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A FACTOR MODEL FOR WORLD TRADE GROWTH

Stéphanie Guichard and Elena Rusticelli[1]

A dynamic factor model (DFM) is applied to forecast quarterly world trade growth by means of relevant monthly indicators. The peculiarity of dynamic factor models to handle larger datasets of information allows for the inclusion of several monthly indicators available on a national and world-wide level such as financial indicators, transportation and shipping indices, supply and orders variables and information technology indices. Kalman smoothers are used to deal with the complex publication lag structure which characterises short-term forecasting exercises. The forecast performance of the DFM is then examined and compared with more traditional bridge equation models as well as autoregressive benchmarking models. Overall, the dynamic factor approach seems to perform better, especially when a large set of indicators is used.

1. The authors are members of the OECD Economics Department. They would like to thank Marta Bańbura for providing programming codes and guidance on the DFM methodology. 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.

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 globalization 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.

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

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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.

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).

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.

The key variables to forecast world trade

5. A large set of 35 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 3 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 A.1 in 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 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 A.1 in Annex):

- World activity is summarized by the following indicators:

  - 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.

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.

- 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 supply and 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 kilometers 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.

- The global technology 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 U.S. 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 their mean). A global export orders series available since 1998 is produced by Markit Economics.

- In addition to export orders, the global PMI index, the stocks of purchases component of the global PMI published by Markit Economics has been considered. The individual country PMIs have not been considered here but will be considered in a future extension of this paper. 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. The individual country CLIs have not been considered here but, as the PMIs, could be considered in a future extension of this paper. 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).

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 Q1 and then a sample ending in 2008 Q2 just before world trade collapsed to assess whether the results are affected by the crisis (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).

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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

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 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
World export orders	2	0.91	-6.61	4	3	0.69	-6.67	2
Largest countries industrial production index	3	0.86	-6.94	0	6	0.62	-6.98	0
Global PMI index	4	0.84	-6.22	2	2	0.69	-6.68	2
International air freight traffic	5	0.80	-6.26	0	5	0.66	-6.83	0
OECD+BRICS CLI	6	0.79	-6.51	1	4	0.67	-7.07	1
G6 export orders	7	0.75	-6.27	2	8	0.49	-6.64	1
US high yield spread	8	0.74	-6.14	4	14	0.39	-6.50	0
World stock market price index	9	0.69	-6.11	1	9	0.49	-6.63	-1
Baltic Dry Index	10	0.65	-5.96	2	18	0.33	-6.41	0
OECD retail sales	11	0.65	-5.94	2	11	0.44	-6.50	2
World steel production	12	0.61	-5.87	1	16	0.34	-6.42	0
World semiconductor billings	13	0.57	-5.83	0	10	0.46	-6.62	0
PMI stock level index	14	0.54	-5.30	0	7	0.51	-6.29	1
US loan officer survey	15	0.53	-5.65	2	13	0.41	-6.53	0
Tech pulse index	16	0.52	-5.72	0	12	0.43	-6.57	0
Oil prices	17	0.52	-5.71	0	15	0.37	-6.47	0
Harpex shipping index	18	0.42	-5.52	0	17	0.34	-6.41	0

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

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	2
World stock market price index	2	0.61	-5.91	1	2	0.49	-6.67	1
Baltic Dry Index	3	0.61	-5.87	2	17	0.33	-6.41	1
US high yield spread	4	0.60	-5.81	3	7	0.41	-6.48	2
Global PMI index	5	0.59	-5.33	2	3	0.46	-6.18	2
World 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
US loan officer survey	11	0.49	-5.59	2	11	0.37	-6.48	1
PMI stock level index	12	0.46	-5.03	1	4	0.44	-6.22	1
Largest countries industrial production index	13	0.46	-5.54	2	14	0.35	-6.43	1
World steel production	14	0.45	-5.58	1	18	0.33	-6.41	1
Oil prices	15	0.44	-5.50	2	16	0.33	-6.41	1
Tech pulse index	16	0.42	-5.47	2	13	0.35	-6.44	1
Harpex shipping index	17	0.36	-5.42	1	15	0.33	-6.41	1
World semiconductor billings	18	0.35	-5.42	1	12	0.37	-6.46	1

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

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 countries only aggregate. Then the OECD CLI, the global 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 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.

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.

