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## Abstract

This paper builds an innovative composite world trade cycle index (WTI) by means of a dynamic factor model to perform short-term forecasts of world trade growth of both goods and (usually neglected) services. The selection of trade indicator series is made using a multidimensional approach, including Bayesian model averaging techniques, dynamic correlations and Granger non-causality tests in a linear VAR framework. To overcome the real-time forecasting challenges, the dynamic factor model is extended to account for mixed frequencies, to deal with asynchronous data publication and to include hard and survey data along with leading indicators. Nonlinearities are addressed with a Markov switching model. In the empirical application, simulations analysis in *pseudo* real-time suggest that: i) the global trade index is a very useful tool for tracking and forecasting world trade in real time; ii) the model is able to infer global trade cycles very precisely and better than several competing alternatives; and iii) global trade finance conditions seem to lead the trade cycle, in line with the theoretical literature.



**Keywords:** real-time forecasting, world trade, dynamic factor models, markov switching models.

**JEL classification:** E32, C22, E27.

## Resumen

Este artículo desarrolla un indicador novedoso del ciclo de comercio mundial (WTI) mediante un modelo de factores dinámicos, con el objetivo de predecir el crecimiento del comercio mundial de bienes y servicios (generalmente, obviados) en el corto plazo. La selección de indicadores de comercio se realiza utilizando un enfoque multidimensional, que incluye técnicas de modelización de promedio bayesianas, correlaciones dinámicas y contrastes de no causalidad de Granger en un marco VAR lineal. Para superar los desafíos que suponen las previsiones en tiempo real, el modelo de factores dinámicos se amplía para poder lidiar tanto con frecuencias mixtas como con la publicación de datos asincrónicos y para poder asimismo incorporar datos fidedignos y de encuestas junto con los principales indicadores. Las no linealidades se abordan mediante un modelo de Markov de cambio de régimen. En la aplicación empírica, el análisis de las simulaciones en *pseudo* tiempo real sugiere que: i) el índice de comercio mundial es una herramienta muy útil para monitorear y pronosticar el comercio mundial en tiempo real; ii) el modelo es capaz de inferir ciclos comerciales globales con mucha precisión y mejor que varias alternativas competidoras, y iii) las condiciones de financiación del comercio global parecen ir por delante del ciclo comercial, en línea con la literatura teórica.

**Palabras clave:** predicción en tiempo real, comercio mundial, modelos de factores dinámicos, modelos de Markov de cambio de régimen.

**Códigos JEL:** E32, C22, E27.

# 1 Introduction

The unexpectedly large collapse in trade flows, both in the aftermath of the Global Financial Crisis of 2008-09 (Martins and Araujo, 2009; Baldwin, 2009; Bussiére et al., 2013) and, to a lesser extent, at present, has led to huge shocks to economic agents. Policymakers and scholars alike seemed to learn the lesson and highlighted the need for new tools able to accurately monitor trade developments in real time owing to their strong association with economic growth. However, in times of uncertainty, when interest in predicting trade is greatest, projecting trade conditions on a higher-frequency basis remains extremely difficult. Indeed, tracking global trade in real time is challenging since trade data are published with a considerable lag given the large number of countries' input needed to compile an estimate of world trade. For example, in September 2019 the most up-to-date information on trade of goods and services provided by the OECD was from Q1 2019.[1] The lack of timelines in releasing this kind of indicator makes it hard to track and predict unexpected and significant swifts in international trade.

Accordingly, publication delays force policy institutions to set their policies without having a clear picture of the current trade conditions. For instance, the World Trade Organization (2016) publishes an aggregate of several sub-indices based on export orders, international air freight, container shipping, automobile sales and production, electronic components and agricultural raw materials with a $t+1$ quarters delay (Figure 1). To address this issue, there is a small but growing literature on forecasting and leading indicators of international trade (Gregory et al., 1997; Burgert and Dees, 2008; Guichard and Rusticelli, 2011, Jakaitiene and Dees, 2012; Stratford, 2013; Golinelli and Parigi 2014; Barhoumi et al., 2016). These papers select a limited number of time series as potential predictors and aggregate them into a composite indicator of the international trade cycle. However, most of the related literature usually: (i) focuses on merchandise trade only, neglecting the role of trade of services; (ii) makes an ad-hoc selection of predictors which are not formally tested; and (iii) does not exploit the potential usefulness and flexibility of a dynamic factor model (DFM) to forecast global trade growth rates in real time.

Our paper makes a number of contributions to the literature on short-run forecasts of developments in world trade. First, this paper tests the potential usefulness and flexibilty of a small-scale Dynamic Factor Model (DFM), which accounts for mixed frequencies and deals with asynchronous data publication, for predicting short-term forecasts of trade growth in real time. We employ the derived common factor to build an innovative composite world trade cycle index (WTI). In contrast with most of the existing literature, our model accounts for both goods and services trade. Predicting services trade (i.e., travel, transportation, insurance, financial services,) is becoming increasingly important because of its growing share in world trade across countries. According to the World Bank database, the ratio of services to world GDP has gradually increased from 7.3% in the nineties to 13.2% in 2018. Moreover, empirical evidence suggests that this trend is not only

[1] The OECD publishes a quarterly index of world trade based on national accounts with a one-quarter lag.

valid at the aggregate level but also on a single country basis as shown in Figure 2 [2].Second, this paper formally tests a large set of trade predictors under an agnostic and multidimensional approach by means of: (i) Bayesian Model Averaging (BMA) techniques; (ii) Granger non-causality tests under a linear VAR framework; and (iii) dynamic correlations. Third, this paper also examines whether it is worth enlarging the single-index DFM with leading indicators. To this end, the baseline model is extended to include leading along with coincident indicators, after Camacho and Martinez-Martin (2014). Finally, forecasting accuracy performances of the WTI are compared with several standard alternatives through a pseudo real-time analysis, where data vintages are constructed by taking into account the lag of synchronicity in data publication that characterises real-time data flow. Plus, turning-point detection is assessed through a non-linear extension: a Markov-switching model.

The main results are the following. First, the WTI explains more than 92% of the variance of world trade growth of goods and services, pointing to a high potential ability of this small-scale dynamic factor model for tracking world trade growth. Second, the *pseudo* real- time analysis shows that our DFM clearly outperforms a number of competing models, especially when forecasting the next unavailable figure of trade growth. This confirms that monthly real and survey data provide useful and forward-looking information to forecast current world trade growth. Finally, among the new insights that emerge from our *in-sample* analysis, it is worth highlighting that global credit and trade finance conditions are significant leading indicators of the world trade cycle in the recent past, in line with the theoretical literature.

The structure of the paper is as follows. Section II briefly summarises the literature on forecasting world trade and places our approach within that literature. Section III contains the data description and outlines the econometric strategy. It starts with a discussion on the criteria for selecting trade predictor series used in the small-scale DFM through a multidimensional approach based on BMA techniques, dynamic correlations and Granger non-causality tests in a linear VAR framework. Then, it describes the DFM underlying the World Trade Index (WTI) to monitor global trade growth by introducing its time series dynamic properties and describing the state space representation. Section IV proves the model effectiveness in real-time forecasting and turning-points detection. Finally, Section V concludes. Online Appendix summarises the main features of the state-space representation and how to mix frequencies.

## 2 Forecasting world trade in real time

A small but growing literature has contributed to our understanding of trade cycles using a range of different approaches. In the context of global trade, Barhoumi et al (2016) is an excellent contribution to the developing debate. In line with the seminal proposal of Stock and Watson (1991), they use a small-scale factor model to produce an accurate leading indicator of trade conditions in real time. Apart from commodity prices, their model benefits from the information

[2]Further evidence is provided by Timmer et al. (2016) as they exploit the more recent World Input-Output Database (WIOD).

provided by five monthly indicators, the US dollar nominal effective exchange rate, the Baltic Dry Index, the Purchasing Managers Index, Ifo business climate and expectations indexes. With the aim of capturing turning points, they use static Principal Components Analysis (PCA) to estimate the factors. Their estimated first factor is intended to reflect the global merchandise trade conditions, benchmarking the monthly index of The Netherlands Bureau for Economic Policy Analysis (CPB). This index, which only measures trade of goods, is available with a lag of two months[3]. Similarly, in a worhty effort to provide "real-time" information on trends in global merchandise trade volumes, the World Trade Organization (2016) has recently launched a very useful, composite indicator, with a three-months lag. It relies on Hodrick-Prescott (HP) filtering to aggregate sub-indices of export orders, international air freight, container shipping, automobile sales and production, electronic components and agricultural raw materials.

