Econometric Forecasting, Intercept Correction and Budgetary Transactions: An Eclectic Approach

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'How can you possibly award prizes when everybody missed the target?' said Alice. 'Well', said the Queen, ' some missed by more than others, and we have a fine normal distribution of misses, which means we can forget the target.'

I. Introduction

Conventional approach to the theory of economic forecasting based on the result that the conditional expectation given the available information delivers the minimum mean square forecasting error assumes that the data generation process (DGP) is known and constant over time. It can be not be applied to budgetary variables, because of frequent shifts in the policy regimes of the national and sub-national governments in a federal set-up as exists in India. Under these circumstances while forecasting of fiscal variables for policy purposes, the main objective ought to be to avoid systematic forecasting errors arising due to deterministic shifts. In the literature, various methods have been suggested such as intercept corrections, differencing, co-breaking, regime switching models, etc for improving forecasting accuracies. The major aim in this paper is to present an eclectic approach of econometric forecasting for the fiscal variables.

Among various approaches of forecasting, including formal and informal ones, the two most popular have been time series and econometric models. Econometric model [1]based forecasting have proved systematically wrong due to shifts in the deterministic factors of forecasting and hence are often modified. In view of this, earlier literature on forecasting has employed simple extrapolation. There is a need to reappraise practices and modelling approaches, which were considered redundant in the classical paradigm. If the data generating process was not truly stationary in level (or after differencing or co integration transforms) without time-invariant parameters, and if the forecasting model did not coincide with that process, then some commonplace macro-econometric forecasting practices, such as

[1] For a review of econometric modelling of fiscal variables for the Indian economy, see Sinha (1999)

intercept corrections or would be employed to explain some of the predictive failures that have occurred in recent economic forecasting. Since, it is widely believed that available forecasts are rarely model based and adjustments are often made to arrive at the revision stage (Sinha et al.2002). Thus the published economic forecasts reflect in varying degrees the properties of the models. Forecasters adjustments do appear to improve forecast accuracy if these are model based: see for example, the work of the ESRC Macroeconomic Modelling Bureau, namely Wallis et al. (1986). Confidence in macro-economic forecasting has periodically been diluted by episodes of dramatic predictive failure resulting from natural and political factors. An econometric theory of economic forecasting will only deliver relevant conclusion about empirical forecasting if it adequately captures the appropriate aspects of the real world to be forecast. It is not surprising that a theory based on a cointegrated-stationary, time invariant data generating process (DGP), perfectly replicated by a forecasting model, and is not consonant with an empirical track record of large predictive failures. A more realistic theory that avoids these restrictive assumptions might better match the historical record.

There are several related lines of research in forecasting. Arising out of anomalies between the outcomes of model-based univariate time-series forecasting methods, and a statistical paradigm of theoretical time-series analysis (see, for example, Box and Jenkins, 1976, and compare Fields and Makridakis, 1995) there are other methods of forecasting specified in terms of non-zero intercept corrections over the forecasting period. Essentially, forecasting methods that appear to work empirically in the forecasting are not those which would have been predicted by statistical theory, and the most serious culprit is the assumption of constancy which underpins that paradigm: this matches the importance attributed to structural breaks (see, for example, Clements and Hendry, 1996, inter alia). Secondly, the 'dynamic linear models attempted in the literature put parameter non-constancy (*a la* Lucas critique) centre stage. The importance of interventions based on an ongoing monitoring of forecast performance, and the adequacy of the model is questioned when the latest observations are in a tail of the forecast distribution. Finally, the recent developments in forecasting has focus on system of cointegrated relations representing macro econometric models, when economies are subject to unanticipated, large regime shifts, as experienced in India when economic reforms were introduced in July 1991. In the context of economic forecasting, a multivariate approach that captures behavioural relationship between variables is usually preferred (see, for example, Hendry and Doornik, 1994), especially under the situations when economic policy frequently responds to forecast changes. The DGP is a simple member of the class of models recently considered by Andrews (1993), where ‘one-shot’ test for a single break in a time series has been developed. Whether economic time series are integrated of order unity (i.e., I (0)) or stationary has important implications in their forecastability, for the former can only be forecast with increasingly wide confidence interval while the later has finite confidence interval as the horizon grows.

The plan of the paper is as follows. Section II describes a data generation process in the context of forecasting followed by a review in section III of the recent developments on macroeconomic forecasting of data both stationary and nonstationary in the presence of structural break and policy regime shifting in co-integrated-stationary processes. Section IV describes the methods used to improve the forecasting accuracy under model based DGP, employing various forecasting models, and section V includes the empirical illustration, which seeks to examine the performance of the methods on an actual data series on government expenditure and revenue receipts of all India on actual empirical data, demonstrating, in most cases, an acceptable concordance. Finally, section VI concludes and summarises.

II. The Data Generation Process and Forecasting

Purely model-based forecasts of any process stationary (I (0)) or nonstationary (i.e., I (1)) rarely exist. Success of such forecasts is normally influenced by the assumption that there being regularities which are informative about future. In other words, whether forecasts are conditional or unconditional, capturing regularities without suffering from non-regularities motivates a different interpretation of parsimony and collinearity. It entails re-examination of the role of causal information when forecasting models are misspecified. Once the model misspecification interacts with non-stationary data the results are suspected to be misleading. Initially, autoregressive integrated moving-average (ARIMA) models based on Wold (1938) decomposition theorem were the most dominate approach used in forecasting. Subsequently, its place was taken by multivariate time series vector auto regression (VAR).

Many potential routes to improving model-based forecast include inter alia use of difference data, or intercept correction. Method of robustifying forecasts by intercept corrections and co-breaking are considered along with pooling devices related to forecast encompassing and non-linear models. Forecasting with systems of integrated (I (1)) variables is a non-trivial extension of the univariate analysis of forecasting with integrated variables because of cointegration, wherein a linear combination of individually integrated variables is non-integrated (I (0)).

Deterministic components (D_t) of a forecast in a univariate process include intercepts and linear trends variables whose future values are known with certainty; and hence are treated as primary source of systematic forecast failure in econometric models. Quantitative impact of structural breaks on system forecast is analysed depending whether it is I (0) or I (1). Deterministic shifts are viewed as a change in the unconditional expectation of the non-integrated transformations of the variables and sometimes describe the structural breaks or policy regime before or after the forecasts. In other words, one of the simplest frameworks is in terms of the DGPs exhibiting a structural break, namely a first-order scalar auto-regression. The scalar framework is for expositional simplicity only. In the simplest location model of a variable y_t:

$$y_t = \alpha \times 1 + \upsilon_t \qquad (1)$$

With $\alpha \neq 0$ where $\{ \upsilon_t\}$ is I(0), a deterministic shift at T is:

$$y_{T+h} = \alpha^* \times 1 + \upsilon_{T+h} \equiv \alpha \times \mu + \upsilon_{T+h} \qquad (2)$$

Where $\mu(=\alpha^*/ \alpha \neq 1)$ is the shifted intercept.

