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Comments welcome

Abstract

In this paper, we shall first briefly outline the traditional approach to econometric model-building and some features of the time series approach to modeling bivariate and multivariate processes. Then we present the main features of the structural econometric modeling and time series analysis (SEMTSA), which integrate the use of econometric and time series techniques in econometric modeling.

In the second part of the paper, the SEMTSA will be applied to a multivariate dynamic model for seven quarterly macroeconomic variables for the Netherlands.

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Structural Econometric Modeling and Time Series Analysis An Integrated Approach

1. Introduction

An important and difficult part of econometric modeling is the specification of the model. Any applied econometrician knows how troublesome it can be to obtain a satisfactory specification of the model.

While the problem of specification analysis has received increasing attention in econometric research in recent years, many of the existing econometric textbooks provide few guidelines on how to obtain a satisfactory specification. This is surprising as the specification of the model is necessary in order to justify the choice of an estimation or testing procedure among the large variety of existing procedures, the properties of which are well established given that the true model is known.

The consequences of misspecification errors due to the exclusion of relevant explanatory variables are more extensively discussed in standard textbooks on econometrics. Misspecification tests such as e.g. the Durbin-Watson test belong to the tools of any empirical econometrician.

Among the exceptions to what has been said about the treatment of specification analysis in textbooks, we should mention the book by Leamer (1978), in which he distinguishes six types of specification searches and presents solutions for each of them within a Bayesian framework.

But the present state of econometric modeling leads us to stress once more Zellner's (1979) conclusion concerning the research on structural econometric models (SEM's):

"Most serious is the need for formal, sequential statistical procedures for constructing SEM's"(p.640).

In this paper, we shall first briefly outline the traditional approach and the time series approach to dynamic econometric model-building. Then we present the structural econometric modeling and time series analysis (SEMTSA, see Zellner (1979)), which integrate the use of econometric and time series techniques to analyze regression and structural equations in a framework of sequential testing of hypotheses.

In the second part of the paper, the SEMTSA will be applied to a set of quarterly macroeconomic data for the Netherlands. Thereby, we shall be concerned with what Leamer calls hypothesis-testing search, interpretive search, data-selection search and postdata model construction. The hypothesis-testing search or model selection consists in choosing one element out of a set of vectors of explanatory variables. In the interpretative search, one looks for interpretable restrictions on a set of regression or structural coefficients. The issue in the data- selection search is to find the data set which is explained by a given relationship. Does the relationship fit the entire sample of observations or should the model allow for a structural change? Finally, the postdata model construction is synonymous with misspecification analysis.

Section 2 will be devoted to a description of (1) the traditional approach to modeling econometric regression and behavioral equations, (2) the time series approach to modeling bivariate and multivariate time series processes and (3) the structural econometric modeling and time series analysis which integrate the best features of (1) and (2).

In section 3, the SEMTSA will be applied to a multivariate dynamic model for seven Dutch quarterly macroeconomic variables for the period 1952 - 1979. A general vector autoregressive (VAR)model will be estimated and its properties will be analyzed.

Then, restrictions on the parameters of the VAR model are formulated and confronted with the information in the data. The dynamic properties of the restricted model are compared to those of the unrestricted model. Finally the forecasting performance of the unrestricted and the restricted VAR models and of univariate auto-regressive - integrated - moving average (ARIMA) models will be investigated.

In section 4, we shall draw some tentative conclusions concerning the application of the SEMTSA in general and the empirical results of our study in particular. We shall point to problems that remain to be solved.

The estimation and testing procedures used throughout this paper are chosen on the basis of their large sample properties. Their finite sample properties are known for special models only.

2. Approaches to econometric model-building

2.1 The traditional approach to econometric modeling

The methodology of traditional econometric modeling will be briefly outlined in this section. For a more detailed description and a schematic representation of model-building activities, the reader is referred to Hamilton and al.(1969) and to Zellner(1979).
After a statement of objectives of the study and preparatory work, viz. review of the literature, preliminary data analysis..., the investigator specifies an initial model, thereby making use of economic theory, knowledge about institutional arrangements and other subject matter considerations. Sometimes a heavily - perhaps too much - restricted model is chosen as an initial model because the estimation of its parameters is straightforward.

In general, the initial model is estimated using an estimation technique which is appropriate according to criteria such as unbiasedness, consistency, efficiency...., provided the initial model is the true model. The estimation results of the model are judged on the basis of the t-values, the plausibility of the parameter estimates and their expected sign, the stability over time of the estimates ,the serial correlation properties of the residuals tested by e.g. the Durbin-Watson test, and the fit of the equation measured for instance by the R^2.
When the initial model is not satisfactory as judged by one or more of these criteria, it is respecified and reestimated. For example, a significant Durbin-Watson test statistic has often led to fitting a regression model with first order autoregressive disturbances. Similarly, insignificant coefficient estimates are used as evidence in favor of excluding the corresponding variable from the equation. The finding that two stage least squares estimates differ slightly from ordinary least squares estimates is used as argument to ignore the simultaneity aspect. Certainly, in many situations the correct remedy has been applied to cure the model. However as in medicine, different diseases may show the same symptom. It is only after a profound analysis of several symptoms, that one can be confident about the diagnosis and the prescription needed to restore the health of the patient. Similarly, as long as there is no systematic way to analyze the sample evidence, the diagnostic checking and the reformulation of the initial model may be done quite differently by two independent investigators. That different final model specifications have been reported in the economic literature for similar data sets and observation periods is evidence for this statement.

The traditional approach to econometric modeling has certainly yielded very valuable results. These lines should not be interpreted as convicting econometricians of bad practice. Instead, we want to emphasize the need for a systematic, formal approach to econometric modeling, in which the best elements of the traditional approach ought to be incorporated.

2.2 Time series identification of dynamic econometric models

Besides the progress made in modeling univariate time series during the last decade, many contributions to formal modeling of regression equations, bivariate and multivariate models have been made by time series analysts [see e.g. Box and Jenkins (1970), chapters 10 and 11, Granger and Newbold (1977), Haugh and Box (1977), Jenkins and Alavi (1981) among many others] .

As for the univariate ARIMA models, modern time series model-building of vector processes consists of three stages: identification, estimation and diagnostic checking. The observations play a central role in time series identification (or specification). More specifically, the time series analysis is directed towards finding a transformation of the data into a vector of innovations that are orthogonal to the lagged variables included in the model. Thereby, the aim of many time series analysts using a time domain approach is to find a parsimonious representation of the data generating process.

Usually, the series to be modeled are made stationary and prewhitened. The cross correlation function between the prewhitened series is used to check for the presence of feedback. When there is unidirectional Wiener-Granger causality [see e.g. Granger (1969)] present, say from x to y only, the bivariate process for y and x can be modeled as a dynamic regression equation for y given x and a univariate (ARMA) model for the input x . The cross correlation function for the prewhitened series ε_y and ε_x is used to determine the degree of the distributed lag polynomials in the regression equation for y .

In vector time series models with feedback present, the autocorrelation and partial autocorrelation matrices are used to achieve a parsimonious parametrization of the model [see e.g. Jenkins and Alavi (1981), Tiao and al.].

At this point, we like to make several comments on the time series approach to econometric model-building.

1) Usually the approach is applied to low dimensional vector processes. In many empirical studies, the authors analyze bivariate processes. Most data in econometrics are non-experimental. When modeling a

dynamic econometric equation, one has to take into account the effects of the explanatory variables, which vary over the sample period. Therefore, there will usually be more than one explanatory variable included in an econometric equation, so that the specification of the lag structure using estimated cross correlation functions becomes difficult, if not impossible in practice.

2) The assumption that all the variables in the model are generated by a vector ARIMA process may be unrealistic. The typical situation in econometrics is that of a structural change during the observation period. Quite often a structural change can be modeled by expanding the set of explanatory variables, using dummy variables or products of explanatory variables and dummy variables.
A structural change in the parameters of the ARIMA process for x does not hamper the analysis of the regression function of y on x as long as the marginal process for x is of no direct interest in the analysis. Nevertheless, if one wants to transform the process of x into a white noise, the presence of a structural change in the process for x will complicate matters substantially.
Special cases such as the effect of interventions on a given response variable in the form of changes in levels have been studied by Box and Tiao (1975).

3) Mostly, the form and the parameter values of the linear filters which prewhiten the variables are not known but have to be determined empirically. Due to the small samples available in many econometric studies, the estimates of the univariate ARIMA models are often not very precise and their use may crucially affect the results of the subsequent analysis.

4) In tests on the cross correlations of prewhitened series, the favorite null hypothesis is that of independence of the series. Under this hypothesis, the population correlation coefficients of the prewhitened series are zero and the asymptotic distribution of the sample cross correlations is known. They are independently normally distributed with mean zero and variance equal to $(n-k)^{-1}$ with n being the sample size and k being the order of the cross correlations. An asymptotic test of the null hypothesis of independent series is easily constructed. However, in economic applications, where economic theory indicates that there is a relationship between endogenous and exogenous variables,the hypothesis of independence of the series is not the most natural null hypothesis. Rather, econometricians often would like to find out what the shape of the lag distribution between y and x looks like, given that there exists a relationship between the series.

5) Finally, for the use of auto- and cross correlations, stationary series are needed. In regression analysis, one can dispense with this requirement. In fact, the mean of the endogenous variable is assumed to vary with the explanatory variables. Also, the nonstationarity of the regressor variables may sometimes help to increase the precision of the estimates of the regression coefficients.

All this is not to say that the time series approach to modeling regression equations and simultaneous equation systems in econometrics is not useful. The approach may not be appropriate in many econometric applications. However, it can be very valuable when a bivariate or a low dimensional vector time series model constitutes the appropriate framework of analysis. For instance, when the aim of an application is to forecast an economic series y, the use of a leading indicator x may increase the forecasting precision. Similarly, when y has to be controlled through x, knowledge of the regression function for y can be useful if not requisite. Sometimes, economic theory implies testable restrictions on the parameters of a joint time series process, such as e.g. the absence of Wiener-Granger causality in one or both directions. Here too, the usefulness of vector time series models has been demonstrated.
From the discussion in this section, we conclude that the time series approach to dynamic model-building is not always appropriate for econometric applications. In empirical work, one has to combine the best features of the time series approach with existing econometric techniques. In the next subsection, we shall present the SEMTSA, which is a blend of econometric and time series methods.

2.3 Structural econometric modeling and time series analysis

Continuing research efforts during the seventies have led to a combination of econometric and time series methods and their joint application in econometric modeling. Besides a large number of theoretical contributions, many empirical studies have been done. A more detailed survey can be found in Palm (1981).
In this section we shall discuss the predominant features of the SEMTSA of regression models and behavioral equations. Under the influence of modern time series analysis, the role of the data for the choice of a specification has become very important.

2.3.1 Testing restrictions

In traditional econometrics, one formally assumes that the model is given. The observations are used to estimate the parameters of the model. In contrast to the econometric approach, time series analysts explicitly rely on the data to determine the specification of the model. In the SEMTSA, economic theory and other subject matter considerations are used to specify a model and to formulate restrictions on the model. The restrictions and the assumptions underlying the model are confronted as much as possible with the information in the data. Restrictions that are not contradicted by the sample information are incorporated in the model. Lag length, parameter stability and exogeneity are tested for. Quite often, one distinguishes between restrictions which have an interpretation in terms of economic behavior and those which have as the main feature to be easily imposed on the model. Examples of restrictions originating from theoretical considerations are:

- a partial adjustment model for the endogenous variable and/or expectation scheme's, such as adaptive or rational expectations,
- exclusion restrictions as a result of some causal mechanism,
- the requirement of homogeneity of degree zero or one with respect to some or all explanatory variables, such as e.g. implied by modern demand theory,
- an 'error correction' mechanism, such as introduced by Davidson and al. (1978), an 'integral correction' term proposed and applied by Hendry and Von Ungern-Sternberg (1979).

The index models introduced by Sargent and Sims (1977) also include theoretically meaningful restrictions. Dynamic econometric models based on more sophisticated optimizing behavior such as presented by Sargent (1981) obviously fall in the first category.
Among the restrictions that are easily imposed on the model without having necessarily an economic interpretation, we mention the common factor restrictions leading to a regression model or a structural equation with autoregressive disturbances [e.g. Sargan (1964)].
However, testing the nonlinear restrictions implied by the presence of common factors can create problems [Sargan (1977, 1980b)]. For an application of common factor restrictions, we refer the reader to Hendry and Mizon (1978).
Other examples of restrictions that are easily imposed on a dynamic model are the well known exclusion restrictions, the Almon (1965) polynomials, which are equivalent to linear restrictions on distributed lag coefficients.

2.3.2 From general to specific

In several recent contributions to SEMTSA, the authors recommend and apply a specification analysis consisting in the formulation of a fairly general initial model and of a sequence of nested testable hypotheses. If the restrictions are not rejected by the data, they have to be imposed on the parameters of the model. Then, additional restrictions are considered in the framework of the restricted model.
The meaning of 'fairly general' is that the number of the explanatory variables and of the lags included in the initial model is sufficient to guarantee the (vector) white noise assumption for the disturbances. An initial finite order dynamic model with autoregressive disturbances can be transformed into a higher order finite distributed lag model with white noise errors.
If the disturbances of the initial model are generated by a moving average process, the transformed model has infinite distributed lags and a finite order starting model can at best be considered as an approcimation to the data generation process. In order to limit the size of the approximation error, the number of lags included in the model will usually have to be large, so that ignoring the restrictions implied by the moving average error process can lead to a substantial loss of degrees of freedom. Finally, although modeling the moving average process for the disturbances jointly with the regression or structural coefficients can be computationally cumbersome, it is necessary for achieving efficient estimation.
Starting the specification analysis with a general model with serially uncorrelated disturbances has the following advantages:

1) All the dynamics are incorporated in the systematic (explained) part of the equation instead of being left in the disturbance term. This enables the investigator to interpret the parameters more easily in terms of economic behavior.

2) If the disturbances of the initial regression model are uncorrelated and homoscedastic, OLS has well-known optimal properties besides its obvious computational advantages, which can be important in a sequential testing set-up.
   In a regression model with autocorrelated disturbances but no lagged endogenous variables present, the OLS-estimator is unbiased and consistent, but it is not efficient and the formula for the standard errors for OLS is no longer appropriate. Similarly, the F- and t-tests for linear and exclusion restrictions are no longer valid as such.

Indeed, Kiviet (1979) derives lower and upper bounds for the effects of ARMA disturbances on tests for regression coefficients. He shows that a 't-value' of about 2 usually falls between the lower and upper bounds, so that the test is inconclusive at least if no additional information on the model is used. For the test to be conclusive, the 't-value' has to be much higher, especially for problems with sample size smaller than 50 .

3) Most importantly, the general initial model can be used as a maintained hypothesis throughout the specification analysis. Of course, the lag length in the initial model can formally be tested for. This problem has been studied in the literature on choosing the length of a distributed lag [see e.g. Amemiya and Morimune (1974), Sargan (1980a) or Geweke and Meese (1981)].

