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Direct vs bottom–up approach when forecasting GDP: Reconciling literature results with institutional practice[☆]

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A B S T R A C T

How should we forecast GDP? Should we forecast directly the overall GDP or aggregate the forecasts for each of its components using some level of disaggregation? The search for the answer continues to motivate several horse races between these two approaches. Nevertheless, independently of the results, institutions producing short-term forecasts usually opt for a bottom–up approach. This paper uses an application for the euro area to show that the option between direct and bottom–up approaches as the level of disaggregation chosen by forecasters is not determined by the results of those races.

1. Introduction

The level of disaggregation underlying an economic forecast is regularly analysed in the literature, by comparing the performance of forecasting directly the targeted variable or aggregating the best forecasts for each of its components. Overall, the literature results depend clearly on the problem under review and thus no general consensus has been reached.

Nonetheless, economic forecasters do not always face this problem. When producing medium-term scenarios, the level of the disaggregation depends clearly of the structural model in use. Different models are used to build different simulations, and thus the option to forecast directly GDP is not even discussed. This dilemma occurs when producing nowcasts (the current quarter) and short-term forecasts (the next one or two quarters), which is done using two main types of models: (i) bridge models; and (ii) factor models.

Bridge models can be seen as a toll to translate the information content of timely short-term indicators into the national accounts variables. Examples of the bridge models can be founded in Ingenito and Trehan (1996) for the US, Zheng and Rossiter (2006) for Canada, Parigi and Schlitzer (1995) and Golinelli and Parigi (2005) for Italy, Barhoumi et al. (2011) for France, Grasmann and Keereman (2001), Rünstler and Sédillot (2003) and Diron (2006) for the euro area; Baffigi et al. (2004) for France, Germany, Italy and the euro area and Sédillot and Pain (2003) for several OECD countries.

Factor models try to explore very large dimensional databases, extracting a few common factors that are able to explain the variable to be forecasted. After the seminal papers of Stock and Watson (1998, 1999), the use of these models is increasing given the developments on economic literature. Among others, some application both to forecast GDP and inflation could be founded in Stock and Watson (1999, 2002) for the US, Marcelino et al. (2003) and Angelini et al. (2008) for the euro area, Artis et al. (2005) for the UK, Schumacher (2007) for Germany, Bruneau et al. (2007) for France, Van Nieuwenhuyze (2005) for Belgium, and Duarte and Rua (2007) for Portugal. Rünstler et al. (2009) evaluate the application of factor models for ten European countries.

In both type of models it is possible to opt for a direct or bottom–up approach, and some papers compare their relative performance. Concerning GDP short-term forecasting, the available empirical results for some European countries and the euro area as a whole using the traditional bridge model approach tend to favour the direct forecast instead of an aggregation of forecasts of its main components Baffigi et al. (2004) and Hahn and Skudelny (2010).[1] Using factor models, Perevalov and Maier (2010) point to a small gain when forecasting US economic activity as the sum of individual forecasts for expenditure components.

Nevertheless, institutions producing short-term forecasts usually rely on the bottom–up approach, namely based on expenditure components. The reason is easy to understand. When producing and presenting a scenario, forecasters must be able to explain what is behind the GDP figure, allowing for a better understanding of current developments and helping to build medium-term forecasts.

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[1] Concerning the benefits of a disaggregated approach based on individual country forecasts, the results available for the euro area are mixed. Both Marcelino et al. (2003) and Baffigi et al. (2004) report that aggregating country specific forecasts is in general more accurate than forecasting the aggregated data. In contrast, dealing with industrial production, Bodo et al. (2000) conclude that the aggregate model for the euro area performs better than the disaggregated approach.

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This paper revisits this issue, presenting an application for the euro area with a standard factor augmented model to claim that the level of disaggregation chosen is not determined by this kind of horse races, but by the type of analyses that forecasters wish to perform and also by their expertise in forecasting some specific components with simple rules of thumb. Three main arguments are presented.

(i) The comparison between direct and bottom–up approaches is usually unfair. When building the bottom–up approach, the specification of the best equation for each variable is done independently, not accounting for the consistency between the forecasts of the several components.
(ii) It is possible to reproduce the GDP direct forecast through a bottom–up approach, if the same set of regressors is used to forecast all the endogenous variables.
(iii) Departing from this benchmark where direct and bottom–up approaches are equivalent, the introduction of some simple rules for several GDP components in line with institutional practice may increase the accuracy of the bottom–up approach. In particular, imports and inventories are not forecasted independently of the forecasts for the other variables given their strong level of endogeneity. Additionally, public consumption is allowed to follow a simple univariate model given their exogeneity.