Assuming a linear closed model in which all nondeterministic components are forecast within the system, the DGP is described as an autoregressive process with a one-off change in the mean only; at an exogenously determined point of time. The scalar first-order autoregressive representation expressing the DGP is given below:

$$y_t = \rho y_{t-1} + \mu^* + \varepsilon_t, \qquad (3)$$

with ρ=0, under an assumption of $\varepsilon_t \sim$ NID $(0, \sigma^2_E)$. Now μ^* is allowed to take on two values: μ_1 when $t \leq T$, and μ_2 when $t>T$. Thus, the baseline DGP is simply white noise (ρ=0) with a shift in mean at time t = T+1. Letting $y_t = \Delta x_t$ where $x_t=\log X_t$ is a natural interpretation, so that μ^* is the growth rate, and the underlying levels process X_t is integrated (after a log transform).

A theory of forecasting applicable to economic time series, which are I (1), that can be transformed to stationarity by differencing or cointegration has been presented in Clements and Hendry (1998). Budgetary environment provides an excellent example of non-stationary processes, which are subject to intermittent structural breaks. A general theory of macroeconomic forecasting must allow for using models that do not coincide with mechanism that has generated the data, and selected from data (possibly inaccurate) evidence. Three classes of models and generating-mechanisms have been identified in the literature. First, the data generation process (DGP) defined over the period t =1,…,T by a first-order vector autoregressive process (VAR) in the variables x_t:

$$x_t = \tau + \gamma x_{t-1} + \upsilon_t \text{ where } \upsilon_t \sim [\text{NID}(0, \Omega)]. \qquad (4)$$

Secondly, denoting an independent normal error with expectation E $[\upsilon_t] = 0$ and variance matrix V $[\upsilon_t] = \Omega$. The DGP is integrated of order unity (I (1)), and satisfies $r < n$ co-integration relations such that:

$$x_t - x_{t-1} = \tau + \gamma x_{t-1} - x_{t-1} + \upsilon_t \tag{5}$$

$$\Delta x_t = \tau + (\gamma - I) x_{t-1} + \upsilon_t \qquad \text{where } \alpha\beta' = \gamma - I_n$$

Finally, if α and β are n x r matrices of rank r, after reparameterisation of equation (4) becomes the vector equilibrium-correction model (VEqCM) expressed as

$$\Delta x_t = \tau + \alpha\beta' x_{t-1} + \upsilon_t \tag{6}$$

Taking expectation, we get

$$E(\Delta x_t) = \tau + \alpha E(\beta' x_t)$$

So that

$$\Delta x_t - E(\Delta x_t) = \alpha\beta' x_{t-1} + \upsilon_t - \alpha E(\beta' x_t)$$

If $E(\Delta x_t) = \zeta$ and $E(\beta' x_t) = \mu$ then $\zeta = \tau + \alpha\mu$

and

$$(\Delta x_t - \zeta) = \alpha(\beta' x_{t-1} - \mu) + \upsilon_t$$

$E(\Delta x_t - \zeta) = 0$ and therefore

$E(\Delta x_t) = \zeta$ and the system grows at the unconditional rate ζ with long run solution $E(\beta' x_t) = \mu$.

If the equation (4) has potentially mis-specified parameters u_p and γ_p, then we may have

$$x_t = \tau_p + \gamma_p x_{t-1} + \upsilon_t$$

Thus, for the purpose of forecasting, three specific models emerge

(a) $\tau_p = \tau$ and $\gamma_p = \gamma$

(b) $\tau_p = \zeta$ and $\gamma_p = I_n$

(c) $\tau_p = 0$ and $\gamma_p = I_n$

The 1-step forecasting models obtained from above conditions are given below.

First model from (a) is termed as DGP in sample and the forecast based on it is given below.

$$\Delta \tilde{x}_{T+1/T} = \zeta + \alpha(\beta' x_T - \mu)$$

Second model is obtained by condition (b) and is termed as VAR in the difference of the variables (DV),so that forecast is

$$\Delta \tilde{x}_{T+1/T} = \zeta \tag{7}$$

Third one is a DV in the difference of the variables (DDV) and is obtained from (c) and its forecast value is given below

$$\Delta^2 \tilde{x}_{T+1} = 0 \text{ or}$$

$$\Delta \tilde{x}_{T+1} = \Delta x_T \tag{8}$$

The vector of all *n* variables is denoted by ω_t and the system is represented by a first-order VAR, determinant component (D_t) that includes a constant and a linear deterministic trend:

$$w_t = \tau_o + \tau_1 t + \gamma w_{t-1} + \nu_t \tag{9}$$

Where $\upsilon_t \sim IN(0,\Omega)$

If α and β are n x r matrices of rank r, then equation (7) is reparameterized and expressed as the VEqCM:

$$\Delta w_t = \tau_0 + \tau_1 t + \alpha\beta' w_{t-1} + \nu_t \tag{10}$$

The impact of the deterministic components on the series depends on the relationship between α and τ_0, τ_1. Following Johansen (1994), above equation may be rewritten as

$$\Delta w_t = \gamma + \alpha\left(\beta' w_{t-1} - \mu_0 - \mu_1 t\right) + \nu_t \tag{11}$$

Finally, a VAR in differences (DVAR) may be used, where sample is misspecified relative to the VEqCM unless γ=0. The simplest formulation is

$$\Delta w_t = \gamma + \eta_t$$

So that when α= 0,the VEqCM and DVAR coincide. In vector notations the system can be expressed in terms of D_t as

$$w_t = A w_{t-1} + \Psi D_t + v_t \tag{12}$$

$$w_t = ALw_t + \Psi D_t + v_t$$

The solution of the system is as given below

$$w_t = (I_n - AL)^{-1}(\Psi D_t + v_t)$$

That unpredictable cannot be forecast is a truism. But the scope and applicability of this statement is often not appreciated: more aspects of reality may be unpredictable than just the stochastic error on postulated equations, which is all that forecast-error variance formulae sometimes reflect. A distinction between two basics concepts, which are often used, interchangeably (un) predictability and (un) forecastability is made here. Unpredictability refers to the relationship between a random variable and information set – a variable is unpredictable if the conditional distribution (given that information set) coincides with the unconditional distribution. Predictability is necessary but not sufficient for forecastability. For the latter, two requirements are a systematic relationship, and known form of the conditional density of the variable, i.e., how the information set enters the data generation process (DGP). Thus, the conditional expectation is either unknown or changes over time.

Non-casual variables may be more relevant than (previously) causally relevant variables if the model is misspecified for the DGP, which undergoes structural breaks. Since a non-constant DGP, and a misspecified model thereof, may occur regularly in public finance, forecasting with an empirical model may be fundamentally different from predicting using the DGP. Given the limited knowledge about the data generation process (DGP) available to investigators, normally a framework is adopted in which the DGP is unknown and non-stationary (due to unit roots, structural breaks and policy regime shifting), and the econometric model are misspecified for that DGP. These features seem descriptive of operational economic forecasting, and provide a rationale for using 'intercept corrections' and differencing transformations to correct forecasting inaccuracy. A key consequence of these results is that the best available forecasting model need not be based on the 'casual determinants' of the actual economic process, and, may be based on 'non-casual' variables, that is, variables that do not enter the DGP.

