Macroeconomic Forecasting Using Pooled International Data

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1. INTRODUCTION

It has long been recognized that national economies are economically interdependent [see, e.g., Burns and Mitchell (1946) for evidence of comovements of business activity in several countries and Zarnowitz (1985) for a summary of recent evidence]. Recognition of such interdependence raises the question, Can such interdependence be exploited econometrically to produce improved forecasts of countries' macroeconomic variables such as rates of growth of output, and so forth? This is the problem that we address in this article, using annual and quarterly data for a sample of European Economic Community (EEC) countries and the United States.

We recognize that there are several alternative approaches to the problem of obtaining improved international macroeconomic forecasts. First, there is the approach of Project Link that attempts to link together elaborate structural models of national economies in an effort to produce a world structural econometric model. A recent report on this ambitious effort was given by Klein (1985). We refer to this approach as a "top-down" approach, since it uses highly elaborate country models to approach the international forecasting problem. In our work, we report results based on a "bottom-up" approach that involves examining the properties of particular macroeconomic time series variables, building simple forecasting models for them, and appraising the quality of forecasts yielded by them. We regard this as a first step in the process of constructing more elaborate models in the structural econometric modeling time series analysis (SEMTSA) approach described by Palm (1983), Zellner (1979), and Zellner and Palm (1974). Analysis of simple models for the rates of growth of output for various countries provides benchmark forecasting performance against which other models' performance can be judged, much in the spirit of Nelson's (1972) work with U.S. data. What is learned in this process can be very helpful in constructing more elaborate models. As Kashyap and Rao (1976) remark,

> Since the number of possible classes [or models] in the multivariate case is several orders larger than the corresponding number of univariate classes, *it is of utmost importance that we develop a systematic method of determining the possible classes*. This is best done by considering the equations for the individual variables $y_1, \ldots, y_m$ separately. (p. 221)

The plan of our article, which reports our progress to date, is as follows. In Section 2, we analyze data on annual growth rates of real output for nine countries. The forecasting performance of several naive models is compared with that of more sophisticated models that incorporate leading indicators, common influences, and similarities in models' parameter values across countries in a Bayesian framework. (For some other studies comparing the properties of alternative forecasting procedures, see Harvey and Todd 1983; Makridakis et al. 1982; McNees 1986; Meese and Geweke 1984; Zellner 1985.) In addition, the quality of forecasts so obtained is compared with that of other available forecasts. Section 3 deals with an analysis of quarterly data for six countries. Again the forecasting performance of several naive models is compared with that of several slightly more complex models. Finally, in Section 4 a summary of results is presented and some concluding remarks regarding future research are presented.

2. ANALYSES OF ANNUAL DATA FOR NINE COUNTRIES

Annual data, 1951–1981, for nine countries' output growth rates, measured as $g_t = \ln(O_t/O_{t-1})$, where O_t is real output (real gross national product or real gross domestic product), have been asssembled in the main

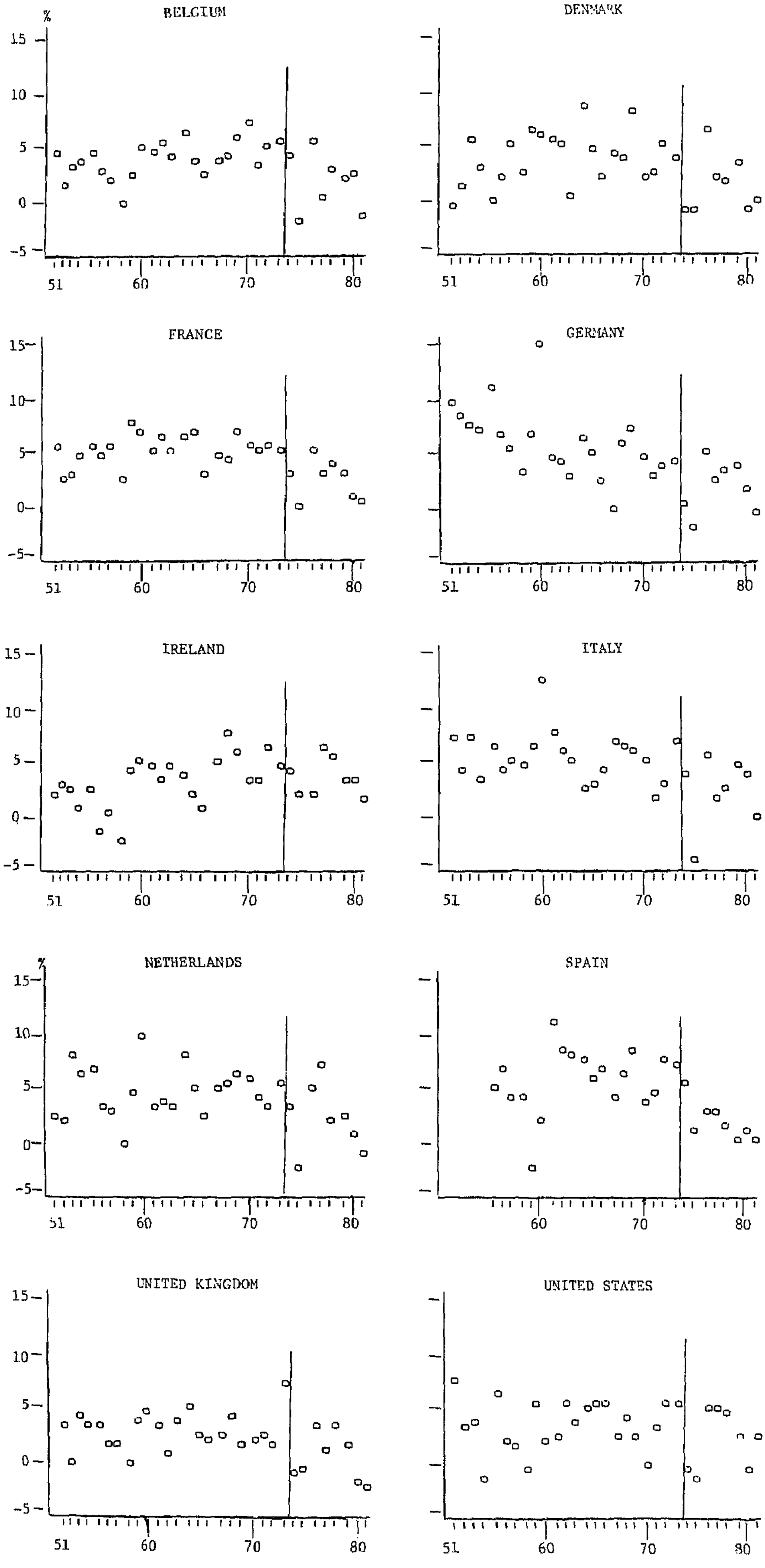

Figure 1. Annual Growth Rates of Real Output by Country, 1951–1981.

from the International Monetary Fund's International Financial Statistics data base. (An appendix giving the data is available on request.) The data relate to the following countries: Belgium, Denmark, France, Germany, Ireland, Italy, the Netherlands, the United Kingdom, and the United States. Plots of the basic data are shown in Figure 1, including data for Spain that have not as yet been analyzed.

Our procedure in analyzing our data was as follows:

1. We used the data, 1954–1973, 20 observations to fit each of our models, with the 1951–1953 data used for initial lagged values of variables.
2. Then the fitted models were employed to generate eight one-step-ahead forecasts for the years in our forecast period, 1974–1981. In making one-step-ahead forecasts, models were reestimated using all past data prior to each forecast period.
3. Forecast errors were computed for each forecast period and country. The root mean squared errors (RMSE's) by country and overall measures of forecasting precision have been computed to appraise the forecasting performance of different models.

2.1 Individual Country Models

Years ago, Milton Friedman suggested that the forecasting performance of naive models (NM's) be determined to serve as a benchmark in evaluating the forecasting performance of more complicated models and procedures, a suggestion pursued by Christ (1951) in his evaluation of the forecasting performance of a structural econometric model of the U.S. economy and many others. Here we use the following two NM's to forecast the growth rate g_t:

$$\text{NMI: } \hat{g}_t = 0 \tag{2.1}$$

$$\text{NMII: } \hat{g}_t = g_{t-1}. \tag{2.2}$$

The forecast of NMI, $\hat{g}_t = 0$, is optimal in a mean squared error (MSE) sense if the logarithm of output, O_t, follows a random walk—that is, $g_t \equiv \ln O_t - \ln O_{t-1} = \varepsilon_{1t}$, where ε_{1t} is a white noise error term with zero mean. Then $\hat{g}_t = 0$ is the minimal MSE forecast. The NMII forecast is a minimal MSE forecast if g_t follows a random walk, $g_t = g_{t-1} + \varepsilon_{2t}$, where ε_{2t} is a white noise error term with zero mean. For this latter process, $E(g_t \mid I_t) = g_{t-1}$ (where I_t denotes values of g_t prior to period t) is a minimal MSE forecast. For each country, the two NM forecasts in (2.1)–(2.2) were calculated for each of eight years in the forecast period 1974–1981 with results shown in lines A and B of Table 1.

