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VAR VS SEM MODELING OF THE TURKISH ECONOMY: FORECAST COMPARISONS

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I.Introduction

The purpose of this paper is to evaluate the forecast performance of a small-scale, montly several Vector AutoRegressive (VAR) models and the Structural Econometric Model (SEM) of the Turkish Economy. The macroeconomic variables of interest are used in the model which is originally established by the research Department of Central Bank of Turkey. Their main aim is to forecast the Turkish Private sector Manufacturing Industry Price Index every month using a first difference VAR model (CB model). However, our main concern is not estimating the index, what is vital for us is to examine the overall forecast performance of the various VAR models and structural econometric models using the same variables of interest.

In the model, the private sector manufacturing industry whole sale price index is used as a representative of inflation. Indeed, the private sector manufacturing industry has an important share in the GNP which affects the price, investment and production decisions of the industry dynamically in the short run. Besides, exports and imports, general price level and wage movements will be affected indirectly by the behaviour of the firms in the manufacturing industries.

Having considered the variables of interest of the Central Bank model, we aimed at to estimate several forms of the VAR representation and structural econometric model and compare their forecast performances using one-step ahead forecast statistics. In the meantime, the time series properties of the variable set and the issue of cointegration, the seasonality and the stochastic trend are

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considered when modelling the data. All models are estimated over the period 1982:1-1993:12. A comparison of the forecast performance of the several models is made on the basis of the one steps ahead forecasts produced for this period.

The remainder of the paper is divided into five sections. In section II, we outline the recent developments in forecasting in cointegrated systems. Section III discuses the time series data and their properties. Section IV presents the implementation of the models and summarizes the results. Section V concludes.

II. Background

Vector autoregressions (VAR) provide a valid representation for forecasting of system of economic time series (see Sims (1980) and Litterman(1986)). The forecasting performance of unrestricted vector autoregressions (UVAR) has not been given particularly qood results. The question of data transformations (i.e. differencing the series under consideration for stationarity) has some contribution on this result. Difficulties for such a system is that how much differencing is required depends upon the linear combinations under consideration. If all variables are differenced as would appear appropriate for their univariate representation but this will damage their multivariate linear time series representation with moving average, (MA), since this system will be over-differenced.

Obviously differencing is not the only way to make the series stationary, indeed, a vector of time series may have linear combinations which are stationary without differencing. Those variables are to be so-called cointegrated.

It is the fact that cointegrated systems are isomorfic to error correction representation (ECM) which incorparates both changes and levels of variables such that all the elements are stationary (see Engle and Granger (1987)).

Therefore, ECM reperesentation provides the framework for estimation, forecasting and testing cointegrated system. Engle and Yoo (1987) investigated the gains from utilising cointegrated information when making multi-step ahead forecasts from dynamic systems. They used a dynamic bivariate system and contrasted an

ECM formulation based on two step Engle-granger type procedure with UVAR.

Using the common trends representation

$$x_{t+h} = C(1) \sum_{j=0}^{t+h-1} e_{t+h-j} + C^{*}(L)e_{t+h} \qquad (1)$$

where the first term on the RHS of (1) is a stochastic trend of rank n-r. It means that n time series share n-r trends and in this way forecasts of the series move together in linear combinations even if forecasts of individual series diverge from outcomes.

If $C^{*}(L)$ weights decay rapidly as a function of powers of L, then for large step ahead forecast conditional on information given at time period t is

$$x_{t+h} \mid t \cong C(1) \sum_{j=0}^{t-1} e_{t-j} \qquad (2)$$

Then, forecast errors are given as,

$$f_{t+h} \mid t = x_{t+h} - x_{t+h} \mid t \cong C(1) \sum_{j=0}^{h-1} e_{t+h-j} + C^{*}(L)e_{t+h} \qquad (3)$$

Such forecast errors have variances for individual series is

$$\text{var}\,[f_{t+h} \mid t] = O(h)$$

but remain O(1) for the combinations of

$$\alpha' f_{t+h} \mid t$$

since $\alpha' C(1)=0$. Therefore

$$E(\alpha' f_{t+h} \mid t) = 0$$

and

$$\text{var}(\alpha' f_{t+h} \mid t) < \infty$$

to the order of approximation in (2).

