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THE VALUE OF A PRIORI INFORMATION IN ESTIMATING A FINANCIAL MODEL

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by

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I. Introduction

This paper reports our initial efforts to use an explicitly Bayesian approach in estimating the asset demands of mutual savings banks and savings and loan associations. This is a part of a larger effort to construct and estimate a model of financial markets which can serve as a "module" to be used in conjunction with the real sectors of the MPS model for forecasting and policy simulation.[1] The complete financial model is based on flow of funds data, and includes 11 sectors (six of which are financial institutions) and 12 assets. This is a level of aggregation comparable to the existing financial sector of the MPS model.

The general strategy followed in the construction of this model is somewhat different from that used in the design of most existing models. Each sector's allocation of its financial wealth among a variety of assets and liabilities is fully specified; the demand equations explicitly take into account the fact that a decision to hold funds in a particular form is simultaneously a decision to not hold these funds in an alternative

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[1]The MPS--MIT, Penn, Social Science Research Council--model is one of a family of models developed initially by a group from the Board of Governors of the Federal Reserve System and from Massachusetts Institute of Technology.

form. Typically the demand equations for a given sector include as explanatory variables rates of return on all assets held by the sector, and it is assumed that the assets are less than perfect substitutes. In contrast, most financial models, including the MPS, focus attention on a subset of asset demands, the excluded assets being relegated to a residual category, and replace some of the markets by rate structure equations. Elsewhere, we have argued that specification of a complete set of sectoral demand and supply equations is a valuable safeguard against inadvertant use of inconsistent or nonsensical behavioral equations. Likewise, we have argued that for some of the policy questions being explored in large scale financial models it is undesirable to assume the perfect substitution implied by rate structure equations. However, there is a major problem with the strategy we have advocated: it widens the already large gap between the number of parameters appearing in financial models and the number that can be reliably estimated from aggregate time series data. Indeed, it is undoubtedly the inadequacy of time series data which has led to the simplifications we find objectionable, and to the tireless search for the right combination of explanatory variables that will yield correctly signed and statistically significant coefficients.

It has seemed to us that an attractive alternative to the simplification of structure and deletion of variables is the use of a priori information. In principle this information could come from a variety of sources: theoretical calculation, cross-section studies, previous time series studies on different data, or even practical experience. The procedure we have followed in arriving at our priors is informal and subjective; we have tried to exploit ex ante the same information which gives rise to that almost inevitable disappointment one feels when confronted with a straightforward estimation of one's preferred structural model. Having specified our prior means and the variance-covariance matrix of the various parameters, the Theil-Goldberger mixed estimation technique was used to combine them with the data.

Section II discusses the general form of the equations used to describe sectoral behavior. Section III briefly discusses some estimation considerations and Section IV reports our results.

II. The General Form of the Sectoral Models

Although different sectors have different assets and liabilities, we have assumed that their demand equations have the same general form. Each sector's balance sheet items can be divided into two groups according to whether or not the items are directly controlled as part of the sector's management of its financial portfolio. This decision differs from sector to sector, and in the short and long run. The management of the directly controlled assets and liabilities can then be thought of as the allocation of a predetermined aggregate of prior claims. Thus a typical sector is constrained by

$$\sum_{i=1}^{n} a_i = W = \sum_{i=1}^{q} R_i$$

where the a_i are directly controlled financial items and the R_i are prior claims.

We have separated the portfolio decision into two parts: the determination of a long run desired portfolio and the short run adjustment to that portfolio. Each sector's long run portfolio allocation is assumed to depend upon such variables as the expected rates of return, income and wealth.

$$a^* \frac{1}{W^E} = AX^E$$

where a^* = nx1 vector of desired holdings in current period

W^E = scalar anticipated value of W in current period

X^E = kx1 vector of anticipated values of various explanatory variables

A = nxk matrix of coefficients.

If it is assumed that the sector's desired demands satisfy its balance sheet constraint:

$$1 = \Sigma\, a_i^*/W^E = \sum_{i=1}^{n} a_{i1} + \sum_{j=2}^{k} \Big(\sum_{i=1}^{n} A_{ij}\Big) X_j^E$$

can hold for all values of X_j^E if and only if

$$\sum_{i=1}^{n} A_{i1} = 1$$

$$\sum_{i=1}^{n} A_{ij} = 0 \qquad j = 2, \ldots, k\ .$$

That is, an increase in funds must be held somewhere, and a change in any proportion must be at the expense of the remaining proportions.

In the short run it is assumed that the asset demands are of a simple partial adjustment variety. However, our specification differs in two respects from the type frequently assumed. First, the adjustment of any particular asset depends, in principle, on a complete description of the short run disequilibrium. For example, the speed with which a discrepancy between desired and actual holdings of bonds is eliminated depends upon whether the bond disequilibrium is the counterpart of a discrepancy between desired and actual holdings of cash, or desired and actual mortgages. Second, consistency requires that the variables which give rise to partial adjustment in the demand for one asset must give rise to offsetting adjustments in the demand for other assets, given the wealth constraint. The equations are assumed to be of the form:

$$\Delta a = \underset{(nxn)}{E} [a^* - a_{-1}] + \underset{nxp}{F} (S - S^E) + \underset{nxq}{G} z$$

where the z_i are q explanatory variables that are thought to directly influence adjustment behavior and the $S_i - S_i^E$ are the sources of unanticipated changes in W (such as unplanned saving or unexpected capital gains) with $\Sigma(S_i - S_i^E) = W - W^E$.

The E_{ij} can be interpreted as the partial effect on holdings of the i^{th} asset of a unit increase in $W^E - W_{-1}$ (and $W - W_{-1}$) which the sector desires to hold as the j^{th} asset. The E_{ij} will sum across equations to one. (This can be readily verified using the technique applied above to the A_{ij} .) F_{ij} is the partial effect on holdings of the i^{th} asset of a unit increase in $S_j - S_j^E$ with $W^E - W_{-1}$ constant and $W - W^E$ increasing by one unit. The F_{ij} will therefore sum across equations to one. Finally, the G_{ij} will sum to zero since $W - W_{-1}$ is held constant.

III. Some Estimation Considerations

Much of the difficulty in estimating financial models from aggregate time series data can be traced to the high degree of multicollinearity among the variables. Although it is not hard to find asset demand equations which fit well, the coefficients on individual variables cannot be reliably estimated. The sample history may provide very little information about what would happen if two variables, which have typically moved together, were to move differently in a future period. The high degree of collinearity permits the researcher to fit the data well with a variety of subjective parameter restrictions, and it is commonplace to use an "ex post" Bayesian approach--variables with the "wrong" sign or low t-statistics are dropped, a variety of lags are tried, etc., until "plausible" results are obtained. Although it is obvious that the various test statistics lose their meaning when this procedure is used, these practices can be defended as a practical method for protecting against the breakdown of collinearity among independent variables in the forecast period. It is less obvious why the process should be ex post, and why only exact zero parameter restrictions should be considered. A preferable, but also suboptimal, procedure was used by Smith in his dissertation. He used the collinearity patterns among explanatory variables to determine, ex ante, where to place coefficient restrictions (typically non-zero). The rate structure equations in the MPS model could be viewed similarly as a set of (non-zero) restrictions to protect against an out of sample breakdown in collinearity.

Although the use of parameter restrictions may protect against such breakdowns, they have the obvious problem that they may be wrong. As an illustration of the resulting ambiguity in their value consider the principal components procedure sometimes recommended for dealing with collinearity.[2] (This technique offers the expositional advantage

[2] E.g., by M. Kendall or W. Massy. See Smith for a fuller discussion of the limitations of this approach.

of avoiding correlations between the retained and omitted variables.)

Suppose that a variable Y is related to a set of variables X according to the following normalized (zero mean, unit variance) equation:

$$\underset{T\times 1}{Y} = \underset{T\times p}{X}\ \underset{p\times 1}{\beta} + \underset{T\times 1}{\epsilon} \ .$$

Now let F consist of the principal components of X , which we can partition

$$X = \underset{T\times p}{F}\ \underset{p\times p}{A} = [\underset{T\times m}{F_1} \ \vdots\ \underset{T\times p-m}{F_2}] \begin{bmatrix} \underset{m\times p}{A_1} \\ \underset{p-m\times p}{A_2} \end{bmatrix} = F_1A_1 + F_2A_2 \ .$$

where $[\underset{T\times m}{F_1} \ \vdots\ \underset{T\times p-m}{F_2}] = F = XA^{-1} = X[\underset{p\times m}{H_1} \ \vdots\ \underset{p\times p-m}{H_2}]$

and the columns of A^{-1} are the orthonormal eigenvectors of $X'X$ so that

$$A(X'X)A^{-1} = D = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_p \end{bmatrix} .$$

Suppose that p-m components are dropped. It is usually suggested that p-m components with eigenvalues (λ_i) close to zero be selected so that the remaining m components explain a large part of the generalized variance of X . Dropping p-m components

$$Y = F_1A_1\beta + F_2A_2\beta + \epsilon = F_1\gamma + u$$

is equivalent to placing the p-m parameter restrictions on β that $A_2\beta = 0$.

We can measure forecasting inaccuracy for n out-of-sample periods

$$\underset{n\times 1}{Y^0} = \underset{n\times p}{X^0}\ \underset{p\times 1}{\beta} + \underset{n\times 1}{\epsilon^0}$$

by the expected value of the mean squared error of the out-of-sample forecasts

$$\text{EMSE} = E\left[\frac{(\hat{Y}^0 - Y^0)'(\hat{Y}^0 - Y^0)}{n}\right] .$$

With the usual assumption that both the in-sample and out-of-sample residuals have zero means, zero noncontemporaneous covariances and constant (but possibly different) variances (σ^2 and σ_0^2), the ordinary least squares unconstrained and constrained predictions

$$(\hat{Y}^0)^u = X^0\hat{\beta}$$

$$(\hat{Y}^0)^c = F_1^0\hat{\gamma} = X^0H_1\hat{\gamma}$$

can be shown to have expected mean squared errors given by

$$\text{EMSE}(\hat{Y}^0)^u = \sigma_0^2 + \frac{1}{n}\sigma^2\text{Tr}[(X'X)^{-1}X^0{}'X^0] + 0$$

$$\text{EMSE}(\hat{Y}^0)^c = \sigma_0^2 + \frac{1}{n}\sigma^2\text{Tr}[D_1^{-1}F_1^0{}'F_1^0] + \frac{1}{n}\text{Tr}[\gamma_2\gamma_2'F_2^0{}'F_2^0] .$$

These consist of the irreducible out-of-sample variance of the disturbance term, the effects of the errors in the estimated coefficients, and the effects of the inaccurate parameter restrictions embodied in the decision to drop p-m components.

