

## Chapter 2

# Forecasting World Output: The Rising Importance of Emerging Asia

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**Abstract** The rapid growth of the emerging markets and of China in particular has changed the economic landscape: emerging Asia's share of world trade has grown from about 13% in 1990 to almost 23% in 2008, and its aggregate GDP now accounts for more than 25% of world output, compared with less than 12% in 1990. In this paper we focus on the consequences for the assessment of the global outlook and the specification of forecasting equations. Our main results are that (1) the rise of the emerging countries has led to a sharp change in the correlation of growth rates among main economic areas; (2) this is clearly detectable in forecasting equations too, as a structural break occurring in the 1990s; (3) hence, inferences about global developments based solely on the industrialized countries are highly unreliable; (4) the otherwise cumbersome task of monitoring many – and little-known – countries can be tackled by resorting to very simple bridge models (BM); (5) BM performance is in line with that of the most widely quoted predictions (*WEO*, *Consensus Forecasts*) both before and during the recent crisis; and (6) for some emerging economies, BMs would have provided even better forecasts during the recent crisis.

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## 2.1 Introduction

The assessment of the current and future global economic outlook is a key issue for international financial institutions, governments and central banks. Over the last 20 years the economic landscape has changed considerably: the share of world trade of the most dynamic emerging Asian economies has almost doubled, from about 13% in 1990 to 23% in 2008, and their aggregate GDP now accounts for more than a quarter of world output, whereas it was less than 12% in 1990. The rise of China played a crucial role in this process, as it progressively became a new centre of gravity for the other Asian economies.

During the last decade, Brazil, Russia and India have also started on a path of rapid growth. Led by the BRIC,<sup>1</sup> the emerging countries has thus become central in economic analysis, a development borne out by the replacement of the G8 by the G20 as the main global economic forum. However, while reliable models and data have long been available to analyse cyclical developments in the advanced countries in a timely and comprehensive fashion, this is not true for the emerging economies.

The recent literature still analyses and forecasts global economic trends focusing on either the G7 or the OECD group of countries (Arouba et al. 2010; Kose et al. 2008; Golinelli and Parigi 2007; Chauvet and Yu 2006).<sup>2</sup>

Is this approach still sound? We do not believe so. We provide some new and original evidence on the excessive limitations of this approach and propose a viable alternative by modelling explicitly both the advanced and the main emerging economies' contributions to world economic growth.

In recent years the elasticity of world growth to that of emerging markets has risen from virtually 0 to 0.4. Two phenomena explain this and became apparent in the data during the 1990s: an *emerging Asia effect*, mainly driven by the rise of China as a new centre of gravity, and a *globalization effect*, whereby increasing trade flows and stronger financial linkages proceeded almost in parallel with the expansion of new economic powers.

The first aim of this paper is to prove that these phenomena must entail a significant change in our way of monitoring and forecasting the world economy. A second task is to present an easy, almost automatic, way of obtaining a timely assessment of global economic activity.

That something is amiss in a “business as usual” approach is shown by the dramatic failure of the traditional as well as more innovative forecasting models during the last crisis. No matter what argument is put forward to explain this failure, it surely underscores the importance of frequent forecast updates in a rapidly

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<sup>1</sup> Acronym derived from the initials of Brazil, Russia, India and China.

<sup>2</sup> GVAR models are more general but they have not been devised for short-run analysis and forecasting (see Pesaran et al. 2004, 2009).

changing environment.<sup>3</sup> Updating predictions, however, is a far from simple task as it implies maintaining and estimating high dimension models, as well as very a complex database.

Our proposal for a monthly assessment of global perspectives is to estimate, for the main advanced and emerging countries, very simple bridge models (BM), i.e. equations where the information content of short-run indicators is “translated” into the more coherent and complete “language” of GDP and national accounts. Our BMs are based solely on industrial production in order to show the advantage of this approach without incurring in criticism of “data mining”.

GDP forecasts are obtained with BMs for 15 developed and developing countries/areas, subsequently aggregated into three main groups:

- JEU (Japan, European Union and USA);
- ASE (China, India, Hong Kong, Korea, Singapore, Taiwan, Indonesia, Malaysia, Philippines and Thailand);
- BRRU (Brazil and Russia).

Finally, we specify a world bridge model (WBM), where world GDP growth is the aggregation of the growth rates of these three main areas. While BMs are not a novelty, to our knowledge this is the first attempt to “nowcast” (Banbura et al. 2010) and forecast GDP growth for advanced and emerging markets and, hence, for the world.

BM forecasts for the growth rates of the main countries and areas outperform those of simple benchmarks (like AR or VAR). Comparing WBM predictions with the projections on the *annual* growth rate of world output published in the IMF-*WEO* provides further corroboration: WBM forecasts, estimated at monthly frequency are a reliable *update* of the last available *WEO*.

Focusing on the most recent and dramatic recession, we show that the simple BM proposed track economic developments at least as well as other, more sophisticated models. In particular, augmenting the BM with an indicator that takes into account the “confidence” effects, like the PMI, limits the undershooting of the actual GDP dynamics that becomes apparent in the case of the BM based solely on industrial production.

We have chosen to focus on the forecast of world GDP growth because it is immediately and more easily comprehensible as an indicator of global activity, compared for instance with cyclical, synthetic indicators of economic activity.<sup>4</sup>

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<sup>3</sup>The International Monetary Fund (IMF) decided to publish two updates of its World Economic Outlook (WEO) projections, in January and July, to bridge the complete WEO projections released in April and October, in conjunction with the semi-annual meetings of the Fund.

<sup>4</sup>See Camacho and Perez-Quiros (2008) and Barhoumi et al. (2009) for alternative ways of performing a similar task for euro-area growth. See Altissimo et al. (2010) instead for the second route to obtain a monthly indicator of euro-area growth.

**Table 2.1** Country share of world GDP (based on PPP valuation of country GDP)

	1990	1995	2000	2005	2008
World (billions of US dollars based on PPP)	25,626.1	32,290.2	42,116.0	56,504.7	69,569.4
	Share of world total				
<b>Japan</b>	9.0	8.7	7.6	6.9	6.2
<b>EU 15</b>	24.2	23.5	22.6	20.6	19.3
<b>United States</b>	22.6	23.0	23.6	22.4	20.8
<b>China</b>	3.6	5.7	7.2	9.4	11.5
<b>NIEs<sup>a</sup></b>	2.7	3.4	3.6	3.8	3.8
<b>Other developing Asian economies<sup>b</sup></b>	5.5	6.6	6.7	7.5	8.2
<b>Russia</b>	5.6	3.0	2.7	3.0	3.3
<b>Brazil</b>	3.1	3.2	2.9	2.8	2.9

<sup>a</sup>Includes Hong Kong, Republic of Korea, Singapore, Taiwan

<sup>b</sup>Includes India, Indonesia, Malaysia, Philippines, Thailand and Viet Nam

Source: IMF WEO

## 2.2 The Rising Importance of Emerging Markets

### 2.2.1 *Change in Weights and Correlation Pattern Among Main World Areas*

In 1990, the GDP of Japan, the European Union (15) and the United States (JEU hereafter) together accounted for 55.8% of world output (evaluated at purchasing power parity, PPP hereafter); by 2008, their combined share was only 46.3%.<sup>5</sup> In the meantime, China's weight alone grew from 3.6% to 11.5% (see Table 2.1).

The same rising importance of the emerging world is even more astounding in the case of trade flows: China's share of world exports grew sixfold (from 1.5% to 9%), while that of JEU shrank from 63.6% to 44.6% (see Table 2.2).

Similarly, while the average growth rate of JEU in the 1990s was 2.5%, it fell to 1.5% in this decade; in the same two periods the emerging Asian economies grew by 7.1% and 7.6% on average and China alone by 9.9% and 10.3%. In the last decade, more than 60% of world output growth originated in the emerging world (notably China), with respect to about 40% in the 1990s (see Fig. 2.1).

Once again, the difference is even greater when we consider trade flows: since the mid-1990s, the share of Chinese exports has increased rapidly in all destination markets. In 2008 they accounted for 18.8%, 16.5% and 13.3% of Japanese, US and EU imports respectively (see Appendix A). At the same time, trade within the most

<sup>5</sup> In comparing GDP levels and growth rates, as well as in weighting trade flows and correlation patterns, we focused on the period prior to the world economic crisis (i.e. before 2009). We turn to an analysis of the impact of the financial turmoil on economic performance of the main areas and its predictability in the last section of the paper.