However, in this paper, we attempt to shed some light on the global trade cycle, in line with the tradition of a single, composite index by Burns and Mitchell (1946) and much subsequent research. Yet our approach contrasts with most the recent literature on short-term forecasting world trade. Burgert and Dees (2008) compare the forecasting abilities of aggregate models with those of disaggregated models, in which world trade results from the aggregation of country forecasts. Guichard and Rusticelli (2011) forecast aggregate world trade using large-scale dynamic common factors extracted from aggregate indicators. Jakaitiene and Dees (2012) improve on this model further by taking into account monthly trade, industrial production and prices when forecasting short-run world trade. Although some recent empirical proposals try to examine the empirical reliability of these models in computing real-time inferences of the global trade cycle states, the analyses are not developed in actual real time. The only recent real-time approach is based on the combination of bridge equations under a data-intensive (7000 series) framework, developed by Golinelli and Parigi (2014).

The main methodological advantage of our linear dynamic factor model with respect to the previous literature is that it converts the information in the macroeconomic indicators (also leading) into inferences of the state of the global trade cycle. Hence, we are able to create a WTI, which, in this context, is very easy to interpret and can be automatically updated in a timely fashion.

The original DFM was initially designed to deal with balanced panels of business cycle indicators, so it could not handle the typical problems of the day-to-day monitoring of macroeconomic activity: mixed frequencies and ragged ends. To overcome such limitations, Camacho and Martinez-Martin (2014) is close example of how to adapt DFMs to allow any business cycle coincident (and leading) economic indicator based on Stock and Watson (1991), Mariano and Murasawa (2003) and Aruoba and Diebold (2010), regardless of publication delays and frequency. Based on the techniques described in this context about how to handle missing data, our procedure deals with missing observations by using Kalman filtering[4].

[3] Starting in 2000, the CPB index is built based on the trade series (prices and values) of 85 countries, covering around 97% of the world trade volume.

[4] Whenever the data are not observed, the missing observations are replaced by random draws from a variable whose distribution cannot depend on the parameters space that characterises the Kalman filter. The corresponding row is then skipped in the Kalman recursion and the measurement equation for the missing observation is set to the random choice

## 3 The modelling strategy

In this section, we provide an empirical framework to generate the WTI. We proceed in two steps. First, given the plethora of available time series, all possibly correlated with world trade, the selection of predictors is a crucial step in the construction of dynamic factor models. Boivin and Ng (2006) found evidence that selecting a smaller subset of potential indicators improves substantially the forecast performance. Accordingly, we select a subset of world trade predictors among the initial thirty series on the basis of their good forecasting properties as indicated in the related literature such as in Guichard and Rusticelli (2011) and in Barhoumi et al. (2016). Then, we apply three different selection methods: pairwise vector autoregressions, BMA techniques and dynamic correlations. Second, conditional on the predictors selection obtained from the first step, we develop a small-scale DFM to monitor global trade growth and extend it under a Markov-switching framework to capture trade cycle turning points.

The data employed in this paper span the period from 1967 to 2016. Table 1 summarises the indicators used in the empirical analysis and their respective release lag-time.

### 3.1 Multidimensional selection of predictors

A transparent multidimensional approach has been conducted to select a subset of world trade predictors, by combining three different methods: (i) pairwise vector autoregressions; (ii) Bayesian model averaging techinques; and (iii) dynamic correlations.

#### 3.1.1 Pairwise vector autoregressions

Linear vector autoregressions (VARs) are estimated to investigate the predictive ability of the selected indicators. To this end, Granger non-causality tests are run on the growth rate of world trade of goods and services. Bivariate vector autoregressive models (the lag order is fixed according to AIC criteria) for each indicator and the associated marginal significance levels are estimated to assess their predictability.[5] In Table 2, the $p-$values for Wald tests of Granger non-causality based on heteroskedasticity-robust variance estimators are reported over the evaluation period January 1967 – September 2016.[6]

The results from the pairwise VARs suggest that some soft indicators (i.e., IFO surveys and PMIs) are highly statistically significant predictors of the growth rate of world trade of goods and services. In contrast, the evidence of predictability is weaker for geographical industrial production indices and neither steel production nor world semiconductor billings have significant predictive power. This does not necessarily mean that all bilateral covariates lack predictive power. The explanation presumably is that some of them are forward-looking and embody information about

[5] In the absence of structural breaks, the existence of predictability in population is a necessary precondition for out-of-sample forecastability (see Inoue and Kilian, 2004).

[6] In some cases, we need to consider the possibility of cointegration in levels. In those cases, all rejections remain significant if we follow Dolado and Lütkepol (1996) in conducting a lag-augmented Granger non-causality test.

future movements in world trade of goods and services that cannot easily be captured by alternative means.

#### 3.1.2 Bayesian Model Averaging (BMA)

Assuming that traditional statistical practices may be ignoring model uncertainty since the Data Generating Process (DGP) is unknown and may lead to over-confident inferences on information selection, we conduct Bayesian Model Averaging (BMA) techniques based on Hoeting et al. (1999). They are applied to assign a weight to each variable included in an "optimal" model accurately selected among all possible regressors combinations to explain world trade growth variations. [7] For the sake of simplicity, let us assume a combination of predictors such that: $y = \alpha_i + x_i\beta_i + \epsilon$ where $\epsilon \sim N(0, \sigma^2 I)$ and for each model, $i$, the parameter space is defined by $\alpha$ and $\beta$. Thus, the posterior distribution of the quarterly world trade growth, $WT$, given dataset $D$ is defined as:

$$p\left(WT|D\right) = \sum_{k=1}^{K} p\left(WT|M_k, D\right) p\left(M_k|D\right) \tag{1}$$

This probability is computed as an average of the posterior distributions under each of the $M_1, ..., M_k$ models under consideration. Therefore, the weight is represented by the posterior probabitlity for model $M_k$ given by:

$$p\left(M_k|D\right) = \frac{p\left(D|M_k\right) p\left(M_k\right)}{\sum_{l=1}^{K} p\left(D|M_l\right) p\left(M_l\right)} \tag{2}$$

where $p\left(D|M_k\right) = \int p(D|\delta_k, M_k) p(\delta_k|M_k) d\delta_k$ is the integrated likelihood of model $M_k$ and $\delta_k$ is the vector of parameters of model $M_k$ [8].

It assumes that the posterior distribution is proportional to the marginal probability by the *prior* probability assigned to each model, in this case, a uniform variable. The result gives the cumulative model probabilities of the predictor's selection based on the whole spectrum of model combinations. Given a *prior* inclusion probability of 50%, the chosen threshold for the variable selection in the model is that the posterior inclusion probability (PIP) should be above 50%.

The entire model space is fully explored by iterating all possible regressor combinations (meaning $2^k$ iterations, where $k = 30$ is the number of covariates). Table 3 summarises the main results of the BMA estimation to select robust world trade growth determinants, for both a balanced panel (2001-2016) and unbalanced panel (1967-2016). These results suggest that soft indicators such as global PMI new orders and manufacturing indices along with IFO Expectation and Climate surveys contain significant information. Hard indicators such as global and US industrial production indices and world semiconductor billings ought to be included with a higher probability. Finally, a financial (leading) predictor such as the US high-yield spread may also be considered.

[7] For an overview of model averaging methods in the field of economics, see Moral-Benito (2015).

[8] For instance, for regressing $\delta = (\beta, \sigma^2)$, $p(\delta_k|M_k)$ is the prior density of $\delta_k$ under model $M_k$, while $p(D|\delta_k, M_k)$ is the likelihood, and $p(M_k)$ is the prior probability that $M_k$ is the true model (given that one of the models considered is true).