If the out-of-sample variances and covariances among the explanatory variables are identical to the in-sample ones

$$\frac{1}{n}X^{0\prime}X^0 = \frac{1}{T}X'X$$

Then

$$\text{EMSE}(\hat{Y}^u) = \sigma_0^2 + p\sigma^2/T$$

$$\text{EMSE}(\hat{Y}^c) = \sigma_0^2 + m\sigma^2/T + \frac{1}{T}\text{Tr}\ \gamma_2\gamma_2' D_2 \ .$$

Thus, if the correlation matrix for the explanatory variables is replicated out-of-sample, then there is a direct trade-off between the fewer estimated parameters and the inaccuracy of the restrictions, and these restrictions will normally have to be fairly accurate if the constrained model is to outforecast the unconstrained model.

If, on the other hand, the explanatory variables are uncorrelated out-of-sample but replicate the in-sample variances

$$X^{0\prime}X^0 = \frac{n}{T}I_p \ ,$$

Then

$$\text{EMSE}(\hat{Y}^u) = \sigma_0^2 + \frac{\sigma^2}{T}\sum_{i=1}^{p}\frac{1}{\lambda_i}$$

$$\text{EMSE}(\hat{Y}^c) = \sigma_0^2 + \frac{\sigma^2}{T}\sum_{i=1}^{m}\frac{1}{\lambda_i} + \frac{1}{T}\text{Tr}\ \gamma_2\gamma_2'$$

where the m characteristic roots in the second expression are those associated with the retained components. Thus, when the in-sample multicollinearity evaporates out-of-sample, the deletion of $p-m$ components with eigenvalues close to zero can easily be profitable even if the implicit parameter restrictions are only vaguely accurate.

The details of the two variable case are presented on the following page. The EMSE for the unconstrained method becomes very large as r approaches ± 1, unless r_0 is close to r. This suggests that there is a great need for parameter restrictions when the explanatory variables are highly correlated, unless one is willing to rely on that collinearity persisting. The effectiveness of the parameter restrictions that are imposed will depend upon how accurate they are, how difficult the constrained parameters are to estimate, and how important it is in the out-of-sample period to have accurate values for the constrained parameters. Consider, for instance, the deletion of a principal component when r_0 is not close to r. If r is close to 1, then deleting the component associated with $\lambda_2 = 1-r$ can be extremely beneficial while deleting the component associated with $\lambda_1 = 1+r$ will be of little help; for r close to -1, the situation is reversed. The usefulness of the first deletion will however require that β_1 be fairly close to β_2, while the value of the second depends upon β_1 being close to $-\beta_2$.

Thus, while this analysis indicates that with highly collinear explanatory variables parameter constraints will be required to obtain accurate predictions in a wide variety of situations, it does not provide any straightforward procedure for deciding when and how to impose such restrictions. That is, the decision whether or not to apply restrictions is a judgmental weighting of the type and severity of the in-sample collinearity, the likelihood of such collinearity continuing, and the faith one has in the restrictions.

Conceptually, we could combine this information with a loss function and obtain optimal (minimal expected loss) estimates. However, it does not seem advisable (or easy) to commit oneself to a particular density

Estimation Equation	Effective Constraint	EMSE ($\hat{Y}$)		
		In General	When $r_0 = r$	When $r_0 = 0$
$Y = X_1\beta_1 + X_2\beta_2 + \epsilon$	none	$\sigma_0^2 + \frac{2\sigma^2}{T}\frac{1-rr_0}{1-rr}$	$\sigma_0^2 + \frac{2\sigma^2}{T}$	$\sigma_0^2 + \frac{2\sigma^2}{T}\frac{1}{1-r^2}$
$Y - F_2\delta_2 = F_1\gamma_1 + U_1$ (F_2 = principal component associated with $\lambda_1 = 1+r$)	$\frac{\beta_1 - \beta_2}{\sqrt{2}} = \delta_2$	$\sigma_0^2 + \frac{\sigma^2}{T}\frac{1+r_0}{1+r} + \frac{1-r_0}{T}\left[\frac{\beta_1 - \beta_2}{\sqrt{2}} - \delta_2\right]^2$	$\sigma_0^2 + \frac{\sigma^2}{T} + \frac{1-r}{T}\left[\frac{\beta_1 - \beta_2}{\sqrt{2}} - \delta_2\right]^2$	$\sigma_0^2 + \frac{\sigma^2}{T}\frac{1}{1+r} + \frac{1}{T}\left[\frac{\beta_1 - \beta_2}{\sqrt{2}} - \delta_2\right]^2$
$Y = F_1\delta_1 = F_2\gamma_2 + U_2$ (F_1 = principal component associated with $\lambda_1 = 1+r$)	$\frac{\beta_1 + \beta_2}{\sqrt{2}} = \delta_1$	$\sigma_0^2 + \frac{\sigma^2}{T}\frac{1-r_0}{1-r} + \frac{1+r_0}{T}\left[\frac{\beta_1 + \beta_2}{\sqrt{2}} - \delta_1\right]^2$	$\sigma_0^2 + \frac{\sigma^2}{T} + \frac{1+r}{T}\left[\frac{\beta_1 + \beta_2}{\sqrt{2}} - \delta_1\right]^2$	$\sigma_0^2 + \frac{\sigma^2}{T}\frac{1}{1-r} + \frac{1}{T}\left[\frac{\beta_1 + \beta_2}{\sqrt{2}} - \delta_1\right]^2$

r = in-sample correlation between X_1 and X_2

r_0 = out-of-sample correlation between X_1 and X_2

function regarding future collinearity. Nor would one want to reestimate the model for every forecasting situation. Fortunately, these considerations are only important if one is forced to choose between assuming no knowledge or perfect knowledge. Information about future collinearity is necessary only because the estimation technique has no way to handle the degree of belief in the parameter restrictions themselves. In contrast, Bayesian procedures, which allow for uncertainty in the prior distribution of parameters give estimates which minimize forecast error irrespective of the out-of-sample collinearity.

For a simple Bayesian procedure, we decided to use a Theil-Goldberger mixed estimation technique that would incorporate a priori expected values, variances, and covariances for all of the parameters in each sector's demand equations. The parameter estimates will be the posterior means under the convenient assumption that the priors and the residuals, ϵ , are normally distributed. The remainder of this section discusses some of the problems encountered and the technique that was actually employed.

For a given sector, each demand equation can be written as

$$\underset{T\times 1}{Y_i} = \underset{T\times K}{X}\ \underset{K\times 1}{\beta_i} + \underset{T\times 1}{\epsilon_i} \qquad i = 1, \ldots, n .$$

In this study, the a priori information was of the form

$$\underset{K\times 1}{\beta_i} = I_K \underset{K\times 1}{r_i} - \underset{K\times 1}{u_i} \qquad i = 1, \ldots, n .$$

This data can be combined

$$(1) \qquad \begin{pmatrix} Y_i \\ r_i \end{pmatrix} = \begin{pmatrix} X \\ I \end{pmatrix} \beta_i + \begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix} \qquad i = 1, \ldots, n$$

where the disturbances are assumed to have zero expected value and a variance-covariance matrix of the form

$$E \begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix} \begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix}' = \begin{bmatrix} \sigma_i^2 I & 0 \\ 0 & \Sigma_{ii} \end{bmatrix} = \sigma_i^2 \begin{bmatrix} I & 0 \\ 0 & \frac{1}{\sigma_i^2} \Sigma_{ii} \end{bmatrix} .$$

We could apply an Aitken generalized least squares (GLS) estimator to each sector's system of demand equations:

$$(2) \qquad \begin{bmatrix} Y_1 \\ r_1 \\ Y_2 \\ r_2 \\ \vdots \end{bmatrix} = \begin{bmatrix} \begin{pmatrix} X \\ I \end{pmatrix} & & 0 \\ & \begin{pmatrix} X \\ I \end{pmatrix} & \\ 0 & & \ddots \end{bmatrix} \begin{bmatrix} \beta_1 \\ \\ \beta_2 \\ \\ \vdots \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ u_1 \\ \epsilon_2 \\ u_2 \\ \vdots \end{bmatrix}$$

or rearranged as

$$(3) \qquad \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ r_1 \\ r_2 \\ \vdots \end{bmatrix} = \begin{bmatrix} X & & 0 \\ & X & \\ 0 & & \ddots \\ I & & 0 \\ & I & \\ 0 & & \ddots \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_1 \\ \beta_2 \\ \vdots \end{bmatrix} \quad \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ u_1 \\ u_2 \\ \vdots \end{bmatrix} .$$

However, the variance-covariance matrix of disturbances is singular since

$$\sum_i \epsilon_i = 0 \quad \text{and} \quad \sum_i u_i = 0$$

and we consequently have to work with the Moore-Penrose generalized inverse. This is equivalent (see Powell) to deleting one of the data equations and one of the a priori information equations; the parameter estimates will be independent of the particular equations that are deleted.

With this modification, the variance-covariance matrix of the disturbances for (3) will be

$$E\begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ u_1 \\ u_2 \\ \vdots \end{bmatrix}\begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ u_1 \\ u_2 \\ \vdots \end{bmatrix} = \begin{bmatrix} \sigma_1^2 I & \sigma_{12} I & \cdots & 0 \\ \sigma_{21} I & & & \\ & & & \\ & 0 & & E(UU') \end{bmatrix} = \begin{bmatrix} \Omega \times I & 0 \\ 0 & \Sigma \end{bmatrix}$$

assuming that the noncontemporaneous covariances among the ϵ_i are zero.

The GLS parameter estimates will be

$$\hat{\beta} = \left\{ \begin{bmatrix} I \times X \\ I \end{bmatrix}' \begin{bmatrix} \Omega^{-1} \times I & \\ & \Sigma^{-1} \end{bmatrix} \begin{bmatrix} I \times X \\ I \end{bmatrix} \right\}^{-1} \begin{bmatrix} I \times X \\ I \end{bmatrix}' \begin{bmatrix} \Omega^{-1} \times I & 0 \\ 0 & \Sigma \end{bmatrix} \begin{bmatrix} Y \\ r \end{bmatrix}$$

$$= [(\Omega^{-1} \times X'X) + \Sigma^{-1}]^{-1} [(\Omega^{-1} \times X')Y + \Sigma^{-1} r] .$$

Unfortunately, this requires the inversion of 2 matrices of the same dimension as Σ (for the household sector Σ is 147×147). The enormity of the a priori specification task also makes convenient simplifying assumptions very attractive.