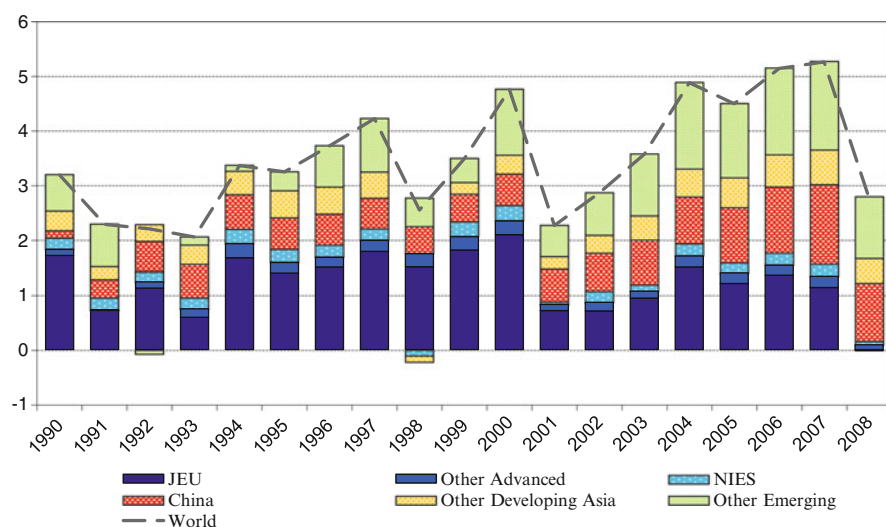
**Table 2.2** World trade and countries' export shares (current US dollars and percentages)

	1990	1995	2000	2005	2008
World (billions of US dollars based on PPP)	3,448.1	5,077.0	6,358.8	10,333.5	15,858.9
Share of world total					
<b>Japan</b>	8.2	8.5	7.2	5.5	4.7
<b>EU 15</b>	44.1	39.6	34.9	34.5	31.9
<b>United States</b>	11.2	11.3	12.1	8.6	8.1
<b>China</b>	1.5	2.5	3.9	7.4	9.0
<b>NIEs<sup>a</sup></b>	7.8	10.7	10.8	9.8	8.8
<b>Other developing Asian economies<sup>b</sup></b>	3.1	4.5	5.1	5.0	5.0
<b>Russia</b>	1.5	1.6	1.7	2.4	3.0
<b>Brazil</b>	0.9	0.9	0.9	1.1	1.2

<sup>a</sup>Includes Hong Kong, Rep. of Korea, Singapore, Taiwan

<sup>b</sup>Includes India, Indonesia, Malaysia, Philippines. Thailand and Viet Nam

Source: IMF WEO



**Fig. 2.1** Contributions to world GDP growth (Yearly data, composition based on PPP valuation of country GDP) (Source: IMF WEO)

industrialized countries has shrunk as a share of the total in the face of the growing importance of China and other emerging economies.

For instance, in the case of Japan the cumulative weight of the US and the EU in its total exports declined dramatically from 31% in 2000 to about 19% in 2008. By contrast, intra-regional trade among the east Asian countries gained importance over the last decade. At present, more than one third of Chinese trade takes place with Japan and other east Asian countries; for the latter, the weight of intra-regional trade exceeds 50% of the total.

The integration of China within the international production chain has made a crucial contribution to this phenomenon. The growth of the Chinese exporting sector has intensified the fragmentation of production processes among Asian partners, while China itself has become the hub of this regional network.<sup>6</sup> In particular, China has turned out to be a favourite location for assembling parts and components produced in other east Asian countries. Although the rising prominence of the *processing trade* may artificially boost the weight of intra-regional trade in East Asia, it also reveals an increasing interdependency among the economies belonging to the same production network.

From these developments we can anticipate that along with the rising weight of emerging areas, the correlation pattern among world economies has also changed. Table 2.3 shows the correlations of annual GDP growth rates for the main countries and economic areas computed at three time intervals about 20 years apart.

On the principal diagonal appears the average pairwise correlation within each country group, while the off-diagonal figures measure the correlation between them. We focus on the G6 group of western advanced economies (i.e. the G7 without Japan), two groups of east Asian dynamic economies (newly industrialized Asian economies, NIEs, and developing Asia, excluding China), Brazil and Russia; Japan and China have been singled out from their respective reference groups, given the peculiar evolution of their economies. The maximum correlation between the G6 and world GDP is attained during the 1970s and 1980s (0.93), while it has almost halved in the most recent period (0.49).

Co-movements between Japan and the G6 follow a similar pattern, while during the last 20 years Japan's correlation with other Asian economies has risen. Similarly, co-movements among the growth rates of Asian economies have steadily increased over time, both within the NIEs and developing Asian economies and between these country clusters. Looking more closely at the evolution of GDP co-movements within east Asia, we note a sharp increase in the pair-wise correlations between China and most of the other Asian countries in the last 20 years, with India and the Philippines the only exceptions. Brazil and Russia have also shown an increase in co-movement with China's economy, which in recent years has driven the demand for industrial commodities of which Russia and Brazil are large producers. The correlation of growth rates between emerging economies and the G6 has remained quite low (especially with China), while over the last 20 years the correlation with world growth has risen sharply for the emerging Asian economies, Brazil and Russia.

We can tentatively conclude that (1) the rising importance of emerging markets is clearly visible in terms of GDP and trade flows as well as in terms of contribution to overall world growth; and (2) that fast growth in China and emerging Asia has given rise to new regional centers of gravity that have affected the linkages among

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<sup>6</sup> Wang and Wei (2008), Koopman et al. (2008), Amiti and Freund (2008), He and Zhang (2008), Schott (2008).

**Table 2.3** Contemporaneous correlations of annual GDP growth (Annual data; intra-group average correlation on the principal diagonal)

	1951–1970							
	World	G6 <sup>a</sup>	Japan	China	Oth. Dev. Asia. <sup>b</sup>	NIEs <sup>c</sup>	Russia	Brazil
<b>G6<sup>a</sup></b>	<b>0.72</b>	0.14						
<b>Japan</b>	<b>0.42</b>	0.31	1					
<b>China</b>	0.37	0.04	−0.29	1				
<b>Other Developing Asia<sup>b</sup></b>	0.15	−0.22	<b>0.44</b>	−0.10	−0.04			
<b>NIEs<sup>c</sup></b>	0.05	−0.10	−0.15	0.05	0.20	0.16		
<b>Russia</b>	0.32	−0.18	0.08	0.04	0.24	−0.02	1.00	
<b>Brazil</b>	−0.14	−0.23	0.25	−0.27	0.23	0.02	0.02	1.00
<b>1971–1990</b>								
<b>G6<sup>a</sup></b>	<b>0.93</b>	<b>0.54</b>						
<b>Japan</b>	<b>0.63</b>	<b>0.63</b>	1					
<b>China</b>	0.05	0.23	0.21	1				
<b>Other Developing Asia<sup>b</sup></b>	0.11	0.11	0.21	−0.03	0.24			
<b>NIEs<sup>c</sup></b>	<b>0.80</b>	<b>0.76</b>	<b>0.41</b>	0.08	0.16	0.39		
<b>Russia</b>	<b>0.50</b>	0.37	0.00	0.00	0.21	<b>0.61</b>	1.00	
<b>Brazil</b>	<b>0.53</b>	0.31	0.12	−0.21	−0.31	0.25	<b>0.42</b>	1.00
<b>1991–2008</b>								
<b>G6<sup>a</sup></b>	<b>0.49</b>	<b>0.46</b>						
<b>Japan</b>	<b>0.45</b>	0.01	1					
<b>China</b>	−0.01	−0.10	0.18	1				
<b>Other Developing Asia<sup>b</sup></b>	<b>0.52</b>	−0.10	<b>0.62</b>	<b>0.51</b>	<b>0.45</b>			
<b>NIEs<sup>c</sup></b>	0.15	0.13	<b>0.67</b>	<b>0.40</b>	<b>0.63</b>	<b>0.61</b>		
<b>Russia</b>	<b>0.65</b>	0.00	0.21	−0.51	0.20	−0.16	1.00	
<b>Brazil</b>	<b>0.52</b>	0.00	<b>0.30</b>	0.35	<b>0.59</b>	0.29	0.20	1.00

Values greater than 0.4 in bold scripts

<sup>a</sup>Includes Canada, France, Germany Italy, U.K., U.S.A

<sup>b</sup>Includes India, Indonesia, Malaysia, Philippines. Thailand and Viet Nam

<sup>c</sup>Includes Hong Kong, Rep. of Korea, Singapore, Taiwan

Source: A. Maddison – OECD, IMF WEO

world economic areas and the degree of co-movement within and across the different country groups.