The rest of the paper is organised as follows. The next section presents the data and the method used in this exercise. The main results are presented in Section 3, while Section 4 summarizes the conclusions.

2. Data and methodology

The paper compares the direct and the bottom–up approaches through an application for the euro area. The exercise is carried-out using the well known factor model of Stock and Watson (1998, 1999), exploring its simplest version, i.e. the one without any lagged endogenous variable or factor

$$Y_t = \Lambda F_t + u_t. \tag{1}$$

The endogenous variable Y_t is explained by a linear combination of a set of common factors F_t plus a residual u_t. The set of common factor corresponds to the first main components of a large dataset of information, while the vector Λ represents the coefficients that are given to each one of the common factors.

Therefore, the first step is the selection of the dataset underlying the computation of the components F. This dataset covers 99 series for the euro area: qualitative surveys European Commission (44) – covering consumer (15), industry (18), retail trade (6) and construction (5), Purchasing Managers Indices (PMIs) (22) – covering manufacturing (10), services (7) and construction (5) – total and sectoral industrial productions indices (9), total and sectoral retail trade sales (4), car sales (1), total and sectoral nominal external trade of gods (intra and extra) (9), total and sectoral employment and unemployment (9), and nominal effective exchange rate (1). Both GDP and the expenditure components are measured in quarter-on-quarter growth rates, except inventories that are expressed as contribution to GDP growth, while all the other series were also differentiated to warrant stationary. The sample period adopted starts in the first quarter of 1991, i.e. after the German reunification. The information of National Accounts considered is the one available at the Eurostat for the period after 1995. Those series were then retropolated until the beginning of the sample period using the Area Wide Model (AWM) database presented in Fagan et al. (2005) and downloadable from the European Central Bank (ECB) website. In order to increase the number of observations available, given the traditional lack of information for the euro area as a whole, some of the indicators selected are extended backwards in line with the EM algorithm presented in Stock and Watson (2002).

The second step corresponds to choice the number of main components underlying the matrix F. This is done, using the well known IC2 criterion of Bai and Ng (2002). The factors are estimated using principal components.

Finally, in the last step, the vector Λ is estimated using an OLS regression between the endogenous variable and the main common factors previously selected.

The exercise compares the results of using this model to nowcast directly GDP or using it to estimate each expenditure component, which are aggregated at the end to obtain a forecast to GDP. Thereafter the performance of the two approaches is compared through an out-of-sample exercise with recursive estimations of the above presented model.

Two periods are considered for these out-of-sample exercises: 2003Q1–2007Q4 in order to allow for some comparison with the results presented in Hahn and Skudelny (2010); and 2005Q1–2009Q4 to account for the most recent period.

Finally, it should be mentioned that this application is not a real time exercise, given that data revisions are not accounted for, and it does not consider that series composing the selected dataset are not available at the same time, that is, the release lag.

3. Results

3.1. Equivalent approaches

When using this factor augmented models with a constant number of factors and a common set of information, the comparison between the direct and bottom–up approaches two becomes irrelevant. In fact, in this case it is equivalent to forecast directly GDP or to aggregate forecasts for the several expenditure components.

Indeed, it is very easy to see that if y is a linear combination of two variables x_1 and x_2 (i.e., $y = \alpha x_1 + \beta x_2$), the direct forecast of y from an OLS regression on F is equal to forecast x_1 and x_2 using separate OLS regressions on the same F and to aggregate them with the weights α and β.

As argued in Perevalov and Maier (2010), in a context of factor models, the use of the lagged values of the endogenous variable in each equation may produce differences between the direct and disaggregated approaches. However, within the factor models, it is possible to use an extended version where each endogenous variable depends on the lagged values of all endogenous variables. In this context, the set of explanatory variables is the same and the direct and the bottom–up approaches produce once again the same results.

When working with bridge models as in Baffigi et al. (2004) and Hahn and Skudelny (2010), typically a common set of regressors for all the equations is not considered, as the selected economic indicators depend on the variable to forecast. However, in a bridge model environment, it is possible to build a bottom–up approach that is able to reproduce the same direct GDP forecast if the specification of equations chosen to model GDP is also the one used to estimate all the expenditure components.

