MEASURING MONETARY POLICY IN THE UK: A FACTOR-AUGMENTED VECTOR AUTOREGRESSIVE APPROACH *

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March 2004

Abstract

This article investigates the transmission mechanism of the British monetary policy using a factor-augmented vector autoregression model, similar to the one suggested by Bernanke, Boivin and Eliasz (NBER, wp. 10220 (2004)). The novelty of the present study is that an approximate dynamic factor model, of the kind proposed by Stock and Watson (Journal of Business & Economic Statistics, 20 (2) 2002, 147), is applied to a large UK dataset, consisting of 108 monthly macroeconomic time series. The estimated factors, which summarise all relevant information contained in the series, are then added to a vector autoregression (VAR). This factor-augmented vector autoregressive approach avoid the limited information problem typical of "low dimensional" VARs and gives the opportunity to investigate the effect of policy innovations on a large number of economic variables. Results indicate that extending the information set of the VAR to include a small number of estimated factors using static principal components avoids the price puzzle and gives the opportunity to check impulse responses for all the variables included in the dataset. Results appear to be robust to changes in the number of factors, lags and sample period.

JEL Codes: E3, E4, E5, C3.
Keywords: Factor Model, Principal Component, Monetary Policy, VAR.
Fields: Monetary Economics, Macroeconomics, Econometrics-Time Series.

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* This paper is part of my Ph.D. Dissertation, Royal Holloway College, University of London, U.K.

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1. INTRODUCTION

Vector autoregression models (VARs) provide a simple framework within which monetary policy shocks and their effects on macroeconomics variables can be identified and measured[1].

The great appeal of using VARs to study the monetary policy transmission mechanism is that they appear, even making simple identification assumptions on the nature of the shocks[2], to deliver empirically plausible assessments of the dynamic responses of key macroeconomic variables to monetary shocks without requiring a complete structural model of the economy (for a survey see Christiano, Eichebaum and Evans, 2000). Despite this advantage, however, there are at least a few reasons to be sceptical about low dimensional VARs[3].

In general, the choice of the identification method may constitute a topic of disagreement among economists, especially because alternative identifications lead to different results.

More importantly, the small information set of low-dimensional VARs is at odds with the current practice of monetary authorities known to monitor a large number of economic time series before setting monetary policy.

The fact that the VAR information set is likely to be smaller than that used by policy-makers creates at least two potential problems. Firstly, an under-specified VAR model may generate an erroneous innovation measure. The price puzzle represents only one of the serious consequences of not correctly specifying a VAR model[4] [5]. This is particularly true regardless of the model being used to make forecasts, quantify the knowledge know about the true structure of the economy, and advise macroeconomic policymakers.

Secondly, impulse responses can only be checked for the variables included in the model, (which constitute only a subset of the variables of interest to policy-makers) whereas economists are most likely to be interested in studying the effect of policy innovations on a large number of time series[6].

With these thoughts in mind and motivated by recent developments in factor analysis, this paper attempts to solve the VAR limited information problem by conditioning its performance on a richer information set than usual.

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[1] These models were first introduced by Christopher Sims in 1980. Bernanke and Blinder (1992) and Sims (1992) were the first to use these models to identify and estimate the effect of monetary policy on macroeconomic variables.

[2] An important identifying assumption has to be made on the relation between structural shocks and reduced form errors of the VAR (see Christiano, Eichenbaum and Evans, 2000).

[3] Due to the high degrees of freedom costs in the estimation, VARs typically include fewer than 10 variables. Exception are represented by the Bayesian VARs models which can generally include up to 20 variables (e.g. Leeper, Sims and Zha (1996)).

[4] Sims (1992) noted first, that the conventional finding in the VAR literature that after a monetary policy contraction there is a slight increase rather that a decrease in inflation might be due to imperfectly controlling for information that the central bank may have about future inflation.

[5] Uhlig (1997) and Faust (1999) try to overcome this kind of problems adopting an agnostic identification procedure (e.g. imposing sign restrictions on the variables); Sims (1992) suggests the inclusion of additional variables such as the commodity price index in the VARs.

[6] Bernanke and Gertler (1995) try to solve this problem assuming no feedback from variables outside the VAR, that is, by using a block-recursive structure with the VAR ordered first. Unfortunately this kind of assumption does not appear to be easily justified in practice.

Factor literature was first introduced into macroeconomics by Sargent and Sims (1977) and Geweke (1977)[7]. It was further developed by Engle and Watson (1983); Sargent (1989); Stock and Watson (1991, SW); Quah and Sargent (1993) and Forni and Reichlin (1996, 1998)[8]. Recently, factor models have been rediscovered in macroeconomics as tools for extracting information from a large cross-section of time series. The two main approaches represent the variables by using dynamic factor models to estimate factors. These can be used to improve forecasts for several variables. The first method, introduced by SW (1998, 1999, 2002), which is followed in this paper, relies on the estimation of factors by static principal components. The other, introduced by Forni, Hallin, Lippi and Reichlin (2000, 2001, 2003), estimates factors using dynamic principal components.

Bernanke and Boivin (2003) and Bernanke, Boivin and Eliasz (2004, BBE) apply the SW (1998, 2002) two-step principal component approach to monetary policy[9].

The present study is closer to the work of BBE, 2004. Their paper proposes to condition VAR analysis of monetary policy on a larger information set, using a factor-augmented vector autoregressive approach. This approach measures the impact of US monetary policy on the economy[10]. They found that this new methodology offers plausible responses of a wide variety of macroeconomic variables to monetary policy shocks.

This paper departs from the existing literature because it uses a dynamic factor model to explore the effect of UK monetary policy on the economy, exploiting a large number of UK macroeconomic variables. In other words, an alternative to selecting and including a few variables in a VAR would be to summarize the information contained in many series in a handful of estimated factors, then augment the VAR with these factors. The approach begins by calculating, using static principal components, the factors that summarise the most relevant information contained in the series. (These estimated factors are then added to a VAR).

This improves upon the limited information problem of the VARs and allows us to investigate the effect of monetary policy on all variables included in the data set. It should be stressed that the number of factors will be much smaller than the number of variables in the dataset. As a result, the relationship between the amount of information which can be handled by the model and the amount of information needed for the identification changes dramatically. Results indicate that an unexpected target change: 1) raises unemployment, consumer confidence and the rate of exchange; 2) decreases employment, investment goods, average earning index, loans, M4, bond rates, dividend yields and the terms of trade; 3) avoids the price puzzle. Results appear to be robust to changes in the number of factors, lags and sample period.

Furthermore, the advantage of using factors is that each of them can represent one or more categories of indicators, such as real activity or prices, not just a single indicator.

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[7] Sargent and Sims (1977) and Geweke (1977), analysed these models in the frequency domain for a small number of variables.

[8] Engle and Watson (1983), Sargent (1989) and Stock and Watson (1991) estimated small time domain dynamic factor models by maximum likelihood.

