SHOULD FIXED COEFFICIENTS BE REESTIMATED
EVERY PERIOD FOR EXTRAPOLATION?

by

P.A.V.B. Swamy and Garry J. Schinasi

Abstract

This paper demonstrates that forecast accuracy is not necessarily improved when fixed coefficient models are sequentially reestimated, and used for prediction, after updating the database with the latest observation(s). This is at variance with the now popular method (see Meese and Rogoff (1983, 1985)) of sequentially reestimating fixed coefficient models for prediction as new data "rolls" in. It is argued that although "rolling" may minimize the variance of predictions for some classes of estimators, "rolling" does not necessarily yield accurate predictions (i.e., predictions that are close to actual data). Minimizing the mean squared prediction errors is a necessary condition for maximizing the probability that a given predictor is more accurate than other predictors. This minimization need not require, and may even exclude, the most recent data. A by-product of the demonstration is that for predictors based on the same sample size, a predictor with smaller variance need not be more accurate than another predictor with a larger variance.

Should Fixed Coefficients be Reestimated Every Period

for Extrapolation?

P.A.V.B. Swamy and Garry J. Schinasi*

1. Introduction

In making forecasts of future variables, some econometricians reestimate their models using all past data prior to each forecast period. The process involves fixing the starting date and the initial size of the sample and enlarging the sample by adding successive observations for reestimation and prediction as new data become available (see, e.g., Fromm and Klein (1976, p. 9) and Meese and Rogoff (1983, 1985)). It has been suggested that such a procedure improves forecast accuracy for two reasons: first, because a larger sample reduces the variances of fixed coefficient estimators; and second, because sequential estimation or "rolling" captures any variation in coeffiecients.

The theory underlying the common impression that one should always use all the available observations in estimation and prediction is more ambiguous than may be generally realized.[1] Without proper theoretical justification, like an explicit risk minimizing motivation (favoring good predictions), a procedure that sequentially updates estimates of coefficients and predictions in a model assumed to have constant coefficients is meaningless. The primary purpose of the paper is to demonstrate that any sequential method

---

[1] This impression is also not fully supported by the asymptotic theory, some simple normal cases apart. For example, Lehmann (1983, pp. 352-388) analyzes various nonnormal situations showing that a parameter is more efficiently estimated even in large samples by discarding some sample observations than by using all the observations.

of estimating constant coefficients does not necessarily yield accurate forecasts. A by-product of the demonstration is that a predictor with a smaller variance need not be better than another predictor with a larger variance, even though both predictors are based on the same sample.[2]

The logic of the basic argument of this paper is as follows. If the objective of estimation is forecast accuracy, then one should prefer predictions that are close to actual realizations to predictions that are close to some other quantities (such as the means of predictors). Consequently, one should select the predictor that has the highest probability of being close to actual realizations. Although it is difficult to derive estimators based on this general criterion, a necesary condition for this probability to be a maximum is for the mean square error of a predictor (i.e., the expected squared deviation of a predictor from realization) to be a minimum. "Rolling" (i.e., sequential estimation) may minimize the forecast variance for broad classes of estimators, but minimizing variance does not necessarily minimize mean square error.[3] Hence, for any given estimator, "rolling" may reduce the variance of a predictor, but it does not necessarily improve, and may

---

[2] The constant coefficient approach is inherently incorrect if some or all of the regression slopes change over time, sample enlargement notwithstanding.

[3] In practice, many of these optimal predictors involve unknown parameters and their operational versions based on some sample estimators of the parameters may not satisfy all the conditions for achieving minimum variance. This makes it difficult to recognize an operational predictor with minimum variance in small samples. Because of this difficulty, attention has been shifted to the asymptotically optimal predictors which have the smallest asymptotic variance within the class of asymptotically normal predictors. This does not eliminate the difficulty because some asymptotically optimal predictors do not possess finite variances in small samples and hence violate a necessary condition for maximizing the probability of obtaining forecasts within an interval around actual realizations.

even reduce, forecast accuracy. Note that this is a theoretical result about the forecasting properties of "rolling" regressions and it simply states that there is no reason to believe that "rolling" improves forecast accuracy. The logic of this argument extends to more general cases, where two or more predictors are compared for forecast accuracy using the same sample.

