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AGGREGATION OF MICRO FORECASTS

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1. Introduction

When considering forecasting an aggregate time series directly or alternatively aggregating forecasts of its components, several issues have to be taken into account. First, there is the general question of whether disaggregated forecasting is better than aggregated fore-casting. Second, if the micro series are forecasted, should they be estimated and forecasted individually or jointly? Third, if a macro equation is analyzed, how should it be specified so that it is consistent with the micro equations? Finally, if the micro equations are used in forecasting, how are the forecasts aggregated optimally? In this paper we concentrate on the last issue.

The disaggregated series may be aggregated using weights that are correct by a priori reasoning. For example, the aggregate may be simply the sum of the micro series. It is shown below that even in this case it may be optimal to estimate the weights. The procedure we suggest is closely related to the problem of combining competing forecasts. In that work alternative forecasts of the <u>same</u> variable are combined to obtain a better composite forecast. In contrast, we discuss combining forecasts of <u>different</u> micro variables for forecasting a macro variable.

In section 2 we briefly review relevant literature on forecasting and aggregation. In section 3 we present the theoretical results on aggregating micro forecasts and in section 4 the use of the method is illustrated in an empirical application. Section 5 concludes the paper.

2. Aggregate vs. Disaggregate Forecasting

It is commonly agreed upon that disaggregate time series contain more information than aggregate time series and should therefore be used in forecasting. There may, however, be situations where macro-level forecasting is preferable. Aigner and Goldfeld (1974), for example, argued that ofter aggregate data is measured more accurately than disaggregated data. This gives rise to a tradeoff between aggregation bias and measurement error. They showed that when the micro equations have the same coefficients and this constraint is imposed in estimation, micro forecasting dominates macro forecasting. When the micro parameters are different, there are conditions under which macro forecasting dominates.

Related work has recently been done in time series analysis. Several authors have discussed a situation where a macro time series to be forecasted is a linear combinations (transformation) of micro variables, which follow e.g. ARMA processes; see e.g. Lütkepohl (1984a) and references cited these. The common result in this work is that by mean squared error (MSE) criterion it is preferable to aggregate forecasts from the micro equations rather than to forecast the macro relation directly. These results generalize to the case where the micro series follow a vector ARMA process. Empirically, however, the optimality of disaggregated forecasting may not hold if the orders and parameters of the processes have to be estimated (Lütkepohl (1984b)).

A related issue is whether it is preferable to forecast the micro variables jointly or to forecast them separately and then combine the individual forecasts. Zellner and Huang (1962) showed in a regression framework that forecasts from a seemingly unrelated (SUR) system of equations minimize the generalized MSE, defined as $|\Sigma|$ where Σ is the MSE matrix of the individual forecasts $x^{e\prime} = (x_1^e,\ldots,x_k^e)$. It is easy to show that this result holds also for a linear combination $w'x^e$ of the forecasts, where w is a kx1 vector of weights.

Similarly, Lütkepohl (1984a) shows that it is better to forecast a linear transformation of a vector ARMA process than to take a linear combination of univariate ARMA forecasts. The former leads to a smaller MSE matrix than the latter or the macro forecasts. However, the MSEs from a combination of univariate forecasts and from the macro forecast cannot be ranked a priori.

Further, we can note that the macro equation should be consistently aggregated from the micro equations. Results in aggregation theory show that if one has equations whose coefficients vary over the micro units, an aggregation bias is induced by taking a simple weighted average of the micro equations (e.g. Theil (1971b)). As noted above, this may have an influence on whether micro or macro forecasting dominates. A related issue is that if the micro series follow ARMA processes, a macro series, which is a linear transformation of the micro series, is also an ARMA process. The micro series imply constraints on the order and coefficients of the macro process. If these constraints are taken into account, forecasting the macro series leads to the same MSE as combining forecasts of the micro series. In practice, since the restrictions and parameters are unknown, forecasting the macro equation may lead to a smaller MSE than forecasts from the micro equations (Lütkepohl (1984b)).

The papers mentioned above do not discuss how to choose optimally the transformation (or weights) used for aggregating the micro forecasts. In the next section we show how this can be done using a regression procedure.

