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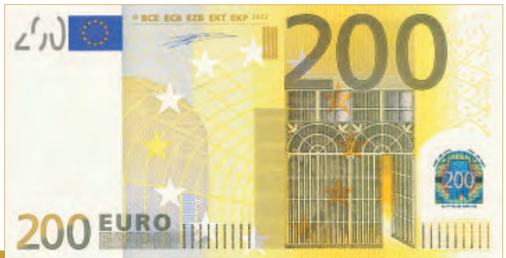
by Audrone Jakaitiene[2] and Stéphane Dées[3]



In 2009 all ECB publications feature a motif taken from the €200 banknote.

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CONTENTS

Abstract

Forecasting the world economy is a difficult task given the complex interrelationships within and across countries. This paper proposes a number of approaches to forecast short-term changes in selected world economic variables and aims, first, at ranking various forecasting methods in terms of forecast accuracy and, second, at checking whether methods forecasting directly aggregate variables (direct approaches) outperform methods based on the aggregation of country-specific forecasts (bottom-up approaches). Overall, all methods perform better than a simple benchmark for short horizons (up to three months ahead). Among the forecasting approaches used, factor models appear to perform the best. Moreover, direct approaches outperform bottom-up ones for real variables, but not for prices. Finally, when country-specific forecasts are adjusted to match direct forecasts at the aggregate levels (top-down approaches), the forecast accuracy is neither improved nor deteriorated (i.e. top-down and bottom-up approaches are broadly equivalent in terms of country-specific forecast accuracy).

Keywords: *Factor models, Forecasts, Time series models.*
JEL Classification: *C53, C32, E37, F17*

Non-technical summary

Forecasting the world economy is a difficult task given the complex interrelationships within and across countries. While global models have developed both their theoretical background (with general equilibrium features) and/or their statistical properties (with improved econometric methods), they only aim at forecasting the world economy in the medium-term.

Forecasting short-term economic developments relies more on statistical methods that make use of the leading properties of a large number of economic indicators. At the global level, the only attempt to our knowledge of short-term forecasting effort concerns the construction of leading indicators for economic activity by the OECD.

This paper proposes to extend such an approach to several dimensions: (1) we remain agnostic about the forecasting methods and test the forecast performance of those that are widely used in short-term forecasting; (2) we aim at forecasting short-term developments at different level of aggregation: country, group (advanced and emerging economy aggregates) and world level; (3) we forecast not only activity but also inflation, trade volumes and prices. These variables, available at a monthly frequency, provide a good overview of world economic developments.

The empirical analysis mostly focuses on out-of-sample forecasting performance of the various methods. The forecasting exercise is performed for six variables (industrial production, import and export volumes, consumer prices, import and export prices). For trade prices, as we want to analyse the impact of the choice of reporting currency, we do the exercise both in US dollar and in national currency. The forecasting exercise is done for 12 different horizons (from 1 month to 1 year ahead).

We analyse the forecast performance for individual country/region forecasts as well as for aggregate forecasts. The empirical analysis is made at two different levels of aggregation. In a first level, we aggregate country data for advanced economies only and compare the aggregation of country-specific forecasts with the forecasts of the aggregate series. In a second level, we perform a similar exercise by including data for emerging economies in order to obtain forecasts for world aggregates. Owing to data availability issues, the emerging economies are treated as a single block.

The presentation of our empirical results starts with a comparison analysis to determine the relative forecast performance of the different modelling approaches. Overall, all methods outperform a naive benchmark for relatively short horizons (from 1 to 3 months ahead). Among the forecasting approaches used, factor models (both diffusion indices and dynamic factor models) appear to perform the best. Also, an average of all methods appear to be the best performing approach as it beats the other approaches in most cases.

In a second step, we focus the performance analysis on aggregate variables (for advanced economy group and world) and analyse whether it is preferable to forecast directly aggregates (direct forecasts) or to perform an ex-post aggregation of individual forecasts (bottom-up forecasts). This analysis shows that direct forecasts are preferable for real variables, but not for prices.

Finally, we check whether the gains in forecast accuracy obtained at the aggregate level could help in improving the forecast performance at the individual level. The so-called "top-down" approach aims at modifying country-specific forecasts so that they are fully compatible with the direct forecasts for the aggregates. The forecast performance comparison exercise shows that the "top-down" approaches neither improve nor deteriorate country-specific forecasts.

Overall, we have designed a comprehensive framework that makes use of a large set of monthly economic indicators and provides satisfactory forecasts for short horizons (up to three months ahead). By forecasting trade variables, activity and consumer price inflation, such a framework can provide a good overview of world economic developments in the short-term. It also provides forecasts for the main advanced economies, as well as for the main country groups, that are consistent with the world outlook.

1 Introduction

Forecasting the world economy is a difficult task given the complex interrelationships within and across countries. Global macroeconometric models have aimed at improving the ability of forecasting global variables. This started in the 1960s with macroeconometric models in the tradition of Lawrence Klein like the project LINK (Moriguchi, 1973). Subsequently, global models have developed both their theoretical background (with general equilibrium features) and/or their statistical properties (with improved econometric methods)[1]. However, all these approaches focus on yearly changes (or quarterly at best) and only aim at forecasting the world economy in the medium-term.

Forecasting short-term economic developments relies more on statistical methods that make use of the leading properties of a large number of economic indicators. Factor models in particular have been widely used to forecast macroeconomic variables at a country level (e.g. Stock and Watson, 2002a or 2002b).

At the global level, the only attempt to our knowledge of short-term forecasting effort concerns the construction of leading indicators for economic activity by the OECD. Focusing on economic activity, the OECD provides monthly Composite Leading Indicators (CLI) that are constructed from several component series that meets the three following criteria: economic significance, cyclical behaviour and data quality (OECD, 1998). These indicators aim at helping the analysis of current trends and the forecasts of the short-term economic developments up to 12 months (OECD, 2002).

This paper proposes to extend such an approach to several dimensions:

[1] See for instance models in the main international organisations (IMF, OECD), McKibbin (1998) or GVAR-based forecasts by Pesaran et al. (2009).

(1) we remain agnostic about the forecasting methods and test the forecast performance of those that are widely used in short-term forecasting; (2) we aim at forecasting short-term developments at different level of aggregation: country, group (advanced and emerging economy aggregates) and world level; (3) we forecast not only activity but also inflation, trade volumes and prices. These variables, available at a monthly frequency, provide a good overview of world economic developments.

More precisely, the variables to be forecasted include industrial production[2], consumer price index (CPI), import and export volumes, import and export prices. The forecasts are done for the five major advanced economies (the U.S., euro area, Japan, the U.K., Canada), for the advanced economies and emerging economies as groups and at the world aggregate level.

