BANCA D'ITALIA
EUROSISTEMA

Temi di Discussione

(Working Papers)

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July 2013

Number 920

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ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

TRACKING WORLD TRADE AND GDP IN REAL TIME

by Roberto Golinelli[*] and Giuseppe Parigi[**]

Abstract

This paper proposes a simple procedure to obtain monthly assessments of short-run perspectives for quarterly world GDP and trade. It combines emerging and advanced countries' high frequency information to explain quarterly national accounts variables through bridge models. The union of all bridge equations leads to our world bridge model (WBM). The WBM econometric approach is new for two reasons: its equations combine traditional short-run bridging with theoretical level-relationships; it is the first time that forecasts of world GDP and trade are computed for advanced and emerging countries on the basis of a real-time database of about 7,000 time series. Although the performance of the equations that are automatically searched for should be taken as a lower bound, results show a better WBM forecasting ability than the benchmark case and confirm the usefulness of combining WBM real-time forecasts with preliminary releases to improve the prediction of world trade. Finally, we show that the (unrealistic) use of revised data leads to a systematic overstatement of model forecasting performance.

JEL Classification: C53, C22, E37, F47.

Keywords: world trade and GDP forecasts, augmented bridge models, real-time data, forecasting ability.

Contents

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1. - Introduction[1]

The analysis of the current and future evolution of the world economic activity is a central concern for international financial institutions, governments and central banks. Recent failures in assessing global economic developments have questioned the appropriateness of widely used econometric models. In particular, they have shown a clear deficiency in the treatment of emergent market economies (EME), the importance of which has steadily grown in the last ten to fifteen years (for a recent analysis of such developments in a historical perspective, see Hanson, 2012, and Borin et al., 2012). The great recession of 2008-2009 has brought to the fore the increasing divide in the GDP dynamics of advanced and emerging countries, with the former still mired in recession or struggling to recover, and the latter on a stronger or more solid growth path. This does not mean that there has been a decoupling between the two groups of economies: the EME continue to be heavily dependent on the rich markets of advanced countries, but domestic factors are gaining a more prominent role.

In this situation, commercial links and the related flows at global level have been steadily changing and nowadays they appear completely different from the past. The widespread globalisation, fostered by the powerful liberalisation tide, and the information technology revolution have paved the way for a greater fragmentation of production. Global supply chains tend to locate productive activities where human and other resources make those activities competitive. Manufacturing output has therefore shrunk in advanced economies, where entire sectors have practically disappeared. Links in these global chains are not limited to industry, but include a growing range of services as well (such as research and development, business processes, etc.) given the strong reduction in transaction, organisation and communication costs. Such factors help understand the important divergence which has recently characterised the dynamics of world trade and GDP, particularly evident in the much deeper drop of the former during the 2008-2009

[1] Preliminary drafts of this paper were presented at the 6th Eurostat Colloquium on "Modern Tools for Business Cycle Analysis: the lessons from global economic crisis", Luxembourg, September 2010; at the 4th Italian Congress of Econometrics and Empirical Economics, ICEEE, Pisa, January 2011; at the CIRET/KOF/HSE Workshop "National Business Cycles in the Global World", Moscow, September 2011; at the 32nd International Symposium on Forecasting of the International Institute of Forecasters, Boston, June 2012; at the EABCN/CEPR Conference on "Global Spillovers and Economic Cycles", Banque de France, Paris, May 2013, and in seminars at the University of Rome "Tor Vergata" and at Brunel University of London. We are grateful, without involvement, for support and comments to Francis Atsu, Ray Barrell, Alessandro Borin, Mauro Constantini, Jan Fidrmuc, Kajal Lahiri, Russ Moro, Filippo Natoli, Adrian Pagan, as well as to conferences' participants. In addition, the suggestions of two anonymous referees of the Bank of Italy Working Papers series (*Temi di Discussione*) are also gratefully acknowledged. The opinions it expresses are the authors' only, and do not necessarily reflect those of the institutions they work for. PRIN financing is gratefully acknowledged (R. Golinelli).

recession (see, among others, Cheung and Guichard, 2009, Levchenko et al.,2010 and Bussière et al., 2012).

The scant attention devoted to the evolution of the EME can be explained by an insufficient knowledge of their socio-political and economic features and, more importantly, by the lack of reliable statistical information. The immediate reaction of most analysts has been to update their forecasts quite frequently, notwithstanding the difficult and time consuming task of specifying, estimating and maintaining large models and very complex datasets (see e.g. Pain et al, 2005, and Hervé et al., 2011). Figure 1 shows the evolution of IMF's World Economic Outlook and of OECD's Economic Outlook updates of world GDP forecasts. The closer the forecast release is to the publication of the actual GDP figure, the closer the prediction is to the target, because - over time - valuable new indicator information is available.

Figure 1 suggests that better predictions of world variables could be obtained with a timely monitoring of GDP and trade by using a set of simple and easy-to-update empirical models to exploit the information of indicators as soon as they are released. To do so, these models should refer to a mix of advanced and emerging "representative" countries in order to provide a balanced view of the world as a whole, and should be specified and estimated before each forecasting round on the basis of only real time data in order to avoid any bias in measuring their forecasting performance because of the knowledge of information or data revisions not available at the time the forecast is made.

On this respect, the issues of short term modelling the world economy (i.e. what country to consider and what variables to target) and of acknowledging the real time nature of data have been only partially addressed in the literature.

Regarding the modelling approach, while many alternative methods have been proposed to predict short run GDP for the group of advanced countries - essentially the G7 countries (see, among the others, Baffigi et al., 2004, for bridge models; Stock and Watson, 2006, for factor models; Clements and Galvao, 2008, for MIDAS regressions; Camacho and Perez-Quiros, 2008, for approximate Kalman filter models) - the literature on short term forecasting for the EME is still in its infancy (Liu et al., 2011, is a recent exception for 10 Latin American countries). In this context, it is not surprising that world GDP developments are extrapolated either through the G7 or the OECD country groups (see Arouba et al., 2010, Chauvet and Yu, 2006, Golinelli and Parigi, 2007, Kose et al., 2008, and Nilsson and Guidetti, 2008). More recently, however, Matheson (2010) and Borin et al. (2102) show the improvement in world GDP forecasting ability of models which consider not only the advanced countries, but also a set of 19 developing countries (the first), and

10 Asian economies plus Brazil and Russia (the second). About world trade forecasting, Burgert and Dees (2009) compare the ability of aggregate models and of models where world trade results from the aggregation of country forecasts, but the emerging world is considered as a single entity.[2] A step forward is undertaken in Jakaitiene and Dees (2012), where the short run prediction of world variables is enlarged from trade to industrial production and prices, all measured at monthly frequency; again, as in Burgert and Dees (2009), the EME are treated as a single country. In general, it is probably better to forecast quarterly national account (QNA) series rather than monthly indicators because, notwithstanding their publication lag, QNA provide a more complete and consistent framework where the link between GDP and world trade may be explicitly considered.

Regarding real time data, because of the dearth of data vintages, all contributions to the world trade and GDP forecasting literature is essentially based on latest available data, with no consideration of the implications of data revisions (see Croushore and Stark, 2001, and Pesaran and Timmermann, 2005). However, since the seminal paper of Diebold and Rudebush (1991), the use of latest available data might significantly overstate the forecasting performance of models which usually work only with preliminary and unrevised data.

The aim of this paper is to devise a simple and automatic procedure to obtain monthly assessments of global, short run perspectives for quarterly world trade and GDP by combining advanced and emerging countries high frequency indicators with their QNA variables. More specifically, for every month over the period from March 2006 to May 2012 (i.e. 75 times), we estimate a model of simultaneous bridge equations linking 6 advanced (France, Italy, Germany, Japan, UK and US) and 4 emerging countries (Brazil, Russia, India and China), using a fully real time dataset.[3]

The choice of limiting the emerging world to just the so called BRIC countries (see O'Neill, 2001) has been dictated by their economic as well as political and demographical weight. From 2000 to 2011, the BRIC's share of global output rose rapidly, from 16 to 26 percent (in purchasing power parity), and their economies performed better than average in the subsequent recession. In 2011, the four countries contributed $2.2 trillions in additional GDP to the world, equivalent to another Italy (note that Italy is the eight economy in the world). The same rising importance of the BRICs is witnessed in the case of trade flows: their export share in world exports grew from 6.6 to 15.3 percent from 2000 to 2011. Along with these figures, already sufficient to justify the inclusion

[2] See Guichard and Rusticelli (2011) for the forecast of world trade with dynamic common factors.

[3] The starting period of our analysis is due to the availability from OECD of data vintages, balanced with the need of time spans sufficiently long to estimate parameters to forecast the year 2006. More generally, the large use of OECD data in this study depends on the on-line availability of Main Economic Indicators monthly vintages.

of the BRICs in our WBM, one has also to consider their strict links with most of the other economies in their regions and all over the world (see Borin et al, 2012 and Hanson, 2012, for a more thorough analysis and evidence on these points).[4]

For each country there are seven equations; four translate the monthly information of country-specific soft and hard indicators into quarterly forecasts of volumes and deflators of domestic demand (the sum of consumption, investment and inventory change), imports in volume, and export deflators; two convert the quarterly forecasts of imports in volume and export prices from the bridge models of the other countries into the forecasts of exports in volume and import prices of that country; GDP in volume is obtained through the demand-side accounting identity.

The forecasts of world GDP and of world trade are given by the aggregation of the ten country forecasts of GDP, and of imports and/or exports, respectively. The forecast horizon is six quarters ahead, so that we have always an estimate of the current year and, starting with the forecast round of September, a projection for the next one.