A rewarding assumption is that

$$(4) \qquad \frac{1}{\sigma_i^2}\Sigma_{ii} = \frac{1}{\sigma_j^2}\Sigma_{jj} \; .$$

This says that (after deflation by the variance of the disturbance term) the variances and covariances among the errors in the a priori specification of the parameters in any equation are the same for each equation. This is a substantial simplification, which unfortunately, is not easy to rationalize.

An immediate consequence of this assumption is that the application of GLS to each equation (1) will automatically impose the adding up constraints. To see this, it is only necessary to recall that GLS is equivalent to ordinary least squares (OLS) applied to data that has been transformed so that the variance-covariance matrix of disturbances is of the form $\sigma^2 I$. To accomplish this, define (since Σ_{ii}^{-1} is symmetric and positive definite) a non-singular matrix P such that

$$P'P = \sigma_i^2 \Sigma_{ii}^{-1} \; .$$

Premultiplying (1) by

$$H = \begin{pmatrix} I_T & 0 \\ 0 & P \end{pmatrix}$$

yields

$$(5) \qquad \begin{pmatrix} Y_i \\ Pr_i \end{pmatrix} = \begin{pmatrix} X \\ P \end{pmatrix} \beta_i + \begin{pmatrix} \epsilon_i \\ Pu_i \end{pmatrix}$$

$$E\begin{bmatrix} \epsilon_i \\ Pu_i \end{bmatrix}\begin{bmatrix} \epsilon_i \\ Pu_i \end{bmatrix}' = \begin{bmatrix} \sigma_i^2 I_T & 0 \\ 0 & P\Sigma_{ii}P' \end{bmatrix} = \sigma_i^2\begin{bmatrix} I_T & 0 \\ 0 & P(P'P)^{-1}P' \end{bmatrix} = \sigma_i^2 I_{T+K} .$$

Thus, the BLUE estimator of β_i is OLS applied to (5) [GLS applied to (1)]:

$$\hat{\beta}_i = [X'X + \sigma_i^2\Sigma_{ii}^{-1}]^{-1}[X'Y_i + \sigma_i^2\Sigma_{ii}^{-1}r_i] .$$

Now, from our assumption (4) we have that P , and hence the right hand side (RHS) variables in (5), are independent of the particular equation being estimated. It is well known (see Nicholson) that this insures that OLS estimates will add up properly when some linear combination of the RHS variables is always equal to the sum of the LHS variables. In our model, the only as yet unassumed requirement is that the a priori restriction add up: $\Sigma r_i = \Sigma\beta_i$.

What remains to be considered is the efficiency of this single equation procedure as compared to the fully efficient GLS estimator applied to the complete system (2) or (3). To evaluate this we can premultiply (2) by

$$\begin{pmatrix} H & & 0 \\ & H & \\ 0 & & \ddots \end{pmatrix}$$

yielding

$$\begin{bmatrix} Y_1 \\ P_1 r_1 \\ Y_2 \\ P_2 r_2 \\ \vdots \end{bmatrix} = \begin{bmatrix} \begin{pmatrix} X \\ P \end{pmatrix} & & 0 \\ & \begin{pmatrix} X \\ P \end{pmatrix} & \\ 0 & & \ddots \end{bmatrix} \begin{bmatrix} \beta_1 \\ \\ \beta_2 \\ \\ \vdots \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ Pu_1 \\ \epsilon_2 \\ Pu_2 \\ \vdots \end{bmatrix}$$

with a variance-covariance of disturbances

$$\begin{bmatrix} \sigma_1^2 I_T & 0 & \sigma_{12} I_T & 0 & \cdots \\ 0 & \sigma_1^2 I_K & 0 & P\Sigma_{12}P' & \\ \sigma_{21} I_T & 0 & \sigma_2^2 I_T & 0 & \\ 0 & P\Sigma_{21}P' & 0 & \sigma_2^2 I_K & \\ \vdots & & & & \end{bmatrix} .$$

If $P\Sigma_{ij}P' = \sigma_{ij} I_K$ then it is easy to demonstrate (and well known) that the invariance of the RHS variables will render this GLS system estimate identical to the single equations OLS estimates of (5), which are in turn identical to the single equation GLS estimates of our original equations (1).

The inefficiency of the single equation method therefore depends upon the extent to which $P\Sigma_{ij}P' \neq \sigma_{ij} I_K$, something that we cannot know without a priori specification of Σ_{ij} , which our technique set out to spare us. Thus, the attainment of full efficiency would depend upon our success in alternatively specifying Σ_{ij} , and the avoidance of rounding errors in working with a full system estimator.

IV. Estimation and Results

The general procedure outlined above was followed for the two sectors, Savings and Loan Associations and Mutual Savings Banks. In each case, prior means, variances and covariances were specified, OLS and mixed estimates were calculated and the performance of the priors and estimates were compared in out-of-sample forecasting. The variables and equations actually used are most easily seen by inspection of the various Tables of Coefficients. Table I gives the definition of variables.

IV.A. Savings and Loan Associations

The long run demands for assets by Savings and Loans are specified in Table II. As indicated in that Table, it is assumed that these demands are proportional to W^E, and depend linearly on the inverse of the various nominal rates. In earlier work, Smith found that the wide range of interest rates observed in the post-war period created difficulties for the assumption that rates enter linearly and that a variety of non-linear transformations of the rates (including the inverse used here) worked equally well. Nominal rates were used on the grounds that these institutions are dealing entirely in nominally denominated claims, all subject to the same erosion by inflation. This is equivalent to assuming that the real income effects of inflation are negligible. The constraint, W, equal to the sum of the assets listed in Table II is essentially the volume of deposit liabilities plus FHLB borrowing. In order to obtain W^E, we estimated normal savings (deposit inflows) to be:

$$SN = 1.161(1.0068)^{\tau}, \quad \tau = 1 \text{ in } 1952 - I$$

and assumed that

$$W^E = W_{-1} + S^E = W^{-1} + SN + .7(S_{-1} - SN_{-1}) \ .$$

Thus, $W - W^E$ can be divided into new FHLB borrowing and unexpected deposit inflows:

$$W - W^E = (S - S^E) + \Delta FHLB \ .$$

Although the priors in Table II are obviously highly subjective, they are based on three presumptions which many may find agreeable. First, they embody the assumption of gross substitutes; i.e., ceteris paribus, an increase in the rate on an asset increases its demand and decreases or leaves unaffected the demand for other assets. While it is obviously possible for assets to be complements, for example because of negative correlation in the returns, we felt that case to be implausible for the assets held by these institutions. Gross substitutes, of course, also implies the own effect is greater than any cross effect. Second, we found it plausible to assume a natural ordering of the assets in question, with currency at one end and mortgages at the other--the rate on a particular asset having smaller impacts on assets which are further from it. Similarly we assumed that if the rate on asset i had a large effect on the demand for the asset j, the rate on j would have a large effect on asset i. Third, we assumed that assets that formed a large proportion of the portfolio have large rate responses; that is, the elasticities across assets have less variation than the marginal propensities.

The long run coefficients reported for OLS (which were derived from the estimated short run equations) are quite different from these priors. Six out of twelve coefficients have the "wrong" sign. Although most of these are small in absolute value, some are quite substantial.

For example, according to OLS an increase in the long rate from five to seven per cent <u>increases</u> the proportion of the portfolio in shorts by approximately .019 (the average holdings have been approximately .02), while <u>decreasing</u> the proportion of longs by .004. There are similar difficulties with each of the other rates.

The short run coefficients are given in Table III. The a priori adjustment coefficients are specified directly; the short run rate responses are the product of the long run and adjustment matrices. Again, the OLS estimates have a substantial number of peculiarities. For example, a $1 billion increase in desired holdings of longs, associated with an increase in expected wealth, leads to only a $.21 billion increase in longs, while mortgage holdings increase by $.91 billion. Surprisingly, currency plus demand deposits fall by $.33 billion. On the other hand, some columns look remarkably good, e.g. the effect of an unanticipated deposit inflow $(S - S^E)$.

The variance-covariance matrix of priors used to combine the a priori means and the data is given in Table IV. We found that construction of this Table put a great strain on our intuitions. Introspection is complicated by the fact that what is needed is a variance-covariance matrix for the short run coefficients involving the products of adjustment and long run coefficients. The assumption of normality is also occasionally an embarrassment in that it seems reasonable to bound the distribution of some parameters, with a resulting asymmetry in the distribution.

Not surprisingly, the mixed estimates appear more reasonable to us than the OLS estimates. In the case of the long run coefficients, however, a substantial number of peculiarities remain. Three (rather than six) of the signs remain "incorrect" and some of the magnitudes remain quite far from the priors. The adjustment coefficients, on the other hand, turn out to be generally quite close to the priors. This suggests that multicollinearity may indeed have been the problem in trying to estimate the relatively elaborate adjustment mechanism that we have specified.

In order to get some measure of the value of the a priori information we computed root mean square forecast errors (RMSE) for an in-sample and an out-of-sample period. (For the pure priors, only the intercepts were estimated from the early period to go with the a priori information.) For comparison, forecasts were also made with an eight quarter auto-regressive "naive" model estimated over the same in-sample period.

We also calculated the dynamic predictions that would have resulted if the forecaster had known the future course of interest rates and deposit inflows, but was forced to give bootstrap predictions of the course of asset holdings. Thus, the two-quarter ahead forecasts would be

$$\hat{y}^{+2} = EAr + (I-E)\hat{y}_{-1}^{+1}$$

where $\hat{y}^{+1}$ is the one-quarter ahead forecast. In general, the τ-quarter ahead forecasts $\hat{y}^{+\tau}$ would be generated by

$$\hat{y}^{+\tau} = EAr + (I-E)\hat{y}_{-1}^{+\tau-1} .$$

The analogous treatment of the naive forecasts (N1) would consequently be

$$\hat{y}^{+\tau} = \sum_{i=1}^{\tau-1} \alpha_i \hat{y}_{-i}^{+\tau-i} + \sum_{i=\tau}^{8} \alpha_i Y_{-i} .$$

It might be argued that the parameters of both the naive and theoretical model should have been estimated so as to minimize forecasting errors τ rather than one-quarter ahead. A sequence of alternative naive models (N2) were therefore constructed so as to minimize in-sample RMSE for forecasts τ quarters ahead

$$\hat{y}^{+\tau} = \sum_{i=\tau}^{\tau+8} \beta_i Y_{-i} .$$

We did not do this re-estimation for the theoretical model. The in-sample and out-of-sample RMSE's are displayed in Tables V and VI.

