Short term forecasting methods of international trade variables[1]

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Abstract

Forecasting monthly changes in international trade variables (volumes and prices) is a difficult task given the high variability of the series. This paper proposes a number of approaches to forecast short-term changes in trade volumes and prices and aims, first, at ranking various forecasting me-thods in terms of forecast acuracy and, second, at checking whether me-thods forecasting directly aggregate variables (direct approaches) outperform methods based on the aggregation of country-specific forecasts (bottom-up approaches). Overall, all methods peform better than a simple random-walk benchmark. Among the forecasting approaches used, bridge equations and diffusion indices appear to perform the best. Moreover, direct approaches outperform bottom-up ones for volume variables, while the opposite is found for trade 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 equivalent in terms of country-specific forecast accuracy).

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

1 Introduction

Forecasting monthly changes in international trade variables (volumes and prices) is a difficult task given the high variability of the series (see Fig. 1). Even by using methods that smooth the monthly growth rates (changes over three previous month period or year-on-year changes), the series still feature large standard deviations.

[FIGURE 1 HERE]

At the same time, part of this large variability is common across countries. Table 1 shows the pair-wise average cross-section correlation for the four types of series considered in this paper (import volumes and prices as well as export volumes and prices). Given the volatility of the series, pair-wise correlation appear rather high, suggesting that common variables might influence country-specific trade developments.

[TABLE 1 HERE]

Partly building on Burgert and Dees (2008), this paper proposes a number of approaches to forecast short-term changes in trade volumes and prices. As our analysis focuses on short-term forecasts, we have restricted our study to time series models, whose explanatory variables are selected either by their well-known leading properties in forecasting trade variables (bridge equations) or via a statistical analysis without any theoretical basis (factor models: diffusion indices and dynamic factor models). We have therefore excluded more structural approaches - like error correction models -, which assume some theoretical relationships to hold -at least- in the long run. Moreover, we have tried to make use of the information content included in various short-term indicators relevant for international trade (leading indicators, manufacturing activity, 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 international trade is 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 whether the accuracy gained at the aggregate level can improve the forecast accuracy at the country-specific level (following top-down approaches, where the coutry-specific forecasts are adjusted so that they match - once aggregated - the direct forecasts of the aggregates).

Overall, all methods peform better than a simple random-walk benchmark. Among the forecasting approaches used, bridge equations and diffusion indices appear to perform the best. As in Burgert and Dees (2008), direct approaches outperform bottom-up ones for volume variables, while the opposite is found for trade 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 equivalent in terms of country-specific forecast accuracy).

Section 2 presents the forecasting models considered and deals with the issues of specification selection and unbalancedness. Section 3 presents the empirical results and Section 4 concludes.

2 Forecasting models

We investigate several time series methods for forecasting world trade variables and consider empirically which methods perform best and whether it is better to build aggregate trade forecasting models, or whether there are gains from aggregating country-specific forecasts. To ensure the robustness of our analysis, we use and compare several forecasting models. We compute first random-walk based forecasts, which serve as benchmarks for the other models. Another simple approach consists in estimating auto-regressive models. In addition to these simple approaches, we estimate models where the trade variables depends on exogenous fundamentals. We first estimate bridge equations, i.e. simple linear models that depend only on Industrial Production and Composite Leading Indicators (CLIs). We also 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[1].

2.1 Benchmark model: Random walk (RW)

We use, as a benchmark a simple random-walk based approach, where the forecast of variable x_i for country i is equal to the latest observed value.

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

where u_{it} denotes the residual.

The variables are all expressed as a first log-difference (i.e. in month-on-month growth rate terms).

[1] MATLAB codes developed in the Directorate General Research of the European Central Bank have been adopted and used here.

2.2 Autoregressive models (AR)

The first approach, which will be compared with the benchmark, is a first-order autoregression model. For country i, we estimate the AR(1) model 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:

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

2.3 Bridge equations (BE)

Bridge equations are a widely used method 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 trade variables, we use auto-regressive models to forecast these indicators over the horizon. In a second step, the indicator forecasts are used to predict the trade variables.