Section 2 introduces and briefly discusses two forecast criteria that compare forecasts with realizations rather than the means of predictive distributions. We then discuss conventional estimators satisfying certain sampling properties in Section 3. Operationally, some versions of these estimators may not have finite variances. Using the realization-based criterion, Section 4 shows that the best predictor must have minimum mean square error, and that there is no reason why the method of sequential estimation achieves this. Conclusions are presented in Section 5.

2. Forecasting Criteria Based on Realizations

Suppose that we are interested in predicting the value that would be taken by the random variable y_t^* in a future period T+s, where T is the terminal period of the currently available sample observations on y_t^*.[4] We now define two criteria for comparing predictors.

Criterion of Highest Concentration

The criterion of highest concentration compares predictions with actual realizations and is defined as follows: an operational predictor $\hat{y}_{T+s}$ of the

---

[4] We distinguish a random variable from its value by an asterisk. For example, y_t is the value taken by the random variable y_t^* in period t.

actual value y_{T+s} is better than any other operational predictor $\tilde{y}_{T+s}$ if the probabilities satisfy the condition

$$\Pr(y_{T+s} - \lambda_1 < \hat{y}_{T+s} < y_{T+s} + \lambda_2) \geq \Pr(y_{T+s} - \lambda_1 < \tilde{y}_{T+s} < y_{T+s} + \lambda_2) \qquad (1)$$

for all possible values of λ_1 and λ_2 in a chosen interval $(0, \lambda)$ and for all possible realizations y_{T+s}.

A <u>necessary</u> condition that (1) be satisfied for all λ is

$$E(\hat{y}_{T+s} - y_{T+s})^2 \leq E(\tilde{y}_{T+s} - y_{T+s})^2 , \qquad (2)$$

that is, the mean square error of $\hat{y}_{T+s}$ about the actual realization y_{T+s} is a minimum (see Rao (1973, p. 315)). This condition indicates, for example, when a predictor does not satisfy the so-called criterion of <u>highest concentration</u> in (1).

Now <u>sufficient</u> conditions will be given for a criterion weaker than (1) to be satisfied. This weaker criterion is based on the concept of Pitman's nearness (PN) which is defined as follows:

<u>Pitman's Nearness (PN)</u>

A predictor $\hat{y}_{T+s}$ is nearer to the value y_{T+s} than another predictor $\tilde{y}_{T+s}$ if $\Pr[L(\hat{y}_{T+s}, y_{T+s}) < L(\tilde{y}_{T+s}, y_{T+s})] > 1/2$, where $L(\hat{y}_{T+s}, y_{T+s})$ represents a loss in predicting y_{T+s} by $\hat{y}_{T+s}$. We may consider two standard loss functions, namely,

$$L_1(\hat{y}_{T+s}, y_{T+s}) = |\hat{y}_{T+s} - y_{T+s}| \text{ and } L_2(\hat{y}_{T+s}, y_{T+s}) = (\hat{y}_{T+s} - y_{T+s})^2.$$

With these assumptions, Peddada (1985) has proved that if

$$\text{(i)} \quad EL_i(\hat{y}_{T+s}, y_{T+s}) < EL_i(\tilde{y}_{T+s}, y_{T+s}) \text{ for } i = 1,2; \tag{3a}$$

$$\text{(ii)} \quad \bar{e}_i = Ee_i = EL_i(\hat{y}_{T+s}, y_{T+s}) - EL_i(\tilde{y}_{T+s}, y_{T+s})$$

$$< -2.67 \text{ for } i = 1,2; \text{ and} \tag{3b}$$

$$\text{(iii)} \quad E(e_i - \bar{e}_i)^j < j! \qquad \text{for } i = 1,2; \ j = 1,2,\ldots, \tag{3c}$$

where

$$e_i = L_i(\hat{y}_{T+s}, y_{T+s}) - L_i(\tilde{y}_{T+s}, y_{T+s}),$$

then $\hat{y}_{T+s}$ is closer to y_{T+s} than $\tilde{y}_{T+s}$ in the PN sense.