From line A of Table 1, it is seen that NMI's RMSE's in percentage points range from 4.38 for Ireland to 2.21 for the United Kingdom. The median RMSE across countries is 3.09.

In line B of Table 1, the RMSE's for NMII are shown. These range from 2.06 percentage points for Ireland to 4.88 for Italy, with a median of 3.73. Thus the range of the RMSE's and the median RMSE for NMII's forecasts are both larger than those for NMI. Both NM's forecast errors are rather large, however, particularly in the vicinity of turning points in the rate of growth of output that occurred in the neighborhoods of 1974–1975 and 1979–1980 for most countries. Thus possible improvement in forecasting performance relative to that of the NM's performance might be attained through improved forecasting of turning points.

As a first step in the direction of attempting to improve on the forecasting performance of NM's I and II, we fitted autoregressions of order 3 [AR(3)'s] to each country's data. That is,

$$g_{it} = \alpha_{0i} + \alpha_{1i}g_{it-1} + \alpha_{2i}g_{it-2} + \alpha_{3i}g_{it-3} + \varepsilon_{it},$$
$$t = 1, 2, \ldots, 20, \quad i = 1, 2, \ldots, 9, \tag{2.3}$$

was considered for each country. We chose an AR(3) model to allow for the possibility of having two complex roots, associated with a cyclical solution, and one real root associated with a trend in the growth rate.

The AR(3) model in (2.3) was estimated for each

Table 1. Root Mean Squared Errors of One-Step-Ahead Forecasts of Annual Real Output Growth Rates for Nine Countries

Model	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	United Kingdom	United States
					Percentage points				
A. NMI ($\hat{g}_t = 0$)	3.09	2.83	2.96	2.95	4.38	3.72	3.77	2.21	3.48
B. NMII ($\hat{g}_t = g_{t-1}$)	4.25	3.73	2.43	3.26	2.06	4.88	4.04	3.91	3.60
C. AR(3)[a]	3.66	3.46	2.89	3.39	1.69	4.75	3.52	3.50	2.48
D. AR(3) with leading indicators[b]	2.70	3.29	3.21	2.14	1.82	3.95	2.29	2.89	2.31
E. AR(3) model as in D plus world return[c]	1.54	3.04	2.39	2.31	1.84	3.06	2.36	2.91	2.43
F. AR(3) model as in E plus money growth rate[d]	1.56	2.92	2.43	1.47	1.83	2.57	2.63	2.23	1.82

NOTE: The forecast period is 1974–1981; the initial fitting period is 1954–1973.

[a] The AR(3) model is $y_{it} = \alpha_{0i} + \alpha_{1i}y_{it-1} + \alpha_{2i}y_{it-2} + \alpha_{3i}y_{it-3} + \varepsilon_{it}$; see Equation (2.3).

[b] This model is that shown in footnote a with the addition of two terms $\beta_{1i}SR_{it-1} + \beta_{2i}SR_{it-2}$, where SR_{it} denotes the real stock return for the ith country in period t.

[c] This model is that described in footnote b plus the addition of a term $\gamma_i WR_{t-1}$, where WR_{t-1} is the median of the countries' real stock returns in period $t-1$.

[d] This model is that described in footnote c plus the addition of a term $\delta_i GM_{it-1}$, where GM_{it-1} is the lagged growth rate of the ith country's real money supply.

country separately using 20 observations, 1954–1973. Using a diffuse prior distribution for the parameters and given initial starting values, it is well known that the posterior means of the autoregressive parameters are identical to least squares estimates. In addition, the mean of the one-step-ahead predictive distribution is identical to the least squares point prediction. Thus these diffuse prior estimates and diffuse prior predictions are the same as those provided by application of least squares (see, e.g., Zellner 1971, chap. 7). Later, these diffuse prior predictions will be compared with those based on more informative prior distributions.

For many countries, the autoregressive parameters were not estimated very precisely, and if one performed mechanical "t tests" of hypotheses that coefficients of lagged terms are equal to 0 at an approximate 5% level of significance, many coefficients appeared equal to 0 with the exception of those for Ireland. Moreover, the residuals from the fitted relations appeared to be non-autocorrelated. In cases in which the autoregressive coefficients are "truly" equal to 0 or very small in value, there should not be much if any improvement in forecasting precision relative to that of the NM's. It is recognized, however, that the preceding approximate t tests or F tests are not very powerful; and thus it was decided to compute AR(3) forecasts and their RMSE's that are shown in row C of Table 1. It is seen that the largest RMSE is 4.75 for Italy, whereas the smallest is 1.69 for Ireland. The median RMSE is 3.46, that for Denmark; it is considerably higher than the median RMSE for NMI, namely 3.09. The AR(3) model resulted in a lower RMSE relative to NMI just for Ireland and the United States, where the improvement is relatively large, 1.69 versus 4.38 and 2.48 versus 3.48, and for France and the Netherlands, where the improvement is slight, 2.89 versus 2.96 and 3.52 versus 3.77.

Thus, using AR(3) models did not produce substantially improved overall performance, perhaps because unneeded parameters were added and/or because the effects of lagged terms were masked due to omitted relevant variables, a possibility explored hereafter. It was also noted that AR(3) models had large forecasting errors in the vicinity of turning points.

Since the NM's and the AR(3) models generally performed rather poorly in the vicinity of turning points, it was decided to add a leading indicator variable, lagged real stock returns for each country—see Fischer and Merton (1984), who found that lagged stock market variables were useful in forecasting U.S. real gross national product (GNP). This indicator variable is close to being white noise and thus could be buried in the error terms of our AR(3)'s that also appeared to be non-autocorrelated. By taking a measurable white noise component out of our approximately white noise error terms, we are effectively attempting to "forecast white noise" along the lines suggested by Granger (1983). In these experiments, we used the AR(3) model in (2.3) with each country's equation containing that country's real stock returns lagged one and two years. Thus two terms, real stock returns lagged one and two years, were added to (2.3) and the relations were fitted for each country by least squares. The results of forecasting from these "leading indicator" models are shown in row D of Table 1. The lowest RMSE is 1.82 for Ireland and the largest is 3.95 for Italy, with a median equal to 2.70, that for Belgium. This median RMSE of 2.70 is quite a bit lower than that for the AR(3) without leading indicator terms, namely 3.46. Thus use of the leading indicator terms in the AR(3) model has led to about a 22% reduction in median RMSE. On comparing rows C and D of Table 1, it is also seen that the RMSE's in row D are with two exceptions, France and Ireland, lower (many considerably lower) than the corresponding RMSE's in row C for the AR(3) model. It appears that use of each country's real stock returns has produced a noticeable and important improvement in forecasting performance relative to those of the AR(3) model and the NM's. Note that the median RMSE for NMII is 3.73, whereas that for the leading indicator model in row D is 2.70, approximately a 38% reduction.

The leading indicator AR(3) models' RMSE's in row D of Table 1 do not reflect any allowance for inter-country effects, except insofar as these are reflected in each country's lagged variables. There are many ways to model interdependencies among countries. One simple way of doing this is to view the median real stock return of all countries as representing a "world effect" that exerts an influence on individual countries as an indicator of future world conditions. With this possibility in mind, we expanded the AR(3) model in (2.3) to allow for two lagged own-country real stock return terms and a one-period lagged effect of the world real stock return as measured by the median of the nine countries' one-period lagged real stock returns. With the addition of this lagged world return variable to the model used in row D of Table 1, the model was fitted by least squares for each country. The residuals for each country's model were found not to be very highly correlated with those of other countries, suggesting that the world return variable was indeed picking up a common influence affecting all countries. RMSE's of forecasts for these "leading indicator, world return, AR(3)" models are shown in row E of Table 1. The largest RMSE is 3.06 for Italy, and the smallest is 1.54 for Belgium. The median RMSE is 2.39, about a 12% reduction relative to the median RMSE in line D, 2.70.

Another leading indicator that has received considerable attention is the rate of growth of a country's real money supply. Thus the one-period lagged real money supply growth rate was added as a variable in each country's AR(3) model along with the two lagged stock return variables and the lagged world return variable. The forecasting performance of this model, fitted by least squares for each country, is shown in row F of Table 1. The median RMSE is 2.23 percentage points, lower than that for all other models. The lowest country

Table 2. Summary Measures of Forecasting Performance for Single Equation Forecasts

Model	Largest country RMSE	Smallest country RMSE	Median of nine countries' RMSE's
		Percentage points	
A. NMI ($\hat{g}_t = 0$)	4.38	2.21	3.09
B. NMII ($\hat{g}_t = g_{t-1}$)	4.88	2.06	3.73
C. AR(3)	4.75	1.69	3.46
D. AR(3) with two lagged own real stock returns*	3.95	1.82	2.70
E. AR(3) as in D plus one lag of real world return*	3.06	1.54	2.39
F. AR(3) as in E plus one lag of real money growth rate*	2.92	1.47	2.23

NOTE: Based on information in Table 1.
* See the footnotes in Table 1.