9 . But world export orders do not perform better than G7 export orders on a common sample (ie when comparing the bivariate regression on a 1998-2010 sample)

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.[10]

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 7 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. 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 we estimate the quarterly bridge equation, i.e. an Autoregressive Distributed Lag ADL(p,q)

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

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 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

10 . 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.

forecast and three quarters ahead forecasts.[11] 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 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

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

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

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

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 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

11 . 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.

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

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 modeled.

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 $z_t = (x_t, y_t^Q)$ 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

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

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 $\hat{y}^{Q}_{t+h|t}$ 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.[12]

Empirical results

24. The dataset considered in the analysis starts in January 1990 and has been downloaded in July 2010. It contains 35 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 first and second 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.[13]

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 June 2010. Four quarterly forecasts for the world trade growth series are produced starting from 2010 Q2 (i.e. previous quarter or backcast)[14], 2010 Q3 (i.e.current quarter or nowcast) and until 2011 Q1 (i.e. two quarters ahead or forecasts).

26. By construction the dynamic factor model allows a large set of observations in few common factors to be summarized. For this reason, in order to assess the different contribution of aggregate and disaggregate monthly indicators on world trade, 3 sets of monthly variables have been examined. DFM1 includes the same 6 world level indicators of the bridge model; DFM2 extends the previous model with 9

12. 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-parametrization 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.

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

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

country/macro-region level industrial production series; [15] DFM3 considers all 16 global level indicators plus 9 more on a country or macro-regional level.[16]

27. The performance of the bridge and the dynamic factor models is compared with a benchmarking autoregressive model of 2 and evaluated on several forecasting error measures recursively computed and averaged over the period 2003 Q1 - 2007 Q4: [17] the Mean Absolute Error (MAE), the Mean Absolute Percentage Error (MAPE) and the Root Mean Square Error (RMSE).[18] 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.[19] In particular, the improvement is more relevant in correspondence of both one- and two-quarters ahead forecasts. The inclusion of country level industrial production indexes, 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. Overall there seems to be an improvement in the forecasting accuracy of world trade when increasing the number of monthly indicators, in line with Burgert and Dées (2008). 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 does not necessarily improve the accuracy of the GDP forecasts.

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15. 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.

16. 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.

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

18 . 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.

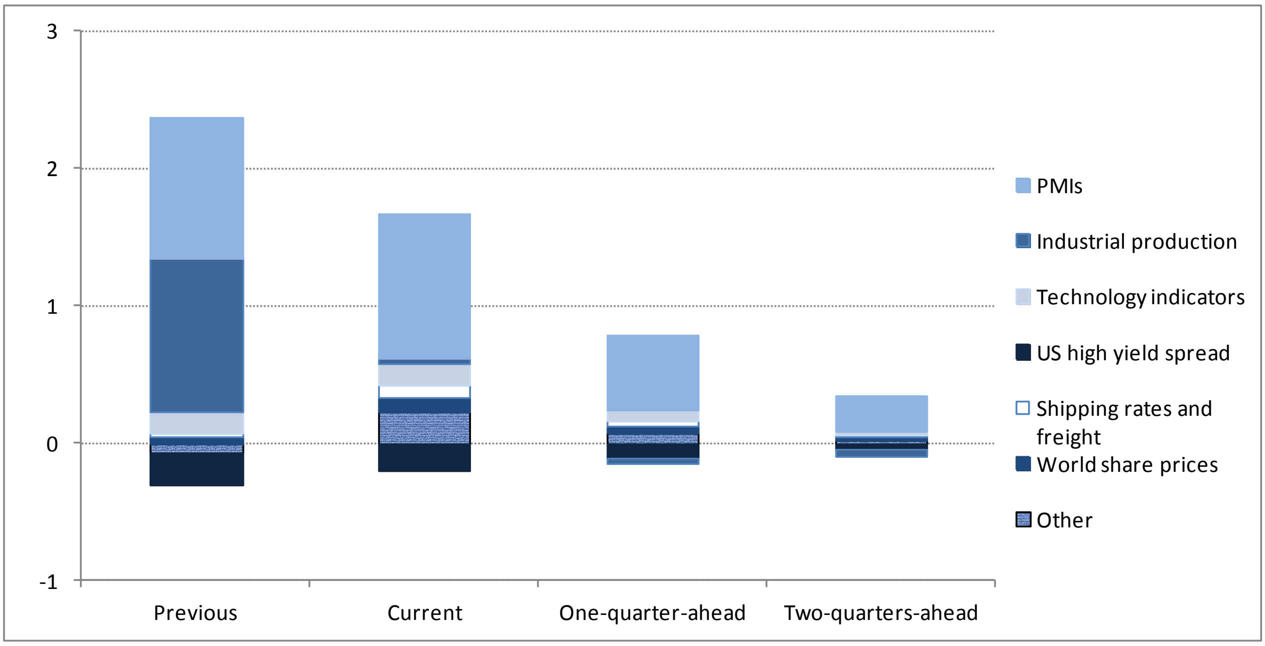
19 Both world industrial production indexes have been evaluated with better results provided by the one released by CPB, which has been adopted in the whole analysis.

