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PANEL DATA MODELS AND MEASUREMENT OF STATES' TAX EFFORT IN INDIA

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Abstract

An important objective of a federal setup is to induce federating units to put in efforts to realise their potential resource levels. In India, such efforts by states are given weightage in schemes of tax sharing and grants-in-aid by successive Finance Commissions, and in allocation of plan grants by the Planning Commission. However, objective measurement of the relative efforts of State governments in raising resources through taxes has eluded the economists so far. The two approaches, namely, the Representative Tax System Approach and the Aggregate Cross-section Regression Approach, which are used at present to assess the state tax efforts in this way, suffer from various drawbacks. To overcome some of the drawbacks, a covariance approach is sometimes employed. The Ninth Finance Commission (NFC) has paved the way in India by following this approach, using a model of the 'Fixed Effects' type, in its first report [NFC, 1988].

The covariance approach consists of a number of models with varying assumptions and the model used by the NFC is but one type. The main intention of the present paper is to examine the suitability of different types of panel models for assessing relative tax efforts of states both on *a priori* grounds as well as on grounds of statistical efficiency. The basic versions of alternative types of panel models are estimated by way of illustration and their relative empirical performances are compared.

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1. Assessing States' Tax Efforts

An important objective of a federal setup is to induce federating units to put in efforts to realise their potential resource levels. In India, such efforts by States are given weightage in schemes of tax sharing and grants-in-aid by successive Finance Commissions, and in allocation of plan grants by the Planning Commission. Yet, objective measurement of the relative efforts of State governments in raising resources through taxes has eluded the economists so far.

The tax revenue behaviour of states in India is conditioned not only by the type of federal arrangements, but also by the divergent tax rules and numerous state-specific socio-economic factors affecting tax compliance. The norms used for assessing tax efforts can either be set up exogenously, based on certain overall economic policy objectives or derived endogenously from the tax behaviours of states. The latter involves separation of common and non-common traits in the tax behaviours. While the common characteristics can be directly interpreted as one part of the norms, a standard has to be evolved out of the state-specific aspects, to be used as the other part of the norms. Generally, two approaches are used to assess the state tax efforts in this way: The Representative Tax System (RTS) approach, and the Aggregate Cross-Section Regression (ACR) approach. The RTS approach, developed by the Advisory Committee on Inter-governmental Relations [ACIR, 1971] in the United States of America seeks to compare a set of effective tax rates applicable to different components of tax base in a state with the corresponding all-state average effective tax rates, and to interpret the aggregate difference between the two sets as a measure of the State's tax effort. The ACR approach, on the other hand, seeks to establish a stochastic relation between tax revenues and a set of variables representing taxable 'capacity', and to interpret the difference between the actual and estimated tax revenue of each state as a measure of its relative tax effort [Lotz and Morse (1967), Bahl (1971), Chelliah (1971), Chelliah and Sinha (1982)].

The shortcomings of the two approaches are well known. While the major limitation is the failure to distinguish residual variation due to factors affecting tax effort from that due to random disturbances arising out of 'sampling' fluctuations, the RTS method, in addition, demands data in great detail on the tax base and its components in respect of each state.

To overcome some of these drawbacks of the above two approaches, a covariance approach is sometimes employed, which provides tools not only to identify the common traits among tax behaviours of states but also to separate out the the effects of state-specific factors from that of pure random disturbance factor, and thereby helps evaluation of states' tax efforts in a better way. For example, Sahota (1975) has used a covariance model in the context of the Brazilian economy. The Ninth Finance Commission (NFC), for the first time in India, has followed this approach by using a model of the 'Fixed Effects' type, in its first report [NFC, 1988]. It has estimated a stochastic tax function - where per capita tax revenue is specified as being determined in all states by their respective per capita SDP, share of non-primary sector in SDP and Lorenz ratio of consumption expenditure distribution - on pooled time-series and cross-section observations.

The 'pooled' or 'panel data' models such as the one employed by the NFC are not new to economists and find many applications in the literature relating to consumer behaviour and behaviour of firms, apart from tax and expenditure studies. In many instances covariance models are found to perform better as compared to the conventional models based on single-dimension (either time-series or cross-section) data. For example, the problem of multicollinearity is minimised since the tendency of most economic series to move together may be neutralized by using pooled data. Further, the quality of parameter estimates might be better as the sample is purged of the peculiarities of individual groups/states. Also, where the researcher does not have access to sufficient number of single-dimension observations, covariance models provide feasible alternatives to conventional models. Therefore, it was only a matter of time before this class of models were employed for measuring relative tax efforts of states in India, as done by the NFC.

While the methodology adopted by the NFC marks a welcome departure from those of the earlier finance commissions, further improvements are possible within the covariance approach itself. The approach includes a number of models with varying assumptions - regarding the behaviour of residual disturbance term, the behaviour of unit-specific and time-specific effects, as also regarding the stability of the tax function parameters across the units as well as over time. Keeping these aspects in view, the models can be divided into two broad categories:

A. Those which assume that tax function differs across the states in terms of intercept coefficients only and that slope coefficients are same, and

B. Those which relax the assumption and allow slope coefficients also to vary across states along with intercepts.

Models under category A can be further subdivided on the basis of the hypothesised nature of variation of residuals, into `Fixed Effects' (FE) type, or `Random Effects' (RE) type. Models under category B include the `Seemingly Unrelated Regression Estimation´ (SURE) models and the `Random Coefficient´ (RC) models besides state-wise Ordinary Least Squares (OLS) models. As each class emphasises a particular set of assumptions regarding the extent and nature of commonalty in the tax behaviour of states, it is imperative to examine the applicability of different types of models for the purpose.