RMSE is 1.47 for Germany, and the highest is 2.92 for Denmark. Relative to the RMSE's in row E of Table 1, those in row F show large reductions for Germany, from 2.31 to 1.47; Italy, from 3.06 to 2.57; the United Kingdom, from 2.91 to 2.23; and the United States, from 2.43 to 1.82. In the cases of Belgium, France, and the Netherlands, there are slight increases in the RMSE's. Thus it appears that introducing the lagged money growth rates has provided an improvement in forecasting performance.

For convenience some of the summary measures mentioned previously are collected in Table 2. We see from Table 2 that the world return, own stock return, money growth rate leading indicator AR(3) model in row F of Tables 1 and 2 has produced the lowest median RMSE of forecast, the lowest country RMSE, and the lowest, largest country RMSE. For the model in row F,

$$g_{it} = \alpha_{Oi} + \alpha_{1i}g_{it-1} + \alpha_{2i}g_{it-2} + \alpha_{3i}g_{it-3} + \beta_{1i}SR_{it-1} + \beta_{2i}SR_{it-2} + \gamma_i WR_{t-1} + \delta_i GM_{it-1} + u_{it}, \quad (2.4)$$

the RMSE's of forecast ranged from 2.92 percentage points for Denmark to 1.47 for Germany, with a median of 2.23 for the nine countries. Except for Denmark and the United Kingdom, RMSE's are much smaller than those for NMI (see Table 1). The RMSE's for Denmark and the United Kingdom are about the same as those for NMI. Relative to NMII, the RMSE's for forecasts from (2.4) are all substantially lower with the exception of France, for which they are equal. Thus, in summary, use of the model in (2.4) has produced improvement in terms of median RMSE relative to all other models. Use of (2.4) has also produced improvements for most countries.

It has been recognized in the literature that parameters may not be constant through time because of aggregation effects, policy changes, and so forth; thus time-varying parameter (TVP) versions of our models were formulated, estimated, and used in forecasting. For some other works using Bayesian TVP models, see Doan, Litterman, and Sims (1983), Harrison and Stevens (1976), Highfield (1984), Los (1985), and West, Harrison, and Migon (1985). The TVP model that we employed for each country is in the following form:

$$g_{it} = \mathbf{x}_{it}'\boldsymbol{\beta}_{it} + u_{it} \quad (2.5a)$$

$$\boldsymbol{\beta}_{it} = \boldsymbol{\beta}_{it-1} + \mathbf{v}_{it}, \quad (2.5b)$$

where $\mathbf{x}_{it}'$ is a vector of input variables including a unit element for the intercept term, three lagged values of g_{it}, and lagged leading indicator variables. The time-varying coefficient vector $\boldsymbol{\beta}_{it}$ is assumed to follow a vector random walk, as shown in (2.5b). Further, we assume that u_{it}'s have been independently drawn from a normal distribution with zero mean and variance σ_i^2 and that the $\mathbf{v}_{it}$ vectors have been independently drawn from a multivariate normal distribution with zero mean vector and covariance matrix $\phi_i\sigma_i^2 I$—that is,

$$u_{it}\text{'s: NID}(0, \sigma_i^2) \quad \text{and} \quad \mathbf{v}_{it}\text{'s: NID}(\mathbf{0}, \phi_i\sigma_i^2 I). \quad (2.6)$$

If $\phi_i = 0$, this model reduces to a fixed parameter model.

The model in (2.5) was estimated using a Bayesian recursive state–space algorithm with various values of ϕ ranging from 0 to .50. The mean of the one-step-ahead predictive distribution was used as a forecast, since the mean is an optimal forecast relative to a squared error loss function with results shown in Table 3. In part A of Table 3, results for the AR(3) model with two lagged own real stock return variables, SR_{it-1} and SR_{it-2}, included as leading indicator variables are presented. For $\phi_i = 0$, the RMSE's are identical with those in row D of Table 1. For positive values of ϕ_i, including some not shown in the table, there were declines in the country RMSE's, some large, but the improvement was not encountered in all cases. For example, on comparing row A.1 ($\phi_i = 0$) with row A.3 ($\phi_i = .50$), it is seen that the RMSE's for Belgium, Denmark, France, and Italy show declines, some large, on allowing pa-

Table 3. RMSE's of One-Step-Ahead Forecasts, 1974–1981, Yielded by Time-Varying Parameter Models (2.5)–(2.6)

Model	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	United Kingdom	United States	Median RMSE
					Percentage points					
A. AR(3) with two lagged own real stock returns										
1. $\phi_i = 0$[a]	2.70	3.29	3.21	2.14	1.82	3.95	2.29	2.89	2.31	2.70
2. $\phi_i = .25$	2.55	2.85	2.59	2.19	2.39	3.55	2.32	2.77	2.39	2.55
3. $\phi_i = .50$	2.52	2.80	2.49	2.26	2.56	3.39	2.36	2.88	2.49	2.52
B. AR(3) as in A, plus one lag of world return and real money growth rate										
1. $\phi_i = 0$[b]	1.56	2.92	2.43	1.47	1.83	2.57	2.63	2.23	1.82	2.23
2. $\phi_i = .25$	1.63	2.82	2.17	1.01	2.29	1.92	2.62	1.82	1.80	1.92
3. $\phi_i = .50$	1.56	2.89	2.08	.97	2.59	1.68	2.59	1.82	1.81	1.82

[a] $\phi_i = 0$ yields the fixed parameter model in row D of Table 1.
[b] $\phi_i = 0$ yields the fixed parameter model in row F of Table 1.

rameters to vary. In the cases of Germany, Ireland, the Netherlands, and the United States, however, the RMSE's increased slightly, except in the case of Ireland, where the increase was large. For $\phi_i = .50$, the median RMSE is 2.52, whereas for $\phi_i = 0$, the fixed parameter case, the median RMSE is 2.70. Thus there is a slight overall reduction in median RMSE in going from $\phi_i = 0$ to $\phi_i = .50$.

In part B of Table 3, a time-varying parameter AR(3) model including own lagged stock return variables, SR_{it-1} and SR_{it-2}, the lagged world return, WR_{t-1}, and lagged money growth rate, MG_{it-1}, was used to produce one-step-ahead forecasts for the years 1974–1981. Its RMSE's of forecast are shown in rows B.1–3 of Table 3. For $\phi_i = 0$, the model reduces to the fixed parameter model in row F of Table 1. The median RMSE for the country forecasts with $\phi_i = 0$, the fixed parameter case is 2.23, and for the time-varying parameter cases, $\phi_i = .25$ and $\phi_i = .50$, the median RMSE's are 1.92 and 1.82, respectively, the latter about 18% lower than that for $\phi_i = 0$. For $\phi_i = .50$ relative to $\phi_i = 0$, there are large reductions in country RMSE's for France, Germany, Italy, and the United Kingdom and small reductions for Denmark and the Netherlands. For Belgium and

Table 4. RMSE's for One-Step-Ahead Forecasts From Models Using Unpooled and Pooled Data, 1974–1981

Model	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	United Kingdom	United States
					Percentage points				
A. NMI ($\hat{g}_t = 0$)	3.09	2.83	2.96	2.95	4.38	3.72	3.77	2.21	3.48
B. NMII ($\hat{g}_t = g_{t-1}$)	4.25	3.73	2.43	3.26	2.06	4.88	4.04	3.91	3.60
C. NMIII ($\hat{g}_t$ = past average)	3.23	3.48	3.06	3.87	1.88	3.90	3.74	2.95	2.81
D. AR(3): Unpooled[a]	3.66	3.46	2.89	3.39	1.69	4.75	3.52	3.50	2.48
E. AR(3) plus two lagged real stock returns									
1. Unpooled[a]	2.70	3.29	3.21	2.14	1.82	3.95	2.29	2.89	2.31
2. Pooled[b]	2.47	3.49	3.03	3.08	1.86	3.88	3.61	3.10	2.68
F. As in row E plus lagged world return									
1. Unpooled[a]	1.54	3.04	2.39	2.31	1.84	3.06	2.36	2.91	2.43
2. Pooled[c]	2.21	2.72	1.70	2.28	1.77	2.62	2.91	2.75	3.08
G. As in row F plus lagged real money growth rate									
1. Unpooled[a]	1.56	2.92	2.43	1.47	1.83	2.57	2.63	2.23	1.82
2. Pooled(1)[c]	1.69	2.37	1.35	2.03	1.77	2.22	2.87	2.26	2.75
3. Pooled(2)[d] ($\eta = .5$)	1.68	2.21	1.61	1.25	1.52	2.01	2.52	2.46	1.78

[a] Least squares forecasts for individual countries.
[b] Seemingly unrelated regression forecasts based on an estimated disturbance covariance matrix.
[c] Forecasts computed using the pooled coefficient vector estimate in (2.7).
[d] Forecasts computed using the pooling technique in (2.11) with $\eta = .5$.

the United States, the RMSE's are essentially the same for $\phi_i = .50$ as for $\phi_i = 0$, whereas for Ireland the RMSE is increased from 1.83 to 2.59 in going to time-varying parameters with $\phi_i = .50$. Thus although the overall reduction in median RMSE is large (approximately 18% in using time-varying parameter models and encountered for six of the nine countries), for three countries there was no improvement in RMSE. Current research is focused on use of time-varying parameter models along with the pooling techniques described in the next section.