Partly building on Burgert and Dees (2008), this paper proposes a number of approaches to forecast short-term changes in economic variables that make use of the information content included in various short-term indicators relevant for the world economy (leading indicators, surveys, financial variables, manufacturing activity indicators, ICT indicators, commodity prices, ...).

The aim of the paper is twofold. First, to evaluate the various forecasting methods considered, we carry out a forecasting performance comparison. Second, as macroeconomic variables are influenced by common factors, we check whether methods forecasting directly aggregate variables (direct approaches) outperform methods based on the aggregation of country-specific forecasts (bottom-up approaches). When it is the case, we also check

[2]Industrial production has been chosen as a measure of economic activity owing to its timeliness (our world measure is available with only a two-month lag) and to its frequency (monthly). World GDP could have also been considered, as including also activity in the services sector, but no timely and representative measure is available, even at a quarterly frequency. As our aim is to monitor the world economy in the short-term, we have preferred to neglect any measure of world GDP.

whether the accuracy gained at the aggregate level can improve the forecast accuracy at the country-specific level (following top-down approaches, where the country-specific forecasts are adjusted so that they match - once aggregated - the direct forecasts of the aggregates).

Overall, all methods outperform a naive benchmark for relatively short horizons (from 1 to 3-months ahead). Among the forecasting approaches used, factor models (both diffusion indices and dynamic factor models) appear to perform the best. As in Burgert and Dees (2008), direct approaches outperform bottom-up ones for real variables, but not for prices. Finally, when country-specific forecasts are adjusted to match direct forecasts at the aggregate levels (top-down approaches), the forecast accuracy is neither improved nor deteriorated (i.e. top-down and bottom-up approaches are broadly equivalent in terms of country-specific forecast accuracy).

Section 2 presents the data and the forecasting models considered, Section 3 presents the empirical results and Section 4 concludes.

2 Data and forecasting models

2.1 Data

We use a large database including information on a monthly basis to explain short-term economic developments over the period 1991:1 - 2007:12.

The dataset can be divided into three groups:

• **Dependent variables**: Industrial production and consumer price index (CPI) series are from national sources and are collected for 22 advanced economies and 54 emerging economies. The aggregation of the series to get group or world aggregates is made using geometric averages and a weighting scheme based on value-added data. The trade data are monthly volumes of imports of goods in 1995 constant prices. The series are published by the Central Planning Bureau (CPB) and are available for the majority of advanced economies and for emerging economies considered as a single block[3].

• **Country-specific macroeconomic and financial data (explanatory variables)**: The country-specific macroeconomic data are represented by OECD's Composite Leading Indicators, survey indicators (like Purchasing Manager Indices), industrial production (total and components), retail sales, consumer and producer prices and labour market variables. Financial and monetary data at a country specific level include series on interest rates and money supply, as well as exchange rates in effective terms and vis-a-vis the US dollar. Overall, the country-specific dataset of explanatory variables includes 369 series.

• **Global data (explanatory variables)**: As for the series at the global level, which are supposed to have an impact on domestic developments, we introduce variables such as oil prices and non-oil commodity prices. The set of global series is completed by semi-conductor sales as an indicator of the ICT cycle, stock market prices for the major financial centres and the Baltic Dry Index[4]. Overall, the dataset of global explanatory variables includes 12 series.

The countries included in our advanced economy sample are: the United States, Canada, Japan, the euro area and the United Kingdom. Taken together these countries represent more than 90% of the advanced economies in terms of import volumes in 1995[5]. When extending the analysis to world

[3]For more details about the trade data, see van Welzenis and Suyker (2005).

[4]The Baltic Dry Index is produced daily by the London-based Baltic Exchange. It provides an assessment of the price of moving the major raw materials by sea.

[5]Advanced economies are defined as OECD countries excluding Turkey, Czech Republic, Hungary, Poland, Slovak Republic, Mexico and Korea. In our analysis, the missing countries are: Switzerland, Norway, Iceland, Denmark, Sweden, Australia and New Zealand. The weight of these countries in the aggregate "advanced economies" being relatively small, their omission should not affect the main results of this study.

aggregates, we include, in addition to the countries listed above, emerging economies, treated as a single block. While the country-specific data are available for most emerging economies, there are data availability problems at the level of aggregate macroeconomic and financial data as well as at the level of the various countries in the block. We prefer therefore to only select data for a few countries that are representative of emerging markets. These countries are: China, Brazil, Russia, Indonesia, South Africa, Thailand, Argentina, South Korea, Taiwan, Singapore and Malaysia. Although these countries only represent around 50% of emerging markets' imports in 1995, we reasonably assume that they are sufficient to give a good approximation for the whole aggregate. This is confirmed by inspecting and comparing the series visually and by conducting some simple statistical analysis of co-movements between the individual series and the emerging markets' aggregates.

All data are seasonally adjusted and cleaned from outliers[6]. For the analysis, the data are differenced to be stationary. For trending data (such as industrial production) we take logarithms beforehand, which amounts to calculating rates of change, while survey and financial data are not logarithmised. All data are standardised to mean zero and variance one in a recursive manner. As the series are very volatile, we follow Stock and Watson (2007) and Barhoumi et al. (2008) and use three-month differences of the monthly data, i.e. the rates of change against the same month of the previous quarter. Smoothing the series has the advantage that noise in the data is reduced and data irregularities are smoothed out[7].

[6]Outlier detection was based on a simple rule applied to the differenced series: we identified those observations as outliers, which were 5 times larger in absolute value than the 20% quintile of the series' distribution. We either set these outliers as missing values (model DFM) or replace them with the largest admissible value.

[7]D 'Agostino et al. (2006) also smooth the series before considering forecasting methods.

Although the changes of these variables remain somewhat volatile, it is worth noting that part of this variability is common across countries (Table 1 shows the mean, the standard deviation and the pair-wise average cross-section correlation for the series considered in this paper). Given the volatility of the series, pair-wise correlations appear rather high, suggesting that common variables might influence country-specific economic developments. This is consistent with empirical evidence of the importance of the world components in country-specific economic developments, both for activity (see Canova et al., 2005 or Kose et al., 2003) and for prices (see Ciccarelli and Mojon, 2008).

[TABLE 1 HERE]

2.2 Forecasting models

We investigate several time series methods for forecasting world economic variables and consider empirically which methods perform best and whether it is better to build forecasting models for aggregate variables, or whether there are gains from aggregating country-specific forecasts. To ensure the robustness of our analysis, we use and compare several forecasting models. All forecasting models are compared to a benchmark model. First, we use simple auto-regressive models. Second, we estimate regression equations where the macroeconomic series to be forecasted depends on selected exogenous variables. Third, we estimate factor models, where the factors are extracted out of a large set of predictors. We consider both static factor models (or diffusion indices) and dynamic factor models[8].

