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FORECASTING WORLD TRADE

DIRECT VERSUS "BOTTOM-UP" APPROACHES

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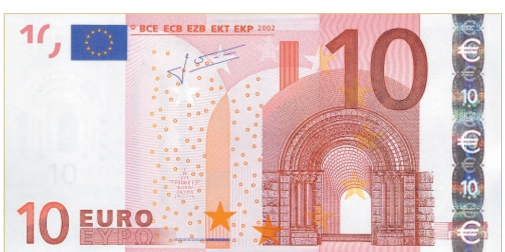

In 2008 all ECB publications feature a motif taken from the €10 banknote.

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Abstract

In a globalised world economy, global factors have become increasingly important to explain trade flows at the expense of country-specific determinants. This paper shows empirically the superiority of direct forecasting methods, in which world trade is directly forecasted at the aggregate levels, relative to "bottom-up" approaches, where world trade results from an aggregation of country-specific forecasts. Factor models in particular prove rather accurate, where the factors summarise large-scale datasets relevant in the determination of trade flows.

Keywords: *World trade, Factor models, Forecasts, Time series models.*

JEL Classification: *C53, C32, E37, F17*

NON TECHNICAL SUMMARY

Traditionally, import volumes are forecasted on a country basis by relating them to a domestic demand indicator and the forecasts for world trade result simply from an aggregation of country-specific forecasts. However, despite a positive correlation between imports and domestic demand, the growth rates of the former are much more volatile than those of the latter. Therefore, this traditional approach often yields import forecasts that are too smooth and leads to a very poor forecast performance.

Moreover, trade volumes are also influenced by many factors that are not only country-specific but also related to global developments. With increasing globalisation, it is more likely that global factors have become more predominant to explain international trade activity at the expense of country-specific traditional determinants. The development in the internationalisation of production processes, the rise in intra-firm trade and the increasing import content of export all support to have a more global view of the world trade outlook. World trade might also have a specific cycle that could differ from country-specific cycles. If world trade is synchronised more with industrial production at the world level than with country-specific activity indicators, forecasting aggregate world trade directly might give better results than aggregating country-specific forecasts.

These ideas have been applied in this paper, which presents a number of approaches to forecast monthly data for world trade and compares the relative forecasting performance of methods forecasting directly aggregate variables (direct approaches) with methods based on the aggregation of country-specific forecasts (bottom-up approaches).

This paper shows empirically the superiority of direct forecasting methods, in which world trade is directly forecasted at the aggregate levels, relative to "bottom-up" approaches, where world trade results from an aggregation of individual country forecasts. Factor models in particular prove rather accurate for short-term horizons (1 to 3 months), where the factors summarise large-scale datasets relevant in the determination of trade flows. Simple time-series models, where trade volumes depend on leading indictors of manufacturing activity outperforms other models for longer horizons (up to 12 months).

1 Introduction

Traditionally, import volumes are forecasted on a country basis by relating them to a domestic demand indicator (see for instance, Le Fouler et al., 2005)[1] and the forecasts for world trade result simply from an aggregation of country-specific forecasts.

However, despite a positive correlation between imports and domestic demand, the growth rates of the former are much more volatile than those of the latter (see Keck and Raubold, 2006). Therefore, this traditional approach often yields import forecasts that are too smooth and leads to a very poor forecast performance[2].

Moreover, trade volumes are also influenced by many factors that are not only country-specific but also related to global developments. With increasing globalisation, it is more likely that global factors have become more predominant to explain international trade activity at the expense of country-specific traditional determinants. The development in the internationalisation of production processes, the rise in intra-firm trade and the increasing import content of export all support to have a more global view of the world trade outlook. World trade might also have a specific cycle that could differ from country-specific cycles. If world trade is synchronised more with industrial production at the world level than with country-specific activity indicators, forecasting aggregate world trade directly might give better results than aggregating country-specific forecasts.

These ideas have been applied in this paper, which presents a number of approaches to forecast monthly data for world trade and compares the rela-

[1] Changes in competitiveness also influence these forecasts. However, due to their limited changes going forward (owing to the random walk assumption for exchange rates used by most forecasters), relative prices do not in practice impact significantly the trade projections beyond the very short term.

[2] Keck and Raubold (2006) show that simple time series approaches outperform forecasts based on such traditional models

tive forecasting performance of methods forecasting directly aggregate variables (direct approaches) with methods based on the aggregation of country-specific forecasts (bottom-up approaches). Overall, the results of this empirical analysis support direct approaches, which perform well in terms of forecast accuracy relative to other benchmarks.

Section 2 presents some theoretical considerations about the problem of aggregation in the forecasting literature. Section 3 presents the different forecasting models and the dataset used in the empirical analysis which is presented in Section 4. Section 5 gives some concluding remarks.