If the initial model is formulated such that the true model is nested within it, the specification analysis aims at searching for the true model inside the initial model. As long as the true model is nested in the restricted model under the null hypothesis H_0 , the distribution of the test statistics under H_0 is correct and the data can guide us towards the true model. Usually, the investigator will formulate a sequence of nested hypotheses on the parameters of the initial model and test whether more restricted versions of the model are compatible with the data. Restrictions such as discussed in section 2.3.1 will be included in the sequence of restrictions. Tests of specification in the form of a uniquely ordered nested sequence have optimal asymptotic properties. They are uniformly most powerful (see Anderson (1971), p. 263) in the class of unbiased tests.

Although starting with a loosely parametrized model implies a loss of degrees of freedom and possibly the presence of high multicollinearity between the regressors, it reduces the danger of analyzing inappropriate and too restricted models.
In agreement with Zellner and Palm (1974), rejecting the nested model, when it is true, will be a less serious error than using a restricted model when the restrictions are not true. This is an argument in favor of a specification analysis starting with a general model.

Several authors advocate - for very different reasons - to start with a general model. For instance, Sims (1980) argues that we do generally not have strong a priori knowledge (restrictions) to impose on the model. Therefore, he works with models with a large number of parameters. Mizon (1977), Hendry and Mizon (1978), Davidson and al. (1978), Mizon and Hendry (1980) among others propose to start with a general model, specify a uniquely ordered sequence of nested hypotheses and compare them using formal statistical tests.

As stated above, we shall follow the same line in this paper. Economic theory and other a priori knowledge play an important role in the choice of the explanatory variables to be included in the initial model and in the formulation of restrictions. Selecting a uniquely order sequence of hypotheses will be quite difficult in practice, as several alternative sequences might be a priori reasonable. Theoretically meaningful restrictions ought to be preferred to other kinds of restrictions.

In general, when a hypothesis in the sequence is not rejected by the data, it is imposed on the model. As a safeguard against misspecification, the serial correlation properties of the residuals of the restricted model should be checked. The sequence of tests stops, when one hypothesis is rejected or when the last hypothesis cannot be rejected while the residuals of the most restricted model do not indicate any misspecification. In the next section, we shall discuss the misspecification analysis.

2.3.3 Model diagnostic checking

Under the constant emphasis in the time series literature on residual correlation analysis and other diagnostic checks, econometricians have shifted their attention from the analysis of low order autoregressive and moving average processes to more general auto- and cross correlation scheme's. Tests such as the Box-Pierce (1970) test have been very useful and have led to the development of many new tests for the presence of correlation in time series.

Diagnostic checking is synonymous with misspecification analysis. Given a model, one investigates whether more general models are more appropriate according to some criterion. It is going from specific to general, to use the terminology of Mizon and Hendry (1980) [see also Mizon (1977)]. Silvey's (1959) Lagrange multiplier and Rao's (1973) efficient score testing principle are well suited for misspecification analysis and many of the recently developed tests are applications of these principles [see e.g. Godfrey (1978 a,b), Breusch and Pagan (1980)].

Misspecification analysis is and has to be part of thorough econometric modeling. In the SEMTSA approach, the initial and the most restricted version of the model will have to be subjected to misspecification analysis.

2.3.4 Checking the overall consistency of the model

An econometric model should be consistent with a priori knowledge and with the information in the data. Granger (1981) provides several examples of non-consistent models. Points such as raised in his paper should be taken into consideration when formulating a model.
Checking the overall consistency of the model is an important part of econometric modeling. One of the first questions asked by model-builders is whether the different equations specified separately fit together. Common practice is to solve the complete model, either analytically, if the model is linear, or numerically, if the model is nonlinear. Implausible values for the multipliers and for the solution of the model may lead to a reformulation of the model. Subsequently, the implications of the restricted structural form for the properties of the transfer functions have to be checked along the lines proposed by Zellner and Palm (1974, 1975). The set of transfer functions associated with the structural form of a dynamic simultaneous equation model with vector moving average errors is the solution of the system which expresses each endogenous variable as a function of its own lagged values, of the current and lagged values of the exogenous variables and of an error term which can be represented as a moving average in one variable.

As pointed out by Zellner and Palm (1974), the autoregressive polynomials of the transfer functions associated with a simultaneous equation model are identical, provided the structural form polynomial lag operator of the endogenous variables has no special structure such as a diagonal, block diagonal, triangular or block triangular matrix. Further, as the transfer function equations are dynamic regression equations, the lag length and the parameter values for the individual transfer function equations can be determined empirically. Any incompatibility between the results of the empirical analysis of the individual transfer functions and those derived from the tested structural form is an indication of a misspecification in one or both forms of the model and can be used to reformulate the model. Examples of how to respecify the model, when an incompatibility is detected, are given by Zellner and Palm (1974, 1975).

The transfer functions can also be used to study the dynamic properties of a model. The roots of the characteristic equation associated with a dynamic simultaneous equation model can be calculated from the estimated autoregressive polynomials of the transfer function equations.

Under the additional assumption that the exogenous variables are generated by a multivariate ARMA model, the set of final equations for the endogenous (and exogenous variables) can be obtained after substitution for the exogenous variables. In the system of final equations, the endogenous variables are expressed as a set of seemingly unrelated ARMA equations, in which all the endogenous variables usually have identical autoregressive polynomial.
As for the transfer functions, any incompatibility between the results of the empirical analysis of the individual final equations, e.g. along the lines proposed by Box and Jenkins (1970), and those for the structural model is an indication of a misspecification of the system of final equations and/or of the finally accepted structural form of the model. The role of the empirical analysis of the final equation form for the structural form and for the properties of a simultaneous equation model has been discussed and illustrated by Zellner and Palm (1974). The analysis of the final equations as a means for checking out the dynamics of a simultaneous equation model has been pursued by Prothero and Wallis (1976), Trivedi (1975), Wallis (1977) and Zellner and Palm (1975) among others.

When the implications of the structural form of the model are in agreement with the results of the empirical analysis of the transfer functions and final equations, the model can be used to predict the post sample period [see Christ (1975) on this point].
If post sample data are available, the predictive performance of the structural form can be compared to that of the transfer function and/or the final equations. If it predicts less well than the transfer functions or the final equations, there are good reasons for believing that the structural model is misspecified. If all three forms predict badly, the model is either misspecified or it has been subject to a structural change during the post sample period.
The predictive performance of the model can be formally checked using a test based on the distribution of the forecasting errors - either assuming that the parameters of the model are known [see e.g. Hendry (1978)] or that they have been estimated [see e.g. Dhrymes and al. (1972)] .

2.3.5 Some general remarks on SEMTSA

The procedure outlined in the preceding sections ought to be considered as a guideline for modeling systems of dynamic equations. Zellner (1979) discusses some of the statistical problems associated with the SEMTSA approach, that require further research.

In many occasions, the data will not contain sufficient information to validate or reject all the assumptions underlying a simultaneous equation model, so that the tests will be inconclusive or that the investigator has to rely on non-tested assumptions.

Also, before starting with the specification analysis, one has to decide whether a full information analysis of the complete initial model is feasible and desirable or whether one has to opt for an analysis under limited information (not necessarily through limited information maximum likelihood).
Due to the size of the simultaneous equation models used in practice, a full information analysis will hardly be feasible in most instances - except perhaps for models constructed for a small scale purpose. In addition, one might expect an analysis under limited information to be robust against errors of misspecification in the remaining equations. With respect to the single equation methods applied to a simultaneous equation model with autoregressive errors, Hendry (1974) concludes that they pointed up the existence of misspecification and provided clues to its solution (p. 576). About the disadvantages of testing subgroups of larger hypotheses, as will happen with a specification analysis under limited information, Darroch and Silvey (1963) write (p. 557): "Separate tests of h_1 and h_2 may induce a poor test of $h_1 \cap h_2$ because it is possible that for some Θ with high probability, $L(h_1)$ and $L(h_2)$ are both 'near 1' while $L(h_1 \cap h_2)$ is small". For this reason, Byron (1974) suggests to test the restrictions on single structural equations first and, on the acceptance of all these tests, to test jointly for all overidentifying restrictions on the reduced form.

The computational intractability of an analysis under full information due to the size of the model has been put forward by Drèze (1976) as an argument in favor of limited information analysis in a Bayesian context. More recently, Malinvaud (1980) stressed this argument in a call for more research into estimation and testing procedures under limited information. In our application, we opt for an analysis under limited information and formulate the restrictions on the parameters of each equation separately.

3. An application of SEMTSA

3.1. Restricting a multivariate autoregressive model

3.1.1 Introduction

In this section we report the results of an empirical analysis of a vector autoregressive (VAR) model specified for seven quarterly seasonally unadjusted macroeconomic variables for the Netherlands. The VAR model serves as an initial model to which we subsequently apply a specification analysis, check for possible misspecification and investigate the overall consistency of the finally retained version of the model.
The sample covers the period 1952-1979. Among the chosen variables, there are the major macroeconomic indicators: the aggregated gross national expenditures in constant prices (Y) and their price index (P), the unemployment rate (U) and a wage variable (W), the nominal money balances (M) as measured by M_2 and a long term interest rate (R) on government bonds, and an index of import prices (PI). Domestic variables are included in pairs of a real or a nominal variable and the associated price index. The index of import prices is introduced in order to take into account some of the effects of changes abroad on the open economy of the Netherlands. The choice of the variables is quite similar to that made by Sims (1980). All the variables, except the interest rate, are logged.
In order to detect possible structural changes, the empirical analysis has first been done for the subperiod 1952-1973. Obviously, the choice of the year 1973 is not arbitrary. Two major developments are thought to have induced a structural change in the Dutch economy: the increase of the price of oil in 1973 and the change from a regime of fixed exchange rates to a system with partly flexible rates.

Given that a specification analysis starts with a fairly general model, we first fit an unrestricted fourth order VAR model to the seven variables described above. We also include a trend term and seasonal dummies, denoted by S_i , $i = 1, 2, 3$, and being equal to one in the i th quarter and zero otherwise. The variables have been arranged in the following order M, W, U, Y, P, R, PI .
As expected, the estimates of the unrestricted reduced form parameters are not very precise. They do not exhibit any regular pattern. Many coefficients are not significantly different from zero. The estimates are not reproduced here.

In order to investigate whether a four period lag structure is sufficiently general, the residual correlation matrices for the unrestricted VAR model have been computed. The overall picture is that the estimated correlations are quite small. If we use $2T^{-\frac{1}{2}}$ (twice the approximate large sample standard error), with T being the sample size, as a yardstick for the precision of the estimates, very few residual correlations are significantly different from zero. We conclude that the fourth order VAR model is acceptable as a starting point for the specification analysis. Of course, the visual inspection of the residual correlations is not a perfect substitute for formal testing of the appropriateness of the starting model with respect to the lag length.

A formal test such as implemented by Sims (1980) requires that we extend the set of explanatory variables and is expensive in terms of degrees of freedom.
For the period 1952-1973, none of the coefficients of the variables M, W, P, R and PI, lagged four periods was significantly different from zero at the conventional significance levels. This result led to the formulation of the null hypothesis of the coefficients of the five variables listed above. Using a large sample likelihood ratio test, we get $\chi^2(35) = 47.630$, which is not significantly different from zero at a 5% level $[\chi^2_{.95}(35) = 49.517]$.
A similar picture arises for the fourth order VAR model for the period 1952-1979. In order to take into account possible structural changes, a dummy variable, denoted D74 and with value one in 1974-1979 and zero elsewhere, has been included in the VAR model.
For the complete sample period too, it was decided to use a VAR model excluding the fourth lag of the five variables given above. The likelihood ratio test $\chi^2(35) = 55.08$ is significant at the 5% level. If we correct it for the loss of degrees of freedom, it will become insignificantly different from zero. The estimated residual correlations of these VAR models, which we will call the unrestricted models, are given in tables 8 and 10. Keeping the maximal lag for a given variable the same in all the equations of the model has the advantage that OLS estimates of the unrestricted reduced form separately will also be maximum likelihood estimates.

After the determination of the lag length, we next formulate restrictions on the parameters of the reduced form of the VAR model. Quite naturally, one is interested in the exogeneity of PI, which implies block triangular reduced form matrices [see e.g. Geweke (1978) for a discussion on exogeneity in systems of equations]. These restrictions are easily incorporated and tested.

A large sample likelihood ratio test yields a χ^2 (20)= 95.95 for 1952-1973 and a χ^2(20) = 115.10 for 1952-1979, wich are significant at the level .005. For the hypothesis of the block exogeneity of PI, R, P, Y and U, the test statistics χ^2 (30) = 193.69 for 1952-1973 and χ^2 (30) = 141.44 are significant at the level .005 too.

In the monetary approach to the balance of payments under a regime of fixed exchange rates, the variables PI, R, P, Y (and U) are sometimes assumed to be jointly exogenous with respect to the reserves flow, wich form a component of the money supply. The exogeneity of the five variables with respect to M is stronger than what is needed in the monetary approach to the balance of payments.

Rather suprisingly, there is little evidence in our data set pointing towards some block triangular structure of the VAR process.

This also holds true for the joint exogeneity of the real sector with respect to the monetary sector.

As the hypotheses of exogeneity formulated above do not seem to be supported by the data, we decide to use the unrestricted VAR model as a maintained hypothesis and to analyze it equation by equation.

Our aim is to formulate restrictions that are meaningful in terms of economic behavior and that are not contradicted by the information in the data.

A limited information single equation approach is clearly a second best strategy in terms of the power or the efficiency of the statistical procedures. However it is tractable and computationally less demanding compared to handling the complete model, possibly with nonlinear restrictions.

When modeling the equations separately we take the unrestricted VAR model as a maintained framework in which the alternative specifications for the single equations will be nested.

In this way, the maximum lag length is determined and the list of predetermined variables needed for two stage least squares (2 SLS) is given.The following specifications were chosen using theoretical considerations and the information from the estimated unrestricted reduced form. Here, the inclusion of a variable in differenced form in a specification is equivalent to imposing a linear restriction on the coefficients of the lag polynomials. As we assume that all the dynamics are incorporated in the 'systematic' part of the model, the equations can be consistently estimated by OLS or, when more than one current endogenous variables are present in an equation, by 2 SLS.

The results of the single equation analysis are reported in tables 1 to 7. The symbols Δ and c are used to denote the first difference operator and a constant term respectively.
The symbol D 74 represents a dummy variable wich is equal to one in the period 1974-1979 and zero otherwise.
A subscript indicates the number of lags. A variable denoted as x_0/x_{-2} can be written as $\Delta x_0 + \Delta x_{-1}$, when x is expressed in logarithms. Figures between brackets are t-values (in absolute value). The sign GP denotes Godfrey's π (1976), which has an approximate standard normal distribution. The choice of the specifications for the individual equations deserves a short explanation.