3. Optimal Aggregation

Consider a situation where a variable y_t is a linear combination of micro variables $X_t = (x_{1t},...,x_{kt})$: $y_t = X_t w$, where w is a kx1 vector of weights. For example, if the weights are $w_j = 1$, $j = 1,...,k$, y_t is the sum of the micro variables. Another example is that the variables y_t, X_t are in percentage change form and, using bars to denote variables in level form, $\bar{y}_t$ is the sum of the elements of $\bar{x}_t$. Then the weights w_t are variable over time and are approximately equal to the shares of $\bar{x}_{it}$'s in $\bar{y}_t$.

From the forecasting point of view an essential question is whether it is optimal to use the "correct" weights w or some other ones. This problem is related to the work on taking linear combinations of competing forecasts. Granger and Ramanathan (1984) have recently generalized some earlier work in this area. Let $y^e = (y_1^e,...,y_k^e)$ be competing forecasts of y. Granger and Ramanathan show that the sum of squared forecast errors is smaller if the forecast of y is based on $\alpha + y^e w$ or $y^e w$ rather than on $y^e w^*$, where , w and w* are weights to be estimated; $i_k' w^* = 1$ (i_k is a kx1 vector of 1s), but w is unconstrained. Our problem is clearly fairly similar to this.

Other proposed methods for combining forecasts that thave worked well in practice include averages of competing forecasts, i.e. $w = i_k/k$, and methods that take into account correlations between forecast errors (see e.g. Clemen and Winkler (1986) and Figlewski (1983)). Clearly, averaging forecasts makes little sense when the forecasts are on different variables, as in this paper. The approach where the cross-correlations are taken into account usually assumes that the forecasts are unbiased, which is, however, not the case below. We therefore concentrate on the regression-based approaches along the same lines as Granger and Ramanathan (1984).

Let y be a nx1 vector of the macro variable to be forecasted for n time periods and x_i, i = 1,...,k, be nx1 vectors of k micro variables in the same time periods. The whole micro data is given by the nxk matrix $X = (x_1,...,x_k)$. The forecasts of x_i and X are denoted x_i^e and X^e, respectively.

The usual case is to form first the forecasts x_i^e individually or jointly using e.g. SUR or vector ARMA methods. The forecast of y is then $X^e\bar{w}$, where $\bar{w}$ is the kx1 vector of by a priori reasoning correct weights. The sum of squared forecast errors (SSFE) is

$$\begin{aligned} SSFE_1 &= (y-X^e\bar{w})'(y-X^e\bar{w}) \\ &= \bar{w}'(X-X^e)'(X-X^e)\bar{w} \ . \qquad (1) \end{aligned}$$

Taking expectations we obtain $E(SSFE_1) = \bar{w}'\Sigma\bar{w}$, where Σ is the MSE matrix of the micro forecasts. As discussed in Section 2, $|\Sigma|$ is minimized using a joint estimation and forecasting method. Clearly, also $SSFE_1$ is minimized by this.

Let us now consider the case where the weights are unconstrained. The sum of squared forecast errors is minimized by choosing $w = \hat{w} = (X^{e\prime}X^e)^{-1}X^{e\prime}y$, i.e. choosing the weights obtained from a regression of y on X^e. We have

$$SSFE_2 = (y-X^e\hat{w})'(y-X^e\hat{w})$$
$$= y'M_2y \qquad (2)$$
$$= SSFE_1 - (\bar{w}-\hat{w})'X^{e\prime}X^e(\bar{w}-\hat{w}),$$

where $M_2 = I-X^e(X^{e\prime}X^e)^{-1}X^{e\prime}$.

Expression (2) is smaller than $SSFE_1$. This follows from the simple fact that any coefficient vector that differs from least squares coefficients leads to a larger sum of squared errors. Hence the forecasts can be further improved by estimating the aggregation weights.

We can also consider adding a constant in the forecasting rule, i.e. using $\alpha i_n+X^e w$ as the macro forecasts for the periods 1,...,n. This amounts to running a regression of y on X^e and a constant. The structure of the problem is exactly the same as in Granger and Ramanathan (1984), but it is presented here in the same framework as the methods above.