This equivalence between the direct and the bottom–up approaches is illustrated in Table 1. The reason underlying this exercise

Table 1
Forecasting performance: observed standard deviation vs RMFSE.[a]

	Y[b]	y*[c]	C	G	GFCF	X	M	Inventories
Standard deviation	0.60	–	0.49	0.40	1.50	2.03	1.96	0.35
RMSFE								
Out-of-sample: 2003Q1 to 2007Q4	0.17	0.17	0.25	0.24	0.56	0.92	0.74	0.36
Our-of-sample: 2005Q1 to 2009Q4	0.27	0.28	0.26	0.25	0.79	0.91	0.81	0.31

[a] All the measurers are expressed in qoq rates, except inventories that are in contribute to GDP.
[b] GDP direct forecast.
[c] GDP bottom–up forecast.

with so obvious results is to build a benchmark where the two approaches are equivalent and to highlight the role of the correlations between the forecasting errors for the several GDP components.

The Root Mean Square Forecast Error (RMSFE) for GDP equation is clearly lower than the ones for the expenditure components equations, with the performance being worst for external trade components and gross fixed capital formation, i.e. the variables with higher volatility. It should be mentioned that the RMSFE for inventories is also large since this variable is measured as contribution to GDP growth. Private and public consumption present lower RMSFE. The results point to an increase of uncertainty in the most recent period, with a rise of the RMSFE on GDP estimates from 0.17 to 0.29. However, this increase is not common to all expenditure components, in particular RMSFE for exports and inventories registered some reduction.

Notwithstanding the higher RMSFE in all the expenditure components, the resulting forecasting errors for GDP are the same as in the case of the direct approach.[2] This occurs because the aggregated forecast errors will reflect not just the error dimension in each equation but also the correlation structure across these errors. In particular, imports forecasting errors exhibit a strong positive correlation with global demand errors while errors in inventories have a negative correlation with demand errors and a positive one with imports errors (Table 2).

As already mentioned, for 2003Q1–2007Q4 the results can be compared to the ones presented in Hahn and Skudelny (2010), which performed the same experience for the euro area using bridge models.

Firstly, it should be mentioned that the RMSFE obtained for both the GDP equation and the several expenditure components are higher than the ones presented in Hahn and Skudelny (2010).[3] Nevertheless, this paper does not claim for a superior forecasting performance. The main point is related with the relative evaluation of the direct and the bottom–up approaches.

Secondly, in spite of higher RMSFE for all the expenditure components, the RMSFE for the GDP bottom–up forecasts is clearly lower in the current exercise than in Hahn and Skudelny (2010). This is most probably related with the above mentioned correlations, which may not emerge if estimations are obtained independently. These correlations are well perceptible by institutional forecasters when producing short-term projections. In fact, typically the forecasts for each GDP component are not settled independently. In particular, the effects of new information on GDP are clearly minimized by the high degree of endogeneity of imports and inventories. These two very relevant variables are not kept free during the forecast process, depending clearly on the forecasts of the other variables. The independent specification of the best equation for each component and their aggregation do not take these features into account, and thus does not favour the bottom–up approach.

3.2. Improving the bottom–up approach

Departing from this benchmark where direct and indirect approaches perform equally, this subsection tries to go one step further, proposing some simple changes concerning the forecasts of some expenditure components, in particular public consumption, imports and inventories. All of these simple changes are in line with some practical procedures utilized when producing institutional forecasts and tend to favour the accuracy of the bottom–up approach. The main results are in Table 3, while the correlations structure across forecasting errors is presented in Table 4.

Table 2
Correlation coefficients between forecast errors of expenditure components.

	C	G	GFCF	X	M	Inventories
Out-of-sample: 2003Q1 to 2007Q4						
C	1.00	−0.02	0.04	0.59	0.38	−0.48
G		1.00	0.25	0.35	0.19	−0.12
GFCF			1.00	0.030	0.36	−0.10
X				1.00	1.00	−0.72
M						0.30
Inventories						1.00
Out-of-sample: 2005Q1 to 2009Q4						
C	1.00	−0.07	0.20	0.66	0.36	−0.53
G		1.00	0.34	0.08	0.21	0.05
GFCF			1.00	0.16	0.10	−0.16
X				1.00	0.54	−0.50
M					1.00	0.30
Inventories						1.00

3.3. Public consumption G(AR1)

Firstly, the current forecast for public consumption is replaced by the one obtained from an Auto-Regressive (AR) naïve model estimated also recursively (designated as G(AR1) model in Tables 3 and 4). This is a usual option as the database does not contain relevant information concerning current developments in public consumption. Often quarterly figures for public consumption are based on statistical interpolation methods applied to annual estimates from public budget or public finance experts. This might explain why public consumption follows this type of autoregressive behaviour.