3.1.2 The demand for money (see table 1)

The specification has been retained after an extensive investigation into the shape of a demand for money function for the Netherlands (see Blommestein and Palm (1980)). The relative change of nominal money balances is explained by the relative change of real total expenditures averaged over two quarters and of its price index, the change in the interest rate and by the inverse of the velocity of money as perceived in period t - 1. This last explanatory variable -also called error correction term (see Davidson and al . (1978))- takes into account the effect on the change in money balances of a disequilibrium in money holdings compared to total nominal expenditures in period t - 1. As such the specification describes the serial correlation properties of the monetary balances very well. The steady state solution of the model implies a constant velocity of circulation.
The value of the velocity depends on the rates of change prevailing in a given steady state.
Alternative specifications, in which the interest rate level is included and which imply that the steady velocity of circulation also depends on the interest rate level, do not yield satisfactory results. The coefficient of the level of the interest rate usually was insignificant and had a 'wrong' sign.
The specification for the demand for money is not entirely stable over time. Some estimated coefficients change, when the sample period is extended . In particular , the effect of a change in the interest rates on the growth of money balances becomes positive although it is small and insignificant.

As the effect of ΔR is small, we retain the specification for both sample periods. When the lagged growth rate of money is left out of the specification all parameter estimates have the expected sign. However then there is much correlation left in the residuals, in particular for the complete sample period.

It should not be too surprising that the specification for the demand for money is not entirely stable. The change in the exchange rates system has had its impact on the behavior of economic agents. Furthermore the composition of M_2 has changed during the period of observation. The ratio of currency stock to demand and time deposits has decreased in the sixties and seventies. An analysis of the effects of this change requires a more disaggregated approach.

3.1.3 The wage equation (table 2)

The wage equation is a Phillips-curve type specification in which the relative change in nominal wages is explained by the unemployment rate and the expected rate of inflation, denoted as ΔP^*_t. We assume that expectations are rational, i.e. $P^*_t = E(P_t \mid \Phi_{t-1})$, where the expectations are taken, given the model and the set of variables up to the period t-1, Φ_{t-1}. Following McCallum's (1976) proposal the equation has been estimated by 2 SLS after substitution of ΔP_t for ΔP^*_t. In this way, consistent estimates of the parameters of the wage equation are obtained.

If we assume the 'natural' rate of unemployment to be constant the empirical finding that the coefficient of ΔP^*_t is not significantly different from one suggests that there is little or no long run trade - off between inflation and unemployment.

The constant term can be interpreted as being composed of the 'natural' rate of unemployment and some 'autonomous' wage rate change such as due to an increase of the contributions to social security and tax rates during the sample period. Notice also that there is some seasonality present in the equation. Phillips-curve type equations are used in macroeconomic models for the Netherlands (see e.g. Driehuis (1972)). The specifications of the wage equation in macroeconomic models in which usually the wage sum per worker in enterprises is explained are in general more sophisticated than the specification retained here.

Our choice of explanatory variables is limited through the size of the initial VAR model. Single equation modeling in the framework of a multivariate model naturally leads to an extension of the dimension of the model.

3.1.4 Unemployment (table 3)

The specification for the unemployment rate ought to be interpreted as a restricted reduced form equation. The variables finally included in the specification have been selected because their coefficients were significant in the unrestricted reduced form. The numerical values of the unrestricted reduced form parameter estimates pointed towards restrictions that could easily be imposed on the parameters.
The plausibility of the results in terms of the sign of the parameters, of the presence of some variables also played a role in the formulation of the restrictions. For instance, the restricted equation is homogeneous of degree zero in all nominal variables.
However, when using a formal large sample chi-square test, the set of restrictions imposed on the unemployment equations reported in table 3 are significantly different from zero at conventional levels of significance. Presently we retain the restricted version of the equation . In the analysis of the complete restricted model, we shall pay more attention to the specification of the unemployment equation.

3.1.5 Total expenditures (table 4)

As for the unemployment equation, the specification for aggregate expenditures in constant prices in table 4 should be interpreted as a restricted reduced form equation, where those variables have been included for which the unrestricted reduced form coefficient was plausible and significantly different from zero.
It seems to be difficult to give the specifications in table 4 a behavioral interpretation, given that the variable Y is the total of the expenditures of all agents in the economy. In the restricted equation, total expenditures are explained by real money balances, the change in the unemployment rate, the domestic inflation rate, the foreign price level and lagged expenditures .

Notice that the specification is not homogeneous in the nominal variables. Several alternative specifications, which were homogeneous of degree zero in nominal magnitudes or in which the effect of the level of the interest rate and of the unexpected component of the inflation rate were introduced, did not yield satisfactory empirical results. That a priori meaningful restrictions are apparently not supported by the sample information is possibly explained by the highly aggregate nature of the variable Y. Again, quite naturally one is led to expand the model though disaggregation of Y into consumption, investment and government expenditures, variations in inventory holdings and other expenditure categories.

3.1.6 The domestic price level (table 5)

The rate of change of the total expenditures deflator is explained by the relative change in the wages, the import price and total expenditures in constant prices. The rate of change in total expenditures has a negative impact on the rate of inflation.
As the constant term was very small and insignificant, we opted for a homogeneous specification for the price in the period 1952-1973. For the complete sample period , we include the dummy variable D 74, defined above.
In the specification for the domestic price variable, variations in prices are explained by changes in the major cost components, wages and imports, corrected for the variations is demand. As such the equation is a generalized version of the full cost pricing. (For more details on the theoretical justification of aggregate price equations, see e.g. Nieuwenhuis (1980)). As the first price equation in table 5 is homogeneous, it has a static equilibrium solution.
For the period 1974-1979 it is consistent with a steady state solution of about 8% p.a..

3.1.7 The interest rate (table 6)

Several specifications have been fitted to the interest rate. The closed economy version of the Fisher equation stating that nominal interest rates equal the real rate of interest plus the expected rate of inflation is not very useful in this context.

Furthermore it requires a model for the ex ante real rate of interest which has apparently not been constant in the Netherlands during the period 1952-1979. For our data, the closed economy version of the Fisher equation combined with alternative simple models for the ex ante real rate of interest did not yield standard errors of regression smaller than two percentage points.

An open economy version of the Fisher equation requires a two regime model. For the period of fixed exchange rates, one ought to expect the domestic interest rates of a small economy to be closely linked to the interest rates on international money markets. In a regime of flexible exchange rates, foreign interest rates and the spot and forward exchange rates are the major determinants of the domestic interest rates. For both regimes, the set of variables in the model has to be extended in order to get a theoretically satisfactory relation for the interest rate.

In this paper we do not follow this line, but try to specify a parsimoniously parametrized equation for the nominal interest rate on government bonds.

In the table 6, the nominal interest rate is explained by the liquidity ratio, the rate of inflation of imports, the domestic inflation rate averaged over two quarters, the change in the unemployment rate and the lagged nominal interest rate. The presence of a slight seasonal pattern shows up in the specification. The explanatory variables included in the equations of table 6 also appear in the interest rate equation of some macroeconomic models for the Netherlands. Notice that the rates of change are not expressed as percentage points but as fractions.

The estimate of the coefficient of the domestic price change, which is also a consistent estimate of the coefficient of the expected inflation rate, differs from the value that it ought to take according to the Fisher equation.

Finally, the results in table 6 suggest that the coefficient of R_{-1} is insignificantly different from one, so that a specification in which the change in the interest rate is explained is in line with our empirical findings.

3.1.8 The import price (table 7)

One would have expected that this variable passed the exogeneity test for the period of fixed exchange rates, as the import price is the product of the exchange rate times the price of import goods expressed in foreign currency, which could be assumed to be exogenous.
Given that we had to reject the exogeneity of the import prices, we decided to adopt a strategy of restricting the reduced form equation for the import price. The results of our analysis are reported in table 7, where the price of imports is explained by the change in money balances, the level of total expenditures and lagged import prices. The estimated coefficient of the lagged import price is very close to one, suggesting that the data support a specification in which the rate of change of import prices is the variable to be explained.
A dummy variable, T 89, has been included for the first quarter of 1974, when the shock of the oil price increase worked through in import prices. Notice that the variable T 89 has not been included in the unrestricted initial model. As the import price series includes prices of primary, intermediate and final import products, it is again difficult to give an interpretation in terms of economic behavior of the specification finally chosen. The signs of the estimated coefficients are in line with what one expects. For instance, an increase in the domestic rate of inflation may be expected to lead to an increase of the price of the competitive import commodities and/or to a decrease in the rate of exchange.
To summarize, whenever possible, we fitted a specification with theoretically meaningful restictions. Thereby, we limited ourselves to linear reflationships among the seven variables listed above and with maximum lag equal to four.
The specification analysis of the single equations is very similar to that in the traditional econometric approach.
When it was to difficult to formulate a behavioral relationship due to the limited number of variables included in the model, we opted for a strategy of restricting the single reduced form equations. Thereby we gave more weight to the information in the data than to a priori formulated restrictions. The model consisting of the equations reported in tables 1 to 7 will be called the restricted model.

The number of parameters in the initial model (196 for 1952-1973, 203 for 1952-1979) has been reduced by more than two third (64 for 1952-1973, 67 for 1952-1979).
Among the parameters of the restricted model, there are 15 seasonal parameters. The parameters of the restricted model seem to be fairly stable over the sample period. Three additional parameters have been included in order to take into account the structural changes that occured since 1973.

We have achieved a substantial reduction of the number of parameters, although we do neither claim that our model is the most parsimonious parametrization of the VAR model nor that we have not imposed any false restriction. With the exception of the dummy variable T 89 in the import price equation for the complete sample period, the restricted model is nested in our starting model. The estimates of the restricted model are not fully efficient as they are single equation (limited information) estimates. Due to the nonlinearity of the restrictions implied by the rational expectations assumption and the still fairly large number of parameters in the restricted model, we have not jointly estimated these parameters. Therefore, a test of the set of all restrictions simultaneously is not feasible.

3.2 Diagnostic checking

In order to check the adequacy of the restricted model, we computed the residual correlation matrices. They are given in the tables 9 and 11 for the two sample periods respectively. As the residuals of an equation do not necessarily sum to zero, the residuals have been taken in deviation from their sample mean.
The i-j th element of matrix Θ in tables 8 - 11 is the sample correlation between $\hat{u}_{it+\theta}$ and $\hat{u}_{jt}$. If we use $2\,T^{-\frac{1}{2}}$ as a yardstick for the significance of the individual residual correlations, 21 and 27 among the 392 residual correlations are significantly different from zero in the periods 1952-1973 and 1952-1979 respectively. Among them, there are 2 and 8 significant autocorrelations respectively.
Notice that many correlations are only marginally significant.
Although we did not jointly test the vector white noise assumption of the disturbances, we conclude from the residual analysis that the restricted model performs fairly well (compare the tables 8 and 10 with 9 and 11 respectively). Very few existing econometric models have been checked for the cross equation residual correlations.

3.3 Dynamic properties and forecasting performance of the model

After choosing a restricted specification we now look into the dynamic and predictive properties of the model. Instead of solving the characteristic equation, which is a polynomial of degree 28, we apply the simulation approach used by Sims (1980) to the unrestricted and the restricted versions of the model. First we write the model in recursive form, with the variables arranged in the following order M, W, U, Y, P, R and PI, with the recursive and reduced form equations for PI being identical. The equation for M includes the current values of the remaining six variables in the model. Given the openess of the Dutch economy, we expect that the variables PI, R and P are strongly and quickly influenced by changes in the world economy, while the four remaining variables are also more strongly determined by changes in the domestic economic conditions.

The solution of the model (excluding the seasonals and trend term) for the effect of a shock in the initial period equal to one standard error is given in the figures 1 to 7.

The solution of the homogeneous part of the model seems to be fairly stable. The inclusion of a trend term in the reduced form equations takes up most of the instability due to the sustained economic growth during almost the entire sample period. The value of the shock in the initial period is inferable from the figures. For instance, in figure 1, the shock of the restricted model for the period 1952-1973 equals .012 (see the response of M to M).

The response pattern is given for sixty quarters. In general the unrestricted and the restricted models exhibit a very different dynamic behavior. The length of the period and the amplitude of the dominant cycle increase and the shape of the solution becomes much smoother when restrictions are imposed. This empirical finding clearly shows that the dynamic multipliers of a model can be very sensitive to imposing restrictions on the parameters of the model.

Similar to the results obstained by Sims (1980) for the U.S.A., money innovations have persistent effects on the nominal variables in the unrestricted model. For the restricted model, the reactions to money innovations are cyclical. Monetary shocks have some effects on real variables in the unrestricted model.

The response of U in the restricted model has the same shape for all seven innovations, whereas the phase of the cycles in the response is different. The unemployment innovation is followed by an accomodating monetary policy, a decrease in Y first and an increase in Y later on. The reactions of wages and import prices to an unemployment innovation (in the restricted model) are similar to those for the U.S. data. They differ from the pattern obtained by Sims (1980) for Germany. The impact of wage shocks on real variables (U, Y) is small in the unrestricted model. It takes much longer than for German data, before the wage innovation has a negative effect on Y. The impact of a wage increase on unemployment becomes really perceptible after $2\frac{1}{2}$ year. Prices and wages have similar reactions to shocks in all the variables. Their response to nominal variables is greater than that to real variables. An expenditure innovation is followed by wage and price increases, by a reduction in unemployment first and an increase after a lag of 2 to 7 quarters. Its impact on interest rates is substantial, whereas that on import prices is negligible The shape of the reaction of Y, W and PI to an impulse in Y is the same for the Netherlands and for Germany. The impact of an initial price shock on nominal money balances is very different for the two periods (unrestricted model). In the first period, a price impulse leads to an expansion of money balances, while for the complete period, the money supply finally reacts negatively to an initial price increase. Real variables are not too sensitive to a price shock. However, they are affected by an increase in the interest rates. The reaction of W,P and PI to P has a similar shape in the Netherlands and in the U.S., whereas the responses of M, Y, W, P and PI to a price increase have similar pattern for Germany and the Netherlands. In the reaction of interest rates to a monetary impulse, the Keynesian liquidity effect lasts for two to three quarters in the period 1952-1973. It lasts much longer in the period 1952-1979. The Fisher effect, that increased liquidities lead to more (expected) inflation and therefore to higher nominal interest rates, is absent from the unrestricted model for 1952-1979. It is interesting to note that for long term U.S. interest rates for the period 1952-1971, the liquidity effect disappears after three to four quarters [see e.g. Taylor (1972)].

Finally, import prices have a negative effect on unemployment, followed by a positive effect, and a reverse effect on expenditures. The shape of the reaction of PI to its own impulse in the unrestricted model is similar to that for the U.S. and for Germany.