More precisely, for country i, we estimate bridge 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.

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 ($\widetilde{x}^{BE}_{i,t+1}$) for the first-month ahead horizon are obtained as follows:

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

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:

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

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

The indicators used in theses models are industrial production and the Composite Leading Indicator (CLI) provided by the OECD.

2.4 Diffusion indices (DI)

Diffusion indices due to 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 monthly indicators

$y_{it} = (y_{i1t}, y_{i2t}, ...y_{int})'$.

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 $y_{i,t}$ denotes 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 ($u_{it} \sim N(0, \sigma_i^2)$).

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:

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

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.

We also estimate an alternative version of Eq. (4), by adding an autoregressive term in the model:

$$x_{i,t+n} = \alpha_i + \phi_{i0} x_{i,t-1} + \phi_{i1} f_{i,t} + u_{it} \tag{5}$$

The forecasting equation is a follows:

$$\widetilde{x}_{i,t+n}^{DI\_AR} = \widehat{\boldsymbol{\alpha}}_i + \widehat{\boldsymbol{\phi}}_{i0} x_{i,t-1} + \widehat{\boldsymbol{\phi}}_{i1} f_{i,t}$$

where $\widehat{\boldsymbol{\alpha}}_i$, $\widehat{\boldsymbol{\phi}}_{i0}$and $\widehat{\boldsymbol{\phi}}_{i1}$ are the estimates of Eq. (5).

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 monthly indicators $y_{it} = (y_{i1t}, y_{i2t}, ...y_{int})'$.

As for the DI model, 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 $r < n$. 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 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 dependant variables is obtained directly inserting into bridge equation estimated common factors and their forecast as follows:

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

3 Data

We use a large database including information on a monthly basis to explain trade developments over the period 1991:1 - 2007:12. The dataset can be divided into three groups:

• Trade data (dependent variables): 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 industrial countries and for emerging markets considered as a single block[2].

• Country-specific macroeconomic and financial data (explanatory variables): The country-specific macroeconomic data are represented by OECD's Composite Leading Indicators, other composite 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

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

money supply, as well as bilateral exchange rates vis-a-vis the US dollar and in effective terms.

• 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, stock market prices for the major financial centres and the Baltic Dry Index[3].

The countries included in our industrial country sample are: the United States, Canada, Japan, the euro area and the United Kingdom. Taken together these countries represent more than 90% of the industrial countries in terms of import volumes in 1995[4]. When extending the analysis to world trade, we include, in addition to the countries listed above, emerging markets, treated as a single block. While the trade data for emerging markets are available (from the CPB), 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' importations in 1995, we reasonably assume that they are sufficient to give a good approximation for the whole aggregate. This is confirmed by inspecting

[3]The Baltic Dry Index is produced daily by the London-based Baltic Exchange. Using a panel of international shipbrokers, it provides an assessment of the price of moving the major raw materials by sea. It is therefore a good leading indicator for trade and economic growth.

[4]Industrial countries is defined as OECD coutries 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 "industrial countries" being too small, their omission should not affect the main results of this study.

and comparing the series visually and by conducting some simple statistical analysis of co-movements between the individual series and the emerging markets' aggregates.

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

All data are standardised to mean zero and variance one in a recursive manner. For the factor models, we also clean the data from outliers[5]. The variables are all expressed as a first log-difference or first order difference for the confidence indicators.

4 Empirical results

The empirical analysis mostly focuses on out-of-sample forecasting performance of the various methods. The forecasting exercise is performed for four trade variables (import and export volumes as well as import and export prices). As for trade prices, 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).

We analyse the forecast performance for individual country/region forecasts as well as aggregate forecasts. The empirical analysis is made at two different levels of aggregation. In a first level, we aggregate country trade

[5] 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% quantile of the series' distribution. We either set these outliers as missing values (model DFM) or replace them with the largest admissable value.

data for industrial countries only and compare the aggregation of country-specific forecasts with the forecasts of the aggregated series. In a second level, we perform a similar exercise by including trade data for emerging markets 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 trade aggregates (direct forecasts) or whether an ex-post aggregation of individual forecasts (bottom-up forecasts) give more acurate forecasts of aggregate variables. This analysis shows that direct forecasts are preferable for volume variables while bottom-up approaches perform better for price variables. Finally, for volume variables, 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.