An ECM imposes this condition and forecasts better for long horizons while a VAR does not. However, Engle and Yoo(1987) a Monte Carlo experiment result showed that the VAR performs slightly better on short horizons. Following Banerjee (1992) et.al., the procedure has a mean which is not equal to zero, in the form of $\mu(t+h)$. The variances of forecast errors remain bounded does not solve the problem of long-run forecasting with integrated variables.

If we consider a model as,

$$x_t = \Pi_0 + \Pi x_{t-1} + \varepsilon_t \qquad |\Pi| < 1 \tag{4}$$

by sequential substitution, the h-step forecast at time t will be.

$$\hat{x}_{t+h|t} = \Pi_0(1-\Pi)^{-1}(1-\Pi^h) + \Pi^h x_t \tag{5}$$

as the forecast period (or horizon goes to infinity ($h \rightarrow \infty$), then $\hat{x}_{t+h|t}$ converge to the unconditional mean of the process. The same procedure can be applied to stationary procedures by writing the whole system by in terms of I(0) variables which lose their ability to forecast future values is informative but forecast error variances increase with h.

The system in I(0) space loses predictive power but variances of forecast errors remain bounded. In this system ability to predict the relevant variable set vanishes (or decays) rapidly and very little remain h-period ahead.

However, the system in I(1) space has variances of forecast errors increasing with h. Therefore increase in the forecast standard errors as h increases is obvious.

The mean forecast quickly becomes a trend since the series is I(1) and the forecasts are uninformative after certain periods (say 12) due to the large variances.

Until now we work in a model which assumes no parameter uncertainity with an unrealistic world. Including the parameter uncertainity to the model makes forecast even more uncertain. There will be some effects of parameter uncertainity on the conditional forecast errors variances which grows with the square of the forecast horizon for both unit root (difference stationary and trend stationary models (see Sampson(1991)) and for stationary case see Chong and Hendry (1986); for forecasting in cointegrated systems and model selection see Clements and Hendry (1992, 1993a, 1993b).

Having concerned about the new literature on forecasting, we now set up relevant models for the data under examination. But, before modelling, the time series properties of the data are examined in the following subsection.

III. The Data

Our historical data is summarized as; Public sector whole sale price index is denoted as(WPIp). It is consisted of the weighted average of the price index of the agricultural sector, the Turkish private manufacturing industry price index, mining and energy sectors price indices which have negligable shares in the total index. Agricultural prices are highly dependent on seasonal effects while public sector manufacturing industry prices are influenced by the political cyclical movements. M is the reserve money. $E_{TL/\$}$ is the US dollar Turkish lira exchange rate (monthly average). The Turkish private manufacturing industry whole sale price index is denoted by WPI_{man}. Finally, manufacturing industry production index is shown by Q_{man}. Manufacturing industry general price index some 70 percent shares in the total wholesale price index while private sector manufacturing industry price index has some 49 per cent shares in it. That is why the manufacturing industry production index and private sector manufacturing industry wholesale price index are used in this model. Exchange rate has an important determinant of the general price level and also of the export and import prices. The variation in the public sector price level, possibly will affect the manufacturing industry prices by way of inputs to the production of this sector. Therefore, public sector general wholesale price index has been considered in the model. The data are monthly series from 1982:1 to 1993:12 taken from the research department of the Central Bank of Turkey. None of the series are seasonally adjusted.

The order of integration of each individual series is tested using the Augmented Dickey Fuller testing procedure which based on Dickey-Fuller(1981) and the results are reported in table 1.

It is clear from the examinations of table 1 that the series are not stationary that a linear trend is needed to describe the price series. The first differences are nonstationary, except the manufacturing sector production index which is I(1), all the other series require an I(2) analysis. Here what we can safely assume, however, is that the process are not I(3). The order of integration of the individual series are taken into account when formulating the models in the following section.

