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A Time-Series Disaggregated Model to Forecast GDP in the Eurozone

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Introduction

The aim of this chapter is to present a simple approach to forecasting GDP in the Eurozone. In our study, GDP is broken down into two alternative vectors, and the exogenous variables used are GDP lags and the confidence indicators published by the European Commission. A forecasting evaluation over the last 12 observations shows that in forecasting the year-on-year rate of growth for horizons one to four: (1) disaggregation considerably reduces the RMSE for all horizons, (2) the combination of forecasts from demand and production breakdowns improves the results in almost all cases, (3) forecasts from VEqCM models, alone or combined with single-equation transfer function models, are the best options for forecasting one and two quarters ahead, but the differences from the other disaggregated alternatives are small both for these horizons and for three and four quarters ahead. We also show the importance of taking a break in the seasonality of different GDP components into account.

A global econometric model for forecasting GDP in the Eurozone could be considered for our purpose, but the construction and maintenance of this type of model is costly and only large institutions can afford the approach. In fact, global macroeconomic models can be useful for structural and simulation analysis, even when sometimes they are not built by means of econometric methods for estimation and testing, but by calibration techniques. Besides, they may forecast worse than simpler models and much of the literature shows that this is often the case. Univariate time-series models are at the other end of the spectrum of econometric models for GDP. They can forecast accurately on occasions, but they cannot provide an explanation of the factors determining the forecasts and their usefulness for economic policy is very limited; see Granger (2001). We present an intermediate procedure based on the method developed in the *Bulletin of EU* and *US Inflation and Macroeconomic Analysis*, Carlos III University, Madrid.

This method relies on disaggregation, specific and general leading indicators and non-linear structures when required. In the application of this procedure, models with different information sets or different long-term structures can be considered and, in the end, a combined forecast can be constructed if it improves the results. For these cases, Clements and Hendry (1999) indicate that combining could be preferred to encompassing. The starting point in this approach is the consideration that the information set must be enlarged from the univariate system in directions that really increase the information on relevant features of GDP performance, such as trends, seasonality, business cycle fluctuations, and so on. In this context, disaggregation of GDP taking the cointegration relationships between components into account becomes very useful. Likewise, the breakdown of GDP enables the inclusion of specific leading indicators or general indicators with specific parameters in the equation of each component.

In the case of GDP, two alternative ways of breaking down the aggregate in a vector of n components are possible: (a) by items of the final demand, and (b) by production sectors. In the first case, the components are defined in this chapter as: (1) private consumption (PRCO), (2) government consumption (PBCO), (3) gross fixed capital formation (GFKF), (4) changes in inventories (CHIV), (5) exports (EXPO) and (6) imports (IMPO). In the second case the breakdown was: (a) real gross value added in agriculture, forestry, and so on (VAGR), (b) in industry (VIND), (c) in construction (VCON), (d) in private services (VPRS), (e) in public services (VPBS) and (f) net taxes (NTAX). In the next section tests for positive and seasonal unit roots are applied to both vectors. In the demand case, all the components except changes in inventories, which appear to be stationary, can be considered as I(1) with deterministic seasonality. Besides, a seasonal break in 2001 is found for private consumption and GFKF. For this vector, the exogeneity tests lead to a block diagonal VEqCM model with variables (1), (2) and (3) in the first block, (4) in the second and the rest in the third. For the vector of production sectors, all the components can be taken as I(1) with deterministic seasonality, and a seasonal break appears in components (c), (d) and (e). A VEqCM is built for the whole vector. In both cases, demand and production, the models contain European confidence indicators as exogenous variables. The indicators show asymmetric cyclic behaviour and they are modelled using the Markov switching-regimes model proposed by Hamilton (1989, 1990). This type of non-linear model is also built for the imports and exports block of the demand vector.