### 2.2.2 “Emerging Asia” and “Globalization” Effects and Assessment of the Global Economic Outlook

All this prompts one to ask whether the emerging countries are becoming important also for assessing the global economic outlook and forecasting world GDP. To address this issue we estimate the contributions to world GDP growth of different countries/groups. There is an accounting relationship linking aggregate world GDP to its components, and this is at the basis of the evidence presented in Fig. 2.1.

However, the extent to which each country aggregate affects world GDP growth may differ from its weight in the accounting identity, since a given country/group may play a leading role in the global economy influencing the evolution of many other countries. In this case we can track the dynamic of world output considering a limited number of relevant economies, leaving aside some whose “accounting weight” might be non-negligible. To investigate this we estimate the following relationship:

$$\Delta y_t^W = \alpha + w^{JEU} \Delta y_t^{JEU} + w^{ASE} \Delta y_t^{ASE} + w^{BRRU} \Delta y_t^{BRRU} + u_t \quad (2.1)$$

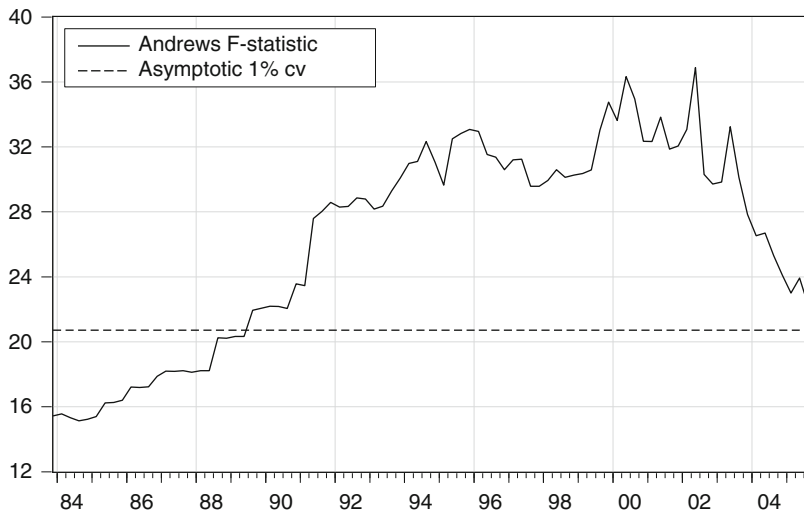
where  $u_t$  are the errors that should mainly capture the contribution of countries not included in the analysis;  $\alpha$  is a constant and  $w_i$  represents the elasticity of world GDP growth to aggregate  $i$ 's output growth ( $i = JEU, ASE, BRRU$ ).<sup>7</sup>

A simple OLS estimate of Eq. 2.1 to identify and quantify precise causal relationships is likely to be affected by endogeneity issues for two main reasons: simultaneity/reverse causality (i.e. world growth may drive the dynamics in some areas, rather than the opposite) and omitted variables bias (i.e. output growth of countries excluded from (1) may significantly affect the evolution of those included). These are essentially endogeneity problems, which can be dealt with using an instrumental variable (IV) approach, employing the first lag of the dependent and the explanatory variables as instruments. Estimates for the whole sample period (1979q1–2010q1) are presented in the first column of Table A.3. The choice of the IV estimator appears justified by the results of the Hausman test; moreover, as the Godfrey test does not detect significant autocorrelation in the residuals, lagged values of the variables may be considered valid instruments. The estimated coefficients for the whole sample highlight the relevance of JEU in explaining the evolution of world GDP, while the elasticity associated with ASE output growth is not statistically significant.

As we are mainly interested in evaluating this relationship over time, we compute the Andrews-Quandt test for the detection of breaking points in the coefficients. Figure 2.2 shows the behaviour of the likelihood ratio  $F$ -statistic over the time span considered for the detection of a breaking point (1983–2006). The  $F$ -statistic rises progressively until 1994, then it fluctuates around values largely above the 1% confidence level until 2003. This clearly shows an instability “phase” during the 1994–2003 period, while the specific break date can be due to the presence of a particular spike (the second quarter of 2002, according to the Andrews-Quandt sup  $F$  statistic).

<sup>7</sup> Country groupings (JEU, ASE and BRRU) are defined in the introduction. Details regarding GDP and other data sources are in the Appendix A1; GDP growth is given by the first differences of log-levels. We found that  $y_t^W - w^{JEU} y_t^{JEU} - w^{ASE} y_t^{ASE} - w^{BRRU} y_t^{BRRU} \sim I(1)$  hence a stable co-integrating relationship cannot be found owing to pervasive and significant parameter (weight) changes over the sample period, as one would expect given the evidence in Sect. 2.1.





**Fig. 2.2** Results of the Andrews (1993) statistic for breaking points (Andrews-Quandt *sup*  $F$  statistic and the asymptotic 1% critical value)

We therefore split the sample into two subperiods: 1979q1–1993q4 and 1994q1–2010q1, consistently with the evidence provided by the  $F$ -statistic. IV estimation results for the two periods are reported in columns 2 and 3 of Table A.3. The elasticity of world GDP growth to that of the ASE group sharply increases from about zero in the first part of the sample to a statistically significant 0.4 in the second, while, not surprisingly, the coefficient associated to JEU decreases from 0.8 to 0.5. The relationship between world and BRRU GDP growth rates is more stable (with an elasticity around 0.065 in both periods). As shown in column 4, the difference of the estimated coefficients between the two periods is statistically different from zero both for the JEU and the ASE groups, providing further evidence in favour of our partition of the sample. This clearly suggests that the relevant factor in the recent evolution of world output has been the robust growth of the East Asian economies (emerging Asia effect).

This point can be further advanced with a VAR(1) model for  $\Delta y_t^{JEU}$ ,  $\Delta y_t^{ASE}$  and  $\Delta y_t^{BRRU}$ , which provides a parsimonious data-congruent representation of the dynamic relationships between the GDP growth of the three groups of interest<sup>8</sup>:

$$\begin{pmatrix} \Delta y_t^{JEU} \\ \Delta y_t^{ASE} \\ \Delta y_t^{BRRU} \end{pmatrix} = \begin{pmatrix} \alpha^{JEU} \\ \alpha^{ASE} \\ \alpha^{BRRU} \end{pmatrix} + \begin{pmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{pmatrix} \begin{pmatrix} \Delta y_{t-1}^{JEU} \\ \Delta y_{t-1}^{ASE} \\ \Delta y_{t-1}^{BRRU} \end{pmatrix} + \begin{pmatrix} v_t^{JEU} \\ v_t^{ASE} \\ v_t^{BRRU} \end{pmatrix} \quad (2.2)$$

<sup>8</sup> The first-order dynamics is enough to have non-autocorrelated reduced-form residuals.

The estimates have been computed over the whole sample and over the two subperiods previously identified. Table A.4 (see Appendix A) presents the  $p$ -values for non-Granger causality tests (NGC), and the correlation coefficients between VAR shocks. In the first subperiod, NGC never rejects the null of non-significant explanatory power of the past values of each aggregate GDP growth to the others, while in the second subperiod ASE output growth becomes significant for the future dynamics of both JEU and BRRU (this last group, though less significant, contributes to predict JEU growth since the mid-1990s). The evidence regarding a relevant predictive power of the Asian emerging economies with respect to the evolution of JEU GDP is confirmed by the estimates obtained over the whole sample (column 1), although these results clearly hide the deep changes occurring between the two subperiods (confirming the emerging Asia effect). Moreover, the simultaneous correlation between JEU reduced-form shocks and both ASE and BRRU innovations rises sharply in the second part of the sample, signalling a general increase in the international integration of the economies during the last 15 years (globalization effect).