Denote $X^{e*} = (i_n,X^e)$, $w* = (\alpha,w')'$, $\tilde{w}* = (X^{e*\prime}X^{e*})^{-1}X^{e*\prime}y$ and $\hat{w}* = (0,\hat{w}')'$. The sum of squared forecast errors when a constant is included is then

$$SSFE_3 = (y-X^{e*}\tilde{w}*)'(y-X^{e*}\tilde{w}*)$$
$$= y'M_3y$$
$$= y'M_2y - (\hat{w}* - \tilde{w}*)'X^{e*\prime}X^{e*}(\hat{w}* - \tilde{w}*), \qquad (4)$$

where $M_3 = I - X^{e*}(X^{e*\prime}X^{e*})^{-1}X^{e*\prime}$. This is smaller than the SSFE when no constant was included.

We can also note that the forecast is unbiased within the sample used for estimating $\tilde{w}^*$, since the sum of the errors is zero in a regression with a constant (e.g. Theil (1971b), p. 40). In contrast, the forecast based on $X^e\hat{w}$ is in general biased if the micro forecasts are biased. This can be seen by writing the forecast error in that case as

$$y - y^e = X\bar{w} - X^e\hat{w} = (X-X^e)\bar{w} + X^e(\bar{w}-\hat{w}). \qquad (5)$$

If X^e is unbiased, the mean of the first term in (5) is zero, but the mean of the whole expression is not zero unless also $\hat{w}$ is an unbiased estimate of $\bar{w}$.

It seems important to adjust for biasedness in the aggregation stage, since the micro forecasts X^e can be biased e.g. by transformations made before aggregation. For example, consider a situation where the aggregate series is the sum of the micro series, but forecasts of the micro series are made in logarithmic form. Before aggregation, antilogs of the micro forecasts have to be taken. Even if the forecasts of $\log x_i$ were unbiased, the resulting forecast of x_i are likely to be biased.

An alternative way to correct for biases is to aggregate the micro forecasts using first the "correct" weights $\bar{w}$ and then adjust y^e for systematic biases by choosing α and β to minimize the sum of squared forecast errors $(y-\alpha-\beta y^e)'(y-\alpha-\beta y^e)$ (e.g. Theil (1971a), pp. 34-5). The corrected forecast is $\hat{\alpha} + \hat{\beta}y^e = \hat{\alpha} + \hat{\beta}X^e\bar{w}$, where $\hat{\alpha}$ and $\hat{\beta}$

are least-squares estimates. Although unbiased, this forecast would be less efficient than the ones considered above. It would, however be better than using the unadjusted forecast with weights $\bar{w}$.

Denote $y^{e*} = (i_n, y^e) = (i_n, X^e\bar{w}) = (i_n, X^e)\bar{w}^* = X^{e*}\bar{w}^*$, $\bar{w}^* = \begin{bmatrix} 1 & 0 \\ 0_k & \bar{w} \end{bmatrix}$, 0_k is a kx1 vector of zeros, $\gamma = (\alpha,\beta)'$ and $\hat{\gamma} = (y^{e*\prime}y^{e*})^{-1}y^{e*\prime}y$. For the unadjusted forecast $\gamma = \bar{\gamma} = (0,1)'$. The sum of squared forecast errors is

$$\begin{aligned} SSFE_4 &= (y-y^{e*}\hat{\gamma})'(y-y^{e*}\hat{\gamma}) \\ &= y'M_4y \\ &= SSFE_1 - (\hat{\gamma}-\bar{\gamma})'\bar{w}^{*\prime}X^{e*\prime}X^{e*}\bar{w}(\hat{\gamma}-\bar{\gamma}) \qquad (6) \\ &= y'M_3y + (\tilde{w}-\bar{w}^*\hat{\gamma})'X^{e*\prime}X^{e*}(\tilde{w}-\bar{w}^*\hat{\gamma}), \end{aligned}$$

where $M_4 = I-y^{e*}(y^{e*\prime}y^{e*})^{-1}y^{e*\prime} = I-X^{e*}\bar{w}^*(w^{*\prime}X^{e*\prime}X^{e*}\bar{w}^*)^{-1}\bar{w}^{*\prime}X^{e*\prime}$. Hence the sum of squared forecast errors is smaller than in the unadjusted case, but larger than in the case where the aggregation weights are also estimated together with the adjustment for bias.