### 3.1.3 Dynamic correlations

The third approach to data selection focuses on those predictors that exhibit high statistical dynamic correlation with the quarterly OECD world trade growth rate, which is the target series to be monitored. [9] To test the forward-looking ability of those predictors that have already shown predictability content by means of Granger non-causality tests and Bayesian averaging techniques, pair-wise dynamic correlations (both lagging and leading) are calculated. Table 4 shows that, as expected, soft indicators lead the world trade cycle, in particular, the global PMI new export orders index. Plus, it is worth mentioning the inverse (leading) relationship of the US high-yield spread with the reference series.

Overall, the merged results of the three above-mentioned methods for the predictor's selection suggest that only 9 out of 30 indicators contain significant predictive power. The selected drivers of global trade cover different dimensions, from hard to soft indicators: (i) global merchandise trade, world semiconductor billings , industrial production from the US and worldwide; and (ii) global PMIs such as manufacturing, new export orders, and IFOs expectations and climate surveys. Moreover, the US High Yield Spread, calculated as the difference between the U.S. Corporate High Yield USD and the US 10 year Treasury Bond, has also been selected as a proxy for the risk premium paid by risky borrowers. It should capture both the global impact of credit conditions on activity as well as via global trade finance conditions (Guichard and Rusticelli, 2011).[10]

Given the small set of monthly indicators selected, a rather small-scale DFM with coincident and potential leading indicators emerges as the most suitable methodological approach to generate the WTI.

## 3.2 From the Dynamic Factor Model to the derived World Trade Index

The dynamic properties of the DFM follow the lines proposed by Aruoba and Diebold (2010), who extended the single-index DFM suggested by Stock and Watson (1991). The main methodological advantages of our new linear DFM with respect to the previous literature are that: (i) it can incorporate information from different series regardless of frequency and publication dates; (ii) it converts the information in the macroeconomic indicators (also leading) into inferences of the state of the global trade cycle. Hence, it is possible to create a WTI, which is very easy to interpret and can be automatically updated in a timely fashion.

The original DFM was initially designed to deal with balanced panels of business cycle indicators so it could not handle the typical problems of the day-to-day monitoring of macroeconomic activity: mixed frequencies and ragged ends. To overcome such limitations, Camacho and Martinez-Martin (2014) show how to adapt DFMs to allow for any business cycle coincident (and leading) economic indicator regardless of publication delays and frequency (based on Stock and Watson, 1991; Mari-

[9] Dynamic correlations are commonly used in this context since they become the best alternative to static analysis for capturing the comovement between predictors (Croux et al. 2001).

[10] This choice is justified by the strong international correlation of international bond spreads. Nonetheless, as a proxy for trade finance conditions, it underestimates the impact on trade if financial crises tend to restrict trade finance relatively more than other forms of credit. This may occur, for example, if international trade is more vulnerable to counterparty risks.

ano and Murasawa, 2003; and Aruoba and Diebold, 2010). On the basis of these techniques, the procedure underlying the WTI deals with missing observations by using Kalman filtering. The Online Appendix provides further details on the state-space representation and how to deal with mixed frequencies.

Let us assume that the predictors included in the model admit a dynamic factor representation. In this case, the time series employed in the model can be written as the sum of two orthogonal components: a common component, $x_t$, which represents the overall trade cycle conditions, and an idiosyncratic component, which refers to the particular dynamics of the series. The latent trade cycle conditions are assumed to evolve with $AR(p_1)$ dynamics:

$$x_t = d_1^x x_{t-1} + ... + d_{p1}^x x_{t-p_1} + \varepsilon_t^x, \tag{3}$$

where $\varepsilon_t^x = i \sim N(0, \sigma_x^2)$.

However, in addition to the construction of an index of the trade cycle conditions, this model is also intended to estimate accurate short-term forecasts of world trade growth. To calculate these forecasts, let us consider $k_1$ quarterly indicators and $k_2$ monthly indicators. For each of the quarterly indicators, $g_t$, we assume that the evolution of its underlying monthly growth rates, $g_t^*$, depends linearly on $x_t$ and on the idiosyncratic dynamics, $u_t^g$, which evolve as an $AR(p_2)$:

$$g_t^* = \beta_g x_t + u_t^g, \tag{4}$$

$$u_t^g = d_1^g u_{t-1}^g + ... + d_{p2}^g u_{t-p_2}^g + \varepsilon_t^g, \tag{5}$$

where $\varepsilon_t^g = i \sim N(0, \sigma_g^2)$. In addition, the evolution of each of the monthly indicators, $z_t$, depends linearly on $x_t$ and on the idiosyncratic component, whose dynamics can be expressed in terms of autoregressive processes of $p_3$ orders:

$$z_t = \beta_z x_t + u_t^z, \tag{6}$$

$$u_t^z = d_1^z u_{t-1}^z + ... + d_{p2}^z u_{t-p_3}^z + \varepsilon_t^z, \tag{7}$$

where $\varepsilon_t^z = i \sim N(0, \sigma_z^2)$. Finally, the errors of the common component and all the idiosyncratic shocks are assumed to be mutually uncorrelated in cross-section and time-series dimensions.[11] Using the assumptions described below, this model can be easily stated in state-space representation and estimated by means of Kalman filtering.[12]

### 3.2.1 State-space representation and estimation

Let us start by assuming that all variables were observed at a monthly frequency for all periods. The state-space model represents a set of observed time series, $Y_t$, as linear combinations of a

[11] We could consider time-varying parameters. However, it is beyond the scope of this paper and is left for further research.

[12] Further technical details can be found in the Online Appendix.

vector of auxiliary variables, which are collected on the state vector, $\xi_t$. This relation is modelled by the *measurement equation*

$$Y_t = H\xi_t + E_t, \tag{8}$$

with $E_t \sim i.i.d.N\,(0, R)$. The dynamics of the state vector is modelled by the *transition equation*

$$\xi_t = F\xi_{t-1} + W_t, \tag{9}$$

with $W_t \sim i.i.d.N\,(0, Q)$. In addition, it is assumed that the measurement equation errors are independent of the transition equation errors.[13]

The estimation of the model is by standard maximum likelihood by using the Kalman filter if all series were observable at the monthly frequency, as we assume so far. However, this assumption is quite restrictive since we are using time series of different length and different reporting lags and we are mixing monthly data with quarterly data.

Among others, Mariano and Murasawa (2003) describe a framework to easily handle this issue. Following these authors, the unobserved cells can be treated as missing observations and maximum likelihood estimations of a linear Gaussian state-space model with missing observations can be applied straightforwardly after a subtle transformation of the system matrices. The missing observations can be replaced with random draws $\vartheta_t$, whose distribution must not depend on the parameter space that characterises the Kalman filter.[14] Thus, the likelihood function of the observed data and that of the data whose missing values are replaced by the random draws are equivalent up to scale. In particular, we assume that the random draws come from $N(0, \sigma^2_\vartheta)$. In addition, the measurement equation must be appropiately transformed in order to allow the Kalman filter to skip the missing observations when updating.

Let $Y_{it}$ be the $i$-th element of the vector $Y_t$ and $R_{ii}$ be its variance. Let $H_i$ be the $i$-th row of the matrix $H$ which has $\varsigma$ columns and let $0_{1\varsigma}$ be a row vector of $\varsigma$ zeroes. The *measurement equation* can be replaced by the following expressions:

$$Y^+_{it} = \begin{cases} Y_{it} & \text{if } Y_{it} \text{ observable} \\ \vartheta_t & \text{otherwise} \end{cases}, \tag{10}$$

$$H^+_{it} = \begin{cases} H_i & \text{if } Y_{it} \text{ observable} \\ 0_{1\varsigma} & \text{otherwise} \end{cases}, \tag{11}$$

$$E^+_{it} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \vartheta_t & \text{otherwise} \end{cases}, \tag{12}$$

$$R^+_{iit} = \begin{cases} 0 & \text{if } Y_{it} \text{ observable} \\ \sigma^2_\vartheta & \text{otherwise} \end{cases}. \tag{13}$$

According to this transformation, the time-varying state space model can be treated as having no missing observations so the Kalman filter can be directly applied to $Y^+_t$, $H^+_t$, $E^+_t$, and $R^+_t$.

[13] For the sake of clarity, a description of a simplified model is set out in the Online Appendix.
[14] Note that replacements by constants would also be valid.