Overall, our findings make it evident that knowledge about a wealth of short-run indicators for JEU countries alone is no longer enough for a good understanding of world dynamics.<sup>9</sup>

## 2.3 Assessing Out-of-Sample Bridge Models' Ability to Forecast Quarterly World GDP

Two main tools have been used in the literature on short-term forecasting: bridge models (BM), based on a small and carefully selected set of indicators, and dynamic factor models (DFM), estimated on a large panel of data.<sup>10</sup> We focus on the first, which has been applied extensively in short-run forecasting for the euro area, the G7 countries and Italy.<sup>11</sup> BMs may be particularly effective in the short-term GDP forecasting of emerging economies, where only a limited number of high frequency indicators are generally available. This is also confirmed by a recent IMF (Matheson 2011) study that uses DFM to develop indicators for tracking growth in various countries. While for advanced economies the use of a large set of variables produces appreciably accurate forecasts, DFM estimates on average provide a much poorer fit of the actual GDP growth of emerging countries.

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<sup>9</sup> Even though we do not consider data revisions this fact does not necessarily lead to an artificial improvement in our model's forecasting ability. In fact, Croushore and Stark (2001, 2002), modelling US GDP growth, do not find a significant difference between the forecast errors generated using real-time data or latest-available data. The same result is broadly confirmed for other countries (see e.g. Golinelli and Parigi 2008, for Italy).

<sup>10</sup> For a comparison and a discussion of BM and DF approaches see Bulligan et al. (2010).

<sup>11</sup> See Baffigi et al. (2004) and Golinelli and Parigi (2007, 2008).

Obviously, although a BM appears an appropriate device in this context, the lack of timely and reliable data for most of the emerging economies is a major limitation for our forecasting exercise as well. In their contribution to this volume, Marini and Zollino (2012) present the weaknesses that still characterize China's official quarterly GDP statistics, the key target variable of our BM predictions.

The bridge models we use in this section exploit only industrial production (IP) to deliver early GDP estimates for JEU, ASE and BRRU countries. We construct a World Bridge Model (WBM) in which world GDP is projected using an aggregator equation of these three country groupings.<sup>12</sup> IP has been chosen because it is reliable as a coincident indicator of GDP and in general subject to small revisions. Furthermore, we focus solely on IP not to incur in the criticism of selecting artificially good models (i.e. with best performing indicators) just because our knowledge of "future" (actually past) events creeps into the BM specification, contaminating the reliability of the pseudo out-of-sample forecasting exercises. Consequently, one can think of the WBM predictions presented in this and the next section as some sort of lower bound of the forecasting ability of short-run indicators.<sup>13</sup> The superiority of the latter BMs in forecasting GDP is manifest: considering the estimates of current GDP growth (the so-called nowcast case), carefully chosen indicators reduce the root mean square errors from 0.69 to 0.31 for Japan, from 0.20 to 0.14 for the European Union and from 0.57 to 0.25 for the US.

We define a simple BM for country  $i$ , as a fourth order autoregressive distributed lags model – ARDL(4,4) – in error-correction form for the log-levels of GDP and IP:

$$\Delta GDP_t^i = \alpha^i + \sum_{j=0}^3 \beta_j^i \Delta GDP_{t-j}^i + \sum_{j=1}^3 \gamma_j^i \Delta IP_{t-j}^i + \pi_{GDP}^i GDP_{t-1}^i + \pi_{IP}^i IP_{t-1}^i + \varepsilon_t^i \quad (2.3)$$

where  $\alpha^i$ ,  $\beta_j^i$ ,  $\gamma_j^i$  and  $\pi_{GDP}^i$ ,  $\pi_{IP}^i$  are the short- and long-run country-specific parameters and  $\varepsilon_t^i$  are country-specific white noise errors.<sup>14</sup>

All BMs are conditioned on simultaneous IP (through the  $\beta_0^i$  parameter), which is a monthly coincident GDP indicator and is available well before the GDP data for the corresponding quarter. However, when forecasting the current quarter, usually not all 3 months are known and, in any case, future IP observations are not

<sup>12</sup> Examples of aggregator equations can be found in Baffigi et al. (2004) and Golinelli and Parigi (2007).

<sup>13</sup> This intuition is confirmed by comparing – over the common sample 2000q1–2003q4 – the forecasting performance of our raw BMs with that of the carefully specified BMs for the advanced countries reported in Golinelli and Parigi (2007).

<sup>14</sup> Four more parsimonious models, nested in (3), can be obtained by imposing parameter restrictions: (3-i) the ARDL(3,3) in log-levels; (3-ii) the ARDL(2,2) in log-levels; (3-iii) the ARDL(1,1) in differences (i.e. which omits all log-levels); and (3-iv) the static model in differences ARDL(0,0). We select the best model out of these five alternatives by minimizing the Schwarz criterion.

available. Missing IP data are forecast with a simple AR(p) for monthly IP log-differences.

We consider four alternative scenarios corresponding to different situations of data availability in typical forecasting practices: when forecasting GDP one quarter ahead, the conditioning IP may be known just for the first month of the quarter, or for the first two, or for all 3 months. In the first two instances, IP has to be predicted for two or one steps ahead prior to forecasting GDP. More generally, in the  $h$ -quarter-ahead GDP forecast, when  $h > 1$ , IP forecasts are needed at least for  $(h-1) \times 3$  months and in the worst case for  $(h-1) \times 3 + 2$  months of the forecast horizon.

For each country, the ordinary least squares (OLS) estimates of both models (AR for IP and BM for GDP) are obtained through rolling regressions as explained in the previous section.<sup>15</sup> The pseudo out-of-sample forecasting exercise covers 10 years and is structured as follows. October 1999 is the month in which we start to simulate the behavior of a forecaster who wants to predict world GDP (first round): IP is available up to August 1999 (1999 m8, 2 months before the calendar date) and GDP up to the second quarter of 1999 (1999q2). In order to obtain predictions over the following 2 years (2000–2001), IP has to be forecast up to 28 months ahead and BM up to 10 quarters ahead. In this first round, the BM estimation period ends in 1999q2 and starts 80 quarters earlier for JEU countries, 60 quarters for the others groups of countries.

These steps are repeated for the next 119 months, the last round being September 2009, when IP is known up to 2009 m7 and forecast up to 2010 m12 (i.e. 16 months ahead) and GDP is known up to 2009q2 and forecast up to 2010q4 (six quarters ahead).

Although BMs are normally used only for short-run predictions, in each forecast round we extrapolate GDP dynamics up to 2 years to give an extended assessment of their forecasting ability. Overall, our exercise delivers 40 pseudo out-of-sample forecast errors for each of the first three one-step-ahead scenarios described above (120 forecast errors). In addition, we measure forecast errors for 2, 4 and 6 steps ahead. We compute statistics for BM forecasting ability (mean error, ME, and root mean squared error, RMSE), and compare them with benchmark models using Fair and Shiller (1990) and Giacomini and White (2006) tests (FS and GW henceforth). Benchmark forecasting ability by country is given by an AR quarterly model for world, JEU, ASE and BRRU GDP growth rates. AR benchmark models are estimated through rolling windows and used in predictions over the same time spans as the BMs.<sup>16</sup>

<sup>15</sup> The size of the rolling widow to estimate AR models parameters is set to 7 years (84 months) for all countries, as in Bulligan et al. (2010). To estimate BM model parameters we set windows of 20 years (80 quarters) for the JEU countries while, to avoid the effects of possible breaks, in the ASE and BRRU specifications we choose a shorter window of 15 years (60 quarters).

<sup>16</sup> In each of the 120 monthly rounds and for each country, the benchmark AR models for first-difference log-GDP are selected by using the Schwarz criterion over a range of lags from 0 to 4.