3. Fixed Coefficients Approaches

With these desirable properties of predictors in hand, we next discuss conventional predictors and their statistical properties. The first step in any statistical method of generating predictions is to formulate a statistical model about the possible data generating process. It is usually postulated that the observations on y_t^* are generated by the following reduced form equation with fixed coefficients:

$$y^* = X\pi + \varepsilon^*, \tag{4}$$

where

y^* = the (Tx1) vector of variables y_t^*, t = 1,2,...T;

X = the (TxK) matrix of sample observations on K "fixed" exogenous variables;

π = the (Kx1) vector of reduced-form coefficients; and

ε^* = the (Tx1) vector of reduced-form disturbances.

It is usually assumed that

$$E(\varepsilon * | X) = E(\varepsilon *) = 0 \text{ and } E(\varepsilon * \varepsilon * ' | X) = \sigma^2 V. \tag{5}$$

If model (4) holds for the post-sample periods $t = T+s$, $s = 1,2\ldots\ldots$, also, then for period $T+s$ the variable y^*_{T+s} given the vector of regressors will be

$$y^*_{T+s} = x'_{T+s}\pi + \varepsilon^*_{T+s}, \tag{6}$$

where

y^*_{T+s} = the scalar regressand;

x'_{T+s} = the (1xK) vector of prediction regressors; and

ε^*_{T+s} = the scalar prediction disturbance.

Goldberger (1962) points out that for model (4), an appealing set of assumptions is one which allows the prediction disturbance to be correlated with the sample disturbances. Therefore, we shall assume

$$E(\varepsilon^*_{T+s} | x'_{T+s}) = E(\varepsilon^*_{T+s}) = 0, \tag{7a}$$

$$E(\varepsilon^{*2}_{T+s} | x'_{T+s}) = \sigma^2_*, \text{ and} \tag{7b}$$

$$E(\varepsilon^* \varepsilon^*_{T+s} | X, x'_{T+s}) = w, \tag{7c}$$

where w is the Txl vector of covariances of the prediction disturbance with the vector of sample disturbances.[5] Thus, implicit in the use of model (4)

_____

[5] If equation (1) represents an autoregressive model, then X consists of the lagged values of y and w can be equal to 0. Alternatively, the vector w can be zero if equation (1) represents a regression model with serially uncorrelated error term.

for prediction is the assumption that the actual value of the regressand for period T+s will be a drawing from a distribution with mean $x_{T+s}'\pi$ and variance σ_*^2.

The second step in any prediction method is to estimate π. The vector π can be estimated by one or more of the following procedures:

Estimation Procedures

(1) The least squares procedure;

(2) The generalized least squares procedure based on an estimated error covariance matrix;

(3) A fully or partially restricted reduced form procedure that fully or partially accounts for the connection between π and the coefficients of a structural model;

(4) A Bayes procedure;

(5) Bayes-like procedures; and

(6) Robust procedures.

Let $\hat{\pi}$ denote any one of these estimators.

The final step is to use an estimated π in predicting the value y_{T+s}. Even though any or all of the estimation procedures (1)-(6) can be considered for sequential estimation, to save some computations we may, if possible, want to first find the most efficient of all the above six estimators and then use it in a sequential estimation. Furthermore, all the criteria of estimation used by the above estimation procedures may not be compatible with the criterion (1) or Pitman's nearness, as we show in the following section.

A Minimum Variance Predictor

It has been shown by Goldberger (1962) that the minimum variance linear "unbiased" predictor of y_{T+s} is[6]

$$\hat{y}_{T+s} = x'_{T+s} \hat{\pi} + w' \frac{V^{-1}}{\sigma^2} (y* - X\hat{\pi}) \tag{8}$$

if $\hat{\pi} = (X'V^{-1}X)^{-1}X'V^{-1}y*$ is the minimum variance linear unbiased estimator of π.[7]

It is also shown by Goldberger (1962) that

$$E(\hat{y}_{T+s} - y^*_{T+s})^2 \leq E(x'_{T+s} \hat{\pi} - y^*_{T+s})^2 \tag{9}$$

with the equality holding when $w = 0$.