2 Aggregating Forecasts or Forecasting Aggregates: What Does the Literature Say?

The problem of aggregation in econometrics was first studied from a theoretical viewpoint by Theil (1954), who analysed the aggregation error resulting from aggregating "micro" equations. Grunfeld and Griliches (1960) extended this analysis by showing that this aggregation error can actually become an aggregation gain. They showed the existence of a relationship between micro and macro correlation coefficients. Under certain assumptions[3], they show that the necessary conditions to have higher R^2 for the aggregate equation relative to the R^2's of the micro equations is that the cross-section correlation between the errors of the micro equations is smaller than the cross-section correlation of the explanatory variables of the micro equations. In this case, the aggregate equation shows a higher R^2 than those of the micro equations.

The issue of comparing forecast performance of methods forecasting the

[3] All micro units have the same parameters, the variance of the explanatory variables in the micro equations is the same, the cross-section correlation of the explanatory variable is the same for all pairs of micro units and the cross-section correlation of the micro equations errors is also the same for all pairs of micro units. Most of these assumptions can be relaxed without affecting the conclusions (see appendices in the Grunfeld and Griliches paper).

components of an aggregate variable and aggregating such forecasts, as against directly forecasting the aggregate has also been widely studied in the literature. Lütkepohl (1987) shows that if the data generation process (DGP) is known, disaggregation as much as possible results in optimal forecasts. In practice, however, this condition is always violated and estimated processes for forecasting have to be used. Lütkepohl (1987) also shows that aggregating forecasts of the individual components is optimal if the components of the disaggregated system are uncorrelated. In other cases, the direct forecast of the aggregate might be superior to the aggregation of the individual components' forecasts.

In practice, the issue remains largely empirical in nature. The empirical studies of this issue have been applied to macroeconomic aggregates, where the components are sub-indices of the aggregate measure, like a price index, or the microeconomic data of a macroeconomic variable, like the different firms or sectors of a real variable. Empirical studies also focus on geographical aggregates, where the components are states, countries or regions. For instance, Marcellino, Stock and Watson (2003) show that, in the case of forecasting euro area-wide inflation and real activity, forecasts constructed by aggregating the country-specific models are more accurate than forecasts constructed using the aggregate data.

3 Forecasting models and data

We investigate several time series methods for forecasting world trade and consider empirically whether it is better to build aggregate trade forecasting models, or whether there are gains from aggregating country-specific forecasts. Our empirical analysis is made at two different levels of aggregation. In a first step, we aggregate country trade data for industrial countries only and compare the aggregation of country-specific forecasts with the forecasts of the aggregated series. In a second step, we perform a similar exercise by including trade data for emerging markets. Owing to data availability issues, the emerging markets are treated as a single block. By taking into account such data, we can extend our analysis to world trade.

3.1 Forecasting models

To ensure the robustness of our analysis, we use and compare several forecasting models. We estimate first auto-regressive models, which serve as benchmarks for the other models. We also estimate simple linear models that depend only on Industrial Production and Composite Leading Indicators (CLIs). Finally, factor models are estimated, where the factors are extracted out of a large set of predictors. 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 (linear models) or via a statistical analysis without any theoretical basis (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.

Forecasts are made at forecast horizons of one, three, six and twelve months. Following Marcellino, Stock and Watson (2003), all models are specified and estimated as a linear projection of a h-step ahead variable, M^h_{t+h} onto t-dated predictors. In other words, different models are set up for each individual forecast horizon ($h = 1, 3, 6, 12$) and used to predict explicitly at time t the variable to be forecasted at horizon $(t + h)$ based on the information available at time t. This so-called "h-step ahead projection" approach contrasts with approaches usually applied in literature. Standard approaches consist in estimating one-step-ahead models and then iterating that model to obtain the "h-step-ahead" forecast. The h-step ahead method has mainly two advantages compared with the standard approach. First, it implies less forecasting work, since the predictor series themselves do not have to be forecasted. Second, as a consequence, one does not have to face the problem of cumulated forecast errors.

The theoretical literature underlines the robustness and bias reduction of the "h-step ahead" forecasts in contrast to the special parametric, finite-lag assumptions that underlie optimality properties for the iterated forecasts (e.g. Bhansali, 1999 and Ing, 2003). However, it appears that, empirically (Marcellino, Stock and Watson, 2006), the robustness and bias reduction obtained using the "h-step ahead" forecasts have to be balanced with the price paid in terms of increased sampling variance. This tradeoff is nevertheless irrelevant for our purposes of comparing aggregation of forecasts and forecasts of aggregates as the forecasting approach is the same across methods.

3.1.1 Auto-regressive models

The AR-model has the form:

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d \ln(M_t) + \varepsilon_t \tag{1}$$

where M_t is the import volumes of goods at t, $d\ln(M_t)$ is the first log difference of M_t and $\Gamma(L)$ is a scalar lag polynomial. ε_t is the error term.