**Table 2.4** Assessment of the forecasting ability of the bridge models<sup>1</sup>

	GDP forecast horizon					
	With 1 m	<sup>1</sup> q With 2 m	With 3 m	2 qs	4 qs	6 qs
<b>World</b>						
ME	0.117	0.121	0.140	0.259	0.437	0.590
RMSE	0.422	0.387	0.370	0.677	1.697	2.551
Ratio to AR	<b>0.710<sup>a</sup></b>	<b>0.651<sup>a</sup></b>	0.622 <sup>a</sup>	<b>0.606<sup>a</sup></b>	0.851 <sup>a</sup>	0.980 <sup>a</sup>
<b>JEU</b>						
ME	−0.063	−0.042	−0.023	−0.102	−0.377	−0.770
RMSE	0.338	0.308	0.277	0.648	1.898	3.029
Ratio to AR	<b>0.590<sup>a</sup></b>	<b>0.534<sup>a</sup></b>	<b>0.481<sup>a</sup></b>	<b>0.554<sup>a</sup></b>	0.791 <sup>a</sup>	0.896 <sup>a</sup>
<b>ASE</b>						
ME	0.068	0.038	0.041	0.082	0.193	0.318
RMSE	0.560	0.487	0.477	0.874	1.785	2.577
Ratio to AR	0.772 <sup>a</sup>	0.678 <sup>a</sup>	0.664 <sup>a</sup>	<b>0.688<sup>a</sup></b>	0.849 <sup>a</sup>	0.930
<b>BRRU</b>						
ME	0.036	0.037	0.070	0.295	0.782	1.051
RMSE	0.814	0.586	0.546	1.245	3.398	4.633
Ratio to AR	<b>0.692<sup>a</sup></b>	0.503 <sup>a</sup>	0.469 <sup>a</sup>	0.532 <sup>a</sup>	0.788 <sup>a</sup>	0.798 <sup>a</sup>

<sup>1</sup>Ratios are reported in italic when GW is significant at 10%, in bold when it is significant at 5%; further, <sup>a</sup>means that the BM parameter in FS equation is 5% significant while AR is not, <sup>b</sup>means that both parameters [FS and AR] are significant. For the GW test we use the test function  $h_t = (1, \Delta L_{t-\tau})$

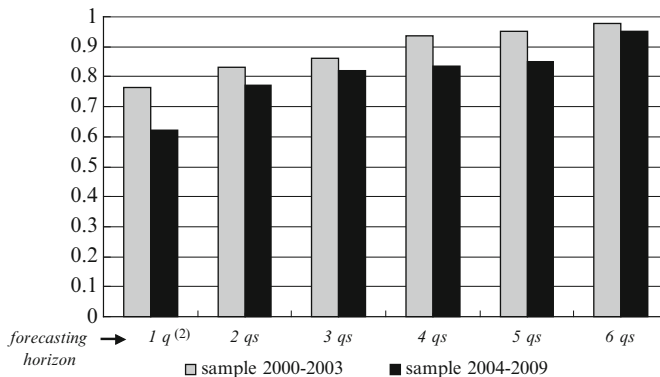
Along the rows of Table 2.4, we report the results for the seven countries which sum to JEU, ASE and BRRU the corresponding aggregates and world GDP. Along the columns six different forecast horizons are listed: the first three are those described in one-step-ahead scenarios from 1 to 3 (see above) and the other three report the results at longer horizons.

Results can be summarized as follows.

First, in the short run, BM forecasts are usually unbiased (see the ME results), while over the medium run forecasts for JEU, the US and the European Union (but not those for Japan) tend to overestimate historical levels; the opposite happens with BRRU forecasts.

Second, JEU countries have lower RMSE than ASE and BRRU. As usually found, the RMSE for the country aggregates is lower than that of their components. The BM improves appreciably upon the benchmark forecasts: ratios of BM RMSE over that of AR benchmarks are almost always below one over horizons up to 6 months (with the sole exception of Hong Kong), showing a clear deterioration only at the end of the forecasting horizon (six quarters).<sup>17</sup>

<sup>17</sup> BM forecasts of Chinese GDP have a lower RMSE with respect to the other Asian economies and improve markedly with respect to the AR benchmark.



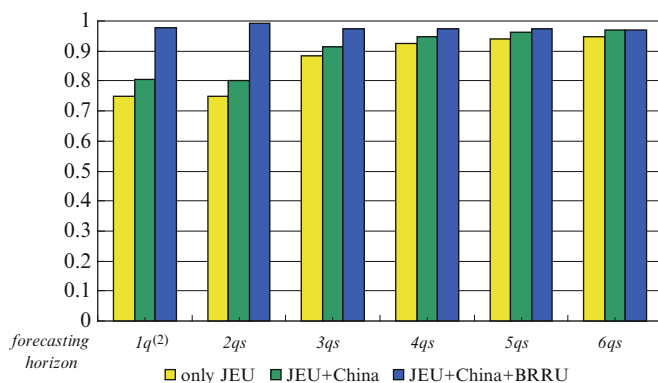
**Fig. 2.3** RMSE ratios between WBM that include or exclude emerging countries (Bars are the ratios of the RMSE of predicting world GDP with a bridge model that includes emerging economies (ASE and BRRU) and the RMSE computed including only advanced economies (JEU). Values below 1 indicate a better performance of the comprehensive model. When *black bars* are shorter, the importance of emerging economies rises over time. (2) Results refer to the case in which the conditioning IP is known for all 3 months of the quarter)

Third, BM RMSE are not only better “numerically” than those of AR benchmarks, but – in the light of the GW test – they are very often significantly better than benchmark ones. Among ASE, the GW tests show statistically significant improvement for China, Malaysia and Philippines. Furthermore, according to the FS test, BM forecasts are significant explanations of actual GDP development, at least up to 1 year (except for Hong Kong and Indonesia), while the significance of benchmark models is often spurious, probably affected by the GDP slowdown of 2008–2009. For this reason, “b” cases in Table 2.4 (where both the BM and AR parameters are significant in the FS regression) tend to be more frequent in JEU, where the recession was particularly severe. Interpreting these particular cases one should bear in mind the extreme simplicity of the BM models considered here.

In Sect. 2.2, we argue that the rising contribution of emerging economies to world GDP growth might have relevant implications also for forecasting purposes. We develop this point by comparing the WBM predictions of world output growth either including or excluding the groups ASE and BRRU in the aggregator equation. In Fig. 2.3 we show the ratios between the RMSE obtained from the more comprehensive model (numerator) and from the model excluding the emerging countries (denominator). RMSE ratios for the different forecasting horizons are computed over two sample periods (2000–2003, histograms in grey, and 2004–2009, histograms in black) to evaluate whether the relevance of emerging markets has increased in recent years.

All the ratios turn out to be lower than one, meaning that the aggregator model which includes also ASE and BRRU provides more accurate predictions for world GDP growth. The gain in precision is greater for short-term forecasts, attaining the maximum in the nowcast case, while it tends to disappear at longer horizons.

The RMSE ratios computed over the second part of the sample (2004–2009) are generally lower than those relating to the first forecasting period (2000–2003). The limited number of observations prevents us from computing tests for the



**Fig. 2.4** RMSE ratios between the WBM that include all the economies or a subset of emerging countries ((1) Sample 2004–2009. (2) Results refer to the case in which the conditioning IP is known for all 3 months of the quarter (nowcast))

significance of these differences. However, these results confirm the evidence presented in Sect. 2.2 about the importance of emerging country dynamics.

Ignoring the whole set of information on emerging economies causes a substantial deterioration in the WBM predictions, especially in recent years. We further investigate how the major emerging economies contribute to world output forecasts. Figure 2.4 shows that adding China to the group of advanced countries in the aggregator equation produces a sizeable improvement in forecasting accuracy: the RMSE ratio with respect to the most comprehensive model increases by about 6% points in the predictions of the current and next quarters. Combining the information on China with that on the major non-Asian emerging economies (Brazil and Russia) delivers a larger gain in precision. This suggests that China can be used to proxy the evolution of emerging Asia, thanks to its increasing integration with China.

While Brazil and Russia carry additional information due to their role as global suppliers of industrial commodities. The evidence reported in Fig. 2.4 also shows that the inclusion of these three major emerging countries is sufficient to restore precision in forecasting world output comparable to that obtained by the most comprehensive model (with 12 emerging markets).