For both vectors of variables we construct alternative models, discussed later in the chapter, in order to evaluate the forecasting performance of the VEqCM models. These alternatives for all GDP components are ARIMA models and single-equation dynamic models with leading indicators and GDP lags as explanatory variables. In the latter case, for each path forecast at a base point, GDP expectations are computed in a recursive way. We also perform a forecast evaluation of all the models considered, vector, single-equation or univariate models, and the importance of disaggregation appears as a very firm result. Compared with an aggregated ARIMA model for GDP, the disaggregated approach reduces the error variance for horizons one and four by 25 per cent and 80 per cent, respectively.

The main conclusions of the chapter are summarized in a final section.

Modelling and empirical results

In the first place, to determine both the integration order and the type of seasonality (deterministic or stochastic) of each component,[1] following Hylleberg *et al.* (1990), unit-root tests are performed both at zero frequency and at all seasonal frequencies, and combinations of both.[2] The tests are performed with constant, seasonal dummies and trends, even when the trend turns out to be insignificant. Nevertheless, the tests without trend lead to the same conclusions,[3] as follows:

- All GDP components are I(1). In other words, the presence of a unit root at zero frequency is detected, except changes in inventories, which is stationary.
- In most cases, the null hypothesis of the existence of unit roots at seasonal frequencies is rejected, indicating the convenience of deterministic seasonality modelling using dummy variables. The only doubtful cases between deterministic or stochastic seasonality correspond to private consumption and GFKF. However, a more detailed examination of these components shows that there is a possible change in seasonality from the first quarter of 2001, and this is confirmed by a regression model with two sets of seasonal dummy variables. Considering this break-point in the HEGY tests, they also reject the existence of unit roots at seasonal frequencies for the above components. In fact, when the break-point is included in the component models, it is significant in six cases (see column 6 of Table 17.2)

Once both the integration order and the type of seasonality have been determined, components are modelled by VEqCM models of the following type (Johansen, 1995; Harris and Sollis, 2003; Lutkepohl, 2004):

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Psi D_t + U_t \qquad U_t \sim N(0, \Sigma) \qquad (17.1)$$

In equation (17.1) the D_t vector includes the model's exogenous variables (in this case, seasonal dummy variables, step variables (LS) and impulse variables (AO) and economic indicators), relations $\beta' Y_{t-1}$ represent the equilibrium correction mechanisms and the α coefficients measure the influence of deviations from long-run relationships on the evolution of the growth rates of each variable. The Γ_i matrices show the short-term effects on the determination of the variables.

To estimate the above model, we follow a two-stage strategy (Doornik, and Hendry, 2001; Harris and Sollis, 2003; Lutkepohl, 2004), using Johansen tests in a VAR model to determine cointegration rank and estimate equilibrium relations and then re-estimating equation (17.1) with said restrictions. The results[4] of Johansen's trace and maximum eigenvalue tests[5] for VAR supply and demand models show evidence of a single cointegration relation in both cases. The

Table 17.1 Estimated β Coefficients

PRCO	*PBCO*	*GFKF*				*Trend*
1.000	−0.30593	−0.34712				−0.0016
(0.000)	(0.0698)	(0.0172)				(3.22*E*−4)
VAGR	VIND	VCON	VPRS	VPBS	NTAX	Trend
−2.147	0.889	−4.152	1.000	9.837	2.045	−0.0505
(0.259)	(0.333)	(0.458)	(0.000)	(1.432)	(0.265)	(0.0069)

Table 17.2 Estimated VEqCM models by FIML

			VEqCM			
	Coef. Coint. Rel.	*Lags*	*Indic.*	*Interv.*	*Seas. Break*	*Std. Dev. Eq.*
PRCO	−0.312 (0.154)	0	No	LS199301	Yes	0.0048
PBCO	0.401 (0.158)	1,4	No	AO199501	Yes	0.00497
GFKF	1.404 (0.477)	0	0.0988 (0.040)	LS199301	Yes	0.01483
			VEqCM			
	Coef. Coint. Rel.	*Lags*	*Indic.*	*Interv.*	*Rupt. Seas.*	*Std. Dev. Eq.*
VAGR	0.079 (0.030)	1,2,3	No	No	No	0.0149
VIND	0.000 (0.000)	0	0.12576 (0.02194)	AO199701	No	0.0123
VCON	0.111 (0.018)	0	No	AO199601	Yes	0.0132
VPRS	−0.013 (0.0076)	1	No	No	Yes	0.0054
VPBS	0.000 (0.000)	1	No	No	Yes	0.0039
NTAX	−0.0714 (0.035)	4	No	LS199301	No	0.0189