Regular occurrence of forecast failure in case of budgetary transactions such as revenue and expenditure reveals that other unanticipated changes do occur over the forecast horizon (Hendry and Doornik, 1997). Forecasts and their confidence intervals derived from linear autoregressive models depend crucially on the time-series properties of the variables. In practice, it may be difficult to discriminate between a trend-stationary and difference-stationary DGP, although the implications of the two for how accurately the process can be forecast are quite different in terms of the 'limit to forecastability' (the horizon up to which forecasts are informative). The SETAR model (Tong, 1983) is an example of a pair-wise linear model, in that the model within a regime but moves between regimes depending upon the realised value of the process a number of periods previously. Some forecasters believe that parsimony is important for multi-step forecasting despite the lack of a formal theory other than model-selection criterion. Decisions based on the t-test for a coefficient being zero in stationary processes, and relate the outcome to the result on non-monotonic forecast confidence intervals in Chong and Hendry (1986). The literature on policy analysis of economic forecasting is vast and can be classified into three categories. First, policy analysis using econometric models and evaluation of policy regimes, include Bryant, Hooper and Mann (1993) on. Second, conducting economic policy with and without forecasts (Budd, 1998); and on the more general topic of policy making with macroeconomics models (Britton, 1989); Third, the econometric analysis of economic policy context as given in Sims (1982), Turner, Wallis and Whitley (1989) and Banerjee, Hendry and Mizon (1996).

Forecasts from models in the face of both deterministic shifts and regime shift are not prominent in that literature. Nevertheless, there exist devices that can robustify forecasting models against such breaks, provided the breaks have occurred prior to forecasting. Imposing an additional unit root, or adding a specific form of intercept correction are some of such 'tricks' that can help mitigate forecast failures, but the policy implications of the resulting models remain unaltered. That result immediately nullifies the value of judging policy implications by any forecast-based criterion: not on its 'closeness' to the data generation process.

None of the methods is robust to unanticipated breaks that occur after forecasts are announced, and same 'robustifying' devices do not offset post-forecasting breaks. Policy changes that occur post-forecasting will induce breaks in any models that do not embody the appropriate policy links. Forecast failures from pre-forecasting breaks, econometric systems, which do embody the relevant policy effects, need not experience a post-forecasting break induced by the policy-regime shift. Point is if both structural breaks and regime shifts occur how they should be combined. It can be accomplished by encompassing. Effects of an economic policy change should not be based on the model that is robust to the policy change. In the presence of structural breaks and regime shifts systematically producing better forecasts need not invalidate the policy use of another model.

III. Forecasting Models and Policy Analysis

The use of econometric models in forecasting and economic policy analysis is not free from problems. A good econometric model may not be suitable for forecasting. This is termed as forecasting versus policy dilemma. The literature on policy analysis of economic forecasting is vast and can be classified into three categories. First, policy analysis using econometric models and evaluation of policy regimes, include Bryant, Hooper and Mann (1993) on. Second, conducting economic policy with and without forecasts (Budd, 1998); and on the more general topic of policy making with macroeconomics models (Britton, 1989); Third, the econometric analysis of economic policy context as given in Sims (1982), Turner, Wallis and Whitley (1989) and Banerjee, Hendry and Mizon (1996). Three aspects of the relationship between statistical forecasting devices and econometric models in the context of economic policy analysis are discussed. First, to see whether there are grounds for basing economic-policy analysis on the 'best' forecasting system. Second, whether forecast failure in an econometric model precludes its use for economic-policy analysis. Finally, whether in the presence of policy change, improved forecasts can be obtained by using 'scenario' changes derived from the econometric model, to modify an initial. The fact that a purely statistical device may provide the best available forecasts induces an apparent paradox when policy change is feasible. When forecasting after a structural break, statistical devices may beat forecasts based on the current econometric model. The statistical forecasting model does not depend on any policy variables and therefore has neither policy implications, nor produces any revisions to its forecasts following policy changes. Best forecast for some future period are presented to the Finance Minister of the country or the Finance Commission in the present case, who thereupon decides that a major policy initiative is essential, and then implements it. The statistical forecasts are not then revised would justifiably be greeted with incredulity. Contradictory statistical device often produces the best forecasts in a world of structural change and policy-regime shifts. The conclusion is that a combination of robustified statistical forecasts with the scenario changes from econometric systems is subject to policy interventions and may provide improved forecasts.

The forecaster does not know role for statistical forecasting methods when an economy is subject to structural breaks, and the econometric model is mis-specified for the DGP.The DGP is non-dynamic, and in particular, the lagged value of y does not affect its behaviour (i.e., y_{t-1} is non-casual). When forecasting after the regime change, on the criterion of forecast unbiasedness, forecasting procedure that ignores the information on both casual variables and only uses y_{t-1} can have smaller bias than forecasts from models, which include the correct casual variable. Here neither the statistical model nor the econometric model based on past casual links is useful for policy.

Based on Monte Carlo studies, it has been shown that forecasts generated from vector auto regressions in differences (DVARs) are more robust than models in levels to certain forms of structural change, but that intercept corrections may help vector 'equilibrium-correction' mechanisms (VEqCM or VEqCMs) to match the performance of DVARs (*a la* Davidson *et al.* (1978) ECM). Benefit of ignoring long-run information for forecasting is given in Mizon (1995) in that models such as VECMs tend to fail badly .For instance, the anecdotal evidence of structural change in the 1990s in response to the economic reforms in 1991 and the change in government economic policies may have altered the long-run relationship between budgetary macro-economic aggregates in Indian economy. Thus the models based on long run information tend to 'error - correct' on the basis of outdated structures and manifest significant forecast errors in comparison to the models that ignore such information and perform better.

Since policy analysis conducted on an incorrect model is rarely useful. The paradigmatic example often encountered in the forecasting of revenue and expenditures by means of an econometric model of the tax and benefits system, which accurately portrays the relevant links, and yields a good approximation to the changes in revenues and expenditures resulting from changes in the basic rates. Its conditional predictions are accurate. However, it would not necessarily provide good time-series forecasts in an economy subject to structural breaks that affected macroeconomics variables such as total government expenditures and revenue receipts.

More generally, the sequential testing procedure of Chu et al. (1996) 'monitors' for structural change as new observations accrue, so is potentially relevant in the forecasting context, and show that 'one shot' tests cannot be repeatedly applied as new observations arrive (the size of that procedure would go to one). We shall not be concerned with the appropriate distributional theory for testing such hypotheses, as the cases of concern here are when forecast errors are so large that no test is necessary to discern if a change has occurred.

Approximating a process with a break by a variety of types of 'model', ranging from predicting the sample mean of the process, to 'no change' type forecasts, and include members of the autoregressive, integrated moving-average (ARIMA) class of the Box and Jenkins (1976) time series modelling tradition are given below.

If the primarily concerned were with short-term forecasts of y_t, then the horizons h would cover 1 to 5-steps ahead for the purpose of the Finance Commission, where the forecast origin is taken to be T. The DGP in (1) is invariant to specifying the dependent variable as y_t or Δy_t so long as y_{t-1} enters unrestrictedly. But, beyond 1-step, most conventional evaluation criteria are not, and it matters for which transform of the dependent variable forecast errors are evaluated (see Clements and Hendry, 1993). The models (M_0 to M_6) of y_t are summarized in Table 1, and each one in turn assumed subsequent sections allowing for $\rho \neq 0$, in which case, following the impact of the break at period τ, the process will undergo period of adjustment to the new equilibrium, in contrast to instantaneous adjustment when $\rho = 0$.