[8]MATLAB codes used here are those developed for the project conducted under the auspices of the Eurosystem working groups on Econometric Modelling and on Forecasting. See description of the project in Barhoumi et al. (2008).

2.2.1 Benchmark model (RW)

In the benchmark model, forecasts of each (transformed) variable x_i for country i are simply a constant. This corresponds to a Random Walk (RW) model with drift:

$$x_{i,t} = c_i + u_{it} \tag{1}$$

where x_i is the 3 month (log) difference of the dependent variables, c_i is the drift and u_{it} denotes the residual.

2.2.2 Autoregressive models (AR)

The first approach, which will be compared with the benchmark, is a simple autoregression model. For country i, we estimate the AR(1) model[9] for variable x_i:

$$x_{i,t} = \alpha_i + \phi_{i1} x_{i,t-1} + u_{it} \tag{2}$$

where α_i and ϕ_{i1} are the parameters to be estimated and u_{it} the residual.

For the one-month ahead horizon, the forecasts are determined as follows:

$$\widetilde{\mathbf{x}}_{i,t+1}^{AR} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i1} x_{i,t}$$

where $\widetilde{\mathbf{x}}_{i,t+1}^{AR}$ denotes the forecast value of x_i for horizon $t+1$, $\widehat{\boldsymbol{\alpha}}_i$ and $\widehat{\boldsymbol{\phi}}_{i1}$the estimates of Eq. (2). The n-month ahead forecasts use the one-month ahead forecast previously computed:

$$\widetilde{\mathbf{x}}_{i,t+n}^{AR} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i1} \widetilde{\mathbf{x}}_{i,t+n-1}^{AR}.$$

[9]We have imposed the lag length of the autoregressive model to be one. For most models, this choice is consistent with both AIC and BIC information criteria.

2.2.3 Regression equations (Regr.Eq.)

Regression equations are widely used in forecasting exercises. The forecasts are obtained in two steps. First, once identified indicators or variables that have proved to have some leading properties in forecasting the variables of interest, we use auto-regressive models to forecast these indicators over the horizon. In a second step, the indicator forecasts are used to predict the variables.

More precisely, for country i, we estimate regression equations for variable x_i:

$$x_{i,t} = \alpha_i + \sum_{k=0}^{p} \phi_{ik} y_{i,t-k} + u_{it} \tag{3}$$

where $y_{i,t}$ is a set of explanatory variables, where α_i and ϕ_{ik} $(k = 0, ..., p)$ are the parameters to be estimated and u_{it} is a white noise term $(u_{it} \sim N(0, \sigma_i^2))$. The number of lags (p) is chosen according to information criteria[10].

As a first step, the forecasts of the explanatory variables $(\widetilde{y}_{i,t})$ are obtained from a AR(p) model. Using the latter, the forecasts of the dependent variables $(\widetilde{x}_{i,t+1}^{RE})$ for the first-month ahead horizon are obtained as follows:

$$\widetilde{x}_{i,t+1}^{RE} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i0} \widetilde{y}_{i,t+1} + \sum_{k=1}^{p} \widehat{\boldsymbol{\phi}}_{ik} y_{i,t+1-k}$$

where $\widehat{\boldsymbol{\alpha}}_i$ and $\widehat{\boldsymbol{\phi}}_{ik}$ $(k = 0, ..., p)$ are the estimates of Eq. (3). The two-month ahead forecasts use the one-month ahead forecast previously computed:

$$\widetilde{x}_{i,t+2}^{RE} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i0} \widetilde{y}_{i,t+2} + \widehat{\boldsymbol{\phi}}_{i1} \widetilde{y}_{i,t+1} + \sum_{k=2}^{p} \widehat{\boldsymbol{\phi}}_{ik} y_{i,t+1-k}$$

[10] For regression equations and factor models, alternative specifications including lags of the dependent variables have also been estimated. As the forecasting performances were very close to those of the specifications presented here, the results have not been included in the paper. They remain however available upon request.

This model is thereafter iterated until we obtain $\widetilde{x}_{i,t+n}^{RE}$, i.e. the forecast value of x_i for horizon $t+n$.

These models all use Composite Leading Indicators (CLIs) provided by the OECD as exogenous variables. The use of CLIs is motivated by the fact that these indicators are "summarising" various series seen as indicating the current developments of an economy. They are used in the regression equations for trade volume variables and for industrial production as indicators of economic activity. CLIs are also used to forecast CPI inflation as they also represent an indicator of cyclical position, which clearly indentify inflationary (desinflationary) pressures during upturns (downturn). According to the variables forecasted, CLIs are accompanied by: industrial production (for forecasting trade volumes and prices) as an indicator of economic activity; exports (for forecasting industrial production) as an indicator of global economic influences; and by a commodity price index (for forecasting CPI inflation), to measure the impact of raw material prices on CPI. These indicators are available not only at the country level but also at the various aggregate levels (advanced economies, emerging economies and world), which are then used when forecasting directly aggregate variables.

2.2.4 Diffusion indices (DI)

Diffusion indices à la Stock and Watson (2002a, 2002b) belong in technical terms to the simplest version of factor models, as the dynamics of the factors is not explicitly modelled. For the extraction of common static factors, we consider a large set of country-specific as well as global monthly indicators $y_{it} = (y_{i1t}, y_{i2t}, ...y_{int})'$. While the factors are country specific, the presence of global indicators should capture foreign influences stemming from interdependence across countries and exposure to common shocks.

We run static principal components (PC) to obtain estimates $\widehat{f_{i,t}}$ of the r common static factors $f_{i,t} = (f_{i1t}, f_{i2t}, ...f_{irt})'$, with $r < n$. The number of factors is determined the information criteria proposed by Bai and Ng (2002). However this model works with balanced data. When unbalanced, the data panel is made balanced using Expectation Maximisation (EM) algorithm proposed by Stock and Watson (2002a). The EM algorithm is an iterative method for maximum likelihood estimation that allows to find missing values under the assumption that the estimators converge. In the first step of the algorithm, the missing values are replaced by the fitted values obtained by the regression of the series on the factors which were obtained from a principal component analysis on the equivalent balanced panel. In the second step the missing values are replaced by the fitted values that were this time obtained from the regression of the series on the factors derived from a principal components analysis on the adjusted panel obtained in the first step. The second step is subsequently repeated in each case with the factors obtained from the previous step until the regressors have converged.

For country i, we estimate the following models for variable x_i:

$$x_{i,t+n} = \alpha_i + \phi_{i1} f_{i,t} + u_{it} \tag{4}$$

where α_i and ϕ_{ik} $(k = 0, ..., p)$ are the parameters to be estimated and u_{it} is a white noise term $(u_{it} \sim N(0, \sigma_i^2))$.

