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The Dynamic Effects of Monetary Policy Shocks

by

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled "The Dynamic Effects of Monetary Policy Shocks" submitted by Victor Chwee in partial fulfilment of the requirements for the degree of Master of Arts.

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ABSTRACT

In the context of vector autoregression (VAR), this study investigates the dynamic effects of U.S. monetary policy shocks using fourteen different policy indicators. They include twelve broad monetary aggregates, the federal funds rate, and the non-borrowed monetary base where innovations in each one of them are identified with policy disturbances. The strategy used is related to recent VAR studies in a closed economy setting examining whether monetary policy shocks produce results that are consistent with traditional Keynesian IS-LM analyses. The results focus mainly on innovation accounting (impulse responses and forecast error variance decompositions), and also on correlation matrices for innovations and Granger-causality tests. The general conclusion, using monetary aggregates and the federal funds rate, lend support to previous VAR studies regarding the puzzling evidence found. The resulting dynamic responses of key macro variables following shocks to policy are inconsistent with theoretical prediction. A more successful attempt in resolving those puzzling evidence is made when using the non-borrowed monetary base to identify monetary policy shocks.

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Dedications

To my family.

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CHAPTER 1

INTRODUCTION

This study uses the vector autoregression (VAR) approach to investigate the dynamic effects of monetary policy shocks on key U.S macro variables. To assess the robustness of the results, twelve monetary aggregates are used including four Simple Sum aggregates (M1, M2, M3, L), four Divisia aggregates (DM1, DM2, DM3, DL), and four Currency Equivalence aggregates (CEM1, CEM2, CEM3, CEL) in addition to two other monetary policy indicators namely the federal funds rate and the non-borrowed monetary base.[1] Thus far, most VAR studies have focussed on using traditional broad monetary aggregates, most notably M1 and M2, as policy indicators and have not dealt extensively with the new Divisia and Currency Equivalence aggregates. In that sense, the key results here will provide a useful comparison to previous VAR studies that have attempted to resolve one of the most unsettling question in monetary economics about the effects of monetary policy.

The link between monetary policy and key macro variables has been studied extensively in the past and continues to be examined today as new empirical techniques and definitions of data develop. The central questions concern how monetary policy actions affect key macro variables such as output, prices and interest rates in a closed

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[1]See Appendix A for definition of the Divisia, Currency Equivalence, and Simple Sum monetary aggregates.

economy setting or exchange rates in an open economy setting. And underneath it all, how long before the effects take place and how long will they last. The influence of monetary policy on aggregate activity can be explained by the standard IS-LM and classical AD-AS models found in most intermediate macroeconomics textbooks. The IS-LM framework shows that an expansionary monetary policy causes the LM curve to shift outward. Under constant prices, interest rates fall (liquidity effect) and output rises (output effect) in the short run. When the sticky price assumption is relaxed in the AD-AS framework, both output and interest rates return to their original position in the long run. The price level is now at a higher level (price effect). Empirically, however, researchers are still unclear about the size and dynamic effects of monetary policy so easily explained by the textbook IS-LM model.

The current empirical evidence surrounding the literature remains controversial. More specifically, the controversy pertains to the puzzling evidence found which is at odds with traditional Keynesian or monetarist predictions. They are also known as the output, price, liquidity, exchange rate, and forward discount bias puzzles.[2] The liquidity puzzle, for example, is associated with increases rather than decreases in interest rates following an expansionary monetary policy. Under the same policy, the output and price puzzles are associated with decreases instead of increases in output and prices respectively.

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[2]The exchange rate and forward discount bias puzzles relate to open economy models and are not dealt with here. See, for example, Sims (1992), Eichenbaum and Evans (1995) and Roubini and Grilli (1995).

In order to resolve some of those puzzles, researchers are exploring with alternative monetary measures and applying recent advances in statistical work. One of such advance is use of the VAR-based methodology. For instance, more researchers are now choosing to work with narrower definitions of the money supply rather than traditional broad monetary aggregates such as M1 or M2.[3] Following the work of Sims (1980), the VAR approach is now a widely used statistical technique. One of the main reasons that the approach it receiving a lot of attention is that it avoids the "incredible identification restrictions" inherent in standard econometric models. More importantly, the VAR approach is useful in studying the dynamic responses of key macro variables to exogenous monetary policy shocks and in measuring the size of these shocks.

Keeping in view the objectives stated earlier, the remainder of this study is organized as follows. Chapter 2 gives a brief overview of the operating procedures of the Federal Reserve and monetary transmission mechanism (interest rate and credit channels). Selected VAR studies are reviewed to show the different and competing approaches used to identify monetary policy shocks.

Chapter 3 is an introduction to VAR analysis entailing a discussion of the importance of innovation accounting analysis (impulse response functions and forecast error variance decompositions). In addition, both the unrestricted and structural VAR

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[3]Christiano and Eichenbaum (1992) and others argue that statistical innovations in broad monetary aggregates do not reflect actual operating procedures of the Federal Reserve Board. Their movements primarily reflect shocks to money demand rather than shocks to money supply. Moreover, the conventional aggregation of the simple sum index, such as M1 or M2, is said to be distortive--See King (1990).

approaches will also be presented to compare the different identifying assumptions used. The methodology applied in this study is based on these two approaches.

Chapter 4 presents the empirical results for the unrestricted VARs based on Sims (1980) using innovation accounting analysis, correlation matrices for innovations, and Granger-causality tests. The dynamic responses of key macro variables are studied by the impulse responses of these variables to a unit shock in the monetary policy variable. This provides a useful empirical link to Friedman's (1968) qualitative dynamic monetary theory. The forecast error variance decomposition mainly addresses how much of the fluctuation in output is in fact due to monetary policy shocks. The correlation matrices for innovations help determine the robustness of innovation accounting analysis. Lastly, the Granger-causality tests are conducted to address a central question about the ability of the Federal Reserve in influencing output. This kind of analysis builds on Friedman and Schwartz (1963) in trying to show that money does have an impact on real economic activity as the literature on money-causality is largely inconclusive as to whether money causes output or the reverse. The marginal significance for exclusion of lags is presented in this study to see whether the money variables Granger causes output or not. In other words, to capture the predictive value of money for output.

Chapter 5 extends the analysis in the previous chapter by using the structural VAR approach following on Gordon and Leeper (1994). The objective is to specify economically meaningful contemporaneous identifying restrictions. The estimated structural parameters and impulse responses are examined here.

Chapter 6 takes a different approach to identify monetary policy shocks by using the non-borrowed monetary base based on Mishkin (1995). Although the idea is not new, McCallum (1996) and others believe that the monetary base should be the centerpiece of monetary policy. The results for innovation accounting analysis, correlation matrices for innovations and Granger-causality tests are presented. Finally, Chapter 7 summarizes the main findings of this study and offers some recommendations for future work in this area.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Current empirical evidence on the effects of monetary policy shocks does not lend support to "conventional wisdom" that an expansionary policy shock leads to a decline in short term nominal interest rates, and a rise in the price level and output. Some recent propositions have been put forth to account for this shortcoming both from theoretical and atheoretical perspectives. First, many researchers dissatisfied with traditional Keynesian and monetarist type analyses are pursuing the agenda of real business cycle models to rationalize the conventional view. Second, from a more atheoretical point of view, the VAR-based methodology has attracted the attention of empirical macroeconomists.

The puzzling evidence found in the literature refers to the inconsistent dynamic responses of key macro variables such as interest rates, prices and output to shocks in monetary policy variables. That is, they produce results that are at odds with the textbook IS-LM and AD-AS models. For example, the liquidity puzzle is associated with increases rather than decreases in interest rates following an expansionary monetary policy, while the price and output puzzles are associated with decreases rather than increases in prices and output, respectively. To compound this problem, the puzzling effects often depend on the definition of money used, the VAR specification (different estimation procedures and restrictions), and the data samples. For example, switching to a different monetary policy indicator may eliminate one puzzle but it may also create another one. The other methodological issues will be discussed in the later sections.

The lack of strong theoretical support and empirical evidence for the liquidity effect of monetary policy has led some prominent economists to search among monetary versions of real business cycle models. However, early versions of those types of models fail to display the liquidity effect because an expansionary policy tends to be dominated by the anticipated inflation effect thus causing interest rates to increase. Although later versions of monetized business cycle models are able to rationalize the liquidity effect, most fail to generate a persistent one. In their models, Grossman and Weiss (1984) and Rotemberg (1984) are able to introduce the liquidity effect where, due to heterogeneity of representative agents, money supply shocks impact different agents. This type of model is now known as the limited participation model incorporating modifications made by Lucas (1990) and Fuerst (1992) where some representative agents absorb a disproportionate amount of money shock. Another promising class of model is known as the cash-in-advance model where money is introduced into the artificial economy assuming that all the transactions are financed with previously accumulated cash. Using variations of the cash-in-advance models, Christiano (1990) and Christiano and Eichenbaum (1995) are able to show that positive money supply shocks drive nominal interest rates down, and employment and output up.[4]

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[4]See Ohanian and Stockman (1995) for a survey of RBC (general equilibrium) models.

Contrary to real business cycle models, the VAR-based methodology introduced by Sims (1980) is also known as atheoretical macroeconometrics. It differs from the real business cycle models because the data are not simulated to produce results similar to the actual data.[5] The VAR approach treats all variables symmetrically by letting each one be determined endogenously thus avoiding the "incredible restrictions" found in most of the standard econometric models. Sims argues that those models incorporate too many restrictions by assuming strict exogeneity based on prior theoretical restrictions and do not allow any feedback from the variables. The VAR methodology, on the other hand, relies on multivariate simultaneous estimation procedure with the aim of studying the interrelationship among all the variables in the model. However, the so called unrestricted VAR approach proposed is not entirely an atheoretical approach. For example, the selection and ordering of the variables in a VAR do involve theory and structure. In monetary VARs, this means selecting appropriate monetary policy indicators and other relevant macroeconomic variables. Furthermore, the ordering of the variables in the VAR system is usually based on some prior notions of how monetary policy operates and how it affects the economy through some specific channels. It is for some of those reasons that Sims' unrestricted VAR approach is sometimes known as loosely restricted.[6]

The following sections take a look at the different and competing approaches

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[5]See Sims (1996) for discussion of computational experiment used in real business cycle modelling.

[6]The identifying restrictions used by Sims (1980) is discussed in Chapter 3.

used in VAR studies to identify monetary policy shocks (section 2.4). First, in order to gain a better understanding of the different monetary measures used, a brief overview of Federal Reserve operating procedures and the monetary transmission mechanism is presented in the next two sections.

2.2 Overview of Federal Reserve operating procedures

Based on Strongin (1995) and Mishkin (1995), the following four periods indicate the operating procedures followed by the Federal Reserve System:

1959-1966: Free reserves targeting before the modern Federal funds market

1966-1972: Free reserves targeting and the bank credit proviso

1972-1979: Money growth/Federal funds targeting

1982-present: Borrowed reserves/Federal funds targeting

The above is a simplification of the actual implementation procedures. Basically, the Federal Reserve cannot directly achieve its objectives of price stability, economic growth, stable interest rates, or even stable foreign exchange rates. The Federal Reserve achieves its goals through operating targets that include bank reserves (borrowed and non-borrowed reserves), the federal funds rate and the monetary base. In addition, there are also intermediate targets such as interest rates, monetary aggregates and exchange rates and it is these variables that form the connecting link between operating targets and economic goals. By controlling the operating targets, the Federal Reserve is indirectly influencing the intermediate targets which in turn bring about changes in, say, employment or output.[7]

Athough most economists believe that monetary policy is important in the economy, their views are split on the channels through which the Federal Reserve's operating procedures affect the economy. Many researchers are considering evidence from a variety of sources to explain how, or even whether, changes in monetary policy get transmitted to the real economy. There are currently two main views that researchers use to explain the transmission mechanism of monetary policy or, alternately, the channels through which monetary policy affects the economy. These two views are briefly discussed next.

2.3 Monetary Transmission Mechanism: Interest Rate and Credit Channels

Generally, there are two main views taken by researchers on how monetary policy affects the economy. The first is the traditional interest rate channels and the other is the so-called credit channel. The credit view is receiving greater attention due to lack of empirical support for the traditional view that interest rates operates through the cost of capital.[8] A brief introduction of the two monetary transmission mechanisms is discussed below following Mishkin (1996).

The interest rate channel is based on the Keynesian IS-LM model which is

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[7]See Mishkin (1995) for a detailed discussion of the different operating procedures and intermediate targets used by the Federal Reserve System to achieve its goals.

[8]See also Lougani and Rush (1995).

commonly found in standard intermediate macroeconomic textbooks. Following an expansionary monetary policy, interest rates fall which lowers the cost of capital. This causes investment spending to rise and output to increase. The key assumption behind the interest rate channel is sticky prices since an expansionary monetary policy which lowers short-term nominal interest rates also lowers short-term real interest rates. For example, an increase in the money supply can be characterized by the following schematic (in the short run):

$$M\uparrow \;\Rightarrow i\downarrow \;\Rightarrow I\uparrow \;\Rightarrow Y\uparrow$$

where M is money supply, i is nominal interest rates, I is investment spending, and Y is output. In the long run, however, both Y and i return to their original levels where i corresponds to a one-for-one increase in inflation.[9]

The credit view, on the other hand, represents an alternative explanation to the traditional interest rate view. The credit view emphasizes two basic channels: the bank lending channel and the balance sheet channel. In the bank lending channel, an expansionary monetary policy increases bank reserves and bank deposits causing the amount of bank loans to increase which in turn causes investment and output to rise. The key assumption is that banks play an important role as lenders to some special classes of borrowers, i.e., those that do not have access to the credit markets unless they borrow

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[9]This phenomenon occurs only when the assumption of sticky prices is relaxed.

from banks. The balance sheet channel, on the other hand, is more complicated. The basic underlying notion is that an expansionary monetary policy causes an improvement in firms' balance sheets.[10] This leads to an increase in lending by banks which causes both investment level and output to rise.

2.3 Identification of Monetary Policy Shocks

Monetary policy indicators used in VAR studies can be categorized as: (i) quantitative measures such as monetary aggregates (M1 or M2) or bank reserves (nonborrowed or borrowed reserves), and (ii) qualitative measures such as the Romer and Romer or the Boschen and Mills indexes. In general, the former is considered to be more appealing because they suffer less from policy subjectivity and endogeneity problems.

It is not surprising why early studies have focused on using broad monetary aggregates as policy indicators given that the Federal Reserve used them as its intermediate targets from 1979 to 1982. For instance, Sims (1980) uses M1 innovations to identify monetary policy shocks by placing M1 first in the Wold ordering in his six-variable VAR system. By doing so, he assumes that M1 innovation disturb all the other variables in the system contemporaneously. In other words, the Federal Reserve and money-supply process do not respond to the current variables in the models and do so only with a lag.[11] Other monetary aggregates such as M2 is receiving greater attention by

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[10]See Mishkin (1996) for detailed discussion of the credit view.

[11]The assumption of weak exogeneity in M1 makes reasonable economic sense by revealing that the monetary policy instrument is perfectly controllable by the Federal

researchers such as Gordon and Leeper (1994) and Cochrane (1995a, 1995b) since the Federal Reserve no longer targets M1, in 1987, and begins to emphasize the growth of broader aggregates such as M2 and M3.[12]

The main criticism associated with using broad monetary aggregates as policy indicators is that their movements reflect non-policy disturbances such as money demand and movements of some other funds. In defence of this argument, Mishkin (1995) points out that the rapid pace of financial innovation and deregulation makes the task of accurately definining and measuring M1 almost impossible due to the increased substitutability among various money market instruments. Furthermore, he attributes the weakness of using broad monetary aggregates to the breakdown of their stable relationship with economic activity.[13] According to Cecchetti (1995, p.84), in order to understand the monetary transmission mechanism, it is crucial to identify a specific policy instrument that the Federal Reserve can use whereby small movements in it translate into "large changes in demand deposits, loans, bonds and other securities,

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Reserve--see Dale and Haldane (1995), Cochrane (1995), and Sims (1996) for more discussion. It is also possible to postulate a linear relationship between policy shocks and several different variables based on economic theory. This is the structural VAR approach.

[12]Karras (1993) shows that using M1 produces inferior results compared to M2 and cites evidence in favour of M2 by Friedman (1988), Mehra (1988), and Belongia and Chalfant (1990).

[13]For instance, the velocity of M1 appears more volatile after 1982 but M2 velocity remains stable during that period. However, in the early 1990s, the instability of M2 velocity led to the Federal Reserve's announcement in July 1993 that monetary aggregates will no longer be used as a guide for conducting monetary policy. See Mishkin (1995).

thereby affecting aggregate investment and output" It is in this respect that broad monetary aggregates fail.[14]

It is currently popular to identify monetary policy shocks with finer measures of money supply such as bank reserves and the federal funds rate. First, they produce better results and, second, they reflect more closely the actual operating procedures of the Federal Reserves. The use of broad monetary aggregates is often associated with the anomalous interest rate effect--the liquidity puzzle. Using non-borrowed reserves and total reserves, Christiano and Eichenbaum (1992) and Strongin (1995) are able to solve the liquidity puzzle. Generally, the use of reserves measurement is viewed as a better policy indicator than broad monetary aggregates since they represent the operating targets directly controlled by the Federal Reserve. Although those studies are able to show the liquidity effect, they are faced with the anomalous price effect--price puzzle.

There are others who claim that other operating targets, namely the federal funds rate, can also be reasonably attributed to monetary policy. For instance, Bernanke and Blinder (1992) argue that the federal funds rate predicts output better than monetary aggregates and other open market interest rates. Early evidence by Sims (1980) shows that when interest rates are included in the VAR specification, monetary aggregates lose their explanatory power for output, i.e., money no longer Granger-cause output. However, identifying monetary policy shocks with innovations in the federal funds rate is associated with the anomalous price effect. That is, a contractionary monetary policy

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[14]Cecchetti (1995) emphasizes the use of outside money such as monetary base or non-borrowed reserves as opposed to using M2.

when identified with positive innovations in the federal funds rate is associated with increases rather than decreases in the price level. To overcome this problem, Sims (1992) and others include another variable into the VAR system which is sensitive to economic conditions such as commodity prices or GDP deflator. This is to capture for any policy changes due to future inflation.

In contrast to the use of quantitative indexes discussed above, monetary policy indicators such as the Romer and Romer (1989) and Boschen and Mills (1991) indexes are classified as qualitative measures.[15] Their intention is to seperate money supply shocks from money demand shocks. For instance, Romer and Romer (1989) obtain minutes of the Federal Open Market Committee (FOMC) and construct a set of dates viewed to be episodes of contractionary monetary policy. This approach is criticized for being inherently subjective since the Romer and Romer dates focus only on policy contractions and there is no distinction between the degree of contraction. On the other hand, Boschen and Mills (1991) provide a monthly index of contractionary and expansionary policy. They also identify in the different months when policy is viewed as "strongly expansionary/contractionary" or otherwise. Like the Romer and Romer index, the Boschen and Mills index also suffers from subjectivity and endogeneity problems. For instance, those indexes show how the Federal Reserve responded to inflationary pressures by contracting the money supply which makes policy endogenous. It is difficult to determine from the FOMC minutes whether the policy changes are truly

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[15]The description is based on Cecchetti (1995) and Bernanke and Mihov (1995).

exogenous.

So far none of the quantitative and qualitative indexes discussed seem to offer themselves as the definitive indicator of monetary policy. What is more, there are econometric problems which researchers have to deal with besides deciding on which definition of money to use. The different findings in the literature are attributed to factors such as different VAR specifications and restrictions, and different sample period used. Studies often rely on fishing for a specific VAR ordering or structure to produce impulse-responses that are consistent with theory. This means experimenting with different Wold orderings or choosing to work with either unrestricted or structural VARs.

Furthermore, the results are also sensitive to the different sample periods. It is obvious from section 2.1 that the operating procedures of the Federal Reserve have changed overtime. This clearly presents some difficulty when it comes to choosing a single policy measure especially one for an extended period of time. According to Pagan and Robertson (1995), observations from 1982 to 1993 tend to produce better results in terms of the liquidity effect than those prior to 1982 when using non-borrowed reserves. Similar evidence is also found by Gordon and Leeper (1994) in the early 1970s when identifying policy shocks with M2 but not during the 1980s when using total reserves. More recently, Geweke and Runkle (1995) argue that most studies are tainted by time-aggregation problems. They claim that since financial variables interact minute by minute, the use of monthly data potentially obscures how variables such as reserves and interest rates interact over time.

2.4 Conclusion

One of the biggest challenge confronting monetary VARs is the identification of policy shocks. The general consensus among recent studies is that narrower not broader monetary aggregate data distinguish the channels of monetary transmission better. That is, innovations to them display results which are more consistent with conventional wisdom. Such studies include Christiano and Eichenbaum (1992), Gordon and Leeper (1994) and Strongin (1995) who use reserves measurements, and Bernanke and Blinder (1992) and Sims (1992) who use the federal funds rate. This is in direct contrast to a monetarist who would argue that shocks to the right aggregate are all that matters but so far the search for such policy shocks seems to be unsuccessful. Interestingly, however, Beaudry and Saito (1993, p. 9) in their study find that " a combined procedure of instrumenting non-borrowed reserves with the Romer dummy variables provides the most defensible means of identifying the effects of monetary shocks."

The next chapter is an introduction to VAR analysis. This methodology is used in this study including those discussed above.

