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A Dynamic Factor Model for World Trade Growth

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A DYNAMIC FACTOR MODEL FOR WORLD TRADE GROWTH

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ABSTRACT/RÉSUMÉ

A Dynamic Factor Model for World Trade Growth

This paper reviews the main monthly indicators that could help forecasting world trade and compares different type of forecasting models using these indicators. In particular it develops dynamic factor models (DFM) which have the advantage of handling larger datasets of information than bridge models and allowing for the inclusion of numerous monthly indicators on a national and world-wide level such as financial indicators, transportation and shipping indices, supply and orders variables and information technology indices. The comparison of the forecasting performance of the DFMs with more traditional bridge equation models as well as autoregressive benchmarking models shows that, the dynamic factor approach seems to perform better, especially when a large set of indicators is used, but also that the marginal gains in adding indicators seems to diminish after a certain stage.

JEL classification codes: F17; F47; C53; E37
Keywords: World trade; forecasting; dynamic factor models; bridge models

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Un modèle à facteurs dynamiques pour prévoir la croissance du commerce mondial

Ce document passe en revue les principaux indicateurs mensuels pouvant aider á prévoir le commerce mondial et compare différents types de modèles de prévision utilisant ces indicateurs. En particulier, il développe des modèles á facteurs dynamiques (DFM) qui ont l'avantage de permettre l'utilisation de plus de séries que les modèles d'étalonnage et donc d'inclure des indicateurs mensuels au niveau national et mondial tels que les indicateurs financiers, de transport et d'expédition, d'approvisionnement et de carnets de commandes ou encore et de technologie de l'information. La comparaison de la performance de prévision des DFM avec des modèles d'étalonnage plus traditionnels ou des modèles autoregressifs montre que l'approche en facteurs dynamiques semble plus performante, surtout quand un vaste ensemble d'indicateurs est utilisé ; les gains marginaux en ajoutant des indicateurs semblent toutefois diminuer après un certain stade.

Classification JEL : F17 ; F47 ; C53 ; E37
Mots-Clés : Commerce mondial ; prévisions ; modèles á facteurs dynamiques ; modèle d'étalonnage

TABLE OF CONTENTS

Tables

Figures

A DYNAMIC FACTOR MODEL FOR WORLD TRADE GROWTH

Stéphanie Guichard and Elena Rusticelli[1]

Introduction

1. The unexpected collapse of world trade in the end of 2008 and in early 2009 clearly underlined the need to better monitor and forecast global trade flows.[2] This is not an easy task as there are important delays in the publication of world trade data that make it difficult to monitor the situation in real time. Preliminary monthly data from the CPB (Netherlands Bureau for Economic Policy Analysis) on world trade of merchandise is available with a lag of close to two months. World trade in goods and services, which is the main interest of this paper, is published only on a quarterly basis and first estimates are available about one quarter after the end of the quarter reflecting late publication of national accounts breakdown in some countries notably outside the OECD.[3]

2. Traditionally, world trade has been forecasted as the aggregation of country trade flows (sometimes even broken down further by sectors at the country level). However, Burgert and Dées (2008) suggest that direct forecasting methods, in which world trade is directly forecasted at the aggregate level, are superior to bottom-up forecasting approaches, where world trade results from an aggregation of country-specific forecasts. Even, when the bottom-up approach is preferred (as in the OECD for instance where the Economic Outlook world trade forecast is the aggregation of individual country forecast made by country experts) direct forecasting can be a useful benchmark, since, with the acceleration of globalisation and development of vertical supply chains, global factors have had an increasing role in international trade activity.[4] In addition, for individual countries forecasts, when detailed forecasts of the rest of the world imports are not available, a direct forecast of world trade could be a shortcut to building detailed foreign demand.

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1. The authors are members of the Macroeconomic Analysis Division of the OECD Economics Department. They would like to thank Marta Bańbura for providing some programming codes and guidance on the DFM methodology and Laurent Ferrara, Michele Modugno and Domenico Giannone for very useful comments. They would also like to thank Harper Petersen & Co for providing historical data of the Harpex index and the International Air Transport Association for providing historical data for air freight traffic. The views expressed in this paper are those of the authors and do not represent those of the OECD or its member countries.

2. On the world trade collapse and the debate on whether world trade was just a victim of the crisis or contributed importantly to it see for instance Baldwin (2009).

3. World trade is calculated as the average of world imports and exports of goods and services in volume of 2005.

4. Cheung and Guichard (2010) propose a simple equation linking world trade to world or OECD GDP and financial conditions. Although this model can help assessing the consistency between world trade and world GDP during forecasting exercises, it is of very little help outside forecasting exercises when GDP projections are not updated.

3. Against this background, this paper proposes a model to directly estimate and forecast world trade growth adapted from the techniques used for short term forecasting of GDP growth that allow the incorporation of the information from monthly indicators as soon as it becomes available.[5] Two main types of approach are used by forecasters to estimate and forecast GDP in the short term. On the one hand, approaches combining quarterly bridge equations and monthly auxiliary models have been developed in several institutions in the early 2000s, including at the OECD (see Sedillot and Pain, 2003 and 2005). On the other hand, over the past few years, dynamic factor models have become more frequently used (see for instance Angelini *et al.* (2008), Bańbura and Modugno (2010), Bańbura and Rünstler (2010), Camacho and Perez-Quiros (2008 and 2009). They have the advantage of allowing the use of a wider information set, including series starting later than others, and recent developments have reduced the computational burden previously associated with dynamic factor analysis.

4. This paper explores different issues. First it reviews a possible set of high frequency indicators that could help monitor and forecast world trade in the short term. Then, it presents two types of models to forecast world trade: a bridge model and a dynamic factor model. Within the factor model framework, it assesses the global factors that play the most important role in explaining world trade growth and explores the respective role of global and country-specific data for world trade forecasts. It shows in particular, that industrial production and PMI indicators are the most important in forecasting world trade, with the former especially relevant for the estimation of world trade in the first quarter of the forecasting horizon and the latter playing an important role also in the subsequent quarters. It also shows that including country/region industrial production indices in addition to the world aggregate can help to improve the accuracy of the forecast. Last, the comparison of the forecasting performance of the dynamic factor model models together with a purely autoregressive process and the bridge model suggests the superiority of the dynamic factor approach, especially when a large set of indicators is used, although above a certain range adding new indicators does not seem to be useful.

The key variables to forecast world trade

5. A large set of 56 monthly indicators that could lead or help forecasting world trade has been considered. All of them are easily accessible and timely, being available with a lag of no more than three months. These indicators are of varying nature, including hard indicators, surveys -- soft indicators and financial indicators, and of a different aggregation level, *i.e.* global and country level, aggregate or disaggregate components (Table A1 in the Annex).