The discussion above deals with situations where the aggregation weights are estimated using data from the same period where the forecasts are made. The optimality of the presented methods therefore applies only within the sample period. The relevant question in actual forecasting is how well the methods perform out of sample. Then even the adjustments do not guarantee that the forecasts are unbiased. We study this issue empirically in the following section of the paper.

4. An Application

We have estimated short-run autoregressive forecasting models for the volume of building construction in Finland. Ten different subcategories and total building construction are forecasted. The micro forecasts are interesting by themselves, since they can be used for predicting construction investment in different industries. They can also be used for forecasting the aggregate volume using the methods described above.

The data used is the index of the volume of building construction (1980=100). Quarterly data 1975.1-1983.4 was used for specification and estimation of the models and 1984.1-1985.2 for out-of-sample checking. Before estimation the data was transformed to four quarter differences of the logarithms of the variable. In the aggregation stage the forecasts were transformed back to the levels of the volume indexes. The way the volume indexes are calculated was changed in 1985. The new indexes have the same base year 1980 as the old ones, but they are available only from 1982 onwards. The four quarter log changes of the old series were used for forming index series for the period 1975-81, which are consistent with the new indexes.

The autoregressive models were specified individually and estimated with OLS. First, four lagged values of the volume and a constant were included in the models. Using the t-values and Schwarz's Bayesian Information Criterion (SBIC), unnecessary terms were dropped. The estimation results are shown in Table 1. Residual autocorrelation was tested with the Lagrange multiplier test. Fourth-order autocorrelation was rejected in all models at the 1 % level and accepted in only one model at the 5 % level.

The specified models were estimated again as a SUR system using the error covariance matrix estimated from the univariate OLS residuals. The SUR estimates did not differ much from the OLS estimates, and are not presented here.

We have compared 6 different forecasts of total building construction (i) macro forecast, (ii) weighted sum of the micro forecasts using a priori chosen weights, (iii) weighted sum of the micro forecasts, using estimated weights, (iv) as (iii), but with a constant, (v) weighted sum of some of the principal components of the micro forecasts, with estimated weights, (vi) micro forecasts summed as in (i) and the sum corrected for bias. Forecasts (ii)-(vi) were calculated also using SUR estimates in forecasting the micro variables. For each case we calculated root mean squared error, RMSE (minimizing SSFE implies minimizing also RMSE), mean absolute error, MAE, and mean error, ME, of forecasts.

The volume of total building construction is the sum of the volumes of the subgroups at 1980 prices. Therefore, the a priori weights for the forecasts of the subgroup indexes are the volume shares of the subgroups in 1980; they are shown in Table 1. This implies an additional way of aggregating the forecasts. We might consider estimating the weights w subject to the constraint that $i_k'w=1$. Granger and Ramanathan (1984) show this to lead to a larger SSFE than estimation of the weights freely. We have transformed the a priori weights to $\bar{w} = i_k$ by multiplying the subgroup forecasts by the 1980 volume shares. We therefore expect to find estimates of the weights to be close to one. This procedure gives approximately the same result as constraining the weights to add up to 1. Since all volume indexes have the same base year, the sum of the estimated weights times volume shares has to be close to 1 when no constant is included.

Table 1. OLS estimates of the models.

