work, it would be interesting to consider exact filtering procedures, such as the one proposed by Aruoba et al. (2009).

$$X_t^A \approx 12\left(X_t^m X_{t-1}^m \cdots X_{t-11}^m\right)^{1/12}$$
$$\ln X_t^A \approx \ln 12 + \frac{1}{12}\left(\ln X_t^m + \ln X_{t-1}^m + \cdots + \ln X_{t-11}^m\right)$$

The annual growth rate of the target variable can therefore be approximated by

$$x_t^A = \ln X_t^A - \ln X_{t-12}^A \approx \frac{1}{12}\left(\ln X_t^m + \ln X_{t-1}^m + \cdots + \ln X_{t-11}^m\right) - \frac{1}{12}\left(\ln X_{t-12}^m + \ln X_{t-13}^m + \cdots + \ln X_{t-23}^m\right)$$

Rearranging the elements above and letting

$$x_t^m = \ln X_t^m - \ln X_{t-1}^m$$

represent the monthly growth rates, we obtain the following approximation of the annual growth rate of a variable in terms of its (unobservable) monthly growth rates.

$$x_t^A \approx \frac{1}{12}x_t^m + \frac{2}{12}x_{t-1}^m + \cdots + \frac{11}{12}x_{t-10}^m + \frac{12}{12}x_{t-11}^m + \frac{11}{12}x_{t-12}^m + \cdots + \frac{2}{12}x_{t-21}^m + \frac{1}{12}x_{t-22}^m \quad (1)$$

3.1.2 Quarterly variables

Let X_t^Q be a variable observable once per quarter. Parallel to the treatment of annual variables described above, this variable can be approximated by the geometric mean of the last three monthly observations.

$$X_t^Q \approx 3\left(X_t^m X_{t-1}^m X_{t-2}^m\right)^{1/3}$$

Taking logarithms and rearranging the terms, we obtain the following approximation of x_t^Q, the quarterly growth rate of the variable, in terms of lags of x_t^m, the corresponding (unobservable) monthly growth rate.

$$x_t^Q \approx \frac{1}{3}x_t^m + \frac{2}{3}x_{t-1}^m + \frac{3}{3}x_{t-2}^m + \frac{2}{3}x_{t-3}^m + \frac{1}{3}x_{t-4}^m \quad (2)$$

Quarterly variables are observed only once every three months and the rest of the series is treated as missing.

3.1.3 Monthly variables

Monthly time series expressed as monthly growth rates can be incorporated directly into the model. We will denote them in this paper simply as

$$x_t^m = \ln X_t^m - \ln X_{t-1}^m \quad (3)$$

However, some sources publish their data not as changes with respect to the previous month, but relative to the same month of the previous year. This requires a special transformation before they are incorporated into the model.

Let x_t^{m12} be the rate of change of X_t with respect to the same month of the previous year. Then the difference in this rate over the preceding month can be expressed in terms of monthly growth rates.

$$\begin{aligned} x_t^{m12} - x_{t-1}^{m12} &= \left(\ln X_t^m - \ln X_{t-12}^m\right) - \left(\ln X_{t-1}^m - \ln X_{t-13}^m\right) \\ &= x_t^m - x_{t-12}^m \end{aligned} \tag{4}$$

3.2 Ragged ends and missing data

The mixed-frequency database that will be used to estimate the model may be affected by the presence of missing data from three sources. First, the series may have some missing information directly from the source and no official imputation is available. Second, some variables are only observed once per year or quarter. Once they are transformed, by following the procedures described above, into functions of monthly growth rates, the data will still be available only when a data point is published and the rest of the series will be treated as missing. And third, because each series has its own starting and ending dates. Although it could be possible to restrict the database to the time window where all the variables are available, this would mean throwing away valuable information that could be used to estimate the model. Moreover, one of the benefits of the nowcasting methodology is that it uses the most recent information available to estimate the target variable, even if this means that only some of the variables are available in the most recent months.

In order to overcome the problem of estimating the model with missing data, we follow Mariano and Murasawa (2003) and substitute all variables by artificial (random normal) observations independent of the model parameters. The authors show that this only adds a constant to the likelihood and does not impact the estimation of the parameters. Let x_t be any of the variables included in the model. This will be substituted by

$$x_t^* = \begin{cases} x_t & \text{if } x_t \text{ is observable} \\ \lambda_t & \text{otherwise} \end{cases} \tag{5}$$

where $\lambda_t \sim \mathcal{N}\left(0, \sigma_\lambda^2\right)$. In this way, for the purpose of estimating the parameters of the model, we will have a database of monthly variables with no empty cells.

3.3 Building the model

With this conformable database, we will structure the model as a dynamic factor model in state-space representation. We therefore assume that the target variables and the different indicators in the model share a common (time-varying) factor ft, in addition to their own idiosyncratic component. We can then apply the Kalman filter and obtain maximum likelihood estimates of the parameters. In this way, we can obtain predictions of the target variable based on the most recent information provided by a list of mixed-frequency indicators.

3.3.1 Annual target variable

To build the state-space model, assume that we have one target variable (y_t^A) available once per year. This will be included in the model by following (1). We also have one indicator of each of the following types: one quarterly variable (x_t^Q) as in (2), one monthly variable measured as month-on-month growth rates (x_t^m) as in (3), one monthly variables measured as year-on-year growth rates (x_t^{m12}) as in (4), and one forecast of the target variable ($\hat{y}_t^A$). If there is more than one variable of any type available, it would suffice to add the corresponding rows to the Kalman matrices.

Following the transformations described in the previous section, we obtain the following measurement equation of the model.

$$\begin{pmatrix} y_t^A \\ x_t^Q \\ x_t^m \\ x_t^{m12} - x_{t-1}^{m12} \\ \hat{y}_t^A \end{pmatrix} = \begin{pmatrix} \beta_1\left(\frac{1}{12}f_t + \cdots + \frac{12}{12}f_{t-11} + \cdots + \frac{1}{12}f_{t-22}\right) \\ \beta_2\left(\frac{1}{3}f_t + \frac{2}{3}f_{t-1} + \frac{3}{3}f_{t-2} + \frac{2}{3}f_{t-3} + \frac{1}{3}f_{t-4}\right) \\ \beta_3 f_t \\ \beta_4\left(f_t - f_{t-12}\right) \\ \beta_1\left(\frac{1}{12}f_t + \cdots + \frac{12}{12}f_{t-11} + \cdots + \frac{1}{12}f_{t-22}\right) \end{pmatrix} +$$

$$\begin{pmatrix} \frac{1}{12}\epsilon_{1,t} + \cdots + \frac{12}{12}\epsilon_{1,t-11} + \cdots + \frac{1}{12}\epsilon_{1,t-22} \\ \frac{1}{3}\epsilon_{2,t} + \frac{2}{3}\epsilon_{2,t-1} + \frac{3}{3}\epsilon_{2,t-2} + \frac{2}{3}\epsilon_{2,t-3} + \frac{1}{3}\epsilon_{2,t-4} \\ \epsilon_{3,t} \\ \epsilon_{4,t} - \epsilon_{4,t-12} \\ \frac{1}{12}\epsilon_{1,t} + \cdots + \frac{12}{12}\epsilon_{1,t-11} + \cdots + \frac{1}{12}\epsilon_{1,t-22} \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ fce_t \end{pmatrix}$$

This can be written more compactly as

$$Gt = Bht + ut \tag{6}$$

with

$$h_t = (f_t, \ldots, \ f_{t-23}, \ \epsilon_{1,t}, \ldots, \ \epsilon_{1,t-23}, \ \epsilon_{2,t}, \ldots, \epsilon_{2,t-5}, \ \epsilon_{3,t}, \ldots, \ \epsilon_{3,t-m_3}, \ \epsilon_{4,t}, \ldots, \epsilon_{4,t-13}, \ fce_t)$$

The factor loading matrix is given by

$$B = \begin{bmatrix} B_{11} & B_{12} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & \mathbf{0}_{1\times 14} & 0 \\ B_{21} & \mathbf{0}_{1\times 24} & B_{22} & \mathbf{0}_{1\times m_3} & \mathbf{0}_{1\times 14} & 0 \\ B_{31} & \mathbf{0}_{1\times 24} & \mathbf{0}_{1\times 6} & B_{32} & \mathbf{0}_{1\times 14} & 0 \\ B_{41} & \mathbf{0}_{1\times 24} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & B_{42} & 0 \\ B_{11} & B_{12} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & \mathbf{0}_{1\times 14} & 1 \end{bmatrix}$$

$$\begin{aligned} B_{11} &= \beta_1\left(\frac{1}{12}, \ldots, \ \frac{12}{12}, \ldots, \ \frac{1}{12}, \ 0\right), & B_{12} &= \left(\frac{1}{12}, \ldots, \ \frac{12}{12}, \ldots, \ \frac{1}{12}, \ 0\right) \\ B_{21} &= \beta_2\left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0, \ldots, \ 0\right), & B_{22} &= \left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0\right) \\ B_{31} &= \beta_3\left(1, \ 0, \ldots, \ 0\right), & B_{32} &= \left(1, \ 0, \ldots, \ 0\right) \\ B_{41} &= \beta_4\left(1, \ 0, \ldots, \ 0, \ -1, \ 0, \ldots, \ 0\right), & B_{42} &= \left(1, \ 0, \ldots, \ 0, \ -1, \ 0, \ldots, \ 0\right) \end{aligned}$$

and $u_t \sim \mathcal{N}\left(0, \operatorname{diag}\{\sigma_{\lambda,i,t}^{2*}\}\right)$ with $\sigma_{\lambda,i,t}^{2*}$ equal to σ_λ^2 if the variable *i* in month *t* is missing and zero otherwise. In case one variable is missing at time *t* and following (5), the corresponding line of *B* is replaced by zeros so that it is not included in the likelihood and it is only linked to a random normal number with variance σ_λ^2.

Notice that available forecasts of the target variable can be integrated into the model. They are treated as the true value of the variable plus a random forecast error fce_t. This could be of interest when "flash" estimates of the target variable are published in anticipation of the final release, or when other sources of forecasts are available and they could improve the accuracy of the nowcast. The random forecast error is assumed to be distributed as $\mathcal{N}\left(0, \sigma_{fce}^2\right)$.

The transition equations of the model consist of the following terms.

$$\begin{pmatrix} f_t \\ \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \end{pmatrix} = \begin{pmatrix} \phi_{01} f_{t-1} + \phi_{02} f_{t-2} + \cdots + \phi_{0m_0} f_{t-m_0} \\ \phi_{11}\epsilon_{1,t-1} + \phi_{12}\epsilon_{1,t-2} + \cdots + \phi_{1m_1}\epsilon_{1,t-m_1} \\ \phi_{21}\epsilon_{2,t-1} + \phi_{22}\epsilon_{2,t-2} + \cdots + \phi_{2m_2}\epsilon_{2,t-m_2} \\ \phi_{31}\epsilon_{3,t-1} + \phi_{32}\epsilon_{3,t-2} + \cdots + \phi_{3m_3}\epsilon_{3,t-m_3} \\ \phi_{41}\epsilon_{4,t-1} + \phi_{42}\epsilon_{4,t-2} + \cdots + \phi_{4m_4}\epsilon_{4,t-m_4} \end{pmatrix} + \begin{pmatrix} \mu_t^f \\ \mu_t^{\epsilon_1} \\ \mu_t^{\epsilon_2} \\ \mu_t^{\epsilon_3} \\ \mu_t^{\epsilon_4} \end{pmatrix}$$

with the error vector μ distributed as an iid $\mathcal{N}\left(0, \operatorname{diag}\{\sigma_f^2, \sigma_{\mu_1}^2, \sigma_{\mu_2}^2, \sigma_{\mu_3}^2, \sigma_{\mu_4}^2\}\right)$. We normalize σ_f^2 to one as the identifying assumption required for the estimation.

By adding the required terms, we can write this equation more compactly.

$$h_t = Dh_{t-1} + v_t \tag{7}$$

where

$$D = \begin{bmatrix} D_0 & \mathbf{0}_{24\times24} & \mathbf{0}_{24\times6} & \mathbf{0}_{24\times m_3} & \mathbf{0}_{24\times14} & 0 \\ \mathbf{0}_{24\times24} & D_1 & \mathbf{0}_{24\times6} & \mathbf{0}_{24\times m_3} & \mathbf{0}_{24\times14} & 0 \\ \mathbf{0}_{6\times24} & \mathbf{0}_{6\times24} & D_2 & \mathbf{0}_{6\times m_3} & \mathbf{0}_{6\times14} & 0 \\ \mathbf{0}_{2\times24} & \mathbf{0}_{2\times24} & \mathbf{0}_{2\times6} & D_3 & \mathbf{0}_{2\times14} & 0 \\ \mathbf{0}_{14\times24} & \mathbf{0}_{14\times24} & \mathbf{0}_{14\times6} & \mathbf{0}_{14\times m_3} & D_4 & 0 \\ \mathbf{0}_{1\times24} & \mathbf{0}_{1\times24} & \mathbf{0}_{1\times6} & \mathbf{0}_{1\times m_3} & \mathbf{0}_{1\times14} & 0 \end{bmatrix}$$

with

$$D_i = \begin{bmatrix} \phi_{i1} & \phi_{i2} & \dots & \phi_{im_i} & 0 & \dots & 0 & 0 \\ 1 & 0 & \dots & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & 1 & 0 \end{bmatrix}, \quad i = \{0,1,2,3,4\}$$

The size of each matrix D_i will adjust according to the type of variable, but its structure remains the same: a row of coefficients for the lag terms and an identity matrix below, concatenated with a column of zeros at the end.[3] The error term is distributed as iid $v_t \sim \mathcal{N}(0, Q)$, with

$$Q = \operatorname{diag}\{\sigma_f^2,\ \mathbf{0}_{1\times23},\ \sigma_{\mu1}^2,\ \mathbf{0}_{1\times23},\ \sigma_{\mu2}^2,\ \mathbf{0}_{1\times5},\ \sigma_{\mu3}^2,\ \mathbf{0}_{1\times m_3},\ \sigma_{\mu4}^2,\ \mathbf{0}_{1\times13},\ \sigma_{fce}^2\}$$

The measurement equation (6) and the transition equation (7) form the state-space representation of the dynamic factor model. The Kalman filter can then be used to evaluate the likelihood function and calculate maximum likelihood estimates (MLE) of the parameters. The prediction equations are initialized at a vector of

[3] Note that the size of some of the submatrices in both the measurement and the transition equations written here may need to be adjusted in certain cases. For example, if the number of lags corresponding to the quarterly variables (m_2) is greater than six, the corresponding rows and columns in all matrices need to be expanded accordingly.

zeros and the identity as the covariance matrix. Once we obtain the MLE, we can use the updating equations of the Kalman filter to estimate the monthly values of the target variable and their variance. This will be the main output of the model. It is also possible to calculate the contribution of each indicator to the nowcast of the target variable; see Camacho and Perez-Quiros (2010) for details.