<u>The sample mean as a predictor (M_0):</u> The forecast function expressed as M_0 is simply the in-sample mean. This form gives forecasts, which are not conditional on the value(s) of the process around the forecast origin, and forecasts are badly biased when the recent behaviour of the process is very different from the history on which the mean is based. Comparisons with respect to the sum of the squared bias and forecast-error (MSFE) variance fares poorly. Consider M_1 (1,0,0) with constant term is described a

$$y_{it} = \alpha + \beta\, y_{it-1} + \varepsilon_t$$

TABLE 1: Forecasting models

Model (ARIMA)	DGP	Constant
M_0	Sample mean as a predictor	
M_1 (1,0,0)	$y_{it} = \alpha + \beta\, y_{it-1} + \varepsilon_t$	Yes
M_2 (0,1,0)	$y_{it} = \alpha + y_{it-1} + \varepsilon_t$	Yes
M_3 (0,1,0)	$y_{it} = y_{it-1} + \varepsilon_t$	No
M_4 (0,1,1)	$y_{it} = \alpha + y_{it-1} + \varepsilon_t + \varepsilon_{t-1}$	Yes
M_5 (0,1,1)	$y_{it} = y_{it-1} + \varepsilon_t + \varepsilon_{t-1}$	No
M_6 (1,0,1)	$y_{it} = \alpha + \beta\, y_{it-1} + \varepsilon_t$	Yes

Differencing: As a polar case, consider M_3 termed as differencing model. Let $y_{j/i}$ denote the forecast function for the model under consideration, where i is the forecast origin (on which the forecast is conditioned), and j is the period being forecast. Here $y_{T+h/T} = y_t$, so that the history of the process, other than the value at the forecast origin, is irrelevant. 'Complete' conditioning on the origin would appear to be a good idea when the future is exactly like the present, but will be costly if the present is atypical, and if in the future the process returns to its long-run average. Hence, differencing offers potential advantages for short-term forecasting when the present pattern persists at least in near future (say less than five years), but may yield unreliable forecasts over longer horizons. As an extreme example, the shift in mean to μ_2 at period T +1 is reversed in period T +2. Multi-step forecasts conditional on period will fare badly compared to using the sample mean. The sample mean is robust to irregular or outlier observation at the forecast origin, whereas differencing quickly incorporates change, and gains if that change persists. These are extremely simple examples of forecasting may be called for, depending upon the expected nature of the nonconstancy. Flides and Makridakis (1995), remark upon the elaborate models, and a change in trend rather than mean, but the upshot of their argument is similar. For example, they suggest that single exponential smoothing or damped trend smoothing may be more robust to a range of changes in trend than ARIMA models.

While differencing may reduce bias, since the process is stochastic, it will not repeat the previous period (barring an event with probability zero), which has implications for the forecast error variance attached to this type of predictor. If the structural break (mean-shift) has occurred prior to the forecast origin (at period (T/2) compared to period T), differencing results are largely unbiased forecast when the constant is not estimated. This is because:

$$E\,[y_{T+h/T}] = E\,[y_t] = \mu^* \text{ and } \quad E\,[y_{T+h}] = \mu^*. \tag{13}$$

However, the cost in forecast error variance arises because the predictor projects y_t, which is $\mu_2 + \varepsilon_T$, so there is an 'error' in the present. Because the future value of the process is $\mu_2 + \varepsilon_{T+h}$, and since ε_T and ε_{T+h} are independent for all h, the forecast error variance is twice the minimum. Formally, when $\rho = 0$ the unconditional variance component is:

$$E\,[(\mu^* + \varepsilon_{T+h} - y_{T})^2\,] = \sigma^2_\varepsilon + (\mu^*)^2 + E[y^2_T] - 2\mu^* E[y_T] = 2\sigma^2_\varepsilon \tag{14}$$

When a constant is included in M_3 we obtain M_2. Ignoring parameter estimation uncertainty; the forecast function has the following form:

$Y_{T+h/T} = y_T + hT^{-1}\delta_\mu$ with forecast bias

$$\text{Bias} = E\,[Y_{T+h} - Y_{T+h/T}] = -hT^{-1}\,\delta_\mu \tag{15}$$

So that the bias is small but increases with the forecast horizon. Again, in large samples, the forecast error variance is $2\sigma^2_\varepsilon$ (ignoring the impact of estimating the constant term). Model M_1 is the DV model.

When there is no structural break, i.e., when $\mu_2 = \mu_1$ and $\alpha = \mu_2$, $\beta = 0$ so that $E\,[\xi] = E\,[\varepsilon_T] = 0$ and hence intercept correcting does not induce a bias. Otherwise, intercept corrections always result in an inflated forecast error variance. Constituting a doubling when there is no mean shift. Moreover, for β close to unity V [.], gets very large. Intuitively, as $\beta \to 1$the stochastic component of ξ_T, namely $\xi_T - E\,[\xi_T] \to \Delta\,\varepsilon_{T,}$

In sum, both intercept correction and differenced model yield unbiased forecasts and double forecast error variances in the absence of structural break. However, these two methods are susceptible to structural breaks. Of course, the more pertinent issue is the effect of intercept correcting the effect is dramatic: unbiased forecasts do indeed result, again with considerable volatility error as well as the impact of any shift.

IV. Improving Forecast Accuracy and Intercept Corrections

Forecast accuracy can only be assessed once a yardstick is agreed upon, and the choice of its indicator may have a greater influence on the success or failure of a forecasting exercise than is often imagined, the MSFE-based measures have been the dominant criteria for assessing forecast accuracy in macro-economic forecasting. However, for multi-step forecasts or multivariate models, such measures are not invariant to non-singular, scale-preserving linear transforms, even though linear models are. Further, unpredictability is not invariant under inter-temporal transforms, so uniquely acceptable measures by choosing alternative yet isomorphic representations of a given model. Thus, the MSFE ranking can be an artefact of the transformation selected. A generalised forecast-error second moment criterion (i.e., GFESM) is invariant, but cannot resolve all problems relating to model choice across different forecast horizons (see Clements and Hendry, 1993), particularly for asymmetric loss functions. Although it is desirable that forecasts be unbiased and efficient, in practice, performance relative forecasts determine the worth of any forecasting procedure (Sinha et al, 2002). The j-step ahead forecast error could be expressed as the sum of three components viz., forecast error due to the changed intercepts and slope parameters; error accumulation; and an interaction term occasioned by the change in the slope parameter, which includes the initial condition.

There is a long history of predictive failure of the budgetary variables using econometric models. Theoretical analysis of several of the other putative causes, demonstrating the central role of deterministic shifts is found in Hendry and Doormik (1997). The causes of this predictive failure, and along with many potential explanations ranging from inaccurate data, inappropriate economic analysis, an invalid model class, bad methodology, structural change (particularly the financial deregulation, possibly demographic change,etc.), and omitted the variables (mainly wealth related measures) have been given in Muellbauer (1994).