IV. Modelling

We use a VAR model for exante forecasting. Obviously it is atheoretical macromodel and there is no economic theory attached to the variables of interest. A general unrestricted VAR model, UVAR is completed by an addition set of deterministic components such as intercept term, deterministic trends and seasonal dummy variables. Existence of stochastic trends may be accomodated by allowing variables integrated of a given order to enter the VAR with an appropriate differencing. But some difficulties might appear if different series have different order of integration.

$$Zt = A_0 D_t + \sum_{i=1}^{k} A_i Z_{t-i} + \varepsilon_t \qquad (6)$$

where Z^t =[LWPIp, $LE_{TL/\$}$, LQ_{Man}, $LWPI_{Man}$, LM]. L denotes the logarithm of each variables in the set. The deterministic components here are seasonals (11 seasonal dummies, constant and trend). Since the model is to be used an ad hoc mechanistic forecast, no adjustment to the data has been made, though from the figures we know that the data are nonstationary(mostly I(2) and I(1)). The lenght of lag (the order of the VAR process) is assumed to be six (so that k=6). This gives 30 parameters to be estimated in the VAR: five elements of the 5x13 vector of A_0 (constant, trend and 11 seasonals) and five in each of six 5x5 A_i matrices. The forecasts are made one-step ahead forecasts where values for the period up to and including period t are used for making prediction for period t+1. The model is estimated by multivariate least squares.

We have used several alternative VAR models all of them formulated for five dimensional vector autoregressive process for the variables of interest. All of the models are VAR(6) models, incorparating up to six lags for each of the variables.

The first model is formulated in the multivariate deterministic trend model with seasonal component. That is model I,

$$Z_t = B_0 T_t + \zeta_t \tag{7}$$

where T_t = [Intercept, Trend and 11 Seasonals).

The second model is formulated in levels of the variables with the same deterministic part of the previous model. Mode[illegible],

$$Z_t = A_0 D_t + \sum_{i=1}^{6} A_i Z_{t-i} + \varepsilon_t) \tag{8}$$

where Dt is intercept, trend and 11 seasonals. It should be noted that forecasting of VAR in level is, for the case where variables are nonstationary (I(1) or I(2)), a most well known but problematic case.

The third model is formulated in first differences with the deterministic part reduced to an intercept or: (note I(1) and I(2) problems). Model III is,

$$\Delta Z_t = A_0 D_t + \sum_{i=1}^{6} A_i \Delta Z_{t-i} + \varepsilon_t \tag{9}$$

where D_t is intercept. We concerned about the time series properties of our data which are non-stationary (I(2) mostly). So, we would expect that the linear combinations of the first difference VAR model will yield stationary procedures. The third model corresponds to the assumption that the seasonal components of the whole system are stochastic while in the second and in the forth, it is assumed that both trend and seasonal components are deterministic.

The forth model is formulated in the first differences of the variables with a more fully developed deterministic part. Model IV is,

$$\Delta Z_t = A_0 D_t + \sum_{i=1}^{6} A_i \Delta Z_{t-i} + \varepsilon_t \qquad (10))$$

where D_t is intercept, trend and 11 seasonals.

The fifth model is derived from the Model II which is a VAR model in levels with appropriate deterministic part, using a general to simple sequential reduction procedure and then estimated.

Finally the last model so called Error Correction Model (ECM) can be defined as,

$$\Delta Z_t = A_0 D_t + \sum_{i=1}^{6} A_i \Delta Z_{t-i} + B_i Z_{t-i} + \varepsilon_t \qquad (11)$$

Having defined above given models, now our task is to estimate them and compare their forecast performances using the several calibrations which will be discussed in the next subsection.

Forecast Calibration

A VAR models here, are calculated as Unrestricted Reduced Form (URF) or system and the multivariate least square estimator are called the direct estimates. The goodness of fit measures reported here for URF estimates are the likelihood value, denoted as likelihood and the logarithm of the determinant of Ω , denoted as a log det Ω which stands for the covariance matrix of the multivariate error term. The model is estimated using monthly data from 1982:1 to 1993:12 and less 1, 2, 4,6, 12 forecasts. The general to simple model is also estimated for the forecast horizons 1, 2, 4, 6, 12 using 2SLS.