This is the main intention in this study - to examine the suitability of different types of panel models for assessing relative tax efforts of states both on *a priori* grounds as well as on grounds of statistical efficiency. We shall illustrate by empirically estimating the basic versions of alternative types of panel models which fall under the four broad categories and compare their relative empirical performances.

The plan of the study is as follows. Section 2 examines the suitability of models with uniform slope coefficients, namely, the FE and RE models. Section 3 deals with the applicability of models with varying slope coefficients, namely, the OLS, SURE and RC types of models. Section 4 compares the empirical performance of the alternative models and Section 5 gives summary and broad conclusions.

The tax function

It should be noted that the discussion that follows regarding the applicability of different types of models is not independent of the specification of the common tax behavioural function of states, both in terms of the determinants as well as the form of causality. With a view not to dilute our focus, rigorous theoretical derivations of the function as also exhaustive empirical experimentations leading to selection of the best determining factors are kept out of the purview of the present paper, as such an exercise itself calls for a separate study. For the present, the tax function considered specifies per capita total tax revenue of a state as being influenced by four factors, two denoting the level and composition of its tax base directly, and the other two representing the level of States' infrastructure, and affecting the tax revenues indirectly.

$$Y = \exp(a).\ X1^{b1}.\ X2^{b2}.\ X3^{b3}.\ X4^{b4}.\ \exp(U). \qquad (1)$$

where **Y** = per capita total tax revenue of a state,

X1 = per capita State Domestic Product (SDP),

X2 = share of non-primary sector in total SDP,

X3 = length of roads and rail line/thousand sq.km.

X4 = per capita consumption of electricity.

The first explanatory variable, **X1** represents the tax base as proxied by SDP while **X2** is taken as broadly denoting the composition of tax base, and **X3** and **X4** indicate the level of infrastructure which represent historical factors constraining tax revenues. Although in the long run the composition factor might be related to the level of SDP to some extent, as theorised by Hinrichs (1966) and Musgrave (1969), the relation may not be clear in the short-run. Since our model is of a short-run nature, it can be presumed that these two factors are not mutually related.[1]

2. Applicability of Constant Slope Models

A. Fixed effects models

The fixed effects (FE) models assume that the slope parameters of the tax function are the same across the states. Let the tax function in matrix notation be of the form

$$\mathbf{Y = Xb + Za + U} \qquad (2)$$

where $\mathbf{m}$ time period observations pertaining to each of the $\mathbf{p}$ states are stacked up so that $\mathbf{Y}$ is a $(\mathbf{pm.1})$ vector of tax revenue variable (in logs); $\mathbf{X}$, $[\mathbf{pm.(k-1)}]$ matrix of `capacity' variables numbering $(\mathbf{k-1})$ (also in logs); $\mathbf{b}$, $[\mathbf{(k-1).1}]$ vector of slope coefficients common for all the states; $\mathbf{a}$, $(\mathbf{p.1})$ vector of state-specific intercepts; $\mathbf{Z=I_p \otimes i_m}$ where $\mathbf{I_p}$ is an identity matrix of order $\mathbf{p}$ and $\mathbf{I_m}$ is a $(\mathbf{m.1})$ vector of units; and $\mathbf{U}$, $(\mathbf{pm.1})$ vector of stochastic disturbances.

On the assumption that the elements of $\mathbf{U}$ are `spherical', the model can be estimated by OLS which yields the `effects' as the vector $\mathbf{a}$. This is equivalent to replacing the original observations by the deviations from their respective state-specific mean values, applying OLS to the variables so transformed, and then deriving the `effects' indirectly, using the estimated $\mathbf{b}$ vector.[2]

The multiplicative nature of the function suggests that the `fixed effects' denoted by $\mathbf{a}$ are related to the overall effective tax rates under certain conditions so that the model includes the RTS approach as a special case. The superiority of FE models over RTS and ACR models can be easily seen. The advantage over RTS method is the ability to keep the effective rate differentials between states free from `white noise' or random disturbances. And, unlike the ACR method, the FE method has the ability to separate out the state-specific `effects' from the random disturbances.

The model can be extended to take care of `time effects' as well. If time effects are assumed to be systematically related to each other, then perhaps they can be captured by including a time trend variable, or by methods suggested in studies such as Bhargava, Franzini and Narendranathan (1982), Lee (1978), and Parks (1967). In cases where time effects are not so systematic, which is especially true for short-period samples, then they can be estimated using time dummy variables.

B. Random effects models

A well-known limitation of FE models is that while estimating the common slope parameters, they ignore the \`between-state´ component of the variation in the variables.[3] The effect of ignoring the \`between´ component would be that the precision of the coefficients of the tax function is reduced. The loss would be substantial if the component is large. The RE models, also known as the \`Error Component´ models provide a solution by assuming that the \`effects´ are random with known mean and variance. such a treatment of the \`effects´ is justified on the ground that the dummy variables used in the FE models also represent some ignorance just as the random disturbances, and that there is no reason why this type of \`specific´ ignorance should be treated differently than the \`general´ ignorance as represented by the random residual term.