As in Eq. (4) the variables to be forecasted appear with a lead of n periods, we need to estimate n models (i.e. one for each forecast horizon).

The forecasting equation is a follows:

$$\widetilde{x}^{DI}_{i,t+n} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i1} f_{i,t}$$

where $\widehat{\boldsymbol{\alpha}}_i$ and $\widehat{\boldsymbol{\phi}}_{i1}$ are the estimates of Eq. (4). As we estimate as many models as forecast horizons, the n-step ahead forecast is found directly and there is no need to forecast the monthly factors.

When forecasting aggregate variables (advanced economies, emerging economies and world), the factors are extracted from all country-specific as well as global indicators. This approach should be able to account for interdependence across countries. Table 2 gives an overview on the number of series collected and how they are used when extracting the factors.

[TABLE 2 HERE]

One could argue that there is a big difference in the data size between country-specific and aggregate series. However as shown by Boivin and Ng (2006), sample size alone does not determine the properties of the estimates. The composition and the quality of the data is shown to be more important for the factor analysis.

2.2.5 Dynamic factor Model (DFM)

Contrary to the DI model, the two-step approach based on principal components and Kalman filtering proposed by Doz et al. (2007) models factor dynamics explicitly. We consider a large set of country-specific as well as global monthly indicators $y_{it} = (y_{i1t}, y_{i2t}, ...y_{int})'$. The indicators used for these models are the same as for the DI models.

As for the DI model, we run static principal components (PC) to obtain country-specific estimates $\widehat{f_{i,t}}$ of the r common static factors $f_{i,t} = (f_{i1t}, f_{i2t}, ...f_{irt})'$, with $r < n$. Contrary to the DI model, the common factors $f_{i,t}$ are assumed to follow a VAR process, which is driven by a vector of q innovations $\varepsilon_{it} = (\varepsilon_{1,t}, \varepsilon_{2,t}, ...\varepsilon_{q,t})'$

$$f_{i,t} = \sum_{s=1}^{p} A_i f_{i,t-s} + B_i \varepsilon_{it}$$

A_i is obtained by OLS from using $\widehat{f_{i,t}}$ and, from the residuals of the VAR, matrix B is estimated by principal components. In the second step, we obtain the forecast for the dependant variables. The Kalman filter delivers the forecast of the common factors needed and takes into account their dynamic properties. Therefore the forecast of the dependant variables is obtained directly by inserting into an equation the estimated common factors and their forecast:

$$\widetilde{x}_{i,t+n}^{DF} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i1} f_{i,t+n}.$$

As for the DI models, the factors are extracted from all country-specific as well as global indicators.

3 Empirical results

The empirical analysis mostly focuses on out-of-sample forecasting performance of the various methods. The forecasting exercise is performed for the six variables to be predicted (industrial production, import and export volumes, consumer prices, import and export prices). For trade prices, as we want to analyse the impact of the choice of reporting currency, we do the exercise both in US dollar and in national currency. The forecasting exercise is done for 12 different horizons (from 1 month ahead to 1 year ahead).

Data releases of the variables to be predicted occur with two-month delay. At the same time, the survey and financial data are available right at the end of the month. There are gains in making use of this information when producing short-term forecasts for the world economy. The monthly data are however themselves published with different delays and the number of missing observations at the end of the sample differs across series. Giannone, Reichlin and Small (2008) and Banbura and Rünstler (2007) have shown that ignoring unbalancedness in the data may have strong effects on the results. To account for this "unbalancedness", we inspect the publication lags in the individual series in our data sets to the time at which the forecasts are made and apply this pattern in a recursive way to the earlier points in time. As in Barhoumi et al. (2008), our pseudo real-time datasets X_t are defined as follows: consider the main set of monthly observations, $T \times n$ data matrix X_T, that has been downloaded on a certain day of the month. We define with $t \times n$ matrix X_t the observations from the original data X_T up to period t, but with elements $X_t(t-h, i)$ eliminated, if observation $X_T(T-h, i)$ is missing in X_T (for $i = 1, .., n$, and $h \geq 0$).

We analyse the forecast performance for individual country/region forecasts as well as for aggregate forecasts. The empirical analysis is made at two different levels of aggregation. In a first level, we aggregate country trade data for advanced economies only and compare the aggregation of country-specific forecasts with the forecasts of the aggregate series. In a second level, we perform a similar exercise by including data for emerging economies in order to obtain forecasts for world aggregates. Owing to data availability issues, the emerging markets are treated as a single block.

The presentation of our empirical results starts with a comparison analysis to determine the relative forecast performance of the different modelling approaches. In a second step, we analyse whether it is preferable to forecast directly aggregates (direct forecasts) or whether an ex-post aggregation of individual forecasts (bottom-up forecasts) gives more accurate forecasts of aggregate variables. This analysis shows that direct forecasts are preferable for real variables, but not for prices. Finally, we check whether the gains in forecast accuracy obtained at the aggregate level could help in improving the forecast performance at the individual level. The so-called "top-down" approach aims at modifying country-specific forecasts so that they are fully compatible with the direct forecasts for the aggregates. The forecast performance comparison exercise shows that the "top-down" approaches neither improve nor deteriorate country-specific forecasts.

3.1 Forecasting performance comparison

We start with a simple forecasting performance exercise where we compare in a pair-wise manner the relative forecast accuracy of the different approaches. Table 3 shows a summary of relative forecasting performance across methods for all variables and horizons. The relative forecast performance is realised as pair-wise comparisons of the Root Mean Square Errors (RMSE) of each of the forecasting methods over the out-of-sample period. For each of the 768 forecasts (eight countries or aggregates, eight variables, twelve horizons), the table shows the fraction of times that the forecast corresponding to the columns of the table has a lower RMSE than the forecast corresponding to the raw. This gives a good overview of the relative performance of the various methods.

[TABLE 3 HERE]

This table shows, first, that overall all methods does not systematically outperform the benchmark model. However, if we restrict the performance comparison on horizons up to three-month ahead (Table 4), the forecasting methods outperform the benchmark model in most cases, except for the regression equations.

[TABLE 4 HERE]

Second, among the forecasting methods, factor models (both diffusion indices and dynamic factor models) appear to perform the best, while regression equations or simple autoregressive models do not perform well on average as they are beaten in most cases. Finally, as usually found in the literature, an average of all methods appear to be the best performing approach as it beats the factor models in almost 60% of cases and the remaining models in more than 90% of cases.

3.2 Direct vs. bottom-up approaches

To answer the question whether direct approaches outperform bottom-up ones to forecasts aggregate variables, we perform forecasting performance tests for two different levels of aggregation (world and advanced economies) and for the eight different variables (industrial production, import and export volumes, consumer price index, import and export prices both in US dollar and national currency).