If we assume that the money supply, the nominal wages and the interest rates are the instruments for economic policy, controlling the money supply or the interest rates seems to be more effective than wage controls in reducing unemployment in the short run - at least according to the unrestricted model. When using the restricted model, monetary and wage policies seem to be more effective in fighting unemployment than an interest rate policy. They are equally effective in stabilizing the price level in the short run. Compared to the results for the U.S. and Germany given by Sims (1980), the pattern of the response functions is much more erratic. This is probably due to the use of seasonally unadjusted data in our study.

Notice finally that there is no indication in the simulation results of absence of Wiener-Granger causality [or of strong exogeneity, which is more stringent, see e.g. Engle and al (1980)] for any variable in the system as each variable is affected by shocks in any of the seven variables included in the model.

In conclusion given that imposing restrictions on the parameters can substantially affect the dynamic behavior of the model, one should be very careful in formulating restrictions and in interpreting the results of the restricted model.

Next, we check the properties of the final equations or the univariate ARIMA models associated with the VAR processes considered in this study. As there are no exogenous variables in these VAR processes, the analysis of the transfer functions outlined in section 2.3.4 cannot be done. From the results of the model simulations, we can conclude that the homogeneous part of our VAR models is stable.

First differencing of the variables eliminates the linear trend in the vector model and should be sufficient to induce stationarity.

Taking annual changes, $1-L^4$, where L is the lag operator, eliminates the linear trend and the seasonal dummy variables. Therefore, this transformation is expected to yield stationary seasonally adjusted series-provided the assumptions on the VAR process hold true.

The empirical analysis of the single series confirmed our findings for the multivariate model. Very simple scheme's are sufficient in order to model the seasonals in the series (see e.g. Zellner (1978) for modeling seasonality). In table 12, we report the estimated autocorrelation functions (ACF) and partial autocorrelation functions (PACF) of the differenced series. In table 13, the estimated univariate ARIMA models*) are given for the period 1952 - 1973.

Parsimoniously parametrized specifications have been chosen after an analysis of the estimated autocorrelation functions. One root of the characteristic equation for M and for P is slightly greater than one. All other roots are substantially greater than one. First differencing apparently induces stationarity, which confirms the results for the vector processes.

We should mention that the estimated ACF's and PACF's for W and for P are insensitive to the choice of the sample period. For Y, the ACF's and PACF's point towards some parameter instability, whereas for M, R and PI, a structural change in 1974 - 1979 shows up in the ACF's and PACF's.

As we had to use seasonal lag polynomials instead of dummy variables in the univariate models, it becomes difficult to check further implications of the unrestricted and the restricted VAR models for the properties of the lag polynomials of the final equations.

Still, as stated above, the univariate ARINA models can be used as a standard of comparison for the forecasting properties of the VAR models.

In the figures 8 to 14 the observations (in logarithms, except R) for the period 1952 - 1979 are plotted. For the period 1974 - 1979, we have also plotted the predictions from the univariate ARIMA processes, the unrestricted and the restricted VAR models. Each model has been estimated from the data up to 1973. The multi-step-ahead predictions, we compute, are mean-square error forecasts of the (logarithms of the) series given the model, observations up to the origin date and parameter estimates. Except for Y and PI, the forecasts of the series using the unrestricted VAR model are above the realized values, those for the restricted model are below the true series. The forecasts for the univariate ARIMA models are usually close to the observed values.

The medium term forecasts of the unemployment rate using the restricted VAR model are rather inaccurate.

*) The computations were performed using a computer program for nonlinear least squares estimation developed by C.R. Nelson, University of Washington, Seattle.

The forecast for U are very sensitive to the effect of the variable $(M/P)_{-1}$ in the restricted unemployment equation in table 3. The coefficient of that variable has been rounded off to 1.5.
The specification of the restricted reduced form equation is not entirely satisfactory.
In order to give an indication of the accuracy of the forecasts, we computed inequality coefficients. The ratio of the root mean square prediction error to the root mean square of the realizations for the period 1974 - 1979, denoted by U_i, is given in the following table.

Inequality coefficients, 1974 - 1979

i	U_i		
	unrestricted VAR	restricted VAR	ARIMA
M	.0192	<u>.0065</u>	.0075
W	.0617	.0240	<u>.0218</u>
U	.5116	.9643	<u>.3580</u>
Y	<u>.0030</u>	.0119	.0078
P	.0377	.0318	<u>.0221</u>
R	.1454	<u>.1039</u>	.1235
PI	<u>.0349</u>	.0842	.0800

For each variable, the smallest inequality coefficient is underlined.
The predictive accuracy of the three models is very different.
All the models are better than no-change extrapolations. The predictive performance of the univariate ARIMA scheme's is remarkably good. For three out of the seven variables, the ARIMA models have a lower inequality coefficient than the VAR models. Of course, these results should be interpreted with care. As we do not have the probability distribution of the inequality coefficients, we cannot use them to formally test the predictive properties. A straightforward way to contruct a statistical test would consist in generating a sequence of l-step ahead predictions, for given l, and establishing the distribution of their average.
Surprisingly the unrestricted VAR model predicts rather poorly compared to the ARIMA forecasts. In the absence of Wiener-Granger causality, one would expect the vector models not to predict better than univariate scheme's .

It should be noticed that the unrestricted model predicts the variables PI more accurately than the ARIMA scheme does.
To summarize this section, we investigated the lag length and the structural stability of a VAR model for seven macroeconomic variables for the Netherlands. Next we tested for the exogeneity of PI and for that of PI, R, P, Y and U jointly. Upon acceptance, these restrictions combined with the absence of instantaneous Wiener-Granger causality would imply a block recursive model, for which the transformation of the structural form into the reduced form would not affect the maximal lag length within a block.
But, given that the exogeneity restrictions had to be rejected, we restricted the individual equations in the model using a limited information approach along the lines of traditional econometric modeling. Thereby, we used the unrestricted VAR model as a framework in which the restricted model ought to be nested. We did not find much evidence in the residual correlations that points towards a misspecification of the restricted and unrestricted models. The dynamic properties of the unrestricted VAR model were found to be different from those of the restricted one. The accuracy of the forecasts from the unrestricted and the restricted VAR models and from the univariate ARIMA scheme's is different too. Both VAR models were found to be consistent on a number of points with the properties of the univariate ARIMA scheme's.
Finally, although the restricted VAR model can be improved in many ways, there is no clear indication of its inferiority compared to the unrestricted model, despite the dramatic reduction of the number of parameters.

4. Some tentative conclusions

In this paper, we first presented the traditional approach to econometric modeling and several procedures proposed and applied in the time series literature on modeling bivariate and multivariate processes. Then we outlined the main features of the SEMTSA, which is an attempt to integrate econometric specification analysis and time series modeling.
In the second part, we applied the SEMSTA to a VAR model for some of the main macroeconomic variables for the Netherlands. Although the restricted model obtained through SEMTSA has different dynamic properties than the unrestricted one, it does not seem to be inferior to the unrestricted VAR model in terms of the results of diagnostic checking and forecasting properties.

Certainly, the specification of the restricted model can be improved. As already indicated earlier, the formulation of behavioral and theoretically meaningful restricted relationships naturally leads to an expansion of the number of variables in the model.
For instance, the restricted reduced form equation for the unemployment predicts rather badly. However there is more information available on the medium term development of the labor market than we used in our model. The change of the total labor force, the hiring for the public sector... can be predicted fairly well over an horizon of two to three years. However, it is not possible to model this kind of details in small dimensional VAR models. High dimensional VAR models with a rich lag structure still are computationally intractable.
Clearly, a better understanding of the interaction of economic variables in time is needed. We fully agree with the statement by Nerlove (1972, p.277): "Without strong theoretical justification for a particular form of lag distribution, and perhaps even strong prior belief about the quantitative properties of that distribution and the factors on which those properties depend, it is generally impossible to isolate the lag distribution in any very definitive way from the sort of data generally available." .
However, we want to add that a theoretically justified dynamic model only lacks a confrontation with 'hard facts', i.e. the empirical validation of the model.
Finally, a number of questions arise with the formal procedures for econometric modeling in general. The statistical properties of the procedures presented and applied in SEMTSA are only partially known. Quite often, one has to reject a set of restrictions tested at once or sequentially when the overall size is fixed at conventional levels (e.g. using the Bonferroni inequality or the Scheffé procedure). This happens for the large sample χ^2 - test even if one corrects it for the loss of degrees of freedom as Sims (1980) does.
More research into the finite sample properties of the sequential tests used in specification analysis is needed and it is expected to be very rewarding. The contributions to the field of pretest estimators may be very valuable too, although some areas of application of pretesting which are relevant for SEMTSA are still relatively unexplored.

Instead of looking for the statistical properties of the modeling procedure as a whole, one can interpret it as a pursuit of consistency of the accepted model in its different forms with the information available such as a priori information on structural parameters and on multipliers, the conformity of the autocorrelations of the endogenous and exogenous variables and the residuals of the different forms with the properties of the autocorrelation functions implied by the finally accepted model. Many, econometricians consider this as a minimum requirement.

The data

The data are quarterly seasonally unadjusted observations on:

M_t = total domestic liquidities (M_2) in hands of the public averaged over the quarter (in millions of guilders).

W_t = index of weekly wages, according to regulations, private and public sector, vacations and other additional pay included, all adult employees, 1975 = 100.

U_t = quarterly average of unemployed males in percentage of total male employees.

Y_t = gross national expenses in quarter t, in millions of guilders per year, expressed in constant prices.

P_t = price index of gross national expenses, 1975 = 100.

R_t = average of the interest rates on the three most recently issued long term government bonds.

PI_t = the price index of all import goods, 1975 = 100.

The series M, U, Y, P and R have been collected at De Nederlandsche Bank, B.V., and were kindly provided to us by Professor Dr. M.M.G. Fase.

The series W and PI are published in Maandschrift van het C.B.S. (Centraal Bureau voor de Statistiek, Den Haag).

Table 1. The Demand for Money (2 SLS)

	ΔM_{-1}	$\left(\frac{M}{PY}\right)_{-1}$	ΔP_{-2}	ΔR_0	$\frac{Y_0}{Y_{-2}}$	S_1	S_2	S_3	C	
1952 - 73	.214	-.055	-.214	-.012	.071	.027	.040	.025	-.315	SER = .013
	(2.025)	(4.195)	(1.875)	(1.222)	(1.046)	(3.501)	(6.564)	(5.154)	(4.284)	DW = 1.888, GP = .075
1952 - 79	.408	-.045	-.059	.003	.069	.037	.044	.019	-.264	SER = .015
	(4.741)	(3.281)	(.523)	(.401)	(.990)	(4.669)	(6.952)	(3.878)	(3.443)	DW = 1.879, GP = .609

Table 2. The Wage Equation (2SLS)

	U_{-1}	ΔP^*_t	S_1	S_2	S_3	C	
1952 - 73	-.0028	.874	.017	.0028	.0058	.0063	SER = .016
	(.694)	(4.630)	(2.694)	(.472)	(1.162)	(1.543)	DW = 2.47, GP = -2.354
1952 - 79	-.0048	.713	.020	.0047	.009	.0073	SER = .016
	(1.801)	(4.050)	(3.786)	(1.008)	(2.071)	(1.944)	DW = 2.24, GP = -1.265

Table 3. Unemployment (OLS)

	$\left(\frac{M}{P}\right)_{-1}$	$\left(\frac{W}{P}\right)_{-3}$	ΔY_{-2}	$\left(\frac{P}{PI}\right)_{-3}$	$\Delta^2 PI_{-1}$	U_{-1}	U_{-2}	U_{-3}	U_{-4}	S_1	S_2	S_3	C	D74	
1952 - 73	-1.522	1.149	-.680	.085	-1.628	1.409	-.826	.513	-.095	.008	-.617	-.002	10.08		R^2 =.966 SER = .103
	(3.192)	(2.814)	(1.461)	(.285)	(3.576)	(13.60)	(4.665)	(2.958)	(.894)	(.073)	(5.937)	(.017)	(3.273)		ln L= 79.046 DW = 2.065
1952 - 79	-1.361	1.032	-1.531	.097	-1.127	1.392	-1.130	.980	-.266	.215	-.279	.091	8.903	.173	SER = .109, R^2 = .971
	(3.572)	(3.083)	(3.906)	(.432)	(3.109)	(16.46)	(8.535)	(7.415)	(2.925)	(2.973)	(4.163)	(1.050)	(3.605)	(2.739	ln L= 93.224 DW = 2.092

Table 4. Total Expenditures (2 SLS)

	$\left(\frac{M}{P}\right)_{-2}$	ΔU_{-1}	$\frac{P_0}{P_{-2}}$	PI_{-2}	Y_{-1}	Y_{-2}	Y_{-3}	Y_{-4}	S_1	S_2	S_3	C	t	
1952 - 73	.169 (2.304)	-.028 (1.116)	-.087 (.451)	-.165 (2.830)	.406 (3.368)	.524 (3.945)	-.302 (2.296)	.229 (1.876)	-.057 (2.737)	.014 (.747)	.027 (1.246)	1.311 (1.511)	.0006 (.626)	SER = .022 DW=2.002, GP =-.609
1952 - 79	.163 (2.573)	-.006 (.380)	-.055 (.296)	-.099 (4.055)	.431 (4.208)	.487 (4.400)	-.305 (2.858)	.152 (1.507)	-.075 (4.871)	.005 (.304)	.036 (2.152)	2.115 (2.467)	.002 (1.903)	SER = .023 DW=1.986, GP =-.428

Table 5. The Price Equation (2 SLS)

	ΔW	ΔW_{-1}	ΔY	ΔPI_{-1}	D74	
1952 - 73	.452 (9.375)	.133 (2.883)	-.036 (1.984)	.104 (1.848)		SER = .010 DW = 1.919, GP = -.803
1952 - 79	.461 (9.026)	.116 (2.636)	-.035 (1.914)	.048 (1.300)	.006 (2.615)	SER = .010 DW = 2.042, GP = -1.668

Table 6. The Interest Rate (2 SLS)

	R_{-1}	$\left(\frac{M}{YP}\right)_{-1}$	$\frac{PI_{-1}}{PI_{-3}}$	ΔU_{-2}	$\frac{P_0}{P_{-2}}$	S_1	S_2	S_3	C	
1952 - 73	.954 (34.72)	-.359 (1.012)	2.426 (2.604)	-.240 (1.425)	3.039 (1.984)	-.043 (.416)	.130 (.769)	.164 (1.106)	1.845 (.977)	SER = .197 DW = 1.621, GP = 1.579
1952 - 79	.928 (41.63)	-.953 (2.847)	2.080 (2.644)	-.424 (2.309)	.819 (.363)	.053 (.450)	.372 (2.187)	.368 (2.460)	-5.103 (2.810)	SER = .289 DW = 1.665, GP = 1.649

Table 7. The Price of Imports (OLS)

	ΔM_{-2}	$\left(\frac{P}{W}\right)_{-2}$	ΔP_{-2}	Y_{-2}	PI_{-1}	S_1	S_2	S_3	C	t	T89	
1952 - 73	.354 (2.635)	.206 (3.483)	.391 (2.952)	.161 (3.548)	.899 (24.63)	.018 (3.610)	.015 (2.290)	.011 (1.720)	-1.607 (3.078)	.0003 (.410)		SER = .016, R^2= .94 ln L= 236.047, DW=1.37
1952 - 79	.245 (2.077)	.176 (3.080)	.360 (2.459)	.080 (1.706)	.987 (61.608)	.017 (3.153)	.018 (2.713)	.008 (1.271)	-1.049 (1.799)	.0010 (1.426)	.167 (8.563)	SER = .018, R^2= .99 ln L= 281.72, DW=1.38

Table 8. Residual Correlation Matrices for the Unrestricted Reduced Form, 1952 - 1979.