6. Although global variables are the most obvious indicators of global activity and trade, there seems to be a case for complementing or replacing such indicators by disaggregated country specific variables. Burgert and Dées (2008) find that in forecasting world trade models using disaggregate information outperform those using aggregate information. Similar results were previously found by Hendry and Hubrich (2006), who focus on disaggregation across components of the CPI and show that prediction mean squared errors of inflation are lower for forecasting models including both aggregate and disaggregate variables in the predictor set compared to models including only aggregate variables or only disaggregate forecasts subsequently re-aggregated.

7. The information set includes the following hard indicators capturing different components of the world trade (all these indicators are plotted against world trade growth in Figure A1 in the Annex):

- World activity is summarised by the following indicators:

5. As shown in several empirical papers dealing mainly with GDP, models that incorporate early releases of monthly indicators, produce more accurate forecasts than models based only on quarterly data (see Sédillot and Pain, 2005, Barhoumi *et al.,* 2008).

- A monthly world trade volume index is computed by the CPB (Netherlands Bureau for Economic Policy Analysis) and is defined as arithmetic average of world exports and world imports of goods. The series covers United States, Japan and EU15 and four groups of emerging countries: OPEC, Asian newly industrialised countries (Taiwan, Hong Kong, Singapore and South Korea), transition countries (central and eastern European countries including Turkey and ex-Soviet Union's countries) and other emerging economies.

- The world industrial production index used here is published by the CPB (Netherlands Bureau for Economic Policy Analysis) and is computed using imports weights. Another measure of world industrial production is also considered and consists of a trade weighted average of the growth rates of industrial production in the United States, the euro area, Japan, and the BRICS. The regional breakdown of these indicators is also considered in the factor model, as each individual country/region's activity may have a contribution to world trade growth that differs from the one implicit in the aggregate index.[6] The world industrial production is usually available two months after the end of the month it refers to, but it is available earlier for some OECD countries.

- Retails sales for the OECD as a whole (in the absence of data for the BRICS) have been also included.

- A global indicator of world production of steel, which is one of the very few components of world production indicators which is easily accessible, has also been included and may act as a leading indicator of industrial production and trade.

• The average Brent oil price series, issued by the UK Department of Energy, is the only available proxy of transports costs on a monthly basis. Shipping costs used below are traditionally chosen as proxies for freight activity rather than transport costs.

• Shipping and freight activity are captured by different indicators:

  - The Baltic dry index measuring dry bulk worldwide international shipping rates reflects changes in the demand for shipping capacity as supply of cargo ships is generally both tight and inelastic. Indirectly, the index measures global demand for the commodities shipped aboard dry bulk carriers, such as building materials, coal, metallic ores and grains. Since dry primarily bulk consists of raw materials used as inputs to the production of intermediate or finished goods, the index may also include information about future economic growth and production. The Baltic dry index is available just after the end of a considered month.

  - The Harpex shipping index focuses on containers freight rather than bulk freight and can be seen as a wider indicator of global trade than the Baltic dry. The Harpex is available just after the end of a considered month.

  - International air freight traffic volumes measure freight tonnes transported by air multiplied by kilometres flown (published by the International Air Transport Association). Air freight accounts for about 35% of the value of goods traded internationally. This indicator is available about one month after the end of a considered month.

6. The specific country/regions breakdown for the CPB industrial production index includes: United States, Japan, euro area, Advanced economies, Emerging economies, Asia, Central and Eastern Europe, Latin America, Africa and Middle East.

- The global technology cycle, which is well correlated with trade flows given the strong vertical integration of the sector and which also tends to lead the world business cycle, can be captured by two indicators: the US-tech pulse index and the world semiconductor billings.

  – The tech pulse is an index of coincident indicators of activity in the US information technology sector and it is produced by the Federal Reserve Bank of San Francisco. This variable has been chosen since there are no other comparable global indicators and the US tech sector generally leads the world technology cycle. It is available less than a month after the end of the considered month.

  – The world semiconductor billings computed by the World Semiconductor Trade Statistics (WSTS) is published by the Semiconductor Industry Association. It is available about a month after the end of the considered month.

8. Several survey and soft indicators are available at a global level and have been included in the analysis.

- Export orders are a leading indicator of trade flows. Over a long period they are available only for the six largest OECD countries (an aggregate measure for these countries has been built as a combination of individual countries export orders, where each is measured as the standardised deviation from its mean). A global new export orders series available since 1998 is produced by Markit Economics and is also considered in this study, together with a wide country breakdown when the time series are sufficiently long.

- In addition to new export orders, the global PMI manufacturing index and the stocks of purchases component of the global PMI index, both published by Markit Economics, have been considered. The individual country PMIs have also been analysed here. PMI surveys are available less than a month after the end of the considered month.

- The OECD produces composite leading indicators of economic activity for all OECD countries and the BRICS, which are aggregated in an OECD+BRICS index. The CLI provides qualitative information on short-term economic movements, which lead changes in industrial production. CLIs are available a bit more than one month after the end of the considered month.

9. Finally, some financial variables have been introduced:

- An index of world stock market prices plays the role of a leading indicator of the economy as a reflection of financial market views on future profits but may also affect activity directly via a wealth effect.

- A measure of US high yield spread is taken as an indicator of the risk premium paid by risky borrowers and should capture both the global impact of credit conditions on activity as well as via global trade finance conditions.[7]

- The US loan officer survey (available only on a quarterly frequency) is also used as a proxy for world credit availability as in Cheung and Guichard (2010).

7. This choice is justified by both the strong international correlation of international bonds 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 risk

10. Bivariate regressions between world trade growth and each monthly indicator can give a first idea of which variables are more likely to help forecasting world trade. In the bivariate regression the world trade growth rate y_t is regressed on its first lag and on every indicator x_{it} in the form:

$$y_t = c + ay_{t-1} + \sum_{l=0}^{4} b_{i,l}\, x_{i,t-l} + e_{i,t} \tag{1}$$

11. The monthly indicators have been aggregated to a quarterly frequency and made stationary by taking growth rate or first order difference.[8] The Schwarz criterion is applied here to select the maximum significant lag for each explanatory variable. Two samples are compared: first the full sample up to 2010 Q3 and then a sample ending in 2008 Q2 just before world trade collapsed to assess whether the results are affected by the crisis and the subsequent sharp rebound (Table 1). Since this approach tends to give high ranking to coincident indicators of world trade, a second set of bivariate estimates was run excluding the contemporaneous values of the explanatory variables so as to assess which variables have higher power as leading indicators of world trade (see Table 2).