The dependent variable of model (1) is represented by the log-difference at horizon h of monthly import data, i.e. the growth rate between t and $t+h$. The regressors on the right side, however, are represented only by first log differences, i.e. the growth rate between the periods $t-1$ and t. Although the auto-regressive technique in model (1) differs substantially from the standard definition in literature of an auto-regressive model, we will nevertheless call it AR-model, following Marcellino, Stock and Watson (2003). The number of lags to be included in the model is fixed a priori to 3 lags[4].

3.1.2 Simple linear models

The second type of models used are simple linear models that depend on indicators or variables that have proved to have some leading properties in forecasting trade variables[5]. The indicators used in theses models are Industrial Production (IP) and the Composite Leading Indicator (CLI) provided by the OECD. The models have a form as follows:

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d \ln(M_t) + \Phi(L) d \ln(X_t^1) + \varepsilon_t \qquad (2)$$

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d \ln(M_t) + \Phi(L) d \ln(X_t^2) + \varepsilon_t \qquad (3)$$

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d \ln(M_t) + \Phi(L) d \ln(X_t^3) + \varepsilon_t \qquad (4)$$

where $X_t^1 = (IP)$; $X_t^2 = (CLI)$; $X_t^3 = (IP, CLI)$ and $\Gamma(L)$ and $\Phi(L)$ are scalar lag polynomials. ε_t is the error term.

We decide furthermore to include lagged values of the dependent variable on the right side of models (2), (3) and (4). The number of lags in these models has also been fixed to 3 lags, which is in most cases consistent with the optimal lag order selected using an information criteria (BIC).

3.1.3 Factor Models

The factor-model forecasts are based on setting the regressors to be the principal components of a large number of predictor series. The goal of a factor analysis is actually to extract a maximum of information out of a panel of time series. It is

[4] Alternatively, we have used an information criteria (BIC) to select the optimal lag order. However, for some countries, the number of lags varying too much from a period to another, we have prefered fixing ex-ante the number of lags, avoiding results that were otherwise difficult to justify.

[5] We are grateful to Gerard van Welzenis for suggesting this type of models.

a way to sum up the enormous amount of information that can be found in the series and extract common trends that are likely to drive the dependent variable. The literature on factors models suggest different methods of extracting the factors (for a survey, see Kapetanios and Marcellino (2003)). Here, we use the method suggested by Stock and Watson (2002a, 2002b), consisting in a Principal Components Analysis on the series, which means that the k factors used are the eigenvectors associated to the k largest eigenvalues of the contemporaneous variance-covariance matrix of the series.

The following four types of factor models are applied:

$$\ln(M_{t+h}) - \ln(M_t) = \phi F_t + \varepsilon_t \quad (5)$$

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d\ln(M_t) + \phi F_t + \varepsilon_t \quad (6)$$

$$\ln(M_{t+h}) - \ln(M_t) = \Phi(L) F_t + \varepsilon_t \quad (7)$$

$$\ln(M_{t+h}) - \ln(M_t) = \Gamma(L) d\ln(M_t) + \Phi(L) F_t + \varepsilon_t \quad (8)$$

where F_t denotes the factor matrix, $\Gamma(L)$ and $\Phi(L)$ are scalar lag polynomials. ε_t is the error term.

Model (5) represents the simple factor model which includes only the factors. We fix the number of factors to be applied to four[6]. Model (6) takes into account the lagged structure of the variable to be explained. Model (7) imposes a lagged structure among the factors. We include therefore the four factors, this time, each with two lags. By including the lagged factors, we allow in this model for some dynamics in the factors. Nevertheless, this method should not in every case be confused with the dynamic factor models (see Forni, Hallin, Lippi and Reichlin (2000 and 2005)). However, Stock and Watson (1998) show under certain conditions the equivalence between principal components forecasts and

[6]The choice of the number of factors follows the selection criteria determined by Bai and Ng (2002).

dynamic factor models. In model (8) we include lagged dependent variables to the previous model.

3.2 Data

We use a large database including information on a monthly basis to explain trade developments over the period 1991:1 - 2006:4. 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[7].

- Country-specific macroeconomic and financial data (explanatory variables): The country-specific macroeconomic data are represented by OECD's Composite Leading Indicators, other composite indicators, 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 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[8].

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

[8] 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.

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

Overall, the dataset includes 171 series at the industrial countries' level and 352 series at the world level[10].

Before using the data for forecasting purposes, we have made several transformation. First, the stationarity properties of the series have been checked. As reported in Table 1, the dependent variables are all stationary. Unit roots have also been tested for all series used as explanatory variables[11]. If not stationary, the series have been transformed as first log-difference in the case of

[9] 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.

[10] Further information on the dataset is available upon request.

[11] Unit root test results are available upon request.

non-negative series that are not already in percentage rates (real series and indices). Negative series and series in percentage rates have been transformed by applying first differences (interest rates and labour market series).