In-sample the OLS estimated model fits best for all cases except shorts 1 quarter ahead and currency plus demand deposits 1 and 2 quarters ahead. The naive models are most accurate in these latter cases and are generally not far behind OLS in forecasting the near future; however, their accuracy seems to fade for more distant forecasts. OLS dominates the mixed estimates,which in turn, dominate the pure priors. This is of course necessarily so for 1-quarter ahead forecasts, though the difference in fit is not statistically significant.

Out-of-sample the priors do surprisingly well, forecasting roughly on a par with the unconstrained estimates. The priors are slightly inferior in 1-quarter forecasts of mortgages and slightly superior to OLS for 1-quarter forecasts of the other three assets. For longer range predictions, priors are superior to OLS for shorts and longs and inferior for mortgages and currency plus demand deposits. The mixed forecasts are roughly comparable, though there is no clear pattern. For instance, the mixed 1-quarter ahead forecasts are superior to OLS for C+DD and Morts, but inferior for shorts and longs; for 8-quarter ahead forecasts, this ranking is exactly reversed. The naive models are very good at 1-quarter ahead predictions and at forecasting shorts and currency plus demand deposits. Their longer range predictions of longs and mortgages (which make up approximately 97% of the S&L's portfolio) are very poor.

The theoretical model's primary forecasting error occurred in the first quarter of 1971. Prior to this date, this sector had been obtaining between $2 and 4 billion of new funds each quarter, of which about $.5 billion went into longs. In 1971.I, they received $7.5 billion of new funds of which $4 billion was put into longs. In the subsequent seven quarters, on average, only $.5 billion of an average $8 billion in new funds went into longs. None of the three sets of parameters estimates correctly anticipated the large increase in longs and the modest increases in shorts and currency plus demand deposits in 1971.I, and although the gap closed considerably, none of forecasts quite reached the permanently higher level of long holdings.

Forecasting out-of-sample provides one test of the performance of the model and the various estimation procedures. Unfortunately such tests are limited by the scarcity of out-of-sample data, and the fact that they relate only to the actual historical path of the exogenous variables. Macro models are constructed with the objective of forecasting the behavior of the economy in situations where the policy and other exogenous variables exhibit new levels and interrelations. Since there is no direct test of models in such circumstances, it seems sensible to investigate the general qualitative and quantitative behavior of the estimated model by analysis and/or simulation.

One of the disconcerting properties of many models is that they display extremely slow, or unstable, adjustment towards equilibrium. Consequently, we have examined the general convergence and the adjustment paths for a variety of initial conditions. With a constant amount of available funds (w) and unchanged desired holdings (a^*), the actual portfolio holdings will behave as follows:

$$(a - a_{-1}) = E(a^* - a_{-1}) .$$

Therefore, the equation

$$(a - a^*) = (I-E)(a_{-1} - a^*) = (I-E)^{\tau}(a_{-\tau} - a^*)$$

will give the portfolio disequilibria τ periods after the initial situation. Hence, the system converges for any[3] initial conditions if

$$\lim_{\tau \to \infty} (I-E)^{\tau} = 0$$

which will be true if the absolute values of all characteristic roots of $I-E$ are less than one. For S&L's, the largest characteristic roots for the priors, OLS, and mixed estimates are respectively .50, .91, and .61.

The speed and pattern of convergence will of course depend upon the specific initial disequilibria. One method of describing speed of adjustment is to report the largest possible discrepancy remaining after τ periods for an initial disequilibrium of specified size (e.g., an initial desire to hold $1 billion more of some assets and $1 billion less

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[3] This is not necessary for convergence from some initial situations. For example,

$$I-E = \begin{bmatrix} 1000 \\ -1000 \\ 0000 \\ 0000 \end{bmatrix}$$

will converge whenever the first two assets are initially in equilibrium.

of others). This will be given by the largest difference between any two elements in a row of $(I-E)^{\tau}$; this largest difference is reported below.

S&L's Largest Disequilibrium ($ Billion)

τ (quarters)	Priors	OLS	Mixed
1	.500	1.196	.614
2	.250	1.007	.377
4	.063	.858	.142
8	.004	.595	.020
12	.000	.409	.003
16	.000	.279	.000
20	.000	.190	.000

Interestingly, for the OLS and mixed estimates, as well as for the priors, a desired shift between longs and mortgages is the slowest to evaporate. The complete patterns of adjustment are displayed in Graphs I-III for this and a variety of other initial disequilibria situations. The impression that emerges from these graphs is that, although they are stable, the unconstrained OLS adjustment coefficients give very slow and often perplexing patterns of adjustment. In particular, it is difficult to rationalize a temporary change in the holdings of an illiquid asset when the desired movement is between two more liquid assets. For example, according to the OLS estimates, when there is a desired movement of $1 billion from longs to cash, Savings and Loan associations sell almost $1 billion in mortgages in order to hold even more cash than they desire throughout the period of adjustment.

IV.B. Mutual Savings Banks

It is widely believed that throughout the 1950's, mutual savings banks held an excessively high proportion of long term government bonds, but were reluctant to sell these bonds and thereby admit on paper that they had incurred capital losses. By the mid-1960's the excess bonds had matured and MSB's became active again in the long term bond market, with a seemingly more flexible, rate responsive behavior than that displayed by savings and loan associations. If this is correct, then we have two distinct regimes, with the early, constrained period of limited use in estimating the later, unconstrained years. Rather than construct a model applicable to both kinds of situations, we chose to estimate a simple model of unconstrained behavior using data from the period 1966.I through 1972.IV. We then backcast with this model to see if it agreed with our presumption that mutual savings banks had held far more long term bonds than they wished.

The procedure followed for the unconstrained period parallels that used for the savings and loans. Normal savings (primarily deposit inflows) were estimated to be

$$SN = .311(1.018)^{\tau} , \quad \tau = 1 \text{ in } 1952.I$$

and we assumed that

$$W^E = W_{-1} + SN + .7[S_{-1} - SN_{-1}] .$$

Tables VII and VIII give the various estimates. Again the OLS estimates look quite wild, and again the use of a priori information makes a very substantial difference. The OLS estimates indicate that a rise in the time deposit rate from 4 to 6 percent would raise the desired proportion of longs in the portfolio by .14 and lower the desired proportion of mortgages by .15. A similar rise in the business loan rate would raise the desired long proportion by .10, lower the desired mortgage proportion by .09, and lower the desired business loan proportion by .02. The OLS adjustment coefficients give the following responses to a one unit increase in desired currency plus demand deposit holdings accompanied by a one unit increase in anticipated funds: C+DD up 1.9, longs down .7, BL down .5, Morts up .4. The OLS response to a one unit increase in desired time deposits accompanied by a one unit increase in anticipated funds is: C+DD up .1, time deposits up .7, shorts down .7, longs up .6, BL up 1.2, Morts down .9.

The most seriously implausible mixed coefficient is perhaps the estimated effect of a change in the long term bond rate on desired business loan holdings. The mixed estimate implies that a rise in the long rate from 5 up to 7 percent would increase the desired share of the portfolio in business loans by .02. Some other troubling estimates are

$$\frac{\partial(C+DD^*/W^E)}{\partial(1/r_M)}, \quad \frac{\partial(Mort^*/W^E)}{\partial(1/r_S)}, \quad \frac{\partial(Long)}{\partial(\varphi BL)} .$$

One of the more striking features of the estimates that we obtained is the high interest elasticities of desired long and mortgage shares with respect to the long and mortgage rates. The following table displays the implied effect of a *ceteris paribus* change in either of these rates from 5 to 7 percent.

		S&L's		MSB's	
		r_L	r_M	r_L	r_M
$\frac{Long^*}{W^E}$	priors	.03	-.05	.06	-.09
	OLS	-.00	.01	.08	-.24
	mixed	.01	-.02	.19	-.27
$\frac{Mort^*}{W^E}$	priors	-.02	.05	-.05	.10
	OLS	-.01	.02	-.08	.25
	mixed	-.01	.02	-.20	.28

Thus the OLS and mixed estimates indicate that mutual savings banks are considerably more rate responsive than savings and loans, and that this distinction is much more pronounced than we had believed.

For unconstrained OLS the backcasts were not impressive. Negative holdings of currency and time deposits were mechanically predicted up until 1961.IV and 1961.II respectively. There were also 7 scattered predictions of negative short holdings and 13 negative business loan positions. Forecast long holdings were generally above and never more than .4 billion below actual holdings.

The mixed estimates in contrast indicate that in the early 1950's the actual long term bond holdings of slightly more than $12 billion were some $2-1/2 to 3-1/2 billion above desired holdings. As late as 1961, actual holdings were still almost $1 billion above predicted desired; and, somewhat fortuitously, the last out-of-sample quarter (1965.IV) is the first period in which predicted holdings exceed actual. Our pure priors predict that long term bond holdings were $6-7 billion too high in the early 1950's, and were not less than desired holdings until 1965.III.

Tables X and XI show the forecasting errors. In order to "backcast" during the out-of-sample period, long term bond holdings were constrained to decrease by no more than 1% per quarter, with any difference between the constrained and unconstrained bond forecasts allocated proportionately to the other asset forecasts.

In-sample, the OLS estimated model is dominant for all assets other than currency plus demand deposits. For this asset, OLS is superior for one quarter ahead forecasts and slightly less accurate than the naive models for farther ahead forecasts. The naive models are generally competitive with the OLS estimated model in-sample, but show some inadequacies (particularly with longs and morts which comprise about 95% of the portfolio) when forecasting several quarters ahead. The priors are not disastrous and the mixed forecasts are close enough to the OLS forecasts to indicate (by the usual test) that our priors are compatible with the data.

Out-of-sample, the success of the pure priors is perhaps the biggest surprise. The pure priors outforecast the pure data (OLS) for 5 of the 6 assets in the one quarter ahead tests and are roughly comparable to OLS in the farther ahead tests. The mixed forecasts are more accurate than the unconstrained estimates for 29 of the 30 out-of-sample comparisons. The mixed estimates outforecast the priors for C+DD, short, long, and mort but are not as accurate as the priors forecasts for TD and BL. The naive models are unambiguously the most successful in tracking the four minor assets, but have serious problems trying to forecast longs and morts more than a few quarters ahead.