3.2.1 Trade volumes

Table 5 and Table 6 show RMSE relative to the benchmark model for import and export volumes of respectively world and advanced economies. The tables also compare forecasting performance between direct and bottom-up approaches. The results show that the various approaches always beat the benchmark model in the short term (from one to three months ahead). For longer horizons, the difference in terms of performance between the various methods and the benchmark is very small (Relative RMSE close to 1).

[TABLE 5 HERE]

[TABLE 6 HERE]

The lines/columns "Fraction" give the number of cases where direct approaches beat the bottom-up approaches. While for world variables, the overperformance of direct approaches is not clear cut, it becomes more obvious when restricting our aggregation to advanced economies. In the latter case, the overperformance of direct approaches is quasi-systematic.

These results are in line with Burgert and Dees (2008), which also shows, for import volumes only, the overperformance of direct approaches. With increasing globalisation, global factors seem therefore more predominant to explain international trade activity than country-specific determinants. Phenomena like the emergence of global supply chains, the rise in intra-firm trade and the increasing import content of export support to have a global view to understand and forecast trade developments.

3.2.2 Trade prices

Table 7 and Table 8 show RMSE relative to the benchmark model for import and export prices of respectively world and advanced economies. In this case, we make the aggregation by using a common currency, the US dollar.

[TABLE 7 HERE]

[TABLE 8 HERE]

To check the influence of exchange rates in our forecast performance comparison, we also undertake the same analysis using national currency prices (Table 9 and Table 10).

[TABLE 9 HERE]

[TABLE 10 HERE]

In all cases, the relative RMSE show that the various approaches chosen perform relatively well, with values well below 1. The direct approaches are however underperforming the bottom-up ones in almost all cases. While for volumes, the direct approaches proved to be the best, as volumes seem to be more related to global factors than to country-specific ones, the results show that for prices, country-specific approaches remain the best. This might be related to the fact that the pricing behaviours are dependent on markets (with varying pricing-to-market behaviours), on exchange rates (with varying degrees of pass-through) and on country-specific factors (like labour costs). Global factors (like commodity prices) cannot drive alone trade prices at aggregate levels.

3.2.3 Industrial production and consumer price index

Table 11 and Table 12 show RMSE relative to the benchmark model for industrial production and consumer price index (CPI) of respectively world and advanced economies. As previously, the tables also compare forecasting performance between direct and bottom-up approaches. The results show that the various approaches beat in most cases the benchmark forecasts for short horizons (up to three months), while they do not outperform the benchmark model for longer horizons.

[TABLE 11 HERE]

[TABLE 12 HERE]

As before, the lines/columns "Fraction" give the number of cases where direct approaches beat the bottom-up approaches. At the world level, the direct approaches outperform bottom-up ones for industrial production, for short horizons. The outperformance is clear in the case of regression equations and average. Like for trade volumes (see above), the outperformance of direct approaches become more clear-cut when forecasting advanced economy aggregates. For CPI, the outperformance of direct approaches is less straightforward. At the world level, direct approaches beat bottom-up ones for factor models and average, but the fraction remains close to 50%, whatever the horizon considered. At the advanced economy level, direct approaches appears to outperform bottom-up ones only for short horizons. Overall, we can conclude that direct approaches are superior for industrial production but not for CPI. As shown for trade variables, it seems that the direct approaches are suitable to forecast real variables (trade volumes and industrial production) but are less so for prices.

3.3 Direct, top-down and bottom-up

For real variables, we have seen above that direct approaches outperform bottom-up ones. Another important issue is whether the gain in predictability obtained at the aggregate level could help to improve the predictability at the country level. In other words, we need to check whether it is worth adjusting country-specific forecasts using the information derived from aggregate forecasts. To do this, we follow a very simple procedure that allows to allocate any discrepancy between direct and bottom-up forecasts to the country-specific forecasts. The distribution of the discrepancy follows the weight of the various countries in the aggregate[11]. The formal derivation of top-down forecasts is detailed in Appendix.

Using this method, we remove any discrepancy between direct forecasts

[11] This adjustment is done only for trade volume variables and industrial production, as for trade prices and CPI we have shown that the direct approaches was underperforming the bottom-up ones.

and "top-down" forecasts.

[TABLE 13 HERE]

[TABLE 14 HERE]

To check whether this adjustment improves or deteriorates the forecast performance at the country/region level, we compute the forecast performance of these "top-down" forecasts relative to the country-specific forecasts obtained initially. Tables 13 and 14 report for each country/region and for each method the fraction of forecasts in which the "top-down" forecast is more accurate than the country-specific forecast. The results are not clear-cut and most of the fractions are close to 50%, meaning that the "top-down" adjustment neither improves nor deteriorates the forecast performance at the country level.

4 Conclusions

This paper proposes a number of approaches to forecast short-term changes in world economic variables and aims, first, at evaluating various forecasting methods in terms of forecast accuracy and, second, at checking whether methods forecasting directly aggregate variables (direct approaches) outperform methods based on the aggregation of country-specific forecasts (bottom-up approaches). Overall, all methods perform better than a simple benchmark. Among the forecasting approaches used, factor models (both diffusion indices and dynamic factor models) appear to perform the best. Moreover, direct forecasts are preferable for real variables, but not for prices. Finally, when country-specific forecasts are adjusted to match direct forecasts at the aggregate levels (top-down approaches), the forecast accuracy is neither improved nor deteriorated (i.e. top-down and bottom-up approaches are broadly equivalent in terms of country-specific forecast accuracy).

Overall, we have designed a comprehensive framework that makes use of a large set of monthly economic indicators and provides satisfactory forecasts for short horizons (up to three months ahead). By forecasting trade variables, activity and consumer price inflation, such a framework can provide a good overview of world economic developments in the short-term. It also provides forecasts for the main advanced economies, as well as for the main country groups, that are consistent with the world outlook.

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Tables and Figures

Table 1: Basic statistics on the variables to be forecasted

	Mean and standard deviation (in parentheses)			Correlations
	World	Advanced economies	Emerging economies	
Industrial production	0.25	0.14	0.51	0.297
	(0.30)	(0.31)	(0.42)	
Import volumes	0.59	0.47	0.81	0.170
	(0.50)	(0.54)	(0.86)	
Export volumes	0.59	0.45	0.85	0.162
	(0.49)	(0.52)	(0.77)	
CPI	0.47	0.15	1.41	0.223
	(0.44)	(0.12)	(1.61)	
Import prices (USD)	0.11	0.11	0.11	0.269
	(0.96)	(1.07)	(0.79)	
Export prices (USD)	0.12	0.11	0.14	0.440
	(0.97)	(1.09)	(0.98)	
Import prices	0.09	0.09	0.11	0.177
(national currency)	(0.48)	(0.46)	(0.79)	
Export prices	0.08	0.04	0.14	0.168
(national currency)	(0.44)	(0.26)	(0.98)	

Note: The statistics are computed on the three-month (log) differences of the original series. Correlations refer to average pair-wise cross section correlations with individual countries as pairs.