The tax function under the RE assumptions can be specified as

$$Y = Xb + U \qquad (3)$$

where $U = I_p \otimes i_m . a + e$, with mean zero and variance s_u^2, e being a $(pm.1)$ vector with mean zero and variance s_e^2, a with mean zero and variance s_a^2, and e and a being independent of each other. Assuming that the variances of the components as well as the combined random residual to be known, the variance-covariance matrix of residuals is formed and the GLS estimators are derived.[4] In practice, as the variances of the random components are not known, a number of alternative procedures are suggested in the literature to derive their estimates which might yield different 'feasible' estimators of the tax function parameters.[5]

The RE models have a slight edge over the FE models in that, while the latter uses the within-state variations to estimate the tax function parameters, the former takes both the 'within' and 'between' state variations in estimating the parameters. Studies such as Maddala (1971) have shown that the RE estimators are in fact a matrix-weighted average of the 'within' (FE) and between estimators, the latter being obtained by estimating a cross-section regression using state-wise means of dependent and independent variables. The weight given to the between estimators is dependent on the ratio of 'within' and 'between' state variances of the random residuals.

However, the main difficulty of applying RE models to the present context would be the assumption of 'randomness' of the state-specific 'effects'. The randomness assumption implies that the effects are conditional to the sample used, and therefore the state-specific effects need not be treated as permanent. It also implies that the 'effects' are uncorrelated with the capacity variables which Mundlak (1978) finds as rather strong.

Therefore, to what extent the assumption of independence of the state-specific effects from the explanatory variables holds in the context of tax effort measurement, will primarily determine the applicability of RE models. If the tax function contains such capacity variables which are also related to tax effort, then perhaps RE models may not be very appropriate. For instance, SDP, the most commonly used capacity factor also subsumes a host of factors representing the level of development such as literacy and infrastructure which play a significant role in improving tax collection efficiency. This is corroborated by a study by Panchmukhi (1979), wherein he finds that tax-SDP ratio is higher in states with higher levels of SDP, larger population and higher literacy rates. Thus, one of the crucial assumptions of RE models may not hold in the present context, even though RE models might yield more 'efficient' estimates statistically. Nevertheless, empirical evidence on the interdependence between SDP level and tax effort has not been firm and conclusive. The consequences of RE components being correlated with the capacity variables are worse than leaving out the 'between' state variance component. For, such a correlation makes the coefficient estimates to be seriously biased.[6]

3. Application of Models with Varying Slope Coefficients

Conventionally, 'slope' coefficients in a tax function of the above log-linear form are assumed to represent the 'responsiveness of tax revenue' of a state to its tax base and related factors. The reasons given for differential tax responsiveness among states is that the composition of the tax base - in terms of 'vertical' classes (goods consumed by rich vs. poor) as well as 'horizontal' classes (agricultural vs. manufacturing goods) differs across the states, as also the tax rate structure. To some extent, such compositional differences are purported to be taken into account by the differential intercepts in the FE model reflecting state-specific effective tax rates.[7] However, differential slopes cannot be entirely ruled out, firstly, if the effective tax rates change over the sample time-period, and secondly, in respect of infrastructural disability factors.

Another reason why slope coefficients differ across the states could be that the proxy variables represent the true base with varying degrees of accuracy in each state. For states where SDP closely resembles the tax base, the corresponding slope coefficient would be expected to be unity provided the effective tax rates do not change over time. Thus, varying slope coefficients also represent the degree of accuracy with which SDP proxies the true tax base. Given that the objective of tax structure rationalisations in many states is to bring the aggregate tax base closer to SDP, it should be conceded that a varying **b** represents the degree of efficiency with which state governments exploit their tax bases. The closer the resemblance between aggregate tax base and SDP, the more efficient is the tax administration. To that extent, differential slopes can also be considered as indicative of tax efforts, and allowance should therefore be made for varying slopes in the tax determination models.

Depending on whether the varying slopes are a result of historical factors or due to purely random factors, the following two broad classes of models can be adopted.

A. Non-stochastic coefficient models

(i) OLS (State-wise) model

The tax function model may now be specified as

$$\mathbf{Y} = \mathbf{X}^{*}.\mathbf{b} + \mathbf{U} \qquad (4)$$

where **Y** and **U** are as defined above, but $\mathbf{X}^{*}$ is a **(pm.pk)** block-diagonal matrix consisting of state-wise explanatory variable matrices $\mathbf{X_i}$ of **(m.k)** order as diagonal elements, and **b**, the coefficient vector now is a **(pk.1)** vector, consisting of sub vectors $\mathbf{b_i}$,(i=1 ... **p**) each containing the state-specific coefficients. Estimating the fixed effects version of the varying slope models is simply equivalent to estimating separate tax functions for each state by OLS provided the elements of **U** are `spherical´.