Overall, this paper contributes to the literature about the short term forecast of world developments in several directions.

i) The modelling and forecasting phases are based on a fully real time data-set made of about 7,000 time series which accounts for both the timing of data releases, and for their revisions. However, the same steps are also accomplished with latest available data, in order to evaluate the likely gain in the forecasting ability when data revisions are accounted for.

ii) Specific and global indicators of price, activity and trade are used for each country, and world predictions come from the aggregation of ten advanced and developing single-country forecasts.

iii) We extend the specification of "traditional" bridge models (based only on indicators and lags of the dependent variable) to level-relationships suggested by economic theory, which may help beyond the current-quarter forecasts; we label such models as "augmented bridge models" (ABM). In this respect, we complement the GVAR approach of Pesaran et al. (2004, 2009), as GVAR models have not been devised for short run analysis and forecasting but for the analysis of level-relationships. An automated modelling and inference approach guards against future information creeping into the model through the modeller’s specification choices. To limit the problem of parameter breaks and shifts, the modelling activity is based on fully adaptive methods,

[4] However, this does not mean that a deeper insight and more accurate forecasts could not be gained by the inclusion of more countries, especially for those areas that are not well represented, such as Africa (one of the next steps in this direction would be the inclusion in the WBM of South Africa, recently aggregated to the previous four countries in the BRICS group).

where econometric specifications may change from one forecast round to the other, and estimates and inferences are conducted over rolling windows.

iv) The availability of a model that summarises high frequency information together with vintages of world trade series, allows to test for the rationality of world trade early estimates in predicting fully revised (i.e. final) data, consistently with forecast encompassing procedures to assess the performance of combining world trade early estimates and our model-based forecasts to anticipate the final data.

The paper is organised as follows. Section 2 contains the main methodological issues about modelling and forecasting world trade and GDP with high frequency indicators, and describes our world bridge model (WBM). Section 3 presents some details about the dataset, broadly covering the OECD Main Economic Indicators monthly issues from March 2006 to May 2012 (75 vintages), and the five steps accomplished each forecast round to compute world trade and GDP forecasts up to six-quarters ahead. Section 4 reports measures of the world trade and GDP forecasting ability of our modelling framework with respect to that of an autoregressive components (AC) benchmark model (see e.g. Fair, 1993). In Section 5, the robustness of our main findings is assessed with respect to: alternative measures of the variables (real-time and latest available); different specifications of the GDP equations in the WBM; different sample sizes; and the exclusion of any EME information. Section 6 deepens the issue of forecasting world trade by merging two topics: the choice of the best modelling approach for forecasting between aggregate or country-specific procedures, and the rationality test of the first world trade release interpreted as a forecast of the latest available data. Section 7 concludes.

2. - The modelling framework: bridge models for the world economy

Since the seminal paper by Klein and Sojo (1989), the literature on the extraction of reliable signals from high frequency indicators has followed two main routes: that of the empirical indicators and that of the bridge models.

The empirical indicator approach lead to the development of factor-based models (FM; see Stock and Watson, 2002a and 2002b, and Forni et al., 2005), which "average" all the available information into the extraction of common factors from the full set of indicators. Bridge models (BM) link the forecast targets to "suitable" indicators, selected *a priori* on the basis of the researcher's experience and statistical inference (early examples of the BM approach can be found in Trehan, 1989, and in Parigi and Schlitzer, 1995). Both approaches may be criticized, as FM may be biased by unbalanced sources of information (see Boivin and Ng, 2006, and Bulligan et al., 2012), and BM may appear excessively *ad hoc* because of the "incredible" exclusion restrictions underlying the list of the selected indicators.

We opted for the BM approach for two main reasons: a) the recent evidence about the better performance of models shrinking the large information set generally used by FM through pre-selection algorithms; b) the possibility of selecting just a few indicators, given the much poorer coverage and quality of emerging countries high frequency data.

Overall, these two points contribute to explain our BM modelling choice. Regarding a), although FM are usually based on large datasets of indicators, it has been shown that too many data are not always good for FM forecasts. What is really important is not only the quantity of data but also their quality: with a large number of mediocre variables it may become very difficult to separate the signal from the noise component. Better forecasting results could therefore be obtained by concentrating on a subset of indicators (which is at the heart of the BM approach), as for the advanced countries, when many indicators are both available and reliable (see the evidence provided in e.g. Boivin and Ng, 2006, and Bulligan et al., 2012).

Regarding b), rich datasets of indicators are however hardly available for EME, especially if real time data have to be used. In the present context, we could find real time data for no more than 18 indicators (listed in Table 1 of section 3.1)[5], far below the minimum size of 30-40 series needed to compute reliable estimates of factors (see Stock and Watson, 2006).

The quarterly bridge equations exploit monthly indicators as well as additional theory-driven explanatory variables (measured as disequilibrium terms), which are modelled by other equations in the system. Quin et al. (2008) show that these "augmented" bridge models (ABM) can somehow improve the medium-run forecasting ability of simple BM.

Formally, traditional BM can be represented by a dynamic relationship of order p between the dependent variable y (usually in log-differences to prevent non-stationarity problems) and a number of pre-selected explanatory indicators *IND* (assumed to be stationary or transformed to stationarity):[6]

$$\Delta y_t = \sum_{i=0}^{p} A_i \, IND_{t-i} + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \varepsilon_t \qquad (1)$$

[5] We are implicitly assuming that this set of indicators includes those carrying genuine forecasting ability, and that our modelling approach is able to select them.

[6] Note that equation (1) could also represent a FM when *IND* is obtained by extracting factors from the full set of available indicators, instead of being pre-selected by the researcher.

where A_i and α_j are parameters (the former is a scalar or a vector, depending on the number of indicators in *IND*) and ε_t are identically and independently distributed (iid) errors. Equation (1) explains the short run fluctuations of y_t in part through its co-movements with IND_t and in part through the idiosyncratic, unpredictable shocks ε_t; the dynamic propagation mechanisms and inertia are represented by lags of both *IND* and *y*.

The forecasting ability of equation (1) relies on the amount of information about short run shocks in *IND*, but does not exploit the covariance of y_t with other explanatory variables (*X*), as could be suggested by some economic theory. To account for the latter effect, we can write:

$$\Delta y_t = \sum_{i=0}^{p-1} B_i \Delta X_{t-i} + \sum_{j=1}^{p-1} \phi_j \Delta y_{t-j} + \pi \ (y_{t-1} - \beta \ X_{t-1}) + \nu_t \qquad (2)$$

where π , ϕ_j, β and B_i are parameters (the latter is a scalar or a vector, depending on the number of variables in *X*); ν_t are idiosyncratic, unpredictable iid shocks; and the term in brackets is a theory-based level-relationship expressed in form of disequilibrium (EqCM). If we substitute *ΔX* in (2) with their BM representation through some short run indicators as in (1), we obtain the augmented bridge model (ABM) specification of this paper:

$$\Delta y_t = \sum_{i=0}^{p} C_i \ IND_{t-i} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \pi \ (y_{t-1} - \beta \ X_{t-1}) + u_t \qquad (3)$$

where π , γ_j, β and C_i parameters (the latter is a scalar or a vector, depending on the number of indicators in *IND*) are combinations of equation (2) parameters' together with the BM representation of *ΔX*; and u_t are iid shocks.

Equation (3) explicitly models the portion of the idiosyncratic shocks ε_t in (1) that is related to macroeconomic adjustment mechanisms; this fact may improve the forecasting ability of the ABM specification, provided that some data-congruent theory (i.e. cointegrated, in a non-stationary context) predicts the level-relationship $y^* = \beta \ X^*$, and that a system of equations for the *X* variables is available for forecasting them over horizons longer than one-step ahead; in our context, other bridge equations of the model.

The ABM approach, although not explicitly tested for stationarity, complements the GVAR models of Pesaran et al. (2004), where QNA variables of a large number of countries and areas are modelled by focusing on their cointegration relationships in vector error correcting specifications similar to equation (2) above, as they do not exploit indicators' information. In this sense, GVAR models have not been devised for short run analysis and their forecasting power outperforms benchmark AR models (based only on latest available data; see Pesaran et al., 2009) to a lesser extent than ABM models (see below).

In terms of the ABM equation (3), the relevant features for a number of country *c* variables can be summarised by a deliberately simple representation:

$$y_t^c = f_y\left(IND_{t-k}^c \ ; \ y_{t-m}^c, \ X_{t-1}^c\right) \tag{4}$$

where *t-k* indicates distributed lags of the indicators in IND^c; *t-m* measures the inertia of the dependent variable, while the theoretical explanatory *X* is set in *t-1*. The list of the variables involved by the level-relationship is reported after the semicolon.

The world bridge model (WBM) of this paper is the system of ABM equations (5) to (11) below summarising the relationships among the QNA variables of interest and a number of relevant indicators (for a generic country *c*) which are treated as exogenous, i.e. generated outside the WBM. The reported equations abstract from specific data transformations and show only a subset of the whole monthly indicators exploited. The complete list of the soft and the hard indicators and their correspondence with the ABM equations can be found in Table 1 of Section 3.