Intercept Corrections and Structural Change: Intercept corrections refer to the practice of specifying nonzero values for a model's error terms over the forecast period. A general theory of the role of intercept corrections in macro-econometric forecasting has been developed having focus on their role in offsetting regime shifts. If the model's (in-sample) error is an innovation on the information set, in the absence of structural breaks over the future, or of other extraneous factors, it is natural to set the future values of the equations error terms to zero. Here, the simplest form of intercept correction is considered, wherein the forecaster reacts to perceived recent predictive failure by adding in the equation the error in predicting T at the forecast origin. For M_1, the AR (1) model, the period T model error is, ignoring estimation uncertainty, given as

$$\begin{aligned} \varepsilon_T = y_T - y_{T/T-1} &= \mu_2 + \varepsilon_T - (\alpha + \beta y_{T-1}) \\ &= \mu_2(1-\beta) - \alpha + (1-\beta L)\, \varepsilon T, \end{aligned} \tag{18}$$

Where L is the lag operator, i.e. $L\varepsilon_1 = \varepsilon_{t-1}$. When the adjustment is held constant over the forecast period, ε_1 is added in at each step ahead:

$$\check{y}_{T+h/T} = \alpha + \beta\check{y}_{T+h-1/T} + \varepsilon_{T,} \tag{19}$$

Where $\check{y}_{T/T} = yt$, so that:

$$\check{y}_{T+h/T} = y_{T+h/T} + \Sigma t\ \beta^i \tag{20}$$

$$= (\alpha + \varepsilon_T)$$

The j-step ahead forecasts of the level of the process are obtained from the initial condition w_τ. When Y is unchanged over the forecast period, the expected value of the conditional j-step-ahead forecast error. The occurrence of w_τ is awkward for comparisons with the VEqCM. Thus, average over w_τ to gives the unconditional bias $E_{w\tau} [\upsilon_{T+j}]$. The VCM results coincide if either there is no regime shift or the shift occurs after the start of the forecast period.

If the model based forecast are conditional with correct specification it can be improved by intercept corrections. Similarly, forecasting inaccuracies due to both initial condition and parameter uncertainties may be improved by employing intercept corrections. Econometric forecasting captures three aspects of the real world in which the forecasting venture is to be undertaken. First, that the data generation process (DGP) is non-stationary due to unit roots. Second, that it is susceptible to structural breaks and policy regime shifting; and third, the forecasting model typically differs from the (unknown) DGP. These features provide a rationale for the improving forecasting accuracy by making adjustments or 'intercept corrections' to purely model-based forecasts. Hendry and Clements (1993) have suggested an econometric theory of intercept corrections and have concluded that such corrections improve forecast accuracy relative to model-based forecasts. Based on Monte Carlo studies it has been shown that forecasts generated from vector autoregressions in differences (DVARs) may be more robust than models in levels to certain forms of structural change, but that intercept correction may help vector 'equilibrium-correction' mechanisms (VEqCMs) to match the performance of DVARs.

An interesting example of the benefit of ignoring long-run information for forecasting appears in Mizon (1995), which shows that only a DVAR has a satisfactory forecasting performance in the context of modelling UK wages and price over the period 1966-93. Models such as VEqCMs, which include long-run information, tend to fail badly. There is anecdotal evidence of structural change for the Indian economy in the 1990s in response to economic reform, and the change in government economic policies may have altered the long run relationships between the budgetary macro aggregates. Thus, models, which include long run information, tend to 'error-correct' on the basis of an outdated structure, and manifest significant forecast errors, while models that eschew such information perform reasonably well. Usefulness of intercept corrections for the class of breaks that affect the deterministic variables is apparent while allowing an assessment of intercept-correcting strategies in terms of squared-error loss. Secondly, some of these correction strategies to econometric models based forecast where wider classes of breaks are analysed analytically may be important.

V. Empirical Illustration of Intercept Correction

The system envisaged here considers government expenditure (total, development and non development) and total revenue receipts for all states taken together have the virtue of allowing a 'statistical analysis' of intercept corrections. Earlier studies, such as those carried out by the ESRC Macroeconomic Modelling Bureau at Warwick, have assessed the impact of intercept corrections on actual forecasts horizon and on the transformation of the data for which forecast accuracy is assessed. We distinguish between one and *h*-steps-ahead forecasting performance, given the lack of invariance of mean-square forecast errors (MSFEs) to evaluating forecasts of levels versus changes (say), and the likely poor discriminatory performance of evaluation in difference. If the aim of an econometric modelling exercise is discovering forecasting models that can be used reliably, then combination is at best a stopgap measure to improve forecast accuracy

Purpose in the present section is to discuss the DGP as used in our study. The vector of all *n* variables is denoted by ω_t and the system is represented by equation (9) i.e., a first-order VAR in terms of the determinant component (D), which includes a constant, and a linear deterministic trend and is reproduced below:

$$w_t = \tau_o + \tau_1 t + \gamma w_{t-1} + \nu_t \qquad (21)$$

Where $\upsilon_t \sim IN(0,\Omega)$

Second equation employed in our estimation is the VEqCM:

$$\Delta w_t = \tau_0 + \tau_1 t + \alpha\beta' w_{t-1} + \nu_t \qquad (22)$$

If α and β are n x r matrices of rank r<n, where w~I (1).The impact of the deterministic components (i.e.,τ_0 and t or D_t) on the series depends on the relationship between α and τ_0, τ_1. Alternatively,

$\Delta w_t = \Pi w_{t-1} + \Psi D_t + \nu_t$

where and $\nu_t \sim IN(0, \Omega)$

$$\Pi = A - I_n = \alpha\beta'$$

In the third model estimated here we have considered the lagged Δw_t for approximating the omitted cointegrating vectors, although its behaviour under structural breaks is rather complicated. Thus,

$$\Delta w_t = \tau_0+\tau_1 t+\alpha\beta\ \Delta w_{t-1}+ \upsilon_t \quad (23)$$

Finally, a VAR in differences (DVAR) may also be used, where sample is misspecified relative to the VECM unless γ=0.The simplest formulation is

$$\Delta w_t = \gamma + \eta_t$$

Now, consider forecasts from a simplified DVAR. Forecasts from the DVAR for Δwt, are defined by setting $\Delta w_{\tau+j}$ equal to the population growth rate γ. When α= 0,the VECM and DVAR coincide.

Forecast biases under deterministic shifts have been discussed in literature.. Numbers of interesting special cases have been considered which highlight the different behaviour of the DVAR and VEqCM under regime changes. The forecast error biases in the DVAR and VEqCM coincide when there is no regime change, even when the DVAR omits an ECM, which includes a non-zero trend. Consider dynamic forecasts and their errors when parameters are subject to change in the forecast period focusing on the bias and variance components and consider the implications of the deterministic terms lying in the cointegrating space. The forecast commences from correct initial conditions (equal to the true value of the process, w_τ) and assume that the model matches the DGP in sample, ignoring from parameter estimation uncertainty. So that forecast functions are based on true (but sample period) values of the process. We must take expectation over w_t relative to the structural change occurring at T + 1; and that occurred at T. For instance during the budget any change in tax, tax rates, etc. likely to alter in response to the fixed policies of the government. When the linear trend is absent and the constant term can be restricted to the cointegrating space (i.e. τ_1=0 and ξ_0=0, which implies λ_1 =0 and therefore μ_1=γ=0) then only the second term appears, and the bias is O (1) in j.