3.3.2 Quarterly target variable

In this case, the structure of the model remains the same than the description given above. The measurement and transition equations are still given by (6) and (7), respectively, and only the underlying matrices need to be adapted. As before, assume that we wish to nowcast the target variable y_t^Q and that the model includes one of each of the following indicators: one quarterly variable (x_t^Q), one monthly variable measured as month-on-month growth rates (x_t^m), and one forecast of the target variable ($\hat{y}_t^Q$).[4]

Using the same nomenclature as before, the matrices of the model are now given by the expressions below. The rest of the process remains identical.

$$h_t = (f_t, \ldots, \ f_{t-11}, \ \epsilon_{1,t}, \ldots, \ \epsilon_{1,t-5}, \ \epsilon_{2,t}, \ldots, \epsilon_{2,t-5}, \epsilon_{3,t}, \ldots, \ \epsilon_{3,t-m_3}, \ fce_t)$$

$$B = \begin{bmatrix} B_{11} & B_{12} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & 0 \\ B_{21} & \mathbf{0}_{1\times 6} & B_{22} & \mathbf{0}_{1\times m_3} & 0 \\ B_{31} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times 6} & B_{32} & 0 \\ B_{11} & B_{12} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & 1 \end{bmatrix}$$

$$\begin{aligned} B_{11} &= \beta_1 \left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0, \ldots, \ 0\right), & B_{12} &= \left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0\right) \\ B_{21} &= \beta_2 \left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0, \ldots, \ 0\right), & B_{22} &= \left(\frac{1}{3}, \ \frac{2}{3}, \ \frac{3}{3}, \ \frac{2}{3}, \ \frac{1}{3}, \ 0\right) \\ B_{31} &= \beta_3 \left(1, \ 0, \ldots, \ 0\right), & B_{32} &= \left(1, \ 0, \ldots, \ 0\right) \end{aligned}$$

$$D = \begin{bmatrix} D_0 & \mathbf{0}_{12\times 6} & \mathbf{0}_{12\times 6} & \mathbf{0}_{12\times m_3} & \mathbf{0}_{12\times m_5} & 0 \\ \mathbf{0}_{6\times 12} & D_1 & \mathbf{0}_{6\times 6} & \mathbf{0}_{6\times m_3} & 0 & \\ \mathbf{0}_{6\times 12} & \mathbf{0}_{6\times 6} & D_2 & \mathbf{0}_{6\times m_3} & 0 & \\ \mathbf{0}_{2\times 12} & \mathbf{0}_{2\times 6} & \mathbf{0}_{2\times 6} & D_3 & 0 & \\ \mathbf{0}_{1\times 12} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times 6} & \mathbf{0}_{1\times m_3} & 0 & \end{bmatrix}$$

$$Q = \mathrm{diag}\{\sigma_f^2, \ \mathbf{0}_{1\times 11}, \ \sigma_{\mu_1}^2, \ \mathbf{0}_{1\times 5}, \ \sigma_{\mu_2}^2, \ \mathbf{0}_{1\times 5}, \ \sigma_{\mu_3}^2, \ \mathbf{0}_{1\times m_3}, \ \sigma_{fce}^2\}$$

[4] Annual variables and monthly indicators expressed as year-on-year growth rates could also be considered in the model, but this would require expanding the matrices considerably. Although we will not do so here, they could be incorporated simply by including the relevant rows and columns in the matrices.

4 Empirical analysis

The dynamic factor model described in the previous section will be applied to several series of international trade, with the objective of forecasting the value of the current year based on the most recent observations of selected indicators (i.e., nowcasting). We will follow three main steps in this process.

The first step consists of building a database of indicators that could potentially contribute to nowcast the target variable. In order to be eligible, the indicators have to meet several conditions. They have to be linked to the target variable on theoretical, structural or empirical grounds, so that we start the process with the hypothesis that they can potentially contribute to the nowcasting exercise. They should also be timely available since this method relies on indicators that are published quickly and reliably; any indicator published simultaneously or after the target has no value for nowcasting. Similarly, they should have a frequency at least as high as the target indicator because, for example, annual variables would likely add little value when nowcasting quarterly variables. The time series of the indicators would ideally be long enough, so that the model can have enough information to distinguish between the common factor and the idiosyncratic component. Finally, we should expect the indicators to be continuously available in the future.

There are five types of indicators that could be considered in the model.

A. Sub-components of the target variable that are released more opportunely. For example, if the target variable is the total exports of goods, we could use the exports of some countries or the exports of a particular product published by industry-specific sources. These variables are part of the target variable and they could also be correlated with trends in other sub-components (for example, other countries or other products), therefore containing important information about the aggregate.
B. Variables that are linked to the target variable through structural economic models. For instance, if our target is total imports of services, we could include determinants of the demand of these imports from different macroeconomic or structural models and incorporate them into the nowcast.
C. Other variables that could carry information about the target variable. For instance, if we are studying the trade of goods, an important indicator would be the movement of vessels through the global network of ports and the amount of cargo they transport. These variables are case-specific and allow for the exploration of innovative sources.
D. "Soft" or opinion indicators from surveys or expert assessments. These could be, for example, business or confidence indicators, purchasing managers' index, new orders estimates, and others. These variables are usually collected from surveys and their signal-to-noise ratio could be low. However, they have the advantage that they are available opportunely, frequently with a very short lag after the end of the period they cover. They are therefore the only information available for the most recent period and the first indication of shocks or trend changes that could affect the target variable.
E. Forecasts of the target variable from other sources. What is the interest of including other forecasts in the model? And why nowcast at all if there are already other forecasts available? There are at least three reasons. First, when we believe that the forecasts provide some information about the target variable, but that they are biased or have high volatility and we believe the nowcast methodology can lead to an improvement. Second, when those forecasts were produced only with low frequency variables and do not incorporate the information provided by other higher-frequency variables. And third, when those forecasts are out of date and do not incorporate the most recent developments.

These variables can by annual, quarterly or monthly. As described in Section 3, variables enter the model in specific ways and should be transformed accordingly. Annual variables are included as year-on-year growth rates, quarterly variables as quarter-on-quarter growth rates, and monthly variables as either month-or-month growth rates or percent changes with respect to the same month of the previous year. Since this requires making intra-year comparisons, all indicators should be seasonally adjusted. Official seasonally adjusted series from the source are preferred; if they are not available, they will be adjusted by applying the X-13-ARIMA-

SEATS methodology (Unites States Census Bureau, 2017).[5] All data is standardized (to a mean of zero and a variance of one) before the estimation.

Once the full database of indicators is compiled, the second step is the selection of the variables that will be included in the nowcasting model. For this, the full dynamic factor model was programmed in GNU Octave version 4.4.0. The calculation of the MLE for the model is computationally intensive. Given the expected proliferation of indicators, standard stepwise selection techniques are generally not feasible. We therefore carry out an *ad hoc* variable selection by following this sequence.

1. Define a set of initial indicators from the full list available, that a priori could be the most significant. Set the number of lags of the transition equation (7) to $m_0 = m_1 = 6$ and $m_2 = m_3 = m_4 = 3$ and run the model. This lag structure was selected because it is long enough to incorporate most of the dynamics present in the time series.
2. Discard the variables that are not significant or that have a low contribution in explaining the variability of the target variable.[6]
3. Choose the number of lags to be included in the model. A grid search across all combinations of lags is not feasible in this case. We will therefore impose that the number of lags of the transition equations for the factor and the first error term (m_0 and m_1) are equal, and so are the number of lags of the other transition equations (m_2 to m_4). This step will lead to the "core" model.
4. Apply a forward model selection process to the rest of the indicators that were not included initially, proceeding by blocks of variables.[7] The lag structure remains unchanged. Only those indicators that are significant are retained. This will lead to the final model.

There are several criteria that could be used to compare models. We will base our comparisons on two of them: (i) the percentage of variability of the target variable explained by the model calculated over the full sample, and (ii) the mean absolute error of the forecasts for the last 20% of the sample at the last data update before the actual values were published.[8] Because missing data is replaced with random draws from a normal distribution, we cannot use likelihood-based model selection criteria (such as the Akaike Information Criterion or the Schwarz Information Criterion). Although this procedure does not affect the calculation of the MLE, it does have an impact on the level of the likelihood and its derived statistics.

This is a time- and computationally-intensive process that, however, does not need to be repeated every time a series is updated. Once the final model is selected, the estimated parameters will remain fixed and they will be used to update the nowcast whenever new data becomes available. The entire variable selection procedure will only be repeated infrequently but regularly to adapt to changes in the underlying trends and correlations among the variables, or whenever new, potentially significant indicators are released.

The rest of this section will summarize the results of the nowcasting exercise for some series of international trade. A full description of the variable selection process and the analysis of the results will not be presented here due to space restrictions, but they are available from the author upon request. The estimations were calculated with data available as of mid-July 2018. All time series were compiled from January 1990 or the earliest period available until the most recent observation. They were seasonally adjusted and transformed, if this was required, according to the rules described in Section 3.

[5] Seasonal adjustment was calculated with the R package seasonal version 1.6.1, using the default options.

[6] Note, however, that "soft" indicators could show low significance since they normally add little information once the "hard" indicators are published. Their principal advantage is that they are available in a timely manner. They should therefore remain in the model even if their contribution seems minimal.

[7] Occasionally, this could require changing the variables in the core model. For example, when the core model includes the industrial production index of a group of countries (such as the Organisation for Economic Co-operation and Development (OECD) or the European Union) and we test if the disaggregation into the individual country series could improve the forecasting performance of the model.

[8] In practical terms, the sample was divided into two periods. The parameters of the model were estimated using the first 80% of the observations (the training sample). The parameters were then fixed at their estimated values and they were used to calculate forecasts for the remaining 20% of the observations (the testing sample). The mean absolute forecast error, calculated at the last data update before the actual figures were published, will be used as a criterion for model selection.

4.1 Global trade in goods

The target variable is the world value of exports of goods, as reported by UNCTADstat.[9] This is an annual time series, currently compiled between UNCTAD and the World Trade Organization (WTO). It complements traditional sources of trade data (namely, the United Nations Statistical Division's Comtrade database) with other sources of official data plus estimations based on mirror statistics and other methods. This series is updated every April, when the final figures for the previous year are published. There are other series for the global value of exports at a quarterly or even monthly frequencies (produced by UNCTAD, WTO or the International Monetary Fund (IMF), for example), but they only include the subset of countries that publish infra-annual trade data. Although this may cover a large share of world exports, it is still not equivalent to the total figure. In addition, the main use of this nowcast will be UNCTAD's Handbook of Statistics[10], which mostly includes yearly data. For this reason, we selected the annual series as the target variable of this exercise. However, in case of interest, the model for quarterly target variables described in Section 3 can be directly applied to the quarterly series.

Table 1 lists the complete list of variables considered for the nowcasting exercise and their sources. It includes monthly series for the largest exporting countries in the world,[11] plus the aggregate for the OECD (comprised of all of the above, except China and Hong Kong, plus 28 additional developed or emerging economies). For structural variables that could drive world exports, we include industrial/manufacturing production and retail trade indices as indicators of the global demand for exported goods. In terms of country coverage, we consider the economies with the largest manufacturing sector and the largest final consumption in the world, respectively.[12] Whenever possible, we also include the aggregates for the OECD and the European Union, as these blocks summarize the totals of some of the largest economies. The list also includes two unique indicators from Eurostat that, although published with a considerable lag, could provide important information on exports: non-domestic manufacturing turnover and new manufacturing orders.

We also consider additional indicators that could contribute in explaining the evolution of the global value of export. First, a quarterly and a monthly series for the export volume, since both have different coverage and publications lags. In addition to the volume, export values are also determined by prices. We use UNCTAD's free-market commodity prices and WTO's manufacturing export prices to incorporate this factor.[13] The mar-

[9] http://unctadstat.unctad.org/EN/Index.html.

[10] op.cit.

[11] According to UNCTAD data, the top 10 largest exporters in the world in 2017 were China, the United States, Germany, Japan, the Netherlands, the Republic of Korea, Hong Kong, France, Italy and the United Kingdom, in that order.

[12] According to national accounts data from the United Nations Statistics Division, the ten economies with the largest manufacturing value-added in 2016 were China, the United States, Japan, Germany, the Republic of Korea, India, Italy, France, the United Kingdom and Brazil. According to the same source, the ten countries with the largest expenditure on final consumption were the United States, China, Japan, Germany, the United Kingdom, France, India, Brazil, Italy and Canada.