	Subgroups										Total building construction
	0	1	2	3	4	5	6	7	8	9	
Constant					.11				.18	.13	
					(2.56)				(2.91)	(4.72)	
VO_{-1}	.36	.53	.62	.56			.94	.37	.31		.55
	(2.36)	(3.76)	(4.69)	(3.48)			(5.86)	(2.20)	(1.81)		(3.81)
VO_{-2}						.31	-.43				
						(1.82)	(-2.75)				
VO_{-3}			-.35								
			(-2.83)								
VO_{-4}	-.36	-.49		-.47	-.45	-.41		-.39	-.46	-.29	-.33
	(-3.26)	(-2.90)		(-2.21)	(-2.63)	(-2.30)		(-2.58)	(-2.67)	(-1.51)	(-2.79)
SBIC	-69.89	8.89	-3.50	12.12	-.34	4.86	-17.48	-.39	9.53	-27.77	-64.55
LM4	12.78	4.73	8.99	10.87	2.79	8.98	6.77	5.27	2.57	.34	5.33
w	.541	.052	.034	.035	.039	.038	.118	.051	.031	.061	

VO four-quarter log difference of volume of construction
w volume share 1980
t-values in parentheses
SBIC Schwartz's Bayesian information criterion
LM4 Lagrange multiplier test statistic for testing 4th order autocorrelation; distributed as $\chi^2(4)$, critical values 5 %: 11,1, 1 %: 13.3

0 Residential buildings
1 Shop, accommodation and restaurant buildings
2 Institutional buildings
3 Office buildings
4 Buildings for assembly
5 Educational buildings
6 Industrial buildings
7 Warehouses
8 Buildings for agriculture, forestry and fishing
9 Transport service buildings and other buildings

	Subgroups										Total
	0	1	2	3	4	5	6	7	8	9	building construction
Constant					.11				.18	.13	
					(2.56)				(2.91)	(4.72)	
VO_{-1}	.36	.53	.62	.56			.94	.37	.31		.55
	(2.36)	(3.76)	(4.69)	(3.48)			(5.86)	(2.20)	(1.81)		(3.81)
VO_{-2}						.31	-.43				
						(1.82)	(-2.75)				
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VO_{-4}	-.36	-.49		-.47	-.45	-.41		-.39	-.46	-.29	-.33
	(-3.26)	(-2.90)		(-2.21)	(-2.63)	(-2.30)		(-2.58)	(-2.67)	(-1.51)	(-2.79)
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Table 2. Estimation of the aggregation weights; OLS forecasts

Constant	20.142	
	(1.108)	
x_0^e	1.050	1.261
	(2.846)	(3.968)
x_1^e	-.698	.141
	(-.455)	(.105)
x_2^e	-.208	1.362
	(-.084)	(.668)
x_3^e	2.191	1.213
	(1.378)	(.912)
x_4^e	.852	1.013
	(.648)	(.769)
x_5^e	-1.837	-.886
	(-1.043)	(-.573)
x_6^e	1.376	1.909
	(1.529)	(2.496)
x_7^e	2.834	2.456
	(2.605)	(2.362)
x_8^e	.250	-1.080
	(.107)	(-.534)
x_9^e	-.238	-.179
	(-.204)	(-.152)
$\bar{R}^2$	.888	.996

t-values in parentheses

x_i^e is forecasted volume of activity in subgroup i.

Table 2 shows the estimation results when the index of total building construction was regressed on the forecasted volumes of the 10 subgroups, multiplied by respective 1980 volume shares. The results show that the estimates differ slightly from one although the difference is not statistically significant. In the case where no constant is included F-value for testing $\hat{w} = i_{10}$ is .83 with 10 and 18 degrees of freedom. Hence the equality of the estimated and a priori weights is clearly accepted. The results when SUR estimates were used in forecasting were similar.

The estimates show that only a few of the aggregation coefficients are significantly different from zero and some are negative. One would expect that subgroups that have large forecast variances would get smaller weights than their volume shares indicate. Also the correlatedness of the individual forecasts affects the signs and magnitudes of the coefficients. If the forecasts are highly correlated, it is not possible to obtain precise estimates of the individual elements of w. This may explain the large standard errors we obtained. In the present case multicollinearity is not a problem within the sample used for estimating the weights, since one still obtains good estimates of $X^e w$. However, out of sample, imprecision of the estimated weights may have a large effect on forecast accuracy. Therefore it is useful to re-estimate the weights using principal components.

If all the principal components are used, RMSE is naturally the same as when all 10 weights are estimated. If less principal components are used, within sample RMSE will increase, but out of sample forecasting performance may improve since the parameter estimates are more precise.