We repeated for the MSB adjustment coefficients the stability and adjustment path tests that we used for S&L's. The largest characteristic roots for the priors, OLS, and mixed estimates are respectively .50, .93, and .84. Below is displayed the largest possible disequilibrium remaining after t periods of adjustment to an initial $1 billion discrepancy:

MSB's Largest Disequilibrium ($ Billion)

τ (quarters)	Priors	OLS	Mixed
1	.500	1.689	.869
2	.250	1.311	.740
4	.063	1.363	.528
8	.004	.909	.266
12	.000	.677	.134
16	.000	.494	.068
20	.000	.362	.034

While stable, the many implausible OLS adjustment parameters imply unlikely adjustment paths to a wide variety of portfolio disequilibria. Some of these paths are displayed in Graphs IV-VI.

TABLE I

Definitions

Interest Rates

RBL : Commercial Loan Rate

RL : Corporate Bond Rate

RM : Mortgage Rate

RS : Treasury Bill Rate

RTD : Commercial Bank Time Deposit Rate

Assets

CDD : Currency, reserve and demand deposits

TD : Commercial bank time deposits other than large negotiable CD's

SHORT: Short-term marketable U.S. government securities, open market paper, and security credit

LONG: U.S. government securities other than short-term marketable, state and local government securities, and corporate and foreign bonds

BL : nonhousehold bank loans n.e.c., sponsored credit agency loans, finance company loans to business, and mutual savings bank loans to business.

MORT : mortgages

FHLB : borrowing from the FHLB

Data: The Federal Reserve Board's quarterly flow of funds data was used for all financial quantities. All interest rate data was taken from the MPS data bank.

TABLE II

Savings and Loan Associations
Long Run Coefficients

		1.0	$1/r_S$	$1/r_L$	$1/r_M$
$\frac{C+DD^*}{W^E}$	priors OLS mixed	none -.019 -.017	.02 -.011 -.003	.03 .130 .092	.01 .040 .083
$\frac{Short^*}{W^E}$	priors OLS mixed	none -.006 .028	-.03 .007 -.006	.03 -.320 -.077	.01 .476 -.064
$\frac{Long^*}{W^E}$	priors OLS mixed	none .059 .034	.01 -.017 .009	-.46 .059 -.172	.78 -.188 .288
$\frac{Mort^*}{W^E}$	priors OLS mixed	none .965 .958	.00 .022 -.000	.40 .130 .157	-.80 -.329 -.309

TABLE III

Savings and Loan Associations Short-Run Coefficients

		Rate Responses				Adjustment Coefficients					
		1	$\frac{1}{r_S}$	$\frac{1}{r_L}$	$\frac{1}{r_M}$	$\frac{\varphi CDD}{W^E}$	$\frac{\varphi Short}{W^E}$	$\frac{\varphi Long}{W^E}$	$\frac{\varphi Mort}{W^E}$	$\frac{S - S^E}{W^E}$	$\frac{\Delta FHLB}{W^E}$
$\frac{\Delta C+DD}{W^E}$	priors	none	.021	.064	-.072	1.0	.0	.1	.2	.3	.1
	OLS	.048	-.004	.063	.225	1.277	.301	-.331	.097	.218	.091
	mixed	.104	-.002	.096	.069	.990	-.003	.087	.123	.351	.192
$\frac{\Delta Short}{W^E}$	priors	none	-.028	.058	-.074	.0	1.0	.2	.3	.4	.1
	OLS	.179	.001	-.076	.113	.192	.428	.211	.179	.037	-.151
	mixed	.302	-.004	-.068	-.088	.013	.996	.213	.279	.147	-.009
$\frac{\Delta Long}{W^E}$	priors	none	.007	-.322	.546	.0	.0	.7	.0	.0	.0
	OLS	.029	-.001	.034	-.156	-.356	-.209	.209	.009	.157	.068
	mixed	.236	.006	-.087	.136	.015	.018	.709	.221	.042	-.003
$\frac{\Delta Mort}{W^E}$	priors	none	.0	.200	-.400	.0	.0	.0	.5	.3	.8
	OLS	.743	.004	-.021	-.182	-.112	.480	.911	.715	.588	.991
	mixed	.360	.000	.060	-.120	-.018	-.011	-.010	.376	.460	.820

$\Delta X = X - X_{-1}$

$\varphi X = X^* - X_{-1}$

TABLE IV

Savings and Loan Associations Priors Variance-Covariance Matrix (Σ_{ii})

	$\frac{1}{r_S}$	$\frac{1}{r_L}$	$\frac{1}{r_M}$	$\frac{C+DD_{-1}}{W^E}$	$\frac{Short_{-1}}{W^E}$	$\frac{Long_{-1}}{W^E}$	$\frac{Mort_{-1}}{W^E}$	$\frac{S-S^E}{W^E}$	$\frac{\Delta FHLB}{W^E}$
$\frac{1}{r_S}$	.0001	.0	.0	.0	.0	.0	.0	.0	.0
$\frac{1}{r_L}$		.0009	-.0003	.0	.0	.0	.0	.0	.0
$\frac{1}{r_M}$			.0025	.0	.0	.0	.0	.0	.0
$\frac{C+DD_{-1}}{W^E}$				.0001	.00005	.00005	.00025	-.00015	.0
$\frac{Short_{-1}}{W^E}$					.0001	.00005	.00025	-.00015	.0
$\frac{Long_{-1}}{W^E}$						.0001	.00025	-.00015	.0
$\frac{Mort_{-1}}{W^E}$							.0025	-.00075	.0
$\frac{S-S^E}{W^E}$								.0025	.0
$\frac{\Delta FHLB}{W^E}$									.0025

TABLE V

S&L's RMSE's for In-Sample Forecasts (1954.I-1969.IV)

Variable	Method	Number of Quarters Ahead				
		1	2	4	6	8
C+DD	priors	.358	.342	.329	.331	.335
	OLS	.191	.180	.198	.197	.194
	mixed	.232	.228	.230	.234	.236
	N1	.102	.153	.223	.319	.409
	N2	.102	.148	.217	.311	.400
Short	priors	.672	.752	.761	.764	.772
	OLS	.196	.239	.268	.313	.321
	mixed	.272	.328	.365	.381	.385
	N1	.195	.263	.325	.427	.454
	N2	.195	.260	.310	.397	.404
Long	priors	1.002	1.294	1.421	1.449	1.471
	OLS	.143	.182	.187	.218	.259
	mixed	.226	.268	.304	.313	.319
	N1	.147	.190	.286	.385	.442
	N2	.147	.182	.265	.359	.414
Mort	priors	.516	.747	.920	.975	.999
	OLS	.237	.294	.353	.420	.502
	mixed	.321	.461	.582	.633	.649
	N1	.298	.744	1.687	2.807	3.998
	N2	.298	.742	1.654	2.756	3.936

TABLE VI

S&L's RMSE's for Out-of-Sample Forecasts (1969.IV-1972.IV)

Variable	Method	Number of Quarters Ahead				
		1	2	4	6	8
C+DD	priors	1.709	2.092	2.518	2.723	2.829
	OLS	1.834	1.012	.948	.706	.557
	mixed	.861	1.038	1.211	1.220	1.248
	N1	.115	.200	.389	.713	.997
	N2	.115	.187	.379	.786	.888
Short	priors	.660	.839	1.096	1.255	1.129
	OLS	.711	1.216	1.971	2.578	2.812
	mixed	1.528	1.992	2.334	2.557	2.502
	N1	.342	.401	.550	.648	.483
	N2	.342	.319	.468	1.048	.325
Long	priors	1.011	1.113	.940	.549	.552
	OLS	1.372	1.720	2.437	2.932	2.993
	mixed	1.614	2.016	2.423	2.096	1.953
	N1	1.342	1.942	2.805	4.129	5.458
	N2	1.342	1.474	2.222	4.141	3.899
Mort	priors	1.598	2.425	3.166	3.467	3.484
	OLS	1.554	1.147	1.143	1.204	.486
	mixed	.764	.950	1.051	1.187	1.245
	N1	1.021	3.051	8.707	16.319	25.682
	N2	1.021	3.439	7.121	14.796	17.627

TABLE VII

MSB Long Run Coefficients

		1.0	$\frac{1}{r_{TD}}$	$\frac{1}{r_S}$	$\frac{1}{r_L}$	$\frac{1}{r_{BL}}$	$\frac{1}{r_M}$
$\frac{C+DD^*}{W^E}$	priors	none	.0	.045	.050	.0	.038
	OLS	.013	.009	-.001	.126	.011	-.159
	mixed	.017	.005	.004	.197	-.009	-.283
$\frac{TD^*}{W^E}$	priors	none	-.0025	.030	.025	.0	.0
	OLS	.007	-.103	.038	.051	.083	.107
	mixed	-.007	-.006	.031	-.067	-.002	.117
$\frac{Short^*}{W^E}$	priors	none	.0025	-.105	.075	.0	.074
	OLS	-.006	-.065	-.078	-.111	-.030	.503
	mixed	.002	.006	-.115	.121	.000	.015
$\frac{Long^*}{W^E}$	priors	none	.0	.030	-1.000	.020	1.450
	OLS	.232	-1.680	-.045	-1.294	-1.168	4.047
	mixed	.019	-.080	.241	-3.271	.017	4.493
$\frac{BL^*}{W^E}$	priors	none	.0	.0	.0	-.040	.038
	OLS	.033	.034	.024	-.157	.219	-.303
	mixed	.018	-.017	.051	-.370	-.036	.359
$\frac{Mort^*}{W^E}$	priors	none	.0	.0	.850	.020	-1.600
	OLS	.721	1.810	.062	1.386	1.053	-4.203
	mixed	.954	.093	-.214	3.410	.029	-4.730