The estimation of the model's parameters can be developed by maximising the log-likelihood of $\left\{Y_t^+\right\}_{t=1}^{t=T}$ numerically with respect to the unknown parameters. Let $\xi_{t|\tau}$ be the estimate of $\xi_t$ based on information up to period $\tau$. Let $P_{t|\tau}$ be its covariance matrix. The prediction equations are:

$$\xi_{t|t-1} = F\xi_{t-1|t-1}, \tag{14}$$

$$P_{t|t-1} = FP_{t-1|t-1}F' + Q. \tag{15}$$

Hence, the predicted value of $Y_t$ with information up to $t-1$ , denoted by $Y_{t|t-1}$, is:

$$Y_{t|t-1} = H^+\xi_{t|t-1}, \tag{16}$$

and the prediction error is:

$$\eta_{t|t-1} = Y_t^+ - Y_{t|t-1} = Y_t^+ - H^+\xi_{t|t-1}, \tag{17}$$

with covariance matrix:

$$\nu_{t|t-1} = H^+P_{t|t-1}H^+ + R_t^+. \tag{18}$$

The way missing observations are treated implies that the filter, through its implicit signal extraction process, will put no weight on missing observations in the calculation of the factors.

In each iteration, the log-likelihood can be calculated as:

$$\log L_{t|t-1} = -\frac{1}{2}\ln\left(2\pi\left|\nu_{t|t-1}\right|\right) - \frac{1}{2}\eta'_{t|t-1}\left(\nu_{t|t-1}\right)^{-1}\eta_{t|t-1}. \tag{19}$$

It is worth noting that the transformed filter to handle missing observations has no impact on the model estimation. In that sense, the missing observations simply add a constant to the likelihood function of the Kalman filter process. Hence, the parameters that maximise the likelihood are achieved as if all the variables were observed.

Finally, the updating equations are:

$$\xi_{t|t} = \xi_{t|t-1} + P_{t|t-1}H_t^{+\prime}\left(\nu_{t|t-1}\right)^{-1}\eta_{t|t-1}, \tag{20}$$

$$P_{t|t} = P_{t|t-1} - P_{t|t-1}H_t^{+\prime}\left(\nu_{t|t-1}\right)^{-1}H_t^+P_{t|t-1}. \tag{21}$$

Therefore, missing observations are skipped from the updating recursion.

# 4 Empirical Results

## 4.1 In-sample analysis

Following the multidimensional approach described in Section III, a first subset of nine predictors of global trade growth was selected on the basis of their higher predictive power. However, this was reduced to eight as the DFM estimation indicated that the world semiconductor index does not improve substantially the percentage of the variance of world trade growth explained by the WTI. Nor does it exhibit a statistically significant factor loading based on the selection criteria of Camacho and Perez-Quirós (2010). More precisely, the information conveyed by the predictor is assumed to be mainly idiosyncratic and therefore it is not included in the final model.

The in-sample results from the DFM sequentially estimated from 1991 to 2017 clearly point to two types of world trade predictors: (i) a first subset of indicators, mainly coincident predictors, which exhibit short publication delays; and (ii) a second subset including potential leading indicators. To ensure the stationarity of the WTI, soft indicators enter the model in levels whereas all other predictors are taken as month-on-month growth rates. [15]

A quick glance at Table 5 shows that the estimated coefficients of the factor loadings, which reflect the linkage of each observable with the latent factor, are statistically significant [16] and show the expected sign. The percentage of the variance of world trade growth explained by the model containing only coincident indicators (i.e. M4) is 62%. The remaining two indicators, meaning both the US high-yield spread and the PMI new export orders index, are leading indicators anticipating world trade cycle dynamics in $h$ months, with $h = 0, 1, 2, 3..., .12$. Both indicators exhibit consistent and statistically significant factor loadings and their inclusions increases the variance of global trade growth explained by the common factor up to 92%

In order to select an optimal number of leads, the log-likelihood values associated with these lead times are computed and plotted in Figure 3. The empirical simulations show that the likelihood function reaches its maximum when treating the PMI new export orders index as a coincident indicator of the common factor rather than a leading indicator (i.e. it leads the common factor by $h = 0$ months). On the contrary, the US high yield spread leads the common factor by $h = 1$ months.

## 4.2 Predictive accuracy: *pseudo* real-time analysis

In the absence of real-time vintages of the selected dataset of both the monthly predictors and the quarterly growth rate of world trade, an out-of-sample analysis in *pseudo* real-time has been carried out to test the predictive accuracy of the WTI over the period 2012Q1-2015Q4. As in Stock and Watson (2002), the method consists of calculating forecasts from successive enlargements of a partition of the latest available dataset. At every iteration, after extending the dataset with one additional month of information, the model is re-estimated and the $h-$periods ahead forecasts computed. The dataset for the out-of-sample analysis starts in January 1991 and is characterised by ragged ends depending on the different data availability of the indicators. More precisely, at every period, an unbalanced dataset is reproduced in order to take into account that different asynchronous data releases have diversified predictive power on global trade growth.

The performance of the WTI in forecasting world trade growth is assessed against three competing forecasting models: (i) an autoregressive model of order two $AR(2)$, which is estimated in

[15] In line with Mariano and Murasawa (2003), the quarterly growth rate of world trade is also included in the model as it adds information on synchronised co-movements to the construction of the single World Trade Index.

[16] To simplify the analysis, the lag lengths used in the empirical exercise were always set to 2 since $AR(2)$ models are able to capture very rich dynamics in the time series.

real-time through iterative forecasts; (ii) a random walk process $RW$, whose forecasts equal the average of the latest available real-time observations; and (iii) the large-scale DFM by Guichard and Rusticelli (2011).

A set of 9-month ahead forecasts is computed at each quarter between 2012Q1 and 2015Q4. Therefore, for each quarter of world trade growth there are 3 monthly forecasts referring to the latest missing quarter of world trade growth before its official release (backcasts), 3 monthly forecasts referring to the current quarter (nowcasts) and 3 monthly forecasts referring to the next quarter of world trade growth (forecasts). World trade growth is released on the third month of the following quarter; as a consequence, the third month of the backcast prediction corresponds to the actual data.

Based on the root mean-squared forecast errors (RMSE) of each model, multivariate models clearly outperform univariate models. However, these gains diminish with the forecast horizon, although they remain statistically significant as reported in Table 6. The intuition behind this result is that factor models use incoming information as it is available from the promptly published economic indicators. This early available information is much less valuable as the forecasting horizon increases. In fact, for large forecasting horizons, the monthly indicators are not available for the reference quarter and all the time series used in the models must be forecast for the quarter of interest, regardless of whether the model is univariate or multivariate.

The pair-wise test introduced by Diebold and Mariano (1995) is used to compare pairs of models. It tests the null hypothesis of equal predictive accuracy based on differences between their RMSEs. Small- and large-scale factor models show similar predictive accuracy (Table 6), but the WTI has the advantage of being less data-consuming.

### 4.3 Turning-points detection: dealing with non-linearities

In the recent past, world trade growth has shown signs of nonlinearity, possibly due not only to major structural breaks (i.e. the latest global financial crisis), but also to the asymmetric dynamics characterising the uneven sequence of cyclical expansions and recessions. To this extent, the WTI itself is tested for the presence of a regime switch. We assume that the WTI at time $t$, $x_t$, might switch state according to an unobservable state variable, $s_t$, which follows a first-order Markov chain. [17] A simple switching model (Hamilton, 1989) can be specified as:

$$x_t = C_{s_t} + \sum_{l=1}^{p} \alpha_j x_{t-j} + \varepsilon_t \tag{22}$$

where $\varepsilon_t \sim i.i.d.\ N\ (0, \sigma)$. The non-linear behaviour of the times series is driven by the state-dependent constant $C_{s_t}$, which is allowed to switch between the two distinct regimes $s_t = 0$ and $s_t = 1$. The transition probabilities are independent of the information set at $t-1$, $x_{t-1}$, and of the trade cycle states prior to $t-1$. As a result, the probabilities of staying in each state are:

[17] Camacho et al. (2015) found that although the Markov-switching dynamic factor model is generally preferred to make inferences from the common factor obtained from a linear factor model, its marginal gains rapidly diminish as the quality of the predictors used increases.

$$p(s_t = i \mid s_{t-1} = j, s_{t-2} = h, ..., x_{t-1}) = p(s_t = i \mid s_{t-1} = j) = p_{ij} \tag{23}$$

Table 7 summarises the coefficients estimated by maximum likelihood. In the state represented by $s_t = 0$ , the intercept $c_0$ is positive and statistically significant, while the intercept $c_1$ is negative in the regime referred as $s_t = 1$. Hence, the first regime is labelled as world trade expansions whereas the second regime is labelled as the contraction state. Yet, according to the related business cycle literature (Hamilton, 2001), expansions are more persistent on average than downturns (estimated $p_{00}$ and $p_{11}$ of about 0.99 and 0.89, respectively). These are novel results from the world trade cycle dating point of view. In fact, this is also reflected in the average duration of expansions and contractions for the world trade growth series being 18 and 14 months, respectively (Table 8).