(ii) SURE models

The basic FE model, despite its superiority over the conventional RTS and ACR approaches, suffers from arbitrary restrictions in some respects. One such restriction pertains to the possible contemporaneous covariances in the random residuals which make OLS to be unsuitable for estimation, and the appropriate method would be the `Seemingly Unrelated Regression Estimation´ (SURE) method. A possible reason to suspect contemporaneous covariances in errors in the present context would be as follows. In a federal setup with minimal tax barriers across the constituent states, it is possible that the tax jurisdictions of states overlap with one another. Such tax overlapping makes the states compete in raising taxes, and this tendency might lead to a situation where those states which could successfully export their tax burden raise higher tax revenue than others who could not do so. Thus, the tax revenue of a state not only depends upon its own base, but also on tax bases of other states. This is particularly true in the case of commodity taxes. While specifying the tax function it is not easy to take into account the effects of tax bases of other states. As a result the regression residuals might be correlated with the missing variables representing tax bases of other states, which in turn might result in correlations between residuals pertaining to different states. Under these conditions, a more efficient way of estimating the tax function parameters is by SURE procedures.[8] The constant-slope-varying-intercept version of SURE model can be obtained by imposing relevant coefficient restrictions.

B. Random coefficient model

One difficulty with varying slope coefficients models is to derive the parameters of the hypothetical representative state to be used for comparing the tax effort of each of the states. This is so because the coefficient vectors of different states are not comparable as their variance-covariance matrices could be different. Instead of simple arithmetic mean one needs to estimate a weighted mean of the state-wise coefficient vectors. Then the weighted coefficient vectors can be compared among the states for judging their tax efforts. Also, as seen above, it is essential to take into account the `between-state´ component of variation to obtain the coefficient vector of a truly representative state. The Random Coefficients (RC) model provides a method to derive such a weighted mean coefficient vector.

The RC model developed by Swamy (1970, 1971, 1974), and Hsiao (1975) assumes that random variation between states is not confined to the residuals but applies to the coefficients as well. The model not only recognises the possibility of varying coefficients (both intercepts as well as slopes) between states but also emphasises that such a variation is not `fixed´ but `random´. The tax function parameters of different states vary around a set of means which could be interpreted as the `representative´ parameters. As in the case of the error component models, the RC models derive the `normative´ set using both `between state´ as well as `within state´ variations.

The tax function is of the form

$$Y = X.b + X^{*}.v + U \qquad (5)$$

where v denotes a (pk.1) vector of state-specific random components of coefficients. On the assumption that **v** are uncorrelated with **X** and **U**, the variance-covariance matrix of residuals is derived and GLS is applied.[9]

The applicability of RC models to the present context is dependent on the extent to which the state-specific coefficients are independent of the explanatory variables, particularly the SDP. For example, we ask the question whether there is any a priori reason to assume that the elasticity coefficient (slope coefficient of SDP) itself is a function of SDP. If the answer is negative, the RC model can be considered as an alternative. The RC estimates can also be viewed as matrix weighted average of OLS estimates for each state, the weights being inversely proportional to the respective covariance matrices, plus a component representing 'between state' covariance matrix (Rao, 1965). The individual state-specific coefficient vectors [conditional on the sample] can be derived such that the 'normative' vector is their simple average. The RC method helps comparisons of state-specific tax function estimates in a better way by taking into account the between-state variations in the variables. However, as in the case of RE models, the requirement that the state-specific coefficient estimates are conditional on the sample and independent of the explanatory variables included, could be a serious drawback.

The three alternative types of models to FE, viz., SURE, RE and RC, subject to the holding of their respective assumptions, can yield asymptotically more efficient 'normative' estimates for the tax function. They all use the 'between state' variation and thus underline the need for using pooled sample rather than either state-wise time series or cross-section samples. However, a severe drawback flaw in these alternatives is that if the a priori assumptions do not hold, then the estimates will be biased and inconsistent. Therefore extra precautions are essential before the estimates are used for policy purposes. Viewed in this light, the FE model appears to be relatively less risky.

4. Empirical Analysis

An attempt is made to illustrate the applicability of the models discussed above by fitting them to the tax behaviour function of the states specified as equation (1). Sample observations of fourteen major states, each with seven time-period points beginning with 1980-81, are pooled together. The precise objectives of the empirical exercise are: (a) to see if panel models improve the goodness of fit over the combined OLS model (which restricts the parameters of the function, including the intercepts, to be same across all the states); (b) to compare the performances of the four alternative types of panel models and examine which of them is more suited, given the specification. The performance is judged, firstly, on a priori grounds - as to whether the empirical results are in line with the underlying assumptions regarding states' tax behaviour, and secondly, on statistical grounds as indicated by the goodness of fit measures and tests of structural change; and (c) to quantify within the framework of each of the four types of models, the variation of the tax efforts between the states, and rank the states accordingly.

As an initial step, ANOVA was conducted on OLS (restricted) residuals which confirms that state-wise grouping of data is necessary as the ratio of the 'between-state' to 'within-state' variation is significant (Table 1). However, the ANOVA does not indicate significant 'between' variation - when grouping by time-period is considered. It shows that there is little need to allow for time-variant effects. This is not surprising as the time-period considered is small, and the model is of short-run nature.

A. Estimates of constant slope models

Within the FE framework four variants were fitted. They are: (a) FE without time effects (FE1), (b) FE with time trend (FE2), (c) FE with time dummies (FE3), and (d) the SURE version with the restriction that slope coefficients across states are equal (SURE1). The first model FE1 assumes that the variation between time groups is not significant, and therefore, ignores time effects. In the second (FE2) and third (FE3) versions time effects are included using, alternatively, time trend and time dummies. The last version allows estimation with contemporaneous correlation among the residuals. The FE results are shown in Table 2.