CHAPTER 3

METHODOLOGY

3.1 Introduction

Following the work of Sims (1980), VAR is becoming an important research tool in monetary economics. This methodology allows researchers to study the dynamic effects of monetary policy through surprise changes in money, called "innovations", and the behaviour of key macro variables through "impulse responses". Furthermore, the contribution of money innovations to the variance of key macro variables can be examined by the forecast error variance decompositions. Taken together, the impulse response functions and forecast error variance decompositions are referred to as "innovation accounting analysis". In monetary VARs, innovation accounting allows quantitative analysis of the size and dynamics of monetary policy. Specifically, VAR allows one to describe how the economy responds to policy changes over time and how policy gets transmitted through the economy. There are, however, limitations to innovation accounting which will be discussed in here.

3.2 Introduction to Vector Autoregression (VAR) analysis

The VAR approach proposed by Sims (1980) represents an alternative style of identification in face of the "incredible identification restrictions" inherent in large-scale models. Sims' methodology treats all variables as endogenous without restrictions based on "supposed a priori knowledge" and is now called unrestricted VAR since it is without any theoretical perspective.[16]

To introduce the VAR analysis, consider a simple bivariate system below, following Enders (1995):

$$x_{1t} = b_{10} - b_{12}x_{2t} + \gamma_{11}x_{1t-1} + \gamma_{12}x_{2t-1} + \varepsilon_{1t} \qquad (1)$$
$$x_{2t} = b_{20} - b_{21}x_{1t} + \gamma_{21}x_{1t-1} + \gamma_{22}x_{2t-1} + \varepsilon_{2t} \qquad (2)$$

The above is called a *structural* VAR or the *primitive system*. It is assumed that both x_{1t} and x_{2t} are stationary; ε_{1t} and ε_{2t} are white noise disturbances. Using matrix algebra both (1) and (2) can be expressed as:

$$\begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}\begin{bmatrix} x_{1t-1} \\ x_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

or

$$Bx_t = \Gamma_0 + \Gamma_1 x_{t-1} + \varepsilon_t \qquad (3)$$

where

$$B = \begin{bmatrix} 1 & b_{12} \\ b_{21} & 1 \end{bmatrix}, \quad x_t = \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix}, \quad \Gamma_0 = \begin{bmatrix} b_{10} \\ b_{20} \end{bmatrix},$$
$$\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}, \quad x_{t-1} = \begin{bmatrix} x_{1t-1} \\ x_{2t-1} \end{bmatrix} \quad \textit{and} \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

[16]However, Sims' unrestricted VAR is sometimes labeled as loosely restricted because it does involve specific identification restrictions (based on Choleski decomposition) beyond the selection of appropriate variables and the lag length. This is discussed in section 3.6.

The VAR in *standard form*, or *reduced form*, is obtained by premultiplying (3) by B^{-1}

$$x_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1 x_{t-1} + B^{-1}\varepsilon_t$$
$$x_t = A_0 + A_1 x_{t-1} + e_t \qquad (4)$$

where

$$A_0 = B^{-1}\Gamma_0$$
$$A_1 = B^{-1}\Gamma_1$$
$$e_t = B^{-1}\varepsilon_t$$

Alternatively, (4) can be rewritten as:

$$x_{1t} = a_{10} + a_{11}x_{1t-1} + a_{12}x_{2t-1} + e_{1t} \qquad (4.1)$$
$$x_{2t} = a_{20} + a_{21}x_{1t-1} + a_{22}x_{2t-1} + e_{2t} \qquad (4.2)$$

In order to identify the primitive system (1) and (2), appropriate restrictions need to be imposed on the standard form (4.1) and (4.2). For instance, if there are 10 parameters in the primitive form and the standard form contains only 9, then 1 parameter needs to be restricted in the primitive form for the system to be exactly identified. Otherwise if the system is underidentified, it is not possible to undertake meaningful innovation accounting analysis.

In the unrestricted VAR, Sims identifies the system by "normalization" which requires the residuals to be orthogonal across equations and the coefficient matrix of current endogenous variables to be triangular. This process is also known as the Choleski decomposition where the resulting normalization is transformed into a Wold causal chain form which is identified. This is done by solving the standard form for a moving average representation using the Wold Theorem. The next section briefly introduces the Wold theorem.

3.3 Wold's Moving Average Representation

According to Wold's theorem (1938), a stationary autoregressive model of nth order can be represented in terms of an infinite order moving average model. Letting x_t be any indeterministic covariance stationary stochastic process with the following moving average representation (without any constant and deterministic terms):

$$x_t = \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \qquad (5)$$

or

$$x_t = \phi(L)\varepsilon_t \qquad (6)$$

where

$$\phi(L) = \phi_0 + \phi_1 L + \phi_2 L^2 + \ldots$$

The above moving average representation is true under these assumptions: (i) x_t is stationary, (ii) $\{\varepsilon_t\}$ is serially uncorrelated, and (iii) $\Sigma\phi_j^2 < \infty$. Moreover, ϕ_0 is normalized to 1 to ensure that the derived ε_t process has a convergent series representation in terms of current and lagged values of x_t.[17]

It can be shown from (6) that the autoregressive representation of x_t is

$$A(L)x_t = \varepsilon_t \qquad (7)$$
where
$$A(L) \equiv \phi(L)^{-1}$$
and
$$A(L) = A_0 - \sum_{i=1}^{\infty} A_i L^i$$

Alternatively,

$$A_0 x_t = A_1 x_{t-1} + A_2 x_{t-2} + \ldots + \varepsilon_t$$
or
$$x_t = A_1 x_{t-1} + A_2 x_{t-2} + \ldots + \varepsilon_t \qquad (8)$$
$$Since\ \phi_0 = 1,\ then\ A_0 = 1$$

Equation (8) is related to (4) but without any constant or deterministic terms. In VAR analysis, the goal is to derive a solution for x_t ,(8), in the form of a Wold moving average representation, (5). Once in this form, the interrelationship among the variables by innovation accounting analysis can then be studied.

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[17]For a greater discussion on the Wold theorem see Wold (1954) and Sargent (1979).

3.4 Impulse Response Function

Given the moving average representation of x_t in (5), ε_t is the sequence of one-step-ahead linear least square forecasting errors. The ϕ_i matrices contain the dynamic multipliers or impulse response functions. For example, using a 2-variable system matrix, (5) can be rewritten as:

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \sum_{i=0}^{\infty} \begin{bmatrix} \phi_{11}(i) & \phi_{12}(i) \\ \phi_{21}(i) & \phi_{22}(i) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t-i} \\ \varepsilon_{2t-i} \end{bmatrix}$$

The elements $\phi_{jk}(o)$ are impact multipliers or impulse responses. For example, $\phi_{11}(o)$ is the instantaneous impact of a one unit-change in ε_{1t} on x_{1t} and $\phi_{11}(1)$ is the one period response of a unit change in ε_{1t-1} on x_{1t}. A useful way to visually represent the behaviour of the $\{x_{1t}\}$ and $\{x_{2t}\}$ series in response of the various shocks is to plot the impulse response functions. However, the estimated impulse responses are sensitive to the ordering of the variables. In this case, reversing the order of x_{1t} and x_{2t} will affect the impulse response functions. This will depend on the magnitude of the correlation coefficients between the VAR residuals. According to Enders (1995), if the correlation coefficients do not exceed 0.2 in absolute terms then the impulse response functions will not be sensitive to different orderings.

The accumulated effects of unit responses in ε_{1t} and ε_{2t} are done by appropriate summation of the coefficients of the impulse response functions. For example, after n periods, the cumulated sum of the effects of ε_{2t} on x_{1t} is

$$\sum_{i=0}^{n} \phi_{12}(i)$$

The long-run multiplier can also be studied by letting n approach infinity. As stated earlier that x_t is assumed to be stationary then the summation of the coefficients for all j and k is finite:

$$\sum_{i=0}^{\infty} \phi_{jk}^{2}(i) \textit{ is finite}$$

It is important to note that unless the underlying structural system can be identified from the estimated VAR, the innovations in do not have a direct economic interpretation. It is important to be able to recover the residuals of the primitive system from the estimated VAR residuals.

The other important part of innovation accounting concerns the relative importance of each shock. For example, in studying monetary VARs, the impulse response functions provide information about the dynamic effects on key macro variables to a unit innovation in the money supply,but we are also interested in asking about the contribution of money innovation to fluctuation in output. In other words, we are interested in measuring the size of monetary policy shocks. This is examined by the forecast error variance decompositions which is discussed next.

3.5 Variance Decomposition

Besides examining the impulse response function, another important question concerns the relative importance of the different shocks produced by the model. In particular, the forecast error decomposition tells how much the movement in x_t is accounted for by its own shocks and by the shocks to the other variables.

For example, if $E_t x_{t+1}$ is the expected value of x_{1t+1} based on all information available at time t then the n-step ahead forecast error of x_{1t+1} is

$$x_{1t+n} - E_t x_{1t+n} = \sum_{i=0}^{n-1} \phi_i \varepsilon_{1t+n-i}$$

The n-step forecast error variances for x_{1t+n} series are the diagonal elements in the following matrix:

$$E(x_{1t+n} - E_t x_{1t+n})(x_{1t+n} - E_t x_{1t+n}) = \sigma_{11t}(n)^2$$

$$or$$

$$\begin{aligned}\sigma_{1t}(n)^2 = {} & \sigma_{1t}^2[\phi_{11}(0)^2 + \phi_{11}(1)^2 + \ldots + \phi_{11}(n-1)^2] \\ & + \sigma_{2t}^2[\phi_{12}(0)^2 + \phi_{12}(1)^2 + \ldots + \phi_{12}(n-1)^2]\end{aligned}$$

The forecast error variance decomposition is derived as

$$\frac{\sigma_{1t}^{2}[\phi_{11}(0)^{2}+\phi_{11}(1)^{2}+\ldots+\phi_{11}(n-1)^{2}]}{\sigma_{1t}(n)^{2}}$$

and

$$\frac{\sigma_{2t}^{2}[\phi_{12}(0)^{2}+\phi_{12}(1)^{2}+\ldots+\phi_{12}(n-1)^{2}]}{\sigma_{1t}(n)^{2}}$$

The above indicates how much of the fluctuation in x_{1t} is explained by ε_{1t} and ε_{2t}. One important implication is when ε_{2t} shocks explain all of the forecast error variance in x_{1t}, then x_{1t} is said to be entirely endogenous. On the other hand, x_{1t} is exogenous if none of its forecast error variance is explained by ε_{2t}.

According to some researchers, VAR analysis is used to primarily study the dynamic interrelationship. Therefore they argue that greater emphasis should be paid to the impulse response functions. The use of forecast error variance decompositions is criticized by Cochrane (1995) because any VAR mechanically accounts for 100% of its fluctuation and it does not address questions about the movement of the variables. In a monetary VAR, Bernanke (1996) believes that an optimal monetary policy should not account for any of the fluctuations at all. Nevertheless, it does provide some crucial information about the main channels of the model.

3.6 Unrestricted VAR

The identifying restriction used by Sims' (1980) is based on Choleski decomposition. He calls this "identification by normalization" by making the residuals orthogonal across equations and the coefficient matrix of current endogenous variables, or the Choleski factor, into a lower triangular matrix. To illustrate this, consider the moving average representation of x_t again.

$$x_t = \phi(L)\varepsilon_t \qquad (6)$$

Equation (6) above is called the structural moving average model and is the final form of Sims' economic model. The elements of ε_t are given structural economic interpretation so that questions regarding how the system's endogenous variables respond dynamically to exogenous shocks (impulse response function) and which shocks were the primary causes of variability in the endogenous variables (forecast variance decomposition) can be studied. This is possible due to the uncorrelatedness of ε_t (orthogonalized innovations).

To achieve normalization, Sims restricts A_0 in (7) to be lower triangular. Notice that its inverse A_0^{-1} is also lower triangular thus premultiplying (7) by A_0^{-1} yields

From (7),

$$A(L)x_t = \varepsilon_t$$

$$A_0^{-1}A(L)x_t = A_0^{-1}\varepsilon_t \qquad (7')$$

where

$$A_0^{-1}\Sigma_\varepsilon A_0^{'-1} = I$$

$$\text{Since } A_0 A_0^{'} = \Sigma_\varepsilon$$

By making the covariance matrix diagonal, Σ_ε, the residuals are now orthogonalized and are uncorrelated across equations.[18] In the process, the residuals are transformed into a triangularized system, $A_0^{-1}\varepsilon_t$. This implies that innovation in the first variable in the Wold ordering, x_{1t}, is assumed to have a contemporaneous effect on all other variables.[19] That is, $A_0^{-1}A(L)$ is lower triangular and this is true if and only if $A(L)^{-1}$ is lower triangular. To prove this,

$$A(L)^{-1} = A(L)^{-1} A_0 A_0^{-1}$$

Suppose that $A_0^{-1}A(L)$ is lower triangular, its inverse $A(L)^{-1}A_0$ is also lower triangular. Given that A_0^{-1} is lower triangular, the product of two triangular matrices, $A(L)^{-1}A_0\, A_0^{-1}$, is also lower triangular. This proves that $A(L)^{-1}$ must be lower triangular.

Therefore, by inverting (7') gives:

$$A_0^{-1}A(L)x_t = A_0^{-1}\varepsilon_t \qquad (7')$$
$$x_t = A(L)^{-1}\varepsilon_t$$
$$or$$
$$x_t = \phi(L)\varepsilon_t \qquad (8)$$
$$where$$
$$A(L)^{-1} = \phi(L)$$

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[18]Orthogonalized innovations can be achieved in many ways by using different factorization. See Doan (1995).

[19]This is based on Sims (1972) concept of strict exogeneity and Granger's concept of causality--see Sargent (1979).

To see this more clearly, (8) can be expanded into a 2×2 matrix given below:

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} = \begin{bmatrix} \phi^{11}(L) & 0 \\ \phi^{21}(L) & \phi^{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

The triangularized system assumes that ε_{1t} contemporaneously affects both x_{1t} and x_{2t}. Conversely, shocks to x_{2t} does not contemporaneously affect x_{1t}. The identifying assumption behind Choleski decomposition corresponds to a Wold ordering in which x_{1t} is causally prior x_{2t}. In the above example, x_{1t} is placed first in the Wold causal chain or ordering of an unrestricted VAR model implying that x_{1t} contemporaneously affects x_{2t}. Whether this makes economic sense is questionable but, econometrically, the triangularity assumption is necessary for identification.

Using Choleski decomposition requires $(n^2 - n)/2$ number of restrictions be imposed on the structural model in order to identify it from an estimated VAR. In the 2-variable system considered above, this requires only $(4 - 2) / 2 = 1$ restriction since A_0 is restricted to be lower triangular. Therefore, the zero restriction is placed on the one element above the principal diagonal in A_0.

Normally, given that Σ_e is symmetric it contains $(n^2 + n)/2$ distinct elements or known values. In addition, A_0 contains $n^2 - n$ unknowns and together with $var(\varepsilon_{it})$ which contains n^2 unknowns. In order to identify the model, n^2 number of unknowns $(n^2 - n + n = n^2)$ need to be recovered from $(n^2 + n)/2$ number of known values. Therefore, it is necessary to impose a total of $n^2 - (n^2 + n)/2 = (n^2 - n)/2$ number of restrictions. Although this is achieved by Choleski decomposition, i.e., the system is exactly identified, there are dissatisfaction with this method since it requires that all elements above the principal diagonal to be zero in A_0, or to be lower triangular. According to Enders (1995) and others, unless there is a strong theoretical foundation for doing so, the impulse responses and variance decompositions can be misleading.

Like any identifying restriction, it should never be used automatically. This restriction used is now widely applied that it has become the default identifying assumptions in many studies. Sims' unrestricted VAR is criticized by many recent studies for contradicting the "incredible identifying restrictions" which it is suppose to avoid. On the other hand, Enders (1995) believes that using the Choleski decomposition is said to provide a minimal set of assumptions to identify the primitive model. Furthermore, Cooley and LeRoy (1985) point out that explicit justification is not necessary if VAR is treated as non-structural, then the assumption of triangularity is in fact arbitrary normalization not requiring theoretical justification.

To overcome the strong assumption made about the underlying structural errors in Choleski decomposition, studies are using the structural VARs instead which is based on economic theory.

3.7 Structural and Semi-Structural VARs

Unlike Sims' unrestricted VAR, the restricted or structural VAR takes into account identifying restrictions that are derived from economic theory. For instance, the identifying restrictions used in the unrestricted VAR is based on Choleski decomposition by making the contemporaneous matrix A_0 lower triangular. That is, in the Wold causal ordering, the first variable is predetermined and contemporaneously affects all the other variables. However, it is questionable whether this method of identification is theoretically plausible since the selection of the Wold ordering is generally ad hoc. Later studies such as Bernanke (1986), Blanchard and Watson (1986) and Sims (1986) propose an alternative set of identifying assumption which does not require the contemporaneous matrix to be lower triangular. The objective is to specify economically meaningful simultaneous interactions among specific variables.

For example, consider the primitive system below:

$$x_t = \sum_{i=0}^{n} A_i x_{t-i} + \varepsilon_t \qquad (9)$$

where

$$x_t = (x_{1t}, x_{2t})'$$

And the standard form is:

$$x_t = (I - A_0)^{-1} \sum_{i=1}^{n} A_i x_{t-i} + (I - A_0)^{-1} \varepsilon_t \qquad (10)$$

and

$$E(\varepsilon_t \varepsilon_t') = (I - A_0)^{-1} \Sigma_\varepsilon [(I - A_0)^{-1}]'$$

In general, the system in (9) is not econometrically identified. The aim here is to identify the structural shocks in (9) from the residuals in (10). This can be achieved by imposing restrictions on the matrix A_0. If this is an n-variable system, the estimated variance-covariance matrix gives $(n^2 + n)/2$ distinct parameters. Furthermore, the estimated variance in (10) also yields n known parameters. Thus, a maximum of $(n^2 + n)/2 - n = (n^2 - n)/2$ non-zero parameters can be imposed on the contemporaneous matrix A_0.

It is possible to impose greater than $(n^2 - n)/2$ number of restrictions on B_0 where the system is overidentified. For example, in choosing to work with an overidentified system, the overidentifying restrictions needs to be tested using likelihood ratio test.[20] Most structural VARs involve using an overidentified system. Other specific examples of structural VARs include the semi-structural VARs proposed by Bernanke and Mihov (1995) and long run restriction VARs by Blanchard and Quah (1989). For example, the distinguishing feature in semi-structural VARs is that the macroeconomic variables are left unrestricted while imposing contemporaneous restriction on the policy variable. In the long run restriction, however, the sum of the dynamic multipliers are restricted.

3.8 Conclusion

This chapter has introduced the VAR methodology which will be applied in this study. In particular, the unrestricted VAR approach is applied in Chapter 4 while the structural VAR approach is used in Chapter 5. Following the discussion in section 3.6, in

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[20]The description of the overidentification test is found in Doan (1995) and Enders (1995).

the unrestricted case, a lower triangular is formed in the contemporaneous matrix by placing the monetary policy variables first. In the structural case, however, the triangularized pattern is no longer assumed and the monetary policy variables are now a linear combination of different variables. The details are given in the introduction section to those chapters.

CHAPTER 4

EMPIRICAL RESULTS OF UNRESTRICTED VARs

4.1 Introduction

The unrestricted VAR approach used in this chapter is based on Sims (1980). Two different identification schemes are explored here. First, the money supply rule (M-rule) is applied by placing the monetary variables first in the Wold ordering. This identifies expansionary monetary policy shocks with positive innovations in money. Second, the interest rate rule (R-rule) places the interest rate variable first thereby identifying shocks to it with contractionary monetary policy. According to theory, under the M-rule ordering, the expected impulse responses of interest rates should decline, and the impulse responses for prices and output should both increase. Conversely, VARs with the R-rule ordering should cause money, prices and output to fall following shocks to the interest rate.

A four-variable VAR system (M-rule and R-rule) is used in section 4.2 and a five-variable VAR system (R-rule) is used in section 4.3. The latter is a modification of the four-variable VAR in that an extra variable is added following Sims (1992). Although monetary policy shocks are still identified with interest rate innovations, the inclusion of the commodity price index is supposed to capture for any future inflation pressures by the monetary authority. By doing so, Sims is able to solve for the price puzzle.

The data used in this study are seasonally adjusted monthly series from 1960:1 to

1995:11. They include four Divisia aggregates (DM1, DM2, DM3, DL), four Currency Equivalence aggregates (CEM1, CEM2, CEM3, CEL), four Simple Sum aggregate (M1, M2, M3, L), the federal funds rate (FF), user costs associated with Divisia aggregates (DUALM1, DUALM2, DUALM3, DUALL), 10-year Treasury bond rate (R10), unemployment rate (U), consumer price index (P), industrial production (Y) and commodity price index (PC). All of the variables are entered as logarithms except for FF, DUAL and U.[21] The number of lags chosen is 13 for each variable.[22]

4.2 Four-variable VARs: Money Supply Rule

Figures 4.1 to 4.4 present the estimated impulse responses of the four-variable VAR system where monetary policy shocks are identified with positive innovations to each of the twelve different monetary aggregates (M-rule). Figures 4.5 to 4.8, on the other hand, present the impulse responses where innovations in FF are treated as monetary policy shocks (R-rule). The top row of each figures plots the impulse response function of all the variables in the VAR system with respect to an innovation in the

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[21]Regarding the issue of non-stationarity, Doan (1995) and others recommend against differencing even if the series contain a unit root. Since the goal is to study the interrelationship among the variables, differencing the variables would throw away information. Enders (1995) shows that the form of variables in VARs with the drift term mimic the true data-generating process. Furthermore, Dale and Haldane (1995) argue that variables entered as logged give the VAR system the interpretation of a vector error-correction mechanism.