The BM equations (5) and (6) explain domestic demand deflator, PD^c, and volumes, DD^c, respectively. Short run fluctuations can be related to some indicators, such as the consumer and production price indices, ICP^c and IPP^c for the deflator; the OECD coincident/leading indicators, $ICLI^c$, and the industrial production index, IIP^c, for demand volumes. In both equations, the long run relationship - if significant - is given by constant steady-state inflation and growth.

$$PD_t^c = f_{PD}\left(ICP_{t-k}^c, \ IPP_{t-k}^c \ ; \ PD_{t-m}^c\right) \tag{5}$$

$$DD_t^c = f_{DD}\left(ICLI_{t-k}^c, \ IIP_{t-k}^c \ ; \ DD_{t-m}^c\right) \tag{6}$$

Imports in volume, M^c in equation (7), are explained by monthly nominal flows of imports of goods and by nominal exchange rates against the US Dollar, IMU^c and IEX^c, respectively. In equation (8), the export deflators, PX^c, are explained by domestic prices and other soft indicators. The long run relationship for imports - if significant - is modelled as a function of the domestic demand and of the relative prices (where PM^c is the import deflator), while export inflation has a possible constant steady-state growth rate.

$$M_t^c = f_M\left(IMU_{t-k}^c,\ IEX_{t-k}^c;\ M_{t-m}^c, DD_{t-1}^c, \frac{PD_{t-1}^c}{PM_{t-1}^c}\right) \tag{7}$$

$$PX_t^c = f_{PX}\left(ICP_{t-k}^c,\ IPP_{t-k}^c\ ,\ IEX_{t-k}^c;\ PX_{t-m}^c\right) \tag{8}$$

Altogether, equations (5) to (8) form the domestic block, which is made of four ABM equations for each country. The following two equations (9) and (10) explain exports in volume, X^c, and import deflators, PM^c, i.e. the two foreign-sector variables which are estimated on the basis of, respectively, the flows of QNA imports in volume and the export deflators coming from all other bridge equations (7)-(8) of the trade partner countries. QNA exports are also explained by monthly, nominal flows of exports of goods, IXU^c. The aggregation of the partner countries is weighted by the ω_p^c parameters, which can be either estimated, or calibrated on the basis of bilateral trade matrixes. In this paper we followed the route of estimating them trough the following relationships:

$$X_t^c = f_X\left(IXU_{t-k}^c,\ ;\ \sum\nolimits_{\forall p \neq c} \omega_p^c M_t^p\right) \tag{9}$$

$$PM_t^c = f_{PM}\left(\sum\nolimits_{\forall p \neq c} \omega_p^c\ PX_t^p\right) \tag{10}$$

Finally, equation (11) is an accounting identity defining the country GDP in volume, Y_t^c, as the sum of domestic demand plus exports minus imports.

$$Y_t^c \equiv DD_t^c + X_t^c - M_t^c \tag{11}$$

Since we consider 10 countries and there are 7 dependent variables, we need 70 equations to model all the country-level variables. The remaining three equations (12)-(14) aggregate the country-level variables into world GDP, Y_t^w, and world trade measured on the basis of both imports and exports, M_t^w and X_t^w respectively.

$$Y_t^w = f_{YW}\left(\sum_{c=1}^{10} \omega_c^y\ Y_t^c\right) \tag{12}$$

$$M_t^w = f_{MW}\left(\sum_{c=1}^{10} \omega_c^m\ M_t^c\right) \tag{13}$$

$$X_t^w = f_{XW}\left(\sum_{c=1}^{10} \omega_c^x\ X_t^c\right) \tag{14}$$

where the parameters: ω_c^y, ω_c^m and ω_c^x can be either estimated or calibrated as above (again, we estimated them). Overall, the World Bridge Model (WBM) is made of 73 equations, of which 63 are stochastic.

3. - Forecasting the world economy in real time

3.1 - Looking for real-time data

In the real-time exercise we mimic a predictor who updates quarterly forecasts for world trade and GDP in each of the 75 months (i.e. forecast rounds), from March 2006 to May 2012.

The country QNA time series for the dependent variables of the WBM come from the Main Economic Indicators (MEI) issue released by the OECD in the second week of each month.[7] The same MEI issues contain the monthly country-specific series of a number of hard (usually revised) and soft (usually not revised) indicators. Additional indicators (mostly provided by financial institutions) can also be used, which are available without lag and usually not revised. Table 1 reports the list of all indicators, along with their publication lags and the relationships with the QNA dependent variable in each ABM.

Table 1 about here

MEI is the source of five hard, monthly, country-specific indicators: three about real activity (coincident/leading indicators, *ICLI*; index of industrial production, *IIP*; and retail sales in volume, *IRET*); two about international trade in goods (exports, *IXU*; and imports, *IMU*, both measured, with few exceptions, at current prices in national currency). Overall, the hard indicators real-time dataset is made of 3,750 monthly time series, released with a publication lag of two months with respect to the reference date.

The dataset of soft indicators includes thirteen indicators (corresponding to 76 time series), which may be divided in two groups. The first one is country-specific (source MEI), and consists of seven indicators: price indexes of consumers, *ICP*, and producers *IPP*; confidence indexes of consumers, *ICCI*, and business, *IBCI*; and three monetary/financial indicators (i.e. narrow money, *IM1*; nominal exchange rates against the US Dollar, *IEX*; and stock market indexes, *ISHA*). The second group is made of six global indicators (their sources are reported in Table 1): four price

[7] OECD QNA seasonally adjusted volume estimates by country for *Y* (GDP), *DD* (domestic demand), *M* and *X* (imports and exports of goods and services) are measured in US dollars, fixed PPPs, 2005 reference year. The 2005 levels of these variables are very close to the figures reported in the IMF's World Economic Outlook dataset. PD, PM and PX are the corresponding deflators. Overall, the OECD QNA real-time data-set is made of 3,030 quarterly series.

indexes for energy, *ISPCE*, non-energy, *ISPCNE*, food, *IWBCF*, and metals-minerals, *IWBCM*; semiconductor sales, *ISCS*; and the Baltic dry index, *IBDI*.

Soft indicators are seldom revised,[8] and are more timely than the hard ones. In particular, the six international indicators and the two financial ones (i.e. exchange rates and stock market indices) are published at the end of the month in which the forecast is made; the remaining five (price- and confidence-indexes, and the narrow money) are available with one-month publication lag.

Regarding the measurement of world aggregates, vintages of quarterly estimates of world GDP in real terms, Y_t^w - i.e. the dependent variable of equation (12) - are released with two-quarters lags by the National Institute of Economic and Social Research (NIESR) in the first month of each quarter. World trade in real terms, M_t^w and X_t^w - both on the import and the export sides as in equations (13) and (14) - can be measured by quarterly averages of monthly series released by the Netherlands Bureau for Economic Policy Analysis (CPB) since January 2009;[9] for this, real-time data of world trade start only from 2009, while for 2006-2008 we have no data revisions.

3.2 - The real-time forecasting exercise: modelling the modeller

Forecasting QNA variables with indicator information using BM raises two relevant issues: mixed (quarterly and monthly) frequency, and ragged-edge data (see e.g. Baffigi et al., 2004, and Mitchell, 2009). As usual in the BM literature, the mixed frequency issue is dealt with by taking quarterly averages of monthly indicators (see Bulligan et al., 2012, for a list of alternative approaches). The ragged-edge issue due to the asynchronous release of monthly indicators and QNA variables is summarised in Table 2.

For each of the 75 monthly forecast rounds, the ragged edge nature of data requires that some monthly indicator observations - which are the explanatory variables in the BM equations - should be at least forecast one or two months ahead with auxiliary models in order to "complete" the current quarter. More generally, monthly auxiliary models are used to project indicators over spans as long as those of the quarterly WBM forecast horizon. This is accomplished in three steps: data transformation, univariate autoregressive (AR) modelling, and monthly extrapolation.

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[8] Data availability forces us to assume that all these thirteen soft indicators are never revised, while money and price indices by country slightly change because of seasonal adjustment.

[9] Since January 2009, CPB's World Trade Monitor publishes the monthly series of the merchandise world trade index, 2000 = 100, on both imports and exports sides over a time span starting in January 1991, and with a two-month publication lag with respect to the reference date (the same as the OECD monthly hard indicators). CPB world trade data before 1991 are back-cast on the basis of MEI quarterly data on import and exports of goods and services in volume which refer to OECD (and not world) countries aggregate. A description of the CPB world trade series is in van Welzenis and Suyker (2005).

Step 1. The log-levels of the indicators listed in Table 1 are first-differenced to remove possible non-stationarity (unit root tests confirmed the appropriateness of this choice). Then, outliers (defined as those points larger/smaller than three standard deviations away from the mean of the series) are replaced by their sample average plus (minus) two standard errors of the remaining observations.

Step 2. All series from *Step 1* are modelled as parsimonious AR, where the number of lags is chosen according to the Schwarz information criterion. Overall, we estimate 12 (indicators) times 10 (countries) times 75 (monthly forecast rounds, i.e. data vintages) plus 6 (world indicators) times 75 (rounds), i.e. 9,450 AR models. The choice of the sample dimension depends on the trade-off between the number of observations (the more they are, the more efficient the inferences) and the risk of parameter structural breaks (increasing with the sample dimension). As suggested by Stock and Watson (1996) and Giacomini and White (2006), we use rolling windows of 7 years (i.e. 84 monthly observations, as in Bulligan et al., 2010) instead of recursive samples.

Step 3. The AR models estimated in *Step 2* are used to extrapolate the monthly indicators in Table 1 over horizons that depend on their specific publication lags: 15-month ahead for exchange rates, stock prices and global world indicators, available without lag; 16-month ahead for soft indicators released one month after the reference date, and 17-month ahead for hard indicators released two months after the reference date. In this way, quarterly averages of each BM equation regressors can be computed, thus enabling to forecast QNA targets up to six quarters ahead. Note that the six-steps ahead horizon always allows to forecast all the quarters of the current year and, since the forecast round of September, the next one as well (see the timing in Table 2).

