FORECASTING ACCURACY OF ALTERNATIVE TECHNIQUES: A COMPARISON OF ALABAMA FORECASTS

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Introduction

Macroeconomists have always been interested in developing a tool to forecast macroeconomic aggregates and to perform policy analyses. Different alternative modeling techniques, at the national and regional levels, were developed to achieve those ends. Economic base and input-output models were among the earlier attempts. Both techniques, however, suffered from certain deficiencies which made their use a difficult matter. To counteract the deficiencies of the above models, new types of models known as econometric models or structural models have been developed. A structural model is a system of reduced form demand equations which attempt to quantify cause-effect relationships among economic variables. More specifically, a structural model is a system of simultaneous equations that specify underlying economic behavioral and equilibrium relationships for a given set of economic variables.

Although structural models created a great deal of excitement at the beginning, their theoretical deficiency, i.e. overidentification problem, and their dismal forecasting performance undermined their usefulness. These problems forced the profession to look for alternative modeling techniques.

The most notable alternatives are Box-Jenkins [1], autoregressive-integrated-moving-average (ARIMA), and vector autoregression (VAR) models. The first is a purely time series model and does not rely on any economic theory. The VAR and ARIMA models, on the other hand, can be derived by specific economic theory, and VAR is by far the most successful in capturing the notion of general equilibrium at the aggregate level. Proponents of VAR claim that the VAR models are superior to the structural models in terms of both theoretical considerations, i.e. identification of the model, and the accuracy of forecasts (Sims [11, 13], Cargill and Morus [2]).

In an effort to evaluate these claims, this paper develops a vector autoregression (VAR) model and a structural forecasting model for the Alabama economy. Both models use quarterly data from 1969:1 to 1985:4. The reason for choosing this specific time period has to do with both data availability and data compatibility. Initially, the models are estimated over 1969:1 to 1982:4, then a real-time scheme of quarterly estimating and forecasting are used to generate out of sample forecasts. The forecasting errors of the two models for different forecasting horizons are then used to compare the models' accuracy.

The use of VAR for the purpose of regional modeling, and comparing its forecasting accuracy to that of regional structural model, is motivated by two considerations. First, the VAR model has been claimed by its proponents to offer a number of advantages over traditional regional structural models. To name a few, it is both more parsimonious in its use of data and offers theoretical advantages over structural demand equation representations. Second, the recession of 1982 and its profound impact on Alabama appeared to have caused some structural changes in Alabama's economy. This in turn led to large forecasting errors by the structural models of Alabama, particularly for the post 1982 period. It is therefore important to try to understand the future prospects for Alabama's economy and to find out whether the VAR model can provide a more reliable forecasting mechanism toward that goal.

The Structural Approach

Structural economic models are defined as a system of equations that specify behavioral relationships among a given set of economic variables. In these models, exogenous variables are said to cause behavioral variables. The behavioral variables, or the endogenous variables, are linked to exogenous variables by behavioral equations. Finally, the behavioral equations are linked to each other through identities. For example, demand and supply equations in terms of relevant opportunity costs, constitute behavioral equations. The equilibrium condition, which makes supply to be equal to demand, is then specified through an identity.

The national structural models evolved from the Keynesian macroeconomic framework of sectoral demand analysis. For example, consumption, investment, government expenditures, and net exports represent the major behavioral equation blocks in the model. National Income is specified as an identity that defines income as summation of all four expenditures.

While national modeling may seem to be fairly straightforward, regional modeling is not as cut and dried. The availability of the data and their frequency present a major problem. Data on regional imports, exports, and nonmanufacturing investment are virtually nonexistent. To overcome these problems, this paper uses an approach known as the top-down technique. This technique involves constructing regional models that act as satellites to already existing national models. This is accomplished by making certain variables in the regional model dependent on national variables. National changes are then channeled into regional variables through these linkages.

The structural model developed here attempts to estimate three major blocks of behavioral equations. These blocks include real Gross State Product (GSP), total nonagricultural employment (NAE), and personal income (PYA). For the GSP and NAE block, demand type equations are estimated for the following industries: durable manufacturing; nondurable manufacturing; mining; contract construction; trade; services; finance, insurance, and real estate; transportation, communication, and public utilities; state and local government; federal government; and the farm sector. GSP and NAE are then estimated through aggregating individual industries' output and employment estimates.

The personal income block is estimated following the design of the national income and product accounts. That is, behavioral equations are specified to estimate Alabama wages and salaries; dividends, interest, and rent income; nonfarm proprietors' income; transfer payments; contribution to Social Security; and farm income.