To assess the accuracy of WBM forecasts we compare them with predictions based on a much richer information sets, the one used by IMF for its World Economic Outlook (*WEO*).<sup>18</sup> We show that WBM<sup>19</sup> predictions are good “updates”

<sup>18</sup> WEO projections are released in April and October of each year. A more detailed description of these exercises, and a complete documentation of the results are reported in a previous version of this work, available at [http://www.bancaditalia.it/studiricerche/convegni/atti/chinese-economy/sessione1/borini/Borin\\_1.pdf](http://www.bancaditalia.it/studiricerche/convegni/atti/chinese-economy/sessione1/borini/Borin_1.pdf)

<sup>19</sup> Obviously, what is said here for the WBM can be replicated for the single BMs of countries and country groups.

**Table 2.5** April's *WEO* forecast errors for next year annual growth

WEO's release	Forecast for target year	Final estimate	Forecast error
<b>Apr. 2006 (Target: 2007)</b>	4.7	5.2	0.5
<b>Apr. 2007 (Target: 2008)</b>	4.9	3.0	−1.9
<b>Apr. 2008 (Target: 2009)</b>	3.8	−0.6	−4.4

Source: IMF and authors' computations

of those published by the IMF until the subsequent release. In particular, in predicting the current year, WBM forecasts are on average more precise than April *WEO* ones, with the exception of the months immediately after release. Considering the single countries/regions, BM forecasts turn out to be good predictors for the GDP of emerging economies, in particular for ASE, compared with IMF forecasts.

## 2.4 Forecast Performance During the Recession: WBM, *WEO* and *Consensus*

During the recession of 2007–09 the main forecasting institutions performed particularly poorly, facing a sequence of unprecedented shocks not comparable with those included in the sample period used for forecasting (see Visco 2009). It is therefore interesting to check whether the bridge models proposed here, although very simple and not tailored for predicting next year growth, could have made a reasonably good job at tracking the evolution of the world economy during the crisis. The sharp slowdown in world GDP growth in 2009 proved particularly hard to anticipate, as shown in Table 2.5. We therefore select this year for our “recession tracking” exercise.

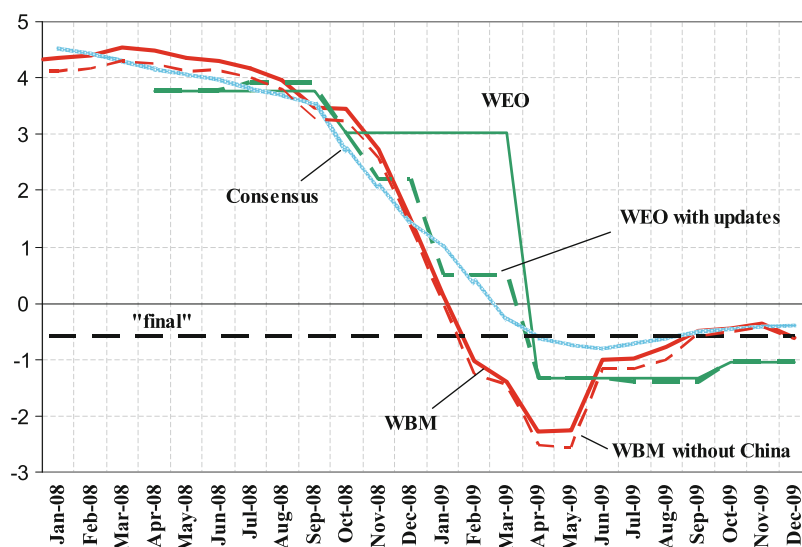
Figure 2.5 shows the monthly predictions for growth in 2009 computed over the January 2008 – December 2009 period.

We compare BM predictions with those of the *WEO*, considering this time also the “updates” published between the main releases of the IMF forecasts.<sup>20</sup> We also look at *Consensus Forecasts* published monthly for all the countries considered in this paper. The prediction of annual GDP growth for the world and for JEU, ASE and BRRU are obtained as a weighted sum of those of the countries involved, with weights given by 2000 GDP shares at PPP.<sup>21</sup>

<sup>20</sup> During this period the IMF published forecast updates every other quarter, thus effectively providing a new scenario for the world outlook every 3 months.

<sup>21</sup> As *Consensus* does not publish world output growth, we computed it as the weighted sum of the following countries: USA, Japan, Germany, France, United Kingdom, Italy and Spain (for JEU), and the four single BRIC countries. Weights – constant over time – are derived from IMF (2010), *World Economic Outlook*, April, p. 148.



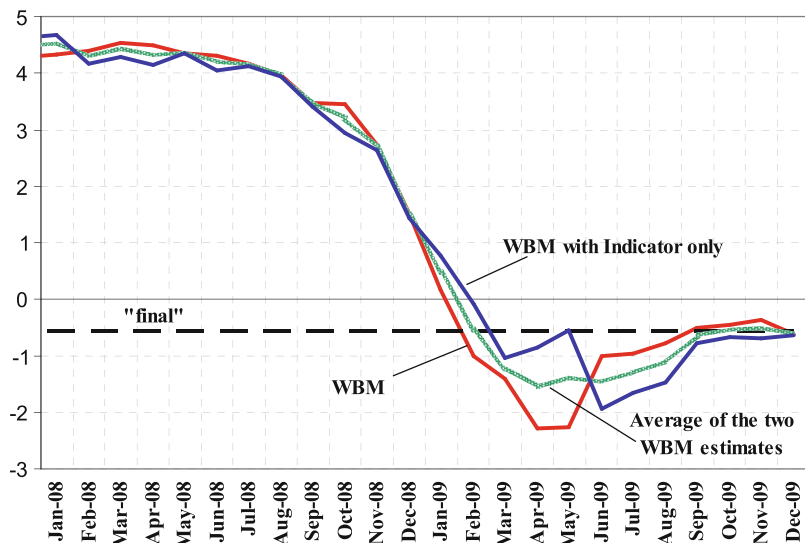


**Fig. 2.5** Comparison of WBM monthly forecasts of World GDP growth for 2009 with *WEO* and *Consensus* predictions (The horizontal axis measures the calendar dates in which the forecasts are made. The WBM line measures the forecasts made with bridge models. The *WEO* plot measures the forecasts released by the IMF. The latest available data are those published in the *WEO* of April 2010)

As shown in the graph, only at the end of the summer of 2008 do the models started signalling an evident deceleration in GDP growth. By the end of that year it had become clear that the economic slump was much more severe than previously envisaged. Quite surprisingly, our simple BMs did not perform visibly worse than *Consensus* or the *WEO* (considering the updates to the world outlook).

Nonetheless, a disturbing feature is the considerable undershooting of the WBM in the spring of 2009, when the US (and probably the world) economy reached a trough according to the NBER business cycle dating.<sup>22</sup> Our BMs – being based solely on industrial production that was hit much harder than the other sectors – are bound by design to produce a starker slump than indicators based on a wider range of activities. We might suspect that a richer specification of the BM would help to reduce the undershooting. Quite interestingly – looking at countries and groupings (see Fig. A.1 in Appendix A) – one can observe that the under-prediction was strong for advanced countries (both JEU and Asian NIEs), where services play a larger

<sup>22</sup> The NBER dating committee has recently agreed to pinpoint June 2009 as the trough month in the US for the recession that started in December 2007, according to the same institution (see <http://www.nber.org/cycles/sept2010.html>).



**Fig. 2.6** Comparison of monthly forecasts patterns of world GDP growth for 2009 among different WBM specifications (The *horizontal* axis measures the calendar dates in which the forecasts are made. WBM lines measure the forecasts made with bridge models)

role in economic growth, while it was not present in the case of China, whose growth is largely determined by manufacturing output and exports. Indeed, a WBM that excludes the information on China (the red dashed line in Fig. 2.5) presents an even more pronounced undershooting in the estimates of world output at the beginning of 2009.

To verify the soundness of our deduction, we introduce a new indicator in our BMs to take into account economic developments over and above those captured in industrial production. For most countries we considered a PMI or similar statistic to exploit information coming directly from firms and not confined to production activity. A general conclusion we can draw is that the introduction of a second variable generally improves the forecasting performance of the BMs, even though, as a rule, BM\_ip outperforms BM\_ind.

Turning now to the tracking ability of BMs during the crisis, as expected taking into account the indicator as well reduces the undershooting of the bridge models (Fig. 2.6). In particular, the forecast combination of the WBM\_ip and WBM\_ind models gives the best results. This is true not only for world GDP, but also for the main countries and groupings considered here (see Fig. A.1 in the appendix).