The monthly forecast round is completed with other two steps about modelling BM equations, and merging them into the WBM described in Section 2.

Step 4. The WBM quarterly estimation requires 4,725 equations to be specified and estimated (63 stochastic equations for each WBM times 75 forecast rounds).

As the BM specification search is based on the researcher's experience, any modelling activity with past real time data must cope with the problem of "modelling the modeller", e.g. of neutralizing the advantage of knowing how the data look ex-post (see Stark and Croushore, 2002). Automated modelling and inference is a viable option, because it is based on predetermined rules and guards against future information creeping into the model specification and the pseudo ex-ante forecasts. As in other analyses emulating the real-time behaviour of the researcher through the LSE general-to-specific modelling strategy (see Golinelli and Parigi, 2008, and Bulligan et al., 2012), we start from a general dynamic equations (our ABM equations, where the variables in the last column of Table 1 are explained by the predictors on the rows) and reduce its complexity by eliminating statistically insignificant regressors and checking that the resulting model satisfies a number of misspecification tests. The alternative specifications are searched over rolling windows of 80 quarters in order to mitigate - as with monthly AR above - the risk of parameters breaks.[10]

This way of "modelling the modeller" is not without costs: the renounce to the researcher's skill implied by the application of the automatic procedure is bound to worsen the performance of the final model. In other words, it has to be taken as a sort of "lower bound" of the researcher modelling ability, which is one of the main ingredients of the "art" of forecasting.

Step 5. The country-specific ABM equations for *PD*, *DD*, *M, PM, X* and *PX* (resulting from *Step 4*) are included in the WBM, which is completed by adding 10 country-specific GDP identities, and 3 world trade and GDP aggregate equations.

This modelling approach, where a new specification is chosen and estimated before each forecast round, is called adaptive, while the non-adaptive alternative implies only the estimation of the parameters of every equation without changing its specification. Swanson and White (1997) show that adaptive models, estimated over rolling windows, perform better than fixed-specification models, since they may limit the effects of heterogeneity over time and structural break (on this point, see also Clements and Hendry, 1998, 1999).

Along the rows of Table 2, the availability of the QNA and indicator time series is classified by monthly forecast round. With reference to world trade targets, the publication lag of the quarterly averages of CPB world trade figures used during the monthly WBM forecast rounds is assumed to be the same as that of QNA data, while the CPB first releases are slightly more timely (their release calendar is the same as that of the hard indicators). Besides the advantage of a symmetrical treatment of all the WBM forecast targets, this *ex ante* choice of making WBM to ignore the latest (but preliminary) knowledge of world trade data might even improve, rather than worsen, its forecasting ability[11].

4. - The assessment of the WBM forecasting practice

The need of timely information on the evolution of economic activity finds a natural limit in the reliability of the statistical data. Timely data are computed with only a subset of information and this makes them liable to future revisions, as more information becomes available. Revised data are therefore supposed to be more accurate and should be used in economic analysis. In this paper,

[10] In Section 5 we show that the WBM forecasting performance may further improve when the sample size is reduced from 80 to 40 quarters.

[11] This occurs when the forecast variance of the model is small relative to the preliminary data variance (Busetti, 2006).

since we want to replicate as closely as possible the day-by-day activity of short run predictors, the WBM are specified and estimated as soon as new data are available, on the assumption that a more precise (because revised) knowledge of the past and some new information (however imprecise) on the present may help in forecasting future realizations (Fernandez-Villaverde, 2008).

To this end, as shown in Section 3, in each of the 75 months over the period from March 2006 to May 2012 we completely update our datasets and the WBM specification and estimation prior to each forecast round and generate up to six quarters ahead predictions.

In Table 2 the differences in the timing of each indicator suggests that the 12 forecast rounds per year may be classified in three different cases according to the timeliness of the indicators.

a) *Case 1 forecasts*. For the March, June, September and December forecast rounds, only one month of hard indicators and 2-3 months of soft indicators are known for the first quarter to be forecast (specific publication lags are in Table 1); this is the worst case of information availability (a = 1).

b) *Case 2 forecasts*. For the January, April, July and October forecast rounds, two months for hard indicators and three months for soft ones are known for the first quarter to be forecast; this is an intermediate case (a = 2).

c) *Case 3 forecasts.* For the February, May, August and November forecast rounds, not only all the indicators are available for all the months of the first quarter to be forecast, but soft indicators are available for 1-2 months of the following quarter; this is the best case often referred to as nowcast (a = 3).

Overall, the 75 forecast rounds at different horizons (i.e. h=1, 2, ..., 6) articulated in three cases above of information availability for each horizon (indicated by a = 1, 2, 3) generate from 24 to 19 prediction errors for h=1 and h=6, respectively. The WBM forecasting ability - for h=1, 2, ..., 6 and a=1, 2, 3 - is measured by the root mean squared forecast errors (RMSE)[12]; it is only reported for country-specific GDP, imports and exports, as well as for world GDP and world trade.

RMSE estimates require the knowledge of the data actually published 1,2, …, 6 quarters after the forecast date. In this way, the RMSEs measure the WBM ability to predict the first data release.[13] For example, in the first forecast round, the statistical information (vintage) available at

[12] Additional results with alternative forecasting ability indicators, such as the mean absolute errors, as well as referring to other WBM endogenous variables, such as inflation rates, are available upon request.

[13] Forecasting the first release of WBM endogenous variables with time series of data which are revised a different number of times could be sub optimal, as better predictions could be obtained by modelling and forecasting using time series of only first-released data; see Corradi et al. (2009). However, in our case this is not feasible because of the small number of available vintages.

the end of March 2006 is used to estimate the WBM parameters over a period of 80 quarterly observations, from 1986q1 to 2005q4. The one-step ahead prediction error is computed by comparing the one-step ahead WBM forecast with the data released in June 2006; the four-steps ahead prediction error is computed by comparing the four-steps ahead WBM forecast with the data released in March 2007 and so on (note that all the horizons of the March forecast round belong to *case* 1).

The forecasting performance is evaluated on the basis of the WBM's RMSE relative to that of a benchmark model. This is a fairly common practice to avoid possible biases due to specific characteristics of the period used for the analysis or to idiosyncratic features of the variables to be forecast. Given that the WBM forecasting approach exploits information from both indicators and economic theories, a natural choice for the benchmark is a model where neither indicators nor theoretical determinants contribute to the explanation of the QNA variables of interest. The benchmark model is therefore defined as a system of univariate autoregressive (AR) models for (the volumes of) domestic demand (*DD*), imports (*M*) and exports (*X*)[14] by country, while the GDP identity (11) and the world trade and GDP aggregate equations (12)-(14) remain the same as in the WBM. This "autoregressive components" (AC) benchmark model can be seen as a sort of parsimonious VAR model (see Adams and Ratcliffe, 1995, and Fair, 1993, among others); its forecasting accuracy usually outperforms that of unrestricted VAR models, because it is less prone to the curse of dimensionality problem. In addition, AC models - that aggregate country-specific forecasts into their world equivalents - have the advantage over simple univariate AR models to exploit the information on the time varying composition of advanced and emerging countries.[15]

The RMSE of the WBM relative to that of the AC model is shown in Table 3; the rows refer to different combinations of the six horizons (*h*) and the three indicator availability cases (*a*) for each of the three target variables: GDP in the upper, imports in the mid and exports in the lower panel. In particular, the first three rows contain the one-quarter ahead forecasting ability for each QNA target for the three cases of indicator availability, while the following rows report the other five horizons (*h*=2, 3, ..., 6) referring only to case 3.[16] Along the columns, results by country and for the world aggregate (in the last column) are reported.

[14] If we modelled benchmark exports with equation (9) in the WBM instead of an AR model, we would miss the principle of parsimony, which is probably the main reason for the good forecasting performance of simple AR models.

[15] We also directly modelled world trade and GDP with AR models, i.e. disregarding the compositional information by country, and the forecasting performances have been largely worse; these results are available upon request.

[16] As the forecast horizon *h* increases from one to six, the RMSE corresponding to the different *a* cases of the same horizon tend to become more similar.

In line with previous findings with latest available data (see e.g. Borin et al., 2012), the present real-time analysis shows that the use of indicator information may improve the forecasting ability of world GDP one-quarter ahead over the AC benchmark by about 20-30 percent. An even larger improvement - about 35-45 percent - is obtained for world trade. These results do not depend on the presence of mere "average puzzle" benefits, as documented in Hendry and Clements (2002), and in Stock and Watson (2004), because both the WBM and the AC models are based on the same aggregation process.

At single country level, the forecasting performance of WBM in advanced countries appears to be better than that of the emerging ones.[17] This difference is less evident in the import and export case, because of the availability of specific trade indicators such as monthly country-specific imports and exports of goods. In the GDP case, however, the AC models for emerging countries very often outperform the WBM. This is probably due to the relationships between domestic demand and short run indicators, which seem to be affected by relevant instability. As we show in the next section, it could be that - besides structural breaks - statistical revisions may play a role in jeopardising the target-indicator relationships.

The increase of the forecast horizon from one- to six-quarters ahead does not alter the main findings: the WBM performance is still superior to that of AC. This fact is not so commonly found in the literature on forecasting with indicators, where instead the RMSE ratios to benchmark usually tend to increase for horizons larger than 2-3 quarters. The better forecasting performance of WBM over AC models even six-quarters ahead is probably due to the inclusion in the WBM system of ABM equations exploiting some theoretical links as in Quin et al. (2008); more on this point in Section 5. This is also supported by the better performance of WBM in forecasting the world trade from the import side, where equation (7) uses more information about level relationships than the simpler equation (9) for exports.