Table 2: Overview of the series collected and occurence in the factor extractions

	Number of series	Factors		
		World	Adv. eco.	Emerg. eco.
World	28	√		
Advanced economies	2	√	√	
United States	38	√	√	
Japan	37	√	√	
Canada	35	√	√	
United Kingdom	69	√	√	
Euro area	65	√	√	
Emerging economies	6	√		√
Argentina	7	√		√
Brazil	15	√		√
China	16	√		√
Indonesia	8	√		√
Malaysia	6	√		√
Russia	22	√		√
Singapore	7	√		√
South_Africa	14	√		√
South_Korea	17	√		√
Taiwan	8	√		√
Thailand	5	√		√
Global variables	12	√	√	√
Total number of series	417	417	258	143

Table 3: Comparison of simulated out-of-sample forecasting results - horizons up to 12 months ahead -

	RW	AR(1)	Regr.Eq. aver.	DI	DFM	Average
RW	-	0.60	0.44	0.56	0.45	0.71
AR(1)	0.40	-	0.32	0.48	0.34	0.65
Regr.Eq. aver.	0.56	0.68	-	0.73	0.65	0.77
DI	0.44	0.52	0.27	-	0.46	0.71
DFM	0.55	0.66	0.35	0.54	-	0.78
Average	0.29	0.35	0.23	0.29	0.22	-

Note: Each entry shows the fraction of times that the forecast corresponding to the columns of the table has a lower RMSE than the forecast corresponding to the raw.

Table 4: Comparison of simulated out-of-sample forecasting results - horizons up to 3 months ahead -

	RW	AR(1)	Regr.Eq. aver.	DI	DFM	Average
RW	-	0.63	0.47	0.89	0.76	0.98
AR(1)	0.38	-	0.30	0.83	0.63	0.94
Regr.Eq. aver.	0.53	0.70	-	0.87	0.83	0.94
DI	0.11	0.17	0.13	-	0.41	0.57
DFM	0.24	0.38	0.17	0.59	-	0.64
Average	0.02	0.06	0.06	0.43	0.36	-

Note: Each entry shows the fraction of times that the forecast corresponding to the columns of the table has a lower RMSE than the forecast corresponding to the raw.

Table 5: Direct forecasts of trade volumes: comparison at world level

Imports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00543	0.00543	0.00544	0.00543	0.00543	0.00542	
	RRMSE						Fraction
AR(1)	1.01	0.98	1.01	1.00	1.00	1.00	**0.92**
Regr.Eq. aver.	0.85	0.79	0.90	0.96	0.99	1.00	**0.58**
DI	0.90	0.90	0.96	1.06	1.07	1.07	**0.67**
DFM	1.41	0.38	1.37	1.15	1.02	1.06	**0.17**
Average	0.93	0.68	0.97	1.01	1.00	1.01	**0.67**
Fraction	**0.50**	**0.83**	**0.50**	**0.17**	**1.00**	**0.33**	

Exports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00520	0.00521	0.00522	0.00521	0.00521	0.00519	
	RRMSE						Fraction
AR(1)	1.00	0.97	1.05	1.00	1.00	1.00	**0.00**
Regr.Eq. aver.	0.86	0.79	0.90	0.99	1.01	1.03	**0.33**
DI	0.85	0.84	0.94	1.13	1.15	1.17	**0.17**
DFM	1.32	0.42	1.26	1.26	1.13	1.09	**0.00**
Average	0.87	0.66	0.95	1.06	1.05	1.05	**0.17**
Fraction	**0.50**	**0.50**	**0.17**	**0.00**	**0.33**	**0.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 6: Direct forecasts of trade volumes: comparison for advanced economies

Imports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00454	0.00455	0.00455	0.00454	0.00454	0.00452	
	RRMSE						Fraction
AR(1)	0.97	1.03	1.06	1.00	1.01	1.00	**1.00**
Regr.Eq. aver.	0.95	0.90	0.94	0.96	1.00	1.01	**1.00**
DI	0.84	0.84	1.02	1.07	1.16	1.01	**1.00**
DFM	1.10	0.31	0.96	1.17	1.09	1.04	**0.58**
Average	0.84	0.73	0.95	0.99	1.02	0.96	**1.00**
Fraction	**1.00**	**1.00**	**0.83**	**1.00**	**1.00**	**1.00**	

Exports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00467	0.00469	0.00470	0.00469	0.00467	0.00465	
	RRMSE						Fraction
AR(1)	0.85	0.97	1.06	1.02	1.01	1.00	**1.00**
Regr.Eq. aver.	0.88	0.84	0.89	0.99	1.04	1.06	**1.00**
DI	0.70	0.70	0.92	1.21	1.29	1.23	**1.00**
DFM	0.88	0.33	0.85	1.26	1.14	1.06	**1.00**
Average	0.68	0.65	0.88	1.09	1.11	1.06	**1.00**
Fraction	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 7: Direct forecasts of trade prices in US dollar: comparison at world level

Import prices in US dollar							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01011	0.01016	0.01019	0.01024	0.01029	0.01036	
	RRMSE						Fraction
AR(1)	0.61	0.86	0.94	0.95	0.92	0.94	**0.00**
Regr.Eq. aver.	0.80	0.80	0.83	0.86	0.93	0.93	**0.00**
DI	0.36	0.35	0.73	0.91	0.96	0.87	**0.17**
DFM	0.90	0.58	0.73	0.92	0.98	0.98	**0.00**
Average	0.46	0.48	0.69	0.89	0.94	0.91	**0.17**
Fraction	**0.00**	**0.33**	**0.33**	**0.00**	**0.00**	**0.00**	

Export prices in US dollar							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01050	0.01054	0.01057	0.01062	0.01067	0.01074	
	RRMSE						Fraction
AR(1)	0.65	0.89	0.97	0.95	0.93	0.95	**0.00**
Regr.Eq. aver.	0.80	0.81	0.84	0.87	0.92	0.93	**0.00**
DI	0.41	0.41	0.78	0.93	0.97	0.90	**0.17**
DFM	0.97	0.59	0.76	0.93	0.99	0.99	**0.00**
Average	0.51	0.51	0.73	0.91	0.95	0.93	**0.00**
Fraction	**0.00**	**0.17**	**0.17**	**0.00**	**0.00**	**0.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 8: Direct forecasts of trade prices in US dollar: comparison for advanced economies