Table 1. Ranking of indicators to explain world trade, including contemporaneous values

	Whole sample				Sample ending in 2008 Q2			
	Ranking	Adj. R^2	SIC value	Max lag	Ranking	Adj. R^2	SIC value	Max lag
World industrial production index	1	0.91	-7.35	0	1	0.80	-7.60	0
Global PMI new export orders	2	0.91	-6.61	4	4	0.69	-6.67	2
World trade volume index	3	0.88	-6.99	1	2	0.78	-7.43	1
Largest countries industrial production index	4	0.86	-6.94	0	7	0.62	-6.98	2
Global PMI manufacturing index	5	0.84	-6.22	2	3	0.69	-6.68	2
Air freight volume	6	0.80	-6.26	0	6	0.66	-6.83	0
OECD+BRICS CLI	7	0.79	-6.51	1	5	0.67	-7.07	1
G6 export orders	8	0.75	-6.27	2	9	0.49	-6.64	1
US high yield spread	9	0.74	-6.14	4	15	0.39	-6.50	0
World stock market price	10	0.69	-6.11	1	10	0.49	-6.63	1
Baltic dry index	11	0.65	-5.96	2	19	0.33	-6.41	0
OECD retail sales	12	0.64	-5.95	1	12	0.45	-6.56	1
World steel production	13	0.61	-5.87	1	17	0.34	-6.42	0
Semiconductor billings	14	0.57	-5.83	0	11	0.46	-6.62	0
Global PMI stock level index	15	0.54	-5.30	0	8	0.51	-6.29	1
US loan officer survey	16	0.53	-5.65	2	14	0.41	-6.53	0
Tech pulse index	17	0.52	-5.72	0	13	0.43	-6.57	0
Oil prices	18	0.52	-5.71	0	16	0.37	-6.47	0
Harpex shipping index	19	0.42	-5.52	0	18	0.34	-6.41	0

Note: Max lag is based on the Schwarz criterion value, but ranking were not affected by changing the lag selection criteria.

Source: OECD calculations.

8. Stationarity has been achieved for all hard indicators and the world stock market prices through month-on-month growth rates (with the exception of the Baltic dry index which was found to be stationary). Among soft indicators, only the PMI stock level index has been transformed with first order differences.

Table 2. Ranking of indicators to explain world trade, excluding contemporaneous values

	Whole sample				Sample ending in 2008 Q2			
	Ranking	Adj. R^2	SIC value	Max lag	Ranking	Adj. R^2	SIC value	Max lag
OECD+BRICS CLI	1	0.81	-6.47	4	1	0.58	-6.76	3
World stock market price	2	0.61	-5.91	1	2	0.49	-6.67	1
Baltic dry index	3	0.61	-5.87	2	18	0.33	-6.41	1
US high yield spread	4	0.60	-5.81	3	7	0.41	-6.48	2
Global PMI manufacturing index	5	0.59	-5.33	2	3	0.46	-6.18	2
Global PMI new export orders	6	0.58	-5.31	2	5	0.44	-6.15	2
International air freight traffic	7	0.57	-5.48	1	6	0.41	-6.27	1
World industrial production index	8	0.56	-5.76	1	10	0.38	-6.45	1
OECD retail sales	9	0.55	-5.73	2	9	0.39	-6.45	2
G6 export orders	10	0.54	-5.70	2	8	0.40	-6.47	2
World trade volume index	11	0.51	-5.54	3	15	0.35	-6.41	1
US loan officer survey	12	0.49	-5.59	2	11	0.37	-6.48	1
Global PMI stock level index	13	0.46	-5.03	2	4	0.44	-6.22	1
Largest countries industrial production index	14	0.46	-5.54	2	14	0.35	-6.43	1
World steel production	15	0.45	-5.58	1	19	0.33	-6.41	1
Oil prices	16	0.44	-5.50	2	17	0.33	-6.41	1
Tech pulse index	17	0.42	-5.47	2	13	0.35	-6.44	1
Harpex shipping index	18	0.36	-5.42	1	16	0.33	-6.41	1
Semiconductor billings	19	0.35	-5.42	1	12	0.37	-6.46	1

Note: Max lag is based on the Schwarz criterion value, but ranking were not affected by changing the lag selection criteria.

Source: OECD calculations.

12. The best coincident indicator of the world trade is the world industrial production, with global measure from the CPB performing better than a large country's only aggregate. Then the global manufacturing PMI index and world export orders perform relatively well.[9] In general, soft indicators enter with longer lags suggesting some leading properties confirmed in Table 2. Also financial variables enter the equation with long lags and their explanatory power is increased when including the crisis period. Air freight seems to be another good coincident indicator. The technology sector variables as well as indicators related to freight demand and other global indicators show a more limited explanatory power, although the explanatory power of the Baltic dry index increases substantially when the crisis period and subsequent rebound is included.

13. Excluding contemporaneous impact of the indicators on world trade reveals the leading properties of the CLI, PMIs and financial variables (mainly the world share prices and the spreads) but also of the Baltic dry index. However, the role of the spreads and Baltic dry index is much reduced when excluding the crisis period.[10]

9. But world export orders do not perform better than largest OECD countries export orders on a common sample (*i.e.* when comparing the bivariate regression on a 1998-2010 sample)

10. Recently also, new capacity supply has resulted in a fall in the Baltic dry which does not reflect less demand, casting doubts about its leading properties.

Overview of the bridge model

14. Bridge models are widely used by many institutions to forecast the quarterly GDP growth from timely monthly data (see for example Baffigi, Golinelli and Parigi 2004). Details of the models used for short-term GDP growth forecasts by the OECD are presented in Sédillot and Pain (2003 and 2005). A variant of this method has been implemented at the OECD to predict quarterly world trade growth.

15. Bridge models combine quarterly multivariate bridge equations to predict the GDP/world trade growth with monthly time series models to forecast the missing observations of monthly indicators over the projection period. This approach enables short-term predictions of quarterly GDP/world trade to be based on the most recent, albeit incomplete, set of monthly information.[11]

16. In the multivariate bridge equation, the quarterly world trade series is regressed on its own lags and on a set of few aggregated monthly indicators selected on the basis of the strength of their relationship with world trade growth, their higher timeliness, availability on a sufficiently long sample and their significance as explanatory variables in the multivariate regression. The indicators' set includes the world industrial production index, the six largest OECD countries export orders, the two technology indicators and the US loans officer survey. The Schwarz information criterion (SIC) is then applied to choose the most appropriate number of lags. The US loan officer survey is projected as an exogenous variable depending on the main scenario on credit conditions decided during forecasting exercise. This financial indicator was preferred to the yield spread variable as it exhibited a stable although weak significance on different sample periods while the spread variable was not significant in periods which excluded the financial crisis.[12] Two more indicators, oil prices and the Baltic Dry index, are included in the monthly Vector Autoregressive (VAR) for their predictive power on the main set of monthly indicators, although they do not have a significant impact in explaining the world trade growth.

17. The monthly indicators forecasts from the Bayesian conditional VAR is obtained from:

$$x_t = c + \sum_{s=0}^{S} B_s\, x_{t-s} + e_t \tag{2}$$

where $x_t = (x_{1,t}, \dots, x_{k,t})$ is a $(k \times 1)$ vector of monthly indicators and B_s a $(k \times k)$ matrix of coefficients. Then the quarterly bridge equation, i.e. an Autoregressive Distributed Lag ADL(p,q) is estimated as:

$$y_t^Q = \mu + \sum_{p=1}^{P} \alpha_p y_{t-p}^Q + \sum_{i=1}^{k} \sum_{q=0}^{Q^i} \beta_{i,q} x_{i,t-q}^Q + \varepsilon_t \tag{3}$$

11. Monthly Bayesian VARs are used here to specify prior restrictions on the lags structure of monthly indicators with different end points in order to reduce large out-of-sample forecasting errors otherwise affecting unrestricted VAR models. An important limitation in Bayesian VARs concerns the fact that the forecast accuracy is sensitive to the choice of the hyperparameters defined in the prior, that if not correctly specified can lead to poor performances of the model.