The type of forecast have been made here, is one-step ahead forecasts conditional on the observed values of lagged variables. This is done under the assumption that one making a forecast for period t+1 knows the realized values of the variable of interest in t. The one-step forecast statistics are as follows. The first is an index of numerical parameter constancy for H forecasts. It is calculated as $\chi 2(NH)/NH$ for N equations and H forecasts.

This gives an appropriate an appropriate F test with a value r the second test. Values are greater than two imply poor exante forecasts. The second is an approximate F test based on the forecast error variance. This is a better calibrated test statistic(see Chong and Hendry (1986)) which ignore inter correlation between forecast errors.

The fact that, mis-specified models could forecast well (if the procedure remained constant) or good models could forecast poorly (if the data variances was high). Therefore, exante confidence intervals also need to be calculated both to establish likely forecast accuracy and to test for an excess frequency of forecast errors lying outside the expected region. Useful models must have small forecast confidence regions.

The goodness-of-fit measures and the related forecast statistics which are supplied by PCFIML are presented in tables 2-7. Forecast confidence interval $\chi 2$ tests are given in the parenthesis (see table 2 and 3).

The forecast performance of the models at each horizon was subsequently evaluated using two measures: the mean forecast error, MFEs and the forecast standard errors, FSEs.

Forecast Performance

A comparison of aggregate forecast error measures and one-step forecast statistics for Model I to Model VII can be summarized as;

The multivariate deterministic trend model, (Model I), with related deterministic components shows a better performance over the other models especially for the higher forecast horizons, such as 6 and 12 (see table 2 column 1). For forecast horizons 12, the forecast F statistics of 3.307 computed for model I is greater than that of model II which is 1.706, though both values are statistically significant at the .05 level of significance. The similar result is obtained for cumulative $\chi 2$ test for the Model I and Model II such as, 3.668 and 2.589 respectively. However, comparison of the forecast standard errors is in favor of one-step VAR in levels for each variables except for LM and LWPIp for 12 and 6 forecast horizons respectively. In addition, the mean forecast errors for both 6 and 12 horizons confirm that Model II performs quite well.

Now, we have considered the VAR model in the first differences, Model III, which is the CB Model and its alternative which is difference VAR with an appropriate deterministic part, Model IV. It is obvious that both model performed badly using the forecast test statistics which are given in table 2 (see coloumn 5 and 6). However, the examination of MFE and FSE show that model III does better than model IV (see table 5). Possibly remained seasonality eliminated by the appropriate differences. Regarding the cointegration issue, it is quite unexpected that differenced VAR failed for forecasting the horizons of the interest.

The examination of the general to simple modelling in table 3 summarizes that Model V estimated by both URF and 2SLS yield significant forecast F, 1.718 and 1.601 respectively at the .05 per cent level. The appropriate $\chi 2$ forecast confidence test values are 2.577 and 1.817 respectively. Interesting comparisons can be made between model V and Model II using MFEs and FSEs (see table 4 and 6). Examination of MFEs give almost no conclusive decision about which model performs well. However, noting that FSEs for both LQ_{Man} and LM are smaller for the VAR Model in levels than for the general to simple model for 12 forecast forecasting horizons.

Finally we examined the ECM model in two specification such as; Model VI includes constant, trend and 11 seasonal dummies while model VII only contains a constant as a deterministic component. The forecast F, 1.708 which is significant at the .05 per cent level, is obtained for model VI whereas the same statistic is insignificant for model VII. The appropriate $\chi 2$ forecast confidence test values are 2.874 and 1.514 respectively for model VI and Model VII (see table 3). Hence, ECM with constant, trend and seasonals has an apparent advantage over ECM with constant. However, MFEs and FSEs did not provide the same clear conclusion that is infavour of the forecast performances of model VI on model VII (see table 7).

Since the relevant characteristics may vary from one model to the another, it is difficult to discuss encompassing in absolute terms (see Mizon (1984) or Mizon and Richard(1986) for encompassing). Instead one might speak of variance encompassing where the variation of errors in model B can be explained by model A or forecast encompassing where the forecast errors from model B can be explined by model A. A specific model derived from a general model will have a larger error variance, since some of the variables have been dropped (or restriction imposed) and therefore the general model will encompass the specific one for variance. On the other hand, a specific model may encompass the general one for forecast. For instance, in Model V, it was the case that the forecast diagnostics for the specific model were generally better than to that of the general model. Without any formal testing, it seems at least plausible that forecasts from the specific model may explain, to some extend, the forecast errors made by the general model.[1]

V. Conclusions

The purpose of this paper has been to report the results of concucting a comparison of forecast performance by small scale VAR models vs structural econometric models for the Turkish Economy.