Note: Coef. Coint. Rel. shows, for each component, the estimated α coefficient in equation (17.1). In the Interv. column, the AO and LS values represent artificial impulse and step variables included in the equation. The digits indicate year-quarter of the intervention. The Indic. column shows the estimated coefficient of the Indicator for the components in which it is significant. The Seas.Break column indicates whether the seasonal break in 2001Q1 is significant.

estimated β coefficients of both cointegration relations are (standard errors in parenthesis) shown in Table 17.1.

Table 17.2 includes the principal results for the final VEqCM models both for the supply and the demand. The finally estimated VEqCM demand model includes three components (priv. cons., publ. cons., and GFKF), since in the initial complete model both exports and imports and changes in inventories are exogenous and therefore modelled separately. The principal features are: (1) cointegration relations are significant; (2) most of the components have very short dynamics (even non-existent in some cases); and (3) the break-point in the first quarter of 2001 is significant for most components, so it is also propagated in the aggregate GDP. This cannot be explained by a change in the behaviour of economic agents and the break is probably due to a change of method in the determination of the variables.

The univariate modelling of economic indicators is carried out using non-linear MSIH(M)-AR(p) models[6] with changing regimes like the following (see Hamilton, 1989, and Krolzig, 1997):

$$\Delta y_t = \nu(s_t) + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + u_t \qquad u_t \sim N(0, \sigma^2(s_t))$$

$$Pr(s_{t+1} = j/s_t = i) = p_{ij} \qquad i, j = 1 \text{ and } 2 \tag{17.2}$$

The MISH(M)-AR(p) designation proposed in Krolzig (1997, 1998) indicates that they are autoregressive heterokedastic switching Markov models with changing intercept between M different states, two in this case. These autoregressive models enable both the intercept and the variance to depend on a non-observable variable, s_t, which represents the state of the economy. The state transition s_t variable is governed by a stochastic process with stationary and ergodic hidden Markov chain structure. The chosen option of changing the intercept instead of the mean enables gradual instead of instantaneous changes of level (Krolzig, 1997).

Exports and imports are modelled with a MSIH(2)-VAR(2) model (including the export orderbooks indicator as an exogenous variable), which has a slightly better forecasting performance than a linear VAR model[7] between the two components. Finally, for modelling changes in inventories, a first order univariate autoregressive model is used on the level of the variable.

Forecasting exercise

With a view to comparing the forecasts obtained with the different models considered, a forecasting exercise is performed, cutting the initial sample[8] into 12 observations and obtaining forecasts for the year-on-year rate with different forecasting horizons (h = 1, 2, 3 and 4). The models are re-estimated using all the information available at each forecasting time (in which case, for each re-estimate, the sample size must be increased by one observation) and forecasts are calculated for the horizons considered. The comparisons between the roots of the mean-square errors of the forecasts obtained by the previous models and those obtained with a univariate linear model for the aggregate GDP are shown[9] in Table 17.3.

Table 17.3 also includes the GDP forecasts obtained using univariate linear models for each component, and transfer models including the economic indicators and the GDP forecast obtained with the information available to date from an ARIMA model as regressors.[10] To calculate the GDP forecasts required to construct the forecast path of a certain GDP component with a transfer function model, the ARIMA model of the GDP is used to forecast the following observation, $T + 1$, which is used to forecast the GDP components for $T + 1$, and thus obtaining

Table 17.3 Summary of the quotients, in relation to the aggregate GDP, between the roots of the mean-square errors (RMSE) for the year-on-year rate (sample: 2001Q1 to 2003Q4)