Among the FE variants, FE1 looks more plausible than the two variants that allowed for time effects despite their low standard errors of estimates (SEE). The coefficients of all the four variables in the FE1 are significant. It is also interesting to note that the coefficient of income, known as `tax buoyancy', tended to be unity, when compositional differences across states and differences in respect of infrastructure are accounted for. This result confirms that the intercept estimates can be taken as state-specific effective tax rates adjusted for compositional and infrastructural differences.

With regard to SURE1 model, a Lagrange-Multiplier (LM) test suggested by Bruesch and Pagan (1980) conducted on the OLS1 residuals shows little evidence of contemporaneous covariances.[10] Compared SURE1 also FE1 results appear to be better. The LM test indicates little impact of inter-state tax overlapping. Perhaps the problem is not serious in the Indian context where taxes such as the Central sales tax inhibit such overlapping.

Among the RE class of models, only three variants are chosen. They are (a) ANOVA version (Maddala, 1971) (RE1), (b) Wallace & Hussain (1969) version (RE2), (c) Nerlove (1971) version (RE3). These involve relatively less complex computations than other versions such as the MINQUE version. It is hoped that the broad conclusions regarding the use of RE models will not vary in view of findings of the Monte-Carlo studies by Maddala & Mount (1973). The time variables are excluded in view of the ANOVA results. The RE estimates are shown in Table 3. The main findings are as follows.

The fits of the three RE models are consistent with each other and do not show much specification bias, although the ANOVA variant appears to have a slight edge over the other two in terms of statistical efficiency.

The transformation statistics indicate that the weight of the `between-state´ estimators is low compared to the `within-state´ estimators. It is indicative of the fact that perhaps, the FE model can take care of a substantial portion of the total variation.

B. Estimates of varying slope models

Three alternative varying slope models are estimated: (a) FE model with varying intercepts as well as slope coefficients which is the same as OLS applied separately for each state (OLS2), (b) SURE model with no restrictions on the coefficients (SURE2) and (c) the RC model. The results are shown in Table 4.

Among these OLS2 appear to be better than RC and SURE2 both in terms of the standard error of estimate as well as interpretability of coefficients. The estimated error variance for the RC model is rather high as compared to the other models. This indicates that the RC estimates are not very consistent. Further, the coefficient estimates of the RC model are not very different from the representative coefficient set for the OLS estimates obtained as weighted average of the state-wise coefficients, the weights being the respective variance-covariance matrices. This shows that while the structural variation between the States is not of stochastic nature, perhaps the weight of the between-state stochastic variation in the coefficient sets is not very high, and therefore the OLS mean coefficient set might as well be considered as all-state representative set.

C. Tests

(i) Testing for structural changes

The `classical' tests of structural change based on residual sums of squares (RSS) show that the combined OLS on pooled data without allowance for state-wise variations is far from sufficient and that models with varying intercepts would be more efficient (Table 5). The difference has narrowed down considerably when state-wise intercept dummy variables are included, thereby indicating that the FE model is better than the combined OLS. Inclusion of either the time trend or time dummies did not make any further improvement in the efficiency.

The tests of structural change also show that in general, models with varying slopes and intercepts have not improved the statistical efficiency any further. This would mean that allowing only the intercepts is perhaps enough to improve the regression fit, while allowing the slopes also to vary leads to very little further improvement.

(ii) Testing for the difference between FE and RE models

Comparing the RE and FE results, one finds that there is very little difference between the two classes of models. To further confirm, a test suggested by Hausman is conducted. The test aids choice between RE or FE models.[11] The test clearly shows that the difference between the results of the FE and RE types of models is insignificant. The closeness of RE to FE models, both in terms of coefficient values as well as standard error of estimates shows that by and large the `between-state´ variation is low and therefore, it is not improper to prefer the FE models.

5. Summary of Conclusions

The above analysis shows that the constant slope type of panel models are better suited to derive norms out of the states´ tax behaviours in India. The tests of structural change also indicate that, by and large, differentials in tax behaviour among the states can be taken care of by means of intercept differences only. Both the fixed effects as well as the random effects models performed better as compared to the three varying slope models considered. The results of the latter models appear to be not as coherent as those of the former models.

Between the fixed effects and the random effects models, there is not much to choose. The Hausman statistic also shows that the difference is insignificant. This suggests that the inter-state variation is smaller than the within-state variation.

Also, the fact that the two SURE versions have not yielded meaningful results, indicates that there may be little contemperaneity in the errors, which implies that the impact of overlapping tax jurisdictions on state revenues may be small. This is not surprising in view of the existing tax barriers such as the Central Sales Tax and the low impact of consignment transfers between states. The new consignment tax, as and when it comes into force, will further reduce the tax overlapping.

The study is not without limitations. A major limitation pertains to the choice of explanatory variables and the form of their relationship with the dependent variable. Much of the outcome of the empirical exercise is directly affected by the choice of the tax function.

The second limitation is that no attempt is made to introduce further refinements of the four basic alternative models by way of reducing the heteroskedasticity or autocorrelation problems. The problem of autocorrelation is dealt unsuccessfully with time trend variable in the FE version FE2. In view of the fewer time-series observations, the problem is left at that. Perhaps, a more refined specification with a longer time-series would have yielded better results.