Θ = 0

1.00	-.01	.16	-.05	.04	.03	.11
-.01	1.00	.03	.13	.53	.21	.08
.16	.03	1.00	-.30	.08	-.01	-.06
-.05	.13	-.30	1.00	-.19	.03	.11
.04	.53	.08	-.19	1.00	.14	.19
.03	.21	-.01	.03	.14	1.00	.39
.11	.08	-.06	.11	.19	.39	1.00

Θ = 1

.02	-.01	.02	-.04	.08	-.02	.08
.08	.00	.04	-.00	.03	.03	.11
.04	.05	.05	.02	-.02	.06	.08
.05	-.00	-.03	.03	-.03	-.04	-.07
.03	.02	.00	-.02	.18	.03	.22
.01	.06	.01	-.07	.03	.04	.14
.01	.06	.03	-.04	.07	.11	.37

Θ = 2

-.07	.01	.10	-.06	.05	-.03	.13
.13	.03	.13	.01	.11	.04	.22
.00	.03	.15	.04	-.01	.01	.12
.09	-.04	.05	-.06	-.02	-.00	-.03
.07	.08	.04	-.03	.16	.09	.26
.06	.03	-.09	.00	.16	.10	.24
.06	.05	-.03	-.03	-.09	.05	.09

Θ = 3

-.04	-.08	-.06	-.10	-.00	.03	.24
-.00	.01	.01	.02	.12	-.02	.11
-.01	.07	-.02	-.13	.03	.17	.14
-.02	-.13	.04	.08	-.01	.01	-.08
.08	-.06	.02	-.01	-.07	-.00	.20
-.12	-.11	-.05	.03	-.09	.10	.08
-.05	-.07	-.06	.04	-.19	.03	-.02

Θ = 4

-.00	.20	.15	-.17	.10	-.05	.12
.04	-.11	.13	-.02	.11	-.00	.13
.01	-.03	-.07	-.01	-.15	-.08	.12
-.03	-.17	.06	-.03	-.02	.01	.08
-.06	.08	.05	-.06	.11	.06	.18
-.08	-.07	-.09	-.12	-.04	-.13	-.10
-.08	-.09	.07	-.13	.01	-.10	-.12

Θ = 5

-.06	-.07	-.26	.12	-.03	.05	.02
.08	-.04	-.07	-.03	-.04	-.03	.11
-.15	.01	-.20	.15	.03	.08	.11
-.03	-.10	.05	-.09	-.05	.00	-.11
.13	.10	.04	.01	-.14	-.02	.15
.01	-.01	-.03	.09	-.13	-.12	-.12
.01	-.12	.07	-.01	-.14	-.12	-.15

Θ = 6

.13	.00	-.04	.12	-.02	.08	-.04
.17	-.08	.05	-.02	-.08	.03	.17
.05	-.12	-.13	.01	-.14	-.05	-.12
-.05	.12	-.05	.16	.07	.07	.10
.23	-.10	.23	-.16	-.15	-.12	.01
.02	.01	.02	.09	.02	-.07	.02
.14	.01	.17	.02	-.04	-.12	-.10

Θ = 7

-.04	.08	-.00	-.18	.11	-.12	-.11
-.00	.08	-.09	-.08	-.04	-.04	-.04
.04	-.02	-.19	.06	-.09	.01	.03
.02	-.05	-.13	-.08	.01	.00	-.01
-.02	-.06	.09	-.06	-.12	-.15	-.10
.04	-.08	.07	.05	-.11	-.26	-.04
.01	-.11	.10	-.08	-.17	-.08	-.16

Θ = 8

-.02	-.22	.12	-.09	-.04	-.16	-.07
.08	.08	.10	-.03	.06	.04	-.00
.03	-.08	.10	.03	-.13	.14	-.09
-.00	.21	-.06	-.12	.08	-.01	-.04
-.07	.03	.15	-.05	.08	.06	-.02
.24	.12	.15	.18	-.03	-.04	-.14
-.04	-.02	.05	-.05	-.00	-.02	-.02

Table 9. Residual Correlation Matrices for the Restricted Reduced Form, 1952 - 1979.

Θ = 0

1.00	-.10	.14	-.10	.02	.01	.09
-.10	1.00	.01	.12	-.19	.13	.05
.14	.01	1.00	-.25	.02	-.09	-.02
-.10	.12	-.25	1.00	-.18	.03	.28
.02	-.19	.02	-.18	1.00	-.10	.07
.01	.13	-.09	.03	-.10	1.00	.25
.09	.05	-.02	.28	.07	.25	1.00

Θ = 1

.05	.04	-.19	-.07	-.04	.11	-.10
.08	-.12	.05	.04	.12	-.15	-.05
-.04	.09	-.05	.07	.08	-.13	-.13
.17	-.18	-.16	.01	.13	.11	.12
.09	-.07	.14	.11	-.06	.05	.21
-.11	.08	.06	-.15	.08	.16	.03
.07	-.03	-.11	.02	.29	.19	.28

Θ = 2

.00	.17	.13	-.08	-.19	.16	.07
.08	.00	.10	-.00	.05	.01	.12
.02	-.10	.18	.17	-.07	-.13	-.02
-.14	.11	-.03	-.09	.06	.07	.05
-.10	.07	-.27	.16	-.02	.08	.01
.07	-.10	.02	.05	.15	-.04	-.03
.13	-.07	-.15	-.06	.00	.17	.01

Θ = 3

-.07	.05	.11	-.07	.06	.07	.10
-.08	.04	-.13	-.12	.08	-.01	-.05
-.14	.07	-.06	.03	.06	.25	.04
-.13	.00	-.09	.12	.09	.06	-.01
.14	-.16	.11	-.00	-.14	.02	-.04
-.03	-.17	-.07	.04	.01	-.02	-.07
-.12	.09	-.22	-.04	-.04	.29	-.01

Θ = 4

.18	.20	.33	-.15	-.04	-.13	.08
.06	.03	.07	-.01	.14	.08	-.01
-.05	-.03	.14	.00	-.02	.03	.19
-.04	-.12	-.03	.06	.15	-.02	.09
-.10	.15	-.02	-.15	.12	-.00	-.14
-.03	.01	-.07	-.09	-.07	-.16	-.30
-.04	.00	.11	-.20	.09	-.05	-.02

Θ = 5

-.13	.04	-.17	.17	.09	-.05	-.18
.05	-.05	-.02	-.03	.03	.03	.14
-.15	.06	-.07	.21	.28	.07	.06
.06	-.09	.02	-.08	-.02	-.08	-.00
.01	.20	.04	.09	-.20	-.09	.02
-.03	-.04	.10	.05	-.15	-.07	-.20
.09	-.05	.06	.01	.05	-.14	-.03

Θ = 6

.06	-.01	.11	-.04	-.06	.06	-.07
.16	-.00	.05	-.02	-.04	.03	.04
.03	-.17	-.05	.07	.06	.00	.06
.03	.04	-.19	.22	-.07	-.01	.02
-.02	-.04	.05	-.01	.05	-.11	-.15
-.06	.11	.13	.00	-.02	-.12	-.03
.16	.10	-.04	.06	-.06	-.08	-.04

Θ = 7

-.15	.15	.06	-.11	.05	-.05	.05
-.02	-.00	-.13	-.07	-.06	-.08	-.18
-.11	-.00	-.16	.08	.08	.10	.10
.13	-.04	-.05	-.13	.00	.03	-.07
-.07	-.10	.07	.04	-.07	.02	.06
-.00	-.03	.10	-.06	.12	-.30	-.16
.01	.06	.01	-.13	-.15	-.05	-.25

Θ = 8

.09	-.11	.22	-.13	.17	-.15	.07
.00	.21	.13	.02	.00	.07	-.01
.09	-.04	.19	.10	-.02	.08	.03
.00	.23	-.06	-.17	-.05	-.04	.07
-.15	.14	.06	-.01	.20	.03	-.02
.10	.09	.16	.22	-.13	.02	.00
-.04	-.02	.13	-.11	-.10	.04	-.07

The underlined figures (in absolute value) are greater than two approximate standard errors, $2T^{-\frac{1}{2}}$, T = 108.

Table 10. Residual Correlation Matrices for the Unrestricted Reduced Form, 1952 - 1973.

θ = 0

1.00	-.14	.15	-.04	-.07	-.09	.24
-.14	1.00	-.14	.17	.42	.22	.11
.15	-.14	1.00	-.28	.06	.07	-.09
-.04	.17	-.28	1.00	-.13	.01	.27
-.07	.42	.06	-.13	1.00	.14	.08
-.09	.22	.07	.01	.14	1.00	.31
.24	.11	-.09	.27	.08	.31	1.00

θ = 1

.01	.01	.01	-.07	.14	-.06	.14
.08	-.07	.05	-.06	.03	.03	.10
.02	.01	.00	-.03	.10	-.02	.09
.15	.02	-.01	.02	-.04	.00	.01
-.04	-.05	-.11	.01	.17	-.04	.17
.04	.04	.03	-.03	.14	-.07	.12
.03	-.01	.03	.05	.09	-.02	.16

θ = 2

-.17	.03	.14	-.02	.00	.04	.06
.11	.01	.05	.06	.13	-.08	.11
-.06	.04	-.06	.04	.15	-.01	.09
.02	-.15	.03	-.08	-.06	-.05	.05
.11	.14	-.02	.08	.17	.08	.23
-.07	.09	-.09	.16	.03	.03	.04
-.05	-.07	-.02	-.01	-.21	-.05	-.05

θ = 3

.09	.06	.07	-.06	-.01	-.02	.14
-.06	-.09	-.07	.06	.06	.08	.04
-.01	.04	-.05	-.13	.13	.19	.16
-.03	-.15	.08	.04	.00	-.15	-.13
.05	-.11	-.04	.07	-.22	.12	.18
.04	-.12	-.05	-.03	-.07	.18	-.19
.12	-.07	.09	.04	-.27	.05	-.07

θ = 4

.07	.17	.20	-.18	.05	-.07	.01
.07	-.16	.18	.05	.01	-.01	.13
.01	.10	-.11	-.03	-.10	-.06	.09
.05	-.10	.20	-.09	-.04	.00	-.01
.01	.08	-.01	.16	-.09	.06	.14
.10	-.12	-.05	-.12	-.06	-.21	-.03
-.02	-.14	.13	-.08	-.04	.02	-.04

θ = 5

-.19	-.16	-.05	.07	-.06	-.07	.01
.02	.03	.00	.09	-.14	.10	.20
-.26	.05	-.12	.11	.01	-.06	-.02
.13	-.06	.14	-.16	.02	.10	.04
.11	.10	-.05	.14	-.28	.16	.18
-.02	.14	-.02	.20	-.02	.06	.08
-.12	-.08	.04	-.04	-.10	.09	.01

θ = 6

.16	-.05	.07	.18	-.16	.13	.06
.05	-.04	.00	.14	-.11	-.01	.14
.08	-.17	-.02	-.05	-.25	-.06	-.22
-.02	.14	-.03	.03	.12	-.06	.18
.17	-.07	.16	-.03	-.10	-.12	-.05
.04	-.01	-.12	.10	.05	-.14	.07
.01	-.06	.04	-.00	-.02	-.01	.02

θ = 7

-.11	.11	-.11	-.10	.10	.15	.11
-.04	-.01	-.12	.02	-.20	-.11	-.15
.15	-.06	-.17	.03	-.16	-.03	.10
.01	.13	-.05	.00	.04	.11	-.07
-.08	-.24	.09	-.04	-.20	-.16	-.15
.06	.03	.01	.11	-.14	-.13	.05
-.07	-.05	.02	-.15	-.18	-.15	-.29

θ = 8

-.18	-.17	.13	-.10	-.05	-.15	-.10
.09	-.09	.07	-.06	-.18	-.00	-.13
-.03	-.13	.16	-.01	-.17	.12	.00
-.01	.27	.05	-.20	.07	.10	.05
-.04	-.07	.18	-.10	.07	-.06	-.17
.10	.09	.00	.17	.00	-.08	-.05
-.23	.10	-.12	.04	.04	-.01	-.08

Table 11. Residual Correlation Matrices for the Restricted Reduced Form, 1952 - 1973.