Contrary to what is usually found in the literature, the nowcast case (i.e. h=1, a=3) in Table 3 is not always associated with the best forecasting performance with respect to the benchmark. This usually occurs when the model specification is fixed in each forecast round, and when the information content increases as the indicators included in the specification are updated. However, in our exercise the specifications may change at each forecasting round, because our automatic modelling procedure can each time select different indicators, which may be characterised by a different degree of updating. All this may prevent the smooth accumulation of information mentioned above, where the same (usually hard) indicators are updated at each forecasting round. In

[17] For the advanced countries, the bad UK GDP performance is the only exception; see Golinelli and Parigi (2007).

this evolving context, it may happen that the larger informational advantage over the benchmark be obtained either slightly before (as for Germany and China) or slightly after (as for France, the UK, Brazil and Russia)[18] the nowcast case. Finally, due to averaging, the best nowcast forecasting performance of world aggregates (and of exports by country) is likely to be due to the aggregation of country-specific forecasts[19].

5. - Robustness analysis

The problems in the GDP forecasting performance of emerging countries may stem from the possible presence of larger breaks in the bridge specifications and/or from heavier data revisions. In order to assess the relevance of these factors, we consider some modifications to the methodological framework underlying the WBM.

Firstly, we substitute the GDP identity (11) – which is based on the levels of the targets - with an estimated bridge equation, where the variables of interest are modelled in log-changes plus some indicators. In the presence of location shifts, a relationship involving variables in rate of changes should be less prone to breaks than one involving variables in levels (Clements and Hendry, 2008). In addition, if we also leave the identity (11) in WBM, another GDP forecast can be obtained by the average of the forecasts from (11) and those from the bridge equation in log-changes. The results of these WBM alterations do not entail relevant modifications with respect to the evidence shown in Table 3, as reported in Table 4, columns labelled "GDP_{dif}" and "GDP_{avg}" respectively for GDP from bridge equation in log-changes and average GDP forecasts.

Secondly, it is well known that a part of the forecast error is given by the difference between population and estimated parameters, which in turn is related to the length of the estimation sample and to the number of parameters to be estimated. On one side, a low number of degrees of freedom due to either too few observations or too many parameters (or both) may affect the precision of estimates and forecasts; on the other, long samples may be associated with the likely presence of heterogeneity and structural change. In order to assess the sensitivity of WBM forecasting ability to the sample length, the columns "T=40" and "T=120" report the results obtained with samples respectively shorter and longer than the baseline setting of 80 quarters, as in the first column ("Base") of Table 4. In shorter samples, characterised by more flexible estimation results, there is a marked improvement of the WBM forecasting ability. This is particularly evident for imports:

[18] Regarding these cases, note also that the use of non-hard indicators carries fresh information not only on the first quarter to be forecast but also on some month of the second quarter; for example, in the light of Table 2, in the forecast round of May we also know one month of soft indicators for the second quarter to be forecast.

[19] The outcomes reported in Table 3 depend also on the historical pattern of the sample period 2006-2012, which includes the recent deep recession, over which the entire forecast exercise is run.

equation (7) is based on level-relationships which are bound to be unstable over the analysed span (see, among the others, Levchenko et al., 2010). In this case, with shorter estimation samples the WBM forecasting ability of world trade from the import side and, symmetrically, with longer sample it worsens. From the export side, as equation (9) has many parameters to be estimated, the beneficial effect of the shorter sample is less evident.

Thirdly, the world trade and GDP forecasting ability can be alternatively evaluated on the basis of the latest available observations (column labelled as "LA-LA"). As in the seminal Diebold and Rudebush (1991), models based on revised data are characterised by a better forecasting ability (see also Heij et al., 2011) but, unfortunately, this is not a realistic case, as revised information is not available at the time the forecast is computed.

Still related to the issue of data revisions and vintages, a latter point regards the choice of the reference series to compute the forecast errors. The most reasonable choice should be the first data release at each forecast horizon, because these are the data used by analysts and policy makers as well. In this respect, the results above suggest that WBM is a valuable tool to improve the month-by-month knowledge of world variables dynamics in the short-medium run. However, the latest (i.e. revised many times) estimates of the QNA target variables are closer to the "true" state of the world than any preliminary release. For this, the column of Table 4 labelled as "LA-RT" reports the RMSE computed against final, i.e. latest available, series.

In line with Diron (2008), the world trade WBM forecasting ability is even better than the AC model when errors are calculated against the latest rather than the first releases. As also suggested in Croushore and Stark (2000), this outcome can be explained by the fact that the AR equations of the benchmark model forecast the future by using regressor data that, being the most recent figures, will be likely subject to several revisions, while the quarterly averages of monthly indicators in the WBM are generally less prone to relevant revisions.

Fourthly, we used in our WBM only BM and not ABM, i.e. we get rid of any information about theoretical links across QNA variables. The column labelled as "no ECM" shows a worsening of the WBM forecasting ability with respect to the "Base" case: the theoretical augmentation lowers WBM RMSEs especially over longer horizons and in the imports case (where ABM exploit more level relationships).

As a last check of our results, the "G6" column of Table 4 reports the forecasting ability of a WBM without the contribution of any EME information. The outcome is clear: the ignorance of EME implies a lower WBM forecasting ability of world aggregates, notwithstanding the worse quality of EME indicators, and the high probability that their relationships with QNA targets be affected by relevant structural shifts (this is in line with the discussion in Hanson, 2012, and with the evidence reported in Borin et al., 2012, regarding GDP forecasts with revised data).

6. - World trade forecasts: early releases, top-down equations and WBM bottom-up

Timely information on world trade is provided by (preliminary) CPB figures released towards the end of each month, with a two-month delay with respect to the reference period. These data are usually taken by short-run analysts as the measure of the state of the world economy. As these releases are subsequently revised, it is important to assess whether they could be considered as rational predictors of the “final” data (in the sense that they incorporate all relevant information; see Muth, 1961). In this paper, we consider as the "final" world trade data (i.e. those no longer subject to revisions) the latest available vintage released by CPB at the end of January 2013, which reports monthly data back to November 2012. The difference between these data and each of the 75 world trade early estimates in our dataset (the latest one was issued in May 2012 and contains the first release for March 2012) can be interpreted as a sort of forecast error of the first release, embodying both statistical and definitional revisions.[20]

In this section, we merge the rationality test literature (see Swanson and van Djik, 2006, and Corradi et al., 2009, for evidence about GDP) with the forecast encompassing approach proposed by Fair and Shiller (1990, henceforth FS). Within the same framework, we assess both the rationality of the first world trade release and, if it is rejected, the appropriateness of a combination with its WBM forecasts, in order to improve the estimate of final world trade data. In practical terms, we regress the quarterly final world trade growth rate on the corresponding growth rate of the quarterly average of each CPB monthly vintage and its WBM forecasts, conditional on the information available at the time of the CPB release.

With reference to the import-side measure of world trade, we have:[21]

$$\frac{{}^{LA}M^{W}_{t+h}-{}^{LA}M^{W}_{t}}{{}^{LA}M^{W}_{t}}=\alpha_h+\beta_h\frac{{}^{t+h}M^{W}_{t+h}-{}^{t+h}M^{W}_{t}}{{}^{t+h}M^{W}_{t}}+\gamma_h\frac{{}^{t+h}M^{WBM}_{t+h}-{}^{t+h}M^{WBM}_{t}}{{}^{t+h}M^{WBM}_{t}}+\varepsilon_{t+h} \tag{15}$$

where the *LA* exponent indicates the final CPB time series of M^W (i.e. the world trade from the import side) released in January 2013; the first regressor refers to the *t+h* quarter of the CPB

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[20] Statistical agencies often revise data because of statistical and definitional changes. Statistical changes stem from the availability of additional information as time elapses, and generally concern the most recent periods. Definitional changes (in the base year, and/or due to methodological innovations, such as changes in classification) are more pervasive and occur at discrete times, involving a retrospective change of the whole series.

[21] Given that world trade can be measured on either the import or the export side, we ran two FS tests. Here we refer to and report results for only the former, as results for the latter are very similar and are available upon request.

early month estimate belonging to quarter $t+1$ of the same CPB variable; the second regressor refers to the h-quarter ahead WBM forecast conditional on the information set available in quarter $t+1$ (i.e.: some months for the indicators, depending on whether we are in case a = 1, 2 or 3, and the QNA data up to quarter t). Usually, the case h = 1 is the most interesting, but the same exercise can also be extended to longer-range horizons, $h > 1$, provided that a model to forecast future M^W realizations of each vintage of world trade series is available. For example, the last (75th) forecast round of this paper (dated May 2012) includes the first release of CPB world trade for March 2012. We can therefore test for the rationality of the 75th CPB vintage to forecast the final world trade figure of the first quarter of 2012, by simply taking the quarterly average of the 75th monthly CPB vintage. However, if we use a monthly model to forecast data from April 2012 to June 2013 (i.e. 15-steps ahead) we may compute the FS test also for any h>1 up to h=6.

The first forecast round of our exercise (at the end of March 2006) includes the first release of CPB world trade for January 2006; the rationality test of the CPB vintage for the first quarter of 2006 cannot be computed as the data for February and March 2006 are not yet available. To forecast them, two approaches are available: (*i*) top-down - i.e. direct modelling of the monthly world trade series with general indicators; (*ii*) bottom-up - i.e. modelling the imports of a number of countries with specific indicators, and forecasting the world trade by aggregating the single-country forecasts. On the choice between the two approaches, see Burgert and Dees (2009), Guichard and Rusticelli (2011), and Jakaitiene and Dees (2012). In the following, we apply the top-down approach (*i*) and compare the results with those of our WBM (which is bottom-up, approach *ii*). The implementation of this comparison can be summarised in three steps.