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

	FORECASTING MODELS				
QUARTERS	*AR*	*BM*	*DFM1*	*DFM2*	*DFM3*
MAE					
Previous	0.84	0.64	0.46	0.39	0.34
Current	0.71	0.80	0.73	0.77	0.59
One-quarter-ahead	0.96	0.83	0.67	0.75	0.69
Two-quarters-ahead	1.03	0.98	0.78	0.80	0.77
Average	0.89	0.81	0.66	0.68	0.60
MAPE					
Previous	0.71	0.72	0.50	0.35	0.35
Current	0.60	0.91	0.85	0.77	0.74
One-quarter-ahead	1.00	0.80	0.93	0.89	0.83
Two-quarters-ahead	1.50	0.95	0.88	0.90	0.85
Average	0.95	0.85	0.79	0.73	0.69
RMSE					
Previous	1.03	0.74	0.51	0.46	0.40
Current	0.92	0.93	0.87	0.86	0.76
One-quarter-ahead	1.25	0.98	0.81	0.88	0.85
Two-quarters-ahead	1.32	1.11	0.91	0.93	0.92
Average	1.13	0.94	0.78	0.78	0.73

28. The role played by the different indicators on each quarter prediction in the model DFM3 is shown in Figure1 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 PMI indicators are also important in the subsequent quarters. 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



Conclusions and directions for further developments

29. 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.

30. Among all monthly variables, the industrial production index and the PMI indicators seem to play the most important role. Including country/regions industrial production indices in addition to the world aggregate can help improving the accuracy of the forecast, as well as adding different components of the PMI index.

31. Further extensions of this work will go in two main directions: on the one hand the dataset will be extended to include country breakdowns for more indicators, starting with the PMIs as well as quarterly indicators such as the US loan officers survey, and assess whether such extension can improve further the accuracy of the forecast. On the other hand, further analyses on the optimal choice of the parameters set and the characteristics of the estimated common factors will be carried out.