The link between the Alabama model and the national economy is established primarily through the GSP block. As suggested by theory, manufacturing, mining, and federal government output are assumed to constitute export industries, and as such are directly tied to their national counterparts. The remaining industries are specified as functions of domestic variables, such as personal income, population, and some domestic energy and labor costs.

Output data are then used as the primary driver in the NAE block to estimate employment in each industry. More specifically, employment in each industry is specified as a function of output, average wage rate, and in some cases lagged employment for each industry. For the personal income block, Alabama's variables are regressed directly on their national counterparts.

When estimating the individual equations, extreme care is taken to adhere to economic and statistical theories in their strictest form. All equations are checked for serial correlation and corrections are made where serial correlation are detected. The signs of all parameters are checked to insure they are in line with the theoretical expectation; variables with reverse signs are dropped from equations.

The VAR Approach

The VAR models' distinctive advantage over the structural models is that VAR models estimate behavioral macrorelationships as unrestricted reduced forms; all variables are treated as endogenous. In other words, there are no *a priori* theoretical or statistical restrictions imposed on the individual equations. This implies that, as suggested by economic theory, any variable which appears on the right side of one of the equations appears on the right side of all the equations in the model. The approach used in the VAR models follows that of frequency-domain time series theory. Each estimated parameter is implicitly part of an infinite dimensional parameter space (Sims [11]).

More specifically, VAR represents a dynamic linear system of equations for modeling the joint serial correlation of a set of two or more variables. The primary intention is to imply the relationship between a number of variables and their past values through a general autoregressive structure (Cargill and Morus [2]). Formally, it is a set of equations

$$(1)\ Y_{i,t} = a + \sum_{j=1}^{N} \sum_{1=1}^{L} b_{i,j,1}\, Y_{j,t-1} + u_{i,t}$$

Where Y is a (N x 1) vector of variables, b is a (N x N) matrix of coefficients, u is a (N x 1) vector of residuals, and a is the constant term. This equation contains no deterministic (or exogenous) variables with exception to the constant term.

Equation (1) is an unconstrained version of VAR. The coefficients or the lag patterns are not restricted, meaning that parameters and the lag patterns are free to take any value. This, however, can present the model builder with a potential problem of overparametization. For example, each equation of a VAR system using a (4 x 1) matrix of variables and just 4 lags of each variable would have 16 parameters to estimate. This process can not only exhaust the degrees of freedom, but can also lead to poor forecasts due to the hazard of reading too much into estimation results.

To overcome this problem, this paper uses an approach developed by Litterman [4] and Doan [3]. Litterman and Doan show that forecast performance of a VAR model can be improved by imposing a prior on the model to restrict its parameters. This approach, which is based on Bayesian statistical theory, provides a modeler with guidance on how to combine prior beliefs (which are known independently of the sample data) and the sample data with which the model will be estimated.

Although in principal any kind of restriction can be imposed, this paper uses the one developed by Litterman known as the random walk prior. The random walk prior is based on the premises that the time series model y(t) = Y(t-1) + u(t) is a reasonable specification for a large number of economic relationships.

To employ the random walk prior in the VAR model, the value of the first own lag in each individual equation is restricted to 1.0. Next, parameters on all other lag variables, including own lags of more than one period, are restricted to zero. The third step involves setting tightness of the prior. This is to set the degree to which the coefficient of the first own lag is allowed to vary away from the assigned value. A tight prior--for example, .05--allows little variance from the imposed prior, while an extremely loose prior--say, 2--allows maximum variance around the prior mean for the first own lag. Once the value and tightness for the first own lag is set, then the modeler can repeat the same process for the other lags. That is, within each equation, different tightness levels, relative to that of the first own lag, can be assigned to other lag variables (Cargill and Morus [2]).

In theory, the initial choice of tightness on prior of the first own lag and other lags is, at best, an educated guess. In practice, however, one can minimize the amount of guess work by estimating a large number of models, each with slightly different prior values and tightness levels. The prior and tightness for the best model, in terms of out of sample forecast, can then be used as the optimal prior. The relative tightness of other lags can also be set using the above approach of trial and error.

Following the above approach, this paper attempts to build a VAR model for Alabama. Two sets of variables constitute the Alabama VAR model. The first set contains the local variable. Local activities are presented by total output (or real GSP), total nonagricultural employment (or NAE), and personal income (or PYA). The second set of data includes national variables and it contains real GNP, real money supply (measured by real M1), and the rate of interest (measured by the six month Treasury bill rates). All the variables are transformed to natural logs and, when applicable, seasonally adjusted data are used. For identification of priors and their tightness, a total of nine models are estimated. These models are different from each other in terms of tightness of the priors imposed on the coefficients. They are estimated over 1969:1 to 1982:4, and forecasts are generated from 1983:1 to 1985:4. The models are then evaluated in terms of their out of sample forecast errors as measured by the room mean square error (RMSE) of the forecasts. The RMSEs are reported in Table 1.