		GDP disaggregations		
	horiz.	*GDP Mixed*	*GDP Dem*	*GDP Sup*
UNIV	1	0.96	1.11	0.98
	2	0.63	0.76	0.65
	3	0.46	0.60	0.49
	4	**0.43**	0.54	0.46
TF	1	0.89	1.02	0.92
	2	0.52	0.51	0.59
	3	0.66	0.61	0.77
	4	0.55	0.66	0.64
VEqCM	1	**0.87**	0.91	1.09
	2	0.67	0.82	0.78
	3	0.71	0.93	0.79
	4	0.75	0.99	0.77

		GDP combinations between different models			
hor.	*GDP Agr*	*VEC-UNV*	*VEC-TF*	*UNV-TF*	*VEC-UNV-TF*
1	1.00 (0.645E-2)	0.94	0.88	0.89	0.87
2	1.00 (0.957E-2)	0.56	**0.45**	0.52	0.49
3	1.00 (1.070E-2)	0.48	0.58	**0.44**	0.53
4	1.00 (1.192E-2)	0.54	0.62	0.45	0.51

Note: The GDP disaggregations columns correspond to GDP forecasts, disaggregating the demand and production components separately. The GDP Mixed is obtained as a linear combination between GDP Supply and GDP Demand. The GDP combinations are obtained by aggregating the GDP Mixed obtained from each model. A value lower than 1 indicates a lower value of the corresponding RMSE. in relation to the aggregate. The GDP Agr includes the exact RMSE values in brackets. The best forecasts with horizon 1, 2, 3 and 4 are marked in bold type.

a new GDP forecast aggregating the components at $T+1$, which is considered as observed data. This information is used by the ARIMA model to forecast the GDP for $T+2$ and the process is repeated.

Besides the GDP forecasts obtained separately by aggregating the supply and demand components, GDP forecasts can also be obtained by combining the two. To obtain the combination's weightings, the root of the mean-square error of the quarter-on-quarter rate is minimized (in order to include more observations) on each forecasting horizon (Diebold, 1998). When we examine the forecast table, we find that the forecast indeed gains by disaggregating and, on many occasions, by combining different models.

Conclusions

The principal conclusions obtained with the above modelling and forecasting are as follows. In general, there is a gain from using GDP forecasts with disaggregate models (of any kind) compared with forecasts obtained with an aggregate model. On many occasions, there is a gain from combining GDP forecasts obtained with different models. In the year-on-year rate for short horizons ($h = 1$), VEqCM models generate forecasts with lower RMSE and the same occurs for $h = 2$ if they are combined with forecasts from transfer function models. For longer horizons, the best combination of VEqCM forecasts is with univariate models, although in this case the disaggregate univariate forecast alone is slightly better.

Although the models employed do not include a theory about the factors determining GDP components, they do provide forecasts on said components and, therefore, on their contribution to GDP growth. This determines which are the most dynamic and which the most sluggish sectors, often providing valuable guidance for economic policy.

Notes

1 All components are in logarithms except changes in inventories.
2 ADF unit-root tests and KPSS stationarity tests have also been performed, seeking the presence of two positive unit roots. However, the existence of a double unit root is rejected for all the components.
3 These tables are available by request from the first author.
4 Calculations are made using the Ox language (Doornik (2001)), integrated in PcGive software (Doornik and Hendry, 2001), and the JMulTi programme developed by Lutkepohl (Lutkepohl and Kratzig, 2003; Lutkepohl, 2004).
5 We also performed the Saikkonen–Lutkepohl cointegration rank test (Saikkonen and Lutkepohl, 2000), which is robust in case of a break-point on an unknown date. The conclusions are similar to those of the Johansen tests.
6 Calculations are performed using the MSVAR programme (Krolzig, 1998) written in Ox language (Doornik, 2001).
7 An equilibrium correction mechanism is not included in the equations, since no cointegration relation is detected between the variables.
8 The complete sample includes data from 1991Q1 to 2003Q4.
9 No forecast comparison test, such as the Diebold-Mariano test, is included, since most of these tests have asymptotic validity and in our case there are only 12 observations available, at most.
10 Logically, the regressors are only added to the equations when they are significant.

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