## 2.5 Conclusions

Over the last 15 years financial and economic globalization has proceeded at great speed. New actors have appeared on the world economic scene, moving rapidly to centre stage. Analysis of global economic developments must not ignore these changes.

We show that a break occurred in the relationship that used to link world GDP growth to that of the main advanced countries (Japan, the EU and the US). This break is due to the increased weight of the Asian emerging economies, which have markedly different cyclical and growth patterns (the emerging Asia effect). This implies that considering only the economic situation of the most advanced countries, as the majority of the literature still does (Golinelli and Parigi 2007; Arouba et al. 2010) is a practice likely to give a biased picture of the main trends at global level.

We propose a natural and easy way to tackle this new environment by exploiting bridge models, which have deliberately been kept very simple and so do not incur indictment of “data mining” and of using ex post knowledge. We show that the inclusion of emerging markets improves the accuracy of world GDP forecasts. This accuracy is evaluated against simple benchmarks and in comparison with predictions published by international institutions, such as the IMF’s *WEO* or *Consensus Forecasts*.

The value of bridge model estimates also lies in their real time availability and in the extreme simplicity of the computations. To assess their usefulness we mimic a real time evaluation of the actual consequences of the economic crisis via recursive predictions of GDP growth in 2009, over the 24 months of 2008–2009. We compare the results obtained with bridge models against those published by the IMF and Consensus over the same period. Bridge models perform reasonably well, but there is some evidence of “undershooting” at the end of period.

Since the bridge models proposed exploit only the information contained in the industrial production index, which was deeply affected by the crisis and clearly provides only a partial view of the evolution of economic activity, the undershooting is not surprising. Introducing an extra variable that broadens the information to the economy at large significantly reduces the undershooting, particularly for the emerging economies.

Other approaches, such as considering synthetic indicators to assess current and future growth, were not pursued (see Altissimo et al. 2010, for an application to the euro area and Banbura et al. 2010, for a survey) but might prove useful.

## Appendix A: Additional Tables and Graphs **CORREZIONI:** Source Con Maiuscolo Ovunque

**Table A.1** China's share in each importing county/group (*values in current US dollars, percentage shares*)

	1995	2000	2005	2008
<b>EU</b>	4.4	6.7	11.8	13.3
<b>USA</b>	6.3	8.6	15.0	16.5
<b>Japan</b>	10.8	14.5	21.1	18.8
<b>NIES</b>	11.3	14.9	23.0	25.2
<i>Hong Kong</i>	36.2	43.1	45.0	46.6
<i>Korea</i>	5.6	8.1	14.8	17.7
<i>Singapore</i>	3.3	5.3	10.3	10.6
<i>Taiwan</i>	0.4	2.9	22.0	25.7
<b>Other developing Asia</b>	7.2	4.8	10.1	12.5
<i>India</i>	2.2	3.0	7.9	10.7
<i>Malaysia</i>	2.3	4.0	11.7	13.1
<i>Vietnam</i>	3.5	9.0	16.4	20.5
<i>Indonesia</i>	30.0	5.2	8.8	11.5
<i>Thailand</i>	3.0	5.5	9.4	11.6
<i>Philippines</i>	2.3	2.4	6.3	7.6
<b>Russia</b>	1.6	2.8	7.3	13.0
<b>Brazil</b>	0.8	2.2	7.3	11.6

Source: UN-Comtrade

**Table A.2** China's weight in total exports from each county/group (*values in current US dollars, percentage shares*)

	1995	2000	2005	2008
<b>EU</b>	<b>2.5</b>	<b>2.5</b>	<b>4.0</b>	<b>4.8</b>
<b>USA</b>	<b>2.0</b>	<b>2.1</b>	<b>4.7</b>	<b>5.6</b>
<b>Japan</b>	<b>5.0</b>	<b>6.3</b>	<b>13.5</b>	<b>16.1</b>
<b>NIES</b>	<b>10.9</b>	<b>13.0</b>	<b>24.3</b>	<b>26.3</b>
<i>Hong Kong</i>	33.3	34.5	45.0	48.5
<i>Korea</i>	7.5	10.8	21.8	21.7
<i>Singapore</i>	2.3	3.9	8.6	9.2
<i>Taiwan</i>	0.4	2.9	22.0	25.7
<b>Other developing Asia</b>	<b>2.8</b>	<b>4.3</b>	<b>8.3</b>	<b>8.7</b>
<i>India</i>	1.0	1.7	7.2	5.6
<i>Malaysia</i>	2.7	3.1	6.5	9.6
<i>Vietnam</i>	5.2	10.6	10.0	7.8
<i>Indonesia</i>	3.8	4.5	7.8	8.5
<i>Thailand</i>	2.9	4.1	8.3	9.3
<i>Philippines</i>	1.2	1.7	9.9	11.2
<b>Russia</b>	<b>5.4</b>	<b>3.9</b>	<b>4.6</b>	<b>5.3</b>
<b>Brazil</b>	<b>2.6</b>	<b>2.0</b>	<b>5.8</b>	<b>8.3</b>

Source: UN-Comtrade

**Table A.3** Explaining world GDP growth: estimation results<sup>a</sup>

Dependent variable: World GDP growth				
	(1)	(2)	(3)	(4)
Sample period	1979 Q1–2010 Q1	1979 Q1–1993 Q4	1994 Q1–2010 Q1	
Observations	125	60	65	
<b>Constant</b>	0.0008 (0.0045)	0.0019 (0.0017)	−0.0016 (0.002)	−0.0035 (0.0026)
<b>JEU GDP growth</b>	0.5188*** (0.1291)	0.8214*** (0.0877)	0.5376*** (0.0866)	−0.2838** (0.1211)
<b>ASE GDP growth</b>	0.2150 (0.2971)	−0.0001 (0.114)	0.4186*** (0.1213)	0.4186*** (0.1636)
<b>BRRU GDP growth</b>	0.1403*** (0.0362)	0.0683* (0.041)	0.0649* (0.0416)	−0.0035 (0.0591)
Sum of $w(i)$	0.8740 (0.1775)	0.8896 (0.0923)	1.0210 (0.1169)	
<b>Godfrey AC (p-val)</b>				
First order	0.0851	0.7470	0.6772	
Fourth order	0.2781	0.8677	0.0773	
<b>Andrews breakpoint</b>				
Sup F-statistic	0.0000	0.1477	0.0952	
((p-val))				
<b>Hausman test</b>				
Weak exogeneity	0.0267			

<sup>a</sup>HAC standard errors are reported in brackets \*, \*\* and \*\*\* denote statistical significance at the 10%, 5% and 1% levels, respectively.

**Table A.4** The dynamic relationship among country groups: VAR estimation results

	(1)	(2)	(3)
Sample period	1979 Q1–2010 Q1	1979 Q1–1993 Q4	1994 Q1–2010 Q1
Observations	125	60	65
<b>Standard errors</b>			
JEU equation	0.004	0.005	0.004
ASE equation	0.009	0.009	0.008
BRRU equation	0.013	0.011	0.012
<b>Godfrey AC (p-val)</b>			
First order	0.794	0.647	0.114
Fourth order	0.746	0.093	0.099
<b>Non granger causality NGC (p-values)</b>			
ASE NGC JEU	0.002	0.147	0.006
BRRU NGC JEU	0.280	0.886	0.035
Overall in JEU equation	0.005	0.347	0.006
JEU NGC ASE	0.154	0.210	0.710
BRRU NGC ASE	0.646	0.566	0.747
Overall in ASE equation	0.360	0.409	0.818
JEU NGC BRRU	0.141	0.574	0.194
ASE NGC BRRU	0.151	0.459	0.001
Overall in BRRU equation	0.113	0.584	0.001
<b>Correlation between VAR shocks</b>			
JEU, ASE	−0.027	−0.280	0.296
JEU, BRRU	0.191	0.053	0.294
ASE, BRRU	0.101	−0.054	0.131