A difficulty with the minimum variance predictor (8) is that w and $\sigma^2 V$ are usually unknown. The inequality (9) may be reversed if $\hat{y}_{T+s}$ represents an operational predictor of the form

$$x'_{T+s}\hat{\pi} + \hat{w}' \frac{\hat{V}^{-1}}{\tilde{\sigma}^2} (y* - X\hat{\pi}) \; , \tag{10}$$

based on some sample estimates of w, σ^2, and V, and $\hat{\pi}$ represents an operational estimator

$$(X'\hat{V}^{-1}X)^{-1}X'\hat{V}^{-1}y* \tag{11}$$

---

[6] A predictor $\hat{y}_{T+s}$ is said to be "unbiased" if $E \hat{y}_{T+s} = Ey^*_{T+s}$.

[7] The minimum variance linear unbiased predictor of an element of a vector variable following a vector autoregressive (VAR) model also has the same form. For example, if equation (4) is an autoregressive model imbedded in a VAR model, then x_{T+s} includes the lagged values of y_{T+s}, w represents the contemporaneous covariances between the dependent variable of equation (4) and the other dependent variables included in the VAR model, $\sigma^2 V$ represents the contemporaneous covariance matrix of these other variables, and $y*$ and X consist of the current and lagged values of the other variables respectively.

or a restricted estimator based on $\hat{V}$, provided the second-order moments of (10) and $\hat{\pi}$ are finite (see Rao (1967, 1975)).[8] In other words, an operational version of (8) may not have the minimum variance (about y^*_{T+s}) and may even have infinite variance. The estimator (11) may also have infinite variances. The predictors with infinite variances violate condition (2). They may not even be good in the PN sense.

The same difficulty may arise if $\hat{\pi}$ represents a partially or fully restricted reduced-form estimator. The conditions for the finiteness of the moments of partially restricted reduced-form estimators in the normal case are given in Swamy and Mehta (1981, 1982), and Swamy, Mehta and Iyengar (1983). If the predictors of y_{T+s} based on the estimation procedure (3) need satisfy conditions (3a)-(3c), then Swamy and Mehta's modifications, that guarantee the existence of moments of all orders in small samples, are necessary. Using these modifications, whether the predictor (10) has a smaller variance about y^*_{T+s} than the predictor $x'_{T+s}\hat{\pi}$ depends on how far $E\hat{\pi}$ is from π and on the precision of the estimators $\hat{w}$ and $\hat{V}^{-1}(1/\hat{\sigma}^2)$.

A result due to Rao (1967) shows that for a matrix Z of maximum rank such that $X'Z = 0$, the estimator (11) will have bigger variances than the least squares estimator $(X'X)^{-1}X'y*$ if and only if $X'VZ$ is sufficiently close to a null matrix. In this case the predictor $x'_{T+s}(X'X)^{-1}X'y*$ may have a smaller variance than the predictor (10) or the predictor $x'_{T+s}\hat{\pi}$. Thus, it is not possible in practice to recognize an operational predictor with minimum variance in small samples.

---

[8] This comment does not apply if we assume that $w=0$ because in this case the second term in (10) will be zero.

Asymptotically Efficient Predictors

If the estimation period is sufficiently long, asymptotic theory may apply and predictors (10) and (8) may have the same limiting distributions. This can occur even when $\hat{\pi}$ represents a partially or fully restricted reduced-form estimator. It is possible that the asymptotic variance of the predictor (10) is smaller if $\hat{\pi}$ represents a robust estimator than if $\hat{\pi}$ represents the estimator (11) or a restricted reduced-form estimator. The comparisons of asymptotic variances are relevant for moderate sample sizes if the estimators of π are convergent in the rth mean. Such estimators are developed in Swamy, Mehta and Iyengar (1983).