12. In the most recent updates of the bridge equation, the US loan officer survey has become insignificant but was kept in the dataset.

where y_t^Q represents the quarterly world trade growth rate and all aggregated indicators are expressed in growth rates except for export orders. The lag orders P and Q^i are automatically determined by the SIC together with the inclusion of lagged world trade growth. The equation (and the optimal lag orders) are reestimated at each update.[13] The bridge equation produces forecasts for four quarters: depending on the month when the forecast is made either the previous quarter forecast (*i.e.* backcast), current quarter forecast (*i.e.* nowcast) and two quarters ahead forecasts or the current quarter forecast and three quarters ahead forecasts.[14] The Root Mean Square Errors (RMSE) are computed to evaluate the predictive performance of the model.

18. Despite their wide application, bridge models suffer from two major empirical limitations. First, the monthly series must be sufficiently long to guarantee the precisions of the estimates. Unfortunately some relevant indicators like the global PMI index or the volume of air freight traffic are available only from 1998 and 1996 respectively, significantly reducing the sample estimated period. Second, it is not possible to include a large number of variables, because of the risk of multicollinearity, losses of degrees of freedom and the increase in the computational burden in the automated SIC selection procedure. This latter is an important limitation when trying to forecast world trade because it prevents the use of country level data when there are available.

Overview of the dynamic factor model

19. Dynamic factor models represent a less restrictive alternative tool than bridge model for short-term forecasting of GDP growth (see *e.g.* Forni *et al.* 2007; Bańbura and Rünstler 2007). A wider set of collinear monthly indicators is parsimoniously summarised by a few common factors, making the projection possible and the number of parameters limited. In this study the quarterly variable corresponds to the world trade growth rate and different sets of monthly indicators have been considered in order to evaluate the performance of the factor model and compare it with the bridge model.

20. The estimation technique consists of a two-steps procedure which combines principal component extraction with Kalman filtering. In particular, the dynamic factor model is given by:

$$x_t = \Lambda f_t + \xi_t \quad \xi_t \sim \mathbb{N}(0, \Sigma_\xi) \tag{4}$$

$$f_t = \sum_{i=1}^{p} A_i f_{t-i} + \zeta_t \tag{5}$$

$$\zeta_t = B\eta_t \quad \eta_t \sim \mathbb{N}(0, I_q) \tag{6}$$

13. Using a data set ending in 2010Q3 for world trade, the estimated bridge equation was

$$\underset{(4.8)}{\mathrm{D(Worldtrade)} = 0.005} + \underset{(3.4)}{0.17} * \mathrm{D(Worldtrade(-1))} + \underset{(1.8)}{0.002} * \mathrm{XORD} + \underset{(1.6)}{0.03} * \mathrm{D(UStechpulse)} +$$

$$\underset{(15.6)}{1} * \mathrm{D(WorldIPI(-1))} + \underset{(2.8)}{0.2} * \mathrm{D(semiconductor\ billings)}, \mathrm{Adjusted\ R2} = 0.92,$$

where the D indicates growth rates, worldIPI is the world industrial production index, XORD is the six largest OECD countries export orders. The numbers in brackets are the t statistics. The US loans officer survey has been kept in the equation but is insignificant.

14. Typically forecast made the first two months of a quarter include the forecast of the previous quarter, while forecasts made the third months of a given quarter (when the previous quarter outcome has become available) include only nowcast and forecasts.

where the $(k \times 1)$ vector of monthly indicators $x_t = (x_{1,t}, \dots, x_{k,t})$ is a linear combination of r common latent factors $f_t = (f_{1,t}, \dots, f_{r,t})$ and an idiosyncratic error component $\xi_t = (\xi_{1,t}, \dots, \xi_{k,t})$ representing variable-specific shocks. The dynamics of the common factors is modelled through the q-dimensional white noise process $\eta_t = (\eta_{1,t}, \dots, \eta_{q,t})$, with $q \leq r$, aiming at capturing common shocks among the variables. The dynamics of the factors f_t are modelled through the application of the Kalman smoother on (5), whereas the $(k \times r)$ matrix of factor loadings Λ is estimated via static principal components. Precisely, the r common factors are assumed to follow a stationary vector autoregressive process of order p, where A_i is a $(r \times r)$ matrix of autoregressive coefficients and B is a $(r \times q)$ matrix of full rank q.

21. In order to combine the monthly factor model with a forecast equation for the observed quarterly series of world trade growth y_t^Q, a latent monthly world trade growth variable y_t is computed as:

$$y_t = \beta' f_t + \varepsilon_t \quad \varepsilon_t \sim \mathbb{N}(0, \sigma_\varepsilon^2) \tag{7}$$

whereas the quarterly world trade figure evaluated in the third month of every quarter (otherwise set to zero) is expressed as the quarterly average of the monthly series within the quarter:

$$\hat{y}_t^Q = \frac{1}{3}(y_t + y_{t-1} + y_{t-2}) \tag{8}$$

with $\epsilon^Q = y_t^Q - \hat{y}_t^Q$ distributed as $\mathbb{N}(0, \sigma_\epsilon^2)$. This aggregation implies that y_t corresponds to the 3-months growth rate, i.e. the growth rate with respect to the same month of the previous quarter. The innovations ξ_t , ζ_t , ε_t and ϵ^Q are all assumed mutually independent at all leads and lags. In case of p=1, the monthly state space representation is then given by the observation equation.

$$\begin{bmatrix} x_t \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \Lambda & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ \hat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \xi_t \\ \epsilon_t^Q \end{bmatrix} \tag{9}$$

and the transition equation:

$$\begin{bmatrix} \mathrm{I}_r & 0 & 0 \\ -\beta' & 1 & 0 \\ 0 & -\frac{1}{3} & 1 \end{bmatrix} \begin{bmatrix} f_{t+1} \\ y_{t+1} \\ \hat{y}_{t+1}^Q \end{bmatrix} = \begin{bmatrix} \mathrm{A}_{r1} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Xi_{t+1} \end{bmatrix} \begin{bmatrix} f_t \\ y_t \\ \hat{y}_t^Q \end{bmatrix} + \begin{bmatrix} \zeta_{t+1} \\ \varepsilon_t \\ 0 \end{bmatrix} \tag{10}$$

where $\Xi_t = 0$ for t corresponding to the first month of the quarter and $\Xi_t = 1$ otherwise. The application of the Kalman smoother and filter provides the minimum mean square linear estimates (MMSLE) of the state vector $\alpha_t = (f_t, y_t, \hat{y}_t^Q)$ and enables the forecasting of the quarterly world trade growth y_t^Q and dealing efficiently with an unbalanced dataset of missing observations at the beginning and at the end of the series, by replacing missing data with optimal predictions. Moreover, when compared with the use of the principal components technique alone, the two-step estimator enables the dynamics of the common factors and the cross-sectional heteroscedasticity of the idiosyncratic component to be modelled.