As shown in Table 1, an unconstrained VAR model (UVAR), a VAR model with no priors, is compared with eight Bayesian VAR (BVAR) alternatives. Two conclusions can be drawn from Table 1. First, a comparison of the RMSEs suggest that the BVAR specifications provide better forecasting statistics than the UVAR model. Second, the most promising version of the Alabama BVAR is a four lag model with an overall tightness prior of 0.1 and a relative tightness prior of .05 for GSP and NAE and .001 for PYA.

Model Evaluation and Comparison

To evaluate the forecast performances, the two models are simulated using a rolling sample, and out of sample forecasts are generated. Using the forecast values, forecast errors are computed. The results are reported in Tables 2 through 4. Forecast errors are measured in terms of mean absolute percentage errors (MAPE) which is defined as the mean of the ratio of the residuals over actual values, expressed as percentages. The advantage of this error over alternative methods of error measurement is that is is more useful for comparison purposes regardless of different variable measurement units. As an arbitrary standard, a MAPE value of less than five percent is perceived as an acceptable or tolerable margin of error.

Three types of forecast errors are generated starting from 1982:4 using a rolling sample or a real-time scheme of quarterly estimating and forecasting procedure. Table 2 reports forecast errors for one quarter forecast horizons. That is, the models are estimated through 1982:4 and then they are simulated to generate forecasts for 1983:1. Next, the 1983:1 observations are included in the sample and the two models are reestimated and simulated to generate forecast values for the proceeding quarter. This process is repeated until all degrees of freedom are exhausted. The same procedure is used to compute forecast errors for longer forecast horizons. For instance, Table 3 contains the MAPEs for four quarters forecast horizons while Table 4 reports the long-term forecast errors (from the end point to 1985:4 period).

As can be seen from Tables 1 through 3, both models appear to do reasonably well. The forecast errors for GSP, NAE, and PYA on the average are well below the five percent tolerable margin of error. For the individual subsamples, with exception to GSP forecasts for 1983:3 (end point 1983:2), no large or unacceptable MAPE is reported.

A comparison of the error statistics also suggest that the errors for the models are comparable. That is, with regard to GSP and PYA, the structural model seems to do marginally better than the VAR model. On the other hand, the VAR appears to generate lower MAPE than the structural model for the NAE variable. These trends seem to prevail for all three forecast horizons. The spread between the errors are not, however, large enough to make any one of the two models clearly superior to the other one.

There are, nonetheless, three interesting observations that can be made from the tables. One, as suggested by the standard deviations of the MAPEs, the forecast errors from the structural model appear to be more stable than those of the VAR model. For instance, the standard deviation of forecast error forecasts from the VAR model for GSP is 183 percent larger than the structural model's for one quarter forecast horizon; also the spread between the two standard deviations appears to widen considerably as longer forecast horizons are considered.

Second, starting with 1984:2, the VAR model seems to generate lower MAPEs than the structural model. This has to do with the fact that the time period from 1984:1 to 1985:4 was a period of economic stability. There were no sharp turning points during this period and therefore, the BVAR is able to generate better forecasts for that specific time period.

This brings us to the third observation regarding the forecasting of turning points. Cursory examination of the data shows that there were no sharp turning points for NAE and PYA. GSP, however, has experienced some sharp fluctuations in the latter part of 1983 and first quarter of 1984. For instance, GSP grew at -3.48 percent, 5.69 percent, and -1.83 percent in 1983:3, 1983:4, and 1984:1, respectively. A close examination of Tables 2 through 4 shows that the structural model does a significantly better job in forecasting these turning points in all three forecast horizons. The forecast errors for the VAR model are more than 200 percent larger than those of the structural model for these specific quarters.

Conclusion

The purpose of this paper was to develop two altérnative forecasting models of the Alabama economy and to compare their forecast's performances. To that end, structural and vector autoregressive time series models have been built to observe and forecast Alabama's key economic variables. Quarterly data, covering 1969:1 to 1985:4 were used to estimate and simulate the models.

Three conclusions are drawn from the above exercise. First, on an overall basis, the two models are comparable. Both models generated reasonable error statistics, well below the five percent critical value. The margin of forecast accuracy from either of the models, however, is not large enough to clearly make one superior to the other.

Second, the VAR model does a better job of forecasting during tranquil economic periods than the structural model. The forecast error from VAR, however, shows greater variation than its counterparts. And finally, the structural model seems to do a far more superior job of forecasting the turning points than the VAR.