Step 1. In each of the 75 monthly forecast rounds, we specify two equations for the world trade (one for the import-side and the other for the exports-side) with an automated specification search similar to the one used for our QNA bridge equations over the pool of three sources of world data: (1) six global indicators of world activity and trade listed in the lower part of Table 1 (similarly to Burgert and Dees, 2009); (2) the weighted averages of country-level industrial production and coincident-leading indicators; (3) imports/exports of goods at current prices; the weights for groups (2) and (3) are given by QNA exports/imports flows in 2000, the base year of the CPB world trade index.

Step 2. The estimates from *Step 1* are used to forecast world trade series over the same horizon as that of hard indicators (which have the same release timing). Conditioning monthly indicators are forecast with AR models, as detailed in steps 1-3 of Section 3.2.

Step 3. Monthly world trade series and forecasts are converted in quarterly data by simple averages and used as the first regressor in equation (15), the second being the corresponding WBM forecasts.

On the basis of the OLS parameter estimates of equation (15), alternative tests are computed by imposing suitable restrictions under different null hypotheses (see Table 5; all statistics are based on the Newey and West, 1987, heteroskedasticity and autocorrelation-consistent standard error estimators). The WBM forecasts in equation (15) correspond to the "T=40" scenario in Table 4, because of its better WBM forecasting ability (see Section 5 above).

Forecast rationality tests can be e.g. computed for the first releases issued by CPB in May, August, November and February (see the timing in Table 2), that are the months corresponding to case *a* = 3 of indicator data availability. The corresponding null hypothesis: $\alpha_1 = 0,\ \ \beta_1 = 1,$ and $\gamma_1 = 0$, for *h*=1 (see the *a*=3 case in the third row, last column) is strongly rejected with a P-value = 0.0025. This outcome means that the first release - alone - does not seem to embody all the information contained in the final estimates of each world trade quarters. This outcome can be better understood by considering the other results on the same third row.

The first three P-values correspond to the null hypothesis that one of the parameters in (15) is equal to zero. In the nowcast case (when all the indicators for the first quarter to be forecast are known, case *a*=3), under the null that only $\gamma_1 = 0$ the early world trade releases should encompass the WBM forecasts one-quarter ahead (*h*=1). In other words, if $\gamma_1 = 0$, the WBM nowcast contains nothing else relevant to explain the final quarterly world trade growth, which is not already in the early release. *Viceversa*, if $\beta_1 = 0$: the WBM forecast encompasses the CPB early release. In the *h*=1, *a*=3 row, both β_1 and γ_1 appear to be significantly different from zero, rejecting forecast encompassing in both directions: the one-quarter ahead WBM nowcast should therefore be combined with early CPB estimates of that quarter in order to obtain a better representation of the final world trade data (which will be known only after some considerable delay).

However, it must be acknowledged that all the results in Table 5 are based on small samples (ranging from a maximum of 25 predictions for *h*=1 to a minimum of 20 for *h*=6) and they should be interpreted with care. Greater efficiency may be obtained by reducing the number of parameters to be estimated; for example, if the forecasts are unbiased, the constant in equation (15) can be excluded. Clements (2005, CL henceforth) introduces a more parsimonious forecast encompassing test, which is nested in the FS equation (15) under the restriction $\beta_1 + \ \gamma_1 = 1$. The acceptance of this restriction (P-value = 0.4443; see the fourth column in Table 5) supports the application of the

CL approach, with a significantly different from zero estimate of the WBM forecast weight ($\hat{\lambda}_1$=0.1722; P-value = 0.0339; fifth and sixth columns). These findings further support the non rationality of the first CPB world trade release, and the combination with its WBM nowcast.

The first two rows of Table 5 refer to one-quarter ahead forecasts (*h*=1) for the *a*=1, 2 cases, where the competitor of WBM forecasts is a mix of the CPB early releases (one or two releases, depending on the month in which the forecast is made) and the top-down forecasts for the months needed to complete the quarter to be predicted. As previously, the rationality test is rejected, underlining the importance of the WBM forecast, with significant $\hat{\lambda}_1$ estimates around 0.2-0.3. The large non rejection of the $\gamma_1 = 0$ null hypothesis in the FS equation is probably due to a mixture of inefficiency and collinearity between the two regressors in equation (15), as suggested by the validity of the $\beta_1 + \gamma_1 = 1$ restriction.

Finally, over horizons longer than one, with *h* = 2, 3, ..., 6, real-time forecast encompassing tests may help shed some light on the trade-off between forecasting world trade with aggregate or disaggregate models. In this cases, the FS/CL tests compare WBM (bottom-up) forecasts, measured by γ_h, with those coming from the aggregate model described above, measured by β_h (and no longer the CPB preliminary releases as in the *h*=1, *a*=1, 2, 3 cases)[22]. Their results are influenced not only by the correlation degree of the country-specific forecasts (the more they are correlated, the better is to forecast with aggregate models), but also by the effect of averaging the forecasts from misspecified model (the higher the degree of misspecification, the greater the benefits of forecast aggregation; for a discussion of these aspects see Burgert and Dees, 2009). Since advanced and developing countries tend to markedly differ over time, and all our models are prone to large misspecification, the best forecasts should result from a sort of an empirical horse race, with the FS/CL tests as a referee.

In the rows of Table 5 from the fourth to the end, for forecast horizons longer than two quarters, both top-down and bottom-up regressors are significant, suggesting a combination of the two competing forecasts (as the $\beta_1 + \gamma_1 = 1$ restriction is rejected, the corresponding CL results are

[22] The AR-based forecasts for all the monthly indicators - see the steps 1-3 of Section 3.2 - are the same, independently of the model where they are used.

not reported). In the two-quarters ahead case, the results are clearly in favour of the top-down approach, thus corroborating the findings of Burgert and Dees (2009).[23]

Overall, the outcomes of this section can be summarised as follows. The rationality of early CPB releases to forecast final world trade is rejected and the best one-quarter ahead forecast for world trade is obtained by combining early CPB releases and WBM nowcasts, with larger weights for the former. Two-quarters ahead (apart from the a=1 case), the mixture of early CPB estimates and top-down world trade forecasts with global indicators seems to encompass the corresponding WBM forecasts. From three-quarters ahead on, the best forecast is the simple average of the two real time forecasts (all the results discussed in this section, obtained with world trade data on the imports side, are robust to the use of world trade data on the exports side).

7. - Concluding remarks

In this paper we have presented a world bridge model (WBM) to forecast economic activity at global level. The model is based on short run indicators, with explicit consideration of advanced as well as emerging countries. The recent evolution of the global economy makes this choice unavoidable. In the last few years, the growth path of advanced and emerging economies has been characterized by a sharp divide: weak and uncertain for the former, stronger for the latter. This implies that any forecasting device at world level can no longer ignore the evolution of the emerging countries. The WBM performance indeed confirms this observation: the root mean square forecast error for world trade and GDP is always significantly lower than that of benchmark models when using both real-time and latest-available data.

In addition, the combination of WBM real time forecasts with the early CPB data clearly improves the prediction of the revised (final) figures of world trade. For horizons longer than one- and up to six-quarters ahead, the mixture of CPB early estimates with the forecasts made by an aggregate (top-down) monthly bridge model cannot forecast-encompass the corresponding WBM (bottom-up) predictions. Therefore, the use of real time data weakens the evidence - coming from latest available data - about the better forecasting performance of top-down models against bottom-up ones in forecasting world trade; see Burgert and Dees (2009).

These encouraging outcomes cannot but be a first step. In effects, the forecasting performance for the single countries included in the model is far from satisfactory, especially for the

[23] While the bottom-up WBM data are revised before 2009, the aggregate world trade data in top-down approach are not because there are no vintages (the CPB World Trade Monitor starts in January 2009). This fact could favour the top-down approach if QNA revisions in WBM before 2009 are substantial.

emerging ones. This may be due to a number of factors related to the particular nature of our exercise.

Firstly, we have chosen to specify and estimate a new model for each of the 75 months of our sample. Given the number of countries and of the equations for each of them, an automatic procedure had to be implemented to avoid any influence on the specification/estimation process stemming from the knowledge of the “future”. However, without intervention of the researcher, the WBM misses one of its most important ingredients, the experience of the researcher, which is at the roots of the so called “art of forecasting”. In this sense, the results of this paper should be interpreted as a sort of lower bound to what can be obtained in a proper bridge model approach.

Secondly, the automatic procedure implies the adoption for all countries of the same estimation sample. If this may have no significant effects on advanced countries, for the emerging ones some possible biases may be expected, as shown by the better results obtained with shorter samples. More generally, given the relatively short statistical history of most of the emerging countries and the different stages of their development process, it would be advisable to tailor the estimation sample by country.

Thirdly, and related to the previous point, the absence of the researcher's judgment prevents from analyzing the characteristics of the sample in order to take properly into account idiosyncratic and exceptional events, which may influence the specification search and/or significantly bias the estimates.

Finally, the choice of including some economic theory under the form of disequilibrium terms needs some deeper analysis. Our augmented bridge models have shown a better forecasting performance than the benchmark even at longer horizons. This is not a common finding in the bridge literature and clearly deserves some further research.

All in all, our world bridge model is nothing but a starting point for researchers interested in short-run forecasting at world level. A deeper, country-specific statistical analysis of the data, a more sophisticated specification search, paying due attention to the evolution of the different economies, can provide further improvements in an already satisfactory forecasting performance.