On the basis of either the exact finite sample distribution theory or the asymptotic theory, a universally preferred choice among the estimation procedures (1)-(6) is not possible.

4. Does Sequential Estimation Necessarily Improve Forecasting Accuracy?

Suppose that one of the estimation procedures (1)-(6) is used in sequential estimation and the corresponding predictors of y_{T+s} are computed, and further assume that the corresponding predictors possess finite variances. Suppose also that these variances decrease as the estimation period increases. What is the correct interpretation of the predictors of y_{T+s} obtained in this sequential estimation procedure?

We can answer this question by using the following standard result in probability theory. Let $\hat{y}_{T+s}$ and $\tilde{y}_{T+s}$ be two operational predictors of y_{T+s} with finite means μ_1 and μ_2, finite variances σ_1^2 and σ_2^2, and distribution functions F_1 and F_2 respectively. Suppose that both $\hat{y}_{T+s}$ and $\tilde{y}_{T+s}$ are based on the same formula but $\hat{y}_{T+s}$ uses a bigger sample than

$\tilde{y}_{T+s}$ so that $\sigma_1^2 \leq \sigma_2^2$. Then according to a standard result in probability theory,

$$F_1(y_{T+s} + \mu_1) - F_1(-y_{T+s} + \mu_1) \geq F_2(y_{T+s} + \mu_2) - F_2(-y_{T+s} + \mu_2) \qquad (12)$$

for each possible value y_{T+s} implies that $\sigma_1^2 \leq \sigma_2^2$. However, the converse proposition is not true. The inequality $\sigma_1^2 \leq \sigma_2^2$ implies that inequality (12) is true for at least one value y_{T+s} but not necessarily for all possible values of y_{T+s}^* (see Rao (1973, p. 96)). Thus, if we have two operational predictors with finite second-order moments, then it is not necessarily true that the predictor with a smaller variance will take values around the actual value y_{T+s} with a higher probability than the predictor with a larger variance.

These general arguments can now be applied to the specific choice of two sets of predictions, based on the same predictor using different samples. We can therefore conclude the following about "rolling:" if we reestimate a model using all past data prior to each forecast period to obtain one-step ahead forecasts to reduce the variance, then the one-step ahead forecasts will not necessarily be closer to the realized values of the forecasted variable than the multi-step ahead forecasts, even though the former are based on more observations and hence may have smaller variances than the latter.

More formally, comparing the inequality (12) with (1) shows that the criterion of minimum variance ("unbiasedness") prediction only satisfies a necessary condition for maximizing the probabilities of intervals around the mean values of predictors (see (12)) while the criterion of minimum mean square error about actual realizations satisfies a necessary condition

for maximizing the probabilities of intervals around <u>actual</u> <u>realizations</u>

(see (1)). Therefore, predictors should satisfy condition (2). If predictors

satisfying the criterion of highest concentration do not generally exist,

then we should satisfy condition (2)(minimum mean square error) as closely

as possible.

How do we nearly satisfy condition (2)? As explained by Chipman

(1976, pp. 612-613), the conditional expectation of the random variable

y^*_{T+s} given y will have the minimum mean square error about y^*_{T+s} within a wide

class of functions of y. If we restrict this class to linear functions or if

we assume that y^*_{T+s} and y* are jointly normally distributed random variables

satisfying equations (6) and (4) respectively, then the conditional expectation

of y^*_{T+s} given y is the same as the predictor (8) with $\hat{\pi}$ replaced by π (see

Chipman (1976, pp. 603-604)). Thus, the conditional expectation of y^*_{T+s} given

y nearly satisfies condition (2), and it can be evaluated fairly accurately,

provided model (6) and assumptions (5), (7a)-(7c) are true.[9] Another difficulty

is that if we believe <u>a priori</u> that model (6) and assumptions (5), (7a)-(7c)

are true, then the conditional mean of y^*_{T+s} given y involves π, w and $\sigma^2 V$

which are usually unknown. The result (12) shows that any procedure of

estimating these unknown quantities that attempts to reduce the variance of

an estimator of π does not necessarily lead to better predictors of y_{T+s}.