Import prices in US dollar							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01100	0.01106	0.01109	0.01114	0.01119	0.01128	
	RRMSE						Fraction
AR(1)	0.62	0.87	0.95	0.95	0.92	0.95	**0.00**
Regr.Eq. aver.	0.86	0.87	0.89	0.90	0.94	0.93	**0.00**
DI	0.36	0.36	0.69	0.96	0.97	0.94	**0.00**
DFM	0.93	0.74	0.89	0.93	1.07	1.08	**0.00**
Average	0.50	0.54	0.72	0.90	0.95	0.96	**0.00**
Fraction	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	

Export prices in US dollar							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01129	0.01135	0.01138	0.01142	0.01148	0.01156	
	RRMSE						Fraction
AR(1)	0.66	0.90	0.99	0.96	0.94	0.96	**0.00**
Regr.Eq. aver.	0.89	0.90	0.93	0.93	0.95	0.95	**0.00**
DI	0.47	0.47	0.76	1.03	0.99	0.98	**0.00**
DFM	0.98	0.81	0.99	0.97	1.05	1.06	**0.00**
Average	0.56	0.59	0.78	0.94	0.96	0.97	**0.00**
Fraction	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 9: Direct forecasts of trade prices in national currencies: comparison at world level

Import prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00571	0.00574	0.00575	0.00579	0.00581	0.00584	
	RRMSE						Fraction
AR(1)	0.60	0.89	0.96	0.92	0.89	0.92	**0.58**
Regr.Eq. aver.	0.81	0.81	0.84	0.89	0.92	0.93	**0.92**
DI	0.47	0.47	0.68	0.85	0.90	0.93	**0.58**
DFM	0.85	0.47	0.65	0.93	1.03	1.05	**0.50**
Average	0.52	0.55	0.73	0.87	0.93	0.94	**0.58**
Fraction	**0.00**	**0.50**	**0.67**	**0.83**	**0.17**	**0.33**	

Export prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00536	0.00539	0.00540	0.00542	0.00543	0.00546	
	RRMSE						Fraction
AR(1)	0.68	0.93	1.02	0.97	0.94	0.96	**0.00**
Regr.Eq. aver.	0.82	0.83	0.85	0.89	0.92	0.92	**0.00**
DI	0.50	0.50	0.76	0.89	0.93	0.95	**0.00**
DFM	0.97	0.50	0.72	0.99	1.03	1.04	**0.00**
Average	0.59	0.59	0.79	0.92	0.95	0.95	**0.00**
Fraction	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 10: Direct forecasts of trade prices in national currencies: comparison for advanced economies

Import prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00520	0.00522	0.00523	0.00526	0.00528	0.00530	
	RRMSE						Fraction
AR(1)	0.66	0.94	1.01	0.95	0.92	0.95	**0.17**
Regr.Eq. aver.	0.96	0.93	0.94	0.95	0.96	0.96	**0.08**
DI	0.67	0.66	0.81	0.94	1.01	1.01	**0.17**
DFM	0.91	0.42	0.65	1.07	1.07	1.10	**0.25**
Average	0.60	0.60	0.79	0.95	0.98	0.99	**0.33**
Fraction	**0.00**	**0.00**	**0.33**	**0.67**	**0.00**	**0.00**	

Export prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00275	0.00276	0.00276	0.00277	0.00278	0.00280	
	RRMSE						Fraction
AR(1)	0.69	0.92	1.01	0.97	0.96	0.97	**0.00**
Regr.Eq. aver.	0.95	0.95	0.97	0.98	0.97	0.97	**0.00**
DI	0.62	0.61	0.91	0.98	0.99	0.96	**0.00**
DFM	0.97	0.49	0.71	0.98	0.99	1.07	**0.00**
Average	0.63	0.62	0.81	0.94	0.94	0.93	**0.00**
Fraction	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 11: Direct forecasts of industrial production and consumer price index: comparison at world level

Industrial production							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00276	0.00278	0.00279	0.00280	0.00279	0.00278	
	RRMSE						Fraction
AR(1)	0.65	0.79	0.98	1.01	1.01	0.98	**0.25**
Regr.Eq. aver.	1.47	1.47	1.53	1.60	1.67	1.66	**1.00**
DI	0.50	0.50	0.65	0.92	1.13	1.13	**0.50**
DFM	0.71	0.33	0.63	1.00	1.11	1.25	**0.33**
Average	0.48	0.46	0.66	0.92	1.03	1.02	**0.67**
Fraction	**0.67**	**0.67**	**1.00**	**0.50**	**0.17**	**0.17**	

Consumer price index							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00335	0.00337	0.00339	0.00345	0.00352	0.00359	
	RRMSE						Fraction
AR(1)	0.25	0.40	0.49	0.47	0.44	0.34	**0.17**
Regr.Eq. aver.	1.09	1.09	1.08	1.05	1.04	1.04	**0.00**
DI	0.45	0.45	0.50	0.53	0.56	0.51	**1.00**
DFM	0.32	0.23	0.34	0.53	0.56	0.63	**1.00**
Average	0.31	0.33	0.42	0.46	0.50	0.47	**1.00**
Fraction	**0.50**	**0.50**	**0.50**	**0.50**	**0.50**	**0.67**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 12: Direct forecasts of industrial production and consumer price index: comparison for advanced economies

Industrial production							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00259	0.00260	0.00261	0.00260	0.00259	0.00257	
	RRMSE						Fraction
AR(1)	0.87	0.94	1.15	1.09	1.05	1.01	**0.83**
Regr.Eq. aver.	1.82	1.81	1.82	1.93	1.96	1.95	**1.00**
DI	0.61	0.60	0.86	1.07	1.38	1.20	**0.58**
DFM	0.86	0.40	0.81	1.15	1.12	1.13	**0.25**
Average	0.62	0.56	0.82	1.04	1.15	1.05	**0.83**
Fraction	**0.83**	**0.83**	**0.83**	**0.83**	**0.33**	**0.50**	

Consumer price index							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00129	0.00130	0.00130	0.00129	0.00129	0.00129	
	RRMSE						Fraction
AR(1)	0.76	1.10	1.19	1.01	1.01	0.98	**0.58**
Regr.Eq. aver.	1.48	1.48	1.50	1.50	1.51	1.50	**1.00**
DI	0.48	0.48	0.83	1.02	1.07	1.05	**0.25**
DFM	1.19	0.73	0.84	1.09	1.00	1.00	**0.67**
Average	0.63	0.66	0.89	1.00	1.00	1.00	**0.58**
Fraction	**0.67**	**0.83**	**0.67**	**0.33**	**0.67**	**0.33**	

Note: "Fraction" refers to cases where direct beats bottom-up.