The most notable problem is modelling relates to the difficulty of the different order of integration of the variables in interest. To model the data seven different models are established. Among them, the overall performance of the VAR model in levels with an appropriate deterministic components is good while the first difference VAR models performs badly. So it has poor exante forecast performance against the others. In addition, the general to simple model has some predictive power over the difference VAR model. The comparison is also made between the VAR in levels and a specific model derived from the VAR in levels. Although both performed individually well, we are not certain about which one has a superior performance over the other. In addition, ECM with constant, trend and seasonals has an explicit advantage over ECM with constant regarding the forecast F test. However, MFEs and FSEs did not fully supported the similar conclusion. This issue requires the detailed

[1]The forecast encompassing test introduced by Chong and Hendry(1986). They have shown that the student-t test is a valid test, at least for the large samples. Here in this paper we have not calculated the forecast encompassing test, which is easy to implement, but it is left for the later research.

forecast encompassing testing which has left as the research topic for the future.

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Table 1 Tests for the order of integration of the variables

Series	ADF tests t-statistics (a)	ADF tests t-statistics (b)
LWPIp	-1.768	-9.410*
$LE_{TL/\$}$	-1.528	-4.673*
LQMan	-7.529*	
$LWPI_{Man}$	-3.288	-6.777*
LM	-1.887	-16.686*

Note: (1) (a) denotes the test statistics is based on variables are in their log levels and (b) denotes the test statistic is based on variables are in the first differenced form from their log levels. (2) Each ADF regression initially includes twelve lagged differences to ensure that the residuals are empirically white noise. Then a sequential reduction procedure is applied to eliminate the insignificant lagged differences. (3) L denotes the natural logarithm of variables. (4) Critical values for the ADF test statistics are obtained from Fuller (1976), Table 8.5.2.

* significant at 1%.

Table 2.Likelihood, Measures of Goodness-of-Fit and Forecast Statistics for the Multivariate Trend Model and Several Alternative VAR Models

Forecast horizons	Test Statistics	Model I 1982(1)-1993(12)	Model II 1982(7)-1993(12)	Model III 1982(8)-1992(12)	Model IV 1992(8)-1993(12)
Less 1 Forecast	Log Det Ω Likelihood Cumulative $\chi^2(5)/5$ Forecast F Test	-26.501452 568482.66 2.154 (1.937) F(5,130)=1.761	-39.031820 298986806.85 2.961 (2.064) F(5,94)=1.416	-37.284998 124834457.47 1.119 (.874) F(5,105)=.675	-38.667823 249236180.53 1.431 (.936) F(5,93)=.640
Less 2 Forecasts	Log Det Ω Likelihood Cumulative $\chi^2(10)/10$ Forecast F Test	-26.513989 572057.33 1.918 (1.724) F(10,129)=1.566	-39.031178 298890770.99 2.303 (1.497) F(10,93)=1.024	-37.299280 125729059.79 1.466 (1.135) F(10,104)=.874	-38.642137 246055752.57 2.266 (1.543) F(10,93)=1.063
Less 4 Forecasts	Log Det Ω Likelihood Cumulative χ2(20)/20 Forecast F Test	-26.539801 579488.28 1.898 (1.704) F(20,127)=1.546	-39.033637 299258491.25 2.171 (1.265) F(20,91)=.859	-37.265199 123604725.15 1.068 (.789) F(20,102)=.605	-38.618665 243184812.82 1.816 (1.157) F(20,91)=.791
Less 6 Forecasts	Log Det Ω Likelihood Cumulative χ2(30)/30 Forecast F Test	-26.650448 612450.75 2.523 (2.263) F(30,125)=2.050**	-39.098370 309103002.32 3.514 (1.823) F(30,89)=1.229	-37.248103 122552650.36 1.108 (.781) F(30,100)=.596	-38.662996 248635408.57 2.199 (1.291) F(30,89)=.877
Less 12 Forecasts	Log DetΩ Likelihood Cumulativeχ2(60)/60 Forecast F Test	-27.002905 730476.64 4.101 (3.668) F(60,119)=3.307**	-39.508491 379454577.66 4.962 (2.589) F(60,83)=1.706*	-37.475965 137341714.5 1.916 (1.439) F(60,94)=1.082	-38.997711 293930898.21 3.084 (1.933) F(60,83)=1.284