TABLE 1

Analysis of Variance on OLS (Restricted Model) Residuals

Source of Variation	MSE	
State-wise groups:		
Between groups	0.1042	
Within groups	0.0041	
F-val (13,84)	41.0	Significant at 5% level
Time-period-wise groups		
Between groups	0.01488	
Within groups	0.02914	
F-val (6,91)	0.5532	Not significant.

TABLE 2

Regression Results of OLS and the Fixed Effects Models

Model	OLS1	FE1	FE2	FE3	SURE1
Goodness of fit Measures.					
R-barsq.	0.91	0.99	0.99	0.99	0.96
SEE	0.17	0.05	0.04	0.04	0.08
Main Expl.vars.:					
Per capita SDP	0.78*	0.98*	0.37*	0.40*	1.25*
Proportion of non-primary SDP in total	0.77*	0.37*	0.07	0.06	-0.27
Length of roads and rly.line per '000 sq.km.	0.19*	0.36*	0.16*	0.11	0.49*
Electricity consumption by households.	0.22*	0.08*	0.08*	0.06	-0.30*
Intercepts:					
Common intercept	-6.31*				
Mean of State-wise intercepts		-6.09	0.23	0.66	-4.74
Standard deviation		0.20	0.33	0.34	0.27
Time comps:					
Time trend			0.07*		
Time dummies:					
1				-0.48*	
2				-0.34*	
3				-0.27*	
4				-0.23*	
5				-0.17*	
6				-0.07*	

Note: For SURE1 version the Bruesch-Pagan Chi-square statistic for testing the contemporaniety in the residuals (20.15 at 91 df) is not significant.

TABLE 3

Results of the Random Effects Models.

Expl.vars.\ Model	RE1 (ANOVA)	RE2 (WH)	RE3 (Ner)
Goodness of fit Measures:			
RBARSQ.	0.95	0.95	0.93
SEE.	0.06	0.06	0.08
Trans.stat.	0.20	0.22	0.17
Hausman Stat.	0.22	2.22	8.72
Main:			
Per capita SDP.	0.99*	0.98*	0.95*
Proportion of non-primary SDP in total.	0.43*	0.40*	0.59*
Length of roads and Rly.line per '000 sq.km.	0.29*	0.20*	0.22
Electricity consumption by households.	0.10	0.11	0.13
Intercept	-0.99*	-1.42*	-2.49*
Mean effect	-4.63	-4.27	-3.44
Std devn.	0.15	0.15	0.14

TABLE 4a

Results of the Varying Slopes Models (FE4 or OLS2)

Expl.Vars. ------ state	Constant	Per capita SDP	Proportion of non-primary SDP in total	Length of roads and Rly.line per '000 sq.km.	Electricity consumption by households	R-barsq.	SEE
1. AP	-5.88*	0.55*	0.97	0.10	0.46	0.98	0.04
2. Bih.	-65.42*	0.69*	-1.83*	15.29*	-2.17*	0.99	0.12
3. Guj.	1.12	-0.04	-0.44	2.17*	-1.04	0.99	0.02
4. Har.	-9.45*	0.98*	0.03	0.95	0.20	0.98	0.03
5. Kar.	-19.31*	0.14	0.30	3.09	0.78*	0.97	0.05
6. Ker.	-14.30*	1.24*	1.59*	0.59*	-0.06	0.99	0.02
7. MP	-15.87*	-0.08	-0.38	5.19*	-0.66*	0.99	0.02
8. Mah.	-6.69*	0.10	0.51	2.60*	-1.04*	0.99	0.02
9. Ori.	-10.35*	0.53*	0.42*	1.76	0.09	0.99	0.02
10.Pun.	12.32	1.01*	1.48*	-3.88*	0.82*	0.98	0.03
11.Raj.	-21.53*	4.49*	5.22*	-3.62*	-2.05*	0.96	0.04
12.TN	-6.30*	1.26*	0.54	0.34*	-0.46*	0.99	0.01
13.UP	-22.10	-0.79	-0.16	5.19	0.85	0.99	0.04
14.WB	-31.66	-0.03	-1.90	7.02	0.83	0.89	0.08
Matrix weighted Mean coefs.	-5.21	0.89*	0.24	0.10	0.38	0.98	0.04

TABLE 4b

Results of the Varying Slopes Models (SURE2)

Expl.Vars. ------ state	Constant	Per capita SDP	Proportion of non-primary SDP in total	Length of roads and Rly.line per '000 sq.km.	Electricity consumption by households	R-barsq.	SEE
1. AP	-8.68	1.58	8.22	-3.06	-1.37		
2. Bih.	-115.15	0.89	-2.32	28.79	-7.20		
3. Guj.	14.28	-1.35	-0.55	3.02	-2.30		
4. Har.	-43.39	-0.05	-0.07	6.93	1.18		
5. Kar.	-10.70	0.12	6.83	-3.45	1.43		
6. Ker.	5.40	-1.06	-8.47	4.10	1.74		
7. MP	-24.12	2.58	2.42	2.38	-2.45		
8. Mah.	-19.35	-2.47	2.74	6.45	-0.75		
9. Ori.	-6.03	0.78	1.88	-2.20	1.68		
10.Pun.	121.60	0.57	2.79	-24.09	4.82		
11.Raj.	-33.91	8.45	8.21	-5.73	-2.76		
12.TN	-10.12	2.91	-0.51	0.77	-1.79		
13.UP	-221.51	-10.09	-0.19	51.27	3.67		
14.WB	-27.12	2.28	5.42	-4.87	4.25		
Mean	-27.06	0.18	1.89	4.31	0.01	0.99	0.014