[22]The lag length is set equal to one year plus one month period. This is done to capture the seasonal effects not removed by seasonal adjustment of the data--See Dueker and Serletis (1996).

monetary policy variables. The other rows in the figures correspond to the impulse responses due to the other shocks in the system and are not in themselves related to the study. The confidence interval bands (of ± two standard deviations) are constructed using Monte Carlo method in RATS *version 4.2* with 500 draws.[23] Tables 4.1 and 4.2 present the results for the correlation matrices for innovations, Granger-causality tests and forecast error variance decomposition over a 60-month horizon for both M-rule and R-rule models respectively.[24]

To begin, Figure 4.1 corresponds to the following VAR models : {DM1, FF, P, Y}, {DM2, FF, P, Y}, {DM3, FF, P, Y} and {DL, FF, P, Y}. The top row of each graph show how the money variables (DM1, DM2, DM3, DL), federal funds rate (FF), price (P), and output (Y) respond to a unit shock in the Divisia monetary aggregates.

Following shocks to DM1, DM2, DM3 and DL, the response of FF is surprisingly high indicating the presence of the liquidity puzzle. There is a also a significant increase in P after DM1 shocks but not a persistent one as theory predicts. On the other hand, following shocks to DM2, DM3 and DL, the response of P is sluggish initially but show a significant and persistent rise after about a year. This is the price effect. Those three systems also show an increase in Y following monetary policy shocks but, according to theory, the response should only be a temporary one. In this case, the response in Y is rather persistent and fails to adjust back to its original level after the 60-month horizon.

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[23]See Example 10.1 in Doan (1995).

[24]Since the Granger-causality tests are identical under both the M-rule and R-rule VARs, the results will be mentioned only for VARs with the M-rule ordering in section 4.2.

Surprisingly, DM1 shocks fail to produce any significant increase in Y at all. This is the output puzzle.

In Table 4.1, panels 1 to 4, the forecast error variance decompositions show that a greater percentage of the variance in Y is explained by shocks to FF compared to DM1, DM3 and DL, ranging from 27 to 36 percent. On the other hand, DM2 innovations account for about 31 percent of the variation in Y compared to 29 percent by FF.

The correlation matrices for innovations are particularly high especially between FF and Y innovations as shown in panels 1 to 4. Their values exceed 0.2 in absolute terms.[25] This implies that the impulse response functions and forecast error variance decompositions are sensitive to the Wold ordering in the VAR system. That is, reordering of the variables in the VAR models may produce different results to those here.[26]

In the Granger-causality test, the null hypothesis being tested is the exclusion of lags for each variables in each equation. In other words, the predictive power of those variables are being tested. For instance, the last row of panels 1 to 4 report the marginal significance level to determine whether DM, FF, P can be properly excluded from the Y equation. The higher the marginal significance level reported, the weaker the evidence

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[25]As a rule of thumb, Enders (1995) states that when the correlation between innovations does not exceed 0.2 in absolute terms then the impulse response functions and forecast error decompositions will be not be sensitive to different Wold orderings.

[26]Although it is not practical to explore all the possible orderings, only one other alternative is explored in section 4.3 whereby interest rate is placed first in the Wold ordering instead of money. This implies an interest rate rule (R-rule).

against the null of no causality. When tested at the 10 percent significance level, the null can only be rejected for DM2 indicating causality from money to income. This implies that of the four Divisia aggregates, only DM2 is found to Granger cause Y or is a better predictor of Y. However, the null is rejected for DM3 and DL at the 20 percent significance level. Interestingly, in the case of DM1, Panel 1 shows that FF is a better predictor of Y.

The next model to be considered is one which replaces the federal funds rate, FF, with the user costs associated with each Divisia aggregates, DUAL. The impulse responses can be seen in Figure 4.2 for models with the following Wold ordering: {DM1, DUALM1, P, Y}, {DM2, DUALM2, P, Y}, {DM3, DUALM3, P, Y}, and {DL, DUALL, P, Y}. In every case, the liquidity puzzle is observed. Compared to the previous VARs, there is weaker evidence of the price puzzle particularly following shocks to DM1. The response of Y is quite significant and persistent following DM2, DM3 and DL shocks. Only a temporary rise in Y observed following DM1 shocks.

In Table 4.1, panel 5 shows a strong correlation between DM1 and DUALM1 innovations while the correlation between the other innovations in panels 6 to 8 is quite insignificant. In the Granger-causality test, DM1 fails to cause Y while most the explanatory power is captured by DUALM1. On the other hand, DM2, DM3 and DL are found to Granger-cause Y at the 5 percent significance level. Furthermore, they also account for over 20 percent of the variance in Y compared to less than 5 percent by DM1 shocks.

Next, the Currency Equivalence aggregates are used as monetary policy indicators. The individual impulse responses are presented in Figure 4.3 for the following models: {CEM1, FF, P, Y}, {CEM2, FF, P, Y}, {CEM3, FF, P, Y} and {CEL, FF, P, Y}. Following a positive shock to CEM1, CEM2, CEM3 and CL, there is an initial rise in FF which is then followed by a sharp decline. Although this is somewhat consistent with the liquidity effect, the results here are not statistically significant as implied by the confidence interval bands. The price effect, on the other hand, is only observed following shocks to CEM2, CEM3 and CEL. Again this cannot be interpreted as significant. The correct response of Y is also observed in those three cases but not for CEM1. Although there seems to be an initial decline in Y, one possible explanation offered by Bernanke and Mihov (1995) is that there is inventory decumulation at the beginning of an expansion.

Panels 9 to 12 show a high correlation between FF and Y innovations in all four cases. The Granger-causality tests show that the null hypothesis is strongly rejected for FF. This implies that FF captures all the explanatory power for Y or that CEM1, CEM2, CEM3 and CEL fail to Granger-cause Y. The forecast error variance decompositions show that FF accounts for a greater percentage of the variance in Y, up to 31 percent in panel 9.

In the last four-variable VARs, traditional Simple Sum monetary aggregates (M1, M2, M3 and L) are used to indicate monetary policy disturbances. The impulse responses can be seen in Figure 4.4 for {M1, FF, P, Y}, {M2, FF, P, Y}, {M3, FF, P, Y}, and {L, FF, P, Y} models, respectively. There is strong evidence of the liquidity puzzle where FF increases following shocks to M1, M2, M3 and L. But P increases significantly and persistently after expansionary monetary policy shocks except for shocks to M1. A significant response of Y is also associated with shocks to M2, M3 and L. The output and price puzzles are present in the case of M1.

Looking at panels 13 to 16, there is a strong correlation between FF and Y innovations. The Granger-causality tests show that M2, M3 and L have better predictive value for Y. In the VAR specification which includes M1, FF is found to Granger-cause Y instead. The results for the forecast variance decomposition show that M2 accounts for the greatest percentage of variance in Y when compared to the other monetary aggregates, about 42 percent.

4.2.1 Summary

The results for the four-variable VARs with M-rule ordering are summarized in Table 4.3. This provides a quick assessment of the ability of each of the twelve monetary aggregates in solving the liquidity, price and output puzzles.

The price puzzle is observed for {DM1, FF, P, Y}, {DM1, DUALM1, P, Y}, {CEM1, FF, P, Y} and {M1, FF, P, Y}. Notice that they all involve measures of M1 only. The Currency Equivalence aggregates are successful in solving only the liquidity puzzle but not the price and output puzzles. Due to the significant correlation matrices for innovation, the results here are not robust. This indicates that the estimated impulse responses and forecast error variance decompositions are sensitive to the different orderings of the variables. In the next section, the R-rule ordering is used where FF is place first instead of the monetary aggregates.

4.3 Four-variable VARs: Interest Rate Rule

In this section, monetary policy shocks are now identified with innovations in FF. In particular, a positive innovation to FF implies a contractionary monetary policy and according to theory this should produce a fall in money, prices and output. Figure 4.5 presents the estimated impulse responses for the following VARs: {FF,DM1, P, Y}, {FF, DM2, P, Y}, {FF, DM3, P, Y} and {FF, DL, P, Y}. The results for the correlation matrices for innovations, forecast error variance decomposition and Granger-causality test are presented in Table 4.2.

The impulse responses of DM1, DM2, DM3 and DL are all negative following shocks to FF. Unfortunately, there is strong evidence of the price puzzle where P increases significantly immediately following FF shocks. Although it decreases after 3 years or more, it is not statistically significant. In the case of Y, there is a small increase after shocks to FF but is followed by a sharp and significant decline. Although the fall in Y is consistent with theory, it also shows some adjustment back to its original level at the end of the 60-month horizon.

In Table 4.2, panels 1 to 4 report a significant correlation between FF and Y innovations. The forecast error variance decompositions show that DM2, DM3 and DL explain very little of the variance in Y. Over 40 percent of the variance in Y is explained by FF compared to less than 20 percent by DM2, DM3 and DL. In the case of DM1, it accounts for almost 30 percent of the variance in Y compared to 24 percent by FF.

Figure 4.7 presents the estimated impulse responses for {FF, CEM1, P, Y}, {FF, CEM2, P, Y}, {FF, CEM3, P, Y}, and {FF, CEL, P, Y} models. There is strong evidence of the price puzzle in all the models. However, the negative response of Y is very significant for all four cases indicating the absence of the output puzzle. Panels 9 to 12 show that the correlation between FF and Y is especially high. In every case, FF innovations account for greater fluctuation in Y ranging from 40 to 20 percent when compared to CEM1, CEM2, CEM3 and CEL. Those monetary aggregates only account for less than 14 percent of the variance in Y individually.

Lastly, the estimated impulse responses for {FF, M1, P, Y}, {FF, M2, P, Y}, {FF, M3, P, Y} and {FF, L, P, Y} are shown in Figure 4.8. The price puzzle is observed following shocks to FF where the response of P fails to decline after a contractionary monetary policy. However, the negative response of Y is significant and persistent for up to about 3 years. There is a high correlation between FF and Y innovations as can be seen in panels 13 to 16. This, of course, suggests that the innovation accounting analysis is not robust to a Wold re-ordering. In terms of forecast error decomposition, M1 and M2 account for over 30 percent of the variance in Y. In the other two cases, however, FF accounts for over 30 percent of the variance in Y

4.3.1 Summary

The summary for the four-variable VARs with R-rule ordering is reported in Table 4.4. The price puzzle is observed in all the models but not the output puzzle. That is, following a contractionary monetary policy, the price level increases rather than decreases while output decreases. Next, a five-variable model will be used to see if the price puzzle can be successful solved by adding an extra variable.

4.4 Five-variable VARs: Interest Rate Rule

As mentioned earlier, the interest in using the five-variable system is to examine whether the inclusion of PC does indeed solve the price puzzle. The estimated impulses are presented in Figures 4.9 to 4.12.

The impulse responses in Figure 4.9 corresponds to the following models: {FF, PC, DM1, P, Y}, {FF, PC, DM2, P, Y}, {FF, PC, DM3, P, Y}, and {FF, PC, DL, P, Y}. Following FF innovations, P decreases significant for {FF, PC, DM1, P, Y} model. The price puzzle is observed for the other three models. The output puzzle, however, is no longer present in all the four models.

The results for the estimated impulse responses for {FF, PC, CEM1, P, Y}, {FF, PC, CEM2, P, Y}, {FF, PC, CEM3, P, Y} and {FF, PC, CEL, P, Y} are presented in Figure 4.11. There is weaker evidence of the price puzzle the first model with CEM1. Although shocks to FF fail to produce a significant price effect, the responses of P much improved compared to the four-variable VARs in Figure 4.7. The response of Y is consistent in all cases showing a significant decline.

The last five-variable VAR system involves using traditional broad monetary aggregates M1, M2, M3 and L. Figure 4.12 show that there is evidence of the price puzzle for the three models with Wold ordering {FF, PC, M2, P, Y}, {FF, PC, M3, P, Y} and {FF, PC, L, P, Y}. In the case when M1 is used, the correct price effect is observed since there is a significant and persistent fall in P. Finally, in all the models, the output puzzle is longer observed.

4.4.1 Summary

By including PC, the price puzzle is solved for the following VAR models: {FF, PC, DM1, P, Y}, {DUALM1, PC, DM1, P, Y}, {FF, PC, CEM1, P, Y}, {FF, PC, M1, P, Y}. Notice that in those models, M1 is used. The results are further summarized in Table 4.5.

4.5 Conclusion

The analysis in this chapter starts with the M-rule VARs based on Sims (1980). The estimated impulse responses show that the Currency Equivalence aggregates (CEM1, CEM2, CEM3, CL) are able to solve the liquidity puzzle but not the price and output puzzles. Under the R-rule ordering, the price puzzle is observed in all cases. But with the inclusion of the commodity prices following Sims (1992), the puzzle is no longer present for models with DM1, CEM1 and M1. The forecast variance error decompositions for the M-rule and the R-rule VARs show that the federal funds rate generally accounts for a larger percentage of the variance in Y as opposed to the Divisia and Currency Equivalence aggregates. In the Granger-causality tests, FF is found to Granger-cause Y in VARs with DM1, CEM1, and M1. This result is consistent with previous VAR where the inclusion of interest rates in the VAR specification reduces the explanatory power of money for output.

It is important also to realize that the innovation accounting analysis undertaken in this chapter is not robust to different Wold orderings. That is, the estimated impulse responses and forecast error variance decompositions are sensitive to the ordering of the variables in the VAR system. Before any strong inference can be drawn from the results here, further investigation with different Wold ordering is needed. That being said, the analysis is extended in the next chapter by using a structural VAR approach.

Figure 4.1. Unrestricted VAR Impulse Responses, {DM1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

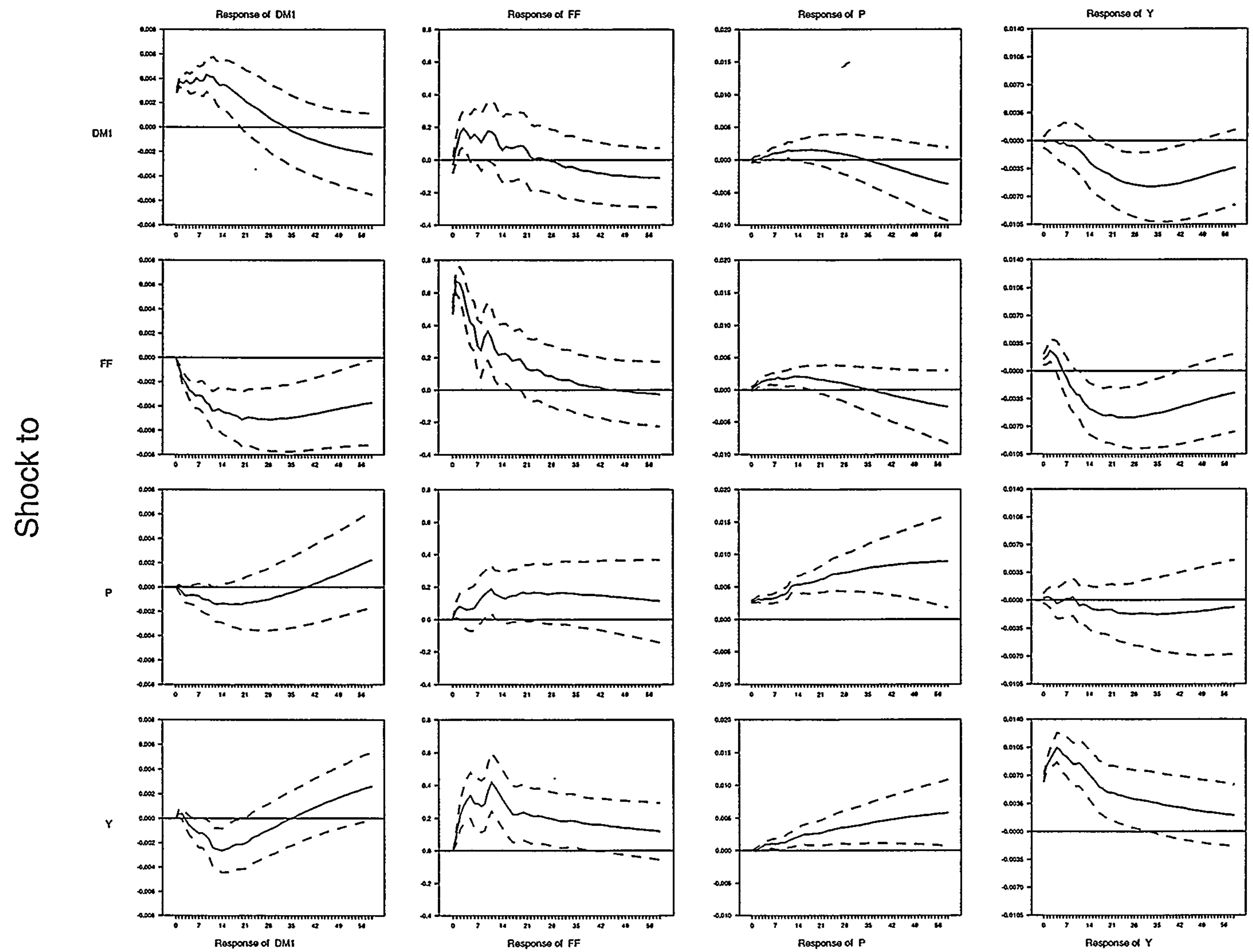

Figure 4.1. Unrestricted VAR Impulse Responses, {DM2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

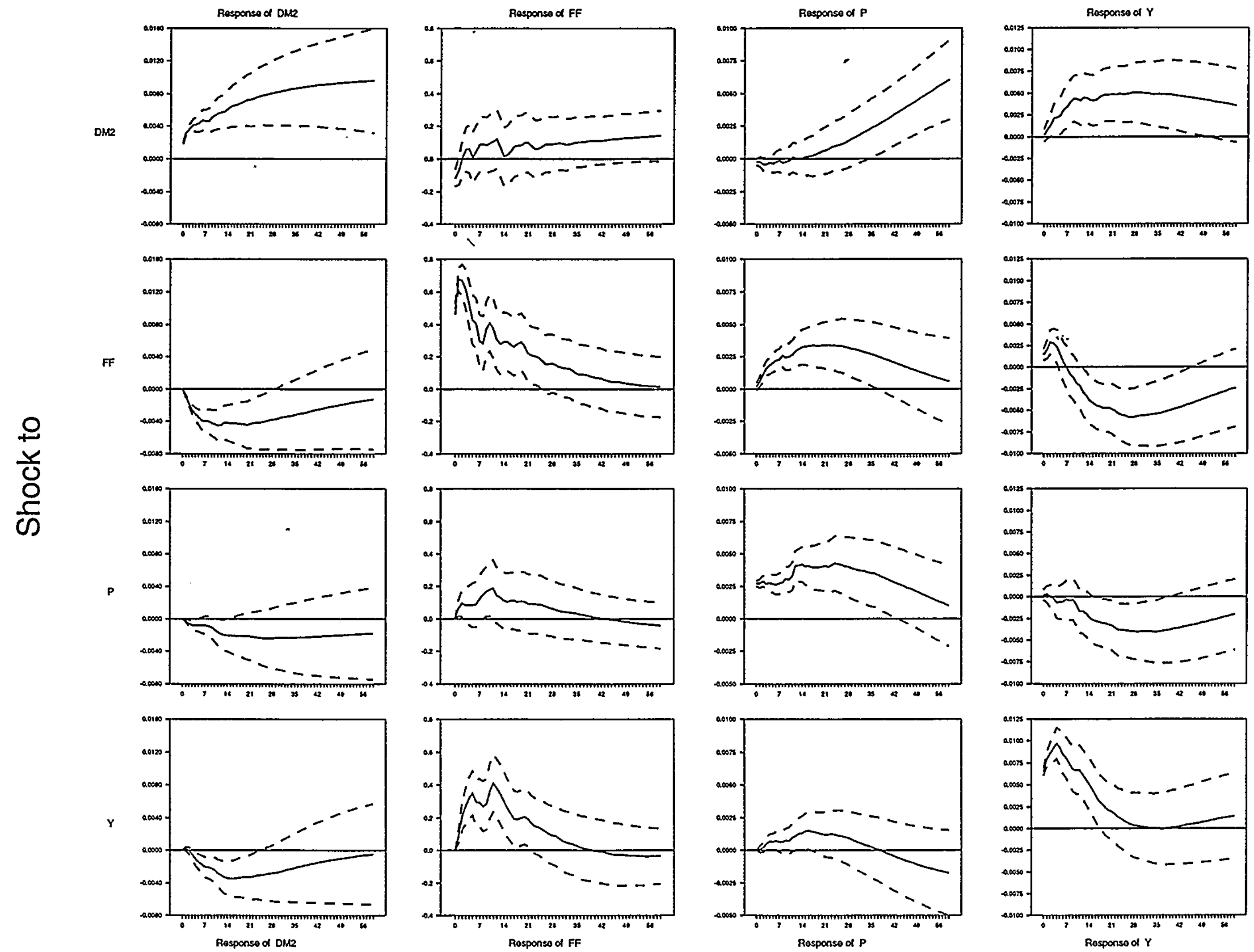

Figure 4.1. Unrestricted VAR Impulse Responses, {DM3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