22. The application of the algorithm by Harvey and Koopman (2003) makes it possible to obtain the weight of each individual series in the estimate of the state vector, and hence the weight of each series in the final forecast. The MMSLE estimates of the state vector equal:

$$\alpha_{t+h|t} = \sum_{l=0}^{t-1} W_l(t,h) z_{t-l} \tag{11}$$

where $z_t = \left(x_t, y_t^Q\right)$ and the dataset downloaded at time *t* is equal to $\mathbb{Z}_t = \{z_s\}_{s=0}^{t}$. Although the matrix of weights $W_l(t,h)$ depends on both the period t and the dataset used, they are time-invariant when the Kalman filter approaches its steady-state (see the Bańbura and Rünstler 2007). Precisely, for a large enough *t*, it holds that $W_l(t,h) = W_l(t+p,h)$ with $p>0$, hence $W_l(t,h) = W_l(h)$. As consequence, the quarterly world trade growth forecasts can be obtained from the state vector via the application of the final row of weights in the matrix $W_l(t,h)$ which corresponds to $\hat{y}_{t+h}^Q$ as:

$$\hat{y}_{t+h|t}^Q = \sum_{l=0}^{t-1} \omega_l(h) z_{t-l} \tag{12}$$

Here, the cumulative smoother weights $\sum_{l=0}^{t-1} \omega_{l,i}(t,h)$ for each indicator i with $i=1,..,k$ are also considered. Moreover, the contribution of series i to the forecast $\hat{y}_{t+h|t}^Q$ can be computed as $\sum_{l=0}^{t-1} \omega_{l,i}(t,h) z_{i,t-l}$.

23. The specification of the model as a linear combination of common factors and shocks allows the lead and lag relations existing across monthly and quarterly variables and the world trade cycle to be captured.[15]

Empirical results

24. The dataset considered in the analysis starts in January 1990 and has been downloaded in January 2011. It contains 56 monthly indicators with different starting years, and the two quarterly series of world trade growth rates and US loan officer survey both start in 1990 and end in the third and fourth quarters of 2010 respectively. The stationarity of all indicators has been previously verified and achieved by taking monthly growth rates or differences transformations where necessary.[16]

25. The dataset is unbalanced with real activity series (e.g. industrial production indices, retail sales, *etc.*) subject to longer publication lags than survey data. In general, as detailed above, hard indicators are subject to a publication lag of two months, whereas soft and financial indicators are normally released at the end of the reference month, in this case known until December 2010. Four quarterly forecasts for the

15. A vast literature considers the right combination between the number of common factors r (static factors) and shocks q (dynamic factors). Bai and Ng (2002 and 2007) develop an information criterion to determine the appropriate number of static and dynamic factors. A robustness check has been carried out on a wide set of parameters combinations with the main result of an over-parametrisation of the factor model when applying the Bai and Ng criterion (similar conclusions were drawn on GDP forecasting by Bańbura and Rünstler). For this reason, the approach preferred here chooses as right combination of parameters (r,q) the one minimizing the RMSE across all possible permutations of r=6, q=3 and p=3.

16. Three-months growth rates of the monthly indicators have been also inspected, but they did not bring any substantial improvement of the estimates.

world trade growth series are produced starting from 2010Q4 (*i.e.* previous quarter or backcast),[17] 2011Q1 (*i.e.* current quarter or nowcast) and until 2011Q3 (*i.e.* two quarters ahead or forecasts).

26. By construction the dynamic factor model allows a large set of observations to be summarised in few common factors.[18] For this reason, in order to assess the different contribution of aggregate and disaggregate monthly indicators on world trade, four sets of monthly variables have been examined. DFM1 includes the same six world level indicators of the bridge model; DFM2 extends the previous model with nine country/macro-region level industrial production series;[19] DFM3 considers all 16 global level indicators plus nine more on a country or macro-regional level; DFM4 includes the entire dataset of indicators. [20] The different datasets for each model are shown in Table A2.

27. The performance of the bridge and the dynamic factor models is compared with a benchmarking autoregressive model of order 2 and evaluated on several forecasting error measures recursively computed and averaged over the period 2003Q1-2007Q4:[21] the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE).[22] Table 3 reports the forecasting performance statistics of each forecasting model over the out-of-sample period. It show the superiority of models bridging the world trade with indicators or common factors relative to a purely autoregressive representation. An improvement in forecasting accuracy is shown by the dynamic factor model in version 1 (DFM1) when compared with the bridge model estimated on the same set of monthly indicators.[23] In particular, the improvement is more relevant in correspondence of both one and two-quarters ahead forecasts. The inclusion of country level industrial production indices, beside the corresponding world level figure (DFM2), shows a marginal improvement in the backcast and nowcast average forecasting errors, most likely due to the higher forecasting weight that real activity indicators have at very short horizons (see also Figure 1). A general net improvement is then obtained when more global level indicators are added in the factor model version 3. These results differ from findings in studies on GDP forecasting, see for instance (Bańbura and Modugno, 2010; Barhoumi *et al*. 2010), which show that widening the dataset of monthly indicators, notably with PMIs, does not necessarily improve the accuracy of the GDP forecasts. The fourth dynamic factor model (DFM4) seems to show a small improvement in the backcast forecasting errors, probably due to the inclusion of additional up-to-date PMIs indicators on a country level, but the general average performance is not higher than the DFM3. Overall there seems to be an improvement in the forecasting accuracy of world trade when increasing the number of monthly indicators,

17. In the specific case of world trade, the previous quarter value is released in the third month of the current quarter.

18. The number of static and dynamic factors chosen, together with the number of lags p, corresponds to the model reporting the lowest RMSE, precisely r=4, q=3 and p=1,2 depending on the models. Extending the set of monthly indicators as for the dynamic factor model version 4 implies incrementing the number of static factors to 5.

19. In the work here, the country industrial production indices are also extracted from the CBP database and all end at the same time as the world index but extra months could be added for the countries where it is available from other sources.

20. Some individual country PMIs could not be included since the data sample length was not sufficiently long.

21. The 2008-2009 period that corresponds to the trade collapse has been excluded on purpose in order to avoid heavy distortions of the estimates.

22. In the recursive computation of the forecasting errors the pattern of publication lags of both quarterly world trade growth and monthly indicators is set to correspond to the real-time one.

23. Both world industrial production indexes have been evaluated with better results provided by the one released by CPB, which has been adopted in the whole analysis.

in line with Burgert and Dées (2008) but that the marginal gain of adding new indicators decreases after a certain stage.

Table 3. Forecasting error measures over the period 2003Q1-2007Q4.