[13] The series of world manufacture export prices is published by WTO on a monthly basis since 2005. However, an extended, quarterly series was produced by UNCTAD between 1960 and 2017. Both series are spliced together, and the minimum common frequency (quarterly) is retained. However, the monthly (and shorter) series is also considered as a separate indicator.

Table 1 List of indicators, global exports of goods

(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
A. Sub-components of the target variable						
Value of goods exports, China	OECD	Monthly	1	✓	✓	✓
Value of exports of goods, OECD	OECD	Monthly	2	✓	✓	
Value of exports of goods, United States	OECD	Monthly	2			✓
Value of exports of goods, Germany	OECD	Monthly	2			✓
Value of exports of goods, Japan	OECD	Monthly	1			✓
Value of exports of goods, Netherlands	OECD	Monthly	2			✓
Value of exports of goods, Republic of Korea	OECD	Monthly	1			✓
Value of exports of goods, Hong Kong	IMF	Monthly	3			✓
Value of exports of goods, France	OECD	Monthly	2			✓
Value of exports of goods, Italy	OECD	Monthly	2			✓
Value of exports of goods, United Kingdom	OECD	Monthly	2			✓
B. Structural variables						
Index of total manufacturing production, OECD	OECD	Monthly	3	✓	✓	
Index of total manufacturing production, United States	OECD	Monthly	2			✓
Index of total manufacturing production, Japan	OECD	Monthly	2			✓
Index of total manufacturing production, European Union	OECD	Monthly	2			
Index of total manufacturing production, Germany	OECD	Monthly	2			✓
Index of total manufacturing production, Korea	OECD	Monthly	2			✓
Index of new manufacturing orders, European Union	Eurostat	Monthly	3			
Index of non-domestic manuf. turnover, European Union	Eurostat	Monthly	3			
Growth rate of value-added of industry, China	NBSC	Monthly	2	✓		
Index of total retail trade value, United States	OECD	Monthly	2	✓	✓	✓

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(1) Variable	(2) Source	(3) Frequency	(4) Publication lag	(5) Models Initial	(6) Models Core	(7) Models Final
Index of total retail trade value, Japan	OECD	Monthly	3	✓	✓	✓
Index of total retail trade value, Germany	OECD	Monthly	3			
Index of total retail trade value, United Kingdom	OECD	Monthly	2			
Index of total retail trade volume, OECD	OECD	Monthly	3			
Index of total retail trade volume, United States	OECD	Monthly	2			
Index of total retail trade volume, Japan	OECD	Monthly	3			
Index of total retail trade volume, Germany	OECD	Monthly	3			
Index of total retail trade volume, United Kingdom	OECD	Monthly	2			
Growth rate of total retail sales of consumer goods, China	NBSC	Monthly	2	✓		
C. Other related indicators						
Index of free-market commodity prices	UNCTAD	Monthly	2	✓	✓	✓
Index of world manufacture export prices	WTO/UNCTAD	Quarterly	3	✓	✓	✓
Index of world manufacture export prices	WTO	Monthly	3			
Index of export volumes, world	UNCTAD	Quarterly	3	✓	✓	✓
Index of export volumes, world	CPB	Monthly	3	✓	✓	✓
Freight traffic of waterways, China	NBSC	Monthly	1			
Cargo vessel arrivals, Hong Kong	MDHK	Monthly	2			✓
Container throughput, Hong Kong	MDHK	Monthly	3			
Suez Canal traffic statistics, net tons	SCA	Monthly	1			
Panama Canal, oceangoing commercial transits	CP	Monthly	1			
Baltic Dry Index	TR	Monthly	1			
Harpex Shipping Index	TR	Monthly	1			
International economic cooperation	GDELT	Monthly	1			
International economic "positive" reporting	GDELT	Monthly	1			
Number of new trade restrictive policies implemented	GTA	Monthly	1			

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
D. "Soft" indicators						
Index of business confidence, OECD	OECD	Monthly	1	✓	✓	✓
Index of business confidence, United States	OECD	Monthly	1			
Index of business confidence, China	OECD	Monthly	2	✓	✓	✓
Index of business confidence, Japan	OECD	Monthly	1			
Index of business confidence, Germany	OECD	Monthly	1			
Index of business confidence, United Kingdom	OECD	Monthly	1			
Index of business confidence, Netherlands	OECD	Monthly	2			
Index of consumer confidence, OECD	OECD	Monthly	1	✓	✓	✓
Index of consumer confidence, United States	OECD	Monthly	2			
Index of consumer confidence, China	OECD	Monthly	1	✓	✓	✓
Index of consumer confidence, Japan	OECD	Monthly	1			
Index of consumer confidence, Germany	OECD	Monthly	1			
Index of consumer confidence, United Kingdom	OECD	Monthly	1			
Purchasing managers' index, United States	TR	Monthly	1	✓	✓	✓
Purchasing managers' index, China	NBSC	Monthly	1	✓	✓	✓
Index of new export orders, China	NBSC	Monthly	1			

Sources: OECD = Organisation for Economic Co-operation and Development; IMF = International Monetary Fund; NBSC = National Bureau of Statistics of China; UNCTAD = United Nations Conference on Trade and Development; WTO = World Trade Organization; CPB = Netherlands Bureau of Economic Policy Analysis; MDHK = Marine Department of the Government of the Hong Kong Special Administrative Region; SCA = Suez Canal Authority; CP = Canal de Panam\'{a}; TR = Thomson Reuters Eikon database; GDELT = Global Database of Events, Language and Tone Project; GTA = Global Trade Alert.

Notes: Publication lag is the number of months between the end of the period and the time of data publication, as recorded at the moment of data collection.

itime transport of cargo can also be used to track the amount of goods traded internationally, potentially a good indicator of global exports. For this, the model includes the freight traffic of waterways in China, whose ports accounted for 37.8% of the total volume of goods transported through the world's 50 largest container ports. We also include the cargo vessel arrivals and the container throughput in Hong Kong, the sixth largest port in the world.[14] Additionally, we consider the total volume of ships crossing the Suez Canal and the number of ships transiting through the Panama Canal. The Baltic Dry Index and Harpex Shipping Index could also provide information on international trade. They measure worldwide international shipping rates for dry bulk and containers freight, respectively. Since the supply of cargo ships is highly inelastic, changes in prices should reflect a corresponding change in demand for shipping. These indices could therefore act as proxy measures of export volumes.

International trade also depends on policies applied by the countries, either positively (through bilateral or multilateral free trade agreements, trade incentive programs, and others) or negatively (taking the form of protectionist measures and other restrictions). Although this is a difficult variable to measure on a global scale, we include three indicators that could give an idea of the overall economic sentiment towards trade: two related indices of international economic cooperation and an account of new trade restrictive measures implemented worldwide. For more details on the construction of these indicators, see Appendix A.

Finally, it is also important to consider "soft" indicators that can quickly provide information in case of shocks or trend changes that could affect exports. For this purpose, we consider a series of business confidence indices, consumer confidence indices and purchasing managers' indices for the largest economies. We also include the index of new export orders from China, which could potentially serve as a leading indicator of exports from this country, the largest world exporter.

We selected 17 indicators for the initial estimation, those that we believe could show a higher correlation to global export values. These are marked in the fifth column of the table above. Table 2 shows the last observations of this initial database. We see that the data is affected by all the problems described in Section 3. The target variable is observed yearly, and the list of indicators include a mix of quarterly and monthly variables. In addition, two monthly variables (the indices of industrial value added and retail sales from China) are only reported as year-on-year growth rates. The variables end at different dates and we want to exploit the most recent data available, and not restrict the sample to the last period when all variables are available (that would be March 2018). Finally, the two mentioned variables from China contain missing observations: the National Bureau of Statistics of that country only publishes combined data for January and February to limit the impact of the "Spring Festival", which falls at a different time between those months every year, on data comparability.

By applying the model selection criteria described above, this list is further reduced to 15 indicators. This is our core model, indicated in the sixth column of Table 1. This model was estimated at different lag combinations and the results are presented in Table 3. The first column reports the percentage of the variance of the world value of exports of goods that can be explained by each configuration of the model, while the second is the mean absolute error of the forecasts produced by the model over the testing sample (the last 20% of the observations) calculated at the last update before the actual data points were published. As mentioned before, these will be our two model selection criteria. We transform both statistics as ratios relative to the best model (the one with the maximum R^2 or the minimum MAE). That is, in columns (3) and (4) of the table, the models with a score of one are the best performers; models with a lower score perform worse relative to the best performers. The final column averages both standardized measures as a summary of the selection criteria. We see that models with a limited number of lags are generally worse, but also that higher lags do not necessarily lead to better performance. The optimal lag structure is given by (8,2), so that the transition equation in (7) is written with $m_0 = m_1 = 8$ and $m_2 = m_3 = m_4 = 2$.

[14] http://www.worldshipping.org/about-the-industry/global-trade/top-50-world-containerports.

Table 2 Initial database, global exports of goods

Period	Exports, China	Exports, OECD	IPI, OECD	IPI, China	RTI, USA	RTI, Japan	RTI, China	Com-modity prices	Manuf export prices (Q)
2017.01	0.004	0.005	0.002		0.009	0.003		0.023	
2017.02	-0.003	0.017	0.004		-0.005	0.003		0.008	
2017.03	0.084	0.010	0.003	7.6	0.002	0.001	10.9	-0.043	0.007
2017.04	-0.035	-0.005	0.007	6.5	0.007	0.009	10.7	0.001	
2017.05	-0.018	0.029	-0.002	6.5	-0.003	-0.009	10.7	-0.024	
2017.06	0.031	0.005	-0.001	7.6	0.004	0.003	11.0	-0.041	0.021
2017.07	-0.013	0.012	0.003	6.4	0.003	0.003	10.4	0.016	
2017.08	-0.012	0.032	0.008	6.0	0.000	-0.005	10.1	0.036	
2017.09	0.017	0.016	-0.002	6.6	0.021	0.006	10.3	0.039	0.041
2017.10	-0.021	-0.026	0.005	6.2	0.006	0.001	10.0	0.016	
2017.11	0.081	0.029	0.007	6.1	0.008	0.010	10.2	0.046	
2017.12	0.014	0.016	0.003	6.2	0.000	0.010	9.4	0.008	0.009
2018.01	-0.039	0.021	-0.008		-0.002	-0.016		0.079	
2018.02	0.324	-0.005	0.002		0.001	0.005		-0.047	
2018.03	-0.262	0.011	0.003	6.0	0.007	-0.006	10.1	0.005	0.037
2018.04	0.080	0.001	0.002	7.0	0.004	0.013	9.4	0.062	
2018.05	0.002	-0.022		6.8	0.011		8.5	0.046	
2018.06	0.035								
2018.07									

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Period	World export vol (Q)	World export vol (M)	BCI, OECD	BCI, China	CCI, OECD	CCI, China	PMI, USA	PMI, China
2017.01		-0.007	0.00115	0.00008	0.00032	0.00384	0.02394	-0.00195
2017.02		-0.002	0.00131	0.00026	0.00035	0.00441	0.03597	0.00585
2017.03	0.016	0.023	0.00060	-0.00010	0.00088	0.00218	-0.01736	0.00388
2017.04		-0.019	0.00017	-0.00071	0.00098	0.00194	-0.02297	-0.01158
2017.05		0.014	0.00055	-0.00013	0.00066	0.00076	0.00362	0.00000
2017.06	0.013	0.001	0.00133	0.00061	0.00017	0.00203	0.02162	0.00977
2017.07		-0.001	0.00122	0.00062	0.00018	0.00359	-0.00353	-0.00580
2017.08		0.007	0.00136	0.00105	0.00048	0.00570	0.04956	0.00584
2017.09	0.011	0.005	0.00114	0.00085	0.00056	0.00948	0.01518	0.01354
2017.10		-0.020	0.00034	-0.00053	0.00074	0.00869	-0.02824	-0.01527
2017.11		0.036	0.00014	-0.00078	0.00027	0.00309	-0.00513	0.00388
2017.12	0.011	0.004	0.00015	-0.00130	0.00005	0.00149	0.01890	-0.00386
2018.01		0.007	-0.00015	-0.00163	0.00034	0.00075	-0.00337	-0.00581
2018.02		-0.011	-0.00046	-0.00107	0.00045	0.00070	0.02876	-0.01949
2018.03	0.002	-0.014	-0.00095	0.00114	0.00023	-0.00061	-0.02467	0.02386
2018.04		0.015	-0.00068	0.00155	-0.00021	-0.00017	-0.03373	-0.00194
2018.05			0.00000	0.00193	-0.00046	-0.00002	0.02443	0.00973
2018.06			0.00055				0.02555	-0.00771
2018.07								

Notes: IPI = industrial/manufacturing production index; RTI = retail trade index; BCI = business confidence index; CCI = consumer confidence index; PMI = purchasing managers' index. For more details on the variables and their sources, see Table 1. This table shows the values of the variables prior to standardization.