TABLE VIII

MSB Short-Run Coefficients

			Rate Responses					Adjustment Coefficients							
		1.0	$\frac{1}{r_{TD}}$	$\frac{1}{r_S}$	$\frac{1}{r_L}$	$\frac{1}{r_{BL}}$	$\frac{1}{r_M}$	$\frac{\varphi C+DD}{W^E}$	$\frac{\varphi TD}{W^E}$	$\frac{\varphi Short}{W^E}$	$\frac{\varphi Long}{W^E}$	$\frac{\varphi BL}{W^E}$	$\frac{\varphi Mort}{W^E}$	$\frac{S - S^E}{W^E}$
$\frac{C+DD}{W^E}$	priors	none	.000	.043	.112	-.002	-.080	1.0	.0	.025	.025	.1	.1	.2
	OLS	.126	-.072	-.004	.122	-.008	-.093	1.858	.079	.122	.139	.254	.084	.058
	mixed	.094	.002	.016	.073	-.010	-.129	1.009	.009	.034	.104	.130	.076	.080
$\frac{TD}{W^E}$	priors	none	-.002	.028	.002	-.004	.042	.0	1.0	.025	.025	.1	.0	.0
	OLS	.014	-.066	.014	.042	-.073	.140	-.049	.697	.145	.007	-.092	.017	-.001
	mixed	.021	-.005	.027	-.010	-.005	.028	.000	1.000	.025	.002	.094	.028	.001
$\frac{Short}{W^E}$	priors	none	.002	-.097	.226	.0	-.257	.0	.0	.95	.1	.2	.3	.4
	OLS	-.051	.039	-.053	-.082	.055	.107	.007	-.667	.351	-.047	.028	-.048	.058
	mixed	.280	.009	-.101	.216	.003	-.172	.014	.013	.963	.236	.250	.282	.262
$\frac{Long}{W^E}$	priors	none	.0	.026	-.765	.019	1.073	.0	.0	.0	.85	.0	.1	.1
	OLS	.888	-.016	.048	-.120	-.099	.076	-.676	.631	.046	.953	.547	.907	.710
	mixed	.287	-.013	.060	-.676	.021	.924	-.023	-.022	-.022	.519	-.085	.292	.369
$\frac{BL}{W^E}$	priors	none	.0	.0	.0	-.024	.023	.0	.0	.0	.0	.6	.0	.0
	OLS	-.077	-.069	.049	-.062	.054	-.014	-.532	1.157	.103	-.124	.496	-.090	-.002
	mixed	.019	-.006	.019	-.063	-.021	-.001	-.006	-.006	-.005	-.036	.577	.010	.076
$\frac{Mort}{W^E}$	priors	none	.0	.0	.425	.010	-.800	.0	.0	.0	.0	.0	.5	.3
	OLS	.100	.184	-.054	.099	.071	-.217	.393	-.898	.234	.073	-.233	.129	.176
	mixed	.299	.014	-.022	.461	.011	-.651	.005	.005	.005	.178	.032	.309	.212

TABLE IX

Mutual Savings Banks Priors Variance-Covariance Matrix (Σ_{ii})

	$1/r_{TD}$	$1/r_S$	$1/r_L$	$1/r_{BL}$	$1/r_M$	CDD_{-1}/W^E	TD_{-1}/W^E	$Short_{-1}/W^E$	$Long_{-1}/W^E$	BL_{-1}/W^E	$Mort_{-1}/W^E$	$S - S^E/W^E$
$1/r_{TD}$	.0001	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
$1/r_S$		.0001	.0	.0	.0	.0	.0	.0	.0	.0	.0	.0
$1/r_L$			.0025	.0	-.0005	.0	.0	.0	.0	.0	.0	.0
$1/r_{BL}$				.0001	.0	.0	.0	.0	.0	.0	.0	.0
$1/r_M$					.0025	.0	.0	.0	.0	.0	.0	.0
CDD_{-1}/W^E						.0001	.00005	.00005	.00025	.00015	.00025	-.00025
TD_{-1}/W^E							.0001	.00005	.00025	.00015	.00025	-.00025
$Short_{-1}/W^E$								.0001	.00025	.00015	.00025	-.00025
$Long_{-1}/W^E$									.0025	.00075	.00125	-.00125
BL_{-1}/W^E										.0009	.00075	-.00075
$Mort_{-1}/W^E$											.0025	-.00125
$S-S^E/W^E$												.0025

TABLE X

MSB RMSE's for In-Sample Forecasts (1966.I-1972.IV)

Variable	Method	Number of Quarters Ahead				
		1	2	4	6	8
C+DD	priors	.344	.342	.353	.366	.375
	OLS	.045	.055	.054	.062	.066
	mixed	.087	.088	.093	.098	.099
	N1	.050	.050	.053	.052	.056
	N2	.050	.050	.051	.051	.051
TD	priors	.172	.141	.129	.132	.138
	OLS	.025	.028	.034	.035	.034
	mixed	.062	.062	.065	.066	.069
	N1	.035	.079	.136	.191	.252
	N2	.035	.077	.131	.163	.167
Short	priors	.434	.427	.411	.423	.443
	OLS	.055	.064	.076	.077	.080
	mixed	.126	.147	.161	.166	.172
	N1	.088	.113	.135	.151	.146
	N2	.088	.110	.127	.139	.128
Long	priors	.880	.995	1.040	1.048	1.060
	OLS	.098	.137	.135	.177	.167
	mixed	.258	.376	.422	.448	.460
	N1	.457	.864	1.423	2.149	2.721
	N2	.457	.813	1.388	2.039	2.624
BL	priors	.305	.413	.473	.491	.506
	OLS	.081	.096	.111	.118	.118
	mixed	.124	.133	.148	.162	.168
	N1	.109	.145	.183	.258	.312
	N2	.109	.112	.131	.181	.196
Mort	priors	.660	.897	1.040	1.030	.979
	OLS	.110	.122	.138	.181	.156
	mixed	.230	.354	.456	.503	.526
	N1	.182	.334	.691	1.136	1.535
	N2	.182	.328	.649	.969	1.245

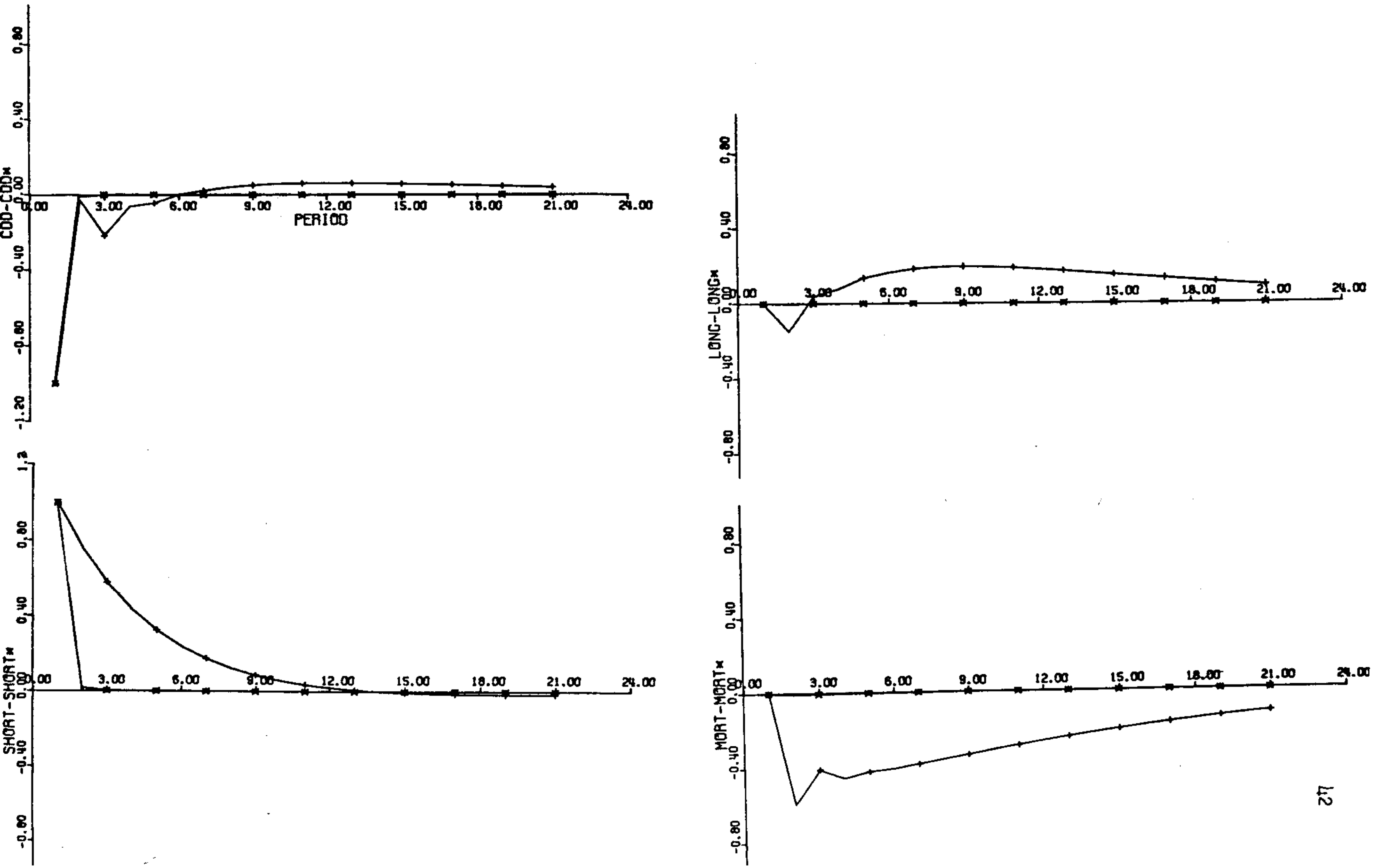
TABLE XI

MSB RMSE's for Out-of-Sample Forecasts (1955.I-1965.IV)

Variable	Method	Number of Quarters Ahead				
		1	2	4	6	8
C+DD	priors	.560	.618	.606	.586	.574
	OLS	1.088	.273	.467	.512	.518
	mixed	.204	.217	.230	.233	.233
	N1	.051	.056	.052	.054	.054
	N2	.051	.058	.054	.059	.068
TD	priors	.162	.160	.150	.150	.153
	OLS	.341	.463	.396	.347	.331
	mixed	.293	.274	.248	.238	.241
	N1	.042	.057	.074	.103	.125
	N2	.042	.055	.061	.076	.112
Short	priors	.519	.709	.822	.837	.816
	OLS	.387	.613	.841	.836	.811
	mixed	.497	.574	.548	.547	.559
	N1	.118	.169	.221	.278	.307
	N2	.118	.176	.244	.298	.339
Long	priors	.179	.181	.186	.188	.192
	OLS	.435	.259	.222	.205	.176
	mixed	.162	.155	.151	.151	.153
	N1	.365	.897	1.996	3.611	5.134
	N2	.365	.682	1.680	2.787	3.410
BL	priors	.124	.169	.195	.202	.206
	OLS	.316	.331	.531	.486	.454
	mixed	.218	.291	.310	.301	.299
	N1	.043	.040	.052	.073	.075
	N2	.043	.046	.060	.091	.104
Mort	priors	.972	1.309	1.467	1.472	1.435
	OLS	1.376	1.091	1.082	1.121	1.119
	mixed	.264	.334	.367	.379	.378
	N1	.142	.322	.818	1.527	2.234
	N2	.142	.309	.764	1.481	2.120