Based on the above considerations, although the structural model is comparable to the VAR with regard to its long-run forecast accuracy, the structural model is by far a better tool for forecasting the business cycle.

Endnote

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Table 1
RMSE For Alabama VAR Model
Forecast Horizon, 1983:1 - 1985:4

MODEL	LNGSP	LNNAE	LNPYA
UVAR (No Priors)	.0322	.0150	.0150
BVAR (2.0, 1.0)	.0313	.0147	.0147
BVAR (2.0, .001)	.0298	.0149	.0090
BVAR (1.0, .05)	.0267	.0133	.0131
BVAR (1.0, .001)	.0299	.0149	.0090
BVAR (0.1, .05)	.0265*	.0120*	.0099
BVAR (0.1, .001)	.0286	.0142	.0090*
BVAR (0.05, .001)	.0279	.0139	.0091
BVAR (0.01, .001)	.0265	.0128	.0091

The first number in the parentheses indicates the degree of tightness for the first own lag, and the second number is the degree of tightness for other lags. Tightness for the other lags is in relative terms. For instance, for the second BVAR model, the tightness for other lags is .002. In all models, prior means for first own lag and those of other lags are, 1.0, and 0.0, respectively. A similar test, although not reported, indicated that a four lag model provides the best RMSEs. For this reason, all of the above models are estimated using four lags for the included variables.

Table 2
Comparison of Mean Absolute Percentage Errors
One Quarter Ahead Forecast Horizon

	GSP		NAE		PYA	
ENDPOINT	STR	VAR	STR	VAR	STR	VAR
82.4	0.23	0.24	.80	1.66	1.94	.68
83.1	0.89	0.35	1.36	2.19	.43	.32
83.2	1.69	6.12	2.21	.36	.58	1.32
83.3	1.64	4.20	2.16	.03	1.12	2.23
83.4	.26	3.47	.63	1.54	1.17	.55
84.1	.43	.29	1.65	1.56	.57	1.09
84.2	1.36	.32	1.9	.51	.50	.110
84.3	1.56	.52	2.16	.40	.92	.74
84.4	.67	.52	.91	1.66	1.23	.78
85.1	.82	1.10	1.18	1.03	.113	.63
85.2	1.59	.64	1.51	.65	.17	1.13
85.3	2.42	.92	2.05	.43	.92	.02
Average	1.13	1.56	1.54	1.00	.81	.80
Standard Deviation .68	1.93	.56	.69	.52	.60	

Table 3

Comparison of Mean Absolute Percentage Errors
Four Quarters Ahead Forecast Horizon

	GSP		NAE		PYA	
ENDPOINT	STR	VAR	STR	VAR	STR	VAR
82.4	1.16	1.10	1.56	1.11	.99	.77
83.1	1.27	1.36	1.54	2.81	.80	1.10
83.2	1.07	5.29	1.68	.58	.84	.95
83.3	.94	1.68	1.57	.56	.82	2.65
83.4	.88	3.78	1.55	.80	.76	.83
84.1	.96	.77	1.63	1.11	.79	1.67
84.2	1.08	.37	1.51	1.49	.68	.59
84.3	1.13	.59	1.41	1.10	.60	.80
84.4	1.32	.50	1.36	1.09	.61	.62
Average	1.09	1.68	1.53	1.18	.76	1.11
Standard Deviation .15	1.72	.09	.67	.12	.66	

Table 4

Comparison of Mean Absolute Percentage Errors
Long-Run Forecast Horizon (End Point to 1985:4)

VARIABLE NAVE MODEL ENDPOINT	GSP		NAE		PYA	
	STR	VAR	STR	VAR	STR	VAR
82.4	1.30	1.22	1.50	1.06	.83	.82
83.1	1.43	2.32	1.63	3.47	.71	1.07
83.2	1.34	6.38	1.71	1.03	.74	.76
83.3	1.23	1.41	1.60	1.37	.75	2.56
83.4	1.12	3.97	1.47	1.60	.69	1.59
84.1	1.27	.55	1.67	.75	.63	2.51
84.2	1.42	.45	1.64	1.72	.65	1.08
84.3	1.39	.66	1.55	1.12	.67	.98
84.4	1.32	.51	1.36	1.09	.60	.62
85.1	1.65	1.36	1.64	.63	.40	1.44
85.2	2.02	.97	1.81	.85	.55	1.22
85.3	2.43	.92	2.05	.43	.93	.02
Average	1.49	1.73	1.63	1.26	.67	1.22
Standard Deviation	.37	1.77	.17	.79	.13	.73