Table 3 Lag order selection, global exports of goods

Lag structure	(1) Results R^2	(2) Results MAE	(3) Results, standardized R^2	(4) Results, standardized MAE	(5) Results, standardized Average
(8, 3)	86.0	0.0451	0.9719	0.6139	0.7929
(7, 3)	82.6	0.0324	0.9330	0.8552	0.8941
(6, 3)	71.8	0.0347	0.8109	0.7972	0.8040
(5, 3)	88.5	0.0386	1.0000	0.7175	0.8588
(4, 3)	85.9	0.0389	0.9702	0.7121	0.8412
(3, 3)	76.0	0.0524	0.8589	0.5281	0.6935
(2, 3)	76.6	0.0509	0.8661	0.5446	0.7054
(1, 3)	24.8	0.0756	0.2799	0.3666	0.3232
(8, 2)	81.5	0.0277	0.9209	1.0000	**0.9605**
(7, 2)	74.9	0.0480	0.8463	0.5773	0.7118
(6, 2)	73.7	0.0514	0.8328	0.5384	0.6856
(5, 2)	82.6	0.0426	0.9334	0.6497	0.7916
(4, 2)	74.6	0.0320	0.8430	0.8666	0.8548
(3, 2)	75.7	0.0493	0.8556	0.5621	0.7089
(2, 2)	75.8	0.0498	0.8566	0.5565	0.7066
(1, 2)	25.1	0.0735	0.2834	0.3767	0.3301
(8, 1)	87.5	0.0355	0.9891	0.7807	0.8849
(7, 1)	86.5	0.0410	0.9771	0.6754	0.8263
(6, 1)	78.5	0.0506	0.8873	0.5473	0.7173
(5, 1)	74.9	0.0532	0.8459	0.5204	0.6831
(4, 1)	68.9	0.0531	0.7785	0.5220	0.6503
(3, 1)	73.1	0.0425	0.8266	0.6510	0.7388
(2, 1)	76.8	0.0521	0.8682	0.5317	0.7000
(1, 1)	81.0	0.0484	0.9153	0.5720	0.7436

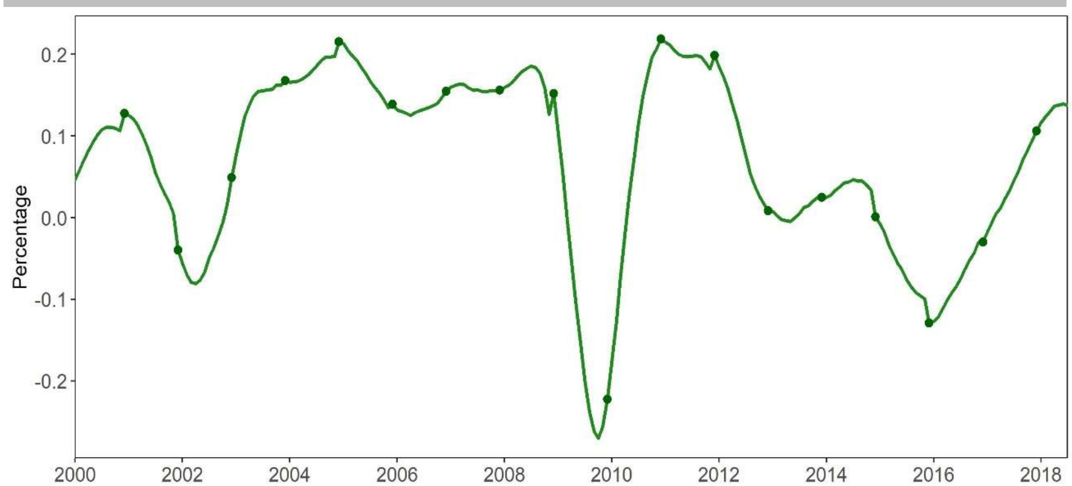
Notes: R^2 is the percentage of variance of the target variable explained by the model; MAE is the mean absolute forecast error over the testing sample at the last update before the actual values were published. Both statistics were standardized so that the best indicator (max R^2 and min MAE) equals one; these are reported in columns (3) and (4), respectively. Column (5) reports the average of both standardized measures.

After this step, the forward selection model process was applied to the rest of the indicators, using the percentage of variance explained and the mean absolute forecast error as selection criteria. This was implemented by blocks, where the indicators of one type were tested and selected, before moving to the next type of variables. The step-by-step outcome of the process is not included here to save space, but it is available from the author on request. The final list of indicators is marked in the last column of Table 1, a total of 27 variables. It can be seen that this does not expand considerably beyond the core model, with the exception that country-disaggregated series are generally preferred to the aggregates, since they provide additional information and they are available sooner.

The method described above takes information from the 27 indicators to estimate the monthly values of the unobserved common factor. Each indicator has a different weight in the estimation of the factor. Moreover, the weights change through time, as the comovements between the indicators and the factor evolve. Table 4 shows the contribution of each variable in the most recent months. The first column corresponds to the target variable, world exports of goods, while the rest of the table shows the selected indicators. There are several points to highlight in this table. First, the model is built in such a way that the estimates are anchored to the actual data. Consequently, whenever the target variable is observed (December 2017 in the Table), it takes all the weight and the other indicators do not contribute to estimate the factor. Second, whenever a variable is missing, its contribution to the estimation is zero. We can see that the weights are evenly distributed between the country-level export variables, with a smaller contribution from the structural variables and most of the other indicators (with the exception of the indices of export volume, which take a relatively higher weight). The soft indicators, as expected, only have a small effect on the estimation. However, in the most recent periods, not all variables are available and the weight of those indicators that are observed increases. We can see that in June 2018 only six of the 27 indicators are available, including some series derived from surveys, and their contribution to the estimation of the factor rises. Starting in July 2018, no additional data is observed and the weight of all variables becomes zero. The estimates for the rest of the sample are obtained solely from the dynamics specified in the model.

By applying the estimated factor loadings, the factor can then be used to calculate monthly estimates of the target variable (and any of the input indicators, if desired). The results are shown in Figure 1. The line represents the estimated annual growth rate of global exports of goods over the past 12 months, with respect to the 12 months before that. That is, the figure for December 2017 is the growth of total exports for the period January-December 2017, with respect to January-December 2016 (i.e., the annual growth rate for 2017). Meanwhile, the figure for November 2017 is the growth of total exports for the period from December 2016 to November 2017, respective to the same period one year before. In other words, it is the rolling cumulative growth rate of the past 12 months. The points show the actual growth rate of global exports of goods. As explained above, it can be seen that the estimate (the line) and the actual figures (the points) coincide when the latter are observed. With this figure we can be study the monthly movements of global exports. For example, one can see the the downturn observed in 2001 continued during the first months of 2002, and reached a positive growth rate towards the end of the year. Also, the worst period of the global financial crisis took place, according to this model, in October 2009, when the annual growth rate reached -27%. This graph extends until June 2018, the last period where we have observed values for at least some of the indicators. The model can indeed explain 98.7% of the variability of the annual target variable.

Figure 1
Annual growth rates, global exports of goods



Note: UNCTAD calculations based on data sources reported in Table 1. The line represents the estimated annual growth rate of the past 12 months with respect the 12 months before that (i.e., it is a rolling cumulative growth rate over the last 12 months). This is the main output of the nowcast model. The points represent the actual values for the growth rate. The model anchors the estimates to the actual figures, so they coincide whenever the growth rate is observed.

The model has a dynamic structure and this allows us to calculate forecasts for the unobserved factor (and, consequently, for the target variable) even when there is no new information available. The final model has a forecasting performance, measured by the MAE calculated at the last point before the release of the final figures, of 0.0118. In other words, the forecasts generated by this model had an average error of 1.18 percentage points. This is a positive result, given the high variability of the target series.

Table 4 Contribution to nowcast estimation, global exports of goods

Period	World exports	Exports, China	Exports, United States	Exports, Germany	Exports, Japan	Exports, Netherlands	Exports, Rep. of Korea	Exports, Hong Kong	Exports, France
2017.01	0.0000	0.0530	0.0682	0.1098	0.0530	0.1114	0.0677	0.0333	0.1299
2017.02	0.0000	0.0543	0.0685	0.1108	0.0523	0.1108	0.0690	0.0342	0.1326
2017.03	0.0000	0.0509	0.0644	0.1034	0.0485	0.1048	0.0645	0.0322	0.1254
2017.04	0.0000	0.0538	0.0685	0.1102	0.0524	0.1116	0.0684	0.0339	0.1320
2017.05	0.0000	0.0543	0.0686	0.1106	0.0521	0.1113	0.0689	0.0342	0.1330
2017.06	0.0000	0.0510	0.0644	0.1035	0.0485	0.1048	0.0646	0.0322	0.1254
2017.07	0.0000	0.0538	0.0685	0.1102	0.0524	0.1116	0.0684	0.0339	0.1321
2017.08	0.0000	0.0543	0.0686	0.1106	0.0521	0.1113	0.0688	0.0342	0.1330
2017.09	0.0000	0.0510	0.0644	0.1035	0.0485	0.1048	0.0646	0.0322	0.1254
2017.10	0.0000	0.0538	0.0685	0.1102	0.0524	0.1116	0.0684	0.0339	0.1321
2017.11	0.0000	0.0543	0.0686	0.1106	0.0521	0.1113	0.0688	0.0342	0.1330
2017.12	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.01	0.0000	0.0530	0.0682	0.1098	0.0530	0.1114	0.0677	0.0333	0.1299
2018.02	0.0000	0.0543	0.0685	0.1108	0.0523	0.1108	0.0690	0.0342	0.1326
2018.03	0.0000	0.0509	0.0644	0.1034	0.0485	0.1048	0.0645	0.0322	0.1254
2018.04	0.0000	0.0538	0.0685	0.1102	0.0524	0.1116	0.0684	0.0339	0.1320
2018.05	0.0000	0.0593	0.0759	0.1221	0.0583	0.1241	0.0755	0.0000	0.1457
2018.06	0.0000	0.2564	0.0000	0.0000	0.3097	0.0000	0.3387	0.0000	0.0000
2018.07	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.08	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.09	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

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Period	Exports, Italy	Exports, UK	IPI, United States	IPI, Japan	IPI, Germany	IPI, Rep. of Korea	RTI, United States	RTI, Japan	Commodity prices
2017.01	0.0889	0.0664	0.0031	0.0203	0.0409	0.0221	0.0208	0.0136	0.0155
2017.02	0.0900	0.0659	0.0026	0.0196	0.0406	0.0216	0.0205	0.0139	0.0144
2017.03	0.0844	0.0611	0.0021	0.0179	0.0376	0.0199	0.0191	0.0130	0.0132
2017.04	0.0896	0.0658	0.0027	0.0197	0.0405	0.0216	0.0206	0.0138	0.0147
2017.05	0.0900	0.0656	0.0025	0.0194	0.0404	0.0215	0.0205	0.0139	0.0144
2017.06	0.0845	0.0612	0.0022	0.0180	0.0376	0.0199	0.0191	0.0131	0.0132
2017.07	0.0896	0.0658	0.0027	0.0197	0.0405	0.0216	0.0206	0.0138	0.0147
2017.08	0.0900	0.0656	0.0025	0.0194	0.0404	0.0215	0.0205	0.0139	0.0144
2017.09	0.0845	0.0612	0.0022	0.0180	0.0376	0.0199	0.0191	0.0131	0.0132
2017.10	0.0896	0.0658	0.0027	0.0197	0.0405	0.0216	0.0206	0.0138	0.0147
2017.11	0.0900	0.0656	0.0025	0.0194	0.0404	0.0215	0.0205	0.0139	0.0144
2017.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.01	0.0889	0.0664	0.0031	0.0203	0.0409	0.0221	0.0208	0.0136	0.0155
2018.02	0.0900	0.0659	0.0026	0.0196	0.0406	0.0216	0.0205	0.0139	0.0144
2018.03	0.0844	0.0611	0.0021	0.0179	0.0376	0.0199	0.0191	0.0130	0.0132
2018.04	0.0896	0.0658	0.0027	0.0197	0.0405	0.0216	0.0206	0.0138	0.0147
2018.05	0.0991	0.0732	0.0031	0.0221	0.0450	0.0242	0.0229	0.0000	0.0167
2018.06	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.07	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.08	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.09	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

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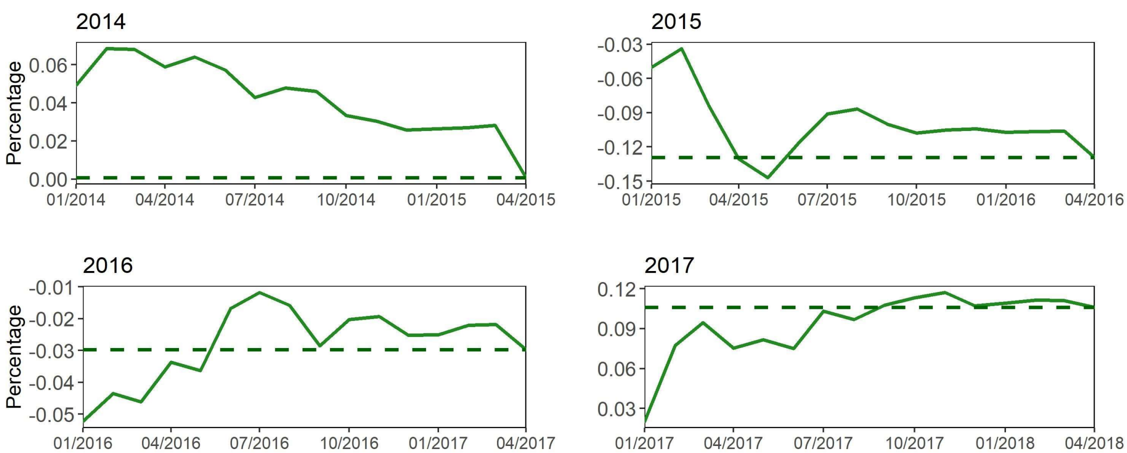
Period	Manuf export prices (Q)	World export volume (Q)	World export volume (M)	Cargo ships, Hong Kong	BCI, OECD	BCI, China	CCI, OECD	CCI, China	PMI, United States	PMI, China
2017.01	0.0000	0.0000	0.0525	0.0109	0.0003	0.0022	0.0006	0.0017	0.0031	0.0109
2017.02	0.0000	0.0000	0.0509	0.0109	0.0001	0.0017	0.0004	0.0007	0.0029	0.0107
2017.03	0.0293	0.0345	0.0470	0.0100	0.0002	0.0020	0.0005	0.0010	0.0026	0.0103
2017.04	0.0000	0.0000	0.0513	0.0108	0.0003	0.0021	0.0006	0.0013	0.0030	0.0109
2017.05	0.0000	0.0000	0.0507	0.0108	0.0002	0.0019	0.0005	0.0009	0.0029	0.0108
2017.06	0.0293	0.0337	0.0471	0.0101	0.0002	0.0019	0.0005	0.0009	0.0026	0.0103
2017.07	0.0000	0.0000	0.0513	0.0108	0.0003	0.0021	0.0006	0.0013	0.0030	0.0109
2017.08	0.0000	0.0000	0.0507	0.0108	0.0002	0.0019	0.0005	0.0009	0.0029	0.0108
2017.09	0.0293	0.0338	0.0471	0.0101	0.0002	0.0019	0.0005	0.0009	0.0026	0.0103
2017.10	0.0000	0.0000	0.0513	0.0108	0.0003	0.0021	0.0006	0.0013	0.0030	0.0109
2017.11	0.0000	0.0000	0.0507	0.0108	0.0002	0.0019	0.0005	0.0009	0.0029	0.0108
2017.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.01	0.0000	0.0000	0.0525	0.0109	0.0003	0.0022	0.0006	0.0017	0.0031	0.0109
2018.02	0.0000	0.0000	0.0509	0.0109	0.0001	0.0017	0.0004	0.0007	0.0029	0.0107
2018.03	0.0293	0.0345	0.0470	0.0100	0.0002	0.0020	0.0005	0.0010	0.0026	0.0103
2018.04	0.0000	0.0000	0.0513	0.0108	0.0003	0.0021	0.0006	0.0013	0.0030	0.0109
2018.05	0.0000	0.0000	0.0000	0.0120	0.0003	0.0025	0.0007	0.0017	0.0033	0.0122
2018.06	0.0000	0.0000	0.0000	0.0000	0.0064	0.0000	0.0000	0.0000	0.0223	0.0665
2018.07	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.08	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.09	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2018.12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: IPI = industrial/manufacturing production index; RTI = retail trade index; BCI = business confidence index; CCI = consumer confidence index; PMI = purchasing managers' index. For more details on the variables and their sources, see Table 1.