[TABLE 1 HERE]

Second, we have checked the seasonal patterns in the series. As only part of the raw series is seasonally adjusted, a harmonization of the seasonal adjustment has been necessary. As a consequence, we have decided to treat all the series, whether already seasonally adjusted, or not, in the same way. All the series have gone through a two step-seasonal adjustment procedure. In a first step, we have regressed the series against eleven monthly indicators and a constant. In a second step, based on the results a Fisher test for joint nullity of the coefficients, the seasonal adjustment procedure has been applied in the eight steps suggested by Wallis (1974).

Third, the series, after transformation and seasonal adjustment, have been adjusted for outliers, omittimg observations that exceed six times the interquartile range, treated subsequently as missing values. The proportion of outliers remain however very marginal, as around 3% of the observations are treated as such (less than 1% for industrial countries and less than 5% for emerging markets).

3.3 Estimation and forecast aggregation

We estimate separately forecasting models for countries (US, Japan, euro area, UK and Canada) and for emerging markets. For the estimation of country/region-specific factor models, the factors are extracted out of a panel of country-specific series and global series. For the aggregate factor models, we estimate models using factors extracted out of the whole database, including also country-specific information. The advantage of the latter method is that a wider set of information can be included to determine the factors, since all the country-specific series are taken into account for the determination of the factors. Moreover, as the Principal Component Analysis provides composite indicators – the factors –, we do not need in principle to aggregate country-specific series. However, to check the importance of disaggregate information when forecasting aggregate variables, we also envisage, as a robstness check, cases where the factors are extracted only from aggregated series (results are also reported in Section 4).

To deal with non-available data or different dates in data releases, we use the method suggested by Stock and Watson (1998), applying the Expectation Maximisation algorithm (thereafter EM algorithm) to extract factors out of an unbalanced panel. 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, using the factors obtained from the previous step, until the regressors have converged.

Finally, we compute bottom-up forecasts for the aggregate series, by aggregating the country/region-specific forecasts using the same weighting scheme applied to the CPB trade series (based on country shares in total trade).

4 Empirical Results

The empirical analysis is conducted in three steps. First, we start computing cross-country correlations to check whether it is optimal or not to aggregate country-specific trade forecasts. Second, we compute model quality measures to check whether the quality of aggregate models is higher than that of the country-specific ones. Finally, we perform forecast performance tests between direct models and bottom-up approaches.

4.1 Correlations between countries and aggregate

As seen in the previous section, some results of the theory of aggregation in econometrics are related to the degree of correlation between the sub-components of an aggregate. More precisely, Lütkepohl (1987) shows that in univariate models, predictors that originate in pooling disaggregate predictions are optimal, if the components of the disaggregate system are uncorrelated. By showing strong correlations between the country-specific trade data, this assumption would be invalid and the optimality of bottom-up forecasts could be questioned. Therefore, preliminary to a more comprehensive econometric analysis, we start with a simple statistical analysis of the correlation between the different trade series. Such an analysis would also allow us to draw some first conclusions on the links between the trade series of the different countries and regions. Table 2 shows the correlations between growth rates of import volumes across the different countries and regions on the sample 1991:1 - 2006:4. It also includes the correlations with respect to the aggregates (industrial countries and world).

[TABLE 2 HERE]

Table 2 shows that the correlation across countries is overall high (0.44 on average), especially between traditional trade partners, like the US and Canada (0.80). Similarly, the correlation between the United Kingdom and the euro area is much higher than the average (0.61). The correlations between Japan and the other industrial countries are noticeably lower than the overall average (between 0.23 and 0.35) and all the industrial countries have their lowest correlations with

Japan. A possible explanation for the low correlation of the Japanese trade with the other industrial country trade might be explained by the large share of other Asian economies in the Japanese trade, as shown by the high correlation with emerging markets.

Interestingly, the cross-section correlations are stronger between the country-specific and the aggregates' import volume growth rates (around 0.7 on average at the industrial countries and world levels), confirming our prior beliefs that trade appears to be driven by global rather than country-specific factors. Based only on a correlation analysis, forecasting methods based on direct approaches are therefore likely to provide good models of trade developments.

4.2 Model performance

As seen in Section 2, Grundfeld and Griliches (1960) show that under certain assumptions, aggregate R^2s are higher than those of the disaggregate equations if the cross-section correlation between errors of the disaggregate equations are smaller than the cross-section correlation of the explanatory variables.

[TABLES 3 AND 4 HERE]

Tables 3 and 4 give cross-section correlations for a sample of country-specific models at a one-month horizon (model (3) and model (5))[12]. The large figures indicate the average cross-section correlations between country-specific explanatory variables. The small figure indicates the cross-section correlation between models' errors estimated over the sample 1992:01-2006:04.

In all the cases, the correlation between regressors is higher than the correlation between the errors. These results are therefore in line with the Grunfeld-Griliches conditions to obtain higher R^2 for the aggregate equations relative to those of the country-specific ones.

[12] Cross-section correlations corresponding to the other models and other horizons are available upon request. They confirm the results presented here.