4.1 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 2 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

288 forecasts (eight countries or aggregates, six variables, twelve horizons), the table shows the fraction of forecasts in which the method corresponding to a given column was more accurate than the method corresponding to a given row. This gives us a good overview of the relative performance of the various methods.

[TABLE 2 HERE]

This table shows, first, that all methods perform better than a simple random walk in almost all cases. Second, among the forecasting methods, bridge equations and diffusion indices appear to perform the best, while dynamic factor models does not perform well on average as they are beaten in 2/3 to 4/5 of cases. Finally, as usually found in the literature, an average of all methods appear to be the best performing approach as it beats all the other approaches in 80-90% of cases. This table gives us only a broad overview of our forecasting exercise. The results are less clear-cut when looking at different variables and different horizons.

4.2 Direct vs. bottom-up approaches

To answer the question whether direct approaches outperform bottom-up ones to forecasts trade variable aggregates, we perform forecasting performance tests for two different aggregation levels (world and industrial economies) and for four different variables (import and export volumes as well as import and export prices).

4.2.1 Volume variables

Table 3 and Table 4 show RMSE relative to our random-walk benchmark for import and export volumes of respectively world and industrial countries. The tables also compare forecasting performance between direct and bottom-up approaches. The results show that the various approaches always beat the random-walk based forecasts, especially in the very short term. The lines/columns "Fraction" give the number of cases where direct approaches beat the country-aggregate approaches (i.e. bottom-up approaches).

[TABLE 3 HERE]

[TABLE 4 HERE]

While for world variables, the overperformance of direct approaches is not clear cut (it holds for very short horizons - 1 to 3 months ahead - and for bridge equations and dynamic factor models), it becomes more obvious when restricting our aggregation to industrial countries. In the latter case, the overperformance of direct approaches is quasi-systematic.

4.2.2 Price variables

Table 5 and Table 6 show RMSE relative to our random-walk benchmark for import and export prices of respectively world and industrial countries. In this case, we make the aggregation by using a common currency, the US dollar.

[TABLE 5 HERE]

[TABLE 6 HERE]

To check the influence of exchange rates in our forecast performance comparison, we also undertake the same analysis using national currency prices (Table 7 and Table 8).

[TABLE 7 HERE]

[TABLE 8 HERE]

In all cases, the relative RMSE show that the various approaches chosen perform relatively well. The direct approaches is however underperforming the bottom-up ones in almost all cases. While for volumes, the direct approaches prove to be the best, as volumes seem to be more related to global factor 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.

4.3 Direct, top-down and bottom-up

For volume variables, we have seen above that direct approaches overperform bottom-up ones. Another important issues 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 discrepency between direct and bottom up forecasts to the country-specific forecasts. The distribution of the discrepency follows the weight of the various countries in the aggregate[6].

More specifically, we first derive direct forecasts (superscript d) for our industrial country (subscript ic) aggregates ($x^d_{ic,t+n}$) for the various n horizons. We then compute their counterpart from bottom-up (superscript bu)

[6] This adjustment is done only for volume variables, as for prices we have shown that the direct approaches was underperforming the "bottom-up" ones.

approaches:

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

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: $d_{ic,t+n} = x_{ic,t+n}^{d} - x_{ic,t+n}^{bu}$.

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:

$$x_{i,t+n}^{td} = x_{i,t+n} + \omega_i d_{ic,t+n}$$

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

$$x_{ic,t+n}^{td} = \sum_{i=1}^{p} x_{i,t+n}^{td}.$$

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

$$x_{w,t+n}^{bu} = x_{em,t+n} + x_{ic,t+n}^{td}.$$

Similarly for industrial country forecasts, we adjust the emerging market forecasts for the discrepency between $x^{d}_{w,t+n}$ and $x^{bu}_{w,t+n}$, so that:

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

Using this method, we remove any discrepency between direct forecasts and "top-down" forecasts.