	FORECASTING MODELS					
QUARTERS	*AR*	*BM*	*DFM1*	*DFM2*	*DFM3*	*DFM4*
MAE						
Previous	0.84	0.59	0.48	0.38	0.34	0.31
Current	0.70	0.78	0.69	0.70	0.60	0.62
One-quarter-ahead	0.94	0.83	0.69	0.72	0.69	0.72
Two-quarters-ahead	1.02	0.92	0.77	0.78	0.76	0.79
Average	0.88	0.78	0.66	0.64	0.60	0.61
MAPE						
Previous	1.01	0.80	0.80	0.46	0.50	0.34
Current	0.84	1.05	1.15	1.08	1.05	0.86
One-quarter-ahead	1.35	0.96	1.35	1.37	1.24	1.44
Two-quarters-ahead	2.23	1.15	1.26	1.29	1.21	1.48
Average	1.36	0.99	1.14	1.05	1.00	1.03
RMSE						
Previous	1.03	0.69	0.56	0.44	0.40	0.38
Current	0.92	0.93	0.85	0.82	0.77	0.78
One-quarter-ahead	1.22	0.98	0.83	0.87	0.85	0.89
Two-quarters-ahead	1.31	1.06	0.90	0.92	0.90	0.96
Average	1.12	0.91	0.79	0.76	0.73	0.75

Source: OECD calculations.

28. Table 4 presents additional statistical measures to compare the forecasting directional accuracy of the competing models. The ability of a forecasting model to correctly predict an acceleration or deceleration of world trade growth between two quarters is of particular relevance especially in case of nowcasting exercises. As a matter of fact, a low RMSE is not always an indication of substantial predictive power in presence of turning points. The rate of success (Diebold and Lopez, 1996) indicates the percentage of correctly predicting the direction of change in the world trade growth rate. Overall, the directional accuracy of all models differs from a random outturn of 50%, but the gain in terms of accuracy increases rapidly in the dynamic factor models, especially for backcast and nowcast estimates. In particular, in the case of the dynamic factor model versions 3 and 4 with an average rate of success of 71%, there is about a three in four chance of correctly forecasting the direction of a change in the world trade growth. As expected, the rates of success are clearly decreasing over the forecasting horizon.

29. Alternatively, the forecast directional accuracy (FDA) test developed by Pesaran and Timmermann (1992) is a non-parametric statistic that evaluates whether there is a significant difference between the observed probability of a correctly signed forecast and the estimate of what the probability would be under the null hypothesis of independence between forecasts and outcomes. On this assumption, independence means that the forecasting model has no power in predicting the direction of the world trade growth series. Table 4 reports the values of the test statistic and its significance computed by considering a dataset available in the first month of the current quarter: the null hypothesis of independence between forecast and outcome is rejected for all forecasted quarters only for the bridge model and versions 3 and 4 of the dynamic factor model. Versions 1 and 2 of the dynamic models do not allow rejecting the assumption of a predictive failure in case of nowcast estimates, as well as one-quarter-ahead forecasts from the autoregressive model cannot be considered correct predictions of the direction of change of world trade growth.

30. Finally, the last section of Table 4 shows the RMSE of the competing models relative to the RMSE of the benchmarking autoregressive model, where a ratio below one indicates that the specific model under analysis outperforms the autoregressive one.[24] The modified version of the Diebold and Mariano (1995) encompassing test proposed by Harvey *et al*. (1997) has been also calculated in order to make pair-wise comparisons between different models.[25] In particular, the null hypothesis of equivalent forecast accuracy between any specific competing model and the autoregressive one is tested and the relative p-values are reported in brackets. P-values lower than 0.10 indicate that there is a significant precision gain in favour of the specific model tested against the autoregressive one. Overall, the dynamic factor model version 3 seems to prevail with the lowest RMSE ratios for nowcast and one/two-quarters-ahead forecast estimates, whereas the dynamic factor model version 4 shows the best forecasting performance in case of backcast.

Table 4. Forecast encompassing and directional accuracy tests over the period 2003Q1-2007Q4

	FORECASTING MODELS					
QUARTERS	*AR*	*BM*	*DFM1*	*DFM2*	*DFM3*	*DFM4*
RATE OF SUCCESS						
Previous	65%	76%	79%	84%	89%	88%
Current	40%	57%	67%	74%	75%	77%
One-quarter-ahead	60%	54%	61%	61%	60%	61%
Two-quarters-ahead	65%	52%	54%	54%	58%	58%
Average	57%	60%	65%	68%	71%	71%
FDA TEST						
Previous	4.18**	4.58**	3.50*	4.58**	7.11***	7.11***
Current	6.90***	4.80**	0.06	0.49	6.90***	4.47**
One-quarter-ahead	1.64	5.94***	4.80**	4.80**	4.80**	2.72*
Two-quarters-ahead	3.06*	5.94***	3.06*	4.80**	4.80**	4.80**
RMSE RATIO						
Previous	-	0.69 [0.089]	0.86 [0.512]	0.75 [0.221]	0.65 [0.098]	0.60 [0.036]
Current	-	1.04 [0.816]	0.84 [0.401]	0.85 [0.426]	0.83 [0.401]	0.90 [0.550]
One-quarter-ahead	-	0.80 [0.255]	0.69 [0.121]	0.72 [0.152]	0.70 [0.159]	0.77 [0.224]
Two-quarters-ahead	-	0.81 [0.321]	0.72 [0.168]	0.72 [0.164]	0.71 [0.168]	0.75 [0.183]

Note: ***, **, * denote significance at 1%, 5% and 10% respectively.

Source: OECD calculations.