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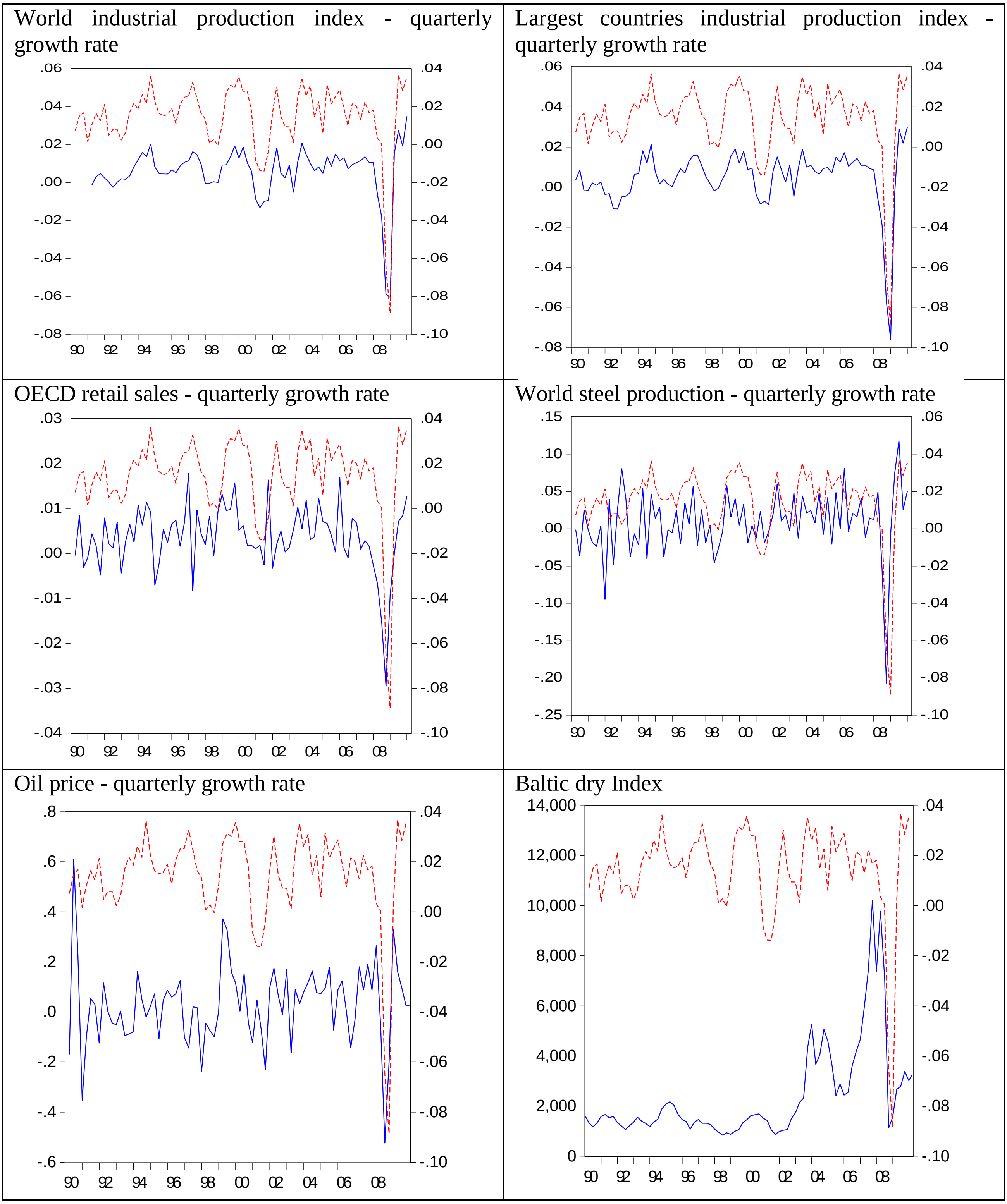
ANNEX - BACKGROUND TABLES AND FIGURES

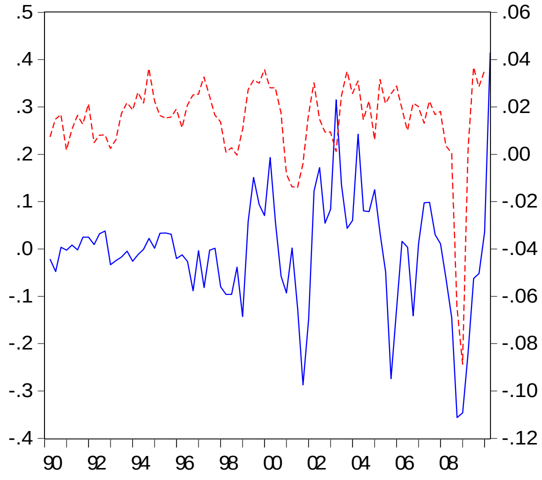
Table A.1: Monthly indicators set

Monthly Indicators	Starting date	Publication lags	Source
HARD INDICATORS			
ECONOMIC ACTIVITY			
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
World export orders	1998	1	Markit
PURCHASING MANAGERS'INDEX			
Global PMI index	1998	1	Markit
PMI stock level index	1998	1	Markit
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

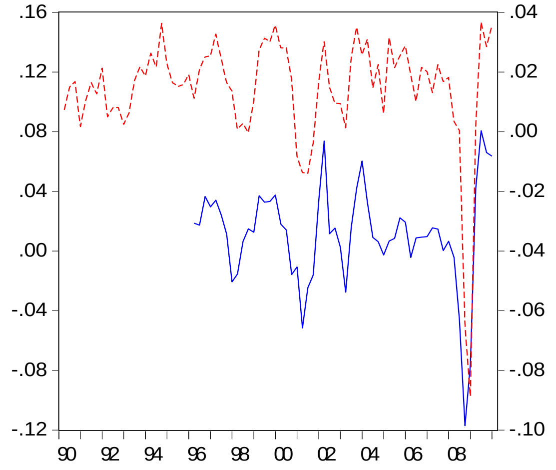
Figure A.1: World trade growth (dotted line) and selected indicators