θ = 0

1.00	-.06	.12	-.08	-.01	.14	.19
-.06	1.00	-.09	.19	-.16	.12	.11
.12	-.09	1.00	-.25	.13	-.08	.00
-.08	.19	-.25	1.00	-.15	-.10	.23
-.01	-.16	.13	-.15	1.00	-.14	.11
.14	.12	-.08	-.10	-.14	1.00	.19
.19	.11	.00	.23	.11	.19	1.00

θ = 1

.02	.01	-.02	-.02	-.01	.01	-.08
.01	-.26	-.03	.09	.18	-.13	-.13
-.11	.22	-.03	.15	-.00	-.07	.03
.14	-.23	-.05	-.01	.09	-.02	.07
.10	.01	.14	.01	-.01	.09	.09
-.07	.13	-.11	.12	.03	.19	.05
.04	.00	.00	.16	.29	-.09	.27

θ = 2

.10	.14	.11	-.03	-.17	.02	.01
.00	-.04	.15	.05	-.02	.15	.20
-.16	-.08	.04	.12	-.05	-.13	.02
-.19	.21	-.01	-.08	.04	.18	.08
-.09	.01	-.20	.15	-.02	-.12	-.01
.26	-.18	-.06	.12	.09	.12	.06
.11	-.05	-.10	-.03	-.01	.02	-.00

θ = 3

-.02	-.04	.04	-.01	.05	-.07	-.06
-.15	.05	-.10	-.12	.11	.04	-.16
-.06	-.06	.09	-.04	.07	.14	.16
-.10	.04	-.10	.09	.11	-.03	-.07
.22	-.18	.08	.02	-.16	-.04	.02
.09	-.10	-.16	-.08	.10	.15	-.20
.01	.05	-.23	-.04	-.02	.20	-.03

θ = 4

.17	.23	.25	-.07	-.05	-.04	.03
.09	-.08	.07	-.01	.12	-.13	-.05
-.09	.00	.11	-.11	.02	.04	.11
.09	-.14	.04	.06	.14	.00	.13
-.07	.10	.03	-.16	.06	.05	-.09
.15	-.08	-.16	-.09	-.10	-.12	-.29
.13	.01	.02	-.17	.10	.13	-.01

θ = 5

-.16	-.04	.05	.25	.13	-.12	-.10
-.02	-.06	-.02	-.03	-.04	.04	.07
-.24	.09	-.02	.18	.22	-.08	.03
.13	-.07	.04	-.08	-.02	.21	.04
.06	.31	-.04	.12	-.20	-.02	.02
.07	-.14	.04	.11	-.12	-.12	-.17
.09	-.05	.18	-.04	.08	-.08	.02

θ = 6

.06	-.10	.19	.09	-.04	.08	.00
.10	.02	.02	.02	-.09	-.03	.00
.05	-.15	-.01	-.01	-.01	.08	-.01
.03	.06	-.16	.12	.05	-.13	-.02
-.01	-.07	.04	.07	.05	-.17	-.13
.04	.11	.01	.03	.01	-.09	.00
.26	.16	.07	.02	.05	-.11	-.08

θ = 7

-.22	.16	-.02	.01	.02	.01	.07
-.14	-.05	-.02	-.03	-.15	-.17	-.24
.10	-.08	-.10	-.06	.10	.06	.15
.07	-.07	-.00	-.08	-.03	.03	-.04
-.02	-.16	.07	-.05	-.01	.08	.04
-.03	.15	.05	.15	-.01	-.18	-.06
.09	-.01	.01	-.05	-.13	-.18	-.30

θ = 8

-.08	-.05	.18	-.07	.15	-.18	-.01
.06	.17	.05	-.07	.02	.02	-.02
.09	.02	.20	.06	-.00	.00	.01
.00	.27	-.04	-.18	-.06	.04	.11
-.17	.16	.03	-.02	.27	-.02	.02
.04	.11	.02	.24	-.10	-.07	-.02
-.03	-.04	.07	-.07	-.07	-.06	-.04

The underlined figures (in absolute value) are greater than two approximate standard errors, $2T^{-\frac{1}{2}}$, $T = 84$.

Table 12. Estimated Autocorrelations (A) and Partial (P) Autocorrelations for the Series, 1952 - 1973

Series*	Filter		1	2	3	4	5	6	7	8	9	10	11	12	S.E.	13	14	15	16	17	18	19	20	21	22	23	24	S.E.
M	$1 - L^4$	A	.83	.62	.41	.23	.15	.09	.03	.03	.08	.15	.18	.17	.11	.14	.12	.17	.24	.30	.33	.33	.31	.28	.20	.13	.05	.21
		P	.83	-.24	-.07	-.08	.17	-.10	-.04	.09	.18	.05	-.12	-.02	.11													
W	$1 - L$	A	-.10	-.08	-.05	.23	-.13	-.09	-.09	.38	-.04	-.06	-.06	.31	.11	-.13	-.04	-.05	.27	-.11	-.07	-.17	.20	-.09	-.05	.00	.28	.13
		P	-.10	-.09	-.07	.22	-.10	-.08	-.10	.32	.05	-.00	-.04	.19	.11													
U	$1 - L^4$	A	.90	.70	.46	.22	.05	-.07	-.14	-.19	-.24	-.28	-.33	-.35	.11	-.33	-.28	-.19	-.09	.01	.09	.15	.17	.15	.09	.04	-.01	.24
		P	.90	-.61	-.10	-.02	.27	-.31	.07	-.21	-.04	-.05	-.08	.09	.11													
Y	$1 - L^4$	A	.73	.55	.31	.07	-.03	-.10	-.18	-.27	-.24	-.24	-.24	-.14	.11	-.12	-.07	-.03	-.05	-.05	-.04	-.01	-.00	-.02	-.09	-.16	-.16	.20
		P	.73	.03	-.23	-.20	.12	.01	-.19	-.21	.19	.02	-.23	.08	.11													
P	$1 - L^4$	A	.82	.66	.44	.25	.20	.18	.20	.23	.23	.21	.16	.08	.11	-.01	-.10	-.17	-.17	-.12	-.06	.01	.04	.07	.08	.07	.08	.23
		P	.82	-.05	-.26	-.07	.31	.06	-.03	.02	.01	-.01	-.05	-.09	.11													
R	$1 - L$	A	.31	.07	.03	-.03	-.05	-.14	-.17	-.01	.02	-.13	-.13	-.12	.11	.05	.09	.08	-.01	-.01	.02	-.03	-.03	.02	.02	-.01	-.00	.13
		P	.31	-.03	.02	-.05	-.03	-.12	-.10	.08	.01	-.17	-.07	-.09	.11													
PI	$1 - L$	A	.19	.15	.16	.23	.03	.00	-.18	.10	.05	-.14	-.07	-.02	.11	-.03	-.02	-.02	-.05	-.03	-.01	.01	.00	.00	.08	.06	.11	.13
		P	.19	.11	.12	.18	-.06	-.06	-.25	.15	.08	-.13	.01	-.07	.11													

*Notice that all series, except R, are logged.

Table 13. Estimated Univariate ARIMA Models for the Series, 1952 - 1973.

series	The estimated model	RSS	DF	$\hat{\sigma}^2_\varepsilon$ (back forecast residuals excl.)	Q_{12}	DF	Q_{24}	DF	Q_{36}	DF
M	$(1 - 1.220L + .240L^2)(1 - L^4) M_t = .0017 + (1 - .666L^4) \varepsilon_t$ (112.8) (6.445) (.745) (6.445)	.0164	80	.00020	8.6	8	15.0	20	19.7	32
W	$(1 - .250L^4)(1 - L) W_t = .015 + \varepsilon_t$ (2.372) (4.911)	.0410	85	.00048	13.7	10	26.8	22	33.5	34
U	$(1 - 1.546L + .634L^2)(1 - L^4) U_t = -.001 + (1 - .601L^4) \varepsilon_t$ (18.24) (7.365) (.242) (6.185)	1.120	80	.0134	7.5	8	11.5	20	20.8	32
Y	$(1 - .721L - .024L^2)(1 - L^4) Y_t = .013 + \varepsilon_t$ (6.396) (.215) (2.531)	.06693	81	.00082	14.0	9	18.9	21	22.3	33
P	$(1 -.864L + .010L^2)(1 - L^4) P_t = .0068 + \varepsilon_t$ (7.812) (.091) (2.219)	.0178	81	.00022	16.2	9	24.9	21	26.6	33
R	$(1 - 313L)(1 - L) R_t = .034 + \varepsilon_t$ (3.043) (1.481)	3.864	85	.0454	6.9	10	8.4	22	11.7	34
PI	$(1 - L) PI_t = .00002 + (1 + .214L + .317L^4) \varepsilon_t$ (.005) (2.111) (3.456)	.0347	84	.00039	18.2	9	21.1	21	26.7	33