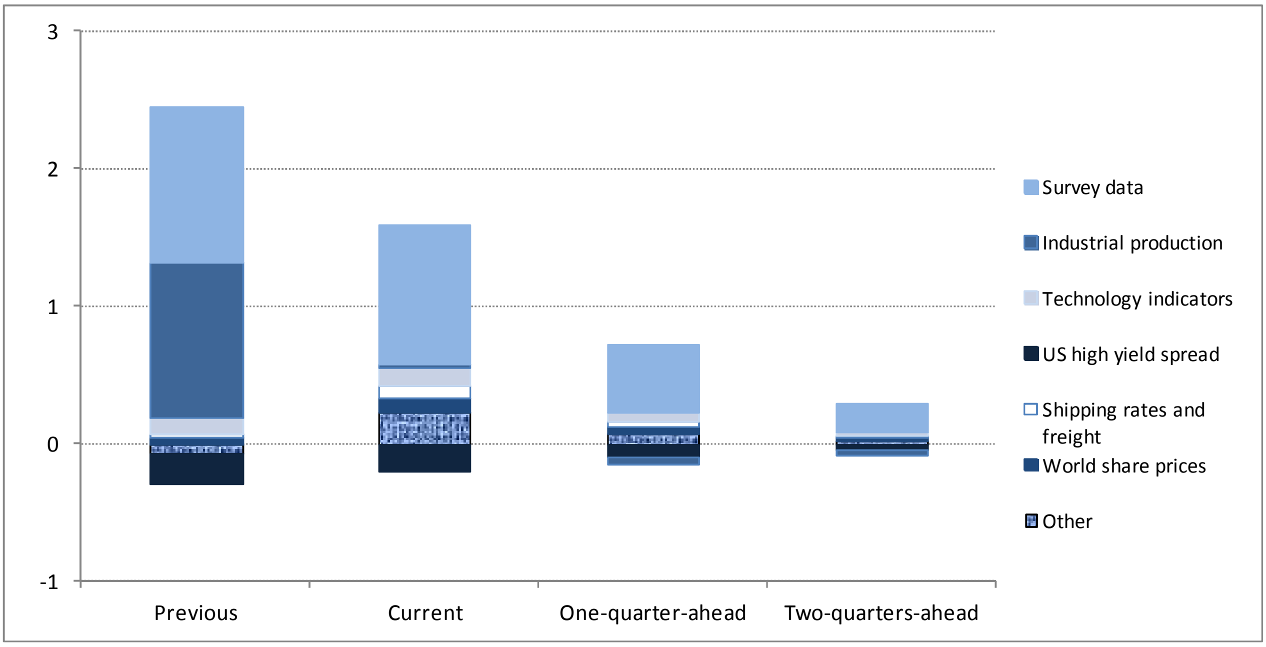
31. In general, all competing forecasting models seem to outperform the simple autoregressive model of order 2, with dynamic factor models producing on average most accurate forecasts than the bridge model. The average rate of success in correctly predicting the direction of change of the world trade growth rate is significantly higher when extending the monthly indicators set, although the most complete DFM version 4 does not show any comparative advantage respect to the DFM version 3. Moreover, in case of backcast and nowcast estimates, the null hypothesis of failing in predicting a possible turning point is more strongly rejected (*i.e.* at a significance level of 1%) by the DFM version 3 than any other model. Finally, among the dynamic factor models, the DFM3 reports the lowest average forecasting errors over four horizons and for this reason it is preferred over the others. From a practical and day to day use point of view it also has the advantage over the DFM4 of a smaller number of variables to deal with.

24. In order to evaluate performance of the forecasting models in case of reduced data availability, the RMSE are computed from forecasts performed with only one month of current quarter information.

25. The modified version of the Diebold and Mariano encompassing test is here preferred given the moderate number of sample observations and the longer than two forecast horizons.

32. The role played by the different indicators on each quarter prediction in the model DFM3 is shown in Figure 1 which reports the weights associated with each indicator (or group of indicators) for each quarter of forecast in the model. Overall industrial production plays a key role in explaining the first quarter of the projection period (previous quarter), while survey data (*i.e.* Global PMI indicators and G7 export orders) are also important in the subsequent quarters and in particular for the current quarter forecasts when hard indicators are not available. The weight of the technology indicators and of the world share prices peaks in the second projected quarter while the risks premium affects mainly the first one.

Figure 1. Weight of the different indicators



Note: Cumulative forecast weights based on the dynamic factor model version 3.

Source: OECD calculations.

33. The goodness of the estimated factors in approximating the monthly indicators is measured by the communality of each indicator, which represents how much of the single indicator's variance is captured by all common factors estimated. Varying from 0 to 1, the closer is the communality of an indicator to 1, the higher is the proportion of its variability which is explained by the common factors jointly, *i.e.* by the estimated model and thereby used to forecast world trade growth. On the contrary, when the communality of an indicator is close to 0, then the idiosyncratic error component specific of that indicator and not explained by the estimated model is high [see equation (4)]. The communalities computed for every monthly indicator included in the DFM3 with four common factors are reported in Table 5. Overall, the communality of the industrial production index on a macro-region level (*i.e.* world, advanced economies, emerging economies, Asia) is higher than single countries' indices suggesting that global level indicators play a more important role in explaining world trade growth. Similarly, the four common factors estimated seem to account for about 80-85% of the variability of the OECD+ BRICS CLI indicator and the six largest OECD countries export orders. In support of the evidence of a much higher communality of the Global PMI manufacturing index and new export orders compared to the stock level index are the results presented in Tables 1 and 2, where this latter show a much lower explanatory power on world trade growth. The quite high communality associated with the US high yield spread is confirmed by its high countercyclical impact when forecasting world trade growth as reported in Figure 1.

Table 5. Communalities of the dynamic factor model version 3

HARD INDICATORS	
World industrial production index	0.91
USA industrial production index	0.54
Japan industrial production index	0.40
Euro area industrial production index	0.54
Advanced economies industrial production index	0.78
Emerging economies industrial production index	0.87
Asia industrial production index	0.69
Latin America industrial production index	0.39
Central and Eastern Europe industrial production index	0.51
Africa and Middle East industrial production index	0.15
OECD retail sales	0.20
World steel production	0.48
Baltic dry index	0.60
Harpex shipping index	0.31
International air traffic	0.22
Tech pulse index	0.41
World semiconductor billings	0.45
Brent oil prices	0.40
SOFT INDICATORS	
G6 export orders	0.86
Global PMI new export orders	0.51
Global PMI Manufacturing index	0.50
Global PMI stock level index	0.11
OECD + BRICS CLI	0.80
FINANCE INDICATORS	
World stock market prices index	0.26
US high yield spread	0.68

Source: OECD calculations.

Conclusions

34. Overall, this paper shows that dynamic factor models, adapted from short-term GDP forecasting, could be a useful tool to project short-term world trade growth. The forecasting accuracy of these models measured through several statistics is higher than bridge equation models. They also have the main advantage of allowing the use of a wider information set enabling the inclusion of shorter monthly series with a more recent starting point. Moreover, the different contribution of aggregate and disaggregate components and country versus global level data can be directly assessed.

35. Among all monthly variables, the industrial production index and the survey data (*i.e.* Global PMIs and G7 export orders) seem to play the most important role. Including country/regions industrial production indices in addition to the world aggregate as well as adding different components of the PMI index can help improving the accuracy of the forecast. However, extending the disaggregation to additional PMI country data does not seem improve it further.