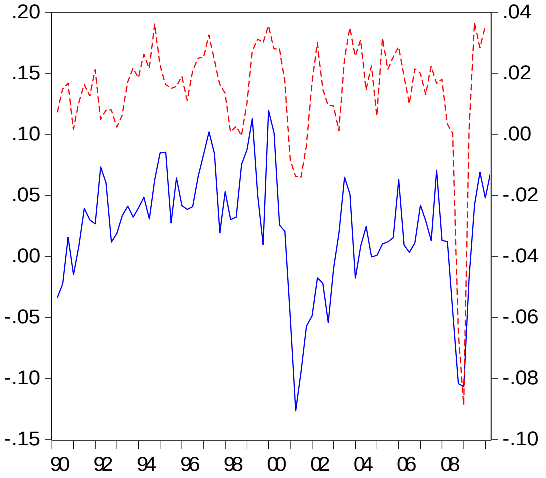
Harpex Index - quarterly growth rate



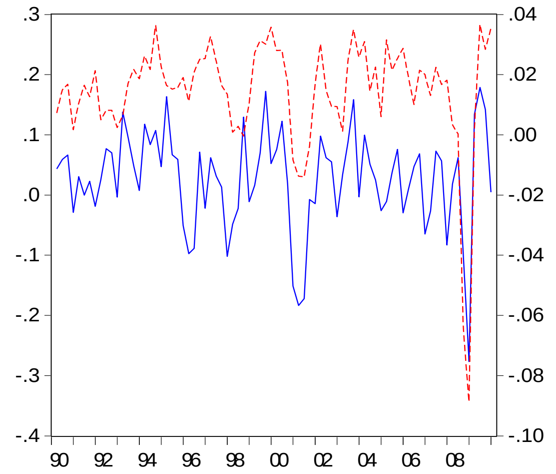
International air freight traffic - quarterly growth rate



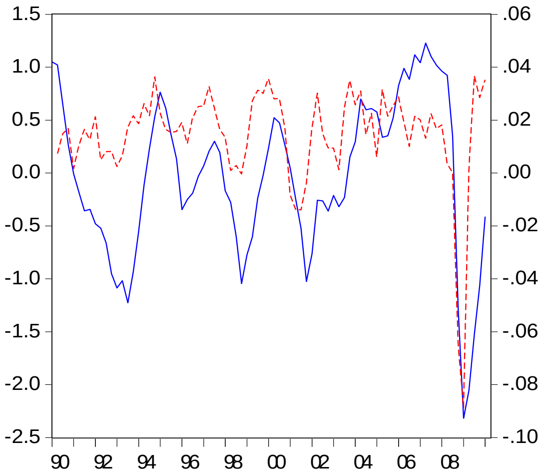
Tech pulse index - quarterly growth rate



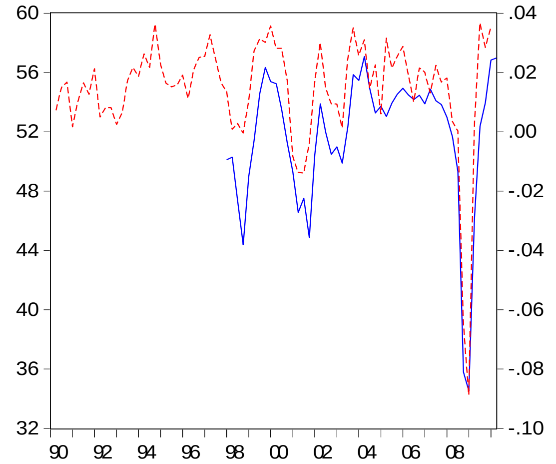
World semiconductor billings - quarterly growth rate