Shock to

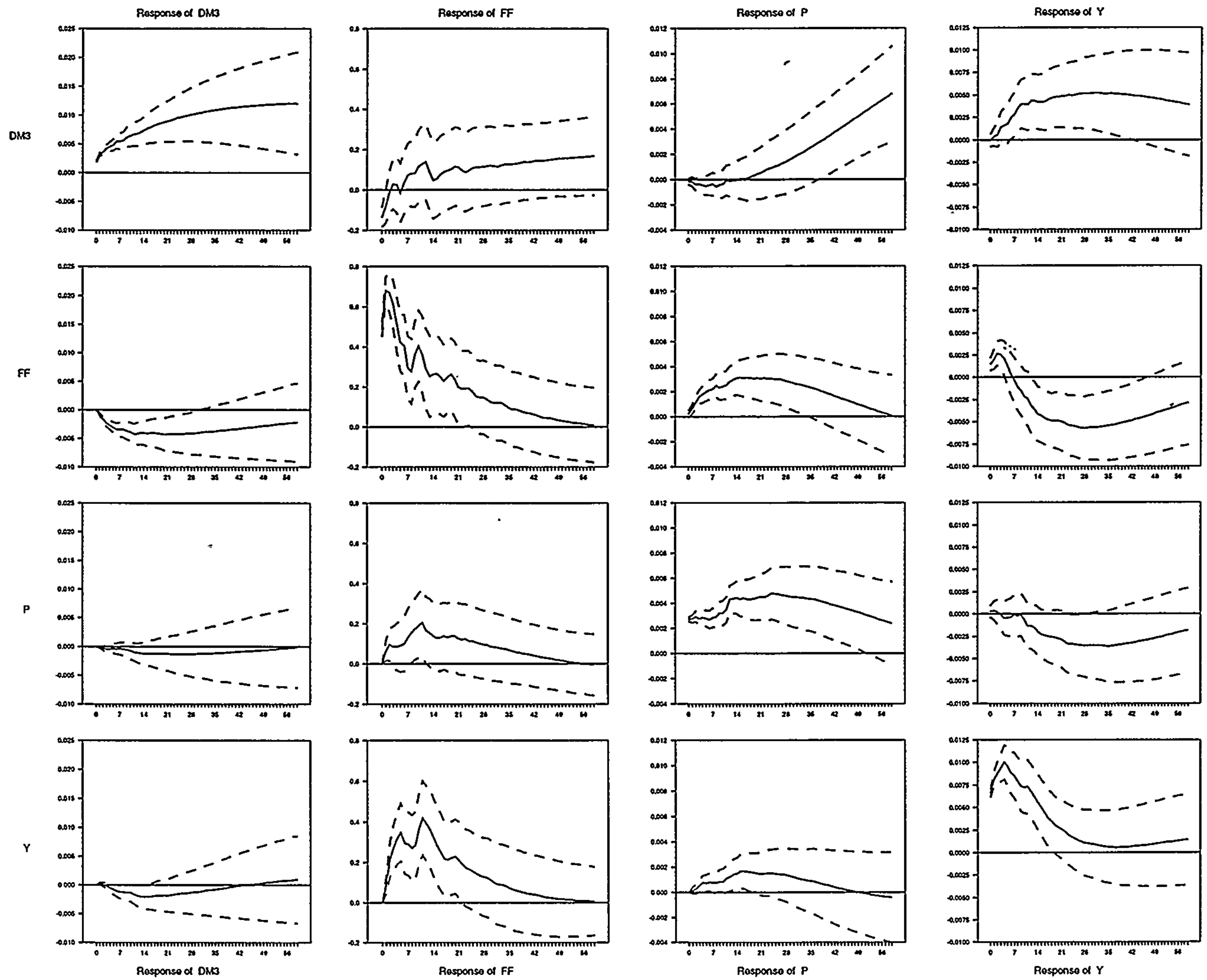

Figure 4.1. Unrestricted VAR Impulse Responses, {DL, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

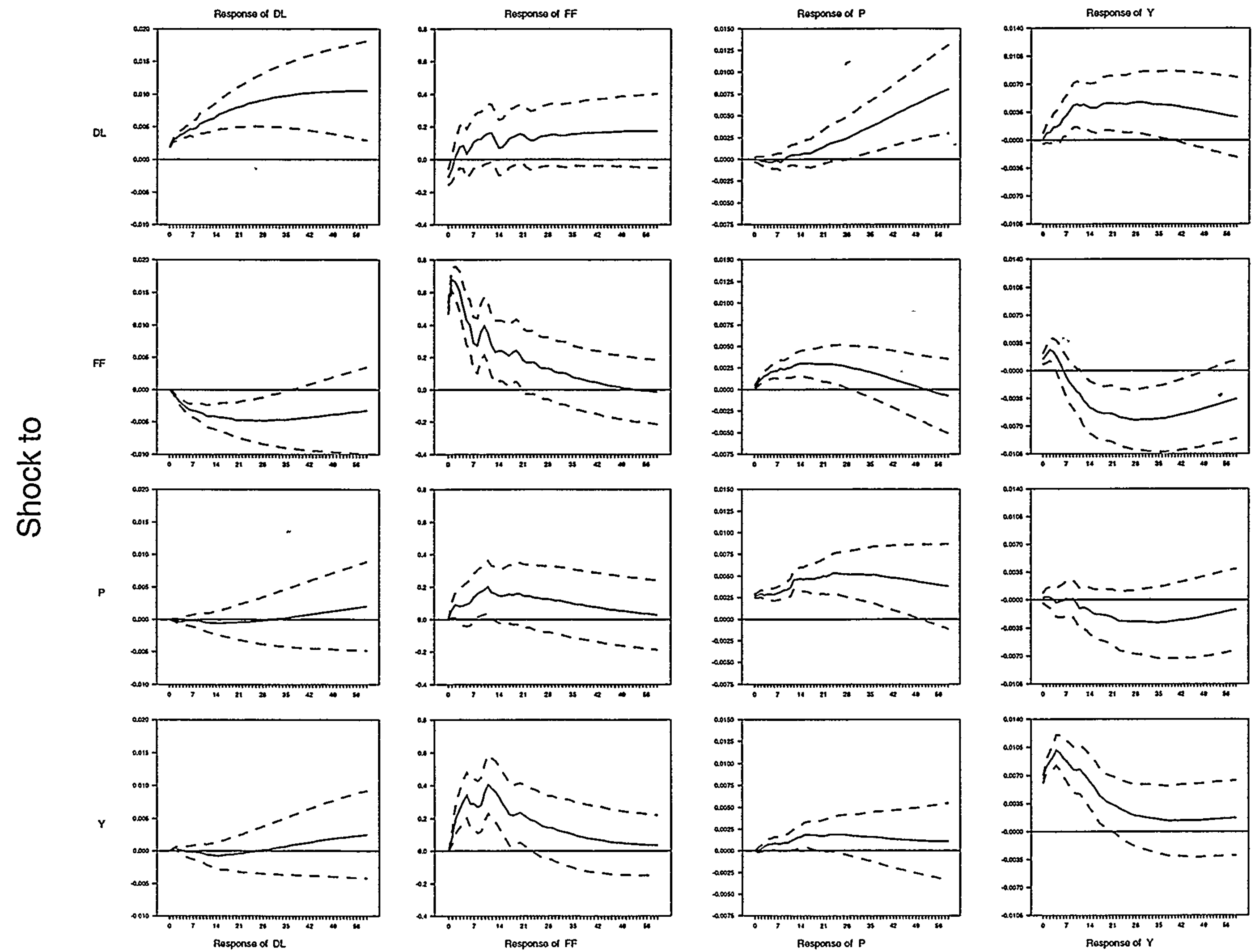

Figure 4.2. Unrestricted VAR Impulse Responses, {DM1, DUALM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

Shock to

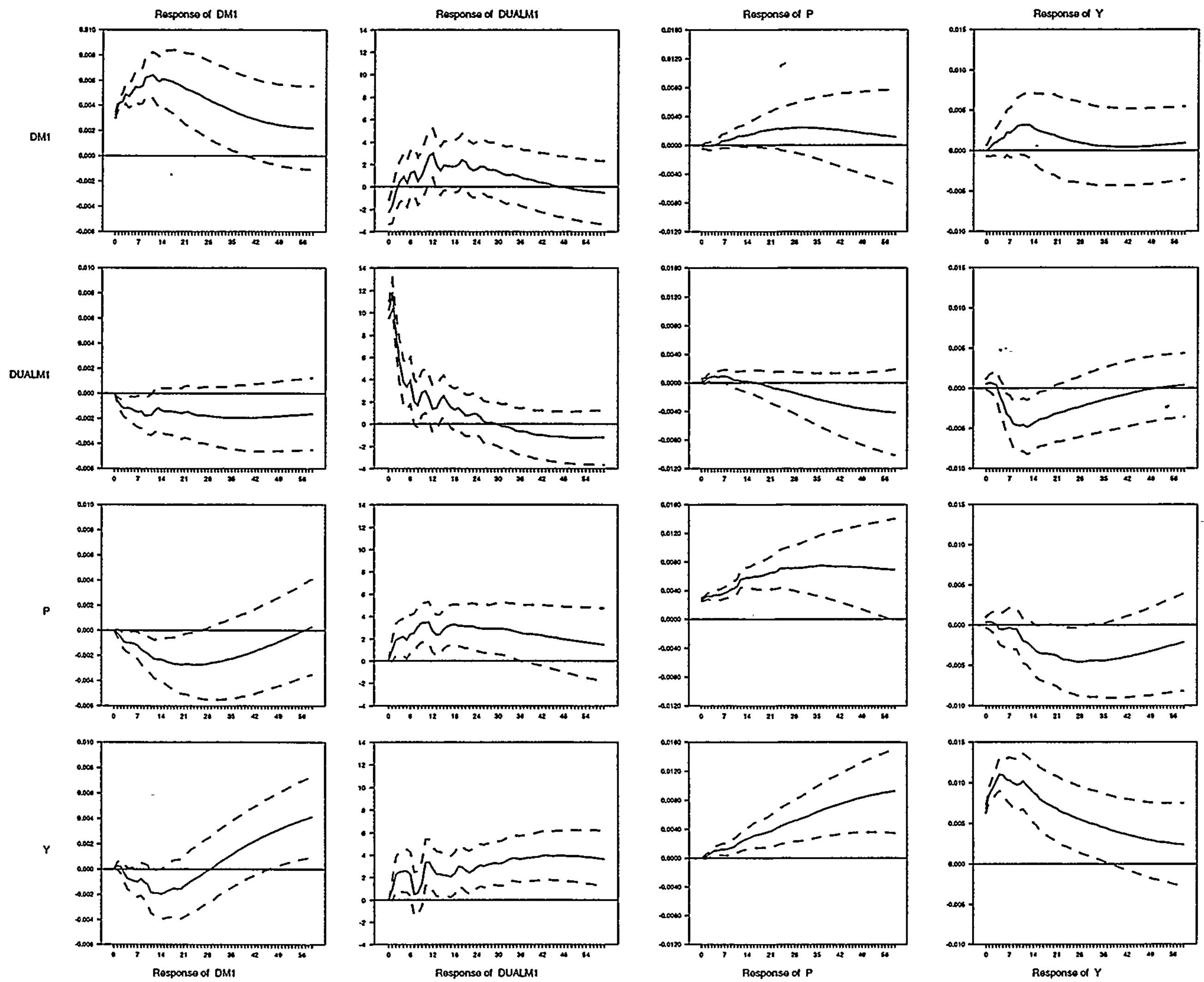

Figure 4.2. Unrestricted VAR Impulse Responses, {DM2, DUALM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

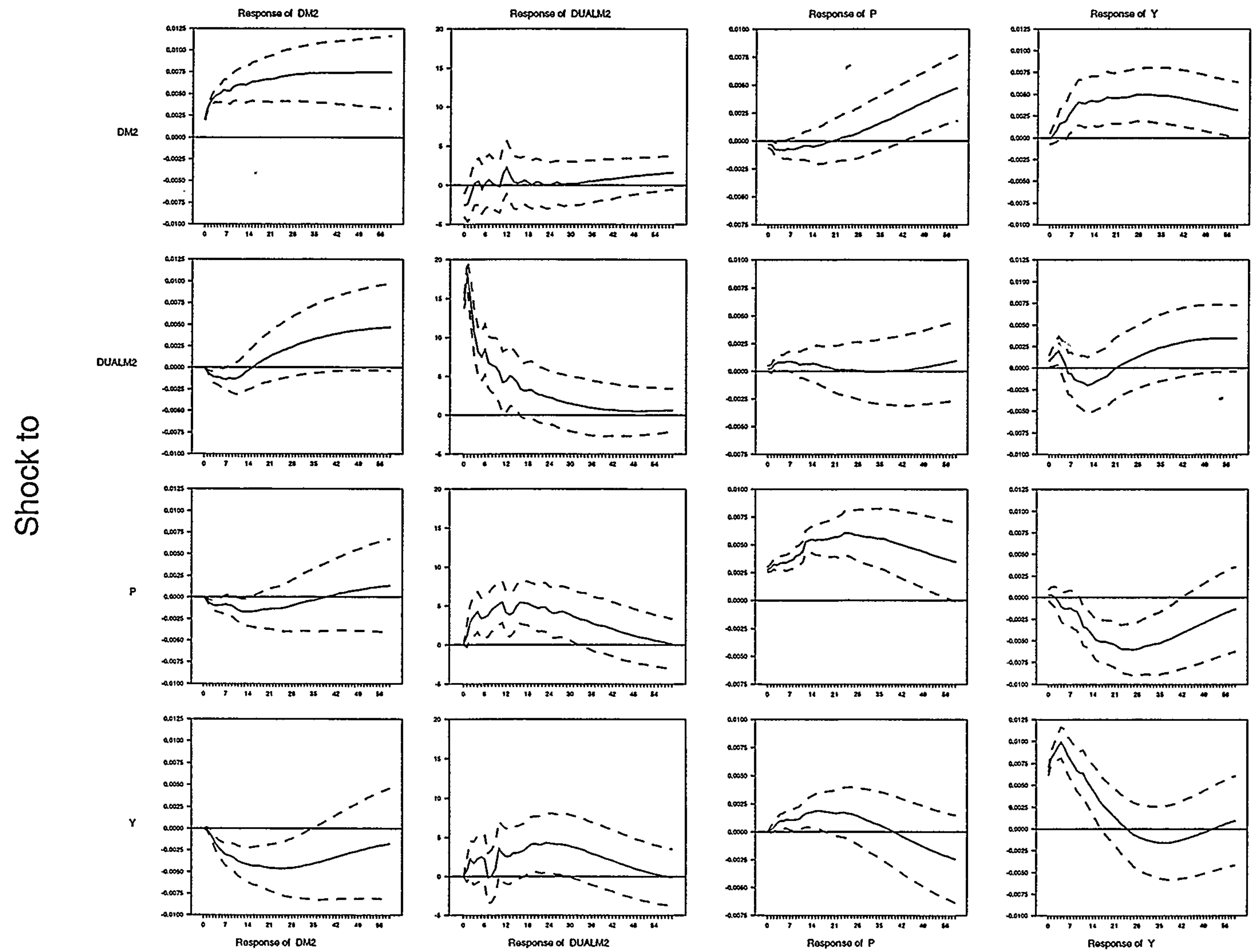

Figure 4.2. Unrestricted VAR Impulse Responses, {DM3, DUALM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

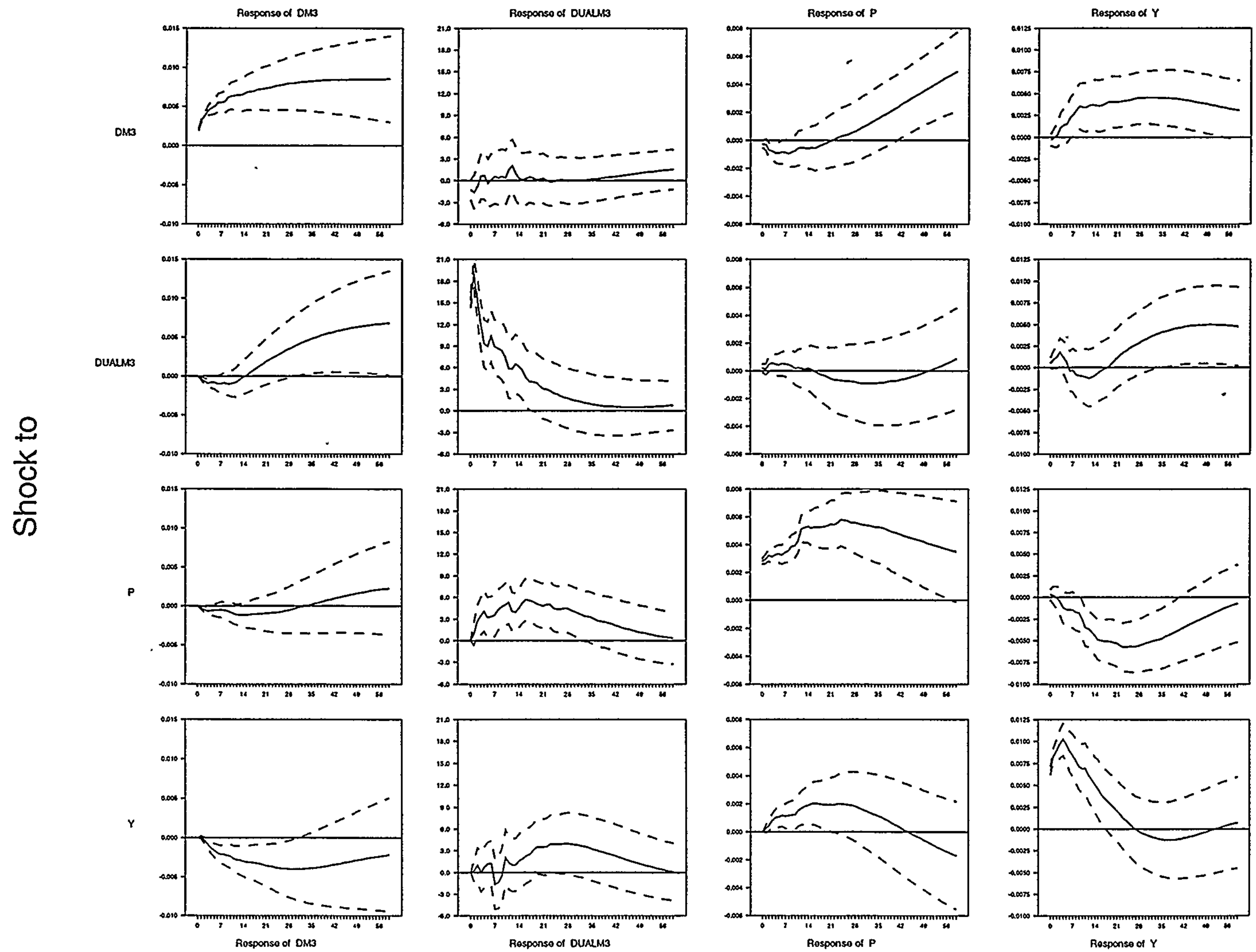

Figure 4.2. Unrestricted VAR Impulse Responses, {DL, DUALL, P, Y} Model

Monthly data: 1960:1 - 1995:11

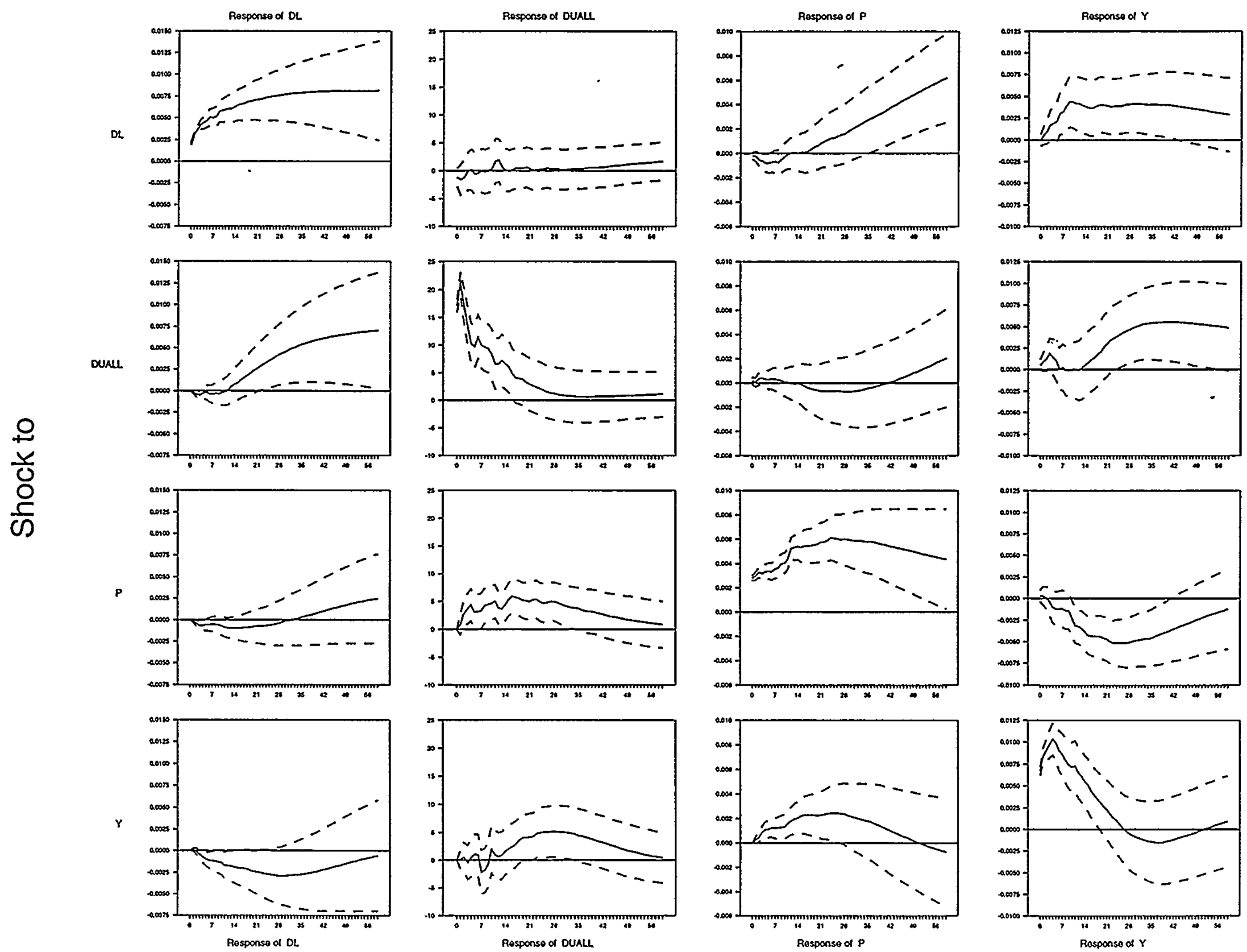

Figure 4.3. Unrestricted VAR Impulse Responses, {CEM1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