To visualize the real-time performance of the forecasts, we simulate the availability of the 27 indicators at every month since 2014.[15] We then use each data vintage to estimate the model and produce a year-end forecast. The first forecast is calculated for January of the respective year, and then every month until March of the following year, the last month before the actual figure is released. This means that for the growth rate of 2014, for instance, we have one monthly forecast from January 2014 until March 2015 and the actual figure is published in April 2015. The four panels of Figure 2 show the results for the last four years. Given the lag structure of the model described above, a few months after the last observations, the model havs no new information and the properties of the autorregresive model will dominate the dynamics. Because of this, we expect the forecasting performance to quickly deteriorate as the forecasting period is extended. Indeed, the first forecasts of each year is relatively poor. However, as new information becomes available, they rapidly improve. It is interesting to note that, by October or November of every year, the model has obtained enough information to forecast the year-end growth rate and this remains practically fixed until the actual figure is finally released in April of the next year.

Figure 2
Real-time growth rate forecasts, global exports of goods



Note: UNCTAD calculations based on data sources reported in Table 1. The solid lines represent year-end growth rate forecasts produced by the nowcast model estimated with the data available at each month. The dashed lines are the actual growth rates, published in April of the following year. Note that every plot has different limits in the vertical axis.

2015 is a noteworthy year because it represents a change of trend into negative growth. The initial forecasts were poor, as expected. However, the incoming information from the indicators quickly pulled the forecast down until it settled at about -11% by October; the final figure was -12.9%. Also, we can see that the first forecast for 2017 was only 2%, but that the positive news announced by the indicators led to quick revisions of the forecast until it reached 10.3% in July. After that, it remained stable and closely approximated the final growth rate of 10.6% that was published in April 2018.

[15] This is only a pseudo-real-time analysis since the actual data availability at each month is unknown. Even if we know the date of each data release, according the publication schedule of each indicator, most of the times historic data is also revised at each release and we do not have the details for each of these backward revisions.

4.2 Global trade in services

Services accounted for 23.5% of total international trade of goods and services in 2017.[16] This share, however, has followed an increasing trend. Services are therefore an important and growing portion of international transactions. Because of their diversity and intangibility, trade in services is generally more difficult to measure than merchandise trade. However, the statistical framework for trade in services is well established and its coverage has been constantly improving as more countries implement it. Internationally-traded services can be classified according to four categories: goods-related services (3.4%), transport (17.4%), travel (24.5%) and other services (54.7%), where the numbers in parentheses refer to the share of each category in total trade in services in 2017. The group "other services" comprises a wide variety of services: construction, insurance and pension services, financial services, charges for the use of intellectual property, telecommunications and information services, other business services, personal and recreational services, and government services. Consequently, the indicators that will provide information for the nowcasting model should reflect this wide variety of economic areas.

The target variable is therefore the global value of trade in services, as reported by UNCTADstat. This is an annual time series calculated in collaboration between UNCTAD, the WTO and the International Trade Center (ITC). It is compiled from data from the IMF, Eurostat, the OECD, the United Nations and other national and international sources. It is published every April, when the data for the preceding year is released. The database also includes a quarterly series for services, but its coverage is more limited, so it will not be pursued here.

The list of indicators that were considered is presented in Table 5. First, the model will include existing series of exports of services at the country level. Although most countries only publish quarterly data as part of their balance of payments statistics, some of them also release monthly series. The ten largest exporters of services in 2017 were included.[17] After this, a long list of indicators aim to capture the different types of services.

- International merchandise trade and trade in services are complementary. First, because internationally traded goods need to be transported from sellers to buyers (transport is one of the types of international trade in services). Additionally, goods transported may also be subject to international insurance. Indirectly, trade in goods could also create opportunities for financial services, telecommunications, information services and other business activities. Different categories of services could then be correlated to trade volumes, trade values or both. For example, while transport will be mostly dependent of volumes, insurance costs will vary with the total value of the merchandise. For this reason, we cover indicators for both volume and value of merchandise trade. For volumes, we include a monthly index of world export volumes, cargo traffic through the Panama and Suez canals, port statistics from China and Hong Kong, and the Baltic Dry and Harpex Shipping indices (both of which are proxies of global export volumes, as described previously). For values, we consider the value of exports of goods for five large world exporters at the individual or group level: OECD, European Union, China, the United States and Germany.
- Travel services are one of the main categories of international services and they can be directly measured through tourism statistics. The nowcast will test international tourism statistics for the 10 largest destinations in the world.[18] The growth rate of world tourism is also included. Since infra-annual statistics for China are not available, we add two series measuring tourist arrivals in North-East and South-East Asia.
- Goods-related services refer to manufacturing services and maintenance and repair. Even if they only represent a small a share of total trade in services, they could be complementary to other service categories (finance and insurance, other business services, etc.) To account for this, we incorporate industrial production indices for the OECD, United States and Japan.
- Capital movements around the world also generate demand for international services, in the form of financial, insurance and other types of business activities. However, not all financial flows require the same amount of added

[16] Author calculations based on data from UNCTADstat.

[17] According to data from UNCTADstat, they were the United States, the United Kingdom, Germany, France, China, the Netherlands, Ireland, Japan, India and Singapore, in this order.

[18] According to World Tourism Organization (2018), the ten most visited destinations in 2017, in terms of international tourist arrivals, were France, Spain, United States, China, Italy, Mexico, the United Kingdom, Turkey, Germany and Thailand.

services. Foreign direct investment (FDI) is, in principle, more service-intensive because it needs to be supported by a wider range of financial and legal services. We therefore cover this area by including FDI indicators. We consider global FDI flows, as well as inward FDI to the OECD and two of the largest emerging markets: China and India.

In addition, there are other variables that could provide relevant information to estimate trade in services. One of them is the performance of the tertiary sector in the largest exporters. However, service-specific production indices are still not widespread and we could only cover the United Kingdom, Japan, France and Brazil, plus the retail trade index for the United States. We also include price information (the average unit value of global exports and a free-market commodity price index) that could directly or indirectly affect the level of traded services. As in the case of global trade in goods, we also consider the three measures of economic cooperation and trade restrictions detailed in Appendix A.

Finally, we include survey-based information that could provide timely information on the target variable. Service-specific indicators are not as common as industrial production or overall econmic activity surveys, so we will only include a business confidence index for the services sector of the European Union; non-manufacturing purchasing managers' indices for the United States, China and Japan; and general consumer confidence indices for the OECD and China.

An initial list of 20 indicators was proposed, but this was further reduced to a core model of 17 variables after the first estimation. The initial and core models are identified in columns (5) and (6) of the table below, respectively. The next step was the selection of the lag structure of the dynamic model, which was obtained by testing several combinations of lags terms and choosing the best performer. The results, presented in Table 6, point to a model with $m_0 = m_1 = 4$ and $m_2 = m_3 = m_4 = 3$.

A forward model selection procedure, parallel to the one described above, suggests a final model consisting of the 25 variables marked in column (7) of Table 5. The monthly estimate for the world trade in services is shown in Figure 3. We can see that this estimate does not have such a good performance as for global merchandise trade. This is evident, for example, in the large jumps registered at the end of 2005 or 2007, caused by sudden revisions of the estimate when the final figures were published. However, the model's performance improves considerably later in the sample. Indeed, the model is chosen so that it minimizes the forecast error over the 20% final section of the sample (the testing sample) and the corrections in the most recent years are much smaller. In total, the model can explain 89.7% of the variability of the annual target variable.

To evaluate the forecasting accuracy of the model, we calculate a final forecast at the last data release before the final figures are published and we measure the absolute error. When we average the errors over the final 20% of the sample, to obtain a forecasting MAE of 0.0118. Figure 4 presents charts of the real-time forecasts generated by the model over the last four years. Although there is a margin of error, as reflected in the MAE, the model correctly identifies trend changes and other dynamics of the series. For example, the model suggested a downward turn for 2015. Although it settled at a forecast of about -2%, short of the actual figure observed, it succeeded in identifying this trend reversal after five years of positive growth. For 2017, the model also correctly forecast the fast recovery in the growth rate of the target variable.

Table 5 List of indicators, global exports of services

(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
A. Sub-components of the target variable						
Exports of services, United States	FRED	Monthly	2	✓	✓	✓
Exports of services, United Kingdom, series 1	TR	Monthly	2	✓	✓	✓
Exports of services, United Kingdom, series 2	OECD	Quarterly	4			✓
Exports of services, Germany	Eurostat	Monthly	2	✓	✓	✓
Exports of services, France	IMF	Quarterly	4	✓	✓	✓
Exports of services, China	OECD	Quarterly	4	✓	✓	✓
Exports of services, Netherlands	IMF	Quarterly	4			✓
Exports of services, Ireland	Eurostat	Quarterly	4			
Exports of services, Japan	BOJ	Monthly	2			
Exports of services, India	OECD	Quarterly	4			
Exports of services, Singapore	IMF	Quarterly	4			✓
B. Structural variables						
Index of export volumes, world	CPB	Monthly	3	✓	✓	✓
Suez Canal traffic statistics, net tons	SCA	Monthly	1			
Panama Canal, oceangoing commercial transits	CP	Monthly	1			✓
Freight traffic of waterways, China	NBSC	Monthly	1			
Cargo vessel arrivals, Hong Kong	MDHK	Monthly	2			
Container throughput, Hong Kong	MDHK	Monthly	3			
Baltic Dry Index	TR	Monthly	1			
Harpex Shipping Index	TR	Monthly	1			
Value of exports of goods, OECD	OECD	Monthly	2	✓	✓	✓
Value of exports of goods, European Union	OECD	Monthly	2			

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
Value of exports of goods, China	OECD	Monthly	1	✓	✓	✓
Value of exports of goods, United States	OECD	Monthly	2			
Value of exports of goods, Germany	OECD	Monthly	2			
Tourist arrivals, world total, growth rate	UNWTO	Monthly	4	✓	✓	✓
Tourist arrivals, France	Eurostat	Monthly	6			
Tourist arrivals, Spain	Eurostat	Monthly	2			
Tourism receipts, United States, growth rate	UNWTO	Monthly	4			
Tourist arrivals, Italy	Eurostat	Monthly	4			
Tourist arrivals, Mexico	Banxico	Monthly	2			
Tourist arrivals, United Kingdom	Eurostat	Monthly	4			✓
Tourist arrivals, Turkey	TSI	Quarterly	4			
Tourist arrivals, Germany	Eurostat	Monthly	2			
Tourist arrivals, Thailand	TR	Monthly	2			
Tourist arrivals, North-East Asia, growth rate	UNWTO	Monthly	4			✓
Tourist arrivals, South-East Asia, growth rate	UNWTO	Monthly	4			✓
Index of total manufacturing production, OECD	OECD	Monthly	3	✓	✓	✓
Index of total manufacturing production, United States	OECD	Monthly	2			
Index of total manufacturing production, Japan	OECD	Monthly	2			
Total inward foreign direct investment, world	OECD	Quarterly	4	✓		
Total inward foreign direct investment, OECD	OECD	Quarterly	4			
Total foreign direct investment, China	TR	Monthly	1			✓
Total foreign direct investment, India	TR	Monthly	1			
C. Other related indicators						
Index of services production, United Kingdom	ONS	Monthly	2	✓	✓	✓
Index of services production, Japan	BOJ	Monthly	2	✓	✓	✓

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(1) Variable	(2) Source	(3) Frequency	(4) Publication lag	(5) Models Initial	(6) Models Core	(7) Models Final
Index of services production, France	Eurostat	Monthly	5	✓		
Index of services production, Brazil	IBGE	Monthly	4			
Index of total retail trade value, United States	OECD	Monthly	2	✓	✓	✓
Index of total retail trade value, Japan	OECD	Monthly	3			
Average unit value of exports, world	CPB	Monthly	3	✓	✓	✓
Index of free-market commodity prices	UNCTAD	Monthly	1			
International economic cooperation	GDELT	Monthly	1			
International economic "positive" reporting	GDELT	Monthly	1			
Number of new trade restrictive policies implemented	GTA	Monthly	1			
D. "Soft" indicators						
Index of business confidence, services sector, European Union	Eurostat	Monthly	1	✓		
Purchasing managers' index, non-manufacturing, United States	TR	Monthly	1	✓	✓	✓
Purchasing managers' index, non-manufacturing, China	TR	Monthly	1	✓	✓	✓
Purchasing managers' index, non-manufacturing, Japan	TR	Monthly	1	✓	✓	✓
Index of consumer confidence, OECD	OECD	Monthly	1			
Index of consumer confidence, China	OECD	Monthly	2			

Sources: Sources: FRED = Federal Reserve Economic Data; TR = Thomson Reuters Eikon database; OECD = Organisation for Economic Co-operation and Development; Eurostat = Statistical Office of the European Union; IMF = International Monetary Fund; BOJ = Bank of Japan; CPB = Netherlands Bureau of Economic Policy Analysis; SCA = Suez Canal Authority; CP = Canal de Panam\'{a}; NBSC = National Bureau of Statistics of China; MDHK = Marine Department of the Government of the Hong Kong Special Administrative Region; UNWTO = United Nations World Tourism Organization; Banxico = Central Bank of Mexico; TSI = Turkish Statistical Institute; ONS = Office for National Statistics of the United Kingdom; IBGE = Brazilian Institute of Geography and Statistics; UNCTAD = United Nations Conference on Trade and Development; GDELT = Global Database of Events, Language and Tone Project; GTA = Global Trade Alert.