[TABLE 9 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. Table 9 reports 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.

5 Conclusions

This paper proposes a number of approaches to forecast short-term changes in trade volumes and prices 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 peform better than a simple random-walk benchmark. Among the forecasting approaches used, bridge equations and diffusion indices appear to perform the best. Moreover, direct approaches outperform bottom-up ones for volume variables, while the opposite is found for trade 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 equivalent in terms of country-specific forecast accuracy).

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Tables and Figures

Table 1: Average pair-wise cross-section correlations of trade variables

	Import volumes	Export volumes	Import prices	Export prices
M-o-m %	0.196	0.235	0.446	0.310
3mma %	0.226	0.347	0.667	0.475
Y-o-y %	0.321	0.525	0.741	0.563

Table 2: Comparison of simulated out-of-sample forecasting results

	RW	AR(1)	BE aver.	DI	DI_AR(1)	DFM	Average
RW	-	0.99	0.99	1.00	1.00	0.99	1.00
AR(1)	0.01	-	0.67	0.51	0.47	0.26	0.85
BE aver.	0.01	0.33	-	0.44	0.40	0.22	0.85
DI	0.00	0.49	0.56	-	0.33	0.30	0.81
DI_AR(1)	0.00	0.53	0.60	0.67	-	0.33	0.82
DFM	0.01	0.74	0.78	0.70	0.67	-	0.89
Average	0.00	0.15	0.15	0.19	0.18	0.11	-

Note: Fraction of series/horizons in which column-method beat row-method.

Table 3: Direct forecasts of trade volumes: comparison at world level

Imports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.03003	0.02402	0.02124	0.02173	0.02002	0.02401	
	RRMSE						Fraction
AR(1)	0.49	0.72	0.83	0.79	0.85	0.71	**0.33**
BE aver.	0.54	0.70	0.80	0.78	0.85	0.71	**0.92**
DI	0.58	0.71	0.80	0.80	0.87	0.72	**0.25**
DI_AR(1)	0.58	0.69	0.79	0.79	0.82	0.72	**0.08**
DFM	0.54	0.72	0.82	0.79	0.82	0.71	**0.75**
Average	0.54	0.71	0.83	0.81	0.87	0.79	**0.33**
Fraction	**0.50**	**0.67**	**0.67**	**0.33**	**0.33**	**0.33**	

Exports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.02642	0.02178	0.01849	0.02017	0.01993	0.02278	
	RRMSE						Fraction
AR(1)	0.51	0.71	0.84	0.76	0.77	0.67	**0.92**
BE aver.	0.56	0.69	0.82	0.75	0.76	0.67	**1.00**
DI	0.58	0.70	0.84	0.77	0.79	0.68	**0.17**
DI_AR(1)	0.59	0.69	0.81	0.77	0.77	0.72	**0.00**
DFM	0.54	0.67	0.82	0.77	0.75	0.68	**0.67**
Average	0.55	0.70	0.86	0.79	0.79	0.73	**0.42**
Fraction	**0.50**	**0.83**	**0.33**	**0.33**	**0.50**	**0.50**	