[9] Giannone, Reichlin and Sala (2002a, 2002b), apply to monetary policy the method proposed by Forni, Hallin, Lippi and Reichlin (2000, 2001, 2003). Favero, Marcellino and Neglia (2002), compare the relative performance of the two approaches (i.e. static and dynamic principal components). They find that the frequency domain approach of FHLR is slightly more parsimonious of the SW time domain method. However, the overall performance of the two methods deliver very similar results.

[10] They use two alternative methodologies to estimate the factors: 1) a likelihood-based approach and 2) a two-step dynamic factor model approach based on Stock and Watson (2002).

This paper is organized as follows. Section 2 describes the econometric framework. Section 3 describes the data. Section 4 reports the econometric results obtained from the model presented in section 2. Section 5 contains the conclusion.

2. THE THEORY

This section discusses the statistical model which motivates the inclusion of estimated factors into a VAR. The main characteristic of dynamic factor models is that they are able to summarise an enormous amount of information in a few estimated factors. Therefore a possible solution to the VARs limited information problem would be to enhance these models with factor analysis.

2.1 The Model

Let X_t denote an $(N \times 1)$ information matrix which contains hundreds or even thousands of economic time series; Y_t an $(M \times 1)$ vector of observable macroeconomic variables which normally contains a maximum of 8-10 predictors, as in a standard VAR, and constitutes a subset of X_t; F_t a $(K \times 1)$ vector of unobservable factors which can summarise most of the information contained in X_t.
The joint dynamics of (F_t,Y_t) and the static representation of a dynamic factor model (X_t, F_t,Y_t) are assumed to be respectively (see BBE, 2004):

$$[F_t,Y_t]' = \mathbf{B}(L)[F_{t-1},Y_{t-1}]' + \varepsilon_t \qquad (2.1)$$

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + u_t \qquad (2.2)$$

where $\mathbf{B}(L)$ indicates an $(N \times N)$ matrix polynomial in the lag operator L of finite order d; ε_t is an $(N \times 1)$ vector of structural disturbances with mean zero and $(N \times N)$ covariance matrix Ω_ε. Λ^f is an $(M \times K)$ matrix of factor loadings; Λ^y is $(N \times M)$; u_t is an $(N \times 1)$ vector of error terms weakly correlated and with mean zero.
The crucial point of this factor-augmented VAR model (2.1)-(2.2) is that the amount of information which can be handled by the model and the amount of information needed for the identification change dramatically $(M + K << N)$. As shown by equation (2.2), F_t and Y_t, which in general can be correlated, represent pervasive forces that drive the common dynamics of X_t. The main advantage of the static representation of the dynamic factor model described by the equation (2.2) is that factors can be estimated by principal components (see SW 1998, 2002). According to SW (1998, 2002), the number of factors should be determined by an information criterion. Bai and Ng (2002), provide a criterion to determine the number of factors associated with X_t. BBE (2004) stress, however, that this criterion does not address the issue of how many factors should enter in the vector F_t, (e.g. in the equation (2.1)). They propose to include a different number of factors (i.e. 3, 5) in the vector F^t.

2.2 Identification of the factors

Since the augmented VAR, described by the equation (2.1), can be estimated just after deriving the unobserved factors, F_t, this sub-section discusses the identification and the estimation of the factors. This paper follows the two-step principal components method proposed by SW (1998, 2002) and is adapted to the VARs by BBE (2004).
The matrix X_t, is divided into slow- and fast-moving series. The slow-moving variables are real variables (these variables are marked with an asterisk in the appendix A), whereas the fast-moving variables are prices and financial assets. Common factors, $\underline{C}_t$, are estimated

using principal components on all variables included in X_t (i.e. to get the first K + M principal components of X_t). The slow-moving factors, $\underline{F}^s_t$, are estimated by using only the slow-moving variables. Then the common components, $\underline{C}_t$, are regressed on the estimated slow-moving factors and on the observed factors (equation 2.3):

$$\underline{C}_t = \mathbf{b}^f \underline{F}^s_t + \mathbf{b}^y Y_t + e_t \qquad (2.3)$$

It is possible to calculate the estimated factors, $\underline{F}_t$, as the differences between the product of the observed variables and their estimated beta coefficients, and the common components. This implies that $\underline{F}_t$ is obtained as the part of the space covered by $\underline{C}_t$ that is not covered by Y_t. Note that if N is large and the number of principal components used is at least as large as the true number of factors, the principal components consistently recover the space spanned by both F_t and Y_t. Prior to the estimation of the factors, however, it is necessary to identify the factors by imposing some restrictions either on the factor loadings matrix, Λ^f, restricting this to be an identity matrix, $\Lambda^{f\prime}\Lambda^f/N = I$, or by restricting the factors to be $F'F/T = I$. Since it is only possible to have an estimate of the factors, $\underline{F}_t$, the selected restriction will be: $(T)^{1/2}\underline{Z}_t$, where $\underline{Z}_t$ are the eigenvectors corresponding to the largest eigenvalues of XX' sorted in descending order. This identification obtains factors without any rotations.

2.3 Identification of the VAR

Having estimated the factors, $\underline{F}_t$, provided that N is large and the number of principal components used is at least as large as the true number of factors, it is possible to estimate the dynamic equation (2.1), which is a factor-augmented vector autoregression model, by replacing the true factors, F_t, with the estimated ones. This model, like standard VARs, requires an identifying assumption on the nature of the shock. In particular, it is necessary to calculate the reduced form innovations (which give a measure of policy shock) from the idiosyncratic error term of the structural model (see CEE, 2001).

This paper extracts the UK's monetary policy shock from the money market rate, which is the appropriate variable under the regime of inflation targeting. Thus, this rate is treated as an observable factor and we order it last in the vector set (equation 2.1).

This innovation measure is obtained by assuming a cholesky decomposition scheme, which implies that the Bank of England does not react contemporaneously to movements in other variables[11].

3. DATA TRANSFORMATION

The dataset used to estimate the factors is a balanced panel which contains 108 monthly time series for the United Kingdom from 1992 (10) to 2003 (1). The series were partly selected by taking into account the Bank of England Monetary Policy Committee's Minutes. These were selected to represent the following 10 categories: employment; Government finance; output; housing starts and vehicles; consumer and retail confidence; prices; money and loans; interest rates; composite leading indicators and stock prices and exchange rates. A list of the series is given in Appendix A. The theory outlined in section 2 assumes that X_t is a matrix of I(0) underlying macroeconomic variables, so these 108 series were subjected to four preliminary steps: possible transformation by taking logarithms, possible differencing, possible seasonal adjustment and screening for outliers. The decision

[11] Even though this paper adopts the cholesky decomposition, which, among the others, has been used by Bernanke and Blinder (1992), Sims (1992), CEE (2000). Many other identification schemes are available in the VAR literature (see Leeper, Sims and Zha, 1996; Bernanke and Mihov, 1998; and for a survey: CEE, 2000).

to take logarithms or to first difference the series was based on data inspection and formal unit root tests. In general, logarithms were taken for all non-negative series that were not already percentages or growth rates. Most series were first differenced. Some series were seasonally adjusted. After these transformations, all series were standardised to have sample mean zero and unit variance.