[TABLE 5 HERE]

Table 5 confirms the theoretical findings by Grunfeld and Griliches (1960). The adjusted R^2 at the aggregate levels are on average higher than at the country-specific levels. Empirically, we show then that when the pair-wise correlations of the explanatory variables is higher than those of the errors, aggregated models are likely to have a higher goodness-of-fit than country-specific ones.

Such a result gives us some interesting indications supporting direct approaches at the expense of bottom-up ones. However, it is far from being conclusive in what concerns the forecasting performance of the different approaches. This aspect is studied next.

4.3 Forecasting performance

In order to measure the forecasting performance of our models we compute the Root Mean Square Forecast Error (RMSFE) of the different models[13]. We chose as benchmarks the AR models estimated for the aggregates (AR - direct) and report results for the other models relative to this benchmark. Therefore, when a model outperforms the AR benchmark, the relative RMFSE is lower than 1. Each model (models (1) to (8)) is estimated at the aggregate level (for industrial countries first and for the world as the whole thereafter) and at the country-specific level. Country-specific forecasts are thereafter aggregated to obtain bottom-up forecasts. These bottom-up forecasts are then compared with the aggregate forecasts (direct methods)[14]. In the forecast performance comparison, we also indicate the levels of significance of the difference between the candidate forecast models and the benchmark by using the test statistics suggested by

[13] We also computed Mean Absolute Forecast Errors (MAFE). For the sake of readibility of the result tables, we do not present such statistics. They are however available upon request.

[14] The out-of-sample forecasting exercise has not been conducted using real-time data (i.e. publication lags in the series have not been taken into account when conducting the exercise). Such real-time data are not available for the series used in this paper.

Diebold and Mariano (1995). As the Diebold-Mariano tests are only valid for the comparison of non-nested models, we use the out-of-sample F (or OOS-F) statistics (see West, 2006, and McCracken,2004) and the corresponding critical values reported in McCracken (2004), when comparing a model including an AR term with the AR benchmark model. The OOS-F test is indeed the right test when comparing the predictive ability of two nested models.

4.3.1 Results at the level of industrial countries

Table 6 indicates the forecast results at the industrial economies' level for the four different horizons.

[TABLE 6 HERE]

In line with the prediction that the forecast accuracy deteriorates with the length of the forecast horizon (Dua, 1988), the RMSFE for the benchmark model increases with the horizon. In most cases (51 out of 60), the proposed models perform better than the benchmark AR, especially for horizons higher than one month. Except the bottom-up model with industrial production (model (2) - bottom-up), all models outperform the benchmark for horizons 3, 6 and 12. Moreover, among the factor models, the models including the lagged dependent variable (models (6) and (8)) perform slightly better than those excluding it. In particular, in 11 cases out of 16, the factor model that includes the lagged dependent variable performs better than the "pure" factor model (model (5)). Interestingly, 3 out of the 4 best-performers per horizon come from the static factor models including lags in the factors (models (7) and (8)). In particular, "model (8) - direct" outperforms all the models at horizons 1 and 6 and "model (7) - direct" is the best performer at a 3-month horizon. The best-performer for the one year ahead horizon can be found among the linear models (model (3) - direct).

From the perspective of comparing the performance of direct vs. bottom-up approaches, we find that in most cases the relative RMSFE of the direct forecasts are smaller than those of the bottom-up ones. In 27 cases out of 32, the forecasts of the aggregate performs better than the aggregate of the forecast. Especially for horizons higher than 1 month, the performance of the direct approach seems to be even more clear-cut.

Overall, we can conclude that the proposed models perform better than the benchmark AR model and that the forecasting performance of the factor models is relatively good. Moreover, the longer the horizon, the less important the lagged dependant variable among the explanatory variables becomes, as the RMSFE of models (6) and (8) seem to converge for long horizons to that of the factor models (5) and (7). Finally, the superiority of the direct approach is verified in most cases.

Figure 1 shows a simple time plot of the actual and the forecast values for various models, illustrating the ability of the forecast models to capture (especially for short horizons) the main turning points of the series in the sampling period.

4.3.2 Results at the world level

Table 7 shows the results for the out-of-sample forecasts at the world level.

[TABLE 7 HERE]

As observed previously for industrial countries, the forecasting performance of all the proposed models, is in most cases better compared to the benchmark (53 out of 60 cases). Also, in 11 cases out of 16 the factor models with the lagged dependent variable (models (6) and (8)) performs better than the factor models excluding it (models (5) and (7)).

As regards the conclusions in terms of direct vs. bottom-up approach comparison, the results are more mixed, as on the one hand, we cannot show the superiority of direct approaches for the linear models (models (2) to (4)) while, on the other hand, the factor-model based forecats of the aggregates outperforms in all cases the aggregation of the forecasts (models (5) to (8)).

The best performers per horizon for the short-term (one to three months ahead) can again be found among the factors models with a lagged structure on the factors (models (7) and (8)). For the medium-term (half a year to one year), the linear model with industrial production and CLI (model (4)) performs slightly better than the factor models.