Minimum Mean Square Error Predictors

An appropriate way to overcome this difficulty is to estimate models

using a smaller mean square error criterion. We can consider two cases:

---

[9] Unfortunately, it is not possible to establish the truth of any logically
valid model (see Swamy, Conway and von zur Muehlen (1985)).

normal and non-normal distributions of the errors. For the case in which a multivariate _normal_ mean under quadratic loss is to be estimated, a paper by Natarajan and Strawderman (1985) establishes the existence of two-stage sequential estimators that are better, both in risk (mean square error) and sample size, than the usual estimator of a given fixed sample size. When ε in equation (1) is normal, the problem of estimating π under quadratic loss becomes identical to the case discussed by Natarajan and Strawderman (1985). Given any sample size T, we can find a two-stage sequential estimator of π truncated at T, with a positive probability of stopping earlier and mean square error lower than that of an estimator of π based on all the T observations. The predictor of y_{T+s} based on a Natarajan-Strawderman-like estimator of π can have smaller mean square error than any of the predictors of y_{T+s} based on an estimator of π that uses all the observations available up to T or T+s-1.

Where normality is not appropriate, the advantages of a median or a trimmed mean or a robust estimator relative to the mean are well-known (see Lehmann (1983, pp. 352-388)). The predictors of y_{T+s} based on these estimators of π may have smaller mean square errors than predictors of y_{T+s} based on other estimators of π that use all the sample observations. Thus, there is no theoretical justification for reestimating models of the type (4) using _all_ past data prior to each forecast period either in the normal case or in a nonnormal case.[10]

---

[10] If, in fact, the slope coefficients of equation (4) change over time, then it is incorrect to stack the observations as
$$[y', y_{T+1}, \ldots y_{T+n}]' = [X', x_{T+1}, \ldots, x_{T+n}]'\pi + [\varepsilon', \varepsilon_{T+1}, \ldots, \varepsilon_{T+n}]'.$$
In other words, the estimators of fixed coefficients are inappropriate when the slope coefficients vary over time. Appropriate estimators for a time-varying parameters model are given in Swamy and Tinsley (1980) and two applications in Resler, Barth, Swamy and Davis (1985) and Swamy, Kennickell and von zur Muehlen (1986).

Rao, C.R., 1973, Linear statistical inference and its applications,
2nd ed. (Wiley, New York).

Rao, C.R., 1975, Simultaneous estimation of parameters in different
linear models and applications to Biometric problems, Biometrics 31,
545-554.

Resler, D.H., J.R. Barth, P.A.V.B. Swamy and W.D. Davis, 1985, Detecting
and estimating changing economic relationships: The case of discount
window borrowings, Applied Economics 17, 509-527.

Swamy, P.A.V.B. and J.S. Mehta, 1980, On the existence of moments of
partially restricted reduced-form coefficients, Journal of Econometrics
14, 183-194.

Swamy, P.A.V.B. and J.S. Mehta, 1981, On the existence of moments of
partially restricted reduced-form estimators: A comment, Journal of
Econometrics 17, 389-392.

Swamy, P.A.V.B. and J.S. Mehta, 1983, The existence of moments of ridge-
like k-class and partially restricted reduced-form estimators,
Communications in Statistics 11, 2793-2799.

Swamy, P.A.V.B., J.S. Mehta and N.S. Iyengar, 1983, Convergence of the
moments of the modified K-class estimators, Sankhyā B 45, 398-412.

Swamy, P.A.V.B. and P.A. Tinsley, 1980, Linear prediction and estimation
methods for regression models with stationary stochastic coefficients,
Journal of Econometrics 12, 103-142.

Swamy, P.A.V.B., R.K. Conway, P. von zur Muehlen, 1985, The foundations
of econometrics--Are there any? (with discussion), Econometric Reviews
4, 1-120.