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

Table 4: Direct forecasts of trade volumes: comparison for industrial countries

Imports							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01853	0.01631	0.01588	0.01549	0.01552	0.01745	
	RRMSE						Fraction
AR(1)	0.57	0.69	0.71	0.72	0.72	0.64	**1.00**
BE aver.	0.61	0.68	0.71	0.72	0.72	0.64	**1.00**
DI	0.61	0.68	0.70	0.73	0.72	0.64	**1.00**
DI_AR(1)	0.62	0.70	0.70	0.75	0.73	0.65	**1.00**
DFM	0.71	0.75	0.80	0.73	0.72	0.65	**0.92**
Average	0.61	0.69	0.70	0.71	0.68	0.65	**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	0.01561	0.01336	0.01355	0.01549	0.01457	0.01509	
	RRMSE						Fraction
AR(1)	0.61	0.74	0.73	0.64	0.68	0.65	**1.00**
BE aver.	0.63	0.73	0.72	0.64	0.68	0.65	**1.00**
DI	0.63	0.74	0.74	0.66	0.69	0.68	**1.00**
DI_AR(1)	0.64	0.78	0.74	0.69	0.72	0.72	**1.00**
DFM	0.71	0.76	0.80	0.69	0.69	0.67	**1.00**
Average	0.64	0.75	0.74	0.64	0.65	0.65	**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 5: 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	0.01706	0.02063	0.01935	0.02092	0.01913	0.02009	
	RRMSE						Fraction
AR(1)	0.82	0.73	0.76	0.71	0.78	0.75	**0.00**
BE aver.	0.86	0.69	0.74	0.70	0.77	0.73	**0.00**
DI	0.81	0.69	0.72	0.70	0.78	0.77	**0.00**
DI_AR(1)	0.81	0.69	0.75	0.70	0.76	0.77	**0.00**
DFM	0.83	0.73	0.75	0.74	0.82	0.80	**0.00**
Average	0.87	0.70	0.74	0.69	0.71	0.54	**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	0.01987	0.02256	0.02184	0.02279	0.02125	0.02216	
	RRMSE						Fraction
AR(1)	0.79	0.72	0.74	0.71	0.76	0.73	**0.00**
BE aver.	0.82	0.70	0.72	0.70	0.75	0.72	**0.00**
DI	0.78	0.69	0.71	0.70	0.76	0.76	**0.00**
DI_AR(1)	0.78	0.69	0.72	0.70	0.75	0.76	**0.00**
DFM	0.83	0.74	0.74	0.73	0.79	0.77	**0.00**
Average	0.82	0.70	0.72	0.69	0.70	0.55	**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 6: Direct forecasts of trade prices in US dollar: comparison for industrial countries

Import prices in US dollar							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01908	0.02313	0.02175	0.02341	0.02071	0.02204	
	RRMSE						Fraction
AR(1)	0.82	0.71	0.75	0.70	0.79	0.75	**0.00**
BE aver.	0.86	0.70	0.74	0.69	0.79	0.74	**0.00**
DI	0.82	0.69	0.72	0.69	0.77	0.78	**0.00**
DI_AR(1)	0.80	0.69	0.74	0.70	0.77	0.78	**0.00**
DFM	0.83	0.73	0.73	0.73	0.85	0.80	**0.00**
Average	0.83	0.67	0.70	0.67	0.75	0.53	**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	0.02032	0.02328	0.02398	0.02416	0.02134	0.02327	
	RRMSE						Fraction
AR(1)	0.80	0.73	0.71	0.70	0.79	0.73	**0.00**
BE aver.	0.83	0.71	0.69	0.69	0.79	0.72	**0.00**
DI	0.83	0.71	0.68	0.70	0.78	0.77	**0.00**
DI_AR(1)	0.84	0.71	0.70	0.71	0.78	0.78	**0.00**
DFM	0.82	0.74	0.71	0.73	0.82	0.76	**0.00**
Average	0.81	0.69	0.66	0.68	0.75	0.53	**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 7: 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	0.00934	0.01160	0.01067	0.01058	0.01148	0.01079	
	RRMSE						Fraction
AR(1)	0.83	0.72	0.77	0.85	0.84	0.79	**0.17**
BE aver.	0.88	0.70	0.75	0.77	0.72	0.77	**1.00**
DI	0.78	0.69	0.75	0.76	0.73	0.79	**0.25**
DI_AR(1)	0.78	0.70	0.75	0.76	0.71	0.78	**0.33**
DFM	0.84	0.75	0.77	0.84	0.78	0.85	**0.00**
Average	0.89	0.70	0.75	0.75	0.65	0.56	**0.33**
Fraction	**0.00**	**0.67**	**0.33**	**0.33**	**0.17**	**0.33**	