The conclusions at the world level are therefore somewhat weaker than those obtained at the industrial countries' level. Nevertheless, among the factor models, the direct approach still seems to be superior to the bottom-up one. Similarly to Figure 1, Figure 2 gives a time plot of the actual and the forecast values for various models at the world level, confirming the visual demonstration of the ability of the models to forecast relatively well the main turning points.

4.3.3 The role of disaggregate information in forecasting aggregates with factor models

In the previous analysis, the factor models used to forecast aggregate variables were based on a large set of indicators including disaggregate information (i.e. country-specific indicators). Hendry and Hubrich (2006) show that disaggregate information should usually improve predictability. Lütkepohl (1987) also shows that the relative forecast efficiency increases in general if disaggregate data is used for estimating the process of an aggregated variable. To assess the role of disaggregate information, we also estimate models using factors extracted only from aggregated series. For data availability reasons, we restrict such an analysis to forecasts at the industrial countries' level. The aggregated series for industrial countries are indicators computed by the OECD. Overall, 29 indicators are available at the OECD aggregate level. They cover most macroeconomic and financial series as described in Section 3.2. In order to make the forecast performance comparable across methods, we had to reduce the data coverage at the country level to match exactly the number of indicators available at the aggregate level. Using this information set, we perform forecast comparisons between three different methods: (1) Direct using disaggregate information, (2) Direct using aggregate information, and (3) Bottom-up. Cases (1) and (3) correspond to those studied above. Only approach (2) is added to check whether restrincting the information set to aggregated variables changes the previous results.

[TABLE 8 HERE]

Table 8 reports the forecast results at the industrial economies' level using these three approaches[15]. In 11 cases out of 16, the direct method using disaggregate information outperforms the two other approaches and in 10 cases out of 16, the direct method using aggregate information outperforms the bottom-up one. In line with Hendry and Hubrich (2006) or Lütkepohl (1987), these results show therefore that using disaggregate information improves the forecast performance of the direct approaches. The overperformance of direct approaches with respect to bottom-up ones remains however valid whatever information set used.

5 Conclusion

In a globalised world economy, global factors have become increasingly important to explain trade flows at the expense of country-specific determinants. This paper shows empirically the superiority of direct forecasting methods, in which world trade is directly forecasted at the aggregate levels, relative to "bottom-up" approaches, where world trade results from an aggregation of individual country

[15] In the table, cases (1), (2) and (3) are labelled respectively "direct with disaggr", "direct with aggr" and "bottom-up".

forecasts. Factor models in particular prove rather accurate for short-term horizons (1 to 3 months), where the factors summarise large-scale datasets relevant in the determination of trade flows. Simple time-series models, where trade volumes depend on leading indictors of manufacturing activity outperforms other models for longer horizons (up to 12 months).

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Table 1: ADF (1st line) and KPSS (2nd line) Tests for Dependent Variables

	World	IC	US	Japan	Canada	euro area	UK	EM
$\ln(M_t) - \ln(M_{t-1})$	-3.99	-4.17	-4.56	-4.61	-4.07	-3.82	-8.08	-3.70
	0.06	0.08	0.40	0.06	0.28	0.10	0.07	0.07
$\ln(M_t) - \ln(M_{t-3})$	-4.24	-3.25	-3.91	-2.69	-4.41	-3.65	-3.90	-3.81
	0.06	0.08	0.35	0.07	0.26	0.09	0.07	0.07
$\ln(M_t) - \ln(M_{t-6})$	-3.46	-3.49	-3.35	-2.46	-3.58	-4.17	-2.97	-4.11
	0.06	0.09	0.34	0.06	0.23	0.10	0.09	0.07
$\ln(M_t) - \ln(M_{t-12})$	-4.28	-3.82	-3.85	-3.57	-2.65	-2.60	-2.52	-3.08
	0.07	0.11	0.44	0.07	0.27	0.11	0.12	0.10

Critical values	1%	5%	10%
ADF	-3.43	-2.86	-2.57
KPSS	0.74	0.46	0.35

Note: IC: Industrial countries; EM: Emerging markets.
For the Augmented Dickey-Fuller (ADF) test, the null hypothesis is: the series has a unit root.
For the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, the null hypothesis is: the series is stationary. See Kwiatkowski et al. (1992).

Table 2: Cross-section correlations for import volume growth rates

	World	IC	US	Japan	Canada	euro area	UK	EM
World	1.000							
IC	0.874	1.000						
US	0.704	0.777	1.000					
Japan	0.538	0.493	0.297	1.000				
Canada	0.682	0.711	0.803	0.230	1.000			
euro area	0.774	0.935	0.547	0.346	0.531	1.000		
UK	0.604	0.620	0.462	0.244	0.324	0.612	1.000	
EM	0.758	0.348	0.345	0.370	0.376	0.297	0.339	1.000

Note: IC: Industrial countries; EM: Emerging markets.