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ANNEX. BACKGROUND TABLES AND FIGURES

Table A1. Monthly indicators set

Monthly Indicators	Starting date	Publication lags	Source
HARD INDICATORS			
ECONOMIC ACTIVITY			
World trade volume index	1991	2	CPB
World industrial production index	1991	2	CPB
USA industrial production index	1991	2	CPB
Japan industrial production index	1991	2	CPB
Euro area industrial production index	1991	2	CPB
Advanced economies industrial production index	1991	2	CPB
Emerging economies industrial production index	1991	2	CPB
Asia industrial production index	1991	2	CPB
Latin America industrial production index	1991	2	CPB
Central and Eastern Europe industrial production index	1991	2	CPB
Africa and Middle East industrial production index	1991	2	CPB
Largest countries industrial production index	1990	2	OECD calculations
OECD retail sales	2000	3	OECD
World steel production	1980	1	IISI
SHIPPING AND FREIGHT ACTIVITY			
Baltic dry index	1985	1	The Baltic Exchange
Harpex shipping index	1996	1	Harper Petersen & Co.
International air freight traffic	1996	2	IATA
GLOBAL TECHNOLOGY CYCLE			
Tech pulse index	1971	1	CSIP
World semiconductor billings	1976	2	SIA
TRANSPORT COSTS			
Oil prices	1957	1	UK Dept. of Energy
SOFT INDICATORS			
EXPORT ORDERS			
G6 export orders	1962	1	OECD calculations
Global PMI new export orders	1998	1	Markit Economics
Country PMI new export orders (Brazil, China, Euro area, India, Japan, Korea, Japan, Russia, Singapore, South Africa, Usa)	1997	1	Markit Economics
PURCHASING MANAGERS'INDEX			Markit Economics
Global PMI manufacturing index	1998	1	Markit Economics
Country PMI manufacturing index (Brazil, China, Euro area, India, Japan, Korea, Japan, Russia, Singapore, South Africa, Usa)	1997	1	Markit Economics
Global PMI stock level index	1998	1	Markit Economics
Country stock level index (Brazil, China, Euro area, India, Japan, Korea, Japan, Russia, Singapore, South Africa, Usa)	1997	1	Markit Economics
OECD + BRICS CLI	1960	2	OECD
FINANCIAL INDICATORS			
World stock market prices index	1973	1	Datastream
US high yield spread	1984	1	OECD calculations
US loan officer survey (quarterly)	1990	1	FED

Table A2. Forecasting models' indicator sets

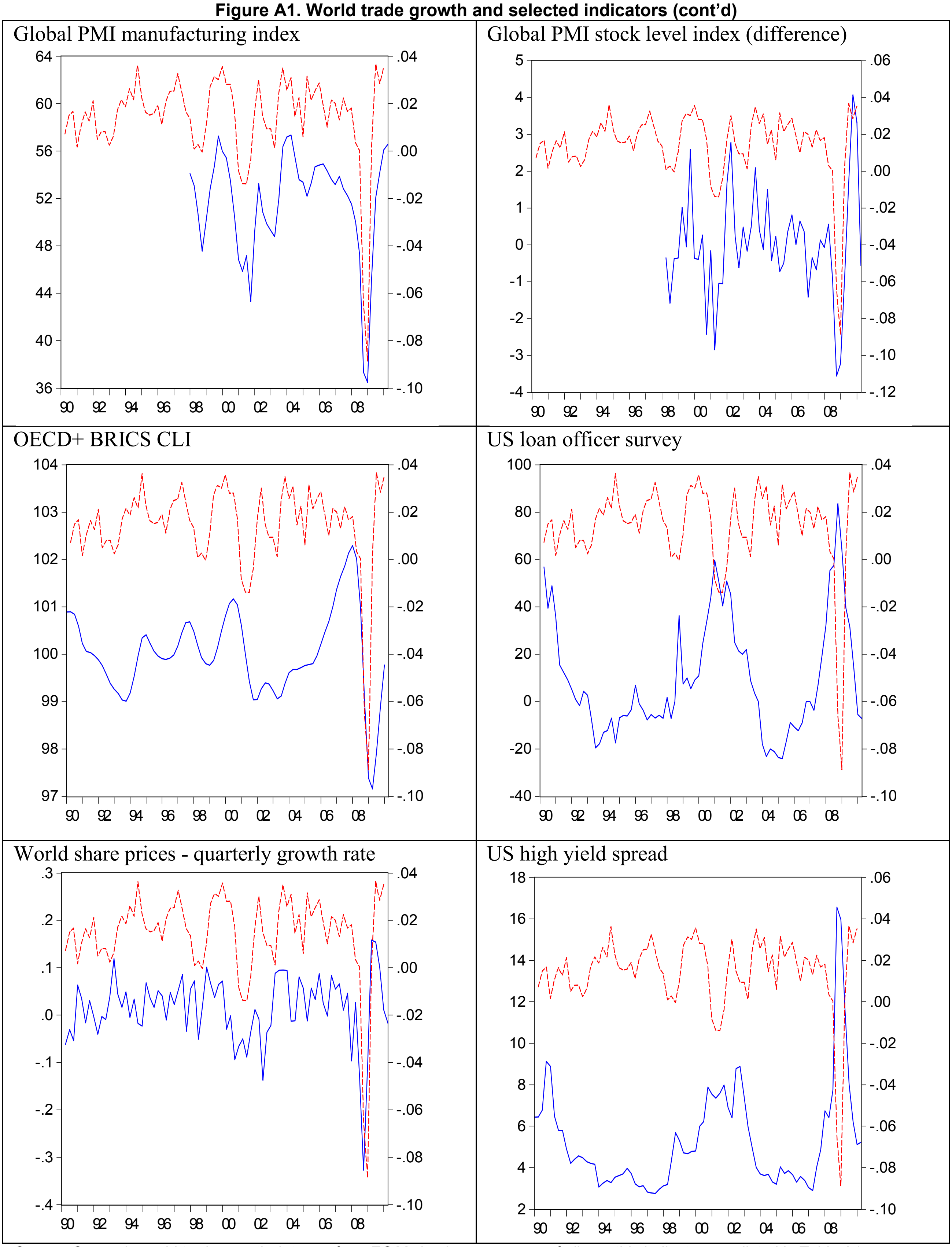
	BM	DFM1	DFM2	DFM3	DFM4
GLOBAL INDICATORS					
World trade volume index					•
World industrial production index	•	•	•	•	•
OECD retail sales				•	•
World steel production				•	•
Baltic dry index	•	•	•	•	•
Harpex shipping index				•	•
International air freight traffic				•	•
Tech pulse index	•	•	•	•	•
World semiconductor billings	•	•	•	•	•
Oil prices	•	•	•	•	•
G6 export orders	•	•	•	•	•
Global PMI new export orders				•	•
Global PMI Manufacturing index				•	•
Global PMI stock level index				•	•
OECD + BRICS CLI				•	•
World stock market prices index				•	•
COUNTRY/MACRO-REGION INDICATORS					
USA industrial production index			•	•	•
Japan industrial production index			•	•	•
Euro area industrial production index			•	•	•
Advanced economies industrial production index			•	•	•
Emerging economies industrial production index			•	•	•
Asia industrial production index			•	•	•
Latin America industrial production index			•	•	•
Central and Eastern Europe industrial production index			•	•	•
Africa and Middle East industrial production index			•	•	•
Country PMI new export orders (Euro area, Russia, Singapore, Usa)					•
Country PMI manufacturing index (Euro area, Russia, Singapore, South Africa, Usa)					•
Country stock level index (Euro area, Russia, Singapore, South Africa, Usa)					•
US high yield spread				•	•
US loan officer survey (quarterly)	•				

Figure A1. World trade growth and selected indicators

World trade = dotted line

Figure A1. World trade growth and selected indicators (cont'd)

Figure A1. World trade growth and selected indicators (cont'd)



Source: Quarterly world trade growth data are from EO89 database; sources of all monthly indicators are listed in Table A1.

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