Table 8 additionaly summarises the main results of comparing predicted probabilities of turning points and actual realisations over the sample period 1991M1 – 2017M7. The dates of turning points for the single-index and the quarterly world trade growth series (monthly basis) are given by applying the Bry and Boschan (1971) algorithm, which indicates peaks and troughs characterising the world trade series following the NBER turning-points detection method. These results show that the WTI is in striking accord with the quarterly world trade series, with an average lag of one month and a maximum lead of two.

Finally, to provide assessment on whether the WTI also performs well at predicting turning points, the forecasting quadratic probability score ($FQPS$) is computed as:

$$FQPS = \frac{1}{T}\sum_{t=1}^{T} 2(\Pi_t - R_t)^2 \tag{24}$$

where $\Pi_t$ is the time$-t$ probability forecast of a turning point over the horizon $h$, and $R_t$ equals one if a turning point (peak or through) occurs within the horizon (i.e., between times $t$ and $t+h$) and equals zero otherwise.[18]

More precisely, $FQPS$ is defined as the mean squared deviation of the probabilities of trade contractions from a recessionary indicator that takes the value of one in the periods dated as world trade contractions by the Bry and Boschan (1971) algorithm and zeroes elsewhere. The $FQPS$ ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The obtained value of FQPS = 0.21 indicates that the WTI performs relatively well at predicting turning points. This is confirmed by the high correlation between the probability of contraction as indicated by the WTI and actual world growth contractions as shown in Figure 4.[19]

[18] It is the only proper scoring rule that is a function of the divergence between predictions and realisations. For further details, see Brier (1950) and Diebold and Rudebusch (1996).

[19] It is worth noting that, given the greater cyclicality of merchandise trade with respect to service trade, detected turning points inferring the state of the world trade cycle are more likely associated with global movements in merchandise trade.

# 5 Conclusions

It is a challenge to construct practical and satisfactory tools to monitor global trade cycles owing to the lags in publishing historical data. This paper proposes a small-scale dynamic factor model with leading indicators under a mixed frequencies framework to monitor global trade growth in real time and to produce accurate backcasts, nowcasts and 1-period ahead forecasts. The indicators used in the DFM are selected through a multidimensional approach by means of Bayesian model averaging (BMA) techniques, dynamic correlations and Granger non-causality predictability tests. The resulting World Trade Index (WTI) is used to predict global trade growth and to capture trade cycle turning points through a Markov-switching model. Our main findings suggest that the WTI is successful not only in computing a coincident indicator, which is in striking accord with the actual history of a global trade cycle but also able to explain a high percentage of the variance of actual trade growth. In addition, empirical simulations suggest that global credit and trade finance conditions have led the global trade cycle by at least one month on average over recent years. Finally, pseudo real-time analysis shows that the WTI outperforms a number of competing models, making it useful for trade cycle monitoring, nowcasting and short-term forecasting of global trade growth.

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Table 1: Indicators, frequency and release date

| | | Start date | Lags | Freq | Source |
|---|---|---|---|---|---|
| | **Merchandise world trade (vol)** | 1968 | 2 | M | CPB |
| 1 | Commodity Research Bureau index | 1991 | 1 | M | CPB |
| 2 | Brent - Oil prices | 1957 | 1 | M | Thomson Reuters |
| 3 | USD Nominal Effective Exchange Rate | 1963 | 1 | M | BIS |
| 4 | Baltic Dry Index | 1985 | 1 | M | The Baltic Exchange |
| 5 | IFO Climate | 1991 | 1 | M | IFO |
| 6 | IFO Expectation | 1991 | 1 | M | IFO |
| 7 | Global PMI (Manufacturing & Services) | 1998 | 1 | M | Markit Economics |
| | **World trade of goods and services** | 1966 | 3 | Q | OECD |
| 8 | World industrial production index | 1991 | 2 | M | CPB |
| 9 | OECD Retail sales | 2000 | 3 | M | OECD |
| 10 | World steel production | 1980 | 1 | M | IISI |
| 11 | Harper shipping index | 1996 | 1 | M | Harper Petersen & Co. |
| 12 | International air freight traffic | 1996 | 1 | M | IATA |
| 13 | Tech pulse index | 1971 | 1 | M | CSIP |
| 14 | World semiconductor billings | 1976 | 2 | M | SIA |
| 15 | Global PMI new orders | 1998 | 1 | M | Markit Economics |
| 16 | Global PMI new export orders | 1998 | 1 | M | Markit Economics |
| 17 | Global PMI Manufacturing index | 1998 | 1 | M | Markit Economics |
| 18 | Global PMI stock level index | 1998 | 1 | M | Markit Economics |
| 19 | OECD+ BRICS CLI | 1960 | 2 | M | OECD |
| 20 | World stock market prices index | 1973 | 1 | M | Datastream |
| 21 | USA IPI | 1991 | 2 | M | CPB |
| 22 | Japan IPI | 1991 | 2 | M | CPB |
| 23 | EuroArea IPI | 1991 | 2 | M | CPB |
| 24 | Adv. Economies IPI | 1991 | 2 | M | CPB |
| 25 | Emerging Economies IPI | 1991 | 2 | M | CPB |
| 26 | Asia IPI | 1991 | 2 | M | CPB |
| 27 | LatinAmerican IPI | 1991 | 2 | M | CPB |
| 28 | Central and Eastern IPI | 1991 | 2 | M | CPB |
| 29 | Africa and MENA IPI | 1991 | 2 | M | CPB |
| 30 | US high yield spread | 1984 | 1 | M | Own calculations |

Table 2: Granger non-causality test: marginal significance levels for predictability

| | Predictors | $p$-values for Wald tests |
|---|---|---|
| 1 | CRB index | 0.000 |
| 2 | Brent - Oil prices | 0.000 |
| 3 | USD NEER | 0.146 |
| 4 | Baltic Dry Index | 0.000 |
| 5 | IFO Climate | 0.000 |
| 6 | IFO Expectation | 0.000 |
| 7 | Global PMI (M&S) | 0.000 |
| 8 | World IPI | 0.365 |
| 9 | OECD Retail sales | 0.022 |
| 10 | World steel production | 0.398 |
| 11 | Harper shipping index | 0.000 |
| 12 | International air freight traffic | 0.914 |
| 13 | Tech pulse index | 0.000 |
| 14 | World semiconductor billings | 0.319 |
| 15 | Global PMI new orders | 0.000 |
| 16 | Global PMI new export orders | 0.000 |
| 17 | Global PMI Manufacturing index | 0.000 |
| 18 | Global PMI stock level index | 0.081 |
| 19 | OECD+ BRICS CLI | 0.000 |
| 20 | World stock market prices index | 0.000 |
| 21 | USA IPI | 0.000 |
| 22 | Japan IPI | 0.031 |
| 23 | EuroArea IPI | 0.204 |
| 24 | Adv. Economies IPI | 0.153 |
| 25 | Emerging Economies IPI | 0.000 |
| 26 | Asia IPI | 0.427 |
| 27 | LatinAmerican IPI | 0.577 |
| 28 | Central and Eastern IPI | 0.901 |
| 29 | Africa and MENA IPI | 0.086 |
| 30 | US high yield spread | 0.000 |

Notes: $p - values$ for Wald tests of Granger non-causality tests based on heteroskedasticity-robust variance estimator. p-values lower than 0.1 indicate significance at the 10 % level. All test results are based on bivariate VAR (p) models, based on AIC. The evaluation period is 1976-2016.