Table 3: Cross-section correlation across regressors (large) and residuals (small) over the sample 1992:01-2006:04 for model (3) at horizon 1

	US	Japan	Canada	euro area	UK	EM
US	1.00					
	1.00					
Japan	0.20	1.00				
	-0.01	1.00				
Canada	0.62	0.19	1.00			
	0.14	0.04	1.00			
euro area	0.45	0.39	0.38	1.00		
	-0.03	0.05	0.18	1.00		
UK	0.42	0.34	0.29	0.35	1.00	
	0.02	-0.09	0.08	0.28	1.00	
EM	0.34	0.43	0.36	0.39	0.31	1.00
	-0.04	0.07	0.11	0.32	0.22	1.00

Note: EM: Emerging markets.

Table 4: Cross-section correlation across regressors (large) and residuals (small) over the sample 1992:01-2006:04 for model (5) at horizon 1

	US	Japan	Canada	euro area	UK	EM
US	1.00					
	1.00					
Japan	0.84	1.00				
	0.16	1.00				
Canada	0.76	0.64	1.00			
	0.27	-0.02	1.00			
euro area	0.85	0.73	0.78	1.00		
	0.13	0.17	0.21	1.00		
UK	0.78	0.71	0.85	0.83	1.00	
	0.15	0.14	0.09	0.47	1.00	
EM	0.81	0.79	0.80	0.82	0.84	1.00
	0.21	0.00	0.11	0.26	0.23	1.00

Note: EM: Emerging markets.

Table 5: Adjusted R2 of aggregate and disaggregate models over the sample 1992:01-2006:04

	Horizons	World	IC	US	Jap.	Can.	EA	UK	EM
AR model (1)	1	0.36	0.50	0.44	0.29	0.43	0.51	0.24	0.28
	3	0.19	0.27	0.14	0.01	0.08	0.25	0.00	0.05
	6	0.22	0.28	0.15	0.01	0.08	0.25	0.00	0.08
	12	0.04	0.08	0.04	0.00	0.02	0.08	0.00	0.01
Linear Model (2)	1	0.36	0.53	0.51	0.32	0.50	0.51	0.26	0.27
	3	0.41	0.39	0.29	0.05	0.25	0.35	0.00	0.22
	6	0.39	0.39	0.33	0.10	0.17	0.35	0.00	0.18
	12	0.13	0.16	0.21	0.02	0.04	0.15	-0.02	0.03
Linear model (3)	1	0.28	0.48	0.48	0.34	0.47	0.51	0.23	0.26
	3	0.43	0.38	0.25	0.12	0.26	0.46	-0.01	0.26
	6	0.57	0.50	0.35	0.21	0.34	0.63	-0.01	0.35
	12	0.52	0.46	0.32	0.30	0.26	0.58	-0.01	0.27
Linear model (4)	1	0.36	0.55	0.51	0.34	0.53	0.53	0.25	0.27
	3	0.50	0.48	0.33	0.12	0.39	0.47	-0.01	0.26
	6	0.61	0.58	0.45	0.23	0.38	0.62	-0.02	0.35
	12	0.51	0.48	0.37	0.28	0.27	0.57	-0.02	0.28
Factor model (5)	1	0.21	0.28	0.17	0.02	0.11	0.21	0.00	0.13
	3	0.45	0.44	0.24	0.06	0.23	0.32	0.00	0.33
	6	0.55	0.42	0.35	0.17	0.33	0.36	0.02	0.48
	12	0.51	0.35	0.22	0.20	0.23	0.36	0.02	0.48
Factor model (6)	1	0.44	0.55	0.47	0.28	0.44	0.54	0.27	0.33
	3	0.47	0.40	0.28	0.06	0.23	0.41	0.00	0.33
	6	0.57	0.50	0.24	0.06	0.23	0.32	0.00	0.48
	12	0.52	0.36	0.21	0.19	0.22	0.37	0.01	0.48
Factor model (7)	1	0.40	0.41	0.22	0.20	0.25	0.35	0.00	0.30
	3	0.56	0.53	0.37	0.18	0.36	0.48	0.01	0.36
	6	0.59	0.48	0.46	0.26	0.48	0.47	0.02	0.51
	12	0.51	0.35	0.30	0.22	0.26	0.39	-0.02	0.48
Factor model (8)	1	0.57	0.59	0.49	0.38	0.49	0.58	0.29	0.42
	3	0.55	0.54	0.39	0.18	0.37	0.50	0.02	0.36
	6	0.60	0.52	0.47	0.26	0.48	0.50	0.02	0.51
	12	0.51	0.35	0.30	0.21	0.25	0.39	-0.02	0.49
Average		0.43	0.42	0.32	0.18	0.29	0.42	0.05	0.31

Table 6: Results for simulated out of sample forecasts for industrial country import volumes