For our empirical illustration, we use total revenue receipts, development expenditure, non-development expenditure and total government expenditure. Assuming a linear, closed system in four non-deterministic variables, four cases are considered here ,viz., time series of the level, log level, first difference, and annual growth rates. The OLS estimates of the above three equations (21), (22) and (23) have been obtained for All States taken together all tests are acceptable and the in-sample estimates of forecasts are given in the Appendix Tables 1.1-1.4.These models have been estimated for 1975-76 through 1999-2000. Projections have been obtained for in sample given in Appendix Tables1-1. Applying Intercept Corrections for the period 2000-01 through 2009-10 the projections are given Appendix Table 2. The precise manner in which forecasts for the period 2000-01 through 2010 have been obtained is described below. The four models are first estimated using 25 annual points i.e. with effect from 1974-75 through 1999-2000.Three sets of forecasts have been generated. First considering, 1999-2000 as the first forecast origin (or initial condition) we obtain the forecast for 1 through 10 steps ahead, i.e., and labelled as residual (1). In the second set, an average of the latest five years preceding 1999-00 is employed in generating the forecast and labelled as residual (5). Finally, the third set of forecasts have been obtained employing constant adjustments based on the average (across the sample of 25 years) for longer horizons and labelled as residual (25).

The BE are available for two years, i.e., 2000-01 and 2001-02, whereas RE is available only for one year 2000-01, our forecasts have been compared with these figures and given in Appendix Table 3. Interestingly the forecast errors obtained here fall in the range below 5%. The causes of predictive failure may have possible explanations ranging from inaccurate data, inappropriate economic analysis, an invalid model class, bad methodology, structural change and other omitted variables. For government expenditure, intercept correcting the 1-step forecasts yields the outcomes shown in the in-sample behaviour is identical by construction, but the forecasts track the outcomes, albeit with a much larger variance.

VI. Conclusions

Modern theory of econometric forecasting captures three aspects of the real world, first the data generation process (DGP) is nonstationary due to unit roots; second it is susceptible to structural breaks; and finally, the forecasting models typically differs from the (unknown) DGP. These features provide justifications for making adjustments to purely model-based forecasts through 'intercept corrections' proposed by Hendry and others. Results on macroeconomic forecasting in the presence of structural breaks departs in several ways from the traditional theory of economic forecasting (see Klein, 1971), and suggests a need to reappraise practices and modelling approaches which appear redundant in the classical paradigm. The systems of cointegrated relations representing macro-econometric model, when economies are subject to unanticipated, large regime shifts, the quantitative impact of structural breaks on systematic forecast errors.

In the literature on economic forecasting, the differenced model and intercept correcting (IC) strategies yield unbiased forecasts and doubled forecast error variances (relative to) in the absence of a structural break. However, these two forecasting methods are differentially susceptible to structural breaks. For the DGP we consider here, the IC strategy fares satisfactorily in terms of forecast error variance, but this may not necessarily be the case generally (see the empirical example in Clements and Hendry (1966). The main aim of the paper was to expound a number of recent results on forecasting after a shift in the mean of a stochastic process. When economic systems are subject to structural breaks, conventional models need not forecast satisfactorily. The empirical example of government expenditures reveals that if some shift in the econometric relation occurs, various strategies considered helped circumvent the implicit shift. The differencing may mitigate the effects of changes in equilibrium means. Alternatively, intercept corrections can offset the mean shift, albeit at the cost of an increased variance. However, models that do neither performed badly analytically and empirically. There was little benefit to multi-step estimation over repeated backward solution of 1-step estimates.

Thus, in sample fit may be a poor guide to ex-ante forecast performance when the assumption of constancy fails, so alternative strategies may be called for. A theory of forecasting allowing for structural breaks when the model is not the mechanism is feasible, and on the limited evidence of the empirical example considered here, provides a useful basis for interpreting and circumventing systematic predictive failure in economics. SC is the Schwarz criterion; and the diagnostic tests in the form of the F-test against the alternative hypothesis and other sample tests are acceptable showing the fitted, actual and forecast values, their cross plot with separate regression lines pre and post 1991; the residuals and forecast errors scaled by the equation standard error; and the forecasts with 1-step 95% confidence bands around the forecasts may also be estimated[2]. The forecast and sample regressions will have distinctly different slopes and the post sample residuals may greatly exceed the in sample ones.

Even if forecasts are poor, there are none better, and perhaps a poor forecast is better than none at all.

[2] The Chow (1964) constancy test over sample period may yield very large F (40,79)=2.90** which rejects at the 1% level, consistent with the low correlation between outturns and forecasts over the later period..

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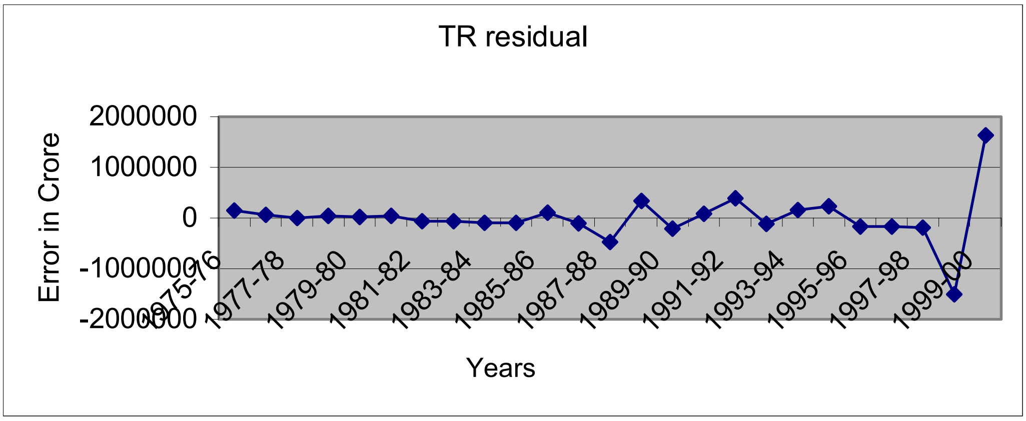