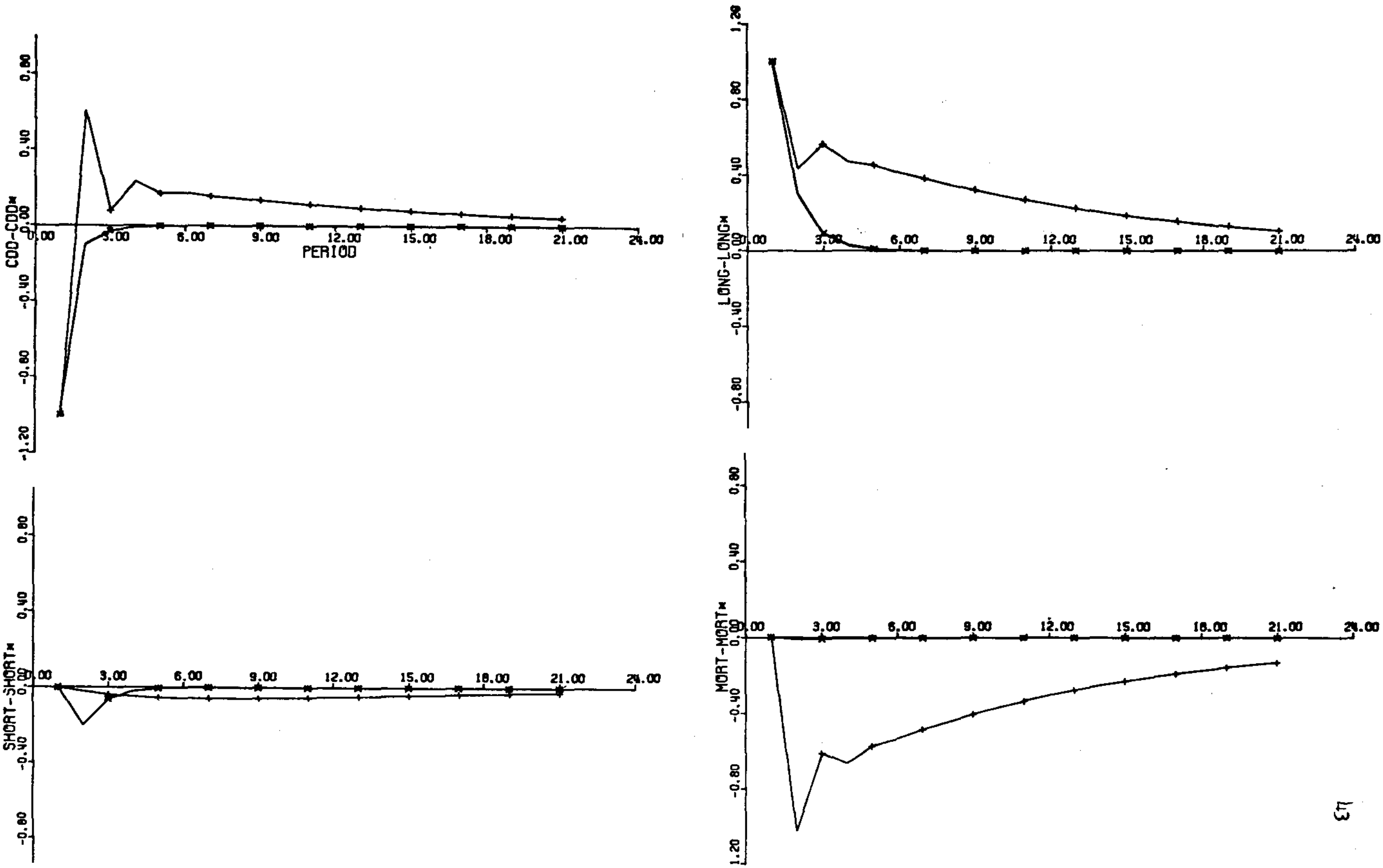
Graph I : S&L's Adjustment to a Desired Shift of $1 Billion From Shorts to C+DD