2.2 Forecasts Based on Pooled International Data

In this section we consider forecasts derived from models implemented with data from all countries—that is, pooled international data. There are many different pooling models. Here we report the forecasting performance of a subset of these models. Of particular interest is the extent to which use of various pooling models results in improved forecasting performance relative to that of naive models and of single equation models implemented just with individual countries' data. As previously, we use the annual data on countries' growth rates of output and other variables for the period 1954–1973 to fit our models. Then these fitted models are employed to compute one-year-ahead forecasts for the eight years 1974–1981 using updated estimates based on all data prior to each forecast period.

The first model that we consider is the AR(3) model including each country's real stock returns lagged one and two years. We have such a model for each of our nine countries. The *seemingly unrelated regression* (SUR) approach was used, with an estimated disturbance covariance matrix, to obtain pooled estimates of coefficient vectors for each country. One-year-ahead forecasts based on these pooled estimates, updated each year, were obtained for the years 1974–1981. The RMSE's of these forecasts are presented in row E.2 of Table 4. For comparison, the RMSE's of unpooled forecasts—that is, individual country least squares forecasts—are presented in row E.1 of Table 4. In this case, the pooled forecasts' RMSE's are smaller in three cases than the corresponding unpooled forecast RMSE's. The lack of substantial improvement through pooling in this case may be due to the large number of elements in the disturbance covariance matrix, 45 elements, that must be estimated and the fact that the sample size is not large. As shown in Table 5, rows E.1 and E.2, the median RMSE's for the unpooled and pooled forecasts are 2.70 and 3.08, respectively. Thus overall there is not much difference in the performance of the unpooled and pooled forecasts in this instance. Both median RMSE's, however, are substantially below those for the NM's and for an unpooled AR(3) model (see rows A–D in Table 5).

In a second pooling experiment, an AR(3) model with each country's real stock returns lagged one and two years and a world return variable lagged one year was considered. Because, as mentioned previously, introduction of the lagged world return variable in each country's equation produced error terms' contemporaneous correlations that were very low, we used the following simple pooling technique. Let $\mathbf{g}_i$ be the observation vector of the ith country's growth rates and

Table 5. Summary Statistics for RMSE's in Table 4

Model	Median RMSE	Lowest country RMSE	Highest country RMSE
		Percentage points	
A. NMI	3.09	2.21	4.38
B. NMII	3.73	2.06	4.88
C. NMIII	3.23	1.88	3.90
D. AR(3): Unpooled[a]	3.46	1.69	4.75
E. AR(3) plus two lagged real stock returns			
1. Unpooled[a]	2.70	1.82	3.95
2. Pooled[b]	3.08	1.86	3.88
F. As in row E plus lagged world return			
1. Unpooled[a]	2.39	1.54	3.06
2. Pooled[c]	2.62	1.70	3.08
G. As in row F plus lagged real money growth rate			
1. Unpooled[a]	2.23	1.47	2.92
2. Pooled(1)[c]	2.22	1.35	2.87
3. Pooled(2)[d] (η = .5)	1.78	1.25	2.52

[a] See footnote a, Table 4.
[b] See footnote b, Table 4.
[c] See footnote c, Table 4.
[d] See footnote d, Table 4.

X_i the matrix of observations of the ith country's input variables with a typical row $(1, g_{it-1}, g_{it-2}, g_{it-3}, SR_{it-1}, SR_{it-2}, WR_{t-1})$. Then the pooled coefficient vector estimate, denoted by $\tilde{\boldsymbol\beta}$, was computed as follows:

$$\tilde{\boldsymbol\beta} = (X_1'X_1 + X_2'X_2 + \cdots + X_9'X_9)^{-1} \times (X_1'X_1\hat{\boldsymbol\beta}_1 + X_2'X_2\hat{\boldsymbol\beta}_2 + \cdots + X_9'X_9\hat{\boldsymbol\beta}_9), \quad (2.7)$$

a matrix-weighted average of the single-equation least squares estimates, $\hat{\boldsymbol\beta}_i = (X_i'X_i)^{-1}X_i'\mathbf{g}_i$ $(i = 1, 2, \ldots, 9)$. The joint estimate $\tilde{\boldsymbol\beta}$ in (2.7) can be rationalized in at least three ways. First, if we assume that countries' parameter vectors and their disturbance variances are not very different, we can consider the following model for the observations:

$$\begin{bmatrix} \mathbf{g}_1 \\ \mathbf{g}_2 \\ \vdots \\ \mathbf{g}_9 \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_9 \end{bmatrix} \boldsymbol\beta + \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_9 \end{bmatrix}. \quad (2.8a)$$

Given that we use least squares to estimate the common coefficient vector $\boldsymbol\beta$, the result is the estimate shown in (2.7).

Second, if for each country we have $\mathbf{g}_i = X_i\boldsymbol\beta_i + \mathbf{u}_i$ and we assume that the $\boldsymbol\beta_i$'s are random satisfying $\boldsymbol\beta_i = \boldsymbol\theta + \mathbf{v}_i$ $(i = 1, 2, \ldots, 9)$, where $\boldsymbol\theta$ is a common mean vector and the $\mathbf{v}_i$ vectors are uncorrelated with the variables in X_i, then $\mathbf{g}_i = X_i\boldsymbol\theta + \boldsymbol\eta_i$, where $\boldsymbol\eta_i = X_i\mathbf{v}_i + \mathbf{u}_i$. Then, under relatively weak conditions, the estimator $\tilde{\boldsymbol\beta}$ in (2.7) is a consistent estimator for $\boldsymbol\theta$. If more were assumed about the properties of the $\mathbf{u}_i$'s and $\mathbf{v}_i$'s it is possible to define asymptotically efficient estimators for $\boldsymbol\theta$ and predictors. This involves introducing possibly questionable assumptions and additional parameters, however. Since our sample size is small and we do not have much data to assess the quality of the needed additional assumptions, we decided to use $\tilde{\boldsymbol\beta}$ in (2.7) for each country to generate pooled forecasts.

A third way of rationalizing $\tilde{\boldsymbol\beta}$ in (2.7) is to consider a version of the Lindley and Smith (1972) pooling model. Here we have $\mathbf{g}_i = X_i\boldsymbol\beta_i + \mathbf{u}_i$ $(i = 1, 2, \ldots, 9)$ or

$$\begin{bmatrix} \mathbf{g}_1 \\ \mathbf{g}_2 \\ \vdots \\ \mathbf{g}_9 \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & X_9 \end{bmatrix} \begin{bmatrix} \boldsymbol\beta_1 \\ \boldsymbol\beta_2 \\ \vdots \\ \boldsymbol\beta_9 \end{bmatrix} + \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \\ \vdots \\ \mathbf{u}_9 \end{bmatrix} \quad (2.8b)$$

or

$$\mathbf{g} = Z\boldsymbol\beta_a + \mathbf{u}, \quad (2.8c)$$

where $\mathbf{g}' = (\mathbf{g}_1'\ \mathbf{g}_2' \cdots \mathbf{g}_9')$, Z is the block diagonal matrix in (2.8b), $\boldsymbol\beta_a' = (\boldsymbol\beta_1'\ \boldsymbol\beta_2' \cdots \boldsymbol\beta_9')$, and $\mathbf{u}' = (\mathbf{u}_1'\ \mathbf{u}_2' \cdots \mathbf{u}_9')$. Further, it is assumed that

$$\boldsymbol\beta_i = \boldsymbol\theta + \mathbf{v}_i, \qquad i = 1, 2, \ldots, 9, \quad (2.9)$$

where $\boldsymbol\theta$ is a mean vector for the $\boldsymbol\beta_i$'s. If we assume that the $\mathbf{u}_i$'s are independent, each with an $N(\mathbf{0}, \sigma^2 I)$ distribution, and that the $\mathbf{v}_i$'s are independent, each with an $N(0, \sigma_v^2 I)$ distribution, the probability density function for $\boldsymbol\beta_a$ given the data, σ^2, $\lambda = \sigma^2/\sigma_v^2$, and $\boldsymbol\theta = \tilde{\boldsymbol\beta}$ in (2.7) has a posterior mean, $\bar{\boldsymbol\beta}_a$, given by