Figure 1. Responses of M to shocks of

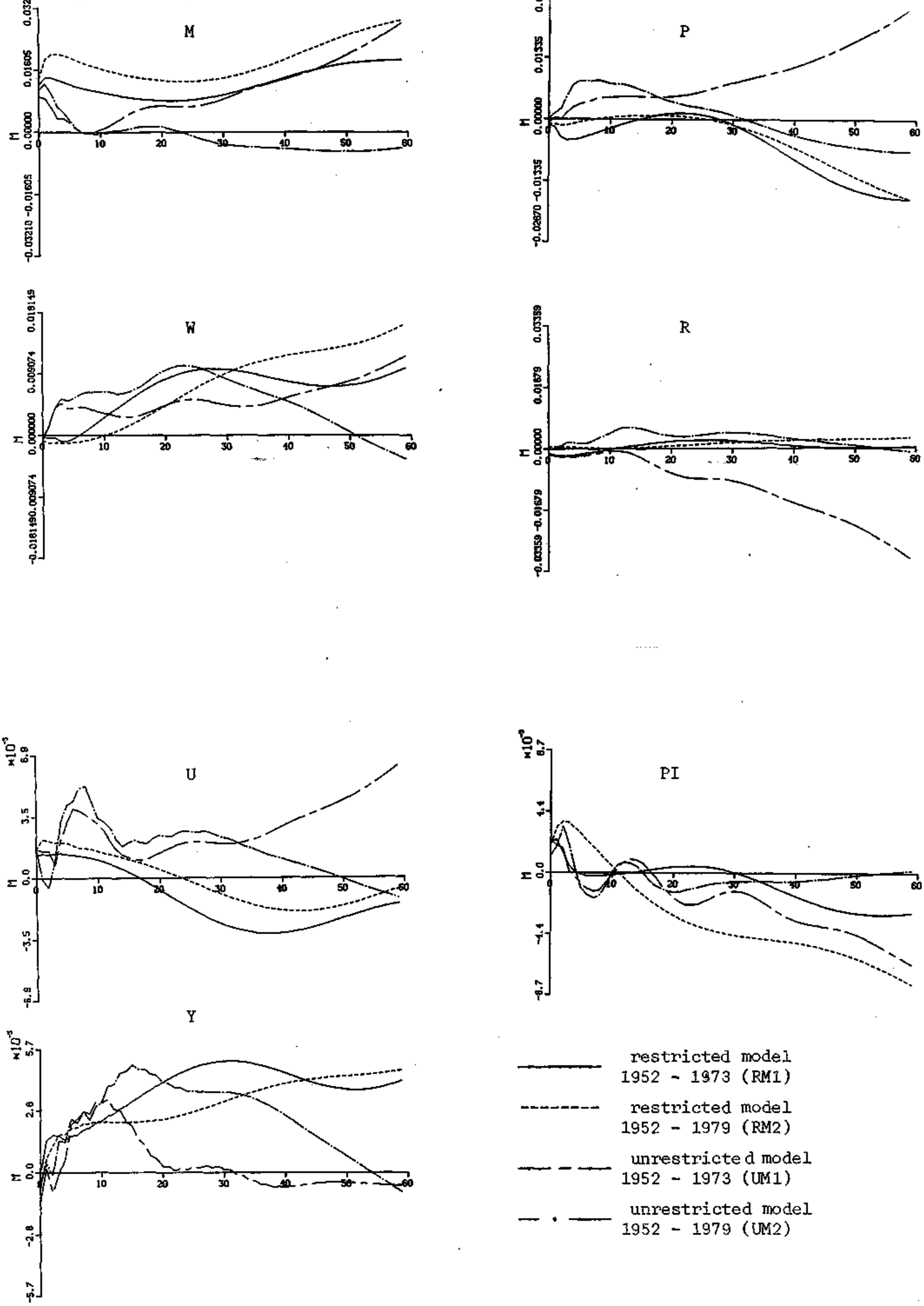


Figure 2. Responses of W to shocks of

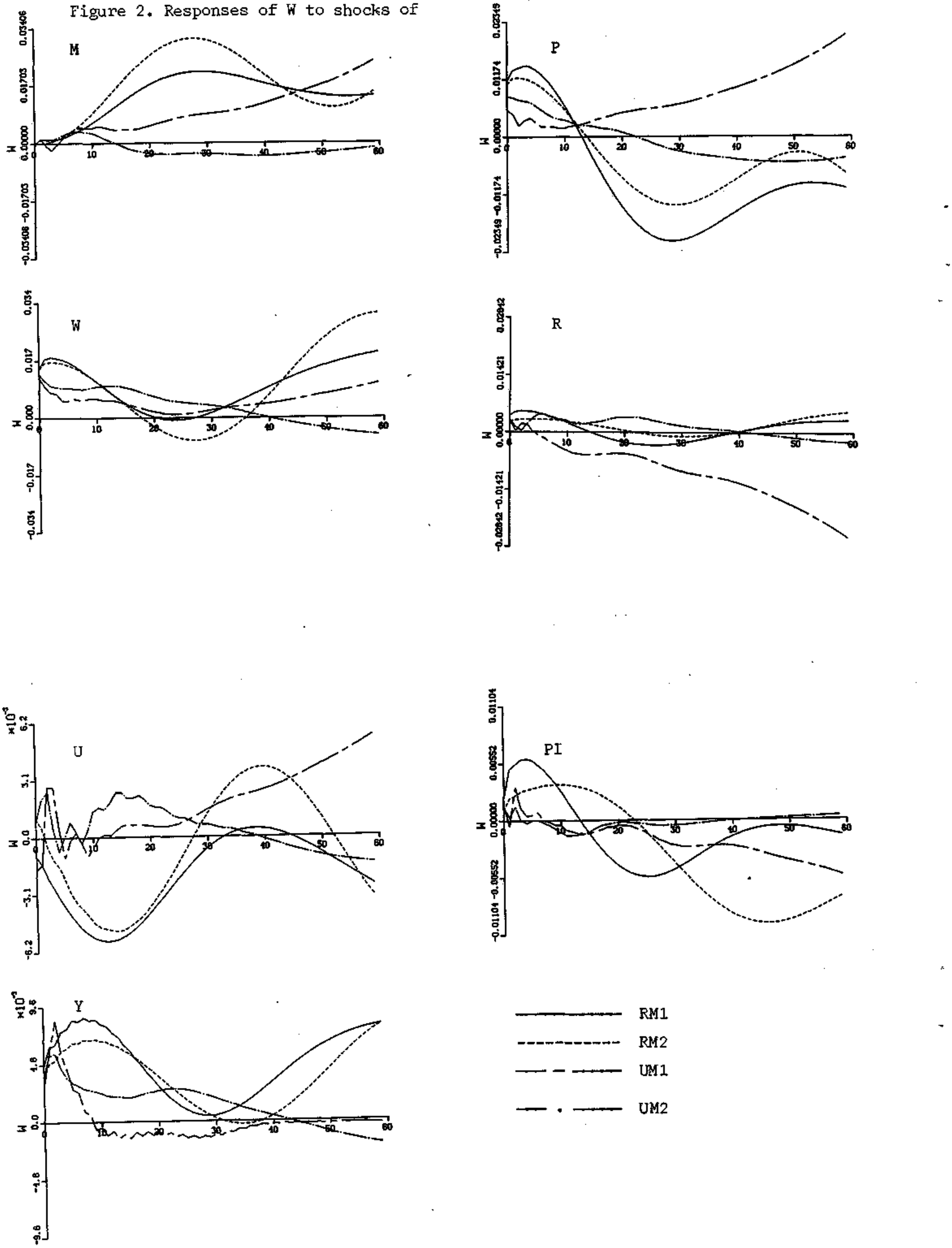


Figure 3. Responses of U to shocks of

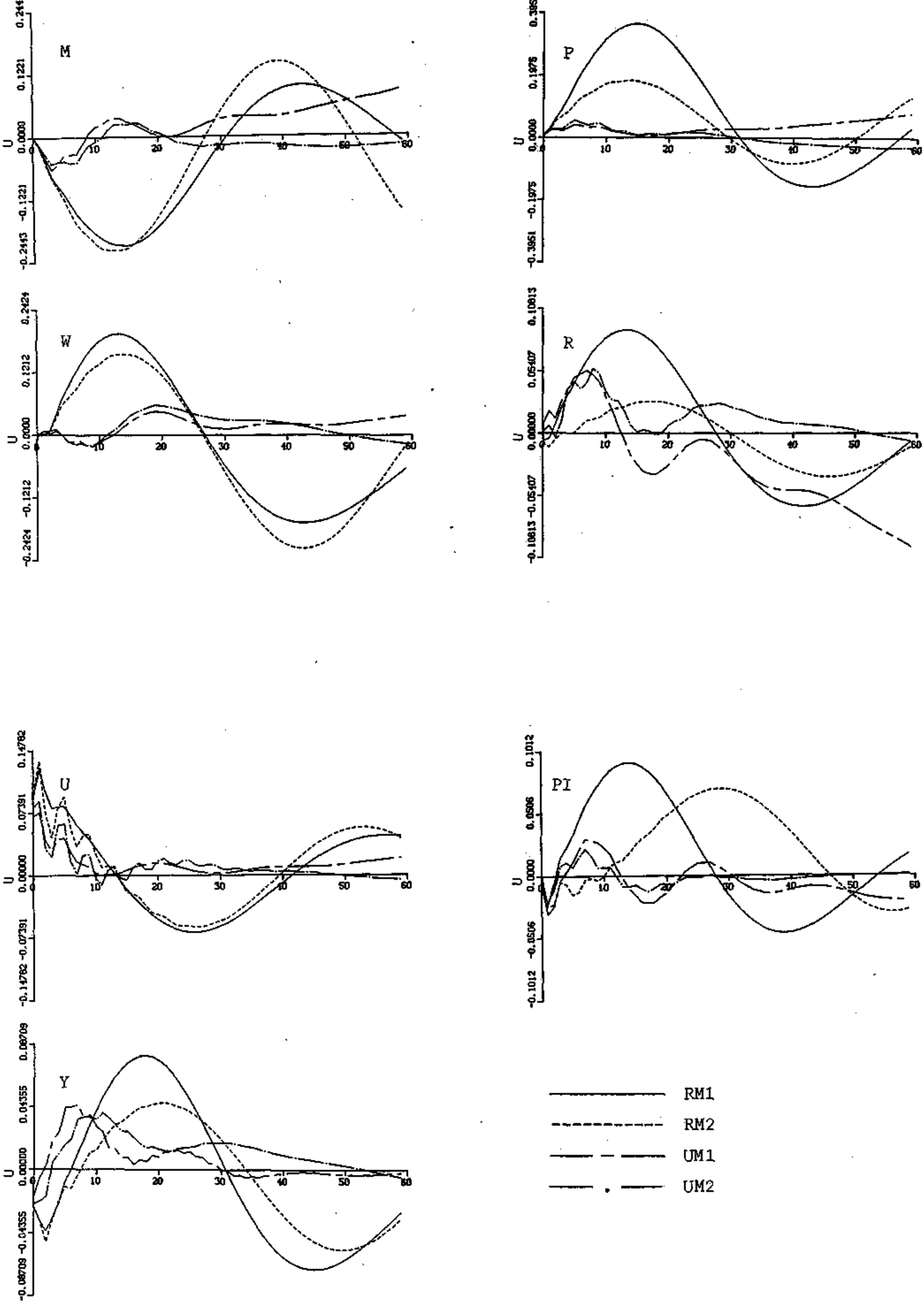


Figure 4. Responses in Y to shocks of

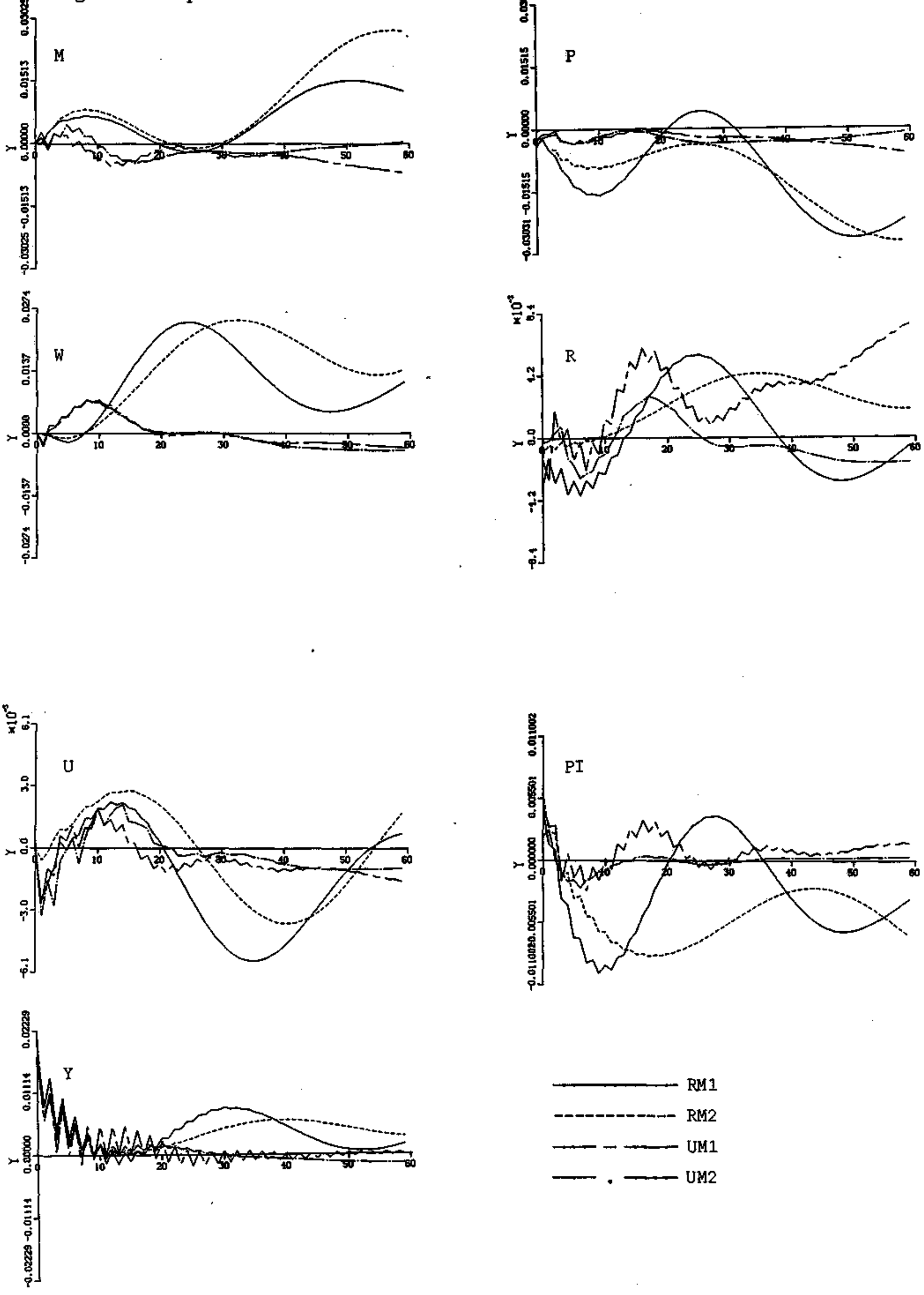


Figure 5. Responses of P to shocks of

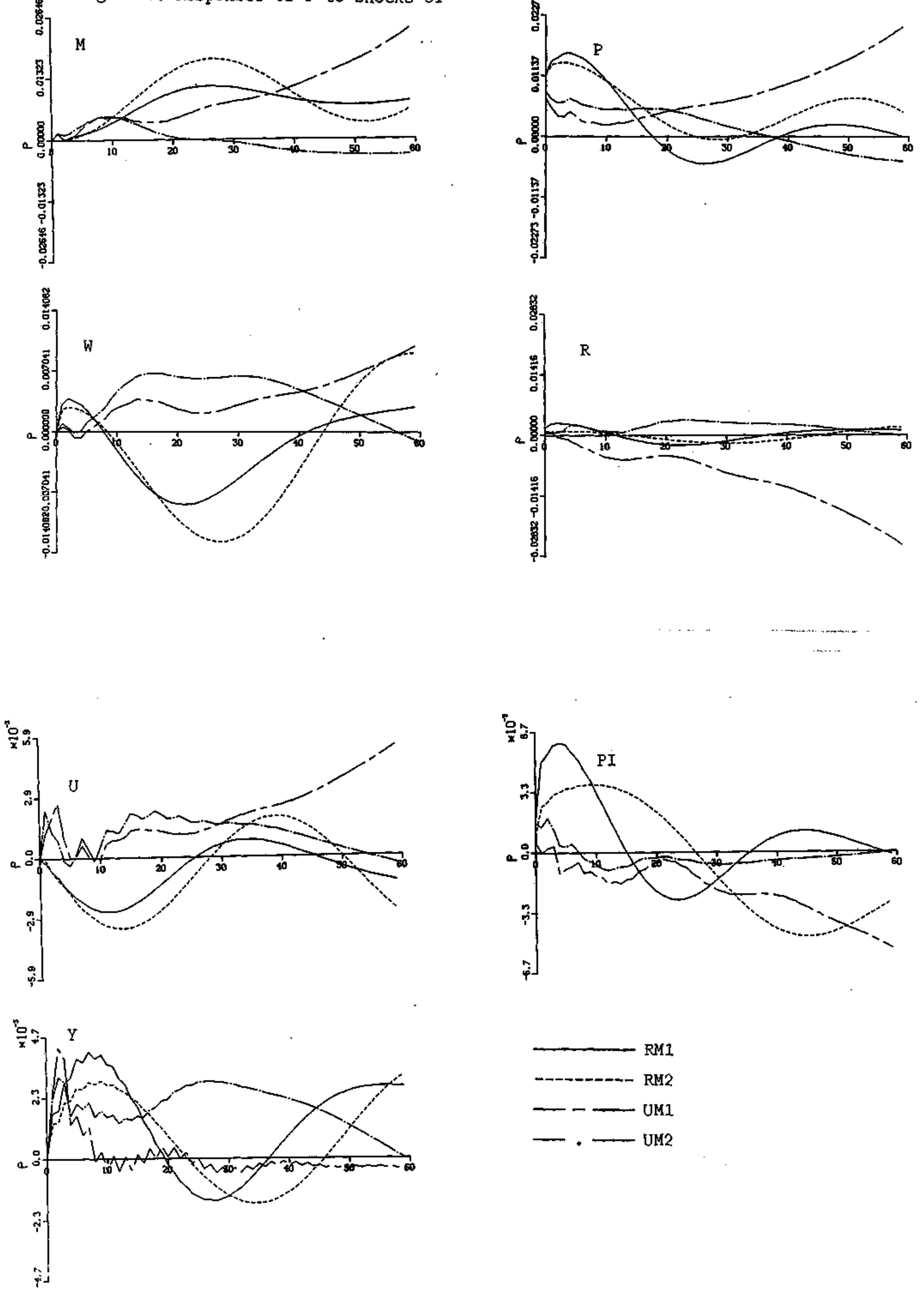


Figure 6. Responses of R to shocks of

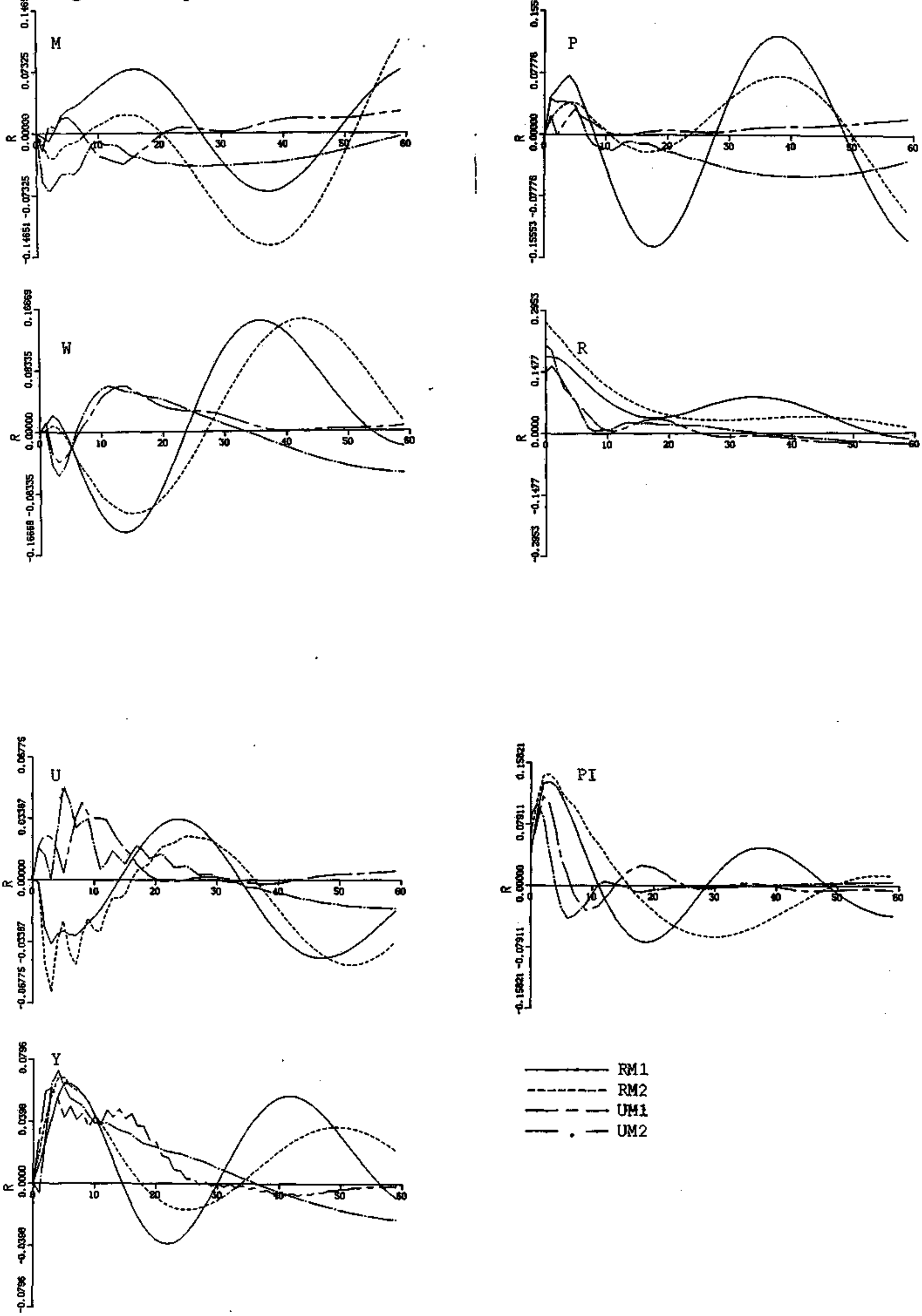


Figure 7. Responses of PI to shocks of

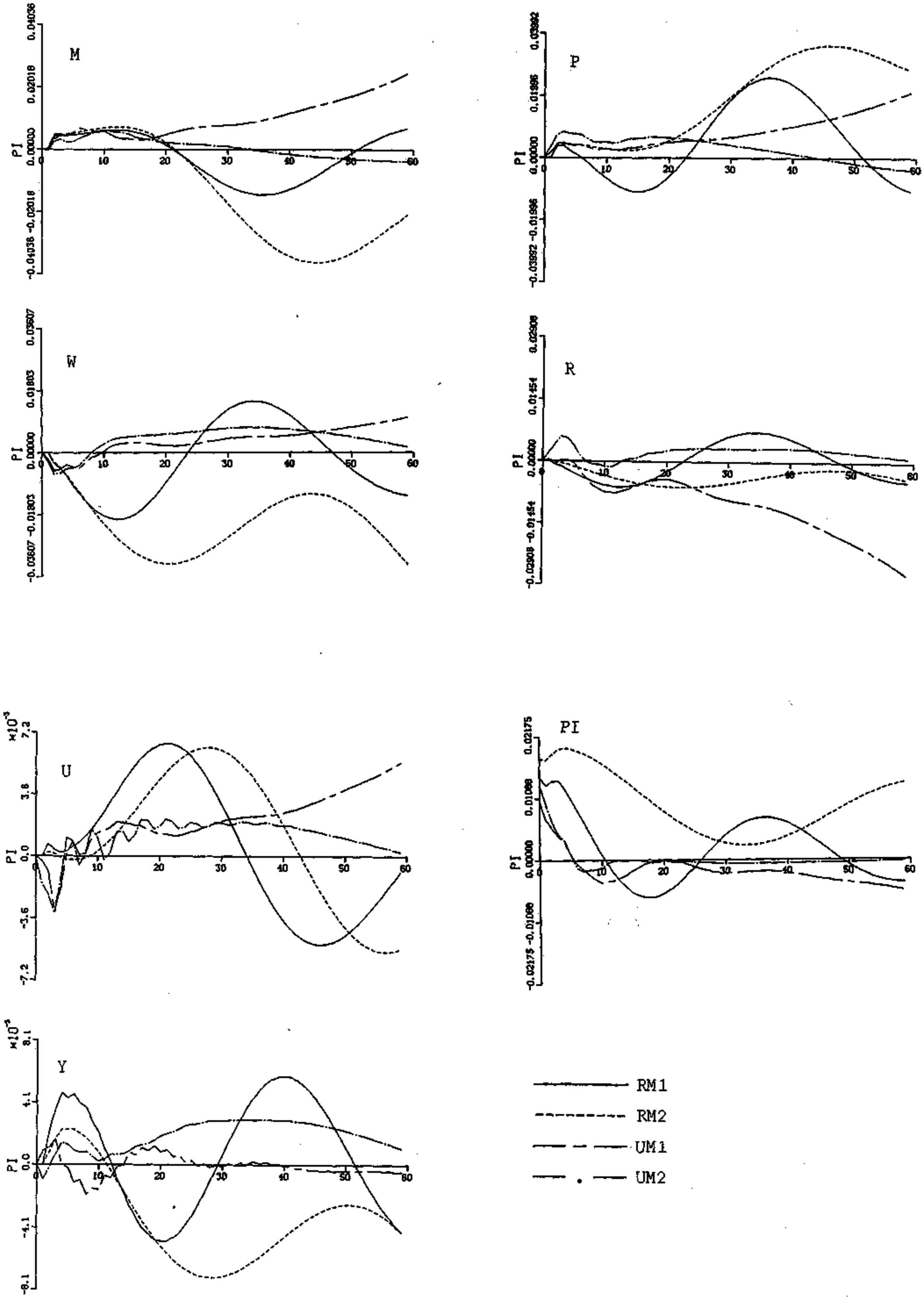


Figure 8. Nominal money balances.

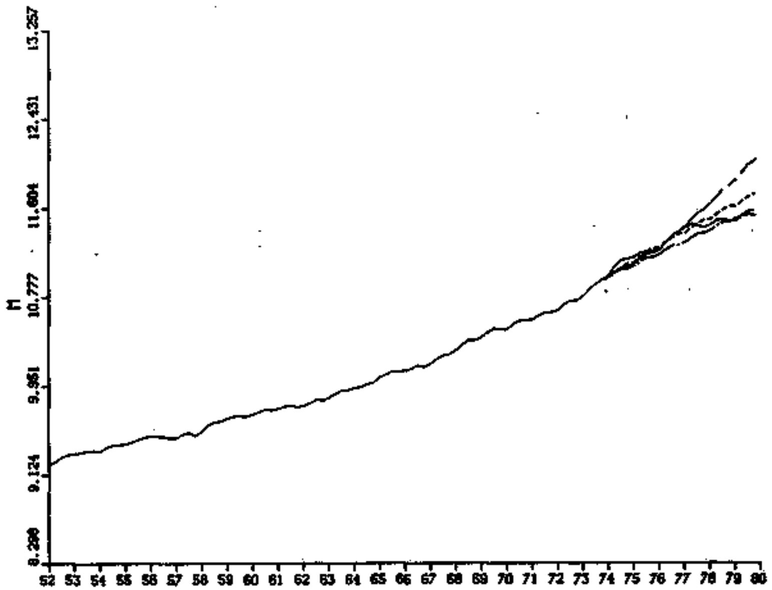


Figure 10. Unemployment.

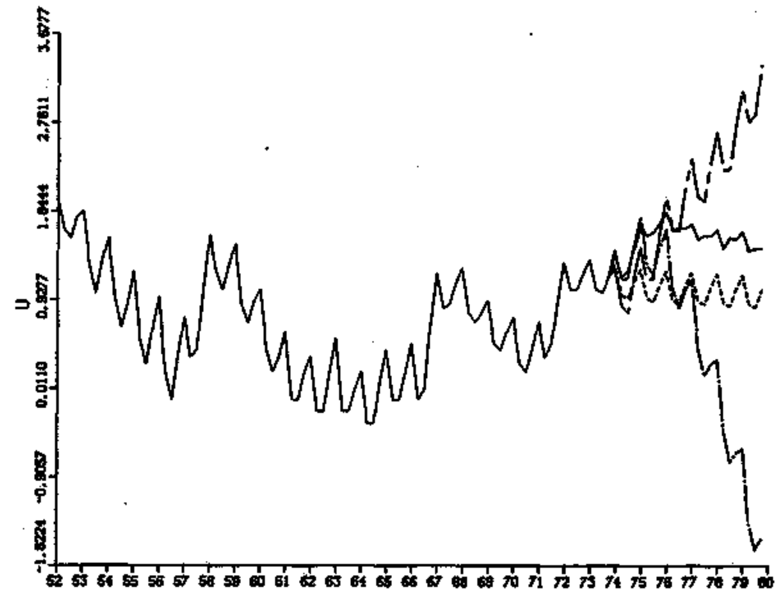