Δ : Priors
+ : OLS
x : Mixed

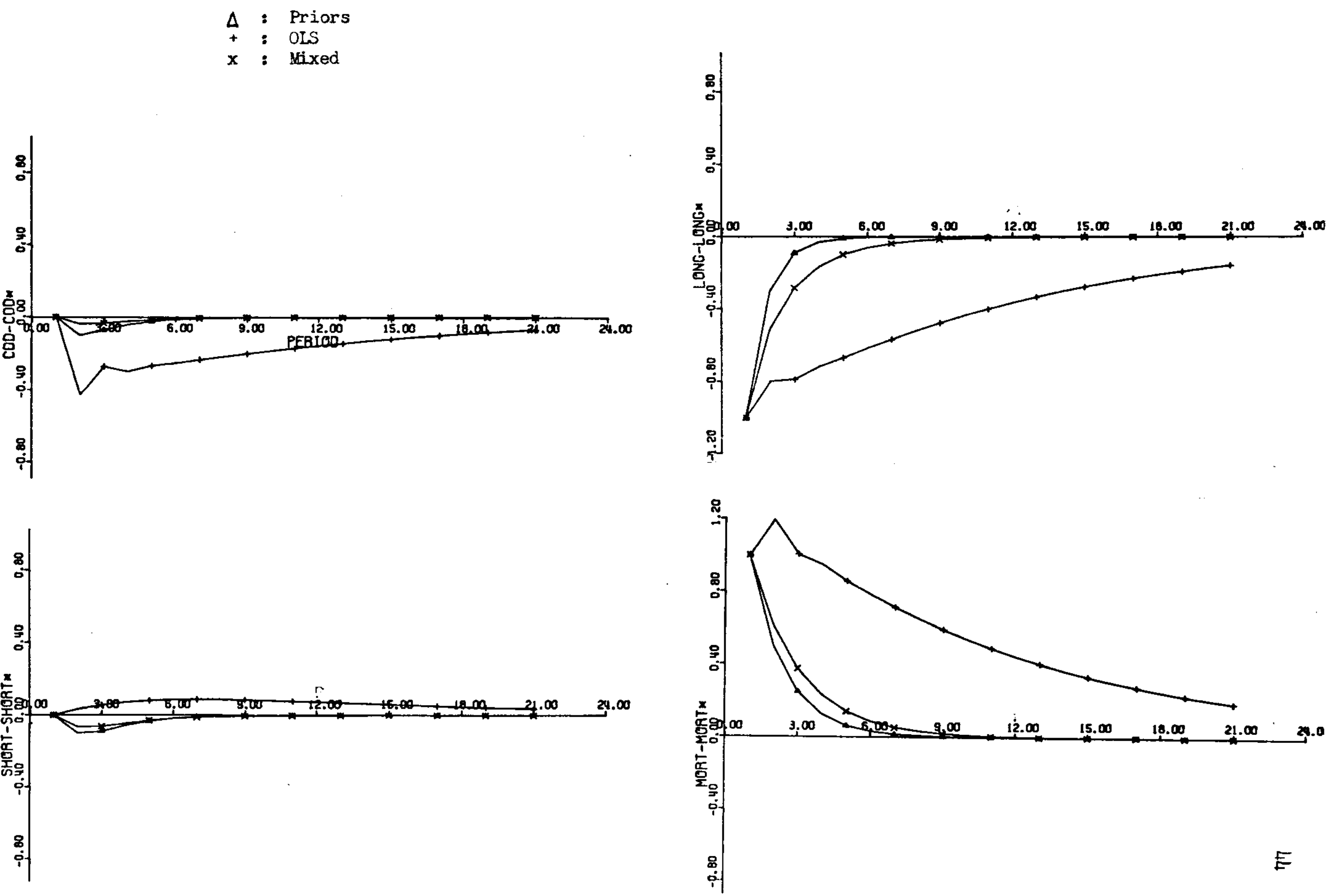


Graph II: S&L's Adjustment to a Desired Shift of $1 Billion from Longs to C+DD

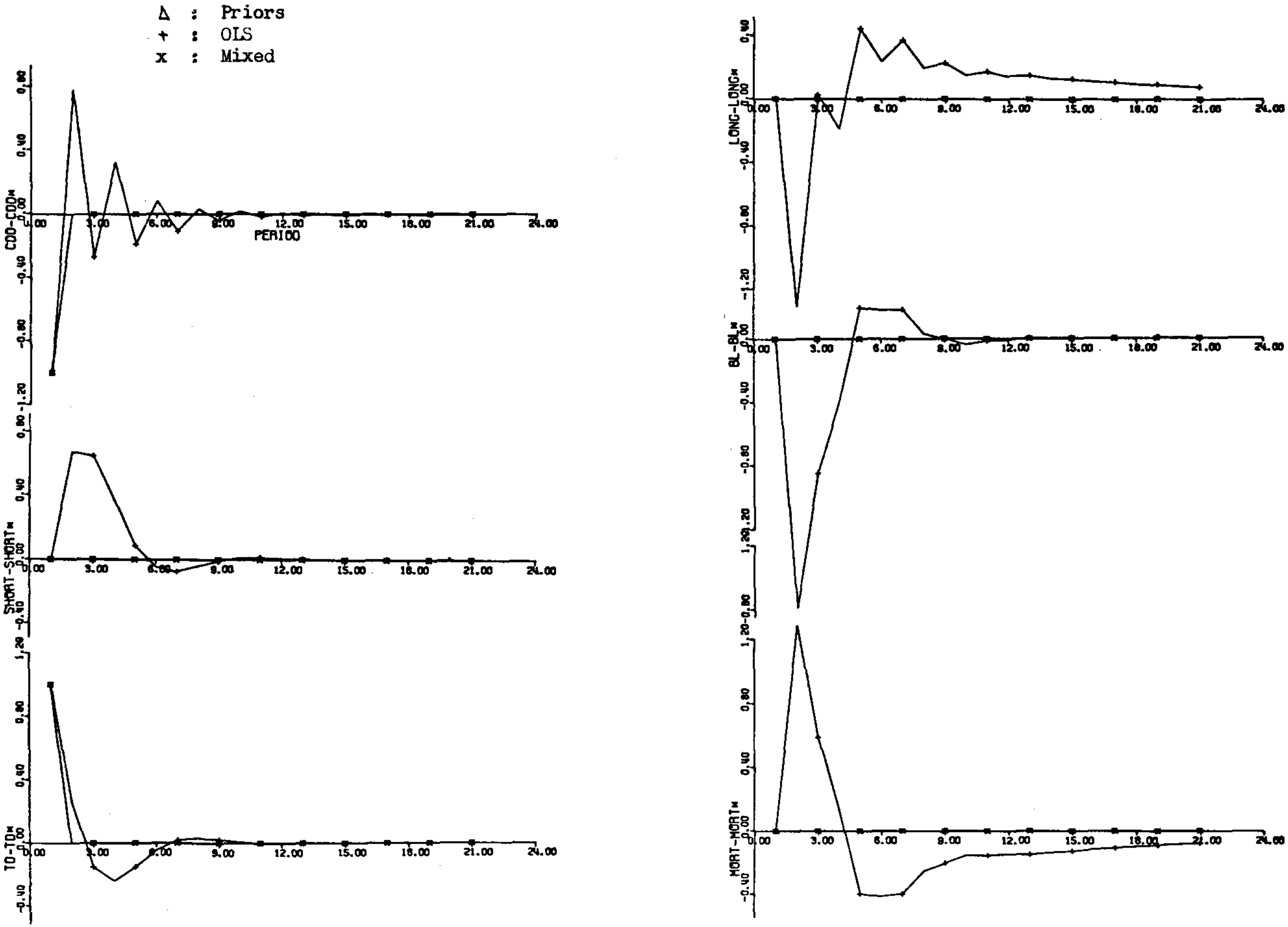
Δ : Priors
\+ : OLS
x : Mixed



Graph III: S&L's Adjustment to a Desired Shift of $1 Billion from Morts to Longs

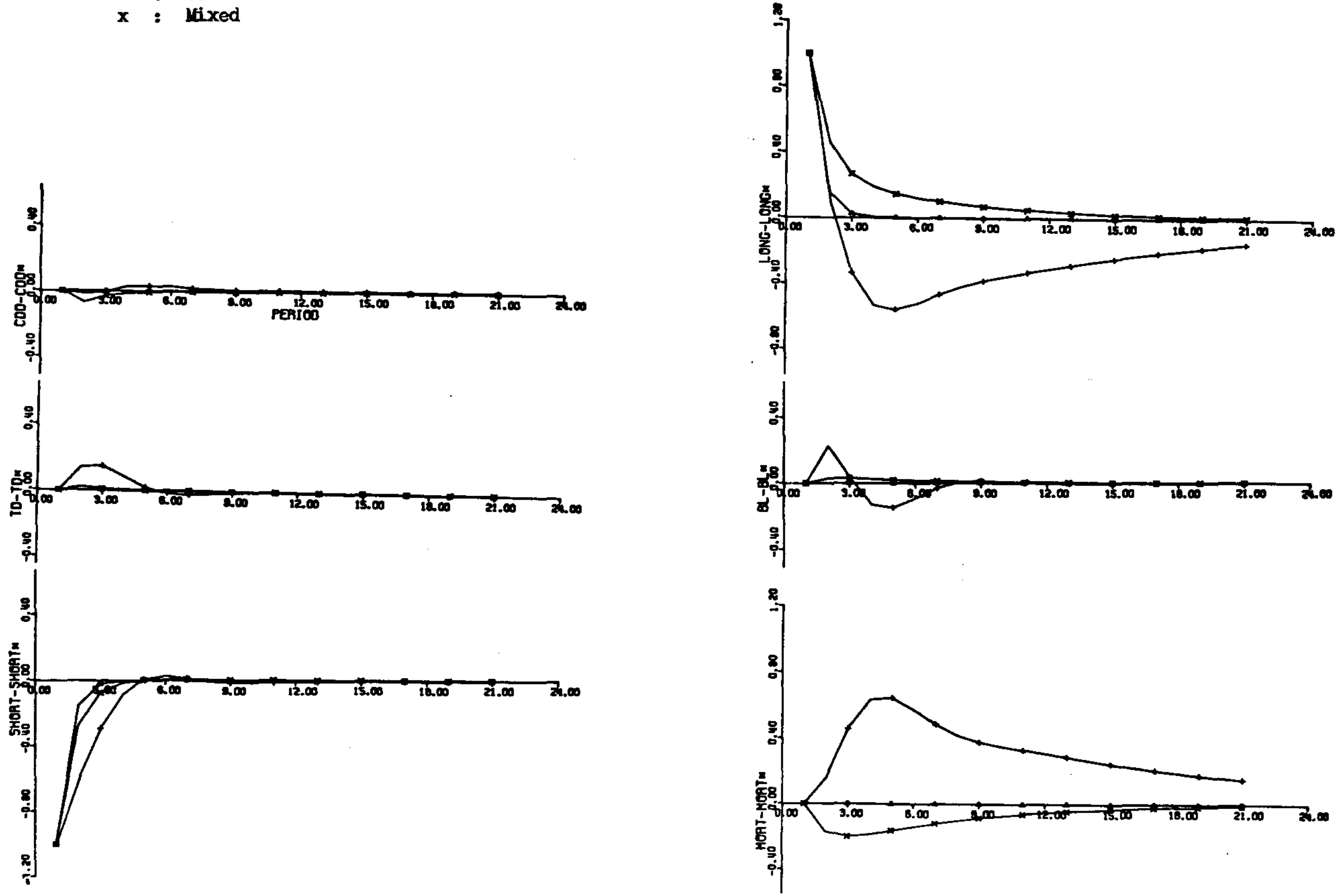


Graph IV: MSB's Adjustment to a Desired Shift of $1 Billion from TD's to C+DD's



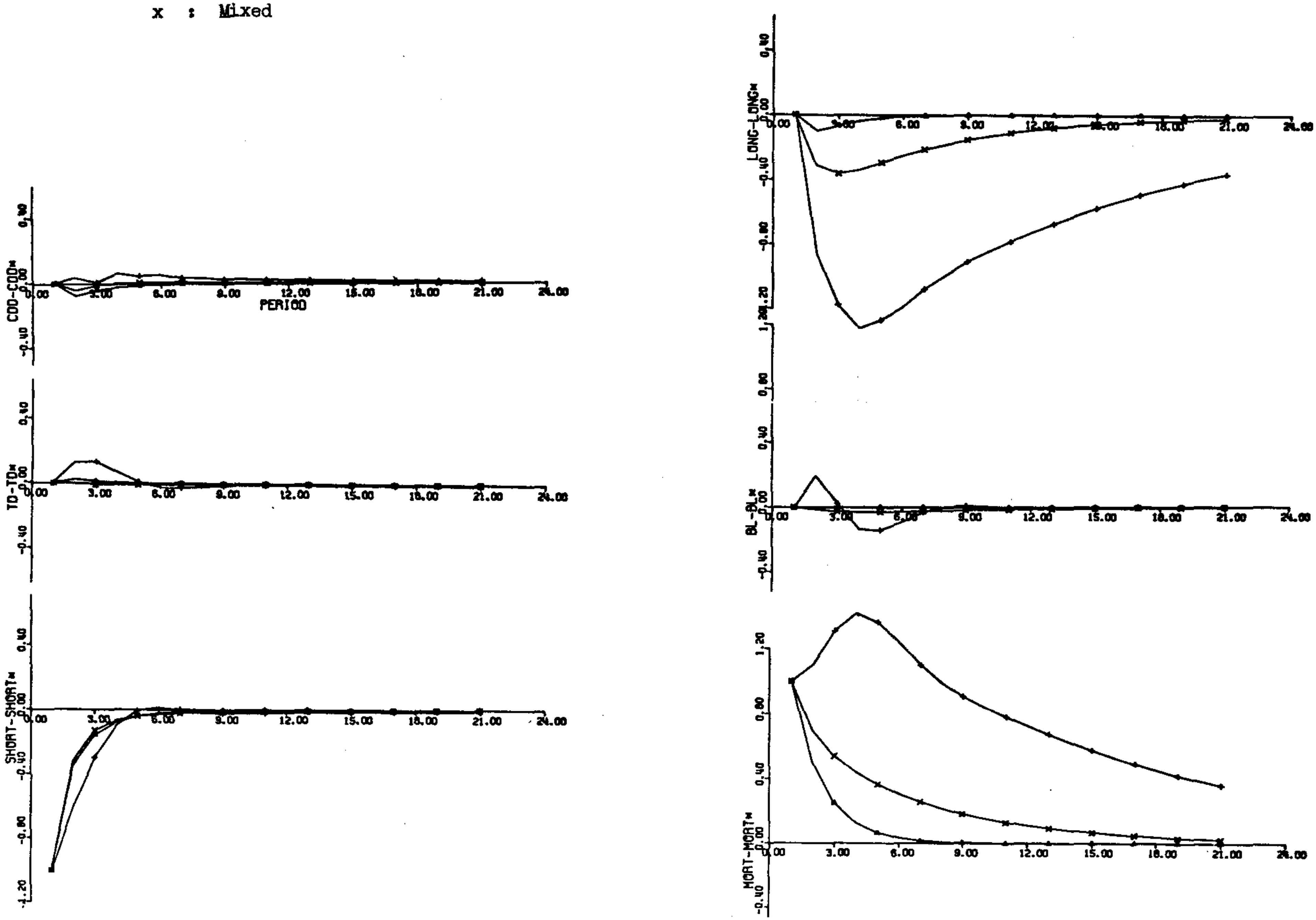
Graph V: MSB's Adjustment to a Desired Shift of $1 Billion from Longs to Shorts

Δ : Priors
+ : OLS
x : Mixed



Graph VI: MSB's Adjustment to a Desired Shift of $1 Billion from Morts to Shorts

Δ : Priors
+ : OLS
x : Mixed



REFERENCES

Brainard, William and James Tobin, "Pitfalls in Financial Model Building," American Economic Review, Papers and Proceedings, 58 (May 1968), 99-122.

Kendall, M. G., A Course in Multivariate Statistical Analysis, third edition, New York: Hafner (1965).

Massy, William, "Principal Components in Exploratory Statistical Research," Journal of the American Statistical Association, 60 (March 1965), 234-56.

Nicholson, J. L.,"The General Form of the Adding-Up Criterion," Journal of the Royal Statistical Scoeity, Series A, 120 (1957), 84-85.

Powell, Alan, "Aitken Estimates as a Tool in Allocating Predetermined Aggregates," Journal of the American Statistical Association, 64 (September 1969), 913-22.

Raiffa, Howard and Robert Schlaifer, Applied Statistical Decision Theory, Ch. 13.

Smith, Gary, "Multicollinearity and Forecasting," mimeographed (1971).

Theil, Henri, and A. S. Goldberger, "On Pure and Mixed Statistical Estimation in Economics," International Economic Review, 2 (1960), 65-78.

Theil, Henri, "On the Use of Incomplete Prior Information in Regression Analysis," Journal of the American Statistical Association, 58 (June 1963), 401-14.