A simple AR of order one was the formulation adopted here. In both out-of-sample periods, there is an increase of the RMSFE for public consumption forecasts, but with an improvement of the bottom–up GDP forecast performance (Table 3). Comparatively to the benchmark (designated as F-model), this change allows to reduce the RMSFE by 4% in both sample periods.

Once again this result for GDP bottom–up forecasts is related with the forecasting errors correlation structure. In particular, in this experience there is some reduction in the correlation coefficients between forecasting errors in public consumption and in the other expenditure components while the correlation with inventories reach more negative figures (Table 4).

3.4. Imports

Secondly, imports are forecasted using a simple rule where imports are linked to the global demand indicator where their components are weighted by the respective import contents (0.15 for private consumption, 0.06 for public consumption, 0.18 for gross fixed capital formation and 0.23 for exports).[4]

This very usual procedure (G(AR1)+M model) allows reproducing a positive correlation between global demand and imports forecasting errors, decreasing the RMSFE of the bottom–up approach in both out-of-sample periods to levels lower than the ones obtained with the direct forecast of GDP. Comparing with the benchmark, the reduction is of 11 and 14% in the two sample periods (see Table 3). As in the case of public consumption forecasts, this improvement of the forecasting GDP performance occurs in spite of the increase of the RMSFE of the imports forecasts. When producing bottom–up

[2] In this case the results are not exactly the same since the several expenditure components are aggregated with non-constant weights, following the National Accounts chain-linking procedure where weights are computed at previous year prices.

[3] Contrarily to the current analysis, in Hahn and Skudelny (2010) the data availability is taken into account. Therefore, the comparison is based on their results obtained two months after the end of the quarter. The RMSFE presented in their graphics for the several expenditure components are almost half of the figures presented in Table 1.

[4] The import contents of the several demand components were gathered from ECB (2010). For a detailed explanation of these figures see van der Helm and Hoekstra (2009).

Table 3
Out-of-sample performance [root mean square forecasting errors (RMSFE)][b].

	Y	G	M	Invent	Y	G	M	Invent	DM test[a]	
					In relative terms to the benchmark (F-mode)					
2003Q1 to 2007Q4										
F-model	0.172	0.243	0.740	0.364	1.00	1.00	1.00	1.00		
G(AR1)	0.165	0.396	0.740	0.364	0.96	1.63	1.00	1.00	0.50	[0.614]
G(AR1) + M	0.153	0.396	0.770	0.364	0.89	1.63	1.04	1.00	1.09	[0.274]
G(AR1) + M + I	0.156	0.036	0.770	0.372	0.91	1.63	1.04	1.02	1.15	[0.250]
2005Q1 to 2009Q4										
F-model	0.276	0.246	0.808	0.311	1.00	1.00	1.00	1.00		
G(AR1)	0.265	0.414	0.808	0.311	0.96	1.68	1.00	1.00	0.78	[0.436]
G(AR1) + M	0.238	0.414	0.884	0.320	0.86	1.68	1.09	1.03	1.11	[0.268]
G(AR1) + M + I	0.225	0.414	0.884	0.320	0.82	1.68	1.09	1.03	1.31	[0.189]

Notes.
G(AR1) — public consumption forecast with an AR(1).
M — imports as function of global demand weighted by imported content[information for the imported content of the major expenditure components were obbtained from ECB (2010)].
I — Inventories as function of imports.
[a] Diebold and Mariano (1995) test. Between brackets the t-prob is presented.
[b] All the measures are expressed in qoq rates, except inventories that are in contribute to GDP.

forecasts, it can thus be preferable to have higher errors in predicting a specific variable, but to ensure a consistent relationship among the forecast errors of the several variables. In this case, errors on imports became more correlated with errors in demand components (Table 4).