Table 13: Fraction of cases in which top-down approaches outperform bottom-up approaches

	U.S.	Jap	Can	U.K.	E.A.	Emerg. Eco.	
Import volumes							
AR(1)	0.25	1.00	0.25	0.50	0.25	0.92	**0.53**
Regr.Eq. aver.	0.25	1.00	0.25	0.75	0.33	0.92	**0.58**
DI	0.08	0.75	0.67	0.75	0.58	0.83	**0.61**
DFM	0.00	1.00	1.00	0.58	0.92	1.00	**0.75**
Average	0.00	0.92	0.67	0.58	0.42	0.75	**0.46**
	0.13	**0.85**	**0.65**	**0.62**	**0.50**	**0.90**	
Export volumes							
AR(1)	0.92	1.00	0.17	0.50	0.33	1.00	**0.65**
Regr.Eq. aver.	0.58	0.58	0.17	0.17	0.67	1.00	**0.53**
DI	0.75	0.83	0.50	0.92	0.58	1.00	**0.76**
DFM	0.92	1.00	0.00	0.67	0.67	1.00	**0.71**
Average	0.83	1.00	0.00	0.58	0.42	0.92	**0.63**
	0.81	**0.89**	**0.22**	**0.60**	**0.53**	**0.96**	

Table 14: Fraction of cases in which top-down approaches outperform bottom-up approaches: industrial production

	U.S.	Jap	Can	U.K.	E.A.	
Industrial production						
AR(1)	1.00	0.75	1.00	0.92	1.00	**0.93**
Regr.Eq. aver.	0.42	0.67	0.33	0.50	0.67	**0.52**
DI	1.00	0.67	0.42	0.83	1.00	**0.78**
DFM	0.33	0.83	0.17	0.58	1.00	**0.58**
Average	0.75	0.92	0.50	0.67	1.00	**0.77**
	0.75	**0.73**	**0.57**	**0.75**	**1.00**	

APPENDIX: Derivation of "Top-Down" Forecasts

In this appendix, we detail the derivation of "top-down" forecasts using direct and country-specific forecasts. It shows for trade volumes and industrial production how to compute country-specific forecasts that are consistent with those obtained from direct approaches.

Trade volumes

For trade volumes (imports and exports) - which are expressed in constant USD levels -, we first derive direct forecasts (superscript d) for our advanced economy (subscript ad) aggregates ($x^d_{ae,t+n}$) for the various n horizons. We then compute their counterpart from bottom-up (superscript bu) approaches by aggregating the forecasts of the p different countries:

$$x^{bu}_{ad,t+n} = \sum_{i=1}^{p} x_{i,t+n}$$

Note that the variables of interest are now expressed in levels (i.e. in constant dollar terms). These forecasts in levels are obtained simply by expanding the historical data with the month-on-month growth rates forecasted.

We compute the difference between the direct and the bottom-up forecast levels as: $d_{ad,t+n} = x^d_{ad,t+n} - x^{bu}_{ad,t+n}$.

We then distribute this difference on the various countries according to their weight in the aggregate (ω_i), so that each country-specific forecasts become "adjusted", with its adjusted value equal to a so-called "top-down" forecast (supercript td) defined as:

$$x^{td}_{i,t+n} = x_{i,t+n} + \omega_i d_{ad,t+n}$$

With such an adjustment, we get the equality between direct forecasts and "top-down" forecasts (i.e. $x^d_{ad,t+n} = x^{td}_{ad,t+n}$), where:

$$x^{td}_{ad,t+n} = \sum_{i=1}^{p} x^{td}_{i,t+n}.$$

Finally, to adjust emerging economy (subscript em) forecasts, we use the direct forecast for world (subscript w) variables ($x^d_{w,t+n}$), and compute their bottom-up counterpart by adding the emerging economy forecasts ($x^d_{em,t+n}$) to the adjusted advanced economy aggregate:

$$x^{bu}_{w,t+n} = x_{em,t+n} + x^{td}_{ad,t+n}.$$

Similarly for advanced economy forecasts, we adjust the emerging economy forecasts for the discrepancy between $x^{d}_{w,t+n}$ and $x^{bu}_{w,t+n}$, so that:

$$x^{td}_{em,t+n} = x_{em,t+n} + (x^{d}_{w,t+n} - x^{bu}_{w,t+n}).$$

Industrial production

For industrial production - which is expressed as an index -, we first derive direct forecasts (superscript d) for our advanced economy (subscript ad) aggregates ($x^{d}_{ad,t+n}$) for the various n horizons. We then compute their counterpart from bottom-up (superscript bu) approaches by aggregating the forecasts of the p different countries (as a geometric average):

$$x^{bu}_{ad,t+n} = \prod_{i=1}^{p} (x_{i,t+n})^{\omega_i}$$

where α_i is the weight of country i in the aggregate.

The forecasts are obtained by expanding the historical data with the month-on-month growth rates forecasted.

We compute the ratio between the direct and the bottom-up forecast levels as: $r_{ad,t+n} = \frac{x^{d}_{ad,t+n}}{x^{bu}_{ad,t+n}}$.

We then multiply various country forecasts by this ratio, so that each country-specific forecast becomes "adjusted", with its adjusted value equal to a so-called "top-down" forecast (superscript td) defined as:

$$x^{td}_{i,t+n} = r_{ad,t+n} x_{i,t+n}$$

With such an adjustment, we get the equality between direct forecasts and "top-down" forecasts (i.e. $x^{d}_{ad,t+n} = x^{td}_{ad,t+n}$), where:

$$x^{td}_{ad,t+n} = \prod_{i=1}^{p} \left(x^{td}_{i,t+n}\right)^{\omega_i}.$$

Finally, to adjust emerging economy (subscript em) forecasts, we use the direct forecast for world (subscript w) variables ($x^{d}_{w,t+n}$), and compute their bottom-up counterpart as a weighted average of the emerging economy forecasts ($x^{d}_{em,t+n}$) and the adjusted advanced economy aggregate:

$$x^{bu}_{w,t+n} = (x_{em,t+n})^{\alpha_{em}} \left(x^{td}_{ad,t+n}\right)^{(1-\alpha_{em})}.$$

Similarly for advanced economy forecasts, we adjust the emerging economy forecasts for the discrepancy between $x^{d}_{w,t+n}$ and $x^{bu}_{w,t+n}$, so that:

$$x^{td}_{em,t+n} = \left[\left(x_{em,t+n} \left(\frac{x^{d}_{w,t+n}}{x^{bu}_{w,t+n}} \right) \right)^{\alpha^{em}} \right]^{1/\alpha^{em}}.$$

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