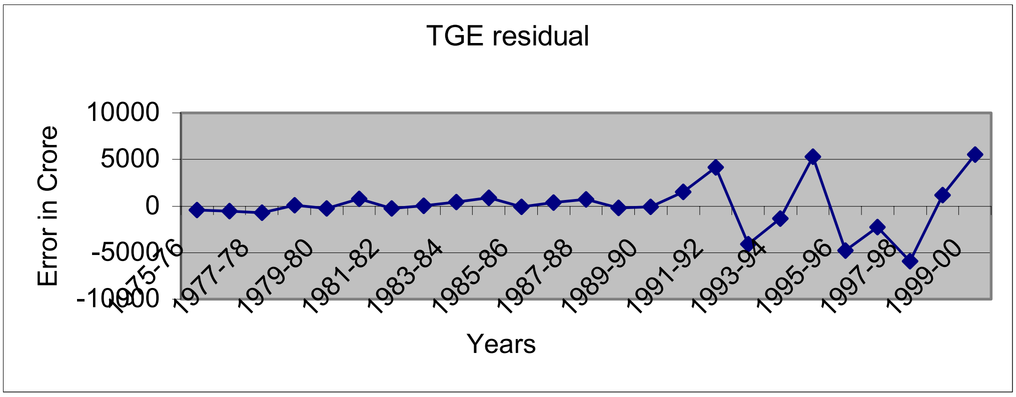

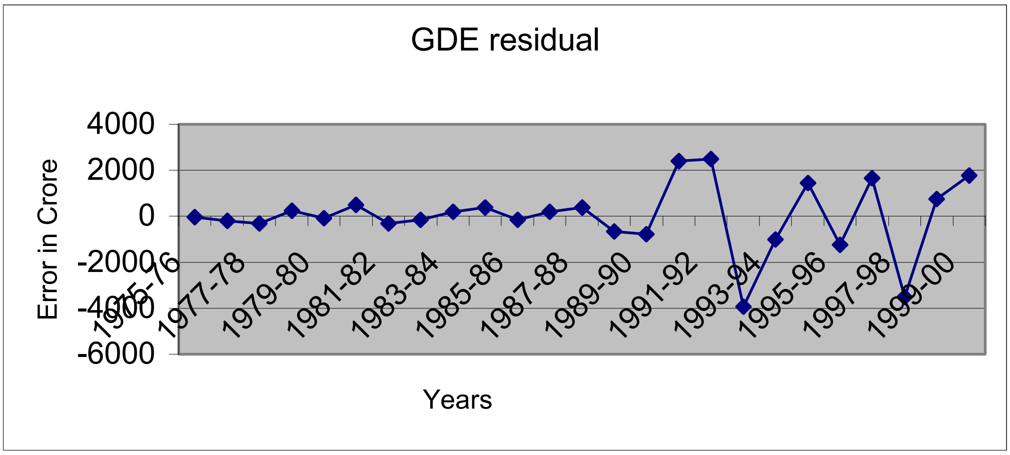

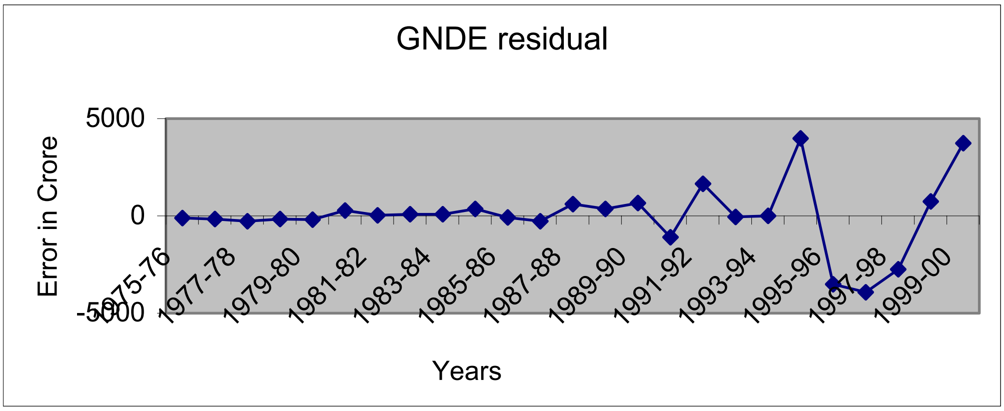

Figure2: Descriptive Statistics of the Model

Appendix Table 1.1 to 1.4

Estimated Forecasting Models(1975-76 to 1999-2000)

Table 1.1:Total Revenue Receipt

Dependent Variable	Intercept	time	Lagged	R Square
Rt t-value P-value	-81726.7	31872.63 0.81 0.43	1.0842 Gt-1 20.50 7.9E-16	0.9937
ΔRt t-value P-value	-81726.7	31872.63 0.81 0.43	0.0842 Gt-1 1.59 0.12	0.6628
ΔRt t-value P-value	-475665	161421.2 6.29 3.08E-06	-0.9601 ΔGt-1 3.04 6.1E-4	0.7393
rt t-value P-value	6.2719	0.0641 2.38 0.03	0.5396 gt-1 2.85 9.2E-4	0.9985
Δrt t-value P-value	5.8129	0.0591 1.48 0.15	-0.4258 gt-1 1.53 0.14	0.1970
Δrt t-value P-value	0.1919	-0.0018 1.31 0.20	-0.2457 Δgt-1 1.06 0.29	0.1073

Table 1.2:Total Government Expenditure

Dependent Variable	Intercept	time	Lagged	R Square
Gt t-value P-value	553.8796	-82.5661 0.42 0.67	1.1622 Gt-1 55.87 3.32 E-25	0.9989
ΔGt t-value P-value	553.8796	-82.5661 0.42 0.67	0.1622 Gt-1 7.79 8.97E-08	0.9435
ΔGt t-value P-value	-1545.86	311.4523 1.13 0.27	0.9401 ΔGt-1 4.32 3E-04	0.8915
gt t-value P-value	2.4625	0.0387 1.70 0.11	0.736 gt-1 4.80 8.44E-05	0.96
Δgt t-value P-value	2.4625	0.0387 1.70 0.11	-0.2641 gt-1 1.72 0.09	0.1444
Δgt t-value P-value	0.1927	-0.0007 0.35 0.95	-0.2508 Δgt-1 0.26 1.16	0.0802

Table 1.3:Development Expenditure

Dependent Variable	Intercept	time	Lagged	R Square
Gt t-value P-value	265.0218	53.2858 0.43 0.67	1.1193 Gt-1 54.74 5.18E-25	0.9991
ΔGt t-value P-value	265.0218	53.2858 0.43 0.67	0.1193 Gt-1 5.83 7.13E-06	0.9359
ΔGt t-value P-value	-1317.91	405.4171 2.45 0.02	0.5357 ΔGt-1 2.33 0.03	0.8738
gt t-value P-value	0.7098	0.0074 0.58 0.56	0.9357 gt-1 10.60 4.12E-10	0.9995
Δgt t-value P-value	0.7099	0.0074 0.58 0.56	-0.0643 gt-1 0.73 0.47	0.2591
Δgt t-value P-value	0.1916	-0.0022 2.57 0.02	-0.1728 Δgt-1 0.79 0.43	0.2472

Table 1.4:Non Development Expenditure

Dependent Variable	Intercept	time	Lagged	R Square
Gt t-value P-value	76.1866	-40.2111 0.36 0.72	1.2089 Gt-1 36.27 4.05E-21	0.9965
ΔGt t-value P-value	76.1866	-40.2111 0.36 0.72	0.2088 Gt-1 6.27 2.63E-06	0.8865
ΔGt t-value P-value	-934.3430	150.1012 1.17 0.25	0.9729 ΔGt-1 4.15 4.5E-4	0.8319
gt t-value P-value	2.0890	0.0464 2.45 0.02	0.7297 gt-1 6.33 2.27E-06	0.9991
Δgt t-value P-value	12.4126	0.3408 2.62 0.02	-0.9886 gt-1 1.24 0.23	0.9631
Δgt t-value P-value	5.6901	0.1928 5.02 5.67E-05	-0.0589 Δgt-1 0.27 0.78	0.9605

TABLE 1: Revenue Receipts, and Government Expenditures (Total, Development and Non-Development)-All States (in Rs. Crores)