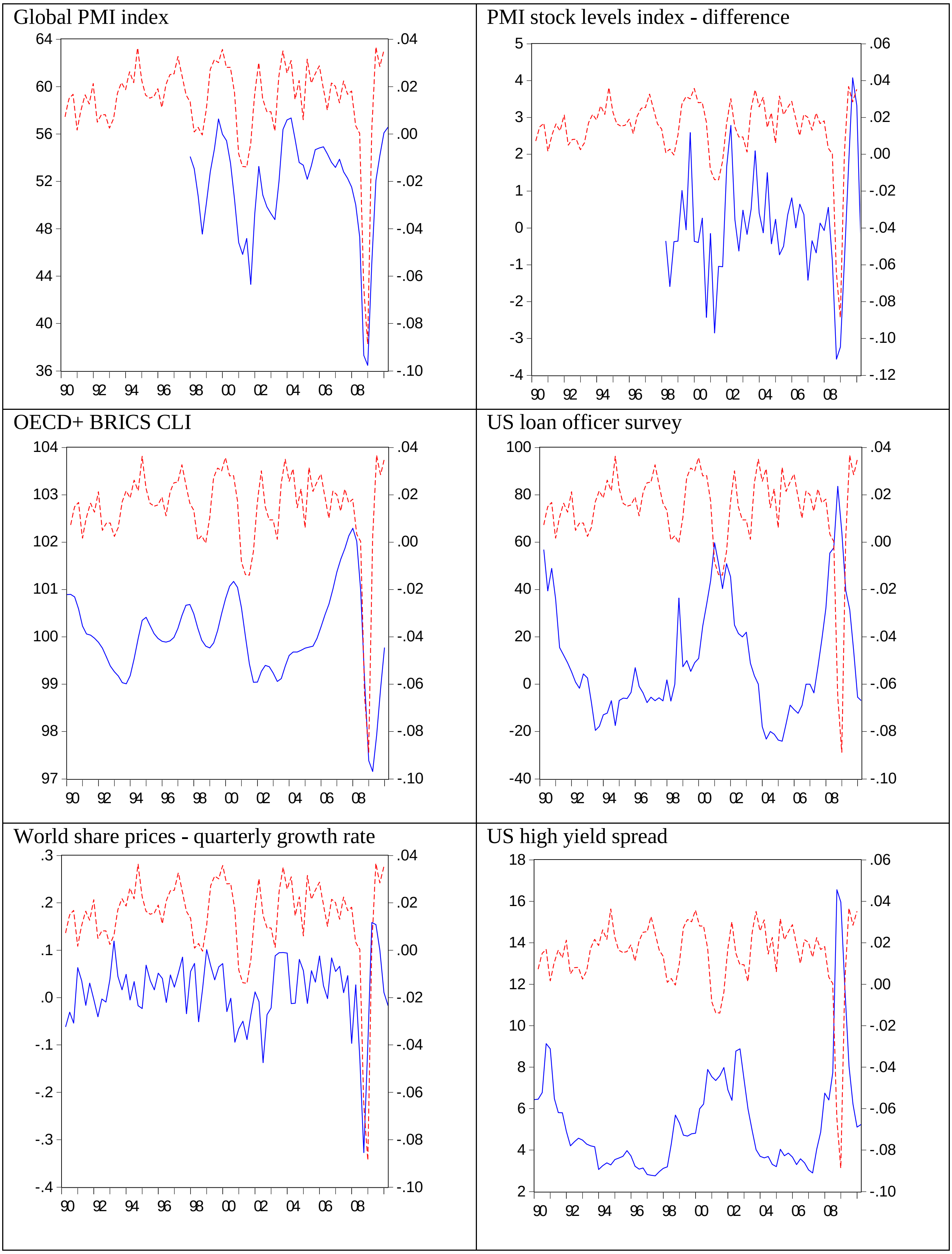


G6 export orders



World export orders




Global PMI index
64
60
56
52
48
44
40
36
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
90 92 94 96 98 00 02 04 06 08
PMI stock levels index - difference
5
4
3
2
1
0
-1
-2
-3
-4
.06
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
-.12
90 92 94 96 98 00 02 04 06 08
OECD+ BRICS CLI
104
103
102
101
100
99
98
97
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
90 92 94 96 98 00 02 04 06 08
US loan officer survey
100
80
60
40
20
0
-20
-40
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
90 92 94 96 98 00 02 04 06 08
World share prices - quarterly growth rate
.3
.2
.1
.0
-.1
-.2
-.3
-.4
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
90 92 94 96 98 00 02 04 06 08
US high yield spread
18
16
14
12
10
8
6
4
2
.06
.04
.02
.00
-.02
-.04
-.06
-.08
-.10
90 92 94 96 98 00 02 04 06 08