Below only the first principal component is used. The largest eigenvalue of the covariance matrix of he micro forecasts, multiplied by 1980 volume shares, was 117.557. This accounted for 89.8 percent of the trace of the covariance matrix. The corresponding principal component is $pc1 = .969x_0^e + .018x_1^e + .010x_2^e + .041x_3^e + .043x_4^e - .007x_5^e + .095x_6^e + .131x_7^e + .108x_8^e + .141x_9^e$. Regression of the volume of total building construction on the first principal component and a constant yielded $\underset{(1.817)}{VO = 12.673} + \underset{(12.432)}{1.577pc1}$ (t-values in parentheses, $\bar{R}^2 = .851$). This equation was used in forecasting case (v).

Finally regression of the volume of total building construction on the aggregate of the micro forecasts using a priori weights resulted in equation $\underset{(-.362)}{VO = -2.499} + \underset{(14.745)}{1.015^e w}$ (t-values in parentheses, $\bar{R}^2 = .889$). If the aggregated series were unbiased, we would have $\alpha=0$, $\beta=1$, which is clearly accepted by the estimation results.

Table 3 shows the comparison of the forecasting performance of the different forecasts. Within sample the macro forecast performs worse than the aggregated one with weights $\bar{w}$. When the weights are estimated, the forecasting performance improves further. The use of principal components results in the highest RMSE. Table 4 gives the comparison out of sample. Here the principal component forecast results in the smallest RMSE and the macro forecast the second smallest. Therefore disaggregated forecasting pays in our example only if principal components are used. We experimented forecasting with more than one principal component. This led to a smaller RMSE within sample but a larger one out of sample. With two principal components, RMSE was 5.731 within and 6.132 out of sample. The RMSEs in Table 4 are slightly larger than in Table 3, except for the principal component and macro forecasts. Estimation of the weights again leads to lower RMSE than using the a priori weights. When also a constant is included, RMSE, MAE and mean error are slightly larger than when the weights are estimated without constant. The results also show that out of sample all the forecasts are biased.

Joint estimation of the micro equations with SUR did not seem to matter much. Within sample the RMSEs were slightly smaller in cases (ii) and (iii). Out of sample SUR led to larger RMSE than OLS in all cases. The fact that the forecasts did not improve from the use of SUR may be due to a deviation of the estimated covariance matrix from the true but unknown one.

Table 3. Performance of one period ahead forecasts within sample; OLS estimates

		RMSE	MAE	ME
(i)	Macro forecast	6.555	5.304	.794
(ii)	A priori chosen weights	6.133	5.120	-1.013
(iii)	Estimated weights	5.077	4.215	.086
(iv)	Estimated weights with constant	4.903	3.918	.000
(v)	Principal component	7.017	5.660	.000
(vi)	A priori chosen weights with adjustment for bias	6.043	4.963	.000

Table 4. Performance of one period ahead forecasts out of sample; OLS estimates

		RMSE	MAE	ME
(i)	Macro forecast	4.718	3.754	-1.825
(ii)	A priori chosen weights	6.912	5.549	-5.212
(iii)	Estimated weights	5.686	5.024	-2.867
(iv)	Estimated weights with constant	6.186	5.070	-3.899
(v)	Principal component	3.811	2.961	1.216
(vi)	A priori chosen weights with adjustment for bias	6.305	5.175	-4.244

5. Conclusions

Out of sample only the forecast based on the first principal component of the micro predictions was better than the macro forecast. Part of the reason for this may be that some of the autoregressive models do not fit very well. Further work is under way to experiment with ARIMA models and models that include other variables, e.g. construction permits. In any case the results show that the gain from disaggregation may be outweighted by imprecise estimates caused by multicollinearity when the aggregation weights are estimated.

The aggregation methods might be developed further. Comparison of the methods when forecasting several periods ahead would be interesting. On the other hand, estimation of time-varying aggregation weights would allow aggregation of the micro forecasts directly in percentage change (or log difference) form; in the case of combining competing forecasts this has recently been suggested by Engle, Granger and Kraft (1984).

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