Table 3. Likelihood, Measures of Goodness-of-Fit and Forecast Statistics for Structural Econometric Models

Forecast Horizons	Test Statistics	Model V General to Simple model 1982(7)-1993(12) URF	Model V General to Simple model 1982(7)-1993(12) 2SLS	Model VI ECM Model 1 1982(3)-1993(12)	Model VII ECM Model 2 1982(3)-1993(12)
Less 1 Forecast	Log Det Ω Likelihood Cumulative χ^2 (5)/5 Forecast F Test	-38.868888 275595291.21 3.182 (2.266) F(5,95)=1.571	-36.961718 106202581.53 1.227 (1.064) F(5,122)=.947	-37.974978 176263211.21 2.096 (1.768) F(5,117)=1.477	-36.490837 839236684.14 .928 (.855) F(5,129)=.788
Less 2 Forecasts	Log DetΩ Likelihood Cumulative χ^2 (10)/10 Forecast F Test	-38.869757 275715086.41 2.422 (1.638) F(10,94)=1.132	-36.968380 106556951.90 1.297 (1.123) F(10,121)=.999	-37.964232 175318722.41 1.530 (1.283) F(10,116)=1.070	-36.472200 83145262.01 .758 (.691) F(10,128)=.636
Less 4 Forecasts	Log Det Ω Likelihood Cumulative χ^2 (20)/20 Forecast F Test	-38.882476 277474077.95 2.351 (1.464) F(20,92)=1.005	-36.927680 104410423.54 .936 (.808) F(20,119)=.717	-37.915866 171129780.66 .954 (.778) F(20,114)=.647	-36.442939 81937660.37 .679 (.608) F(20,126)=.559
Less 6 Forecasts	Log Det Ω Likelihood Cumulative χ^2 (30)/30 Forecast F Test	-38.921092 282883643.15 2.837 (1.620) F(30,90)=1.105	-36.969128 106596800.99 1.265 (1.094) F(30,117)=.970	-37.980433 176744589.46 1.720 (1.274) F(30,112)=1.057	-36.453598 82375550.79 .943 (.810) F(30,124)=.744
Less 12 Forecasts	Log Det Ω Likelihood Cumulative χ^2 (60)/60 Forecast F Test	-39.368973 353886338.26 4.357 (2.577) F(60,84)=1.718*	-37.242917 122235337.77 2.112 (1.817) F(60,111)=1.601*	-38.282866 205597893.47 2.874 (2.078) F(60,106)=1.708**	-36.577049 87620396.83 1.514 (1.297) F(60,118)=1.187

Table 4. Forecast Performance for the Multivariate Trend Model and VAR model in Levels

		Variables	Model I 1982(1)-1993(12)	Model II 1982(7)-1992(12)
Less 6 Forecasts	Mean Forecast Errors	$LWPI_P$	.22589	-.02440
		$LE_{TL/\$}$	.25084	.02958
		LQ_{Man}	.04527	.03413
		$LWPI_{Man}$	.14159	-.01367
		LM	.24680	-.03992
	Forecast Standard Errors	$LWPI_P$	.01489	.03627
		$LE_{TL/\$}$	.03830	.02151
		LQ_{Man}	.07717	.06467
		$LWPI_{Man}$	.01893	.01188
		LM	.01137	.02285
Less 12 Forecasts	Mean Forecast Errors	$LWPI_P$	.21404	-.04741
		$LE_{TL/\$}$	.23071	.01353
		LQ_{Man}	.04534	.03871
		$LWPI_{Man}$	.14398	-.01862
		LM	.27204	.00984
	Forecast Standard Errors	$LWPI_P$	.04097	.03183
		$LE_{TL/\$}$	.05358	.02670
		LQ_{Man}	.06787	.05943
		$LWPI_{Man}$	.02015	.01156
		LM	.05952	.06735