$$\bar{\boldsymbol\beta}_a = (Z'Z + \lambda I)^{-1}(Z'\mathbf{g} + \lambda J\tilde{\boldsymbol\beta}) = (Z'Z + \lambda I)^{-1}(Z'Z\hat{\boldsymbol\beta} + \lambda J\tilde{\boldsymbol\beta}), \quad (2.10)$$

where $\hat{\boldsymbol\beta} = (Z'Z)^{-1}Z'\mathbf{g}$, with typical subvector $\hat{\boldsymbol\beta}_i = (X_i'X_i)^{-1}X_i'\mathbf{g}_i$, and $J' = (I\ I \cdots I)$. $\bar{\boldsymbol\beta}_a$ in (2.10) is a matrix-weighted average of $\hat{\boldsymbol\beta}$, the vector of the equation-by-equation least squares estimates, $\hat{\boldsymbol\beta}_i$, and $\tilde{\boldsymbol\beta}$ the pooled estimate given in (2.7). The weights involve $\lambda = \sigma^2/\sigma_v^2$. If $\sigma_v^2 \to 0$, $\lambda \to \infty$ and $\boldsymbol\beta_i \to \boldsymbol\theta$, from (2.9), and $\bar{\boldsymbol\beta}_a \to J\tilde{\boldsymbol\beta}$ or each subvector of $\bar{\boldsymbol\beta}_a$ approaches $\tilde{\boldsymbol\beta}$, the pooled estimate in (2.7). On the other hand, if $\lambda = \sigma^2/\sigma_v^2 \to 0$, then $\bar{\boldsymbol\beta}_a \to \hat{\boldsymbol\beta}$, the equation-by-equation least squares estimates. Using (2.10) to generate forecasts for various values of λ and for different models, it was generally found that use of a very large value for λ—that is, the pooled estimate in (2.7)—produced the most satisfactory forecasts in a RMSE sense.

Thus, with the preceding considerations and results in mind, we present the RMSE's of forecasts generated using $\tilde{\boldsymbol\beta}$ as the coefficient vector estimate for each country. The RMSE's of these pooled forecasts are presented in row F.2 of Table 4 with the RMSE's of unpooled forecasts in row F.1. The pooled forecasts' RMSE's are smaller in six of nine cases. Also from rows F.1 and F.2 of Table 5, however, the median RMSE for the unpooled estimates is 2.39, whereas that for the pooled estimates is 2.62, a 9% increase. Thus use of pooled forecasts in this case led to an improvement for six of nine countries, but an increase in the overall median RMSE.

Using the same pooling technique—that is, the common coefficient vector estimate $\tilde{\boldsymbol\beta}$ in (2.7)—for all countries and an AR(3) model with own country real stock returns lagged one and two years, the lagged world return, and each country's lagged money growth rate, pooled forecasts were generated. The RMSE's associated with these pooled forecasts are shown in row G.2 and the unpooled forecasts' RMSE's are shown in row G.1 of Table 4. For four of nine countries, the pooled RMSE's are smaller. From Table 5, rows G.1 and G.2, the median RMSE's for the unpooled and pooled forecasts are 2.23 and 2.22, respectively. It is seen that pooling in this instance led to just a very small reduction in median RMSE.

Last, another method of pooling was tried for the model considered in the last paragraph and in row G of Tables 4 and 5. For the ith country, $\hat{g}_{it}$ is its output growth rate least squares forecast for period t. Let $\bar{g}_t$ be the mean of the individual countries' forecasts for period t—that is, $\bar{g}_t = \sum_{i=1}^{9} \hat{g}_{it}/9$. Then we define a pooled forecast, $\tilde{g}_{it}$, as follows:

$$\tilde{g}_{it} = (1 - \eta)\hat{g}_{it} + \eta\bar{g}_t = \bar{g}_t + (1 - \eta)(\hat{g}_{it} - \bar{g}_t), \quad (2.11)$$

where η is a weighting factor. From the second line of (2.11), it is seen that we are "shrinking" the individual forecasts, $\hat{g}_{it}$, toward the mean forecast, $\bar{g}_t$, in a Stein-like manner.

RMSE's for country forecasts, 1974–1981, based on (2.11) for selected values of η are shown in Table 6. With $\eta = 0$, the RMSE's are identical to those shown in row G.1 in Table 4—that is, those for least squares forecasts for individual countries with no pooling. It is seen that for η values .25, .50, and .75 there are large reductions in country RMSE's relative to those for $\eta = 0$ for Denmark, France, Germany, Ireland, and Italy, small reductions for the Netherlands and the United States, and slight increases for Belgium and the United Kingdom. For $\eta = .5$, the median RMSE is 1.78, with the smallest RMSE being 1.25 and the largest 2.52. This median RMSE of 1.78 is about 20% lower than the median RMSE of 2.23 for the unpooled least squares forecasts (see rows G.1 and G.3 of Table 5). Thus the pooling procedure given in (2.11) has produced a substantial improvement in forecasting precision as measured by median RMSE. Plots of pooled forecasts, calculated from (2.11) and actual annual growth rates are presented in Figure 2.

2.3 Comparison With OECD Forecasts

In a very interesting article, Smyth (1983) presented an analysis of the annual forecasts made by the Organization for Economic Cooperation and Development (OECD) for seven countries' rates of growth of real GNP for the years 1968–1979. Although this period is different from our period, 1974–1981, in that the difficult (in a forecasting sense) years 1980 and 1981 are not included, it is thought that a comparison of RMSE's of forecast is of interest.

Smyth (1983) explained that "It is probable that more policy attention in the various countries is attached to the annual forecasts than to the half-yearly ones and that is why we analyse them here" (p. 37). He went on to state, "While account is taken of both official and unofficial national forecasts, the OECD forecasts are entirely the responsibility of the OECD Department of Economics and Statistics" (p. 38). He described the OECD forecasting procedures as follows:

> The OECD's forecasting cycle is semi-annual. The forecasting 'round' begins with a simulation of the interlink model to provide an initial update of the previous set of forecasts in the light of changes in exogenous factors. This, together with an assessment of special factors influencing each economy, provides a basis for preliminary assessments of the level of demand for the individual economies, which permits initial estimates of import and export demand. Exchange rates and the real price of oil are assumed to remain unchanged over the forecast period. Fiscal and monetary policy assumptions are made on the basis of existing stated policies.
>
> Budgetary statements are widely used to estimate public consumption and investment. Private investment components are forecast separately. . . . There is quite extensive reliance on investment surveys. Private consumption depends primarily on personal disposable income. The stockbuilding forecast is often based upon the behaviour of stock-output ratios. (p. 37)

Further, he noted that "judgements are imposed on the forecasting round by individuals not associated with the modelling process—namely, individuals from the OECD's various country desks" (p. 37).

It is clear that the OECD forecasting procedures are much more complicated than those presented here. Whereas we have employed various stock market return variables to reflect "outside influences and information," the OECD approach involves use of detailed data and the judgment of individuals in an attempt to capture outside influences and information. These and other differences in our and the OECD approaches are apparent to the reader from what has been presented previously.

As Smyth (1983, p. 45) showed, the OECD forecasts are better than those of naive random walk models for all countries. The RMSE's of the OECD annual GNP growth rate forecasts, 1968–1979, are given in Table 7, part A, along with those reported in Table 4, rows G.1–3, for countries appearing both in our and the OECD samples. The major results shown in part A of Table 7 are the following:

1. Our unpooled least squares forecasts, 1974–1981, based on (2.4), have lower RMSE's for three of the five countries—Germany, Italy, and the United Kingdom. For France and the United States, the OECD RMSE's are considerably smaller. The median RMSE of our forecasts, 2.23, is slightly larger than that for the OECD forecasts, 2.12.

2. Our 1974–81 pooled forecasts, row G.2 of Table 7, computed using the coefficient estimate in (2.7) and the variables in (2.4), have RMSE's smaller than the OECD's for three countries—France, Germany, and Italy; the same RMSE for the United Kingdom; and a

Table 6. Country RMSE's of the Forecast for 1974–1981, Associated With the Use of the Pooling Model (2.11) for Various Values of η

η	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	United Kingdom	United States	Median
				Percentage points						
0	1.56	2.92	2.43	1.47	1.83	2.57	2.63	2.23	1.82	2.23
.25	1.59	2.48	2.01	1.30	1.59	2.24	2.55	2.32	1.73	2.01
.50	1.68	2.21	1.61	1.25	1.52	2.01	2.52	2.46	1.78	1.78
.75	1.80	2.18	1.26	1.34	1.64	1.89	2.53	2.63	1.97	1.89
1	1.96	2.39	1.01	1.54	1.91	1.92	2.57	2.82	2.25	1.96

NOTE: Individual country forecasts, $\hat{g}_{it}$, were generated using the model in (2.4) and pooled using the relation in (2.11).