Export prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.01147	0.01233	0.01154	0.01149	0.01180	0.01160	
	RRMSE						Fraction
AR(1)	0.76	0.71	0.76	0.77	0.80	0.76	**0.00**
BE aver.	0.75	0.70	0.75	0.76	0.74	0.76	**0.00**
DI	0.72	0.70	0.75	0.75	0.74	0.78	**0.00**
DI_AR(1)	0.72	0.71	0.75	0.75	0.73	0.77	**0.00**
DFM	0.82	0.76	0.78	0.81	0.78	0.80	**0.00**
Average	0.77	0.70	0.74	0.73	0.68	0.59	**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 8: Direct forecasts of trade prices in national currencies: comparison for industrial countries

Import prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00912	0.01094	0.01079	0.00980	0.01067	0.01024	
	RRMSE						Fraction
AR(1)	0.82	0.71	0.72	0.79	0.86	0.79	**0.08**
BE aver.	0.84	0.71	0.72	0.79	0.73	0.76	**0.00**
DI	0.80	0.71	0.71	0.77	0.73	0.74	**0.08**
DI_AR(1)	0.80	0.71	0.72	0.77	0.72	0.73	**0.25**
DFM	0.90	0.84	0.79	0.84	0.78	0.82	**0.00**
Average	0.85	0.70	0.71	0.74	0.64	0.61	**0.50**
Fraction	**0.00**	**0.17**	**0.17**	**0.00**	**0.17**	**0.17**	

Export prices in national currency							
Horizon	1	2	3	6	9	12	
RW RMSE	0.00617	0.00629	0.00606	0.00543	0.00558	0.00571	
	RRMSE						Fraction
AR(1)	0.74	0.72	0.75	0.70	0.76	0.83	**0.00**
BE aver.	0.73	0.72	0.74	0.83	0.81	0.80	**0.00**
DI	0.72	0.70	0.75	0.80	0.81	0.78	**0.00**
DI_AR(1)	0.72	0.72	0.76	0.78	0.81	0.78	**0.00**
DFM	0.86	0.90	0.86	0.86	0.85	0.85	**0.00**
Average	0.73	0.72	0.73	0.77	0.70	0.68	**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: Fraction of cases in which top-down approaches outperform bottom-up approaches

	US	JP	CA	UK	EA	EM	
Import volumes							
AR(1)	0.25	0.92	0.33	0.50	0.42	0.75	**0.53**
BE IP	0.33	0.67	0.50	0.67	0.67	0.25	**0.51**
BE CLI	0.17	0.50	0.67	0.33	0.75	0.50	**0.49**
BE IP CLI	0.25	0.83	0.75	0.58	0.50	0.17	**0.51**
BE aver.	0.17	0.75	0.58	0.58	0.58	0.08	**0.46**
DI	0.50	0.58	0.75	0.67	0.33	0.75	**0.60**
DI_AR(1)	0.50	0.42	0.83	0.33	0.58	0.83	**0.58**
DFM	0.83	0.75	1.00	0.08	0.83	0.83	**0.72**
Average	1.00	0.67	0.67	0.42	0.67	0.42	**0.64**
	0.54	**0.67**	**0.72**	**0.40**	**0.57**	**0.72**	
Export volumes							
AR(1)	0.92	0.83	0.17	0.25	0.08	0.83	**0.51**
BE IP	0.92	1.00	0.67	0.25	0.75	0.08	**0.61**
BE CLI	0.42	0.58	0.17	0.33	0.42	0.67	**0.43**
BE IP CLI	0.83	1.00	0.42	0.17	0.25	0.00	**0.44**
BE aver.	0.58	0.92	0.33	0.17	0.17	0.00	**0.36**
DI	0.58	0.83	0.42	0.58	0.17	0.83	**0.57**
DI_AR(1)	0.83	0.67	0.67	0.67	0.58	1.00	**0.74**
DFM	0.67	0.92	0.50	0.42	0.50	0.42	**0.57**
Average	1.00	0.83	0.50	0.92	0.58	0.50	**0.72**
	0.76	**0.83**	**0.43**	**0.50**	**0.35**	**0.60**	