Table 3: Predictors ol global trade of goods and services

| | Balanced (2008-2016) | | | Unbalanced (1967-2016) | | |
|---|---|---|---|---|---|---|
| | PIP | P. Mean | P.Std | PIP | P. Mean | P.Std |
| | [1] | [2] | [3] | [4] | [5] | [6] |
| Global PMI Manufacturing index | 0.93 | 0.33 | 0.14 | - | - | - |
| World semiconductor billings | 0.76 | 0.00 | 0.00 | 0.88 | 0.00 | 0.00 |
| Global PMI new orders | 0.70 | -0.13 | 0.11 | - | - | - |
| IFO Expectation | 0.62 | 0.08 | 0.08 | 1.00 | -0.25 | 0.00 |
| USA IPI | 0.60 | 0.10 | 0.10 | 0.09 | 0.00 | 0.00 |
| IFO Climate | 0.58 | -0.08 | 0.08 | 1.00 | -0.25 | 0.00 |
| World industrial production index | 0.57 | -0.15 | 0.18 | - | - | - |
| US high yield spread | 0.54 | 0.10 | 0.11 | 0.14 | 0.00 | 0.00 |
| Global PMI stock level index | 0.41 | 0.07 | 0.11 | - | - | - |
| USD Nominal Effective Exchange Rate | 0.40 | 0.01 | 0.02 | 0.18 | 0.00 | 0.00 |
| World steel production | 0.30 | 0.00 | 0.00 | 0.81 | 0.00 | 0.00 |
| Asia IPI | 0.30 | -0.01 | 0.06 | 0.34 | 0.00 | 0.00 |
| Harper shipping index | 0.28 | -0.00 | 0.00 | - | - | - |
| Central and Eastern IPI | 0.25 | -0.00 | 0.10 | 0.74 | 0.00 | 0.00 |
| International air freight traffic | 0.25 | 0.00 | 0.00 | - | - | - |
| LatinAmerican IPI | 0.24 | 0.01 | 0.05 | 0.31 | 0.00 | 0.00 |
| Adv. Economies IPI | 0.22 | -0.02 | 0.11 | 0.17 | 0.00 | 0.00 |
| Commodity Research Bureau index | 0.22 | 0.00 | 0.00 | 0.08 | 0.00 | 0.00 |
| Japan IPI | 0.21 | 0.00 | 0.02 | 0.62 | 0.00 | 0.00 |
| EuroArea IPI | 0.20 | 0.00 | 0.05 | 0.98 | 0.00 | 0.00 |
| OECD+ BRICS CLI | 0.19 | -0.09 | 0.33 | 1.00 | 0.15 | 0.00 |
| Brent - Oil prices | 0.18 | 0.00 | 0.00 | 0.89 | 0.00 | 0.00 |
| Baltic Dry Index | 0.17 | 0.00 | 0.00 | 0.45 | 0.00 | 0.00 |
| Global PMI (Manufacturing & Services) | 0.17 | 0.00 | 0.05 | - | - | - |
| Africa and MENA IPI | 0.16 | 0.00 | 0.03 | 0.98 | 0.00 | 0.00 |
| Tech pulse index | 0.15 | 0.00 | 0.03 | 0.57 | 0.00 | 0.00 |
| Emerging Economies IPI | 0.15 | 0.00 | 0.03 | 0.99 | -0.01 | 0.00 |
| OECD Retail sales | 0.14 | 0.00 | 0.05 | 0.14 | 0.00 | 0.00 |
| World stock market prices index | 0.14 | 0.00 | 0.00 | 0.99 | 0.00 | 0.00 |
| Global PMI new export order | 0.14 | 0.00 | 0.03 | - | - | - |
| Prior Inclusion Probability | | 0.5 | | | 0.5 | |
| Models visited | | 1,073,741,824 | | | 4,194,304 | |

Notes: PIP refers to the posterior inclusion probability of a particular predictor. Given the prior inclusion probability is equal for all the variables (i.e., 0.5), those regressors with PIP above 0.5 are considered as robust drivers of global trade growth; P. Mean refers to the posterior mean conditional on inclusion of a given regressor in the empirical model, which is a weighted average of model-specific coefficient estimates with weights given by the model-specific R-squares; P.Std. refers to the posterior standard deviation, which is a weighted average of model-specific std.

Table 4: Dynamic correlations

| | | $y$ | $y_{t-1}$ | $y_{t-2}$ | $y_{t-3}$ | $y_{t+1}$ | $y_{t+2}$ | $y_{t+3}$ |
|---|---|---|---|---|---|---|---|---|
| | | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| 1 | CRB index | 0.07 | 0.09 | 0.10 | 0.10 | 0.03 | -0.01 | -0.08 |
| 2 | Brent - Oil prices | 0.07 | 0.10 | 0.10 | 0.10 | 0.04 | -0.01 | -0.09 |
| 3 | USD NEER | -0.17 | -0.18 | -0.18 | -0.17 | -0.15 | -0.11 | -0.07 |
| 4 | Baltic Dry Index | 0.25 | 0.26 | 0.26 | 0.25 | 0.23 | 0.19 | 0.12 |
| 5 | IFO Climate | 0.43 | 0.47 | 0.48 | 0.48 | 0.37 | 0.28 | 0.19 |
| 6 | IFO Expectation | **0.75** | 0.72 | 0.67 | 0.58 | **0.73** | 0.68 | 0.59 |
| 7 | Global PMI (M&S) | 0.83 | 0.78 | 0.71 | 0.61 | 0.83 | 0.79 | 0.71 |
| 8 | World IPI | 0.03 | 0.05 | 0.07 | 0.09 | -0.00 | -0.05 | -0.11 |
| 9 | OECD Retail sales | 0.06 | 0.07 | 0.08 | 0.08 | 0.04 | 0.00 | -0.04 |
| 10 | World steel production | 0.10 | 0.10 | 0.09 | 0.07 | 0.08 | 0.04 | -0.01 |
| 11 | Harper shipping index | 0.30 | 0.34 | 0.38 | 0.41 | 0.25 | 0.20 | 0.15 |
| 12 | International air freight traffic | 0.36 | 0.41 | 0.43 | 0.44 | 0.29 | 0.19 | 0.08 |
| 13 | Tech pulse index | 0.05 | 0.12 | 0.18 | 0.23 | -0.02 | -0.10 | -0.17 |
| 14 | World semiconductor billings | 0.29 | 0.39 | 0.47 | 0.53 | 0.19 | 0.09 | 0.00 |
| 15 | Global PMI new orders | **0.82** | 0.76 | 0.68 | 0.58 | **0.83** | 0.79 | 0.72 |
| 16 | Global PMI new export orders | **0.89** | 0.82 | 0.72 | 0.60 | **0.91** | 0.86 | 0.75 |
| 17 | Global PMI Manufacturing index | **0.89** | 0.83 | 0.74 | 0.63 | **0.89** | 0.84 | 0.74 |
| 18 | Global PMI stock level index | 0.58 | 0.66 | 0.71 | 0.73 | 0.48 | 0.37 | 0.24 |
| 19 | OECD+ BRICS CLI | 0.75 | 0.76 | 0.75 | 0.70 | 0.70 | 0.62 | 0.52 |
| 20 | World stock market prices index | 0.14 | 0.15 | 0.16 | 0.16 | 0.10 | 0.06 | -0.01 |
| 21 | USA IPI | 0.16 | 0.22 | 0.27 | 0.30 | 0.08 | 0.01 | -0.08 |
| 22 | Japan IPI | 0.47 | 0.53 | 0.58 | 0.59 | 0.37 | 0.24 | 0.10 |
| 23 | EuroArea IPI | 0.27 | 0.35 | 0.40 | 0.44 | 0.16 | 0.03 | -0.10 |
| 24 | Adv. Economies IPI | 0.27 | 0.34 | 0.40 | 0.43 | 0.17 | 0.06 | -0.07 |
| 25 | Emerging Economies IPI | 0.07 | 0.08 | 0.09 | 0.09 | 0.04 | 0.00 | -0.06 |
| 26 | Asia IPI | -0.08 | -0.08 | -0.08 | -0.08 | -0.09 | -0.10 | -0.12 |
| 27 | LatinAmerican IPI | 0.05 | 0.07 | 0.09 | 0.09 | 0.01 | -0.04 | -0.09 |
| 28 | Central and Eastern IPI | -0.06 | -0.06 | -0.06 | -0.06 | -0.07 | -0.09 | -0.12 |
| 29 | Africa and MENA IPI | 0.02 | 0.05 | 0.08 | 0.10 | -0.02 | -0.08 | -0.13 |
| 30 | US high yield spread | -0.69 | -0.64 | -0.58 | -0.51 | **-0.71** | -0.68 | -0.61 |

Notes: Highlighted cells refer to correlations among quarterly trade growth and predictors (leads/lags) higher than 0.7.