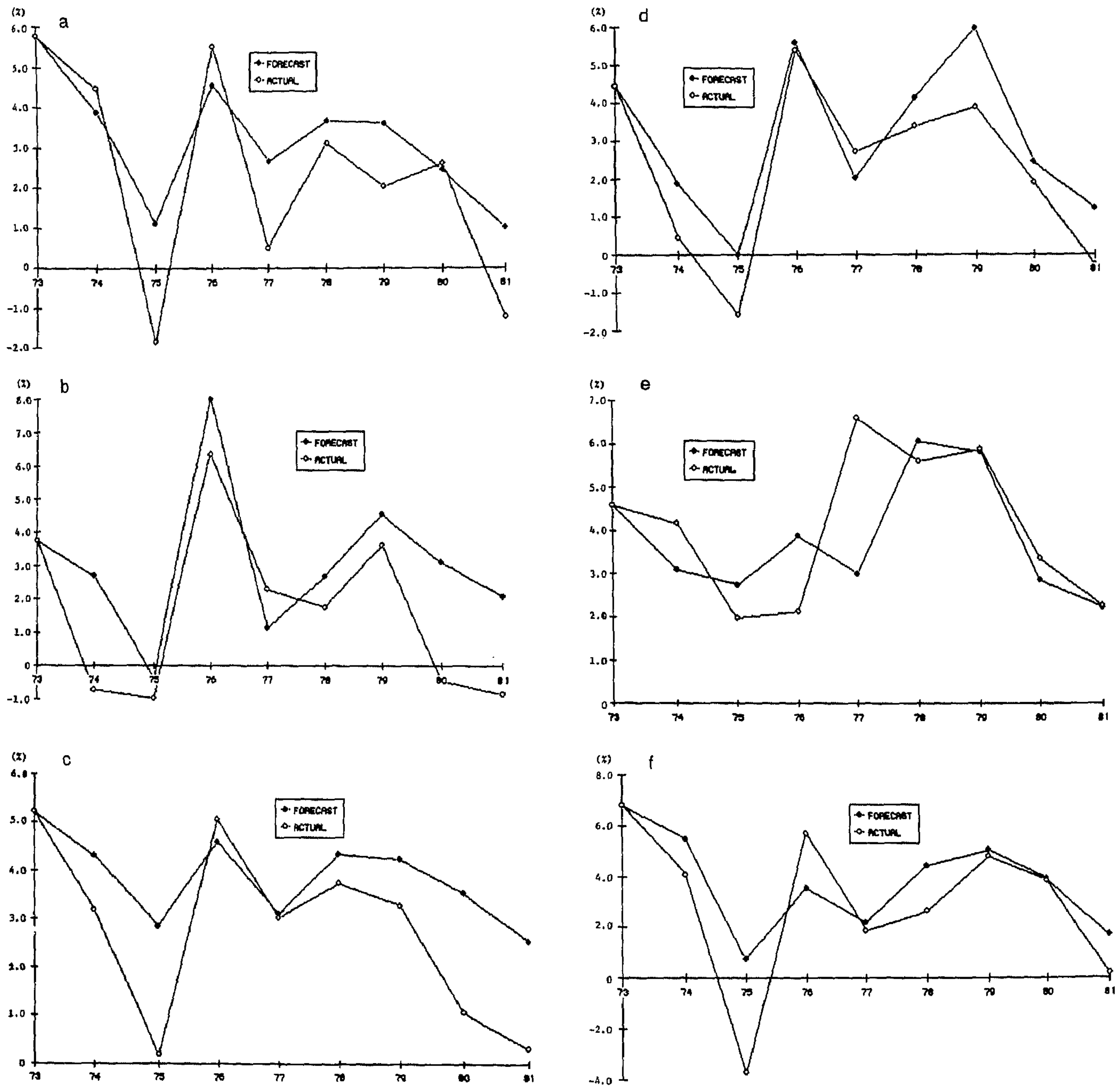

Figure 2. Plots of Annual Pooled Forecasts and Actual Output Growth Rates, 1974–1981: (a) Belgium, (b) Denmark, (c) France, (d) Germany, (e) Ireland, (f) Italy, (g) the Netherlands, (h) United Kingdom, (i) United States. The pooled forecasts are from row G.3 of Table 4 (η = .5).

much larger RMSE for the United States. The median RMSE's, 2.12 for the OECD forecasts and 2.22 for our forecasts, are very similar.

3. Our 1974–1981 pooled forecasts, row G.3 of Table 7, computed using the shrinkage formula in (2.11) with η = .5 and the model in (2.4), have RMSE's that are smaller for two countries, Germany and Italy, and larger for the remaining three countries. The median RMSE for our forecasts is 1.78, somewhat lower than that for the OECD forecasts, namely 2.12.

4. On comparing the OECD forecast RMSE's in Table 7 with those for our Bayesian TVP models' forecast RMSE's for ϕ = .50 in Table 3, it is seen that the latter are much smaller for Germany, .97 versus 2.12; Italy, 1.68 versus 2.86, and the United Kingdom, 1.82 versus 2.26, and somewhat larger for France, 2.08 versus 1.45, and the United States, 1.81 versus 1.38. The median RMSE for the TVP models' forecasts is 1.82, lower than the OECD median RMSE, 2.12.

5. In addition to the OECD RMSE's reported in

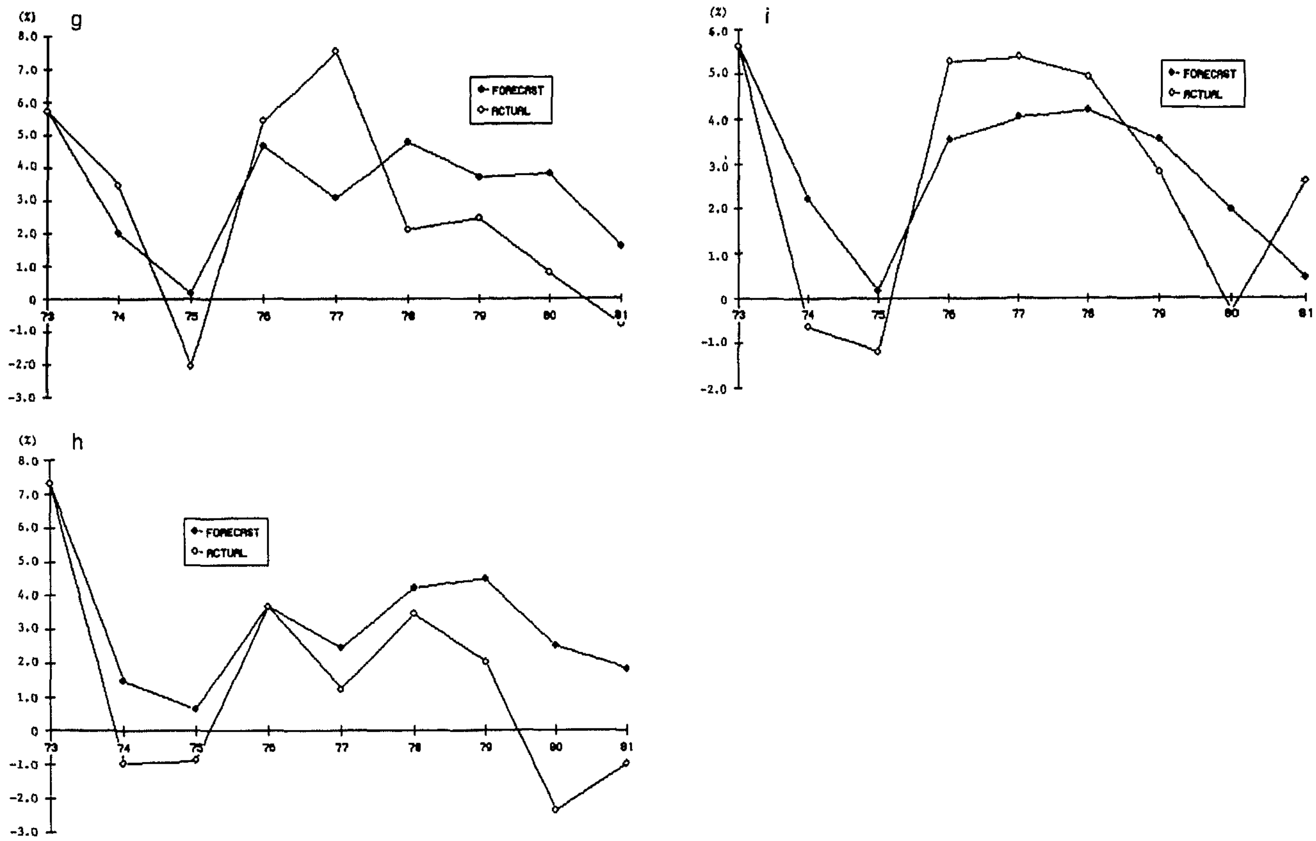

Figure 2 (continued).