Figure 9. Wages.

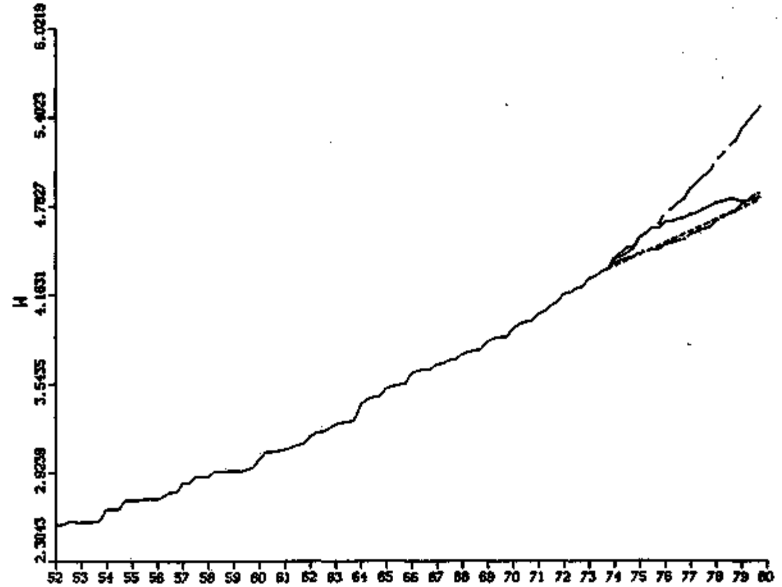


Figure 11. Total gross expenditures in constant prices.

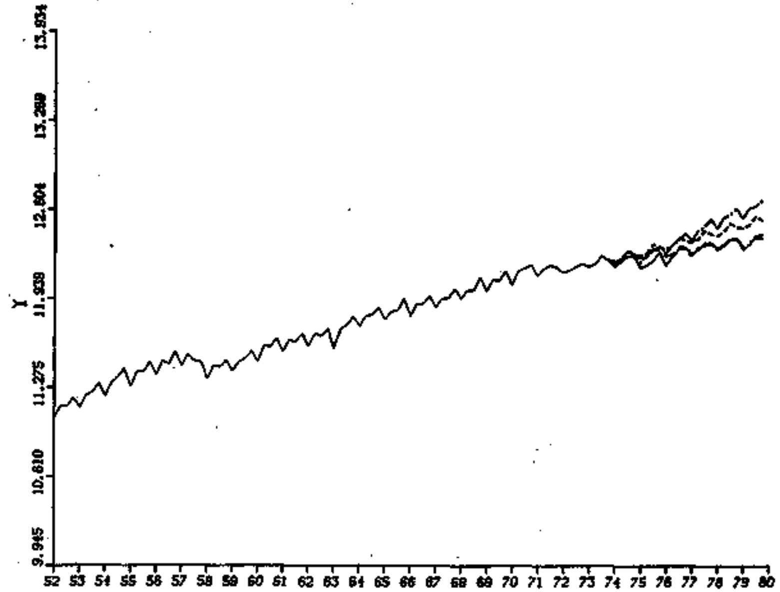


Figure 12. The price index of total gross expenditures.

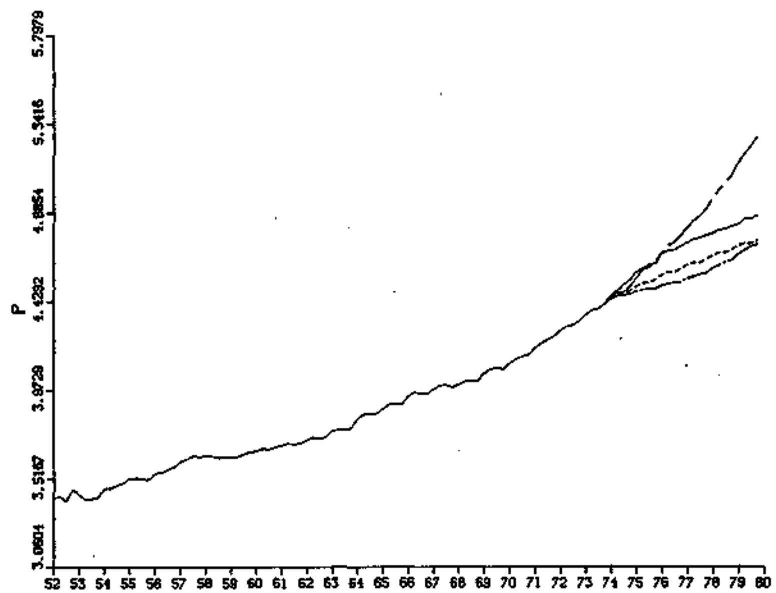


Figure 14. The price index of all import goods.

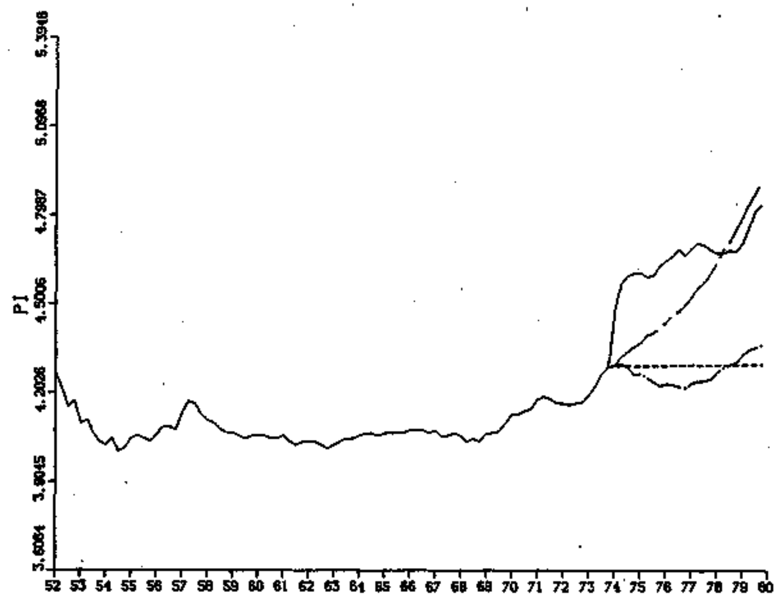
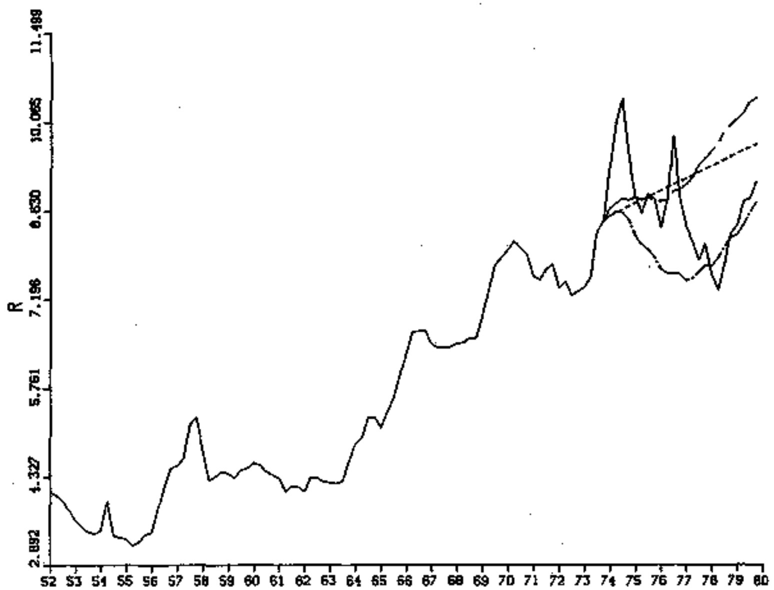


Figure 13. Interest rates on long term government bonds.



All series, except the interest rates, are expressed in logarithms.

Observations	:	————————
Predictions		
ARIMA model	:	------------
Unrestricted VAR model	:	—— – ——
Restricted VAR model	:	—— . ——

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