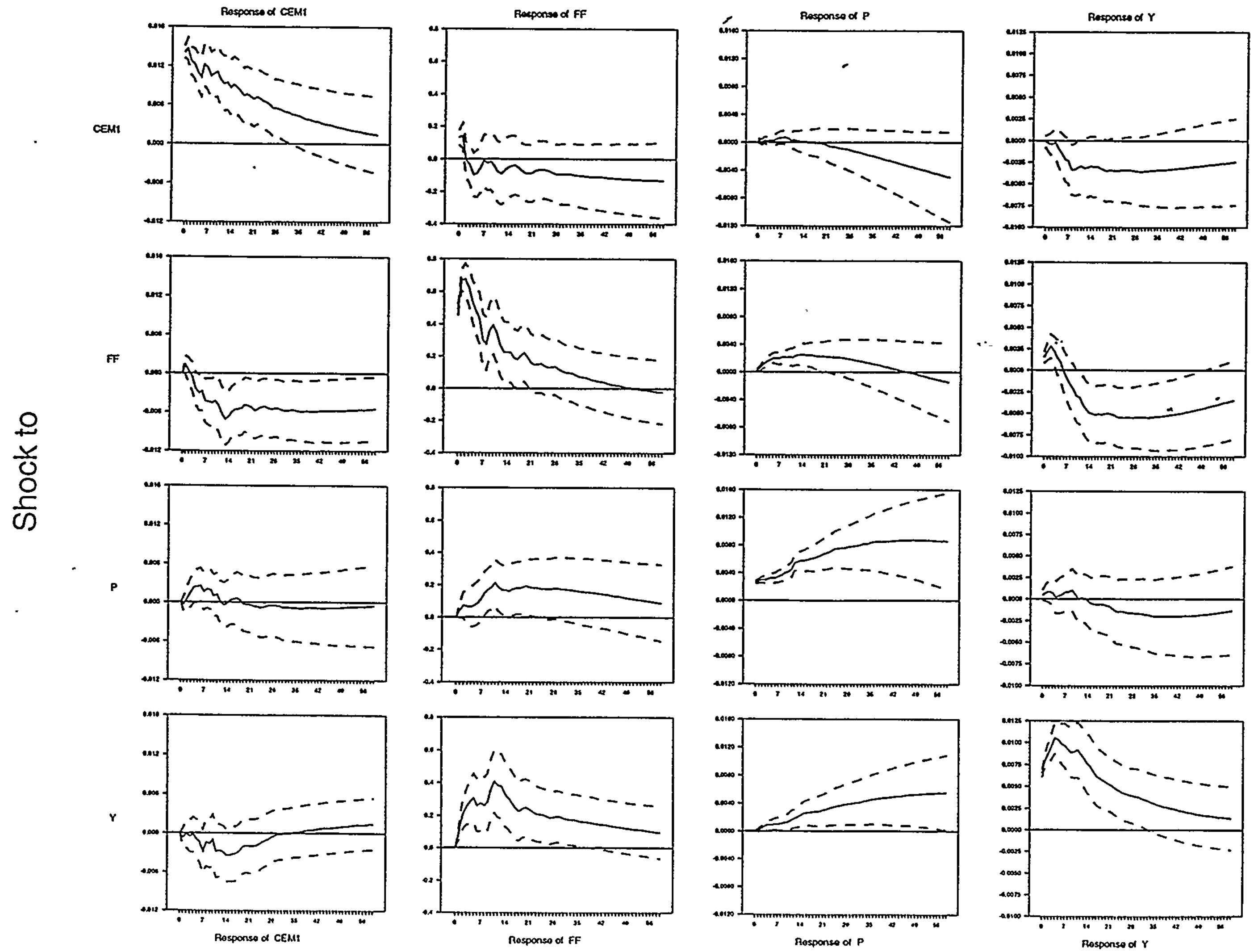

Figure 4.3. Unrestricted VAR Impulse Responses, {CEM2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

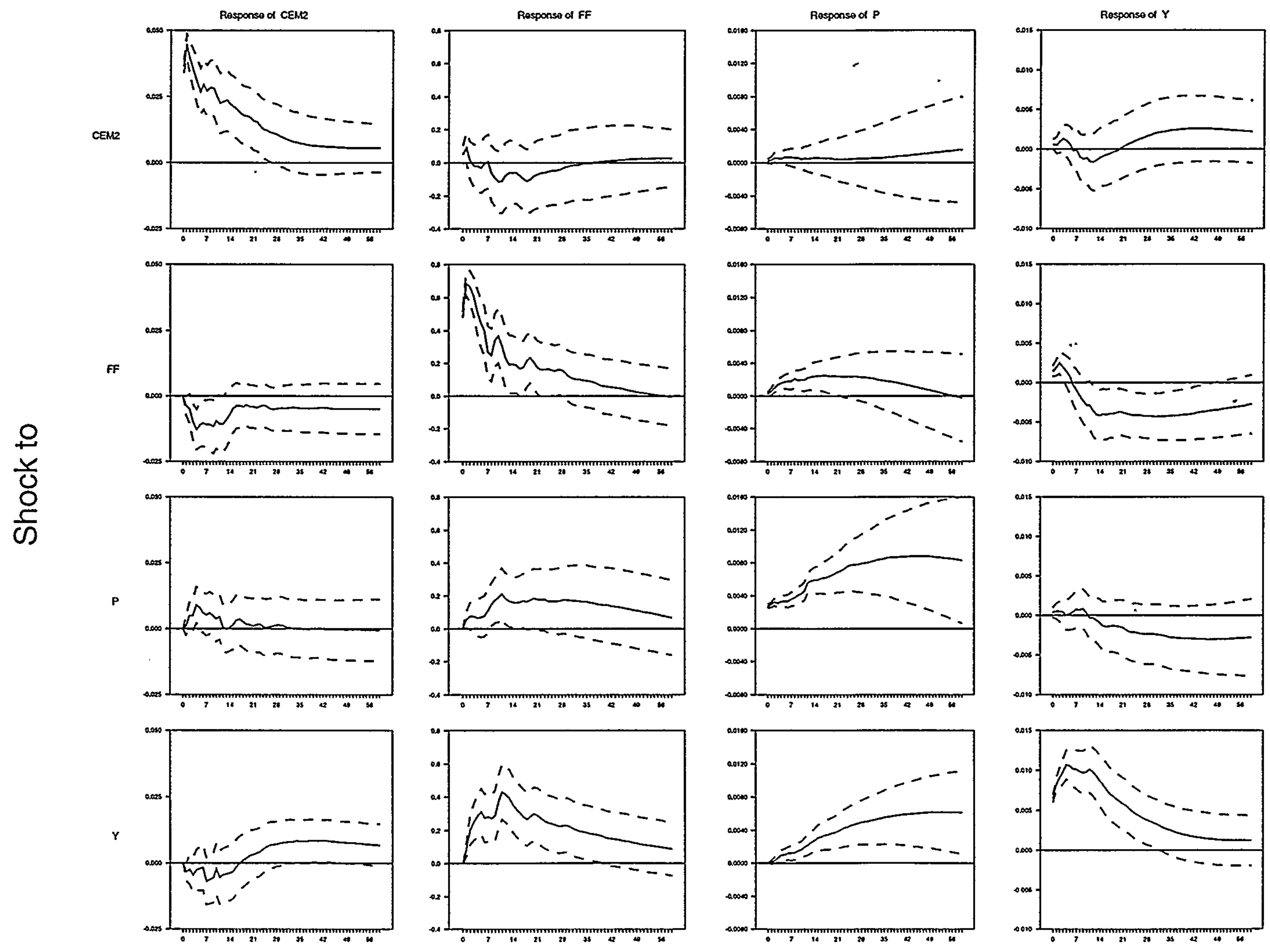

Figure 4.3. Unrestricted VAR Impulse Responses, {CEM3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

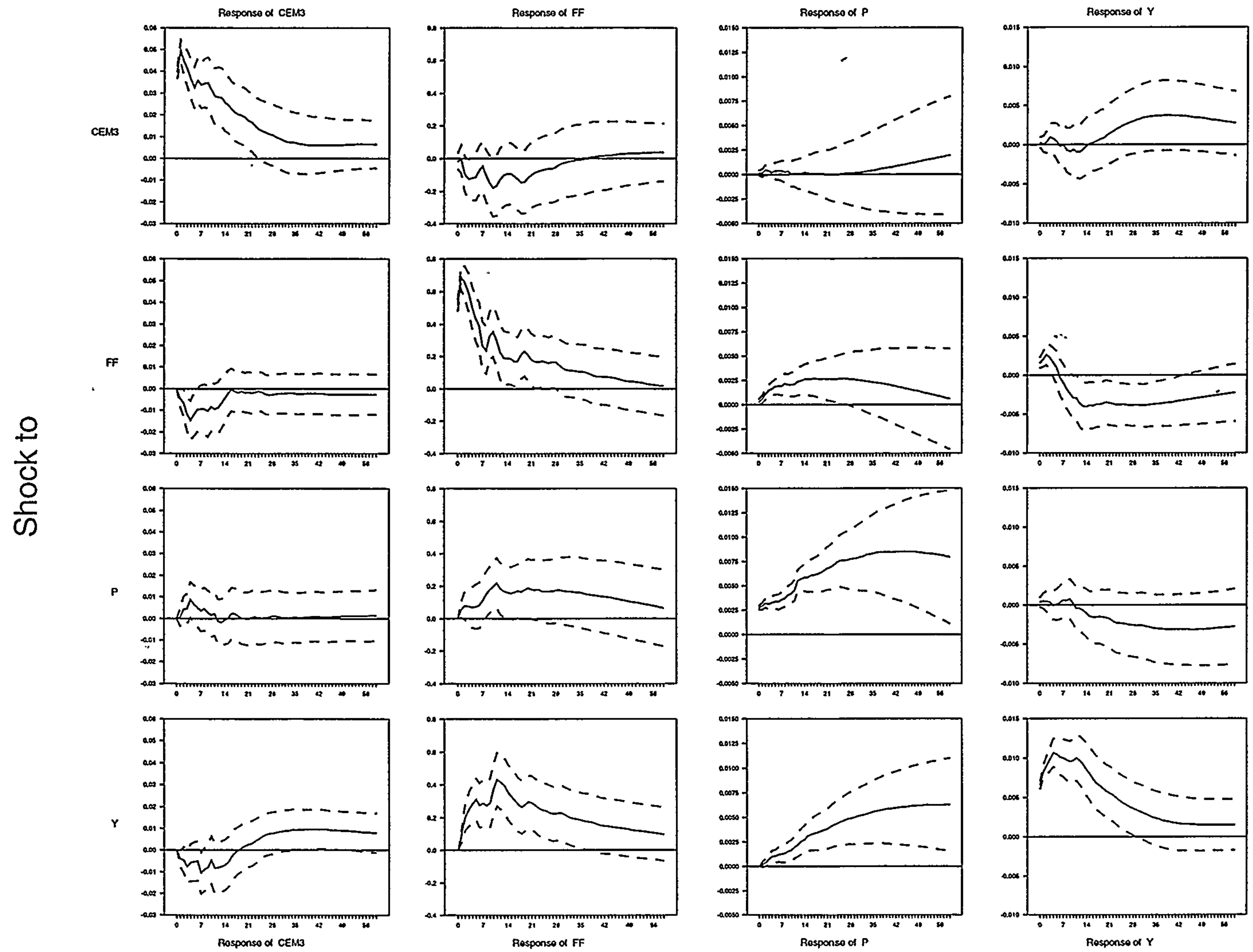

Figure 4.3. Unrestricted VAR Impulse Responses, {CEL, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

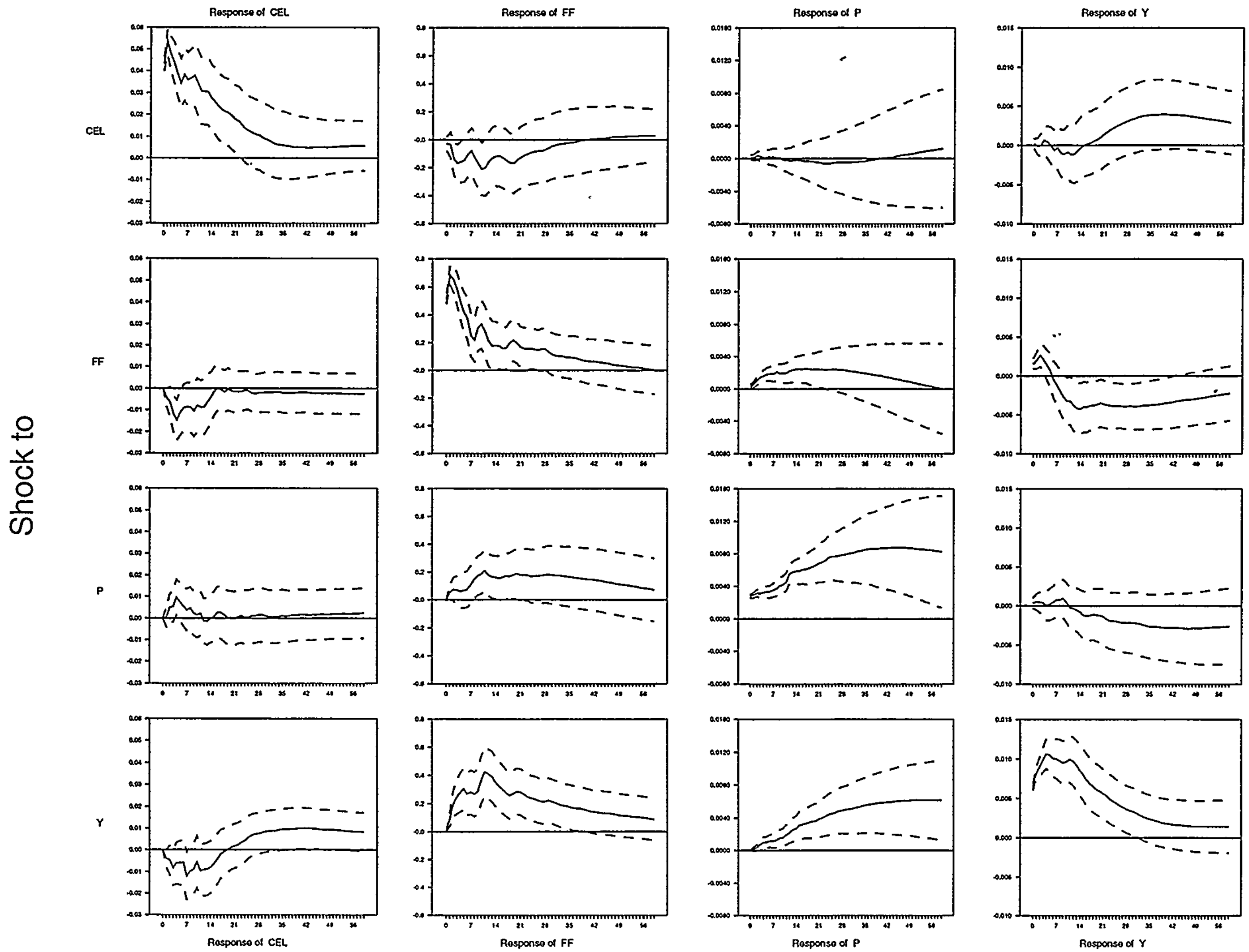

Figure 4.4. Unrestricted VAR Impulse Responses, {M1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

Shock to

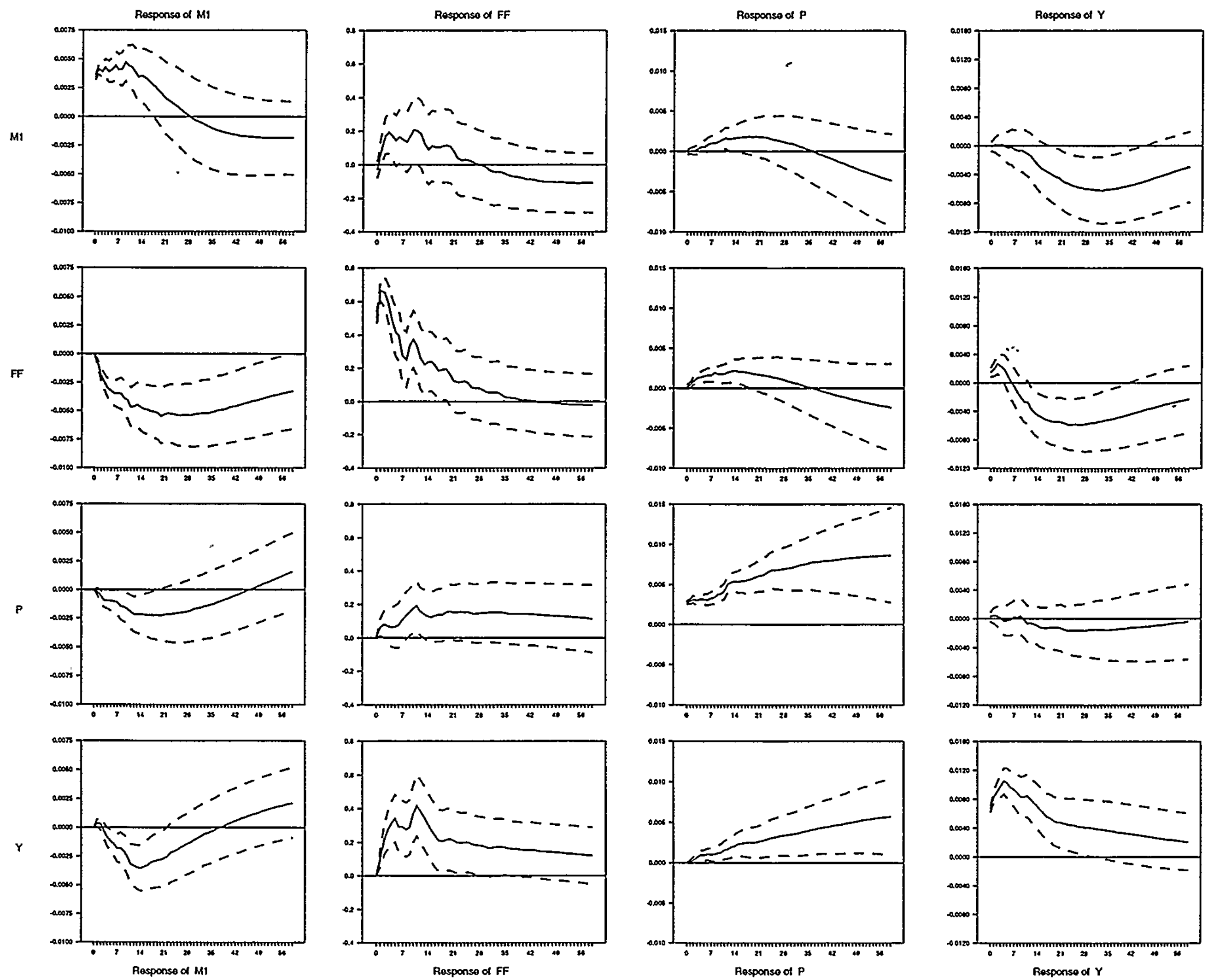

Figure 4.4. Unrestricted VAR Impulse Responses, {M2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