Table 7, Smyth (1983, table 3, p. 47) reported the following RMSE's for countries not in our sample: Canada, 1.71, and Japan, 4.40.

Overall, it is concluded that our pooled and TVP forecasts compare favorably with the OECD forecasts except in the case of the United States, for which the OECD forecasts have a smaller RMSE. This conclusion should be qualified because the periods covered are not exactly the same. As mentioned previously, our period contains the "difficult" forecasting years 1980 and 1981. On the other hand, the OECD forecasts are "on-line"

Table 7. Comparison of Forecasting Performance

Forecasts	France	Germany	Italy	United Kingdom	United States	Median RMSE
			Percentage points			
	A. RMSE's of GNP growth rate forecasts by country					
OECD (1968–1979)[a]	1.45	2.12	2.86	2.26	1.38	2.12
Table 4 (1974–1981)						
G1 unpooled[b]	2.43	1.47	2.57	2.23	1.82	2.23
G2 pooled[c]	1.35	2.03	2.22	2.26	2.75	2.22
G3 pooled[d]	1.61	1.25	2.01	2.46	1.78	1.78
	B. Mean absolute errors of GNP growth rate forecasts by country					
OECD (1968–1979)[a]	1.10	1.63	2.55	1.72	.85	1.63
Table 4 (1974–1981)						
G1 unpooled[b]	1.94	1.08	2.12	1.84	1.42	1.84
G3 pooled[d]	1.32	1.10	1.50	2.02	1.64	1.50
Table 4 (1974–1979)						
G1 unpooled[b]	1.57	1.25	2.39	1.22	1.12	1.25
G3 pooled[d]	.98	1.12	1.74	1.41	1.33	1.33

[a] Taken from Smyth (1983, table 3, p. 45).
[b] Least squares forecasts for individual countries using the model in (2.4).
[c] Forecasts computed using the pooled coefficient estimate in (2.7) and the variables in (2.4).
[d] Forecasts computed using the pooling technique in (2.11) with η = .5 and the model in (2.4).

forecasts made in December of year $t - 1$ for year t and may thus be subject to difficulties associated with use of preliminary estimates of GNP and related variables, whereas we have used data that are currently available for past years. At present, it is difficult to determine how these two considerations affect the comparisons reported in Table 7.

As a final comparison of the OECD forecasts and ours, we present mean absolute errors (MAE's) for the OECD and our forecasts, 1974–1981, in part B of Table 7. Also shown are the MAE's for the years 1974–1979, a period that may be more comparable to the OECD period. Our unpooled forecasts for the 1974–1981 period have lower MAE's for two countries, Germany and Italy, and larger MAE's for the remaining three countries. The OECD median MAE is 1.63, and for our unpooled forecasts it is 1.84. When the 1974–1979 period is used for our unpooled forecasts, our MAE's are lower for three countries and the median MAE is 1.25, much lower than that for the OECD forecasts, namely 1.63.

As regards the MAE's for our pooled forecasts for the 1974–1981 period, the pooled forecasts have lower MAEs for two of the countries and a median MAE of 1.50, almost the same as that for the OECD forecasts. When the 1974–1979 period is used, our pooled forecasts have lower MAE's for four of the five countries and a larger MAE for the United States. The median MAE is 1.33 for our pooled forecasts and 1.63 for the OECD forecasts. As mentioned previously, forecasts for the six-year period 1974–1979 are seen to be more accurate for most countries than those for the eight-year period 1974–1981.

In conclusion, it appears that our relatively mechanical forecasts are competitive with the OECD forecasts except in the case of the United States, in which the OECD forecasts are better. Although several hypotheses to explain this finding could be considered, we shall not pursue this matter further now.

3. FORECASTING QUARTERLY OUTPUT GROWTH RATES

Quarterly data, 1967II–1977IV, for six countries' output growth rates calculated from seasonally adjusted data and other variables have been employed to fit models. Then the fitted models have been used to generate one-quarter-ahead forecasts for each of 16 quarters, 1978I–1981IV. Each model has been reestimated quarter by quarter during the forecast period using data available prior to the forecast quarter. As with our analyses of annual data, we are interested in determining the extent to which pooling data across countries improves forecasting accuracy. For comparative purposes, we provide forecasting results for three naive models and autoregressive integrated moving average (ARIMA) models. The latter were identified using standard Box and Jenkins (1976) procedures and the 1967II–1977IV data. Then they were used to produce one-quarter-ahead forecasts with parameter estimates updated quarter by quarter.

In rows A–C of Table 8, the RMSE's of one-quarter ahead forecasts for the 16 quarters in the period 1978I–1981IV produced by three NM's are reported for each of the six countries. The median RMSE's are 1.16, 1.50, and 1.20 for NM's I, II, and III, respectively. These overall measures suggest that NM's I and III outperform

Table 8. RMSE's for One-Quarter-Ahead Forecasts of Quarterly Output Growth Rates for Six Countries, 1978I–1981IV

Model	France	Germany	Italy	Spain	United Kingdom	United States	Median RMSE
			Percentage points				
A. NMI ($\hat{g}_{it} = 0$)	.97	1.06	1.53	.71	1.65	1.25	1.16
B. NMII ($\hat{g}_{it} = \hat{g}_{it-1}$)	1.09	1.45	1.70	1.13	2.63	1.56	1.50
C. NMIII ($\hat{g}_{it}$ = past mean growth rate)	.91	1.02	1.34	1.18	1.73	1.22	1.20
D. ARIMA[a]	1.20	.94	1.44	.77	1.70	1.16	1.18
E. C, OG(1), S(1), W(1), M(1)[b]							
1. Unpooled[c]	1.29	1.18	1.44	1.17	1.78	1.20	1.24
2. Pooled[d]	1.01	1.03	1.33	.95	1.92	1.24	1.14
3. Pooled[e] ($\eta = .5$)	1.12	1.15	1.34	1.09	1.87	1.23	1.19
F. C, OG(1, 2, 3, 4, 8), S(1), W(1), M(1)[f]							
1. Unpooled[c]	1.31	1.08	1.58	.95	1.92	1.20	1.26
2. Pooled[d]	.98	.94	1.38	.89	1.88	1.23	1.10
3. Pooled[e] ($\eta = .5$)	1.14	1.09	1.44	.95	1.93	1.21	1.18

NOTE: Models were fitted using the data for 1967II–1977IV and reestimated using the data available before each forecast quarter.
[a] ARIMA models, identified and estimated using the 1967II–1977IV data, were used to generate one-quarter-ahead forecasts with parameter estimates updated quarter by quarter.
[b] C = constant, OG(1) = output growth rate lagged one quarter, S(1) = stock returns lagged one quarter, W(1) = world stock return (median of country returns) lagged one quarter, and M(1) = money growth rate lagged one quarter.
[c] Country by country least squares forecasts.
[d] Pooled forecasts using the procedure in (2.7).
[e] Forecasts computed using the pooling technique in (2.11) with $\eta = .5$.
[f] Variables as defined in footnote b but with output growth rates lagged 1, 2, 3, 4, and 8 quarters for each country.

NMII. For NMI, the country RMSE's range from a low of .71 for Spain to a high of 1.65 for the United Kingdom. The United Kingdom's RMSE's are the largest for each NM.

Shown in row D of Table 8 are the ARIMA one-quarter-ahead forecast RMSE's country by country. They range from a low of .94 for Germany to a high of 1.70 for the United Kingdom. The median RMSE is 1.18, about 2% higher than that for NMI. Thus the ARIMA forecasts are not appreciably better overall than those obtained from use of NMI. the RMSE's for NMI are lower than those for the ARIMA models for France, Spain, and the United Kingdom and higher for Germany, Italy, and the United States.

In row E of Table 8, unpooled and pooled forecasting results are presented. Each country's output growth rate was related linearly to a constant, C, its own output growth (OG) rate lagged one quarter, OG(1), its own real stock return lagged one quarter $S(1)$, the median of the country real stock returns lagged one quarter, $W(1)$, and each country's money growth rate lagged one quarter, $M(1)$. The unpooled forecasts are least squares forecasts derived from the individual country models with coefficient estimates updated quarter by quarter. These unpooled forecasts' median RMSE is 1.24, higher than that for two of the NM's and that for the ARIMA models. Thus these unpooled forecasts do not compare very favorably with those of NM's I and III and of the ARIMA models.