Models	Horizons			
	1	3	6	12
	RMSFE			
AR model (1) - direct	0.0041	0.0140	0.0269	0.0538
	RMSFE relative to AR model (1) - direct			
AR model (1) - direct	1.000	1.000	1.000	1.000
AR model (1) - bottom-up	1.025	1.021	1.033**	1.023**
Linear model (2) - direct	0.960	0.931†	0.964	0.981
Linear model (2) - bottom-up	0.960	0.948	1.019	1.051
Linear model (3) - direct	0.967	0.902††	0.806††	0.773††
Linear model (3) - bottom-up	0.965	0.928*	0.900**	0.854**
Linear model (4) - direct	0.940	0.875††	0.826††	0.802††
Linear model (4) - bottom-up	0.941	0.887**	0.872**	0.852**
Factor model (5) -direct	1.244**	0.838**	0.853**	0.849**
Factor model (5) -bottom-up	1.336**	0.946	0.916*	0.878**
Factor model (6) -direct	0.952††	0.825††	0.827††	0.859††
Factor model (6) -bottom-up	0.998	0.894**	0.878**	0.888**
Factor model (7) -direct	1.129**	0.764**	0.830**	0.882**
Factor model (7) -bottom-up	1.224**	0.841**	0.827**	0.850**
Factor model (8) -direct	0.910††	0.773††	0.814††	0.887††
Factor model (8) -bottom-up	0.980	0.839**	0.820**	0.868**

Note: *, ** difference significant at resp. 10 and. 5 % (Diebold-Mariano); †,†† unrestricted model performs significantly better at 10 resp. 5% (McCracken).

Table 7: Results for simulated out of sample forecasts for world import volumes

Models	Horizons			
	1	3	6	12
	RMSFE			
AR model (1) - direct	0.0049	0.0144	0.0264	0.0506
	RMSFE relative to AR model (1) - direct			
AR model (1) - direct	1.000	1.000	1.000	1.000
AR model (1) - bottom-up	0.989	1.011	1.025**	1.016**
Linear model (2) - direct	$0.899^{\dagger\dagger}$	$0.876^{\dagger\dagger}$	$0.916^{\dagger\dagger}$	$0.952^{\dagger\dagger}$
Linear model (2) - bottom-up	0.862**	0.855**	0.919**	0.997
Linear model (3) - direct	$0.941^{\dagger\dagger}$	$0.829^{\dagger\dagger}$	$0.736^{\dagger\dagger}$	$0.764^{\dagger\dagger}$
Linear model (3) - bottom-up	0.902**	0.814**	0.714**	0.733**
Linear model (4) - direct	$0.897^{\dagger\dagger}$	$0.793^{\dagger\dagger}$	$0.755^{\dagger\dagger}$	$0.784^{\dagger\dagger}$
Linear model (4) - bottom-up	0.864**	0.782**	0.708**	0.709**
Factor model (5) -direct	1.116**	0.814**	0.801**	0.802**
Factor model (5) -bottom-up	1.182**	0.911**	0.876**	0.850**
Factor model (6) -direct	$0.926^{\dagger\dagger}$	$0.805^{\dagger\dagger}$	$0.776^{\dagger\dagger}$	$0.793^{\dagger\dagger}$
Factor model (6) -bottom-up	0.958	0.883**	0.855**	0.853**
Factor model (7) -direct	1.050**	0.767**	0.800**	0.782**
Factor model (7) -bottom-up	1.143**	0.876**	0.877**	0.920**
Factor model (8) -direct	$0.843^{\dagger\dagger}$	$0.769^{\dagger\dagger}$	$0.790^{\dagger\dagger}$	$0.794^{\dagger\dagger}$
Factor model (8) -bottom-up	0.998	0.879**	0.875**	0.929*

Note: *, ** difference significant at resp. 10 and. 5 % (Diebold-Mariano); †,†† unrestricted model performs significantly better at 10 resp. 5% (McCracken).

Table 8: Results for simulated out of sample forecasts for industrial countries' import volumes - factor models using different information set

Models	Horizons			
	1	3	6	12
	RMSFE relative to AR model (1) - direct			
Model (5) -direct with disaggr	1.211	0.842	0.842	0.813
Model (5) -direct with aggr	1.242	0.877	0.860	0.851
Model (5) -bottom-up	1.265	0.882	0.861	0.831
Model (6) -direct with disaggr	0.948	0.838	0.825	0.824
Model (6) -direct with aggr	0.958	0.854	0.830	0.871
Model (6) -bottom-up	0.969	0.851	0.838	0.842
Model (7) -direct with disaggr	1.178	0.839	0.835	0.826
Model (7) -direct with aggr	0.972	0.840	0.818	0.873
Model (7) -bottom-up	0.982	0.850	0.810	0.842
Model (8) -direct with disaggr	0.922	0.855	0.831	0.840
Model (8) -direct with aggr	1.167	0.832	0.823	0.864
Model (8) -bottom-up	1.212	0.844	0.807	0.824

Note: "direct with disaggr", "direct with aggr" and "bottom-up" corresponds to respectively cases (1), (2) and (3) in the main text.

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