4. EMPIRICAL RESULTS

This section reports the results of the statistical model presented in section 2. The model is tested on a large UK dataset, consisting of 108 macroeconomic variables. One of the advantages of combining a dynamic factor model with a VAR is that it is possible to study the effect of a monetary policy shock upon many time series and not just those included in a standard VAR.

This section is divided into two sub-sections. The first provides the impulse response functions, together with the variance decomposition, of a selection of key macroeconomic variables subjected to a monetary policy shock. The second compares the factor augmented VAR model with a standard VAR. Then addresses the robustness of the results.

The main results of this section are: (i) - the variables' responses to monetary policy shocks appear reasonable; (ii) - the inclusion of factors in a standard VAR model seems to improve the pattern of the impulse response functions with respect to the standard VAR, making the price puzzle disappear.

4.1.1. Impulse response functions

Figure (1) plots the impulse response functions of the factor-augmented VAR model with 5 unobservable factors, estimated by principal components and 6 lags. The baseline model assumes that the money market rate[12], thought to have a pervasive effect on the economy, X_t, is the only observed factor included in the vector, Y_t. The equation (2.1) is identified using a Cholesky decomposition and ordering the policy instrument last, implying that factors do not respond to policy shocks within the month. All estimates are based on monthly data from 1992 (10) to 2003 (1). An impulse response function traces the effects of a one standard deviation shock to one of the innovations on current and future values of the endogenous variables; the horizon goes from 0 to 48 months. Also plotted are + 1 and – 1 standard error bands[13].

The responses generally have correct sign and magnitude. Only a selection of the 108 macroeconomic variables are reported in Figure 1. It would be possible, however, to check all the variables included in the dataset.

Following a contractionary monetary policy shock there is an immediate and significant increase in the unemployment rate, in consumer confidence and in the exchange rate, a substantial fall in the investment goods industrial production index, in the average earning index, in the loans on dwellings, in the supply of money M4, in the 10-year Government bond rate, in the dividend yield and in the terms of trade, a moderate fall in the employment rate and an initial rise and a subsequent fall in narrow money (M_0) and in market expectation. The impulse response functions of CPI inflation and new motor vehicles

[12] Which represents a measure of the UK monetary policy shock.

[13] It should be stressed, however, that the two-step method would require the confidence interval of the Impulse response functions in the VARs to be determined by a bootstrap procedure. Bai and Ng (2002), however, suggest that when the number of variables of X_t is large relative to its number of observations, the uncertainty in the factor estimates can be ignored.

registration appear to be less sensitive to the policy shock. Results seem generally consistent with conventional wisdom. The price puzzle, common to many VARs specification, is not particularly present in this factor-augmented formulation.

4.1.2. Variance decomposition

Table 1 contains the variance decomposition of the factor-augmented VAR model with five unobserved factors[14]. Of particular importance is the effect of a negative monetary policy shock on the twelve-month forecast error of the fourteen variables. The first row reports the names of the fourteen variables, the second the contribution of the common component to their variance decomposition and the third the R^2 of the common component. The contribution of the policy shock is between 1.5% and 7.2%. This suggests a relatively small effect of the monetary policy shock on the variables. In particular, the policy shock explains about the 7% of the unemployment rate, narrow money "M_0", bond rate and the terms of trade. The third row of the table shows high R^2 values for the consumer confidence (72.5%), investment goods index (61.7%), unemployment rate (49.8%) and consumer price inflation (33%). This implies that the common component has an important explanatory power over variables. Furthermore, given the R^2 of the common components, it is possible to obtain the standard variance decomposition by multiplying the second row of the table by the third. The difference between the variance decomposition of the factor-augmented VAR and that of the standard VAR is quite remarkable.

4.2.1. VAR – FAVAR comparison

To assess the behaviour of the proposed FAVAR model against a standard VAR, Figure 2 compares the impulse response functions of the two models. The first model is a benchmark VAR which includes, in the Y_t vector, the money market rate, the index of industrial production and the rate of inflation. The other is a factor-augmented VAR (eq. 2.1) which, besides the Y_t vector (which contains the same variables as the VAR) includes also the vector, F_t, with five estimated factors.

The dotted line indicates the effect of a negative policy shock on inflation using the first model, whereas the solid line shows that obtained using the FAVAR specification.

From the graph it can be easily observed that the two impulses appear to be generally out of phase with one another. For every rise in the VAR inflation impulse response, there is a fall in that of the FAVAR. When there is no factor there is a strong price puzzle, whereas, it seems that the FAVAR specification mitigates the price puzzle effect. In summary, by comparing VAR-FAVAR results it is possible to determine the marginal contribution of the information contained in the factors. This, given the recursive formulation, implies that the included factors might capture the information missing from "Low-dimensional" VARs (see Sims interpretation of the price puzzle). An apparent criticism of the FAVAR methodology would be that many VAR specifications that lead to sensible results exist. For instance the inclusion of the commodity price puzzle in the VAR often eliminates the price puzzle. BBE (2004) remark, however, that the FAVAR approach has the advantage of relying on a solid statistical ground rather than on the arbitrary selection of variables to include in VARs[15].

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[14] According to BBE (2004) the variance decomposition of a FAVAR should consider only the fraction explained by the common factor.

[15] Therefore, whether or not the commodity price index, added to a VAR, fixes the price puzzle. This is not directly relevant to this comparison.

4.2.2 Robustness

The issue of robustness is explored along a number of dimensions. Firstly, to address the problem of the number of factors to include in the factor-augmented VAR model, twelve estimated factors are included in the F_t vector instead of five[16]. Secondly, the number of lags entered in the model is increased to ten. Thirdly, the sample period is shortened to 1993(10) – 2002(1).

Figure 3 shows the impulse response functions of a FAVAR with 12 estimated factors. The main results of Figure 1 still hold true, although the effect of a negative policy shock is now different for several variables such as the employment rate, which registers a delayed fall and the rate of inflation, which presents a falling rate up to 6 months after the shock.

Figure 4 plots the impulse response functions of the fourteen variables using a factor – augmented VAR with 10 lags. Results do not show substantial changes in the variable patterns, except for the terms of trade and to a lesser extent inflation.

Figure 5 plots the impulse response functions using a shorter sample period: 1993(10)-2002(1). Once again results appear to be consistent with the previous one, apart from the term of trade.

The results of this section seem to confirm an important fact. Enhancing VARs with factor analysis might capture information not present in low dimensional VARs.