TABLE 4c

Results of the Varying Slopes Models (Random Coefficient Model along with State-wise Predictors)

Expl.Vars. ------ state	Constant	Per capita SDP	Proportion of non-primary SDP in total	Length of roads and rly.line per '000 sq.km.	Electricity consumption by households	R-barsq.	SEE
1. AP	-6.29	0.64	0.90	0.17	0.39		
2. Bih.	-50.30	0.72	-1.25	11.41	-1.48		
3. Guj.	-2.16	0.14	-0.16	1.44	-0.18		
4. Har.	-9.74	0.61	0.26	1.16	0.09		
5. Kar.	-15.19	0.50	0.33	2.19	0.45		
6. Ker.	-13.63	1.23	1.43	0.56	-0.02		
7. MP	-12.32	0.21	-0.15	3.62	-0.41		
8. Mah.	-5.73	0.19	0.22	2.32	-0.82		
9. Ori.	-9.05	0.61	0.49	1.34	0.07		
10.Pun.	-5.40	0.61	1.03	-0.11	0.16		
11.Raj.	-21.26	4.41	5.11	-3.50	-2.01		
12.TN	-7.42	1.22	0.84	0.31	-0.42		
13.UP	-14.38	0.15	-0.14	2.88	0.47		
14.WB	-26.13	0.35	-0.74	5.19	0.27		
Mean	-14.21*	0.86*	0.50*	2.07*	-0.24	0.96	1.87

TABLE 5

Results of Tests for the Structural Change

Model	RSS	DF	RSS/DF	F-Values OLS1	FE1	FE2	FE3	SURE1	RE1	RE2	RE3	OLS2	SURE2
1 OLS1	2.740	93	0.0295										
2 FE1	0.220	80	0.0028	70.49*									
3 FE2	0.160	79	0.0020	90.99*	29.63*								
4 FE3	0.120	74	0.0018	85.04*	10.28*	4.93							
5 SURE1	0.512	80	0.0064	28.78*	NA	55.00*	10.21						
6 RE1	0.335	93	0.0036	NA	3.21	3.47	3.14	2.13					
7 RE2	0.335	93	0.0036	NA	2.45	3.47	3.14	2.13	NA				
8 RE3	0.595	93	0.0064	NA	4.51	4.86	3.91	1.00	NA	NA			
9 OLS2	0.034	28	0.0012	34.28*	2.95	2.03	1.54	7.57	3.81	3.81	7.11		
10 SURE2	0.005	20	0.0002	214.64*	23.05	15.46	12.70	49.70	25.85	25.85	46.29	NA	
11 RC	97.930	93	1.0530	NA	7.14	6.63	4.89	7.12	NA	NA	NA	1.43	1.43

Note: The F-values in the second part of the table should be interpreted as that of the model in the row _vis-a-vis_ the model of the column. For example, the F-value that FE1 is not different from OLS1 is 70.49. NA indicates that the test is not applicable. * indicates that the computed value is significantly different from the table value at 5% level.

TABLE 6

Estimates of Relative Impact of State-specific Factors

State \ Model	Fixed Effects Models				Random Effects Models			Varying Slope Models		
	FE1	FE2	FE3	SURE1	RE1 (ANOVA)	RE2 (WH)	RE3 (Ner)	OLS2	S9EE2	RC
1. AP	137.90	124.66	124.77	140.49	126.83	127.63	126.53	112.74	117.49	123.87
2. Bih.	85.33	53.90	52.80	65.70	65.50	85.56	86.53	82.84	38.43	90.92
3. Guj.	103.18	126.11	124.77	131.00	100.33	99.40	96.59	61.58	144.50	99.48
4. Har.	96.21	133.91	135.17	94.16	101.34	102.43	104.64	96.69	170.71	33.36
5. Kar.	118.69	126.11	127.29	127.12	116.57	116.65	116.80	114.50	131.89	58.48
6. Ker.	98.15	116.42	119.66	69.56	105.46	106.61	108.91	130.25	125.18	16.65
7. MP	128.03	66.67	66.19	123.37	115.41	114.34	112.22	97.11	69.32	289.45
8. Mah.	102.16	142.19	142.10	134.99	99.34	98.41	96.59	82.68	174.98	76.45
9. Ori.	84.48	55.54	53.33	71.69	62.15	81.38	81.49	60.24	42.56	244.44
10. Pun.	73.44	126.66	132.49	61.06	62.97	84.70	87.40	71.14	196.19	14.59
11. Raj.	142.10	97.24	93.36	127.12	127.55	126.36	125.27	104.69	74.27	327.26
12. TN	102.18	129.95	136.52	131.00	106.54	107.68	105.69	121.52	146.41	17.01
13. UP	92.43	70.61	70.56	77.11	93.55	93.61	94.68	97.50	57.15	61.20
14. WB	62.01	88.24	87.05	76.68	85.50	85.56	85.67	86.48	86.40	44.17