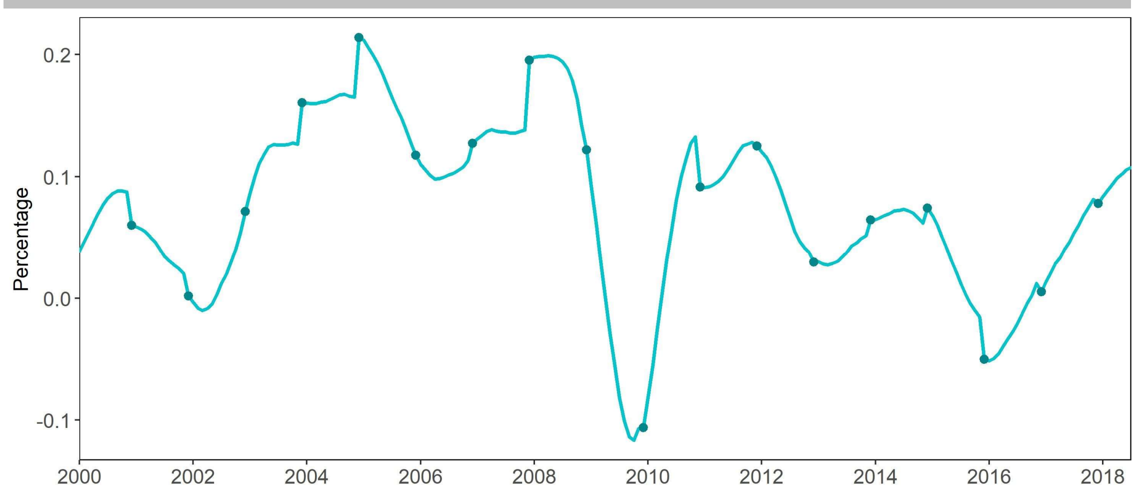
Notes: Publication lag is the number of months between the end of the period and the time of data publication, as recorded at the moment of data collection.

Table 6 Lag order selection, global exports of services

Lag structure	(1) Results R^2	(2) Results MAE	(3) Results, standardized R^2	(4) Results, standardized MAE	(5) Results, standardized Average
(8, 3)	48.2	0.0289	0.9897	0.6935	0.8416
(7, 3)	47.6	0.0302	0.9775	0.6620	0.8198
(6, 3)	48.7	0.0292	1.0000	0.6861	0.8431
(5, 3)	44.4	0.0298	0.9124	0.6706	0.7915
(4, 3)	48.3	0.0200	0.9912	1.0000	**0.9956**
(3, 3)	43.8	0.0316	0.8988	0.6341	0.7664
(2, 3)	44.9	0.0305	0.9230	0.6564	0.7897
(1, 3)	44.7	0.0259	0.9178	0.7738	0.8458
(8, 2)	39.1	0.0332	0.8028	0.6032	0.7030
(7, 2)	40.9	0.0335	0.8394	0.5971	0.7182
(6, 2)	39.5	0.0333	0.8119	0.6010	0.7065
(5, 2)	40.2	0.0336	0.8263	0.5948	0.7105
(4, 2)	39.5	0.0334	0.8103	0.5996	0.7049
(3, 2)	37.4	0.0342	0.7674	0.5850	0.6762
(2, 2)	39.1	0.0331	0.8032	0.6049	0.7041
(1, 2)	38.3	0.0340	0.7864	0.5891	0.6877
(8, 1)	36.9	0.0349	0.7568	0.5725	0.6646
(7, 1)	37.2	0.0335	0.7630	0.5964	0.6797
(6, 1)	37.2	0.0336	0.7638	0.5958	0.6798
(5, 1)	37.4	0.0336	0.7682	0.5958	0.6820
(4, 1)	37.4	0.0336	0.7678	0.5949	0.6814
(3, 1)	35.7	0.0340	0.7332	0.5886	0.6609
(2, 1)	35.7	0.0361	0.7337	0.5549	0.6443
(1, 1)	37.7	0.0344	0.7736	0.5808	0.6772

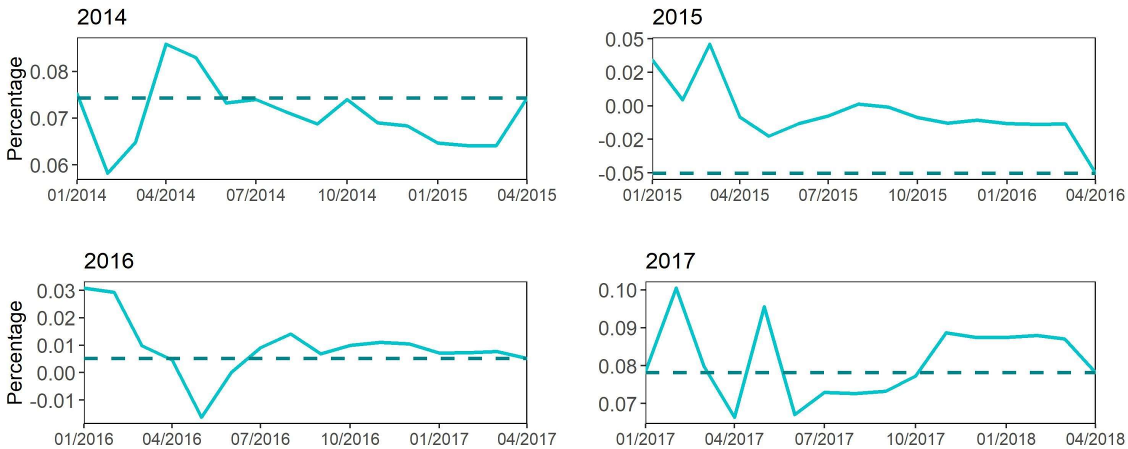
Notes: R^2 is the percentage of variance of the target variable explained by the model; MAE is the mean absolute forecast error over the testing sample at the last update before the actual values were published. Both statistics were standardized so that the best indicator (max R^2 and min MAE) equals one; these are reported in columns (3) and (4), respectively. Column (5) reports the average of both standardized measures.

Figure 3
Annual growth rates, global exports of services



Note: UNCTAD calculations based on data sources reported in Table 5. The line represents the estimated annual growth rate of the past 12 months with respect the 12 months before that (i.e., it is a rolling cumulative growth rate over the last 12 months). This is the main output of the nowcast model. The points represent the actual values for the growth rate. The model anchors the estimates to the actual figures, so they coincide whenever the growth rate is observed.

Figure 4
Real-time growth rate forecasts, global exports of services



Note: UNCTAD calculations based on data sources reported in Table 5. The solid lines represent year-end growth rate forecasts produced by the nowcast model estimated with the data available at each month. The dashed lines are the actual growth rates, published in April of the following year. Note that every plot has different limits in the vertical axis.

4.2 Global gross domestic product

The main target variables reported in this paper are total international trade in goods and services. However, the same methodology can be applied to any other variable, provided that there are sufficient high-frequency indicators available to guide the nowcast. We will briefly present here such an extension to another macroeconomic aggregate of relevance: global gross domestic product (GDP). Specifically, the target variable is the growth rate of world GDP in constant 2010 USD, as reported in UNCTADstat. The underlying data is provided by the United Nations Statistics Division, plus additional UNCTAD estimates. The GDP in national currency for every country is converted to USD using the annual period-average exchange rate of the base year (2010) and then aggregated to the global level. This variable is updated in July, when the final estimate of the previous year is published.

As the most comprehensive macroeconomic aggregate, GDP encompasses economic transactions between different actors across all sectors of economic activity. Therefore, it is possible to construct the nowcast model around a vast list of indicators. Table 7 lists the ones that were selected for this exercise, obtained from identifying variables that are, *a priori*, relevant for each of the categories described above. The variable selection process was also informed by the nowcast models reported in the literature.

We first include real GDP figures of the 10 largest economies.[19] We also add the monthly GDP estimate of OECD, calculated as part of this Organization's opportune indicators system. Country-disaggregated information of economic sectors of relevance to track global product are also included. These are manufacturing, industry, retail trade and import volumes. We cover data for the largest economies in each of the sectors, subject to data availability. Labor markets follow closely the developments of global product and, because of this, employment and unemployment rates of the largest economies are included. Additionally, we introduce some indicators that can gauge the global state of the economy and that have been reported in the literature: cargo transport through the Suez and Panama canals, as

[19] According to the source data, the ten economies with the largest GDP in 2017 were, in decreasing order, the United States, China, Japan, Germany, the United Kingdom, India, France, Brazil, Italy and Canada.

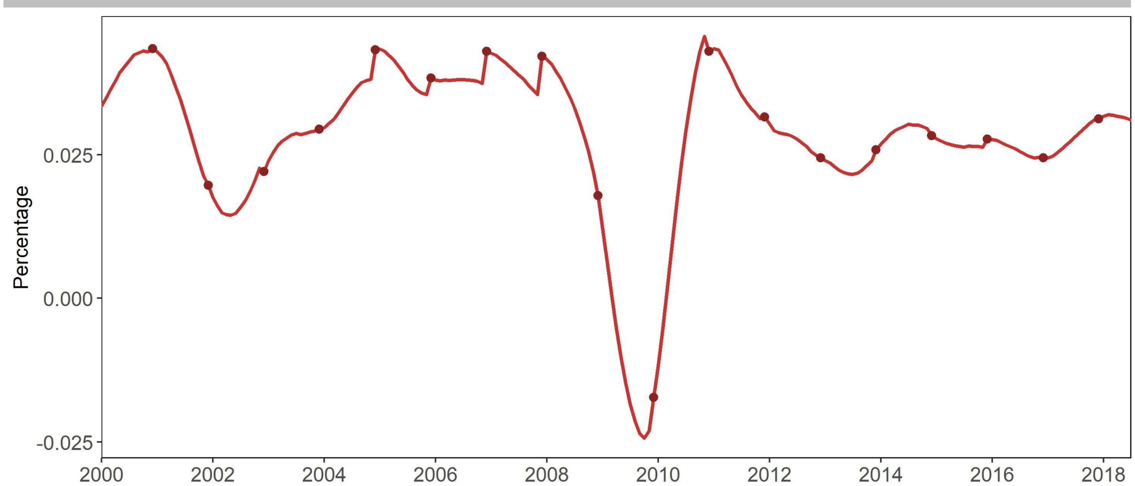
well as global oil and steel production. Finally, we include "soft" indicators, in the form of business confidence indices, consumer confidence indices, purchasing managers' indices, and leading indicators for the largest world economies.

Not all indicators were considered at once. An initial model, consisting of the 22 indicators marked in column (5) of the table above, was estimated. Only the significant variables were retained, leading to the core list of 19 indicators identified in column (6) of the same table. The next step consisted of selecting the lag structure of the model. By following the procedure described before, we selected $m_0 = m_1 = 4$ and $m_2 = m_3 = m_4 = 3$ as the optimal lag structure (see Table 8).

After this, the model selection process implemented added the rest of the indicators, one at a time, by blocks of variables. The final model included 25 variables, identified in the last column of Table 7. These indicators are filtered through the model to estimate the common factor at a monthly frequency, which can then be used to estimate monthly values for the variable of interest. The result is presented in Figure 5. As before, the line represents the estimated annual growth rate of real world GDP, while the points are placed at the actual rates. The final model can explain 95.9% of the total variability observed in the annual series of real GDP.

The lag structure selected for this nowcast exercise kept only a few lags. The model will therefore have no new information a few months after the last indicators are observed and the forecasts will consequently deteriorate. This becomes evident in Figure 6, where the first forecasts are not only far off the actual value, but also very volatile. However, as we draw closer to the end of the year, the information provided by the indicators begins to influence the estimation and the forecasts improve dramatically. In the four years displayed in these charts, by year-end the model has nowcast a growth rate practically identical to the final figure, published months later. Indeed, the forecast MAE calculated one month before the release of the final figures is 0.0006, only 0.06 percentage points away from the actual growth rate observed.