3.5. Inventories

Finally, inventories are estimated as a simple estimated linear regression on imports (the G(AR1)+M+I model). After the two previous changes this one on inventories allows a reduction of the RMSFE only in the most recent out-of-sample period, precisely the period where this rule is able to increase the positive correlation between errors in imports and in inventories. Compared with the benchmark, these changes on the way as public consumption, imports and inventories are forecasted reduce the RMSFE in 18% in the most recent period. Two additional results related with institutional practice could be mentioned.

Firstly, the contribution of inventories to GDP growth exhibits a strong positive correlation with the errors on imports. Even when all the information is disclosed, inventories are difficult to evaluate, and at times their estimation is linked to surprises in imports. Accordingly, surprises in imports that are not demand driven are sometimes accommodated in inventories, which allow reducing the effects of external trade volatility on GDP.

Secondly, given its huge volatility, sometimes inventories are seen as a random-walk variable and thus a null contribution of inventories to GDP growth is considered as an arguable technical assumption when forecasting GDP. The results do not support this view. Considering the most recent out-of-sample period, this procedure would raise the RMSFE of inventories by around 10%, increasing the RMSFE of the GDP bottom–up forecast by 20 and 50%, respectively, vis-à-vis the benchmark model and the model where the above mentioned simple rules were included to estimate public consumption, imports and inventories.

Concerning the statistical difference between the three alternative models and the benchmark model, the last column of Table 3 presents the Diebold and Mariano (1995) test. The results do not allow to easily reject the assumption of equivalence between the several models. Nevertheless, the gains seem to be stronger and statistically more significant when some rules are assumed for public consumption, imports and inventories.

Table 4
Correlation coefficients between forecast errors of expenditure components. Factor-model with rules for public consumption, imports and inventories.

	C	G	GFCF	X	M	Inventories
Out-of-sample: 2003Q1 to 2007Q4						
C	1.00	−0.09	0.04	0.59	0.39	−0.43
G		1.00	0.25	0.32	0.19	−0.17
GFCF			1.00	0.03	0.02	−0.08
X				1.00	0.36	−0.66
M					1.00	0.36
Inventories						1.00
Out-of-sample: 2005Q1 to 2009Q4						
C	1.00	−0.18	0.20	0.66	0.41	−0.34
G		1.00	0.24	0.07	0.20	−0.03
GFCF			1.00	0.16	0.25	0.02
X				1.00	0.55	−0.27
M					1.00	0.43
Inventories						1.00

4. Conclusions

The level of disaggregation underlying the forecasting process is a common problem. Concerning GDP short-term forecasting for some European countries and the euro area as a whole, some available results favour the direct estimation of GDP instead of the aggregation of forecasts for the several expenditure components, which is the approach traditionally adopted by institutional forecasts.

This paper presents an application for the euro area for the period since 1991 to claim that the level of disaggregation chosen is not determined by the usual races between the two approaches. The level disaggregation adopted depends on the analyses that forecasters wish to perform and also on their expertise in forecasting some components with simple rules of thumb.

First, the option between direct and indirect GDP estimations is frequently a false dilemma. In models based on simple OLS regressions with a common set of regressors, it is equivalent to forecast directly GDP or to aggregate the forecasts for the several expenditure components. Therefore, the standard type of models frequently used to forecast GDP (as factor models or bridge models) may be directly used to produce bottom–up forecasts, allowing for a better understanding of current economic activity developments. This is not accounted for in the usual races between the two approaches.

When producing forecasts, it is not only important to try to obtain the best equation for each variable independently, but also to warrant a structure of correlations between the main components forecasting errors that is able to reduce the error of the bottom–up GDP forecast. This type of correlations is well perceptible when producing short-term forecasts given the high degree of endogeneity of some variables such as imports and inventories, and thus should be accounted for when evaluating a bottom–up approach.

Secondly, departing from a standard model based on a common set of regressors where direct and indirect approaches perform equally, the exercise illustrates how some simple changes concerning the forecasts of some expenditure components may favour the accuracy of the bottom–up approach, in particular those of public consumption, imports and inventories. These changes are in line with usual institutional practice: public consumption is forecasted independently of short-term economic indicators, being based on expert's information and on statistical interpolation methods to obtain quarterly figures; imports and inventories are not allowed to evolver freely during the forecast process, depending clearly on the forecasts of the other variables. In the presented application for the euro area, these changes are able to reduce the RMSFE between 10 and 20%.

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