The implications of these results are of paramount importance because they provide more accurate initial conditions for forecasting exercises with macroeconometric world models, as well as more precise and consistent approximations of the short term evolution of the international environment, both at single and at world level.

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Tables and figures

Tab. 1 - Monthly indicators: list, sources and real time data availability assumptions [a]

Label	**Hard indicators (revised); 3,750 time series [b]**	**Source [c]**	**Bridge equation[d]**
	2-month lag between the reference date and the release date		
ICLI[c]	coincident and leading indicators, amplitude adjusted	OECD, MEI	DD
IIP[c]	industrial production, sa 2005 index	OECD, MEI	DD, M
IRET[c]	total retail trade (volume) sa, 2005=100	OECD, MEI	DD
IMU[c]	imports at current prices, sa levels, national currency [e]	OECD, MEI	M
IXU[c]	exports at current prices, sa levels, national currency [e]	OECD, MEI	X
	Soft indicators (not revised); 76 time series		
	1-month lag between the reference date and the release date		
ICP[c]	consumer prices - all items, index 2005=100	OECD, MEI	PD, PX
IPP[c]	domestic producer prices - manufacturing, 2005=100	OECD, MEI	PD, PX
IBCI[c]	standardized business confidence, ampl.adj.	OECD, MEI	DD
ICCI[c]	standardized consumer confidence, ampl. adj.	OECD, MEI	DD
IM1[c]	narrow money (M1) index 2005=100, sa	OECD, MEI	PD
	any lag (reference and release months coincide)		
IEX[c]	exchange rates, national units per US$, monthly average	OECD, MEI [f]	PD, DD, M, PX
ISHA[c]	share prices, index 2005=100	OECD, MEI [f]	DD
ISPCE	Goldman Sachs comm. index, energy spot price in US$	Standard & Poor	PD, M, PX
ISPCNE	Goldman Sachs comm. ind., non energy spot pr. in US$	Standard & Poor	PD, M, PX
IWBCF	commodity prices in current US$, food; index	World Bank	PD, PX
IWBCM	commodity prices in curr.US$, metals & minerals; index	World Bank	PD, PX
IBDI	Baltic exchange dry (Baltic Freight Index), US$ prices	Baltex	DD, M
ISCS	semiconductor sales (world), 3 mth avg, current US$	SIA Report	DD, M

([a]) When labels report *c* superscript, indicators are available by country; otherwise they refer to world aggregates. Real-time availability information: publication lags and revisions. ([b]) 5 (indicators by country *c*) × 10 (countries) × 75 (OECD Main Economic Indicators vintages from March 2006 to May 2012). ([c]) MEI = Main Economic Indicators; SIA = Semiconductor Industry Association Global Sales Report; Baltex = The Baltic Exchange. ([d]) Indicates the QNA dependent variables of the four bridge equations where each indicator is explanatory: PD = internal demand deflator, DD = domestic demand in volumes, M = imports in volumes, PX = exports deflator; ([e]) Since for Brazil, China and Russia OECD MEI data are in US$, they are converted in national currency using IEX. ([f]) Plus Central Banks' sources for the month in which the forecast is made.

Tab. 2 - Data availability at the end of each month of year t

Calendar/forecast month [a]	QNA targets known up to	First quarter to be forecast	of which known month of hard explanatory indicators [b]
January	q3 of year t-1	q4 of year t-1	Oct, Nov
February	q3 of year t-1	q4 of year t-1	Oct, Nov, Dec
March	q4 of year t-1	q1	Jan
April	q4 of year t-1	q1	Jan, Feb
May	q4 of year t-1	q1	Jan, Feb, Mar
June	q1	q2	Apr
July	q1	q2	Apr, May
August	q1	q2	Apr, May, Jun
September	q2	q3	Jul
October	q2	q3	Jul, Aug
November	q2	q3	Jul, Aug, Sep
December	q3	q4	Oct

([a]) The calendar date refers to the release of the monthly OECD MEI issue, and corresponds to the end-month date in which the forecast is made. ([b]) Here we only report the hard indicator data availability for the first quarter to be forecast; the availability of the soft indicators can be simply assessed by adding in each row one/two further months of data, depending on the soft indicator (specific publication lags are in Table 1).

Tab. 3 - WBM forecast ability evaluation (relative RMSEs to AC benchmark) *[a]*

Country Horizon *[b]*	FR	GE	IT	JA	UK	US	BRA	RUS	IND	CHI	World
GDP											
h=1, a=1	0.887	0.776	0.954	0.708	0.960	0.986	1.218	1.180	1.032	1.045	0.891
h=1, a=2	0.786	0.584	0.897	0.617	0.835	0.917	1.078	1.184	1.125	1.206	0.843
h=1, a=3	0.880	0.688	0.774	0.595	1.005	0.711	1.254	1.131	1.159	1.329	0.789
h=2, a=3	0.737	0.726	0.805	0.734	0.765	0.841	0.839	0.978	0.981	1.264	0.802
h=3, a=3	0.676	0.738	0.824	0.846	0.797	0.896	0.907	0.811	1.429	1.377	0.844
h=4, a=3	0.734	0.806	0.850	0.830	0.843	0.951	1.106	0.842	1.490	1.499	0.840
h=5, a=3	0.732	0.814	0.835	0.908	0.847	0.937	1.234	0.874	1.539	1.557	0.842
h=6, a=3	0.760	0.831	0.797	0.823	0.833	0.867	1.225	1.042	1.372	1.634	0.828
Imports											
h=1, a=1	0.773	0.816	0.863	0.773	0.925	0.677	1.019	1.022	0.977	0.941	0.832
h=1, a=2	0.837	0.660	0.724	0.793	0.859	0.622	1.039	1.024	0.968	0.880	0.799
h=1, a=3	0.786	0.572	0.636	0.858	0.806	0.643	1.028	1.063	0.972	0.825	0.668
h=2, a=3	0.586	0.584	0.774	0.671	0.798	0.614	0.955	1.091	0.989	0.807	0.736
h=3, a=3	0.666	0.709	0.896	0.614	0.803	0.646	0.965	0.984	0.991	0.850	0.775
h=4, a=3	0.736	0.837	0.980	0.702	0.846	0.678	0.986	0.983	0.991	0.852	0.805
h=5, a=3	0.803	0.863	1.005	0.696	0.863	0.696	0.936	0.910	1.015	0.828	0.810
h=6, a=3	0.825	0.918	1.006	0.674	0.858	0.720	0.898	0.839	1.028	0.830	0.801
Exports											
h=1, a=1	0.833	0.857	0.801	0.535	0.841	0.683	0.893	1.055	1.231	1.004	0.803
h=1, a=2	0.740	0.717	0.838	0.517	0.792	0.555	0.910	0.997	1.423	0.917	0.701
h=1, a=3	0.680	0.672	0.580	0.525	0.817	0.456	0.910	0.914	1.490	0.807	0.537
h=2, a=3	0.694	0.747	0.714	0.501	0.626	0.546	0.779	0.962	1.162	0.845	0.703
h=3, a=3	0.744	0.810	0.779	0.598	0.668	0.767	0.907	1.019	0.994	0.896	0.810
h=4, a=3	0.833	0.862	0.804	0.631	0.761	0.914	0.962	1.052	1.064	0.933	0.857
h=5, a=3	0.854	0.893	0.819	0.681	0.739	0.953	0.876	1.091	1.163	0.948	0.878
h=6, a=3	0.858	0.916	0.821	0.684	0.743	0.965	0.894	1.088	0.984	0.947	0.896

([a]) Computed over the period from March 2006 to May 2012. ([b]) For one-quarter ahead (h=1) forecasts we report three different cases of growing information availability (i.e. a=1, 2, 3), while for h>1 we only report the results for case 3 (a=3).

Tab. 4 - Robustness of world trade and GDP forecast ability [a]

Settings [b] Horizon [c]	Base	GDP_{dif}	GDP_{avg}	T = 40	T =120	LA-LA	LA-RT[d]	no ECM[e]	G6[f]
GDP									
h=1, a=1	0.891	0.903	0.897	0.790	0.814	0.799	0.924	0.889	0.970
h=1, a=2	0.843	0.855	0.849	0.782	0.798	0.683	0.855	0.851	0.921
h=1, a=3	0.789	0.809	0.799	0.688	0.775	0.605	0.741	0.824	0.868
h=2, a=3	0.802	0.820	0.810	0.684	0.740	0.694	0.855	0.827	0.938
h=3, a=3	0.844	0.846	0.844	0.745	0.773	0.747	0.895	0.847	0.985
h=4, a=3	0.840	0.836	0.838	0.736	0.775	0.786	0.873	0.851	0.963
h=5, a=3	0.842	0.837	0.839	0.727	0.788	0.802	0.862	0.862	0.971
h=6, a=3	0.828	0.822	0.825	0.678	0.793	0.802	0.845	0.860	0.961
Imports									
h=1, a=1	0.832	0.832	0.832	0.644	0.887	0.798	0.795	0.857	0.864
h=1, a=2	0.799	0.799	0.799	0.670	0.806	0.718	0.776	0.813	0.826
h=1, a=3	0.668	0.668	0.668	0.523	0.689	0.599	0.661	0.704	0.706
h=2, a=3	0.736	0.736	0.736	0.544	0.777	0.628	0.708	0.756	0.773
h=3, a=3	0.775	0.775	0.775	0.593	0.840	0.687	0.748	0.813	0.809
h=4, a=3	0.805	0.805	0.805	0.601	0.889	0.741	0.786	0.849	0.838
h=5, a=3	0.810	0.810	0.810	0.613	0.902	0.762	0.790	0.858	0.837
h=6, a=3	0.801	0.801	0.801	0.624	0.908	0.769	0.778	0.861	0.833
Exports									
h=1, a=1	0.803	0.803	0.803	0.739	0.769	0.740	0.755	0.821	0.834
h=1, a=2	0.701	0.701	0.701	0.612	0.675	0.646	0.665	0.724	0.749
h=1, a=3	0.537	0.537	0.537	0.434	0.545	0.541	0.539	0.635	0.590
h=2, a=3	0.703	0.703	0.703	0.589	0.709	0.641	0.685	0.749	0.741
h=3, a=3	0.810	0.810	0.810	0.722	0.809	0.733	0.792	0.837	0.824
h=4, a=3	0.857	0.857	0.857	0.803	0.853	0.794	0.855	0.873	0.876
h=5, a=3	0.878	0.878	0.878	0.854	0.876	0.820	0.874	0.897	0.895
h=6, a=3	0.896	0.896	0.896	0.901	0.904	0.842	0.881	0.910	0.901