Pooled forecasts were obtained from the model in row E of Table 8 by a procedure exactly the same as that described in Equation (2.7). The Lindley–Smith procedure [see (2.10)] was also applied, and it was found that using very large values of the variance ratio parameter produced the lowest RMSE's of forecast; that is, the procedure reduced to the use of the pooling formula in (2.7). The pooled forecasts' RMSE's in row E.2 of Table 8 are lower than those for the unpooled forecasts for four of the six countries. The median RMSE is also 8% lower than the corresponding median RMSE for the unpooled forecasts. The pooling techniques in (2.11) with $\eta = .5$ produced the results in row E.3 of Table 8. It resulted in lower RMSE's for four of the six countries and a 4% decrease in the median RMSE. Thus pooling has generally increased forecast precision. Further, the pooled forecasts' median RMSE's compare favorably with those of the ARIMA and NM forecasts.

Shown in row F are forecasting results for a model similar to that considered in row E except that the output growth rate has been lagged 1, 2, 3, 4, and 8 quarters rather than just 1 quarter. The lags of 4 and 8 quarters were introduced to allow for possible inadequacies in the output seasonal adjustment procedures. The unpooled country least squares forecasts have RMSE's ranging from .95 for Spain to 1.92 for the United Kingdom, with a median RMSE equal to 1.26, about the same as that for the unpooled forecasts in row E.1. Further, the median RMSE for the unpooled forecasts in row F.1 is slightly larger than those for two of the NM's and the ARIMA models. On the other hand, the median RMSE's for the pooled forecasts in rows F.2 and F.3 of Table 8 are 1.10 and 1.18, lower than that for the unpooled forecasts, 1.26, and those for the NM's. Again, pooling has produced an overall gain in forecasting accuracy. Note that on comparing the country RMSE's in row F.1 with those in row F.2 the former unpooled, forecast RMSE's are all larger except in the case of the United States.

Table 9. RMSE's for One-Quarter-Ahead Forecasts of Quarterly Output Growth Rates for Three Countries, 1978I–1981IV

Model	*France*	*Germany*	*United States*
		Percentage points	
A. NMI ($\hat{g}_{it} = 0$)	.97	1.06	1.25
B. NMII ($\hat{g}_{it} = g_{it-1}$)	1.09	1.45	1.56
C. NMIII ($\hat{g}_{it}$ = past mean growth rate)	.91	1.02	1.22
D. ARIMA[a]	1.20	.94	1.16
E. C, OG(1, 2, 3, 4, 8), S(1), W(1), M(1), IN(1)[b]			
1. Unpooled[c]	1.29	1.07	1.17
2. Pooled[d]	.92	.91	1.13
F. C, OG(1, 2, 3, 4, 8), S(1), W(1), M(1), IN(1, 2, 3, 4)[e]			
1. Unpooled[c]	1.50	1.06	1.28
2. Pooled[d]	.89	.93	1.03

NOTE: See the note to Table 8.

[a] See footnote a in Table 8.

[b] Here the model for each country is the same as that described in footnote f of Table 8 with the addition of a country short-term interest rate lagged one-quarter, IN(1).

[c] Country by country least squares forecasts.

[d] Pooled forecasts using the procedure in (2.7).

[e] This model is the same as that on row E of this table except that each country's short-term interest rate enters lagged 1, 2, 3, and 4 quarters, IN(1, 2, 3, 4).

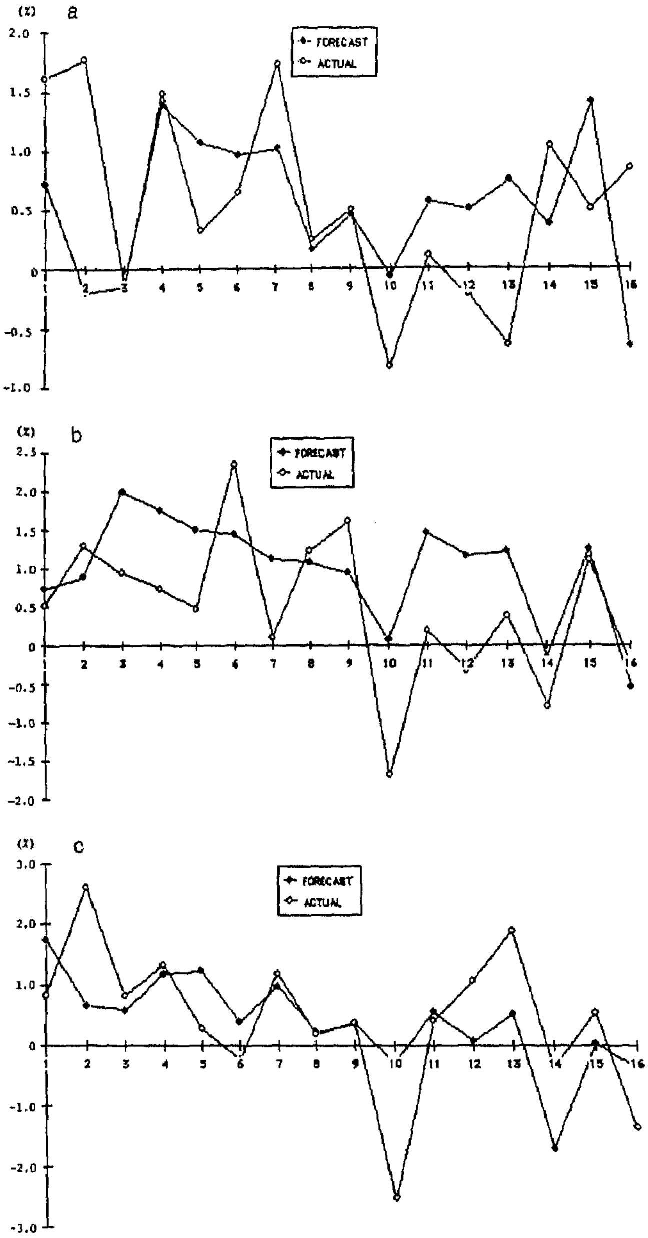

Figure 3. Plots of Quarterly Pooled Forecasts and Actual Output Growth Rates, 1978I–1981IV: (a) France, (b) Germany, (c) United States. The pooled forecasts are from the model in row F of Table 9.

In a last set of experiments with the quarterly data, data on short-term interest rates were obtained for three countries—France, Germany, and the United States. Interest rates lagged one quarter and one through four quarters were introduced in the models of rows E and F of Table 9. The RMSE's of one-quarter-ahead forecasts from these models with lagged interest rates included are shown in Table 9 along with RMSE's for the NM's and the ARIMA models. Adding the lagged interest rate terms generally led to reductions in RMSE's in almost all cases. Further, the pooled country forecast RMSE's are all lower than the corresponding unpooled country forecast RMSE's. The pooled country forecast RMSE's in row F.2 of Table 9 are all smaller than the corresponding RMSE's for the NM's and the ARIMA models. Plots of these forecasts and actual quarterly output growth rates are presented in Figure 3. In future work, lagged interest rate terms will be introduced in other countries' models.

4. SUMMARY OF RESULTS AND CONCLUDING REMARKS

For annual data on the growth rate of real output for eight EEC countries and the United States, one-year-ahead forecasts were generated for the years 1974–1981 using different models and forecasting techniques with the following results in terms of forecasting RMSE's:

1. Our AR(3)-leading indicator models outperformed several naive models and purely autoregressive models. These results underline the importance of using leading indicator variables in forecasting.
2. Our time-varying parameter models that incorporated country lagged stock returns, the lagged median return, and lagged money growth produced improved forecasts for six of the nine countries and improved overall forecast performance as measured by the median of the RMSE's of forecast for individual countries.
3. Relatively simple techniques for pooling individual countries' data or forecasts, applied to our models, led to an improvement in forecasting precision for many countries and overall.
4. The precision of our forecasts, produced by our relatively simple models and techniques, compares favorably with that of annual OECD forecasts, produced by use of much more complicated models and methods and incorporating judgmental information.

As regards our forecasting experiments with quarterly real output growth rates for several countries, one-quarter-ahead forecasts for the period 1978I–1981IV were calculated and compared with the following results:

1. Forecasts derived from our pooled autoregressive–leading indicator models compared favorably with those produced by three naive models and ARIMA models as measured by median RMSE's.
2. As with the annual data, use of relatively simple pooling techniques led to improved forecasting precision in terms of the countries' median RMSE's and in terms of many countries' RMSE's.

The results described are encouraging and indicate that use of relatively simple models and pooling techniques leads to improved forecasting results. In future work, we shall use additional variables—for example, lagged exchange rates that Litterman (1986) has found useful—and more recent data to check further the forecasting performance of our models. We also plan to use combinations of time-varying parameter models and various pooling techniques in an attempt to obtain further improvements in forecasting precision. Finally, an effort will be made to rationalize the forms of our models using relevant macroeconomic theory and to extend them to incorporate additional variables to be forecasted. Such interaction between subject matter theory and statistical analysis is needed to develop "causal" models that explain past data and forecast reasonably well.

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