NOTES

1. The log-linear type of function might be viewed as emanating from the simple identity $Y = r.B$ where Y denotes aggregate tax revenue of a State, r, effective tax rate and B, the aggregate tax base of the State. The present conglomerate nature of the State taxation is such that the tax base cannot be exactly equated to SDP. Nevertheless, many States do attempt to see that the movements of B are not very much out of line with the variation in SDP. Therefore, it is not improper to assume a functional relation between B and SDP. Let such a relation be $B = a.X1^{b}.\exp(u)$, where $X1$ = SDP, a and b are parameters of the relation and u = the stochastic disturbance. The simple identity $Y = r.B$ will become a stochastic relation $Y = (ar).X1^{b}.\exp(u)$. It is easy to see that (ar) represents the average effective tax rate, and b, commonly interpreted as tax buoyancy, also denotes the responsiveness of the aggregate tax base to changes in SDP. The tax base function can be further refined by including such variables which represent certain disability factors that restrain States from widening their tax base such as the proportion of value added from primary sectors consisting of agriculture and mining, and infrastructure development.

2. In other words, a transformation matrix $P = I_{pm}-Z(Z'Z)^{-1}Z'$ is formed which is a symmetric idempotent matrix orthogonal to Z (such that $PZ=0$), so that pre-multiplication with P transforms Y and X into deviations from state-wise means. The estimates are obtained as $b= (X'PX)^{-1}X'PY$, and $a= (Z'Z)^{-1}Z'(Y-Xb)$.

3. In fact, it is for this reason, the FE estimators are also known as 'within estimators'.

4. The variance-covariance matrix can be written as $V=s_u^2.I_p \otimes A$ where A is a square matrix of order m with units as diagonal elements and r as off-diagonal elements, r being defined as the ratio s_a^2/s_u^2, (and $s_u^2=s_a^2+s_e^2$). Given the 'block-diagonal' nature of the V matrix, the inverse can be computed as follows. Since the matrix A can also be written as $A = (1-r).I_m + r.i_m.i_m'$ and its inverse as $A^{-1} = l_1.i_m.i_m' + l_2.I_m$, where $l_1 = -r/(1-r)(1-r+mr)$, and $l_2 = 1/(1-r)$. Thus the matrix V^{-1} can be computed as $V^{-1} = s_u^{2}.I_p \otimes A^{-1}$, and the GLS estimators can be derived as $b=(X'V^{-1}X)^{-1}.X'V^{-1}Y$.

5. For a review of such procedures, see Maddala and Mount (1973). The procedures to derive the estimates of the component variances range from using OLS residuals as suggested by Wallace and Hussain (1969) to the complicated Minimum Norm Quadratic Unbiased Estimators

(MINQUE) suggested by Rao (1970, 1972). The Monte-Carlo study by Maddala and Mount (1973) examines the performance of several alternative estimators derived using different procedures and concludes that there is little to choose between alternative methods. Nevertheless, they recommend that the model should be estimated by a couple of alternative methods and if the estimates vary, it should be taken as indicative of specification errors.

6. See Mundlak (1978).

7. As is well known, the effective tax rate in a state $\mathbf{r_e} = \sum_i \mathbf{r_i}\ \mathbf{B_i}$, where $\mathbf{r_i}$ and $\mathbf{B_i}$ denote tax rate and tax base for ith part of the total tax base, $\sum_i \mathbf{B_i}$. Thus the effective tax rate is nothing but a weighted average of the tax rates $\sum_i \mathbf{r_i}\ \mathbf{w_i}$ where $\mathbf{w_i} = \mathbf{B_i}/\sum_i \mathbf{B_i}$.

8. Under the SURE assumptions, the variance-covariance matrix of residuals is derived as $\mathbf{V} = \mathbf{E(UU')} = \mathbf{\Sigma_p} \otimes \mathbf{I_m}$, where $\mathbf{\Sigma_p}$ is $\mathbf{(p.p)}$ symmetric matrix of contemporaneous variance and covariances, the estimates of $\mathbf{b}$ are obtained by GLS. Since the elements of the variance-covariance matrix are unknown, a feasible estimation procedure is suggested by Zellner (1962).

9. More specifically, the assumptions are, $\mathbf{E(U)=0}$, $\mathbf{E(UU')=D \otimes I_m}$, where $\mathbf{D}$ is a diagonal matrix of order $\mathbf{(p.p)}$ consisting of between-state error variances (not necessarily equal), $\mathbf{E(v)=0}$, and $\mathbf{E(vU)=0}$. The error variance-covariance matrix $\mathbf{V}$ is a symmetric block diagonal consisting of $\mathbf{(X_iDX_i + s_{ii}.I^2{}_m)}$ as diagonal elements, which is used to obtain the GLS estimates of $\mathbf{b}$.

10. The LM statistic for testing the null hypothesis of a diagonal error covariance matrix is computed as the sum of the off-diagonal correlations. Under the null hypothesis the LM statistic is Chi-square distributed with $\mathbf{[p(p-1)/2]}$ degrees of freedom.

11. The test statistic is computed as $\mathbf{m=(b_f-b_r)(M_f-M_r)^{-1}(b_f-b_r)'}$, where $\mathbf{b_f}$ and $\mathbf{b_r}$ are coefficient vectors of FE and RE models respectively and $\mathbf{M_f}$ and $\mathbf{M_r}$ are corresponding VCV matrices. The test statistic is distributed as Chi-square with degrees of freedom as number of coefficients.

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