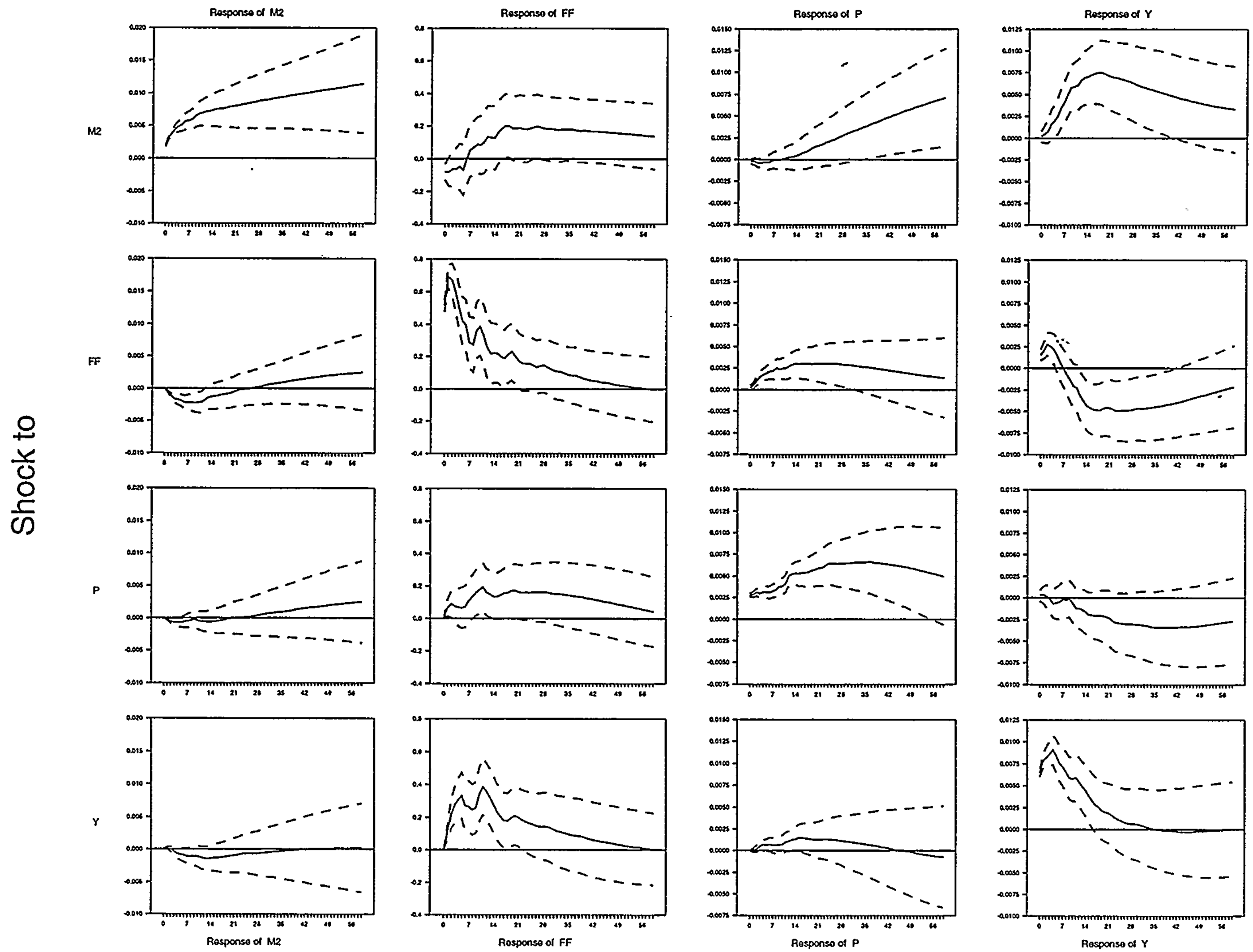

Figure 4.4. Unrestricted VAR Impulse Responses, {M3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

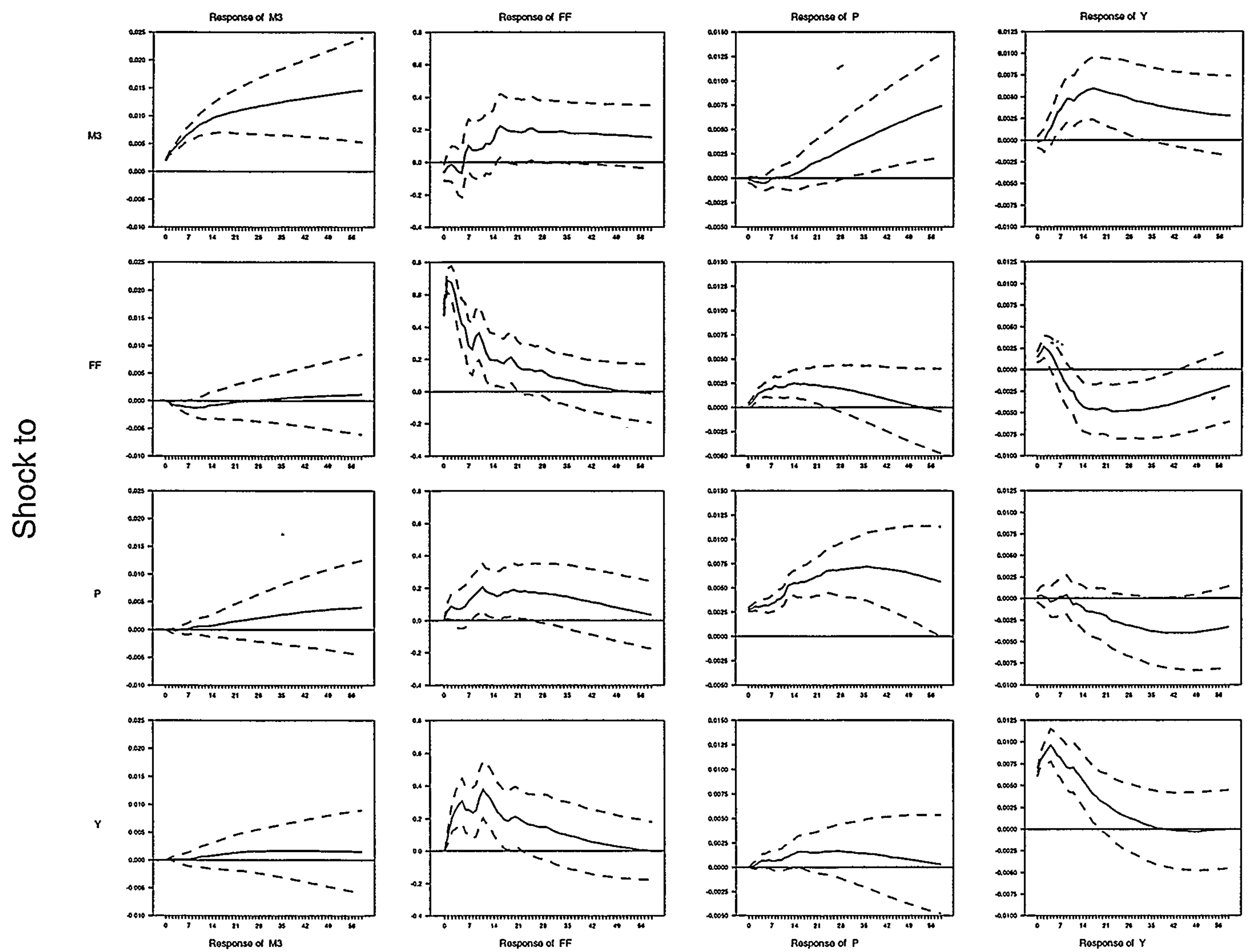

Figure 4.4. Unrestricted VAR Impulse Responses, {L, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

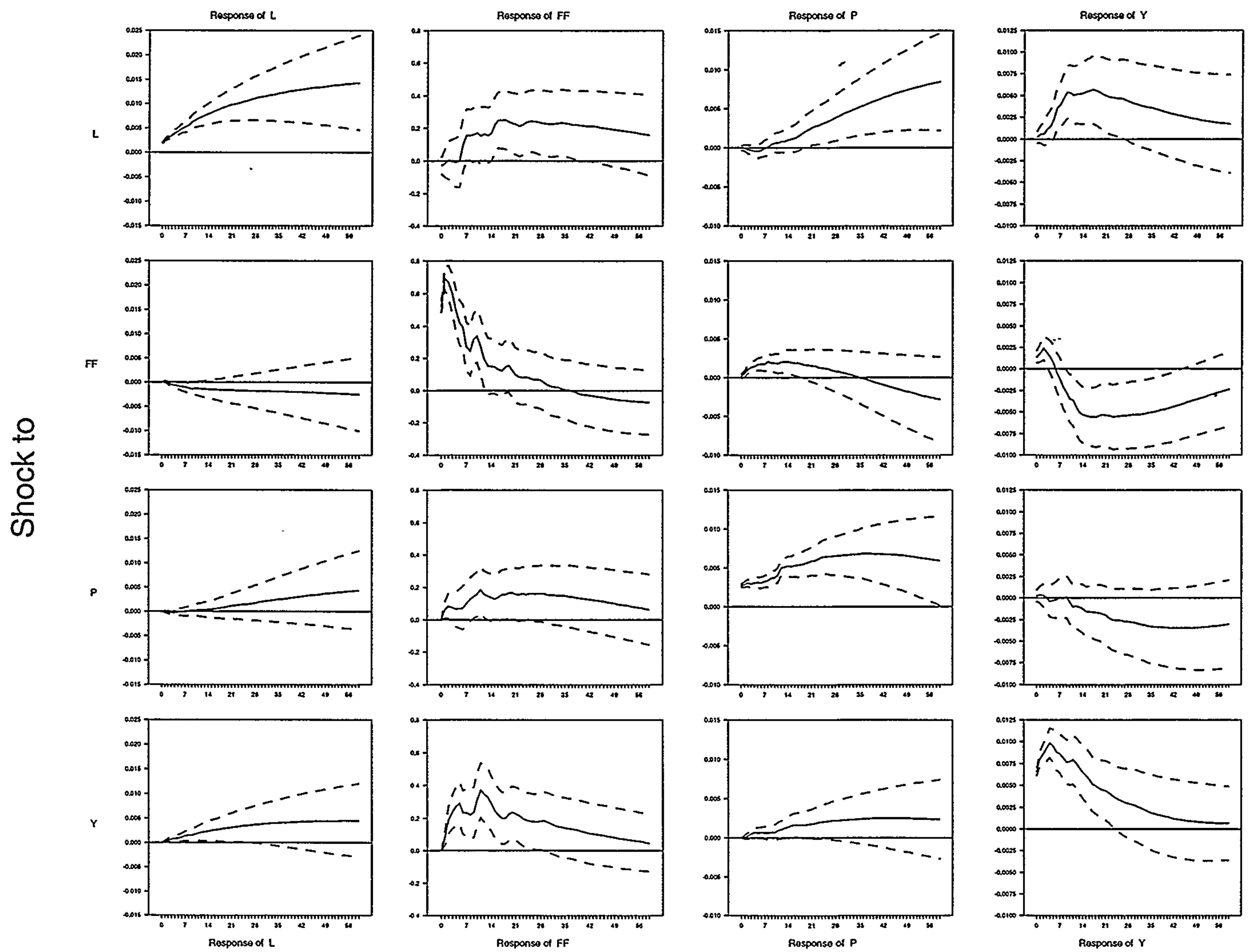

Figure 4.5. Unrestricted VAR Impulse Responses, {FF, DM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

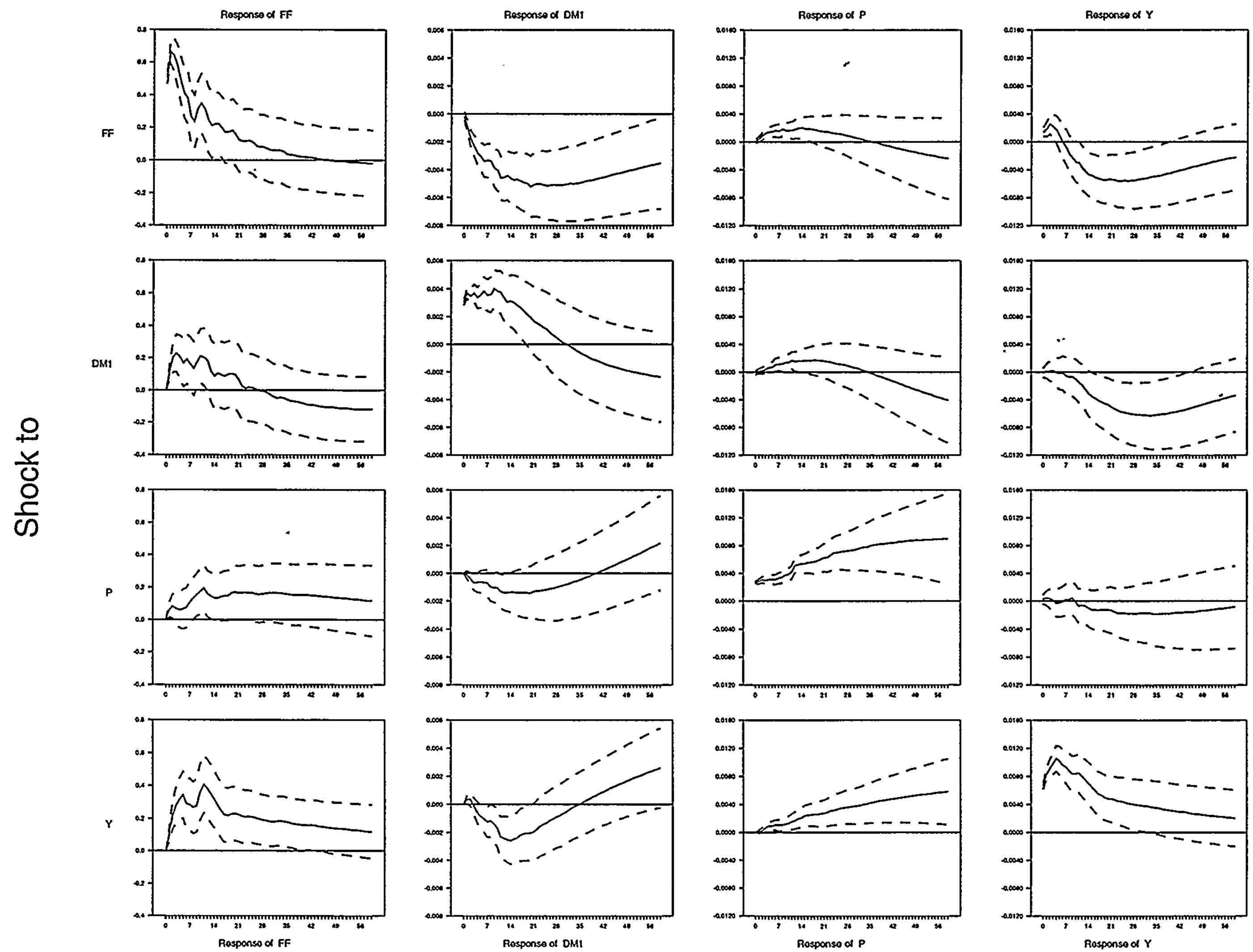

Figure 4.5. Unrestricted VAR Impulse Responses, {FF, DM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

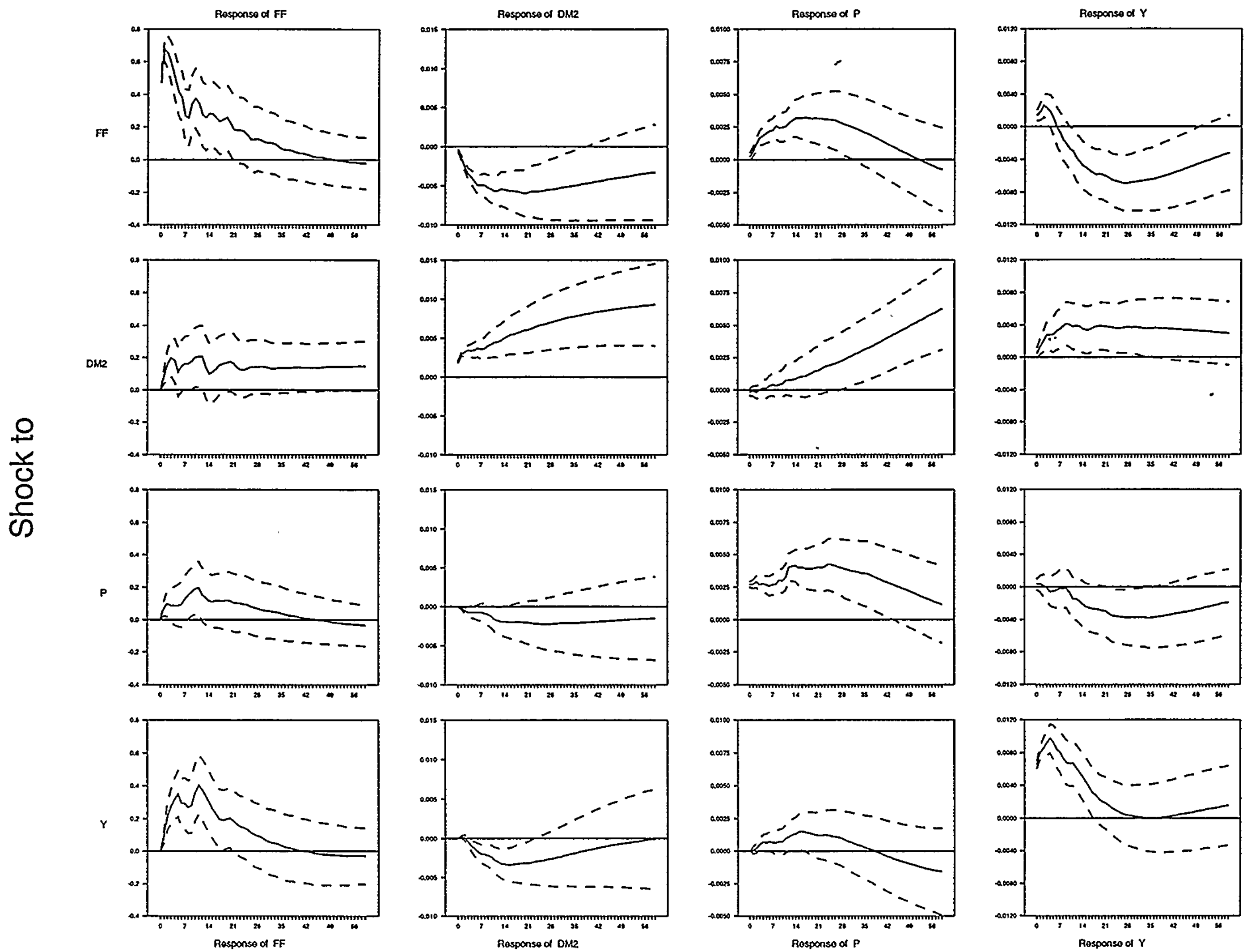

Figure 4.5. Unrestricted VAR Impulse Responses, {FF, DM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