Table 5: Loading factors

| Predictors | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Mod | WT | PMI Man | IPI US | IFOex | IFOc | IPI_world | CPB | US spread | PMI NExO | (% WT growth) |
| M1 | 0.04 | 0.13 | 0.08 | 0.11 | . | . | . | . | . | 48.6 |
| | (0.00) | (0.02) | (0.01) | (0.02) | . | . | . | . | . | |
| M2 | 0.05 | 0.12 | 0.09 | 0.22 | 0.15 | . | . | . | . | 51.2 |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.00) | . | . | . | . | |
| M3 | 0.05 | 0.12 | 0.10 | 0.22 | 0.15 | 0.12 | . | . | . | 55.9 |
| | (0.00) | (0.02) | (0.01) | (0.01) | (0.00) | (0.02) | . | . | . | |
| M4 | 0.05 | 0.13 | 0.10 | 0.22 | 0.15 | 0.12 | 0.09 | . | . | 62.3 |
| | (0.00) | (0.01) | (0.01) | (0.01) | (0.00) | (0.02) | (0.01) | . | . | |
| M5 | 0.05 | 0.13 | 0.10 | 0.22 | 0.15 | 0.12 | 0.09 | -0.07 | . | 77.9 |
| | (0.00) | (0.02) | (0.01) | (0.01) | (0.00) | (0.02) | (0.01) | (0.01) | . | |
| M6 | 0.07 | 0.16 | 0.12 | 0.18 | 0.12 | 0.14 | 0.11 | -0.09 | 0.18 | 92.1 |
| | (0.00) | (0.02) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) | (0.02) | |

Notes: Entries refer to loading factors estimates by maximum likelihood. They measure the correlation between the common factor and each of the indicators (in columns). Std errors are in brackets. WT indicates quarterly world trade growth; PMIman indicates global PMIs manufacturing; PMIex indicates PMI new export orders, IFOex indicates IFOs expectations; IFOclim indicate IFO climate surveys; US IPI indicates US industrial production index; Wold IPI indicates world industrial production index; WT (CPB) indicates merchandise world trade growth; US spread indicates the US High Yield Spread.

Table 6: Predictive accuracy

| | *Backcasts* | *Nowcasts* | *Forecasts* |
|---|---|---|---|
| Root Mean Squared Errors | | | |
| Large-scale DFM | 0.285 | 0.485 | 0.655 |
| RW | 0.611 | 0.673 | 0.691 |
| AR | 0.599 | 0.638 | 0.682 |
| WTI | 0.433 | 0.507 | 0.663 |
| Equal predictive accuracy tests | | | |
| WTI vs Large-scale DFM | 0.831 | 0.890 | 0.927 |
| WTI vs RW | 0.001 | 0.002 | 0.140 |
| WTI vs AR | 0.052 | 0.108 | 0.506 |

Notes: The forecasting sample is 2012.1-2015.4. The top panel shows the Root Mean Squared Errors (RMSE) of the large-scale dynamic factor model (Large-scale DFM) based on Guichard and Rusticelli (2011), a random walk (RW), an autoregressive model (AR), along with those of the WTI based on our extension of the DFM. The bottom panel shows the $p$-values of the Diebold-Mariano test of equal predictive accuracy.

Table 7: Markov-switching estimates

| $c_0$ | $c_1$ | $\sigma^2$ | $p_{00}$ | $p_{11}$ |
|---|---|---|---|---|
| 1.02 | -12.29 | 11.38 | 0.99 | 0.89 |
| (0.20) | (1.05) | (0.91) | (0.00) | (0.07) |

Notes: The estimated model is $x_t = c_{s,t} + e_t$ where $x_t$ is the common factor, $s_t$, is a latent state variable that drives the trade cycle dynamics..

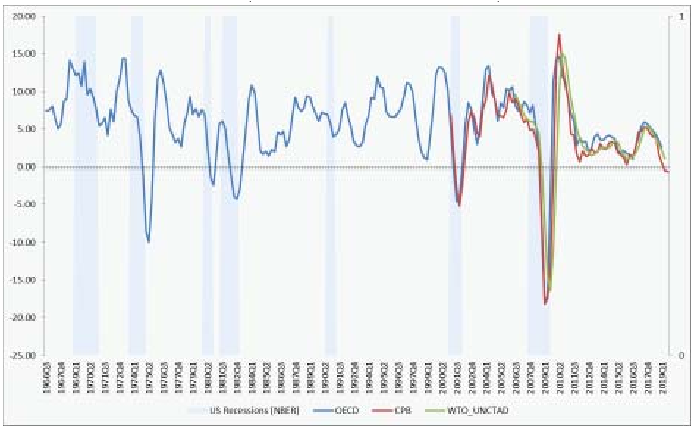
Table 8: Trade cycle accuracy: Turning Points

| | OECD | | World Trade Index | | Accuracy | |
|---|---|---|---|---|---|---|
| | Through | Peak | Through | Peak | Through | Peak |
| | . | . | . | Mar.1992 | | |
| | Nov. 1992 | Jun 1994 | Nov. 1992 | Dec. 1994 | = | -5 |
| | Jul. 1995 | Aug. 1997 | Nov. 1995 | Jun. 1997 | | 2 |
| | Nov. 1998 | Nov. 1999 | Nov. 1998 | Nov. 1999 | = | = |
| | Oct. 2001 | Apr. 2002 | Oct. 2001 | Jul. 2002 | = | -3 |
| | May 2003 | Dec. 2003 | Jun 2003 | Jan. 2004 | -1 | -1 |
| | Mar. 2005 | Jan. 2006 | Mar. 2005 | Feb. 2006 | = | -1 |
| | Sep. 2006 | May. 2007 | Sep. 2006 | Nov. 2008 | = | |
| | Dec. 2008 | Sep. 2009 | Mar. 2009 | . | -3 | |
| | Jul. 2012 | Nov. 2013 | . | Feb. 2014. | | -3 |
| | Mar. 2016 | Jan-2017 | Mar. 2016 | . | = | |
| Avg. duration of contractions | 14.2 | | 17.1 | | | |
| Avg. duration of expansions | 18.3 | | 12.3 | | | |
| Avg. amplitude of contractions | -4.0 | | -10.2 | | | |
| Avg. amplitude of expansions | 3.7 | | 11.2 | | | |

Notes: Min. phase = 5; Min. cycle: 15; Symmetric window = 15; Threshold parameter = 25. Positive signs in accuracy refer to leads and negative to lags.

# 6 Figures

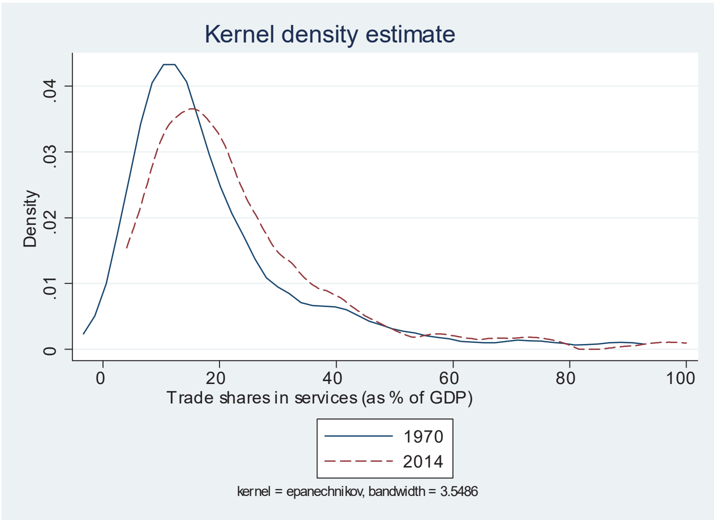
Figure 1: World trade growth (annual, 3-month MA) and recessions in the US.