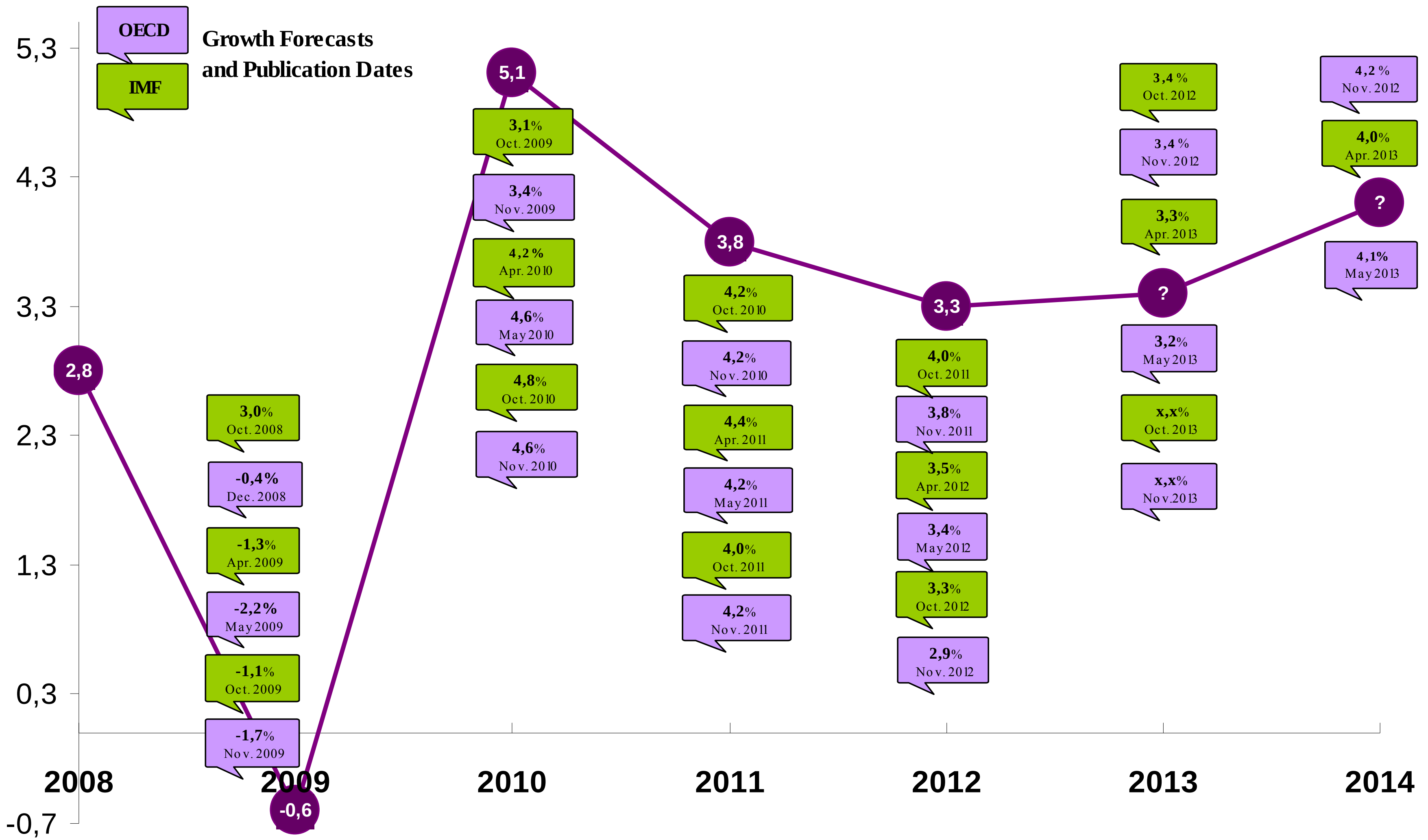
([a]) Relative RMSEs of WBM to the AC benchmark computed over the period from March 2006 to May 2012. ([b]) The basic "Base" settings are: GDP forecast by a level-identity; sample period of T=80 quarters; fully real-time data. The "GDP_{dif}" changes the equation for the GDP forecast which here is a bridge model in differences; "GDP_{avg}" is the simple average of the previous two forecasts; "T=40" and "T=120" results are obtained with shorter and longer samples; "LA-LA" uses only revised (i.e. latest available) data is; in "LA-RT" setting the latest available data are used against the real-time forecasts. ([c]) For the one-quarter ahead (h=1) we report the three cases of information availability (a=1, 2, 3), while for h>1 we report only case 3 (a=3) results. ([d]) In this column, LA-RT results for world GDP are not reported because they are the same as those in the Base column (obtained under the RT-RT setting): given that vintages are not available for world GDP, in both RT-RT and LA-RT simulations the measure of the target variable is the same, the LA one. ([e]) ABM without theoretical augmentation, i.e. only classical BMs. ([f]) Results in this column, are from an altered WBM in which BRIC countries do not contribute at all to the world aggregates, which here are instead computed by combining the forecasts of only the G6 countries (i.e. FR, GR, IT, JA, UK and US).

Tab. 5 - Forecast encompassing and rationality tests in real time [a]

H_0:	$\alpha_h = 0$	$\beta_h = 0$	$\gamma_h = 0$	$\beta_h + \gamma_h = 1$	$\hat{\lambda}_h$ [b]	$\lambda_h = 0$	$\alpha_h = 0$, $\beta_h = 1$, $\gamma_h = 0$ [c]
Horizon							
h=1, a=1	0.1008	0.0000	0.7044	0.0670	0.3484	0.0003	0.0001
h=1, a=2	0.5106	0.0000	0.9202	0.0207	0.1888	0.0091	0.0000
h=1, a=3	0.1373	0.0000	0.0033	0.4443	0.1722	0.0339	0.0025
h=2, a=1	0.1746	0.0141	0.5046	0.1240	0.2245	0.0090	0.0010
h=2, a=2	0.5362	0.0000	0.3624	0.0031			0.0416
h=2, a=3	0.4649	0.0000	0.5041	0.0001			0.0000
h=3, a=1	0.1863	0.0000	0.0210	0.0001			0.0000
h=3, a=2	0.1459	0.0000	0.1040	0.0037			0.0185
h=3, a=3	0.6630	0.0000	0.1413	0.0005			0.0000
h=4, a=1	0.2756	0.0000	0.0025	0.0000			0.0000
h=4, a=2	0.1782	0.0000	0.0098	0.0000			0.0000
h=4, a=3	0.4122	0.0000	0.1850	0.0060			0.0041
h=5, a=1	0.1793	0.0046	0.0089	0.0000			0.0000
h=5, a=2	0.1085	0.0000	0.0061	0.0000			0.0000
h=5, a=3	0.3547	0.0000	0.0955	0.0020			0.0015
h=6, a=1	0.0930	0.0811	0.0831	0.0000			0.0000
h=6, a=2	0.0738	0.0005	0.0225	0.0000			0.0000
h=6, a=3	0.3667	0.0000	0.0488	0.0005			0.0001

([a]) If not otherwise indicated, P-values of the restrictions indicated top of each column are reported. Parameters' restrictions tests are conducted on the regression (with Newey-West, 1987, standard errors): $\frac{{}^{LA}M^{W}_{t+h} - {}^{LA}M^{W}_{t}}{{}^{LA}M^{W}_{t}} = \alpha_h + \beta_h \frac{{}^{t+h}M^{W}_{t+h} - {}^{t+h}M^{W}_{t}}{{}^{t+h}M^{W}_{t}} + \gamma_h \frac{{}^{t+h}M^{WBM}_{t+h} - {}^{t+h}M^{WBM}_{t}}{{}^{t+h}M^{W}_{t}} + \varepsilon_{t+h}$ (the first regressor is a mixture of CPB early estimates and top-down forecasts, the second one is a WBM forecast (bottom-up). ([b]) $\hat{\lambda}_h$ estimate is conditional on $\beta_h + \gamma_h = 1$ restriction; for this, is reported only when this restriction is at least not rejected at 1% and can be interpreted as $\lambda_h = \gamma_h = 1 - \beta_h$. ([c]) This null hypothesis corresponds to the forecast rationality of the mixture of CPB early estimates and top-down forecasts in forecasting final world trade on the imports side.

Fig. 1 - The pattern of IMF and OECD world GDP forecasts, 2009-2011 [a]



([a]) Figures in circles are the latest available figures drawn from the IMF, World Economic Outlook, April 2013. IMF forecasts are from the *World Economic Outlook*; OECD forecasts are from the *Economic Outlook*.

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