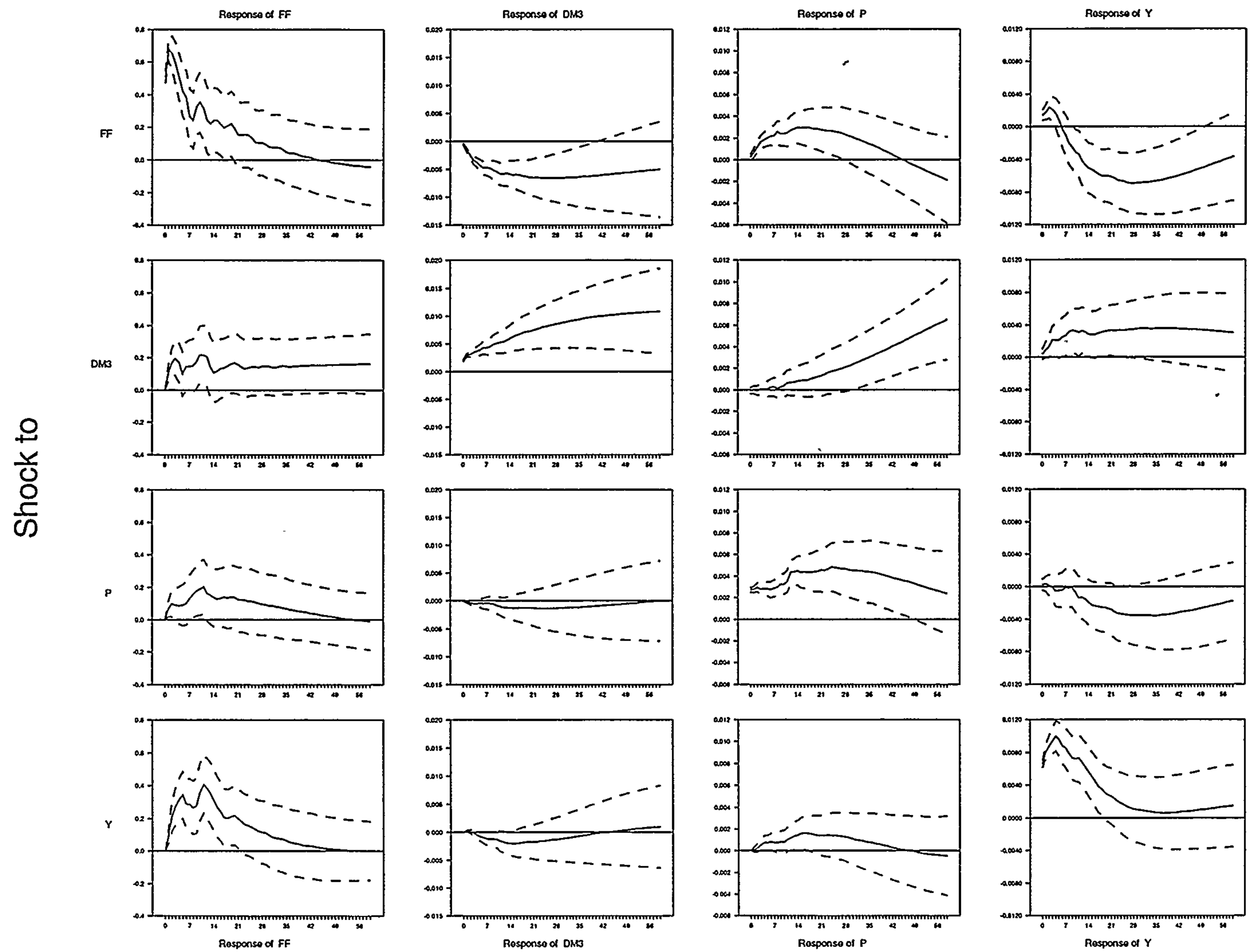

Figure 4.5. Unrestricted VAR Impulse Responses, {FF, DL, P, Y} Model

Monthly data: 1960:1 - 1995:11

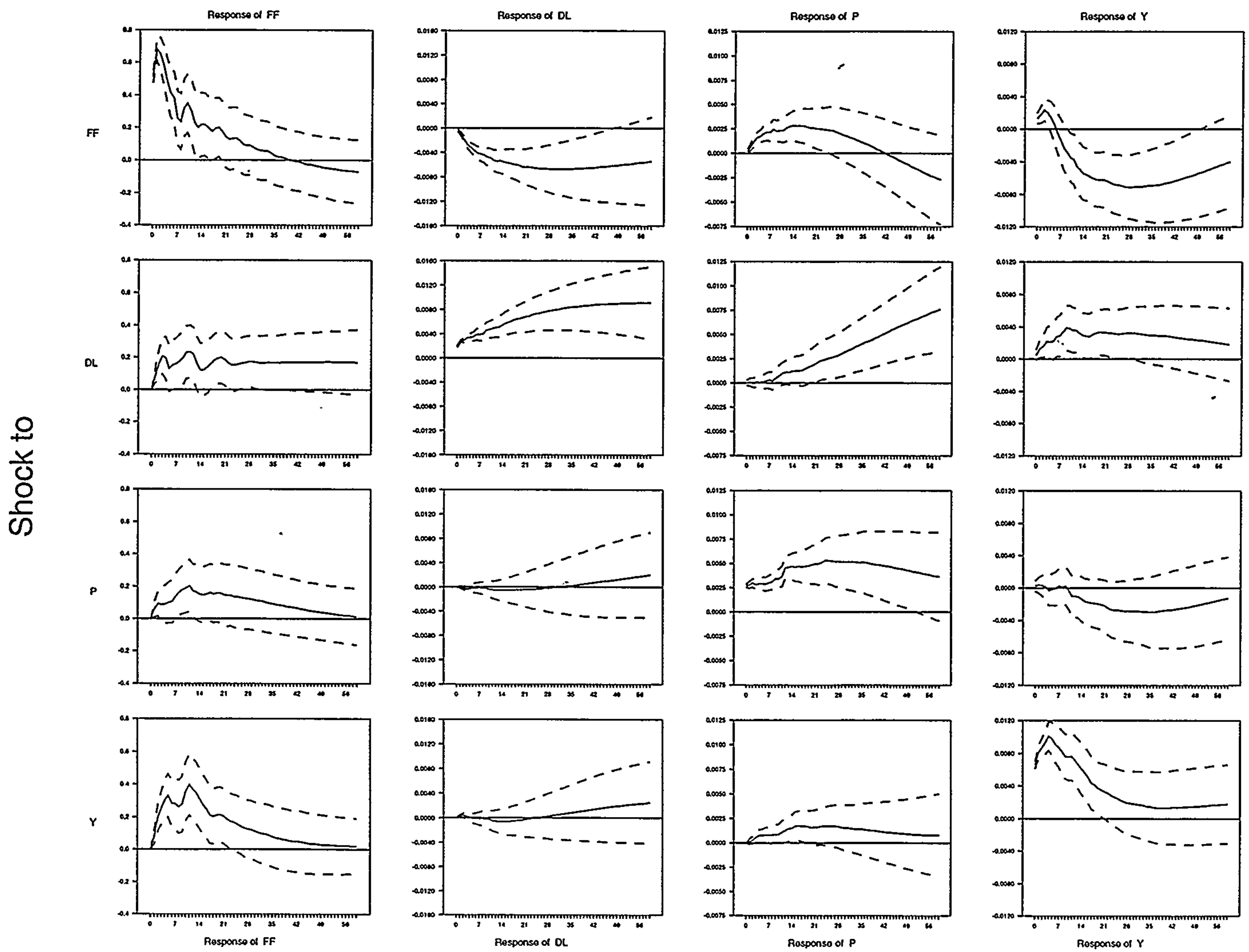

Figure 4.6. Unrestricted VAR Impulse Responses, {FF, CEM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

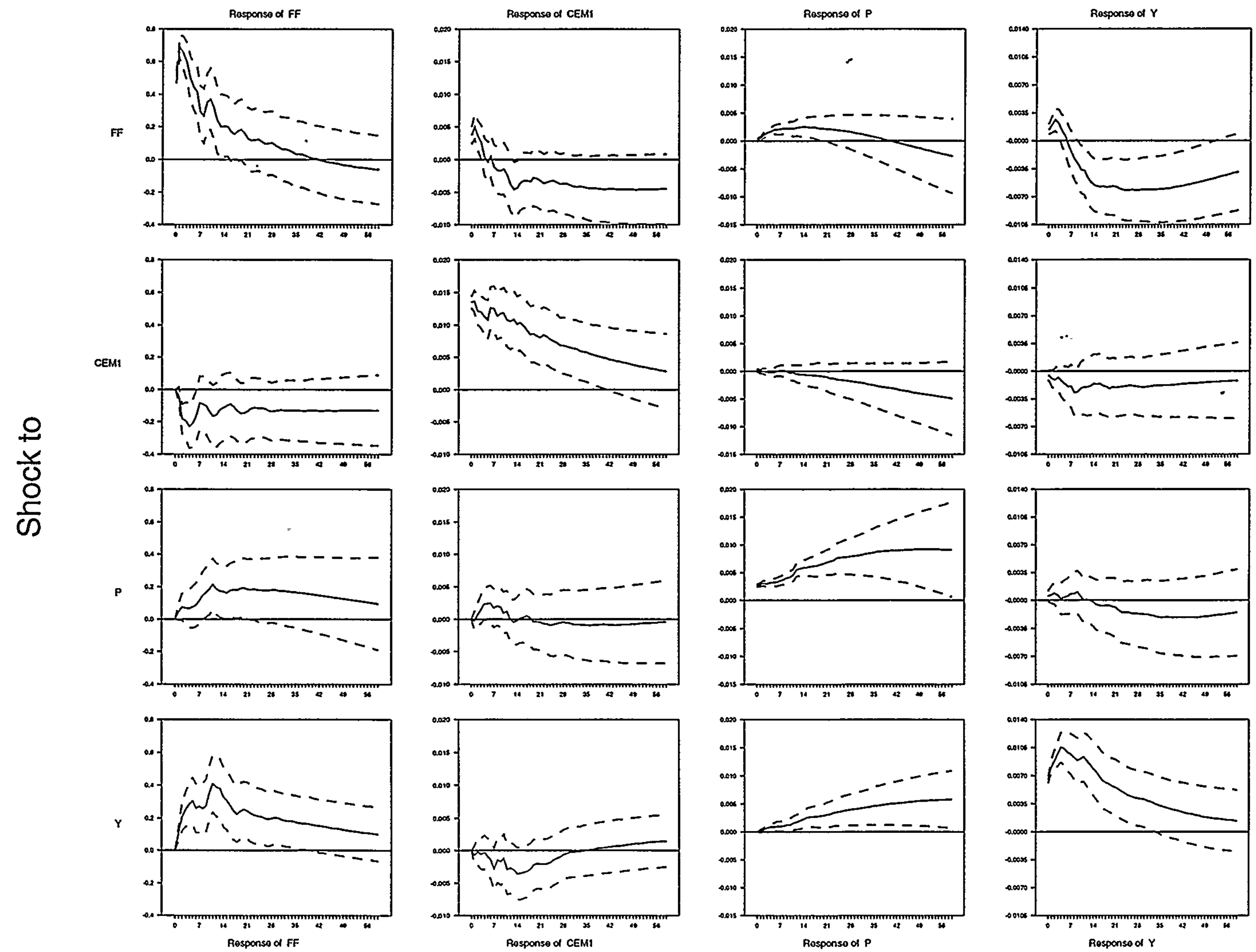

Figure 4.6. Unrestricted VAR Impulse Responses, {FF, CEM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

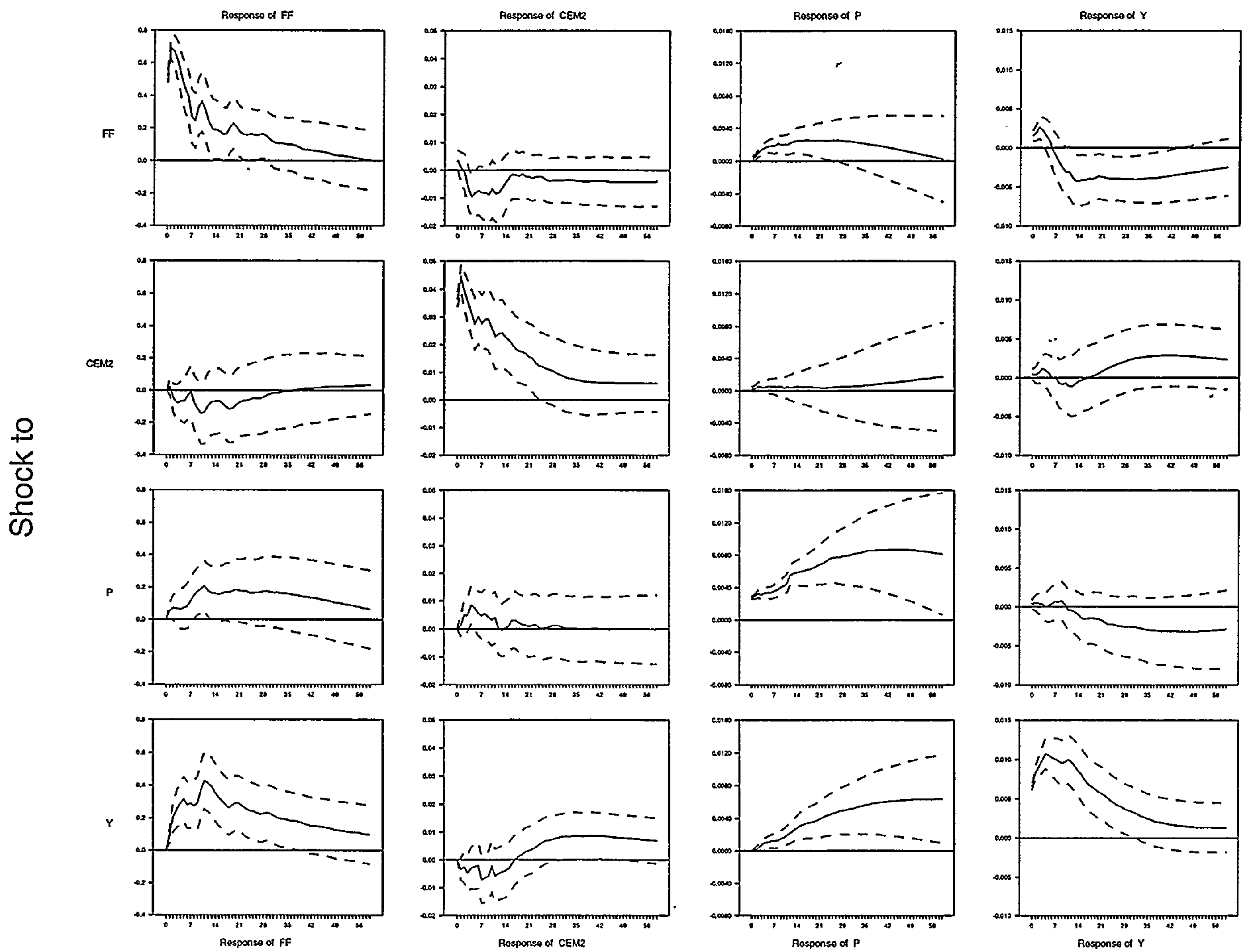

Figure 4.6. Unrestricted VAR Impulse Responses, {FF, CEM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