Years	Total Revenue Receipts			Total Govt. Expenditure			Development Expenditure			Non-Development Expenditure		
	actual	estimate	error	actual	estimate	error	actual	estimate	error	actual	estimate	Error
1	2	3	4	5	6	7	8	9	10	11	12	13
1975-76	793816	647463.1	146352.9	8370.86	8776.953	-406.093	6091.21	6126.98	-35.7698	2205.62	2314.983	-109.363
1976-77	903702	842689.7	61012.26	9594.9	10117.36	-522.461	6992.18	7189.771	-197.591	2510.13	2662.112	-151.982
1977-78	993057	993703	-645.972	10765	11457.37	-692.374	7944.72	8251.555	-306.835	2717.45	2990.019	-272.569
1978-79	1164669	1122456	42212.92	12798.32	12734.7	63.6218	9621.56	9371.064	250.4963	3046.27	3200.435	-154.165
1979-80	1362931	1340394	22537.13	14756.28	15015.26	-258.977	11227.05	11301.32	-74.2654	3352.78	3557.73	-204.95
1980-81	1629330	1587226	42103.87	18007.99	17208.23	799.7584	13643.4	13151.7	491.6984	4159.66	3888.056	271.6045
1981-82	1845460	1907934	-62473.9	20664.61	20904.8	-240.193	15599.65	15909.72	-310.072	4852.79	4823.272	29.51804
1982-83	2112554	2174139	-61585	23956.16	23909.76	46.39946	17994.63	18152.73	-158.1	5714.43	5620.977	93.4526
1983-84	2401382	2495600	-94218.3	28080.01	27652.63	427.3761	21081.32	20886.83	194.4904	6694.92	6622.393	72.52745
1984-85	2742547	2840626	-98079	33260.41	32362.81	897.6038	24770.05	24395.19	374.8574	8133.26	7767.484	365.776
1985-86	3342408	3242397	100011.5	38222.73	38300.9	-78.171	28431.37	28577.45	-146.077	9389.01	9466.065	-77.0549
1986-87	3822626	3924650	-102024	44333.65	43985.54	348.1068	32918.26	32729.02	189.2393	10669.71	10943.91	-274.205
1987-88	4000396	4477185	-476789	51742.78	51005.09	737.6917	38185.75	37804.69	381.0566	13066.39	12451.93	614.4633
1988-89	5042085	4701799	340285.5	59305.91	59533.41	-227.503	43089.86	43754.13	-664.268	15661.42	15309.03	352.3867
1989-90	5653478	5863092	-209614	68180.5	68240.72	-60.2167	48508.64	49296.82	-788.175	19068.87	18405.92	662.9472
1990-91	6646678	6557849	88828.7	79998.87	78472.2	1526.671	57815.23	55415.6	2399.634	21399.59	22484.94	-1085.35
1991-92	8053570	7666569	387000.8	96282.17	92124.94	4157.227	68366.57	65886.19	2480.384	26900.08	25262.31	1637.775
1992-93	9109113	9223822	-114709	106860	110966.8	-4106.88	73808.82	77750.08	-3941.26	31816.41	31871.57	-55.1607
1993-94	10556372	10400136	156236.2	121826.4	123177.8	-1351.37	82889.59	83895.13	-1005.54	37765.54	37774.65	-9.11195
1994-95	12228371	12001156	227215.5	145790.9	140489.2	5301.682	95568.91	94112.95	1455.957	48918.85	44926.27	3992.577
1995-96	13680338	13845843	-165505	163498.7	168258.1	-4759.41	107113.3	108358.8	-1245.48	54854.68	58369.16	-3514.48
1996-97	15283638	15451967	-168329	186489.6	188755.6	-2266.04	122981.3	121334.3	1646.996	61576.35	65504.71	-3928.36
1997-98	17030080	17222170	-192090	209435.7	215393.1	-5957.36	135624.8	139149.3	-3524.55	70853.98	73590.24	-2736.26
1998-99	17644770	19147570	-1502800	243161.8	241978.5	1183.323	154115.9	153355.1	760.7984	85515.33	84765.65	749.6836
1999-00	21480960	19845902	1635058	286597.4	281092.4	5505.017	175878.2	174106.3	1771.866	106179.8	102449.4	3730.395

Source: Cols. 2, 5, 8, and 11 Various Issues of RBIB

TABLE 2: Revenue Receipts, and Government Expenditures (Total, Development and Non-Development)-All States (in Rs. Crores)
Out-of –Sample Projections

	Total Revenue Receipts			Total Govt. Expenditure			Development Expenditure			Non-Development Expenditure		
1	2	3	4	5	6	7	8	9	10	11	12	13
Years	FE (1)	FE (5)	FE (25)	FE (1)	FE (5)	FE (25)	FE (1)	FE (5)	FE (25)	FE (1)	FE (5)	FE (25)
2000-01	256721.1	239583.2	240370.5	336995.7	330231.8	331493.4	200291	198401.1	198519.1	131120.5	126250.3	127390.1
2001-02	284753.4	267615.5	268402.8	389088.1	382324.1	383585.7	225687.4	223797.5	223915.5	156721.3	151851.1	152990.9
2002-03	315465.4	298327.5	299114.8	449547.3	442783.3	444044.9	254168.1	252278.1	252396.2	187629.5	182759.3	183899.1
2003-04	349082.6	331944.7	332732	519730.4	512966.5	514228	286101.1	284211.2	284329.2	224953.9	220083.7	221223.5
2004-05	385849.8	368711.9	369499.2	601214.6	594450.7	595712.3	321898.6	320008.6	320126.7	270034.7	265164.5	266304.3
2005-06	426032.3	408894.4	409681.7	695833	689069.1	690330.7	362021.6	360131.7	360249.7	324492.1	319621.9	320761.7
2006-07	469917.7	452779.7	453567.1	805716	798952.1	800213.7	406986.5	405096.6	405214.6	390284.8	385414.6	386554.4
2007-08	517817.8	500679.9	501467.2	933339.4	926575.5	927837.1	457371.1	455481.2	455599.2	469780.6	464910.4	466050.2
2008-09	570070.8	552932.9	553720.2	1081581	1074817	1076078	513822.3	511932.3	512050.4	565841.9	560971.7	562111.5
2009-10	627043.2	609905.3	610692.7	1253784	1247020	1248282	577064	575174	575292.1	681929.1	677058.9	678198.7

Source: Author's Calculation

TABLE 3: Estimates of Forecasting Errors in Percent

	Years	(B)	(R)	FE (1) BE	FE (1) RE	FE (5) BE	FE (5) RE	FE (25) BE	FE (25) RE
TR	2000-2001	24224270	24961485	5.9768	2.84687	-1.09789	-4.01887	-0.77287	-3.70345
	2001-2002	28254830	NA	0.780435	NA	-5.28504	NA	-5.00639	NA
TGE	2000-2001	325710.6	337868.5	3.464749	-0.25834	1.388088	-2.26027	1.775422	-1.88688
	2001-2002	373034.2	NA	4.303588	NA	2.490375	NA	2.828571	NA
GDE	2000-2001	195896.2	210024.3	2.243438	-4.63437	1.278672	-5.53424	2.243438	-5.47803
	2001-2002	222764	NA	1.312328	NA	0.463924	NA	0.516918	NA
GNDE	2000-2001	124320.2	122571.2	5.469996	6.974991	1.552536	3.001631	2.469365	3.931543
	2001-2002	143849.4	NA	8.948139	NA	5.56252	NA	6.354878	NA

Source: Author's Calculation