Figure 5
Annual growth rates, real GDP



Note: UNCTAD calculations based on data sources reported in Table 7. The line represents the estimated annual growth rate of the past 12 months with respect the 12 months before that (i.e., it is a rolling cumulative growth rate over the last 12 months). This is the main output of the nowcast model. The points represent the actual values for the growth rate. The model anchors the estimates to the actual figures, so they coincide whenever the growth rate is observed.

Table 7 List of indicators, real GDP

(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
A. Sub-components of the target variable						
Real GDP, United States	OECD	Quarterly	4	✓	✓	✓
Real GDP, China	OECD	Quarterly	4	✓	✓	✓
Real GDP, Japan	OECD	Quarterly	4	✓	✓	✓
Real GDP, Germany	OECD	Quarterly	4	✓	✓	✓
Real GDP, United Kingdom	OECD	Quarterly	4	✓	✓	✓
Real GDP, India	OECD	Quarterly	4			
Real GDP, France	OECD	Quarterly	4			
Real GDP, Brazil	OECD	Quarterly	4			✓
Real GDP, Italy	OECD	Quarterly	4			
Real GDP, Canada	OECD	Quarterly	4			✓
Real GDP, OECD	OECD	Monthly	3	✓		
B. Structural variables						
Index of total manufacturing production, OECD	OECD	Monthly	3	✓	✓	✓
Index of total manufacturing production, United States	OECD	Monthly	2			
Index of total manufacturing production, Japan	OECD	Monthly	2			
Index of total manufacturing production, Germany	OECD	Monthly	2			
Index of total manufacturing production, Korea	OECD	Monthly	2			
Index of total manufacturing production, India	OECD	Monthly	2			
Index of total manufacturing production, Italy	OECD	Monthly	2			
Index of total manufacturing production, France	OECD	Monthly	2			
Index of total manufacturing production, United Kingdom	OECD	Monthly	2			
Index of total manufacturing production, Brazil	OECD	Monthly	2			

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
Growth rate of value-added of industry, China	NBSC	Monthly	2	✓		
Index of total construction, OECD	OECD	Monthly	3	✓	✓	✓
Index of total construction, United States	OECD	Monthly	2			
Index of total construction, Japan	OECD	Monthly	2			
Index of total construction, Germany	OECD	Monthly	2			
Index of total construction, Great Britain	OECD	Monthly	2			
Index of total construction, France	OECD	Monthly	2			
Index of total construction, Canada	OECD	Monthly	2			
Construction permits issued, Germany	OECD	Monthly	2			
Construction permits issued, France	OECD	Monthly	2			
Construction permits issued, Canada	OECD	Monthly	2			
Index of total retail trade volume, United States	OECD	Monthly	2	✓	✓	✓
Index of total retail trade volume, Japan	OECD	Monthly	2			
Index of total retail trade volume, Germany	OECD	Monthly	2			
Index of total retail trade volume, United Kingdom	OECD	Monthly	2			
Index of total retail trade volume, France	OECD	Monthly	2			
Index of total retail trade volume, Brazil	OECD	Monthly	2			
Index of total retail trade volume, Italy	OECD	Monthly	2			
Index of total retail trade volume, Canada	OECD	Monthly	2			
Growth rate of total retail sales of consumer goods, China	NBSC	Monthly	2	✓		
Index of import volumes, world	CPB	Monthly	3	✓	✓	
Index of import volumes, United States	CPB	Monthly	3			✓
Index of import volumes, Japan	CPB	Monthly	3			✓
Index of import volumes, European Union	CPB	Monthly	3			✓
Index of import volumes, emerging economies	CPB	Monthly	3			✓

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(1) Variable	(2) Source	(3) Frequency	(4) Publication lag	(5) Models Initial	(6) Models Core	(7) Models Final
C. Labor market indicators						
Employment rate, OECD	OECD	Quarterly	4	✓	✓	✓
Employment rate, United States	OECD	Quarterly	4			
Employment rate, Japan	OECD	Quarterly	4			
Employment rate, Germany	OECD	Quarterly	4			
Employment rate, United Kingdom	OECD	Quarterly	4			
Employment rate, France	OECD	Quarterly	4			
Employment rate, Italy	OECD	Quarterly	4			
Employment rate, Canada	OECD	Quarterly	4			
Unemployment rate, OECD	OECD	Monthly	2	✓	✓	✓
Unemployment rate, United States	OECD	Monthly	1			
Unemployment rate, Japan	OECD	Monthly	2			
Unemployment rate, Germany	OECD	Monthly	2			
Unemployment rate, United Kingdom	OECD	Monthly	2			
Unemployment rate, France	OECD	Monthly	2			
Unemployment rate, Italy	OECD	Monthly	2			
Unemployment rate, Canada	OECD	Monthly	1			
Unemployment rate, Brazil	IMF	Monthly	8			
D. Other related indicators						
Suez Canal traffic statistics, net tons	SCA	Monthly	1			
Panama Canal, oceangoing commercial transits	CP	Monthly	1			✓
Petroleum and other liquids, production	EIA	Monthly	3	✓	✓	✓
Crude steel, production	WSA	Monthly	1	✓	✓	✓
E. "Soft" indicators						
Index of business confidence, OECD	OECD	Monthly	1	✓	✓	✓

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(1)	(2)	(3)	(4)	(5)	(6)	(7)
					Models	
Variable	Source	Frequency	Publication lag	Initial	Core	Final
Index of business confidence, China	OECD	Monthly	2	✓	✓	✓
Index of consumer confidence, OECD	OECD	Monthly	1	✓	✓	✓
Index of consumer confidence, China	OECD	Monthly	1	✓	✓	✓
Purchasing managers' index, United States	TR	Monthly	1	✓	✓	✓
Purchasing managers' index, China	NBSC	Monthly	1	✓	✓	✓
Leading indicator, OECD	OECD	Monthly	2			
Leading indicator, United States	OECD	Monthly	2			
Leading indicator, China	OECD	Monthly	2			
Leading indicator, Japan	OECD	Monthly	2			
Leading indicator, Germany	OECD	Monthly	2			
Leading indicator, United Kingdom	OECD	Monthly	2			
Leading indicator, India	OECD	Monthly	2			
Leading indicator, France	OECD	Monthly	2			
Leading indicator, Brazil	OECD	Monthly	2			
Leading indicator, Italy	OECD	Monthly	2			
Leading indicator, Canada	OECD	Monthly	2			

Sources: OECD = Organisation for Economic Co-operation and Development; NBSC = National Bureau of Statistics of China; CPB = Netherlands Bureau of Economic Policy Analysis; IMF = International Monetary Fund; SCA = Suez Canal Authority; CP = Canal de Panam\'{a}; EIA = United States Energy Information Administration; WSA = World Steel Association; TR = Thomson Reuters Eikon database.

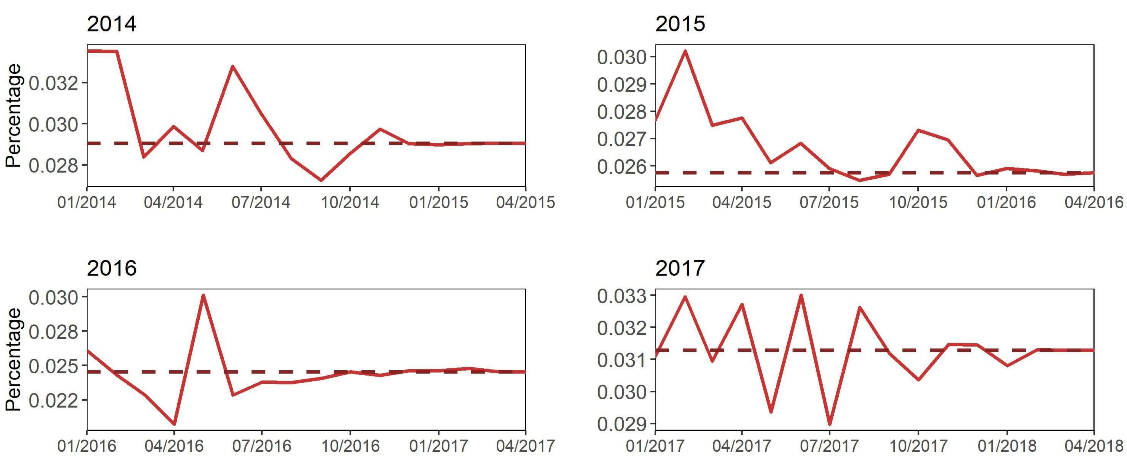
Notes: Publication lag is the number of months between the end of the period and the time of data publication, as recorded at the moment of data collection.

Table 8 Lag order selection, real GDP

Lag structure	(1) Results R^2	(2) Results MAE	(3) Results, standardized R^2	(4) Results, standardized MAE	(5) Results, standardized Average
(8, 3)	95.0	0.0028	0.9675	0.2965	0.6320
(7, 3)	94.6	0.0010	0.9639	0.8552	0.9096
(6, 3)	93.6	0.0010	0.9538	0.8404	0.8971
(5, 3)	95.7	0.0010	0.9752	0.7949	0.8851
(4, 3)	96.6	0.0008	0.9845	1.0000	**0.9923**
(3, 3)	94.9	0.0010	0.9669	0.8433	0.9051
(2, 3)	97.4	0.0010	0.9920	0.7905	0.8912
(1, 3)	95.5	0.0010	0.9728	0.8656	0.9192
(8, 2)	95.5	0.0014	0.9733	0.5785	0.7759
(7, 2)	94.7	0.0009	0.9643	0.9081	0.9362
(6, 2)	94.9	0.0009	0.9671	0.9558	0.9614
(5, 2)	94.6	0.0008	0.9636	0.9736	0.9686
(4, 2)	96.1	0.0010	0.9794	0.8495	0.9145
(3, 2)	95.9	0.0010	0.9771	0.8609	0.9190
(2, 2)	94.9	0.0009	0.9670	0.9477	0.9573
(1, 2)	95.5	0.0010	0.9724	0.8207	0.8966
(8, 1)	95.8	0.0011	0.9759	0.7436	0.8598
(7, 1)	95.8	0.0011	0.9755	0.7370	0.8563
(6, 1)	94.3	0.0012	0.9609	0.7027	0.8318
(5, 1)	94.2	0.0010	0.9592	0.8096	0.8844
(4, 1)	95.4	0.0014	0.9721	0.5941	0.7831
(3, 1)	95.2	0.0011	0.9701	0.7851	0.8776
(2, 1)	98.2	0.0010	1.0000	0.8184	0.9092
(1, 1)	95.5	0.0011	0.9730	0.7544	0.8637

Notes: R^2 is the percentage of variance of the target variable explained by the model; MAE is the mean absolute forecast error over the testing sample at the last update before the actual values were published. Both statistics were standardized so that the best indicator (max R^2 and min MAE) equals one; these are reported in columns (3) and (4), respectively. Column (5) reports the average of both standardized measures.

Figure 6
Real-time growth rate forecasts, real GDP



Note: UNCTAD calculations based on data sources reported in Table 7. The solid lines represent year-end growth rate forecasts produced by the nowcast model estimated with the data available at each month. The dashed lines are the actual growth rates, published in April of the following year. Note that every plot has different limits in the vertical axis.

5 Conclusions

This paper presented a methodology to track the real-time evolution of three global aggregates that could be used to monitor the world economy. They can be used to identify, in a timely manner, any changes that could require the adaptation of economy policy in affected sectors or countries. This tool can also be used to produce short-term forecasts of the target variables based on the most up-to-date information available in a series of underlying indicators.

This model relies on dynamic factor models, a familiar technique in the econometrics toolbox that can be calculated in any standard statistical software. The standard model was adapted to take into account the data characteristics that will be most likely present in this type of data: heterogeneous frequencies, missing data and ragged ends. Moreover, the solution described in Section 3 were developed in a general manner and they can be adapted to a variety of target variables and underlying indicators. Additional requirements (such as infra-monthly series and data available only after known transformations) could potentially be introduced to the model in a straightforward manner.

The results are very promising. The mean absolute forecasting errors are small and the estimated factor can explain a high proportion of the variability of the target variables. The visualizations presented in Section 4 show that the nowcasts quickly incorporate the information provided by the underlying indicators and correctly identify changing trends and turning points in the series. However, it must be noted that the dynamic structure of the model considers only short lags, so these models should only be used to monitor the real-time evolution of the variables and to produce short-term forecasts.

There are several ways to improve this process. First, the co-movements between the variables are constantly changing and previously tested variables may lose or gain significance when monitoring the target variables. There are also new series becoming available or receiving more widespread diffusion. The variable selection process will therefore have to be repeated frequently. Second, it could be interesting to compare the nowcasting performance when the target variable is annual or quarterly. For this exercise, we deliberately chose annual target variables since our objective is to track official data with complete coverage. However, there are other series available at a quarterly frequency that, at a cost of a smaller coverage, provide more timely information on the global aggregates. It would be interesting to compare the performance of the nowcast methodology in both situations. Third, we only developed nowcast models for three target variables. However, there are many more global macroeconomic aggregates. A potentially interesting exercise would be the nowcasting of the separate components of a series (for example, the value of merchandise exports by world regions, or the value of service exports by category), but imposing the condition that their combined trends should match the nowcast for the aggregate. Finally, as a robustness check and a potential source of improvement, we can also attempt to replicate the process with alternative methodologies. The approximation-free model developed in Aruoba et al. (2009) appears like a good candidate for this exercise.

Appendix A Measuring economic sentiment towards international trade

Global economic policy on trade is difficult to measure. All countries apply a constantly-changing mix of measures to encourage or restrict trade. Moreover, there could be a significant lag between the announcement of a measure and its actual implementation, and it can also be rolled out progressively. Some policies apply only to certain sectors or products, while other are more comprehensive. Some are taken in collaboration with other countries, economic blocks or multilateral organizations, while others are appointed unilaterally.