Table 5. Forecast Performance for the First Difference VAR model

		Variables	Model III 1982(8)-1993(12)	Model IV 1982(8)-1993(12)
Less 6 Forecasts	Mean Forecast Errors	$DLWPI_p$	-.00144	-.00006
		$DLE_{TL/\$}$	.01374	.01792
		DLQ_{Man}	.05776	.01085
		$DLWPI_{Man}$	.00132	.00132
		DLM	-.00420	-.00368
	Forecast Standard Errors	$DLWPI_p$	.02948	.03959
		$DLE_{TL/\$}$	.02267	.02636
		DLQ_{Man}	.05427	.08611
		$DLWPI_{Man}$	.01320	.01212
		DLM	.01373	.02892
Less 12 Forecasts	Mean Forecast Errors	$DLWPI_p$	-.00612	-.00459
		$DLE_{TL/\$}$	.00771	.00937
		DLQ_{Man}	.01260	.01501
		$DLWPI_{Man}$	-.00245	-.00233
		DLM	.00976	.00715
	Forecast Standard Errors	$DLWPI_p$	.02264	.03467
		$DLE_{TL/\$}$	.01849	.02447
		DLQ_{Man}	.07599	.08030
		$DLWPI_{Man}$	.01144	.01180
		DLM	.06557	.06865

Table 6. Forecast performance for General to Simple Model

		Variables	Model V General to Simple Model 1982(7)-1993(12) URF	Model V General to Simple Model 1982(7)-1993(12) 2SLS
Less 6 Forecasts	Mean Forecast Errors	$LWPI_P$	-.01772	-.01403
		$LE_{TL/\$}$	.02209	.01546
		LQ_{Man}	-.01605	.04092
		$LWPI_{Man}$	-.01448	.00071
		LM	.01447	.00612
	Forecast Standard Errors	$LWPI_P$	-.03677	.02162
		$LE_{TL/\$}$	.02280	.02081
		LQ_{Man}	.07259	.07073
		$LWPI_{Man}$	.01184	.01021
		LM	.02846	.01937
Less 12 Forecasts	Mean Forecast Errors	$LWPI_P$	-.02960	-.01799
		$LE_{TL/\$}$	.00543	.01076
		LQ_{Man}	-.01253	.01421
		$LWPI_{Man}$	-.01598	-.00463
		[illegible]M	.04193	.00784
	Forecast Standard Errors	$LWPI_P$	.03363	.02186
		LE[illegible]	.02529	.01803
		L[illegible]	.06641	.06821
		LW[illegible]Man	.01164	.01009
		LM	.06888	.08153

Table 7. Forecast performance for ECM Models

		Variables	Model VI ECM Model 1 1982(3)-1993(12)	Model VII ECM Model 2 1982(3)-1993(12)
Less 6 Forecasts	Mean Forecast Errors	$LWPI_P$	-.00780	-.00700
		$LE_{TL/\$}$	.02540	.01538
		LQ_{Man}	.02009	-.00121
		$LWPI_{Man}$	-.00305	-.00547
		LM	-.02911	.00355
	Forecast Standard Errors	$LWPI_P$	.01456	.01327
		$LE_{TL/\$}$	.01949	.01635
		LQ_{Man}	.07056	.08163
		$LWPI_{Man}$	.01159	.00946
		LM	.02603	.03301
Less 12 Forecasts	Mean Forecast Errors	$LWPI_P$	-.03237	-.01570
		$LE_{TL/\$}$	.01811	.00938
		LQ_{Man}	.05178	-.01957
		$LWPI_{Man}$	-.00460	-.00507
		LM	.00792	.02713
	Forecast Standard Errors	$LWPI_P$	.01575	.01136
		$LE_{TL/\$}$	.02504	.01634
		LQ_{Man}	.06797	.06462
		$LWPI_{Man}$	.01099	.00768
		LM	.06329	.06355