5. CONCLUSION

This paper uses a large dataset to investigate the transmission mechanism of UK monetary policy. This work departs from the existing literature because it uses 108 UK macroeconomic time series to measure the dynamics of the UK monetary policy using an approximate factor model approach. A small number of factors, estimated by principal component analysis, which summarise most of the information contained in the dataset can be added to a VAR. This factor-augmented vector autoregressive approach avoids the common problems present in the "low dimensional" VAR literature on monetary policy. Results indicate that a contractionary monetary policy shock leads to a significant increase in the unemployment rate, in the consumer confidence and in the exchange rate, a substantial fall in the investment goods industrial production index, in the average earning index, in the loans on dwellings, in the supply of money M4, in the 10 year Government bond rate, in the dividend yield and in the terms of trade, a moderate fall in the employment rate, an initial rise and a subsequent fall in narrow money M_0 and in the market expectation. The impulse response functions of CPI inflation do not register evidence of price puzzle. Results appear to be robust to changes in the number of factors, lags and sample period.

[16] There is not yet a criteria which tells how many factors to include in a VAR. Different specification have been used as well (3, 7), but the FAVAR results from the 3, 5 and 7 factor model are very similar to the 5 factor model.

7. REFERENCES

Bai, J., and S., Ng (2002) "Determining the number of factors in approximate factor models", Econometrica, 70, 191-221.

Bernanke, B., and Boivin, J. (2003) "Monetary policy in data-rich environment", Journal of Monetary Economics, 50, 525-546.

Bernanke, B., J., Boivin, and Eliasz (2004) "Measuring the effect of monetary policy: a factor-augmented vector autoregressive approach", NBER w.p. 10220.

Christiano, J., M. Eichenbaum and C. Evans, "Monetary policy shocks: what we have learned and to what end?", chapter 2 in Taylor and Woodford, eds., Handbook of Macroeconomics, vol.1A, Elsevier 2000.

Clarida, R., J. Gali and M. Gertler (2000) "Monetary policy rules and macroeconomic stability: evidence and some theory", Quarterly Journal of Economics, 115, 147-180.

Eichenbaum, M. and C. Evans (1995) "Some empirical evidence on the effects of shocks to monetary policy on exchange rates", Quarterly Journal of Economics 110(4): 975-1009.

Favero, C., Marcellino, M., and F., Neglia (2002) "Principal components at work: the empirical analysis of monetary policy with large datasets", IGIER w.p.223.

Forni, M., Hallin, M., Lippi, M., and L., Reichlin (2000) "The generalized dynamic factor model: identification and estimation", The Review of Economics and Statistics, 82, 4, 540-552.

Forni, M., Hallin, M., Lippi, M., and L., Reichlin (2001) "The generalized dynamic factor model: one-sided estimation and forecasting", Mimeo.

Forni, M., Hallin, M., Lippi, M., and L., Reichlin (2003) "Do financial variables help forecasting inflation and real activity in the euro area?", Journal of Monetary Economics, 50, 1243-1255.

Forni, M. and L., Reichlin (1996), "Dynamic common factors in large cross-sections", Empirical Economics, 21, 27-42.

Hamilton, D. (1994), Time Series Analysis, Princeton University Press, Princeton, NJ.

Romer, C., and D. Romer (1989) "Does monetary policy matter? A new test in the spirit of Friedman and Schwartz ", NBER Macroeconomics Annual 1989. MIT Press.

Sims, A.(1980), "Macroeconomics and reality", Econometrica 48(1):1-48.

Sims, A.(1992), "Interpreting the macroeconomic time series facts: the effects of monetary policy", European Economic Review 36(5): 975-1000.

Stock, J., and M. Watson (1998) "Diffusion Indexes", NBER wp. 6702.

Stock, J., and M. Watson (2001) "Vector Autoregressions", Journal of Economic Perspectives, 15(4), 101-115.

Stock, J., and M. Watson (2002) "Macroeconomic Forecasting Using Diffusion Indexes", Journal of Business & Economic Statistics, 20(2), 147-162.

Appendix A - Data Description

All Series were taken from Datastream Database.
The transformation codes are: 1 - no transformation; 2 - logarithm; 3 - first difference;
4 - logarithm of first difference; 5 - second difference; 6 - log of second fifference;
7 - seasonal adjustment; 8 - logarithm of seasonal adjusted series;
9 - first difference of seasonal adjusted series.

Employment

1	UNR*	1992:10-2003:01	3	UK LFS: ILO UNEMPLOYMENT RATE - GREAT BRITAIN, ALL SADJ
2	EIR*	1992:10-2003:01	3	UK LMT: ECONOMIC INACTIVITY RATE: UK: ALL: AGED 65+(M)/60+(F)
3	EAR1*	1992:10-2003:01	3	UK LFS: ECONOMIC ACTIVITY RATE, ALL, AGED 16-59/64 SADJ
4	EMR*	1992:10-2003:01	3	UK LFS: EMPLOYMENT RATE - GREAT BRITAIN, AGED 16-59/64, ALL SADJ
5	EM*	1992:10-2003:01	3	UK LFS: IN EMP.: AGED 16+: ANNUAL = SPRING QUARTER(MAR-MAY) VOLA
6	UN*	1992:10-2003:01	3	UK UNEMPLOYMENT VOLA
7	UNRss*	1992:10-2003:01	3	UK UNEMPLOYMENT RATE SADJ
8	UN6*	1992:10-2003:01	3	UK LFS: UNEMPLOYED UP TO 6 MONTHS, ALL, AGED 16 AND OVER VOLA
9	YE*	1992:10-2003:01	3	UK LFS: EMPLOYEES: ANNUAL = SPRING QUARTER (MAR - MAY) VOLA
10	TCC*	1992:10-2003:01	3	UK TOTAL CLAIMANT COUNT VOLA
11	EJ*	1992:10-2003:01	3	UK EMPLOYEE JOBS-3 MONTHS AVE. - MANUFACTURING INDUSTRIES VOLA
12	CCIW*	1992:10-2003:01	3	UK UK CLAIMANT COUNT - STANDARDISED INFLOWS - WOMEN VOLN
13	CCOM*	1992:10-2003:01	3	UK CLAIMANT COUNT - STANDARDISED OUTFLOWS - MEN VOLN
14	CCOW*	1992:10-2003:01	3	UK UK CLAIMANT COUNT - STANDARDISED OUTFLOWS - WOMEN VOLN
15	CCIM*	1992:10-2003:01	3	UK CLAIMANT COUNT - STANDARDISED INFLOWS - MEN VOLN

Government finance

16	EXPm*	1992:10-2003:01	5	UK BOP: EXPORTS - MANUFACTURES CURN
17	EXP*	1992:10-2003:01	5	UK EXPORTS VOLUME INDEX VOLN
18	NTL*	1992:10-2003:01	3	UK GENERAL GOVERNMENT: NET LENDING(+)/NET BORROWING CURN
19	PSND*	1992:10-2003:01	3	UK PUBLIC SECTOR NET DEBT(AS PERCENTAGE OF GDP AT MARKET PRICES)
20	IMP*	1992:10-2003:01	3	UK IMPORTS VOLUME INDEX VOLN
21	TT*	1992:10-2003:01	3	UK TERMS OF TRADE VOLN
22	TXPI*	1992:10-2003:01	8	UK TAX & PRICES INDEX (TPI) (JAN 1987=100) NADJ