Swamy, P.A.V.B., A.B. Kennickell and P. von zur Muehlen, 1985, Forecasting money demand with econometric models, Special Studies Paper, Federal Reserve Board, Washington, D.C.

International Finance Discussion Papers

IFDP NUMBER	TITLES	AUTHOR(s)

1986

287	Should Fixed Coefficients be Reestimated Every Period for Extrapolation?	P.A.V.B. Swamy Garry J. Schinasi
286	An Empirical Analysis of Policy Coordination in the U.S., Japan and Europe	Hali J. Edison Ralph Tryon
285	Comovements in Aggregate and Relative Prices: Some Evidence on Neutrality	B. Dianne Pauls
284	Labor Market Rigidities and Unemployment: the Case of Severance Costs	Michael K. Gavin
283	A Framework for Analyzing the Process of Financial Innovation	Allen B. Frankel Catherine L. Mann
282	Is the ECU an Optimal Currency Basket?	Hali J. Edison
281	Are Foreign Exchange Forecasts Rational? New Evidence from Survey Data	Kathryn M. Dominguez
280	Taxation of Capital Gains on Foreign Exchange Transactions and the Non-neutrality of Changes in Anticipated Inflation	Garry J. Schinasi
279	The Prospect of a Depreciating Dollar and Possible Tension Inside the EMS	Jacques Melitz
278	The Stock Market and Exchange Rate Dynamics	Michael K. Gavin
277	Can Debtor Countries Service Their Debts? Income and Price Elasticities for Exports of Developing Countries	Jaime Marquez Caryl McNeilly
276	Post-simulation Analysis of Monte Carlo Experiments: Interpreting Pesaran's (1974) Study of Non-nested Hypothesis Test Statistics	Neil R. Ericsson
275	A Method for Solving Systems of First Order Linear Homogeneous Differential Equations When the Elements of the Forcing Vector are Modelled as Step Functions	Robert A. Johnson

Please address requests for copies to International Finance Discussion Papers, Division of International Finance, Stop 24, Board of Governors of the Federal Reserve System, Washington, D.C. 20551.

International Finance Discussion Papers

IFDP NUMBER	TITLES	AUTHOR(s)
274	International Comparisons of Fiscal Policy: The OECD and the IMF Measures of Fiscal Impulse	Garry Schinasi
273	An Analysis of the Welfare Implications of Alternative Exchange Rate Regimes: An Intertemporal Model with an Application	Andrew Feltenstein David Lebow Anne Sibert

<center>1985
(partial listing)</center>

IFDP NUMBER	TITLES	AUTHOR(s)
272	Expected Fiscal Policy and the Recession of 1982	William H. Branson Arminio Fraga Robert A. Johnson
271	Elections and Macroeconomic Policy Cycles	Kenneth Rogoff Anne Sibert
270	Assertion Without Empirical Basis: An Econometric Appraisal of Monetary Trends in ... the United Kingdom by Milton Friedman and Anna J. Schwartz	David F. Hendry Neil R. Ericsson
269	Canadian Financial Markets: The Government's Proposal for Reform	Garry J. Schinasi
268	Was It Real? The Exchange Rate Interest Differential Relation, 1973-1984	Richard Meese Kenneth Rogoff
267	The U.K. Sector of the Federal Reserve's Multicountry Model: The Effects of Monetary and Fiscal Policies	Hali J. Edison
266	Optimal Currency Basket in a World of Generalized Floating: An Application to the Nordic Countries	Hali J. Edison Erling Vardal
265	Money Demand in Open Economies: A Currency Substitution Model for Venezuela	Jaime Marquez
264	Comparing Costs of Note Issuance Facilities and Eurocredits	Rodney H. Mills
263	Some Implications of the President's Tax Proposals for U.S. Banks with Claims on Developing Countries	Allen B. Frankel
262	Monetary Stabilization Policy in an Open Economy	Marcus H. Miller
261	Anticipatory Capital Flows and the Behaviour of the Dollar	Arnold Kling