**Table A.5** Assessment of the forecasting ability of the bridge models for selected countries<sup>1</sup>

	GDP forecast horizon					
	1 q		2 qs	4 qs	6 qs	
	With 1 m	With 2 m				
USA						
ME	−0.481	−0.500	−0.500	−0.901	−1.750	−2.360
RMSE	0.688	0.691	0.675	1.236	2.889	4.657
Ratio to AR	0.957 <sup>a</sup>	0.926 <sup>a</sup>	0.903 <sup>a</sup>	0.819 <sup>a</sup>	0.858 <sup>b</sup>	<b>0.930<sup>b</sup></b>
EU						
ME	−0.243	−0.243	−0.238	−0.615	−1.686	−3.250
RMSE	0.645	0.619	0.612	1.282	3.041	4.972
Ratio to AR	0.834 <sup>a</sup>	0.803 <sup>b</sup>	0.795 <sup>b</sup>	0.744 <sup>b</sup>	0.818 <sup>b</sup>	0.864 <sup>b</sup>
Japan						
ME	−0.011	−0.023	−0.027	−0.089	−0.310	−1.182
RMSE	1.490	1.504	1.512	2.047	3.488	5.393
Ratio to AR	0.675 <sup>b</sup>	0.682 <sup>b</sup>	0.685 <sup>b</sup>	0.589 <sup>b</sup>	0.524 <sup>b</sup>	0.583
China						
ME	0.209	0.168	0.167	0.372	0.543	0.503
RMSE	0.805	0.778	0.779	1.385	2.131	2.637
Ratio to AR	0.864 <sup>a</sup>	0.841 <sup>a</sup>	0.842 <sup>a</sup>	0.841	0.845	<b>0.773<sup>b</sup></b>
India						
ME	0.276	0.406	0.350	0.401	0.383	−0.086
RMSE	1.187	1.233	1.199	1.812	2.808	3.034
Ratio to AR	1.031	1.043	1.014	0.991	0.974	<b>0.915</b>
Korea						
ME	−0.295	−0.250	−0.209	−0.410	−0.761	−0.813
RMSE	1.247	0.872	0.779	1.701	5.076	8.479
Ratio to AR	0.774 <sup>a</sup>	0.542 <sup>a</sup>	0.484 <sup>a</sup>	0.622 <sup>b</sup>	1.171 <sup>b</sup>	1.521
Brazil						
ME	0.321	0.340	0.291	0.591	1.047	0.785
RMSE	1.760	1.607	1.622	2.683	4.102	4.065
Ratio to AR	0.983	0.918	0.926	<b>0.889</b>	<b>0.948</b>	0.918
Russia						
ME	−0.607	−0.519	−0.516	−1.286	−3.606	−7.607
RMSE	1.668	1.367	1.370	3.190	9.451	15.540
Ratio to AR	0.964	0.814 <sup>a</sup>	0.816 <sup>a</sup>	0.843 <sup>a</sup>	1.261	1.631

<sup>1</sup>Ratios are reported in italics when GW is significant at 10%, in bold when it is significant at 5%; further, <sup>a</sup> means that the BM parameter in FS equation is 5% significant while AR is not, <sup>b</sup> that both parameters are significant. For the GW test we use the test function  $h_t = (I, \Delta L_{t-\tau})$

**Fig. A.1** Comparison of monthly forecast patterns of world GDP growth for 2009 between different WBM specifications, *WEO* and *Consensus* predictions

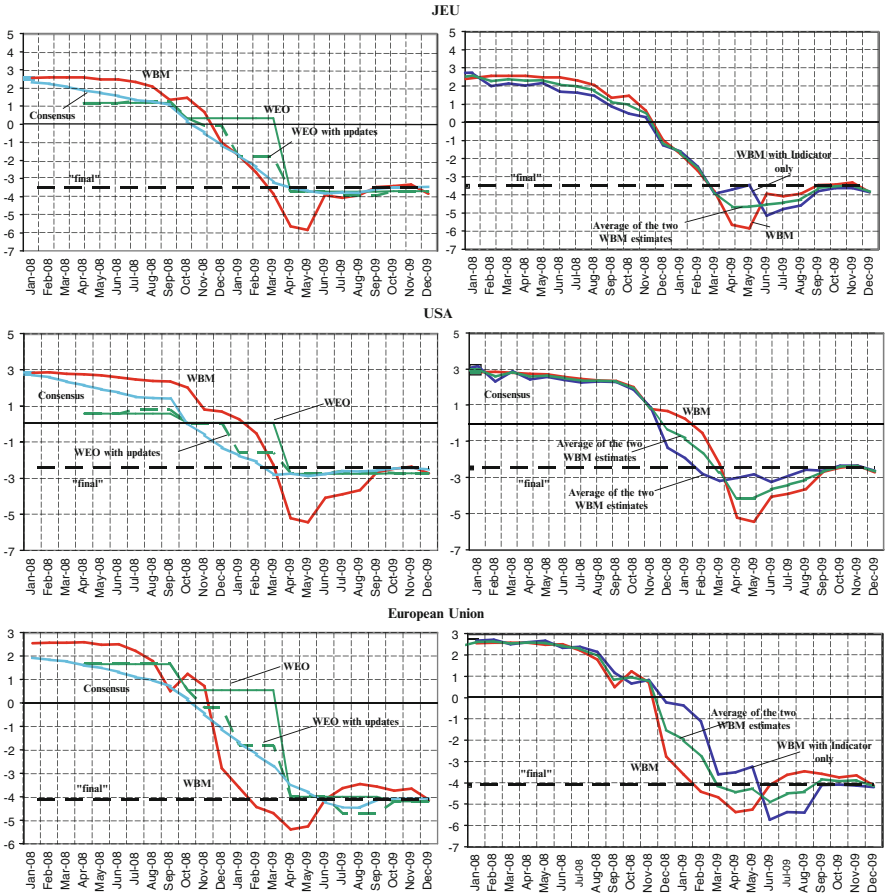
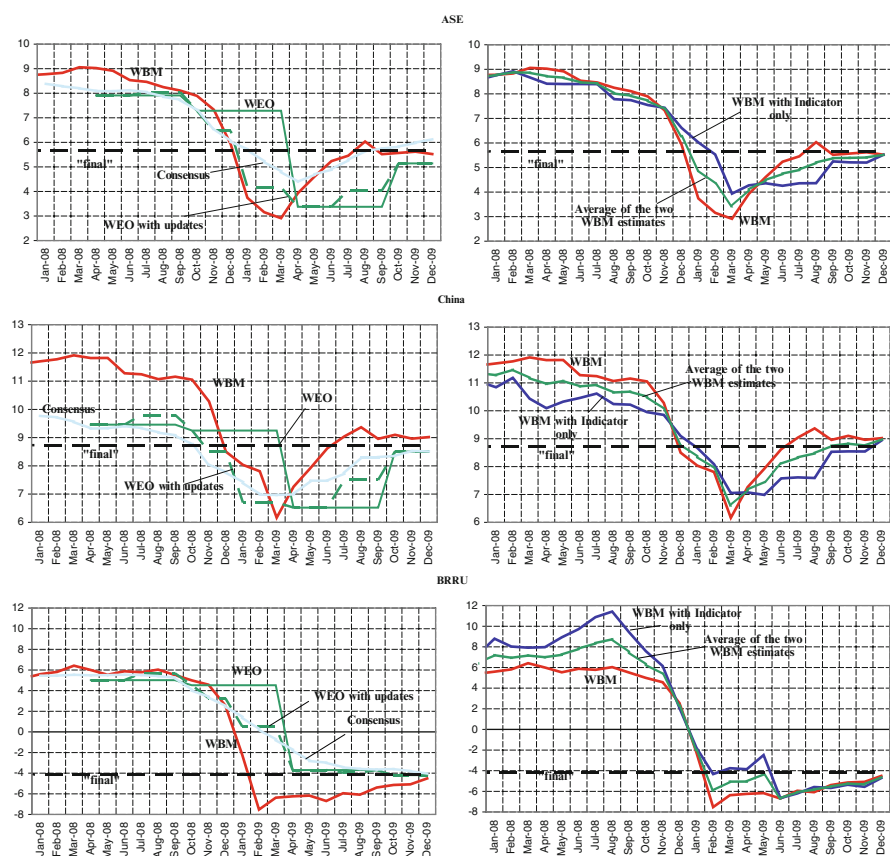




Fig. A.1 (continued)



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