Output

23	ICI*	1992:10-2003:01	3	UK INDUSTRIAL CONFIDENCE INDICATOR - UK SADJ
24	IP*	1992:10-2003:01	3	UK INDUDSTRIAL PRODUCTION VOLA
25	IPIM*	1992:10-2003:01	3	UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA
26	IPIM2*	1992:10-2003:01	3	UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA
27	IPIG1*	1992:10-2003:01	1	UK INDUSTRIAL PRODUCTION: INVESTMENT GOODS - OTHER(DISC.) VOLN
28	IPIG2*	1992:10-2003:01	1	UK INDUSTRIAL PRODUCTION: INVESTMENT GOODS - TOTAL(DISC.) VOLN
29	IPIG3*	1992:10-2003:01	1	UK INDUSTRIAL PRODN.: INTERMEDIATE GOODS - MATERIALS(DISC.) VOLN
30	IPIG4*	1992:10-2003:01	1	UK INDUSTRIAL PRODUCTION: INTERMEDIATE GOODS - FUELS(DISC.) VOLN
31	IPIG5*	1992:10-2003:01	1	UK INDUSTRIAL PRODUCTION: INTERMEDIATE GOODS - TOTAL(DISC.) VOLN
32	ISE1*	1992:10-2003:01	3	UK INDUSTRY SURVEY: EMP.EXPECTATIONS FOR MO.AHEAD-UNITED KINGDO
33	ISE2*	1992:10-2003:01	3	UK INDUSTRY SURVEY: EXPORT ORDER BOOK POSITION - UK SADJ
34	ISE3*	1992:10-2003:01	3	UK INDUSTRY SURVEY: ORDER BOOK POSITION - UK SADJ
35	ISE4*	1992:10-2003:01	1	UK INDUSTRY SURVEY: PROD. EXPECTATION FOR MTH. AHEAD - UK SADJ
36	ISE5*	1992:10-2003:01	3	UK INDUSTRY SURVEY: PRODUCTION TRENDS IN RECENT MTH. - UK SADJ
37	ISE6*	1992:10-2003:01	1	UK INDUSTRY SURVEY: STOCKS OF FINISHED GOODS - UK SADJ
38	ISE7*	1992:10-2003:01	3	UK INDUSTRY SURVEY: SELLING PRC. EXPECT. MTH. AHEAD - UK SADJ

Housing starts and vehicles

39	NEV	1992:10-2003:01	5	UK MOTOR VEHICLES: NEW REG.: OF WHICH ARE BODYTYPE CARS: GB CURN
40	NECv	1992:10-2003:01	3	UK NEW CAR REGISTRATIONS VOLA
41	NECO	1992:10-2003:01	3	UK NEW CONSTRUCTION ORDERS - TOTAL CURN
42	NEW	1992:10-2003:01	3	UK NEW ORDERS OBTAINED - NEW CONSTRUCTION WORK (TOTAL) CONA

Consumer and retail confidence

43	RS*	1992:10-2003:01	3	UK RETAIL SALES: ALL RETAILERS - ALL BUSINESS SADJ
44	RCI*	1992:10-2003:01	3	UK RETAIL CONFIDENCE INDICATOR - UK SADJ
45	CCI1*	1992:10-2003:01	3	UK CONSUMER CONFIDENCE INDICATOR SADJ

Prices

46	AEI*	1992:10-2003:01	1	UK AEI: PRIVATE SECTOR SERVICES INCL. BONUS (%MOM) SADJ
47	AAEI*	1992:10-2003:01	7	UK AEI: PRIVATE SECTOR SERVICES EXCL. BONUS (%MOM) NADJ
48	RPI*	1992:10-2003:01	7	UK RPI NADJ
49	RPIM*	1992:10-2003:01	8	UK RPI - EXC. MORTGAGE INTEREST PAYMENTS & IND. TAXES NADJ
50	RRPI*	1992:10-2003:01	1	UK RPI: ALL ITEMS EXC. MTG. INT. PMTS. (%YOY) CURN
51	RPI12*	1992:10-2003:01	8	UK RPI:PERCENTAGE CHANGE OVER 12 MONTHS - ALL ITEMS NADJ
52	RPI1*	1992:10-2003:01	3	UK RPI: PERCENTAGE CHANGE OVER 12 MONTHS- ALCOHOL & TOBACCO
53	RPI2*	1992:10-2003:01	3	UK RPI: ALL ITEMS EXCLUDING HOUSING (%YOY)
54	AEIW*	1992:10-2003:01	7	UK AEI: WHOLE ECONOMY INCL. BONUS NADJ
55	AEIPS*	1992:10-2003:01	7	UK AEI: PRIVATE SECTOR SERVICES INCL. BONUS NADJ
56	RPID*	1992:10-2003:01	8	UK RPI - CONSUMER DURABLES NADJ
57	CPIH*	1992:10-2003:01	8	UK CPI - ALL ITEMS (HARMONISED) NADJ
58	CPITt*	1992:10-2003:01	8	UK CPI - TRANSPORT NADJ

59	HHPI*	1992:10-2003:01	8	UK HALIFAX HOUSE PRICE INDEX - ALL HOUSES NADJ
60	HHCPI*	1992:10-2003:01	8	UK HARMONIZED CPI NADJ

Money and loans

61	LOHH	1992:10-2003:01	3	UK LOANS FOR HOUSE PURCHASE : BLDG.SOCIETIES : GROSS ADVANCES
62	LSD	1992:10-2003:01	3	UK LOANS SECURED ON DWELLINGS: GROSS CURA
63	LOAPR	1992:10-2003:01	3	UK LOANS TO PRIVATE SECTOR CURN
64	LOAPU	1992:10-2003:01	3	UK LOANS TO PUBLIC SECTOR CURN
65	REF1	1992:10-2003:01	3	UK REFINANCING:TOTAL REFINANCING
66	REF2	1992:10-2003:01	3	UK REFINANCING:REPO PURCHASES:DEBT:GILTS & NON STERLING DEBT
67	REF3	1992:10-2003:01	3	UK REFINANCING:LATE FACILITIES
68	OFI	1992:10-2003:01	3	UK OFI : BLDG. SOCIETIES MORTGAGES COMMITMENT FOR ADVANCES CURA
69	BS	1992:10-2003:01	3	UK BUILDING SOCIETIES MTG. COMMITMENT FOR ADVANCES CURN
70	M4L	1992:10-2003:01	3	UK MONEY STOCK M4 (END PERIOD): LEVEL CURN
71	M0L	1992:10-2003:01	3	UK M0 WIDE MONETARY BASE (END PERIOD): LEVEL CURA
72	NOTE1M	1992:10-2003:01	1	UK NOTES AND COIN - 1 MONTH CHANGE SADJ
73	M06MA	1992:10-2003:01	7	UK M0 - 6 MONTH ANNUALISED CHANGE NADJ
74	MOMB	1992:10-2003:01	3	UK MO: THE WIDE MONETARY BASE: CHANGES CURA
75	NC	1992:10-2003:01	7	UK NOTES AND COIN - 6 MONTH ANNUALISED CHANGE NADJ
76	MS4	1992:10-2003:01	3	UK MONEY SUPPLY M4 (EP) CURA
77	MSR	1992:10-2003:01	3	UK MONEY STOCK: RETAIL DEPOSITS & CASH IN M4 CURA