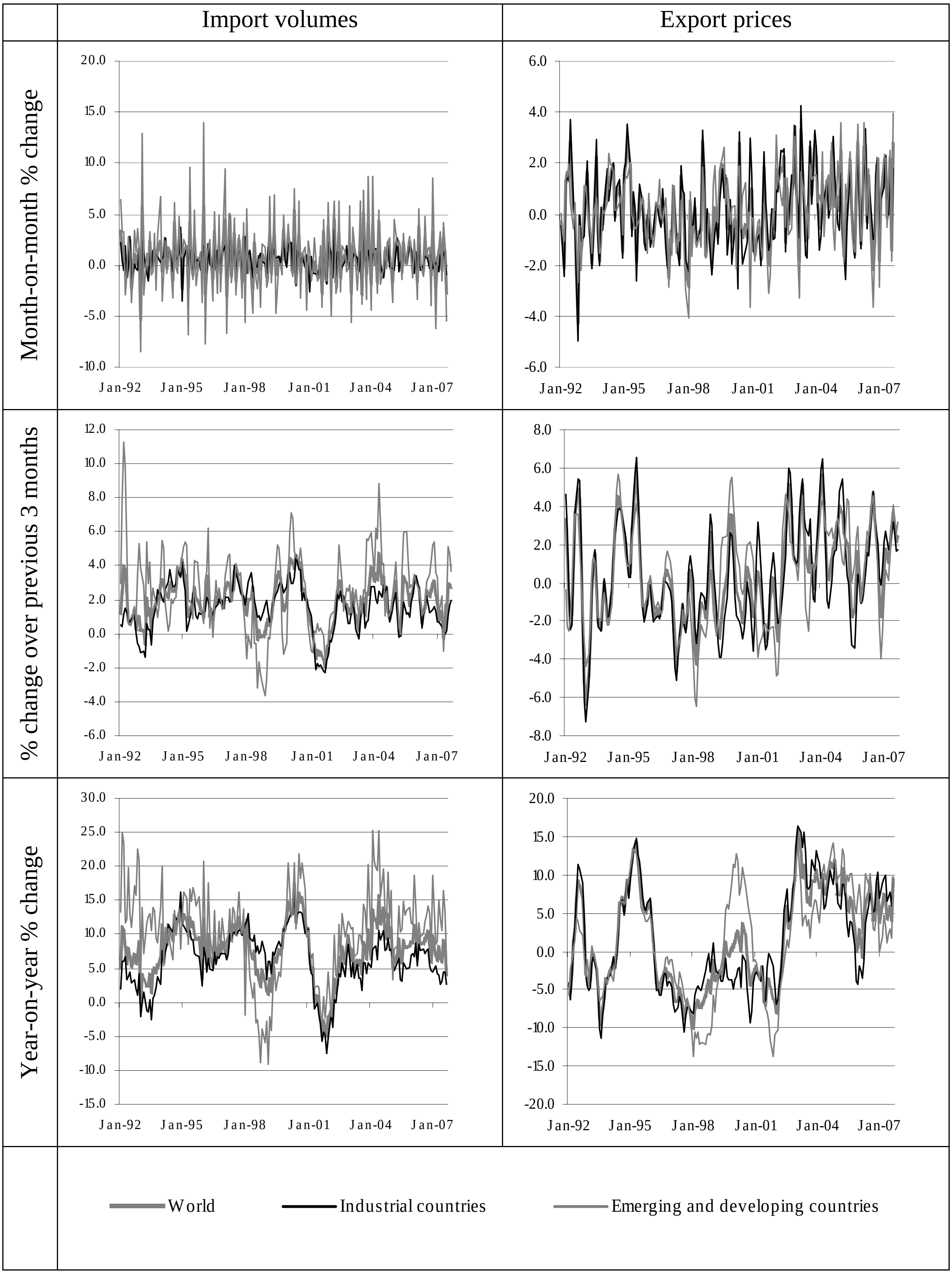

Fig. 1 – Rate of changes of import volumes and export prices.