Economic policy can have an important impact on international trade. However, it is a difficult statistical concept to operationalize and measure. There are several indicators on trade policy and free trade in the literature (see, for example, the Heritage Foundation's Index of Economic Freedom,[20] the Fraser Institute's Economic Freedom of the World,[21] or the OECD's Services Trade Restrictiveness Index[22]). However, these indices can have a limited country coverage, plus they are only published annually. Their usefulness for nowcasting is thus limited.

We propose three indicators that can serve as proxies of global economic sentiment towards international trade and therefore provide information on international trade policies. The first two are derived from the Global Database of Events, Language and Tone (GDELT) project, currently maintained by Google.[23] This database consists of more than a quarterbillion records in more than 100 languages collected from hundreds of thousands of news sources from all over the world. The database covers events since 1979 until the present.[24] Each event is coded according to the actors involved (countries, organized groups, private actors, etc.), along with their characteristics and geographical location, and the action that takes place between them. The latter is classified into more than 300 categories according to the Conflict and Mediation Event Observation (CAMEO) classification.[25] The algorithm also studies the actions and assigns them an average "tone" indicating how negative or positive they are. In order to account for the differences in relevance, the figures are weighted by the number of mentions that each event receives: important events are picked up by a larger number of sources and mentioned more frequently, while minor events will only be mentioned by a limited number of sources.

To construct the indicators, we extract from this database all events with CAMEO codes 0211 ("appeal for economic cooperation"), 0311 ("express intent to cooperate economically"), 061 ("cooperate economically"), 1011 ("demand economic cooperation") and 1211 ("reject economic cooperation"). The first three refer to verbal or material cooperation, while the last two to verbal or material conflict. We further restrict the data to those events where both actors are (different) countries. The classification does not allow to distinguish between cooperation/conflict related to international trade from that in other areas (investment, alignment of regulations, etc.) However, this could still give an indication of the economic sentiment between countries that could lead them to establish economic links, including through trade. Although the data could be constructed at a daily frequency, we collect all events at a monthly frequency to maintain consistency with the rest of the variables in the model.

The first indicator is the proportion of economic cooperation events (0211, 0311 and 061) relative to the total number of events registered. We scale the indicators so that the average of 2005 equals 100.

The second indicator attempts to take into consideration the tone with which the events are reported. A similar approach was taken by Ortiz and Rodrigo (2018). However, the authors do not account for the changes of the tone scale that affect the database. We correct for these changes by comparing an event's tone with the average tone of all events in the same period. "Positive" events are those for which the tone indicator is higher than the period's average. The indicator is then the proportion of positive economic-related events relative to the total number of events. This is also scaled so that the average of 2005 is 100.

Both indicators derived from the GDELT database are proxies of positive economic sentiment in international relations and they are therefore expected to be positively correlated with international trade. Their evolution over the last three decades is shown in Figure 7.

[20] https://www.heritage.org/index.

[21] https://www.fraserinstitute.org/economic-freedom.

[22] http://www.oecd.org/tad/services-trade/services-trade-restrictiveness-index.htm.

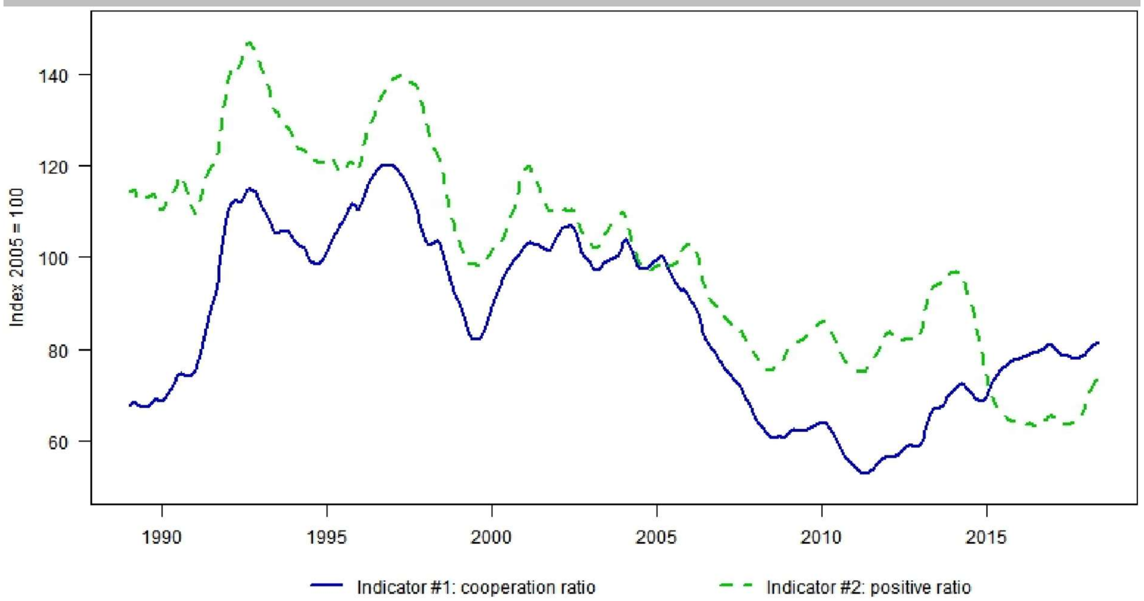
[23] https://www.gdeltproject.org.

[24] The number of global news material is in constant increase. Therefore, all measures taken from this database should take this into account and be normalized relative to the total number of events reported.

[25] See Schrodt (2012).

The third indicator measures the number of policy measures restricting international trade that are implemented every month.[26] The data comes from Global Trade Alert.[27] Note that we account for the measure at the time they are implemented and not when they are announced. A disadvantage of this source is that it does not provide information on the impact or coverage of each policy and all measures receive the same weight. In addition, it is available only from November 2008. As a measure of trade restrictiveness, it is expected to be negatively correlated with international trade. Figure 8 shows this variable for the period when data is available.[28]

Figure 7
Economic cooperation indicators, trend component



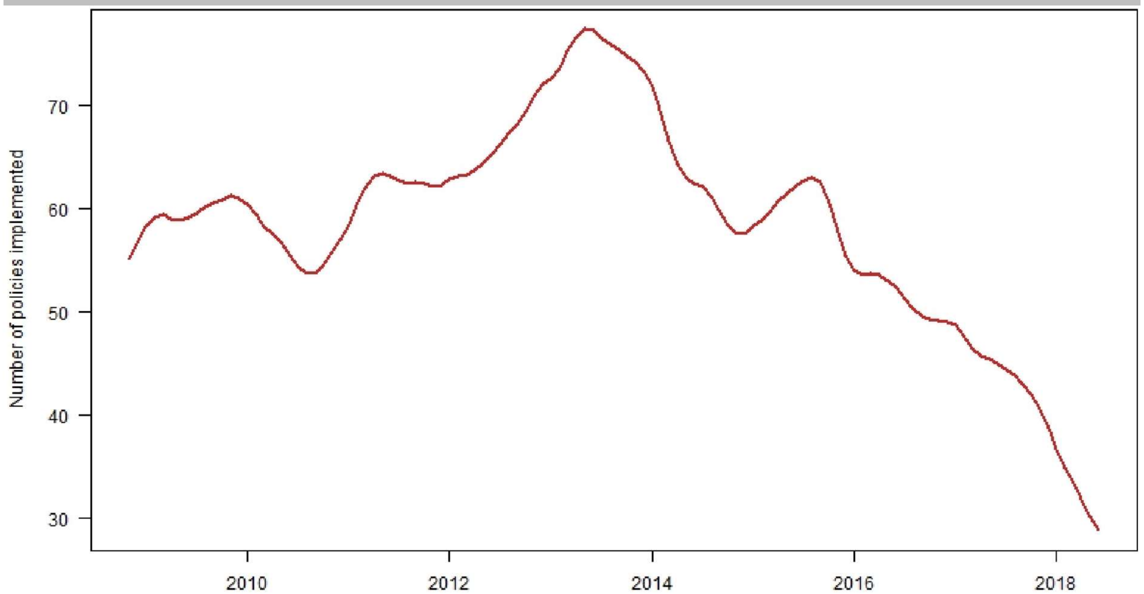
Source: UNCTAD calculations based on data from GDELT.

[26] The list of restrictive or protectionist trade policies includes the following measures: anti-circumvention, anti-dumping, anti-subsidy, export-related non-tariff measures, export bans, export licensing requirements, export quotas, export subsidies, export tariff quotas, export taxes, foreign customer limits, import-related non-tariff measures, import bans, import incentives, import licensing requirements, import monitoring, import quotas, import tariffs, import tariff quotas, intellectual property protection, internal taxation of imports, price stabilisation, safeguards, sanitary and phytosanitary measures, technical barriers to trade, trade balancing measures, and trade payment measure.

[27] https://www.globaltradealert.org/.

[28] In order to eliminate volatility and present the underlying trends, both Figures 7 and 8 show the trend component of the series as extracted by applying the X-13-ARIMA-SEATS methodology.

Figure 8
Trade restrictiveness indicators, trend component



Source: UNCTAD calculations based on data from GTA.

References

Aruoba, S. B., Diebold, F. X., 2010. Real-time macroeconomic monitoring: Real activity, inflation, and interactions. American Economic Review 100, 20–24.

Aruoba, S. B., Diebold, F. X., Scotti, C., 2009. Real-time measurement of business conditions. Journal of Business & Economic Statistics 27, 417–427.

Baffigi, A., Golinelli, R., Parigi, G., 2004. Bridge models to forecast the euro area GDP. International Journal of Forecasting 20, 447–460.

Barhoumi, K., Benk, S., Cristadoro, R., Reijer, A. D., Jakaitiene, A., Jelonek, P., Rua, A., Rünstler, G., Ruth, K., Nieuwenhuyze, C. V., 2008. Short-term forecasting of GDP using large monthly datasets: a pseudo real-time forecast evaluation exercise. Occasional Paper Series 84, European Central Bank.

Barhoumi, K., Ferrara, L., 2015. A world trade leading index (WTLI). Working Paper WP/15/20, IMF.

Bok, B., Caratelli, D., Giannone, D., Sbordone, A., Tambalotti, A., 2017. Macroeconomic nowcasting and forecasting with big data. Staff Reports 830, Federal Reserve Bank of New York.

Burgert, M., Dées, S., 2008. Forecasting world trade: Direct versus “bottom-up” approaches. Working Paper Series 882, European Central Bank.

Camacho, M., Perez-Quiros, G., 2010. Introducing the Euro-STING: Short-term indicator of euro area growth. Journal of Applied Econometrics 25, 663–694.

Clements, M. P., Galvão, A. B., 2008. Macroeconomic forecasting with mixed-frequency data: Forecasting output growth in the united states. Journal of Business & Economic Statistics 26, 546–554.

Conference Board, 2001. Business Cycle Indicators Handbook. The Conference Board, Inc., New York, NY.

Ferrara, L., Marsilli, C., 2014. Nowcasting global economic growth: A factor-augmented mixed-frequency approach. Document de Travail 515, Banque de France.

Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2005. The generalized dynamic factor model: One-sided estimation and forecasting. Journal of the American Statistical Association 100, 830–840.

Ghysels, E., Santa-Clara, P., Valkanov, R., 2006a. Predicting volatility: getting the most out of return data sampled at different frequencies. Journal of Econometrics 131, 59–95.

Ghysels, E., Sinko, A., Valkanov, R., 2006b. MIDAS regressions: Further results and new directions. Econometric Reviews 26, 53–90.

Giannone, D., Reichlin, L., Small, D., 2008. Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics 55, 665–676.

Golinelli, R., Parigi, G., 2014. Tracking world trade and GDP in real time. International Journal of Forecasting 30, 847–862.

Guichard, S., Rusticelli, E., 2011. A dynamic factor model for world trade growth. Economics Department Working Papers 874, OECD.

Hendry, D. F., Hubrich, K., 2006. Forecasting economic aggregates by disaggregates. Working Paper Series 589, European Central Bank.

Marcellino, M., Schumacher, C., 2010. Factor MIDAS for nowcasting and forecasting with ragged-edge data: A model comparison for German GDP. Oxford Bulletin of Economics and Statistics 72, 518–550.

Mariano, R. S., Murasawa, Y., 2003. A new coincident index of business cycles based on monthly and quarterly series. Journal of Applied Econometrics 18, 427–443.

Matheson, T., 2011. New indicators for tracking growth in real time. Working Paper WP/11/43, IMF.

OECD, 2012. OECD system of composite leading indicators. http://www.oecd.org/sdd/leading-indicators/41629509.pdf, retrieved on 20 July 2018.

Ortiz, A., Rodrigo, T., 2018. Monitoring global trade support in real time using big data. Big data analysis, BBVA Research.

Rossiter, J., 2010. Nowcasting the global economy. Discussion Paper 2010-12, Bank of Canada.

Schrodt, P. A., 2012. CAMEO conflict and mediation event observations event and actor codebook. http://data.gdeltproject.org/documentation/CAMEO.Manual.1.1b3.pdf, retrieved on 20 July 2018.

Schumacher, C., Breitung, J., 2006. Real-time forecasting of GDP based on a large factor model with monthly and quarterly data. Discussion Paper Series 1: Economic Studies 33, Deutsche Bundesbank.

Stock, J. H., Watson, M. W., 2002a. Forecasting using principal components from a large number of predictors. Journal of the American Statistical Association 97, 1167–1179.

Stock, J. H., Watson, M. W., 2002b. Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics 20, 147–162.

UNCTAD, 2017. Handbook of Statistics, vol. 2017. United Nations Publications, New York, NY.

Unites States Census Bureau, 2017. X-13 ARIMA-SEATS seasonal adjustment program. https://www.census.gov/srd/www/x13as/, retrieved on 20 July 2018.

World Tourism Organization, 2018. UNWTO Tourism Highlights: 2018 Edition. UNWTO, Madrid, Spain.