Interest rates

78	MMR	1992:10-2003:01	1	UK MONEY MARKET RATE (FEDERAL FUNDS)
79	BYMTT	1992:10-2003:01	3	UK GOVT BOND YIELD - MEDIUM TERM
80	BYLTT	1992:10-2003:01	3	UK GOVT BOND YIELD - LONGTERM
81	bond	1992:10-2003:01	3	UK GOVERNMENT 10-YEAR BOND YIELD
82	INMK3	1992:10-2003:01	3	UK INTER-BANK: 3 MONTH INTEREST RATE - % PER ANNUM CURN
83	PRIMERR	1992:10-2003:01	3	UK LENDING RATE (PRIME RATE)
84	INTBK3	1992:10-2003:01	3	UK INTERBANK RATE - 3 MONTH
85	MM3	1992:10-2003:01	3	UK 3 - MONTH MONEY MARKET (MEAN) NADJ
86	MMT3	1992:10-2003:01	3	UK 3 MONTHS TREASURY BILLS YIELD (EP)
87	MY3	1992:10-2003:01	3	UK 3 MONTHS TREASURY BILLS YIELD (EP)
88	SOE	1992:10-2003:01	3	UK STERLING ONE YEAR INTERBANK RATE
89	SOW	1992:10-2003:01	3	UK STERLING ONE WEEK INTERBANK RATE
90	SOM	1992:10-2003:01	3	UK STERLING ONE MONTH INTERBANK RATE
91	SMT	1992:10-2003:01	1	UK STERLING MEDIUM TERM NOTES-12 MONTH GROWTH RATE CURN

Composite leading indicator

92	CLIAJ	1992:10-2003:01	7	UK COMPOSITE LEADING INDICATOR (AMPLITUDE ADJUSTED) NADJ
93	CLIRT	1992:10-2003:01	7	UK COMPOSITE LEADING INDICATOR (RATIO TO TREND) NADJ
94	CLITT	1992:10-2003:01	3	UK COMPOSITE LEADING INDICATOR (TREND RESTORED)
95	CLI3MM	1992:10-2003:01	7	UK COMPOSITE LEADING INDICATOR: 3MTH PRIME BANK BILLS NADJ
96	CLI6M	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: 6-MONTHS RATE CHANGE AT ANNUAL R
97	CLI3M2	1992:10-2003:01	7	UK COMPOSITE LEADING INDICATOR: 3MTH PRIME BANK BILLS NADJ
98	CLICC	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: CONSUMER CONFIDENCE INDICATOR
99	CLICCC	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: CONSUMER CONFIDENCE INDICATOR
100	CLIFTSEE	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: FTSE-A NON FIN SHARE PRICE INDEX
101	CLIWC	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: NEW CAR REGISTRATIONS SADJ
102	CLIFT1	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: PRODN. - FUTURE TENDENCY SADJ
103	CLIFT2	1992:10-2003:01	1	UK COMPOSITE LEADING INDICATOR: PRODN. - FUTURE TENDENCY SADJ

Stock prices and exchange rates

104	FTYY	1992:10-2003:01	3	UK F.T. ACTUARIES ALL SHARE INDEX - DIVIDEND YIELD
105	FTnn	1992:10-2003:01	7	UK FT ALL SHARE INDEX (EP) NADJ
106	ER1	1992:10-2003:01	3	UK US $ TO £1
107	ER2	1992:10-2003:01	3	UK YEN TO £1 (PURCHASING POWER PARITY LEVEL: 1975 BASED)
108	ER3	1992:10-2003:01	3	UK EURO TO NATIONAL CURRENCY UNIT (AVG)

TABLE 1: Contribution of the policy shock to variance of the common component.

Common Component - factor-augmented VAR

variables names															
UNR	*EMR*	*IPIG2*	*NEV*	*NECO*	*AEI*	*CPIH*	*LSD*	*M4L*	*M0L*	*BOND*	*CLICC*	*FTYY*	*ER2*	*TT*	*ISE1*
			Variance Decomposition												
0.072	***0.015***	***0.004***	***0.019***	***0.027***	***0.013***	***0.031***	***0.049***	***0.025***	***0.070***	***0.070***	***0.060***	***0.050***	***0.032***	***0.068***	***0.060***
			Goodness of Fit - R^2												
0.049	***0.27***	***0.62***	***0.006***	***0.209***	***0.394***	***0.329***	***0.225***	***0.1***	***0.26***	***0.38***	***0.725***	***0.316***	***0.185***	***0.05***	***0.128***

FIGURE 1: Impulse responses generated from FAVAR with 5 factors and FFR estimated by two-step principal components 1992(10) – 2003(1).