Notes: Shaded areas refer to US recessions as dated by the NBER. CPB and WTO refer to merchandise volumes, while OECD includes also services.

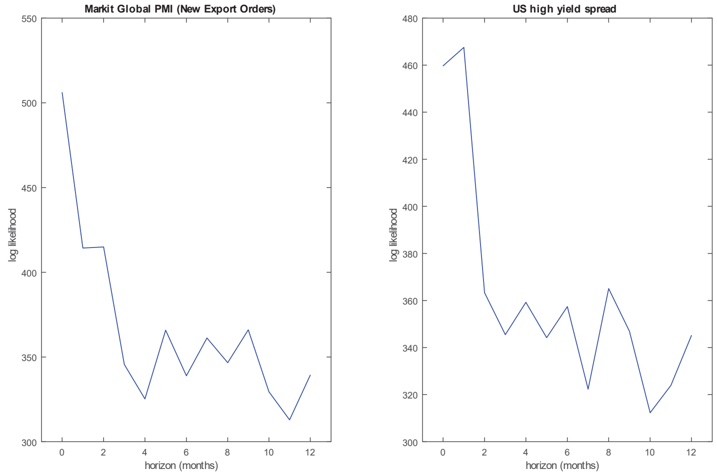
Sources: OECD, CPB, WTO, and NBER.

Figure 2: Kernel densities, shares of trade services as % of GDP.



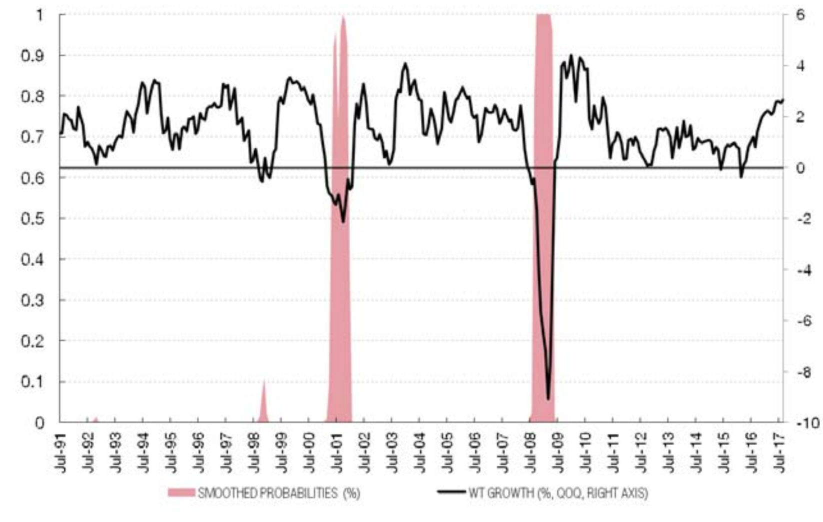

Source:The World Bank Database (217 countries).

Figure 3: Log likelihood and lead time of forward-looking indicators.




Notes. US high yield spread and Markit Global PMI (New Export Orders) at time $t$ have been related to the common factor at time $t+h$. In this figure,$h$ appears in the horizontal axis and the log likelihoods reached by the dynamic factor model appear in the vertical axis.

Figure 4: Smoothed probabilites of WT growth contractions from the common factor.




Notes. Shaded areas refer to (monthly) probabilities of a global trade contraction from the WTI, in-sample estimation over 1991-2016. World trade growth refers to the quarterly growth rate on a monthly basis.
Sources: OECD, authors' calculations.

# 7 Online Appendix

To illustrate what the matrices stated in the measurement and transition equations look like, let us assume that there are only one quartely (world trade) indicator, $g_t$, one monthly coincident indicator, $z_{it}$, and one monthly leading indicator $z_{lt}$, which are collected in the vector $Y_t = (g_t, z_{it}, z_{lt})'$. For the sake of simplicity, let us assume that $p_1 = p_2 = p_3 = 1$ and that the lead of the leading indicator is $h = 1$. In this case, the *measurement equation,* $Y_t = H\xi_t + E_t$,with $E_t \sim i.i.d.N\,(0, R)$, can be stated by defining

$$Y_t \quad = \quad (g_t, z_{it}, z_{lt})\,, \tag{A1}$$

$$H \quad = \quad \begin{pmatrix} 0 & \frac{\beta_g}{3} & \frac{2\beta_g}{3} & \beta_g & \frac{2\beta_g}{3} & \frac{\beta_g}{3} & \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} & 0 & 0 \\ 0 & \beta_i & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ \beta_l & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}, \tag{A2}$$

$$\xi_t \quad = \quad \left(x_{t+1}, x_t, x_{t-1}, x_{t-2}, x_{t-3}, x_{t-4}, u_t^g, u_{t-1}^g, u_{t-2}^g, u_{t-3}^g, u_{t-4}^g, u_t^i, u_t^l\right)', \tag{A3}$$

It is worthy to mention that the model assumes a contemporaneous correlation between non-leading indicators and the trade cycle, whereas for leading indicators the correlation is imposed between the current values of the indicators and future values of the common factor.

In the same way, the *transition equation,* $\xi_t = F\xi_{t-1} + W_t$, with $W_t \sim i.i.d.N\,(0, Q)$ can be stated by defining

$$F = \begin{pmatrix} p_1 & ... & 0 & 0 & 0 & ... & & & 0 \\ 1 & & 0 & & & ... & & & 0 \\ ... & & d_1^z & & & ... & & & ... \\ 0 & ... & 1 & 0 & & ... & & & 0 \\ 0 & ... & & 0 & d_1^g & 0 & 0 & & 0 \\ ... & ... & & & & & & & ... \\ 0 & ... & & & & 1 & 0 & & 0 \\ 0 & ... & & & & 0 & 0 & d_1^i & 0 \\ 0 & ... & & & & 0 & 0 & & d_1^l \end{pmatrix}, \tag{A4}$$

where $Q = diag\ (\sigma_e^2, 0, ..., 0.\sigma_g^2, 0, ..., 0, \sigma_i^2, \sigma_l^2)$. The identifying assumption implies that the variance of the common factor is normalized to a value of one, which is a very standard assumption in factor models.

## 7.1 Mixing frequencies

For the sake of clarity, we illustrate the model using a single low-frequency variable, sampled at the quarterly frequency, and a single high-frequency variable, sampled at the monthly frequency. To mix them, let us consider all series as being of monthly frequency and treat quarterly data as monthly series with missing observations. In this case, the quarterly series are observed in the last month of the quarter, and exhibit missing observations in the first two months of each quarter.

In particular, let $G_t$ be the level of a quarterly flow variable that can be decomposed as the sum of three (usually unobserved) monthly values $G_t^*$. To avoid using a non-linear state-space model, which would complicate the estimation, we follow Mariano and Murasawa (2003) and approximate the arithmetic mean with the geometric mean. Hence, the level of the variable can be written as

$$G_t = 3(G_t^* G_{t-1}^* G_{t-2}^*)^{1/3}. \tag{A5}$$

Taking logs on both sides of this expression and computing the three-period differences for all $t$, we obtain

$$\triangle_3 \ln G_t = \frac{1}{3}(\triangle_3 \ln G_t^* + \triangle_3 \ln G_{t-1}^* + \triangle_3 \ln G_{t-2}^*). \tag{A6}$$

Denoting the quarter-on-quarter growth rate $\triangle_3 \ln G_t = g_t$ the monthly-on-monthly growth rate $\triangle \ln G_t^* = g_t^*$ and applying algebra, we obtain

$$g_t = \frac{1}{3}g_t^* + \frac{2}{3}g_{t-1}^* + g_{t-2}^* + \frac{2}{3}g_{t-3}^* + \frac{1}{3}g_{t-4}^*. \tag{A7}$$

Accordingly, we express the quarter-on-quarter growth rate ($g_t$) as a weighted average of the past monthly-on-monthly growth rates ($g_{t-i}^*$ , $i = 0, ..., 4$) of the monthly series.

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