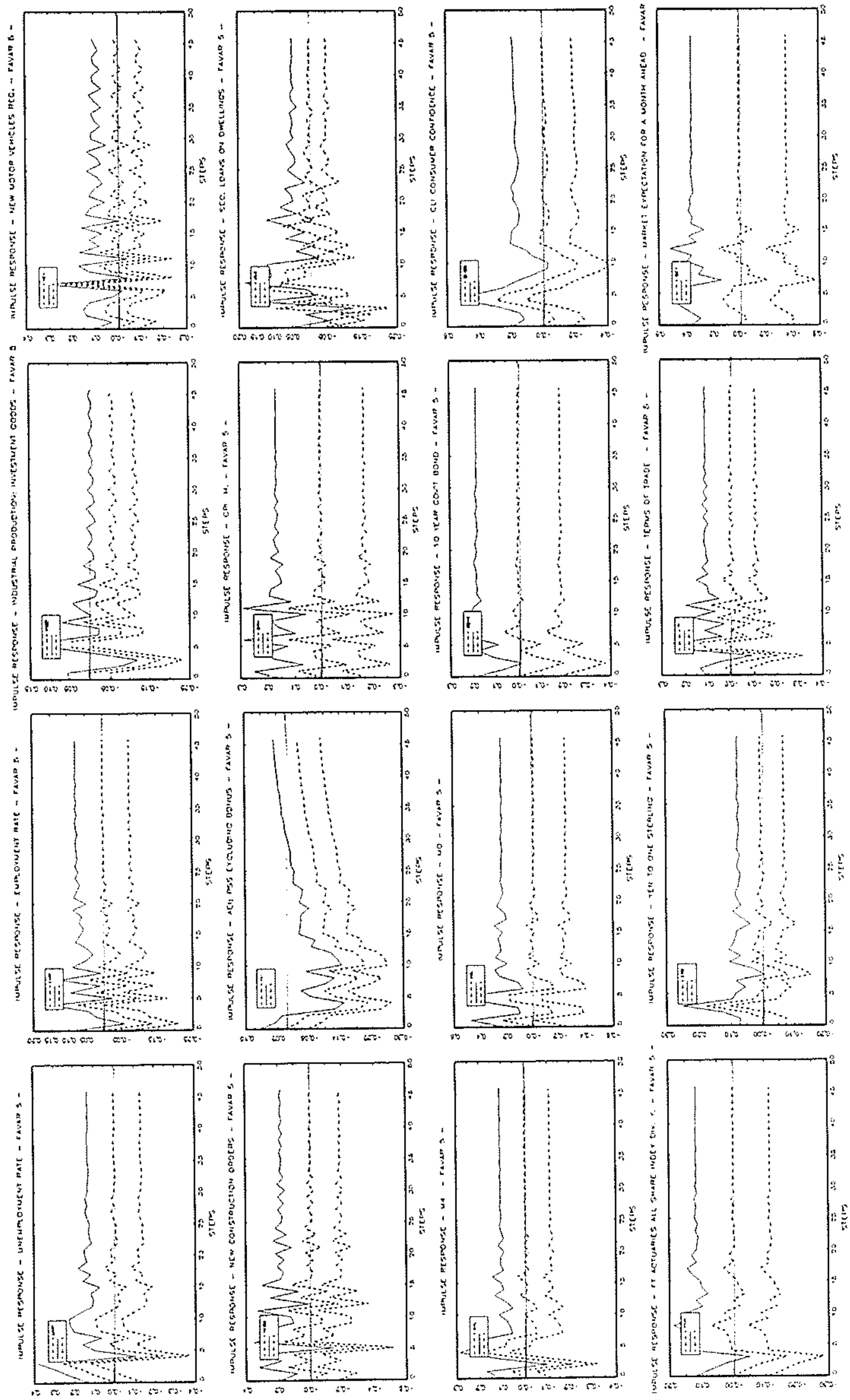

FIGURE 2: VAR (Y = IP, CPI, MMR, F = 0) – FAVAR(Y = IP, CPI, MMR, F = 5) comparison. Impulse responses of inflation to a monetary policy innovation.

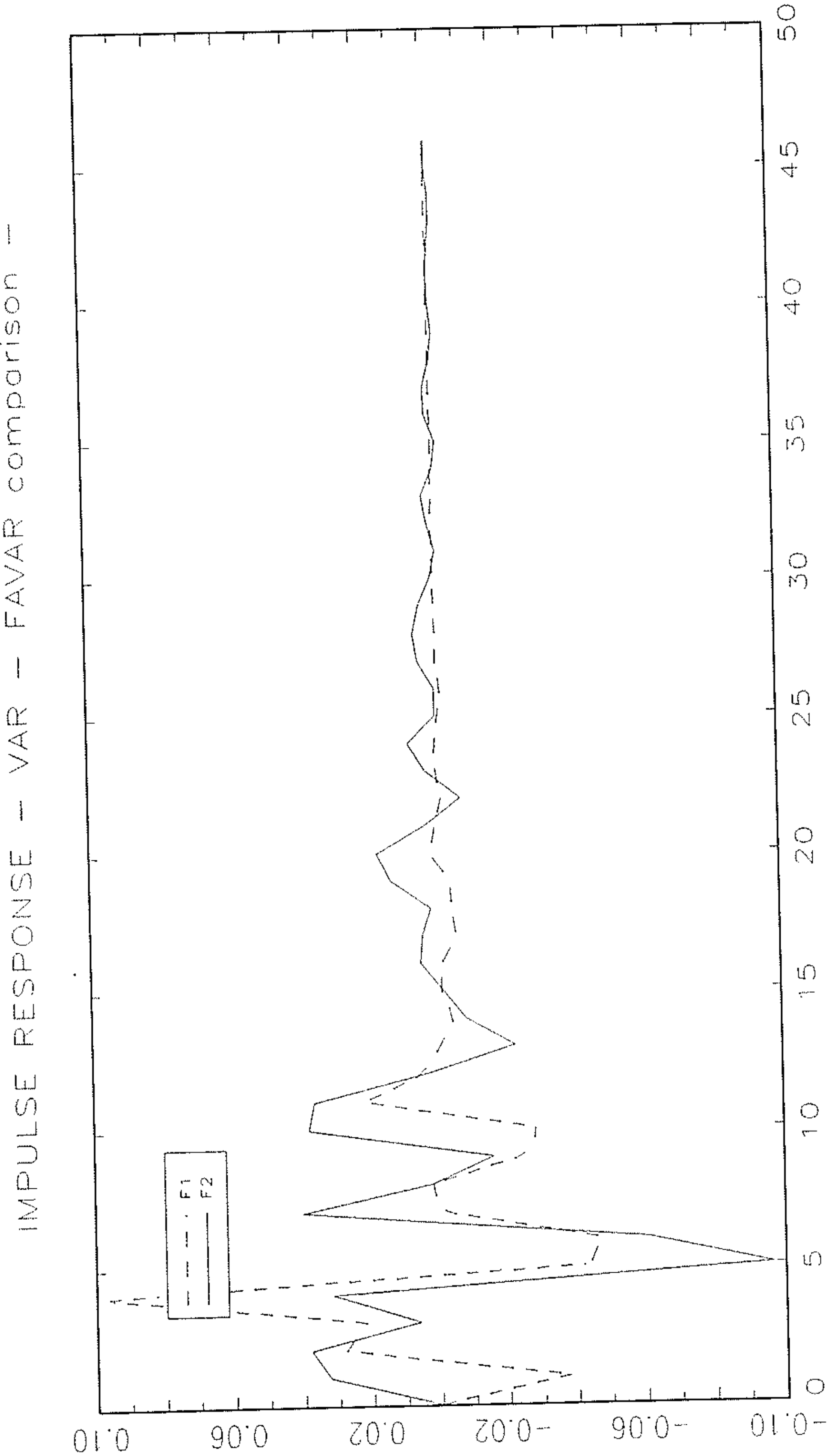

FIGURE 3: Impulse responses generated from FAVAR with 12 factors and FFR estimated by two-step principal components 1992(10) – 2003(1).

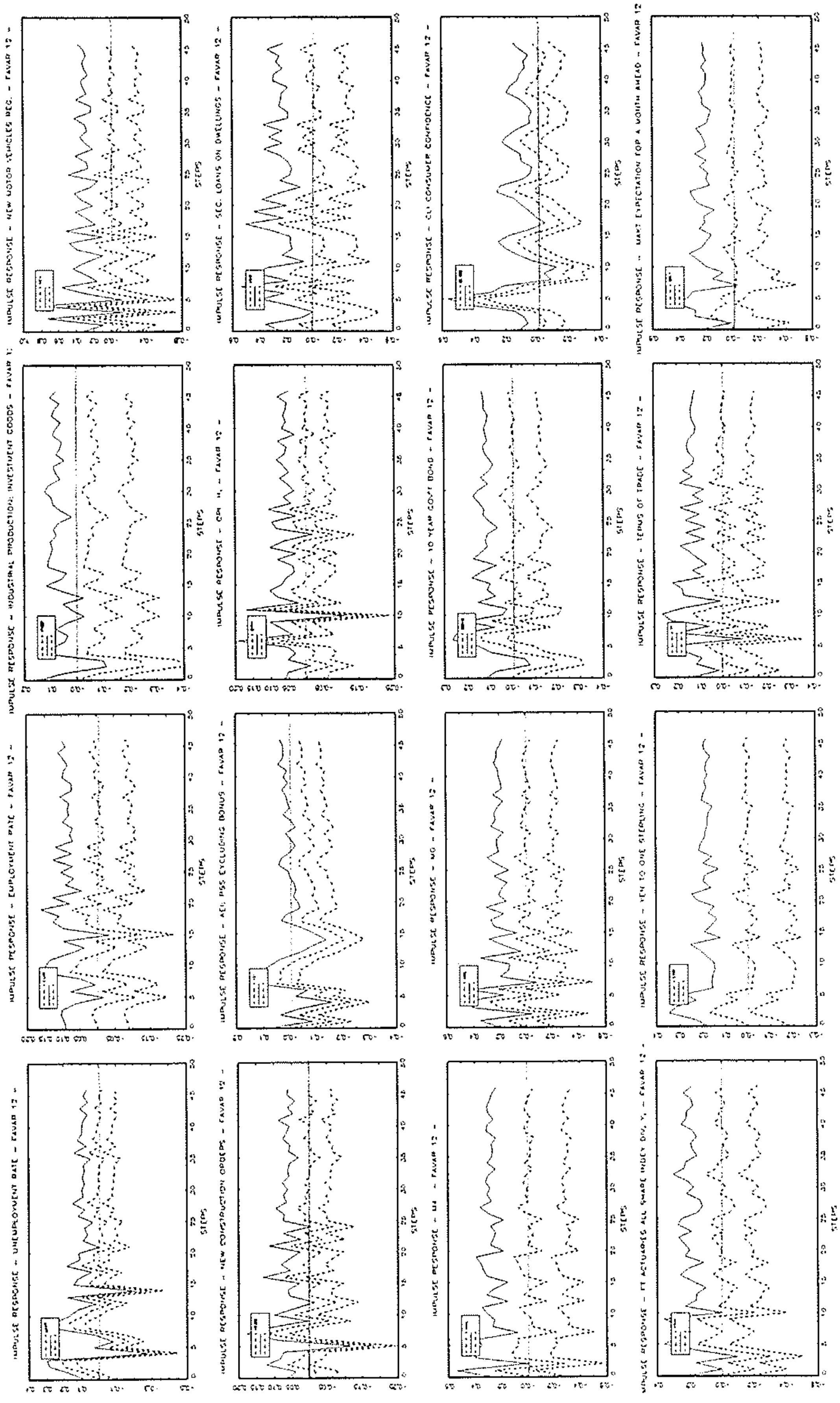

FIGURE 4: Impulse responses generated from FAVAR with 5 factors, FFR estimated by two-step principal components 1992(10) – 2003(1) and 10 lags.

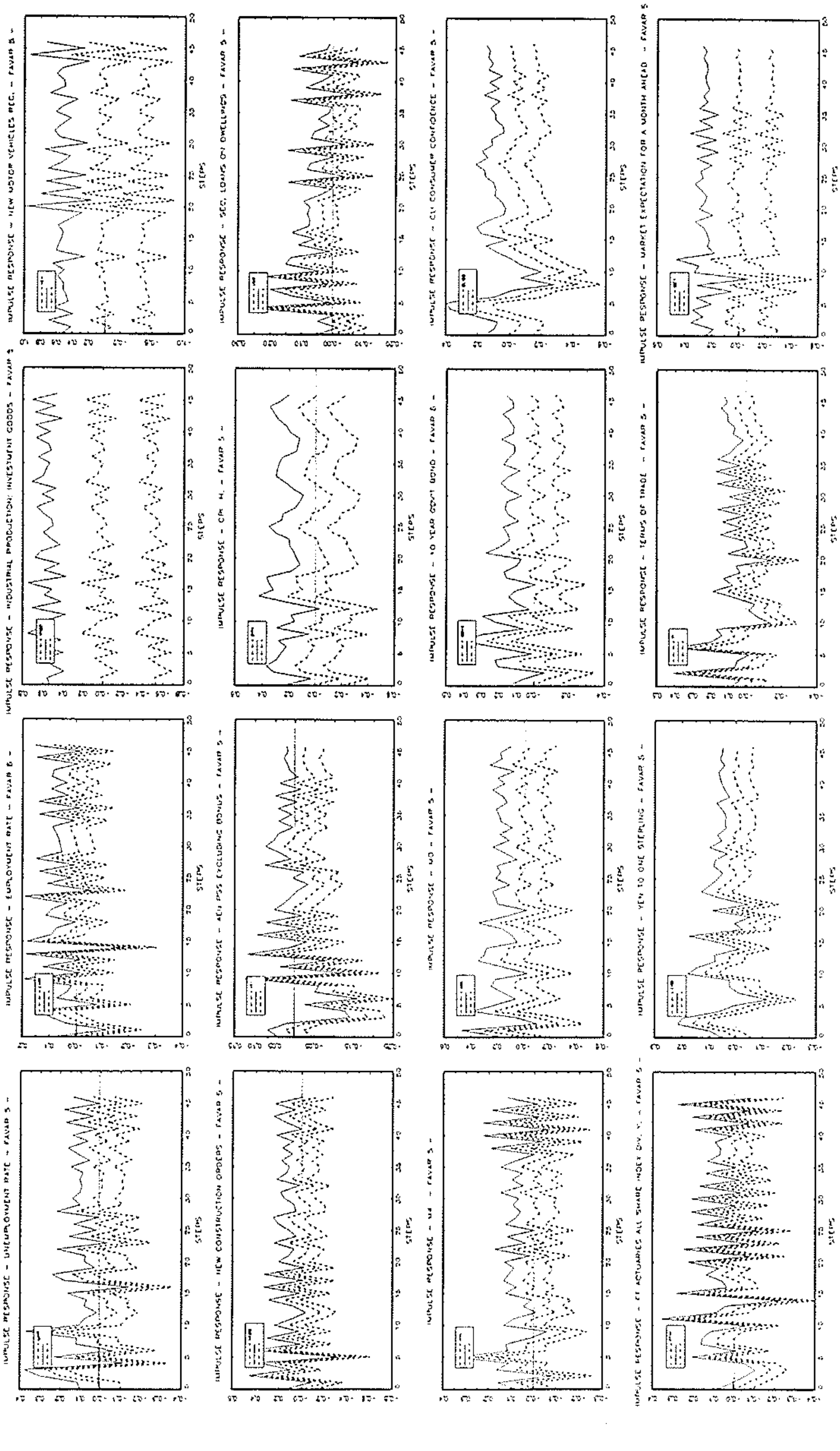

FIGURE 5: Impulse responses generated from FAVAR with 5 factors and FFR estimated by two-step principal components 1993(10) – 2002(1).