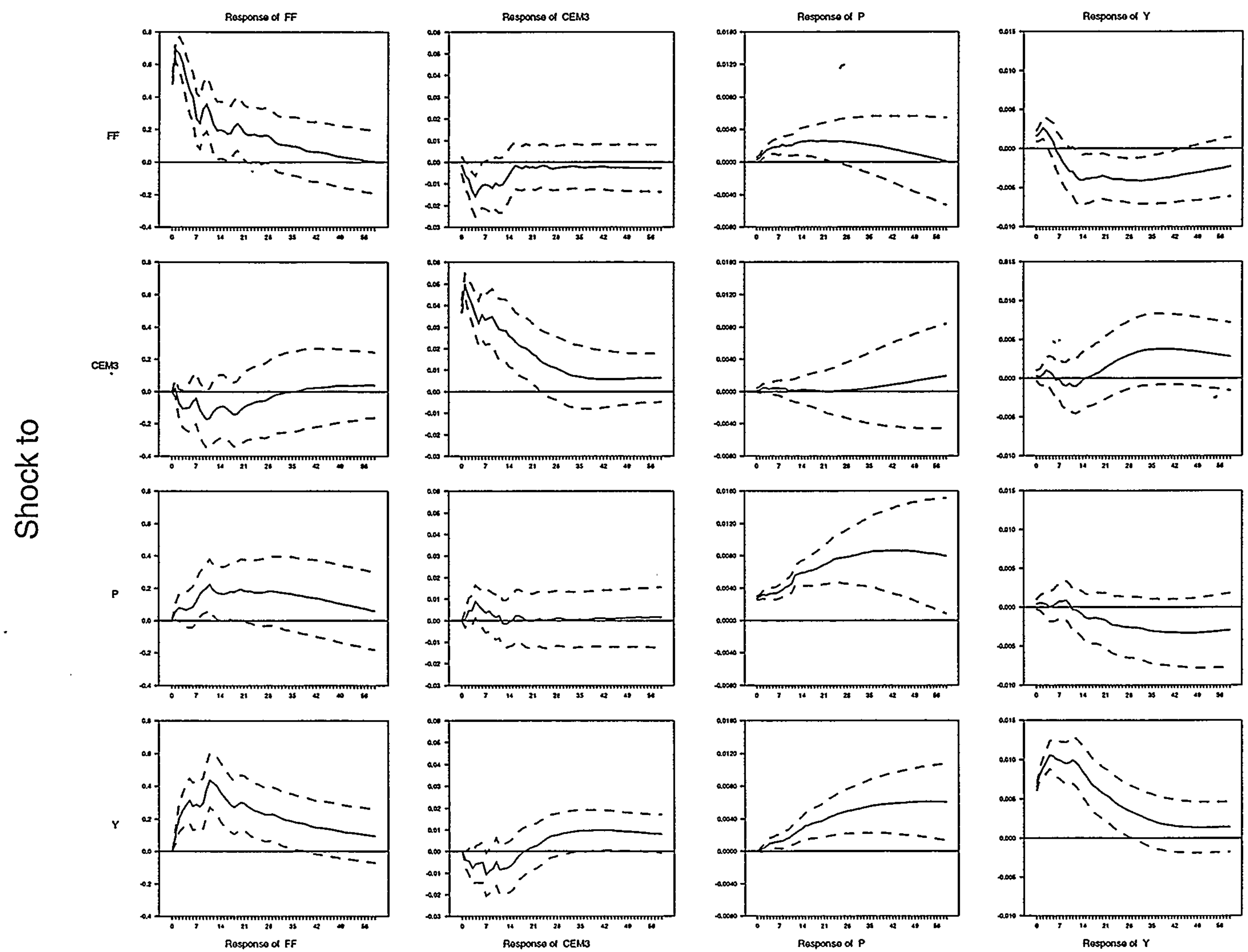

Figure 4.6. Unrestricted VAR Impulse Responses, {FF, CEL, P, Y} Model

Monthly data: 1960:1 - 1995:11

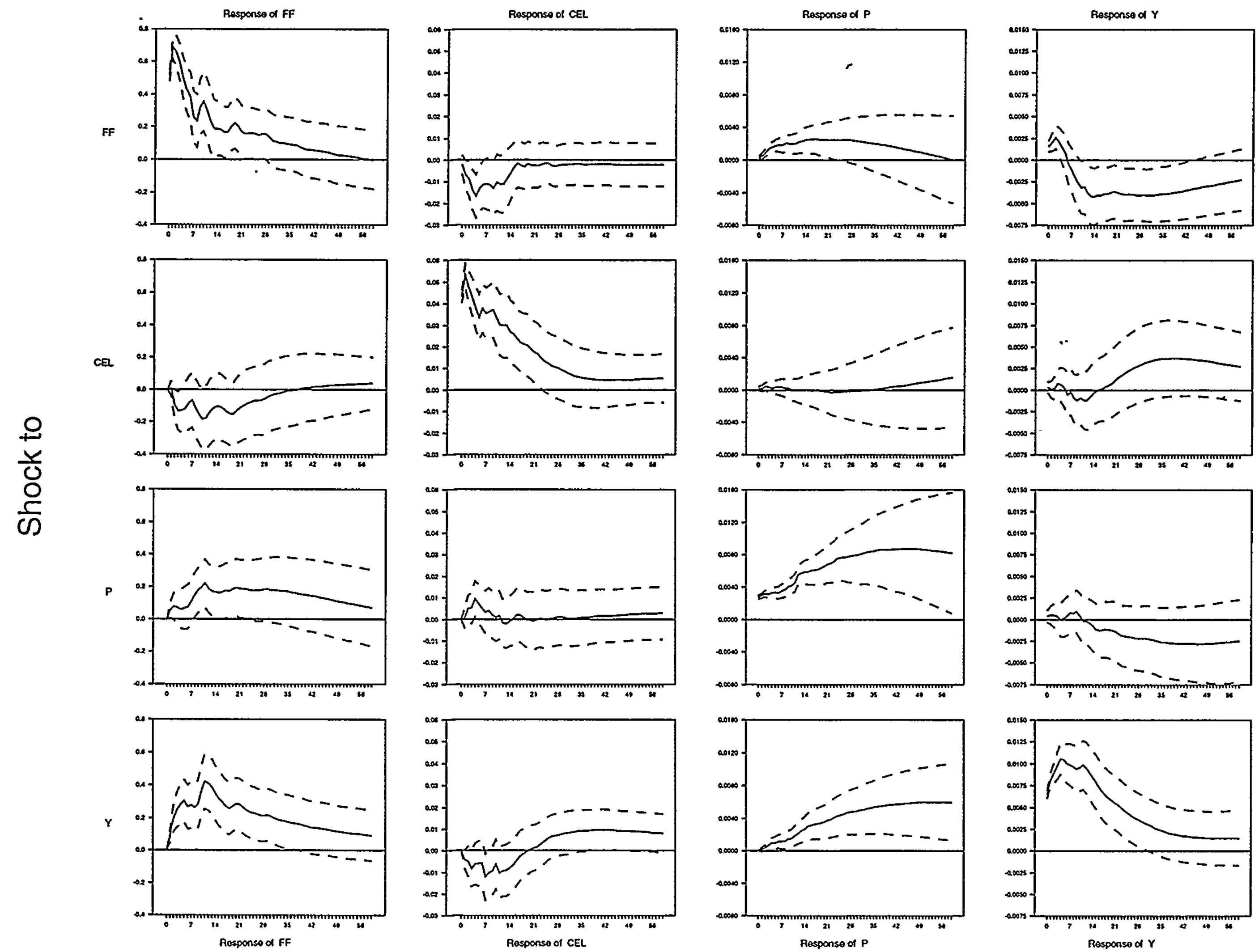

Figure 4.7. Unrestricted VAR Impulse Responses, {FF, M1, P, Y} Model

Monthly data: 1960:1 - 1995:11

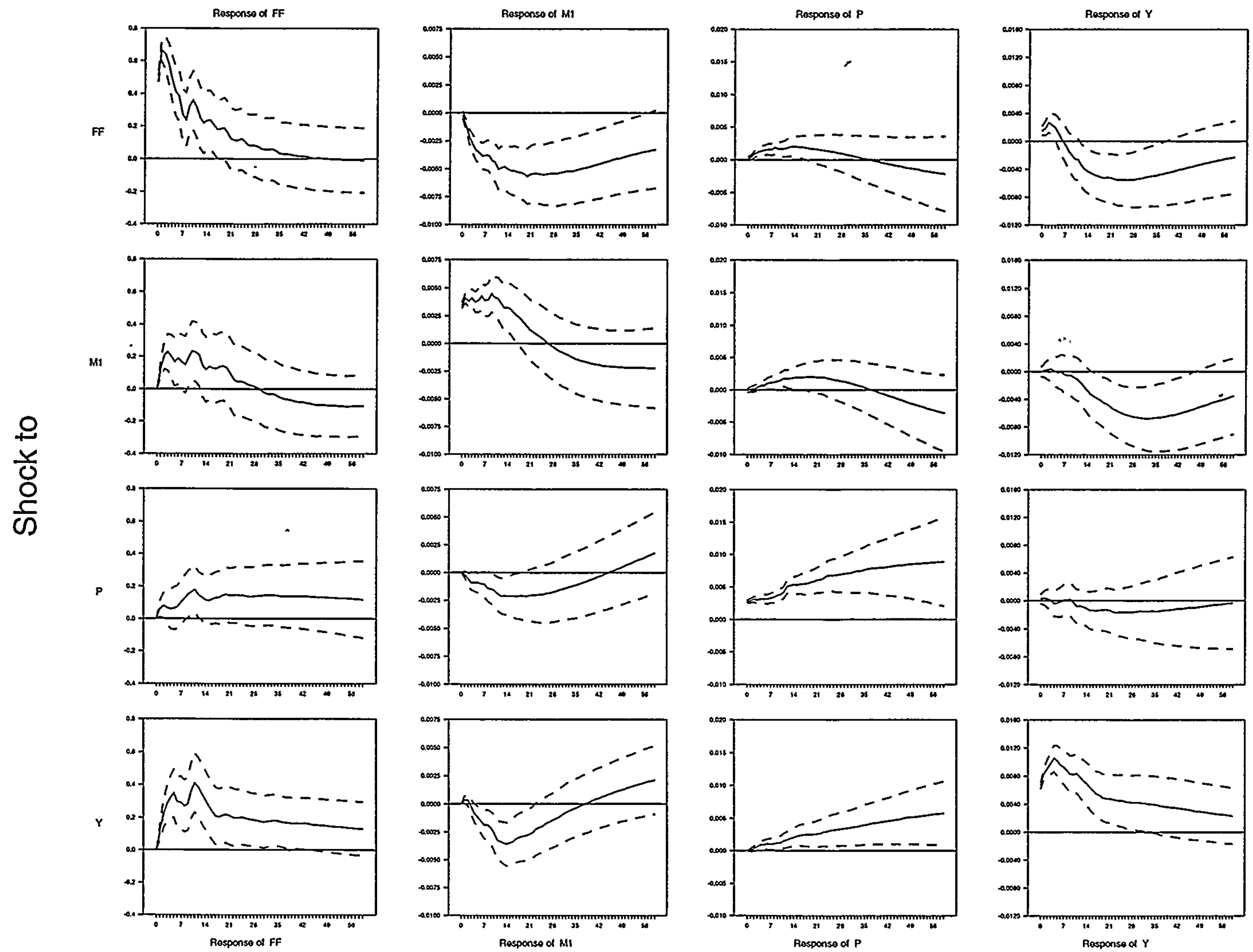

Figure 4.7. Unrestricted VAR Impulse Responses, {FF, M2, P, Y} Model

Monthly data: 1960:1 - 1995:11

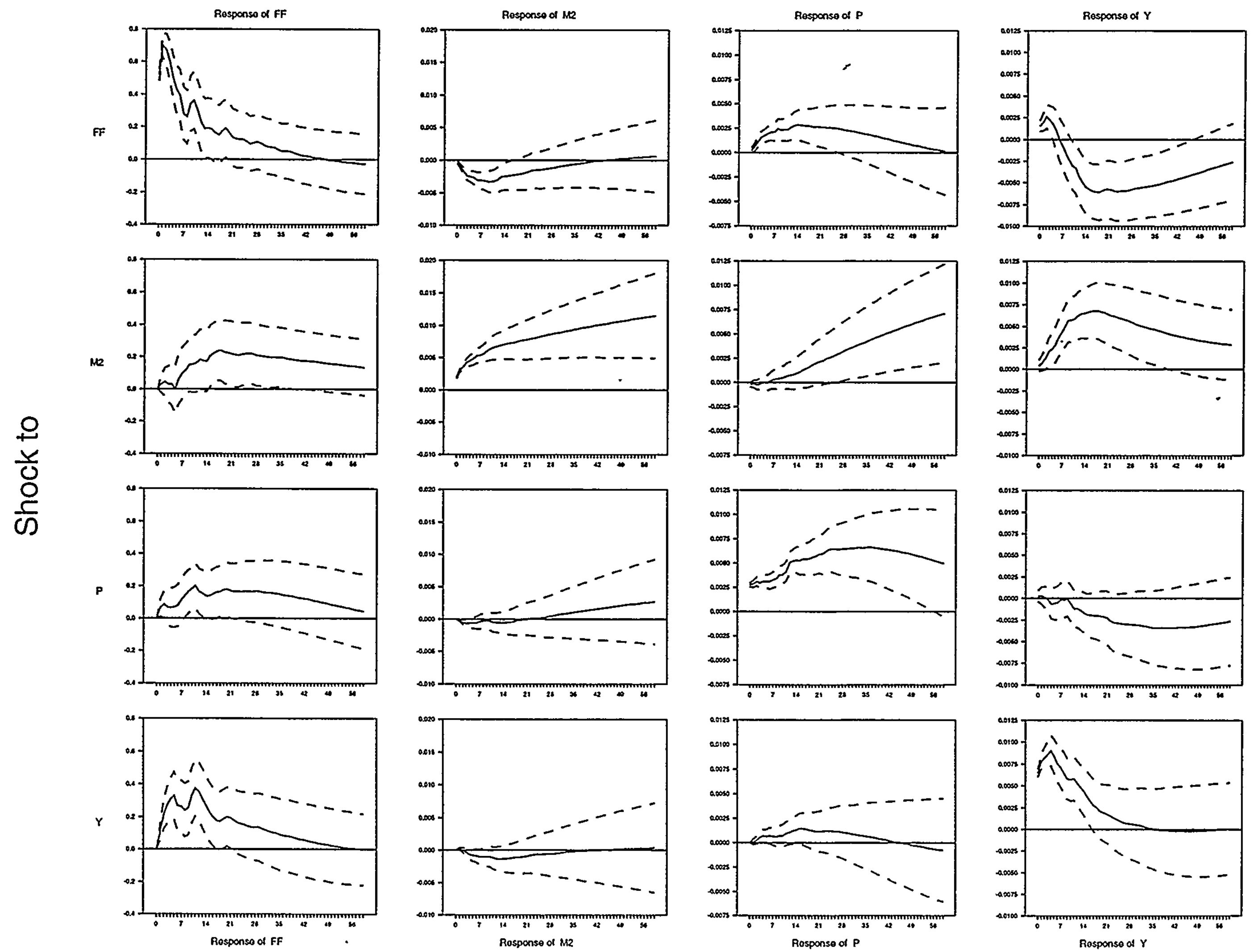

Figure 4.7. Unrestricted VAR Impulse Responses, {FF, M3, P, Y} Model

Monthly data: 1960:1 - 1995:11

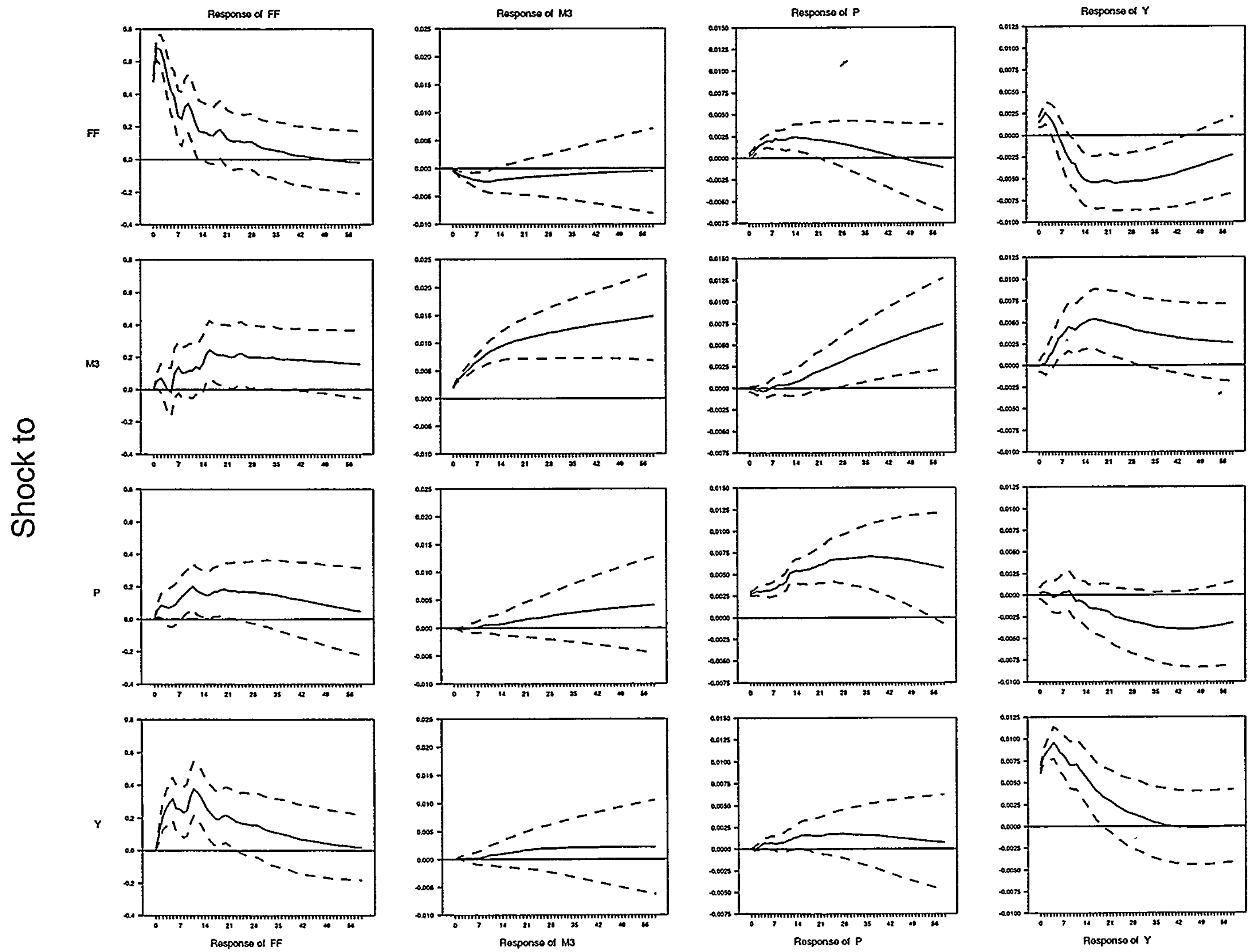

Figure 4.7. Unrestricted VAR Impulse Responses, {FF, L, P, Y} Model

Monthly data: 1960:1 - 1995:11

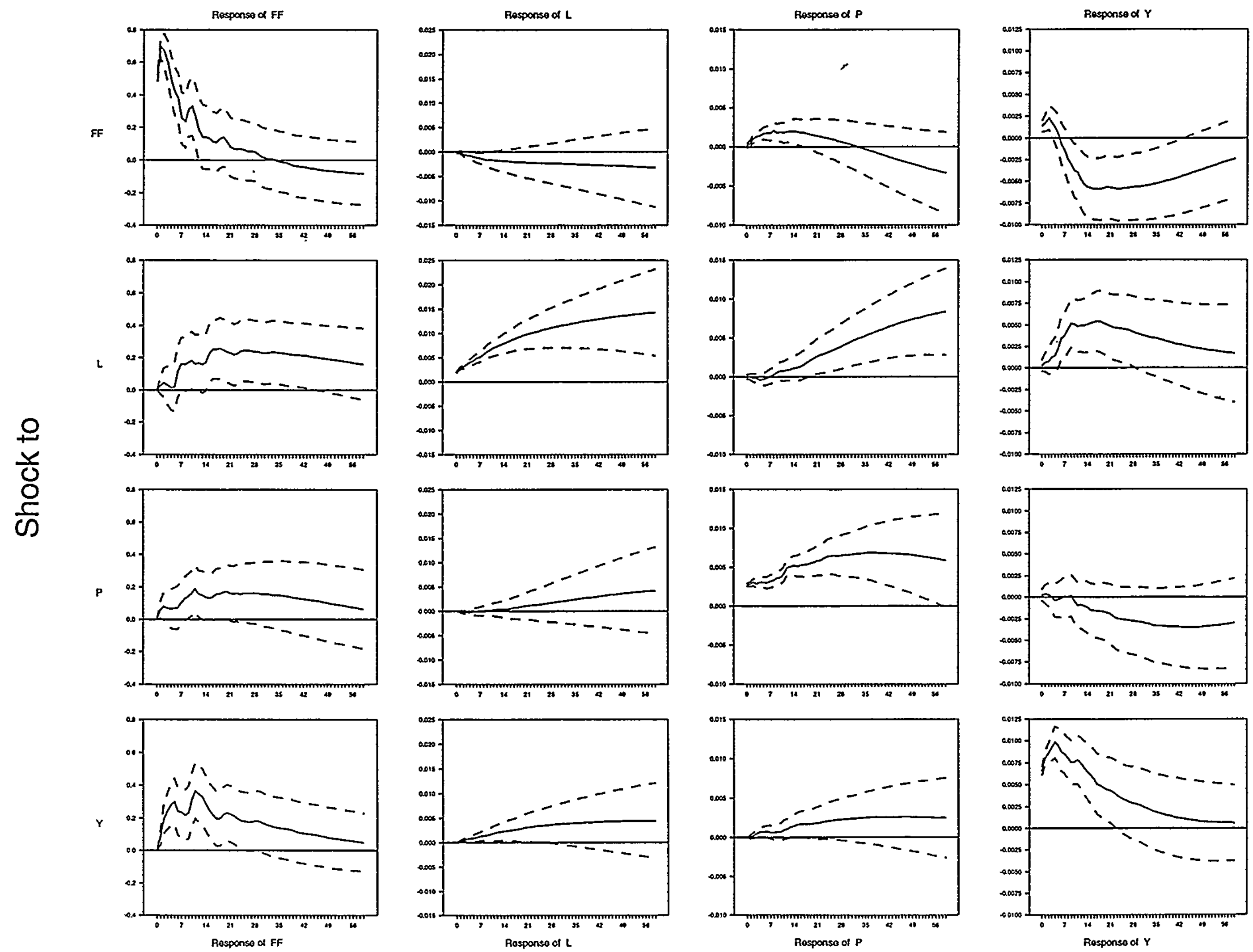

Figure 4.8. Unrestricted VAR Impulse Responses, {FF, PC, DM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

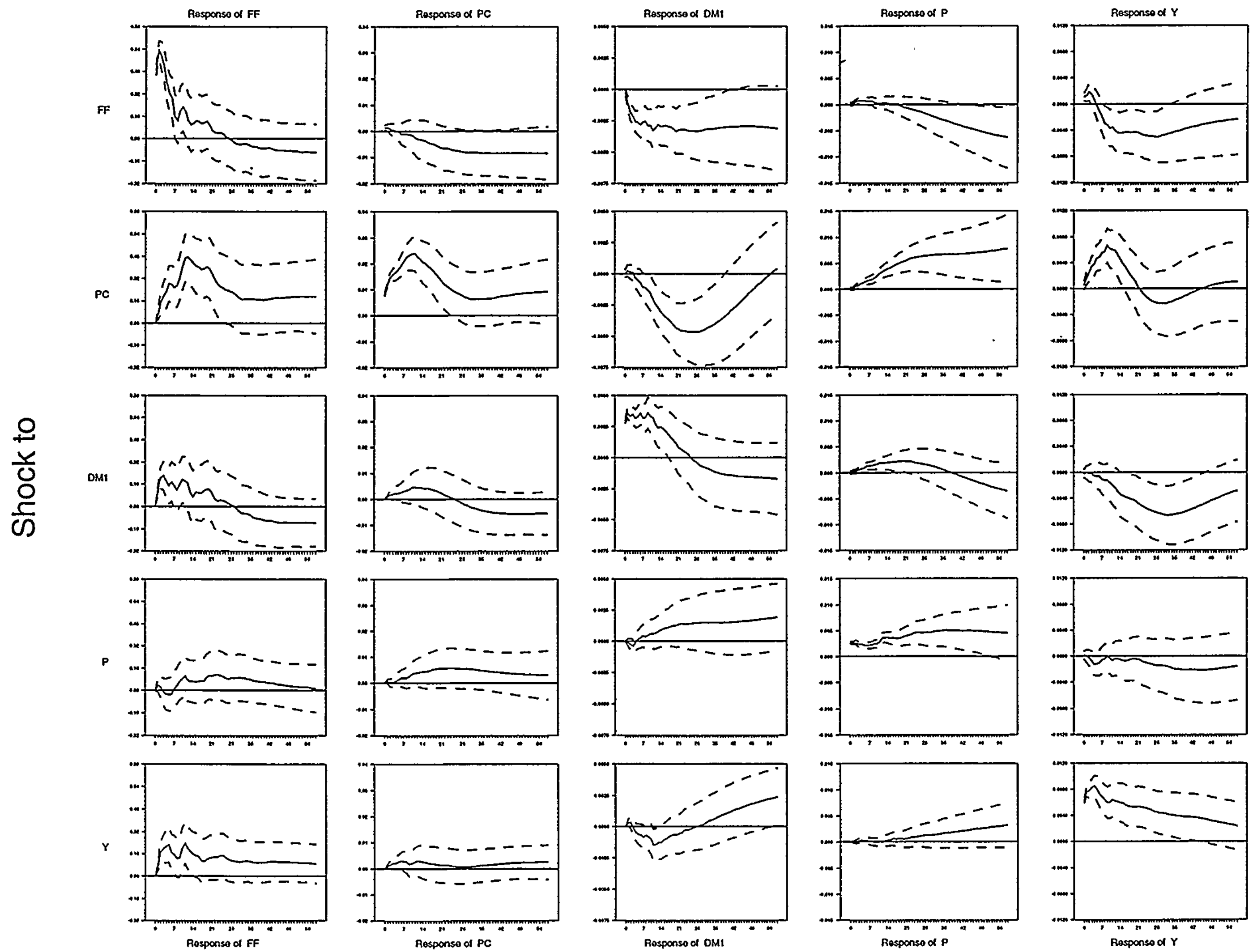

Figure 4.8. Unrestricted VAR Impulse Responses, {FF, PC, DM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

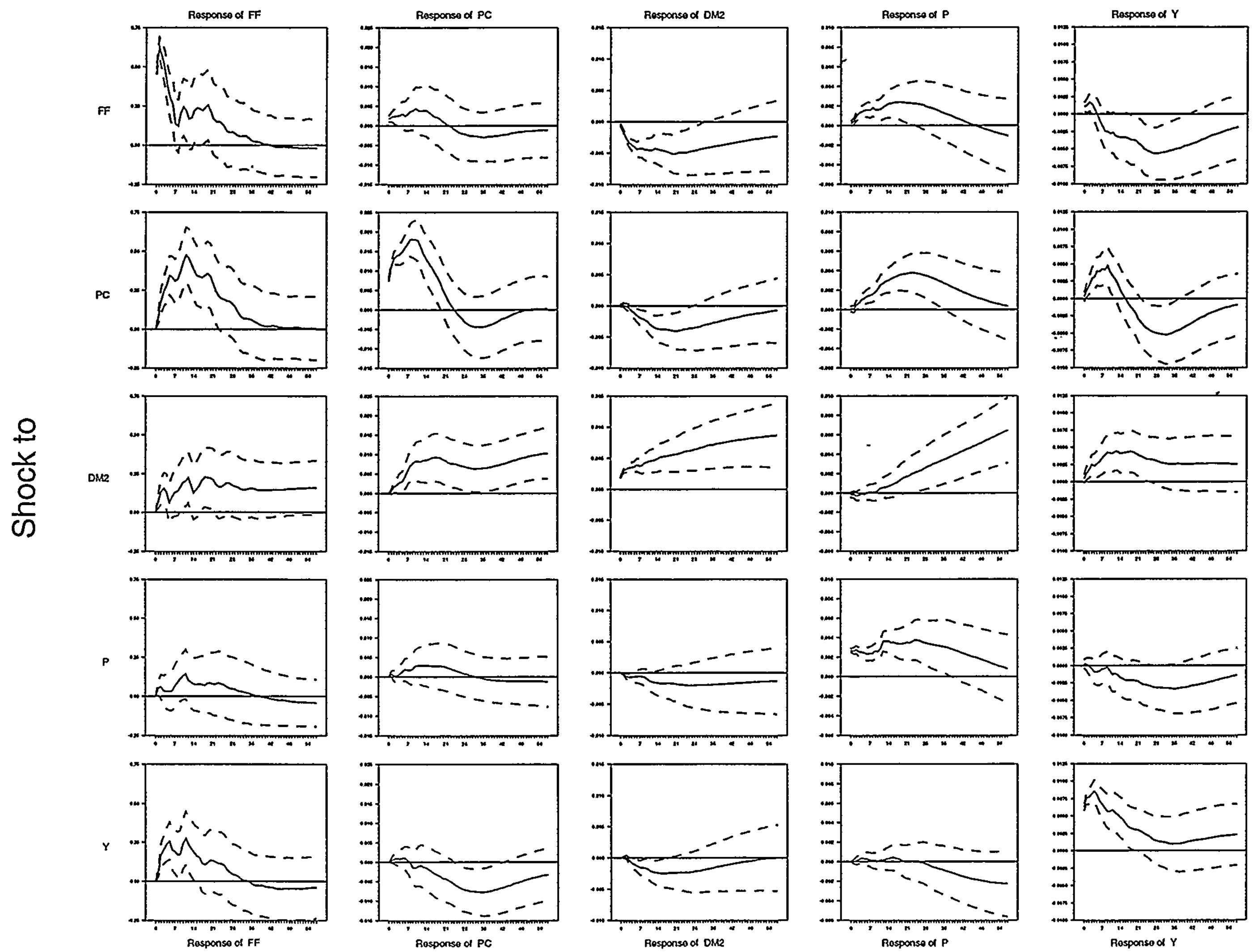

Figure 4.8. Unrestricted VAR Impulse Responses, {FF, PC, DM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

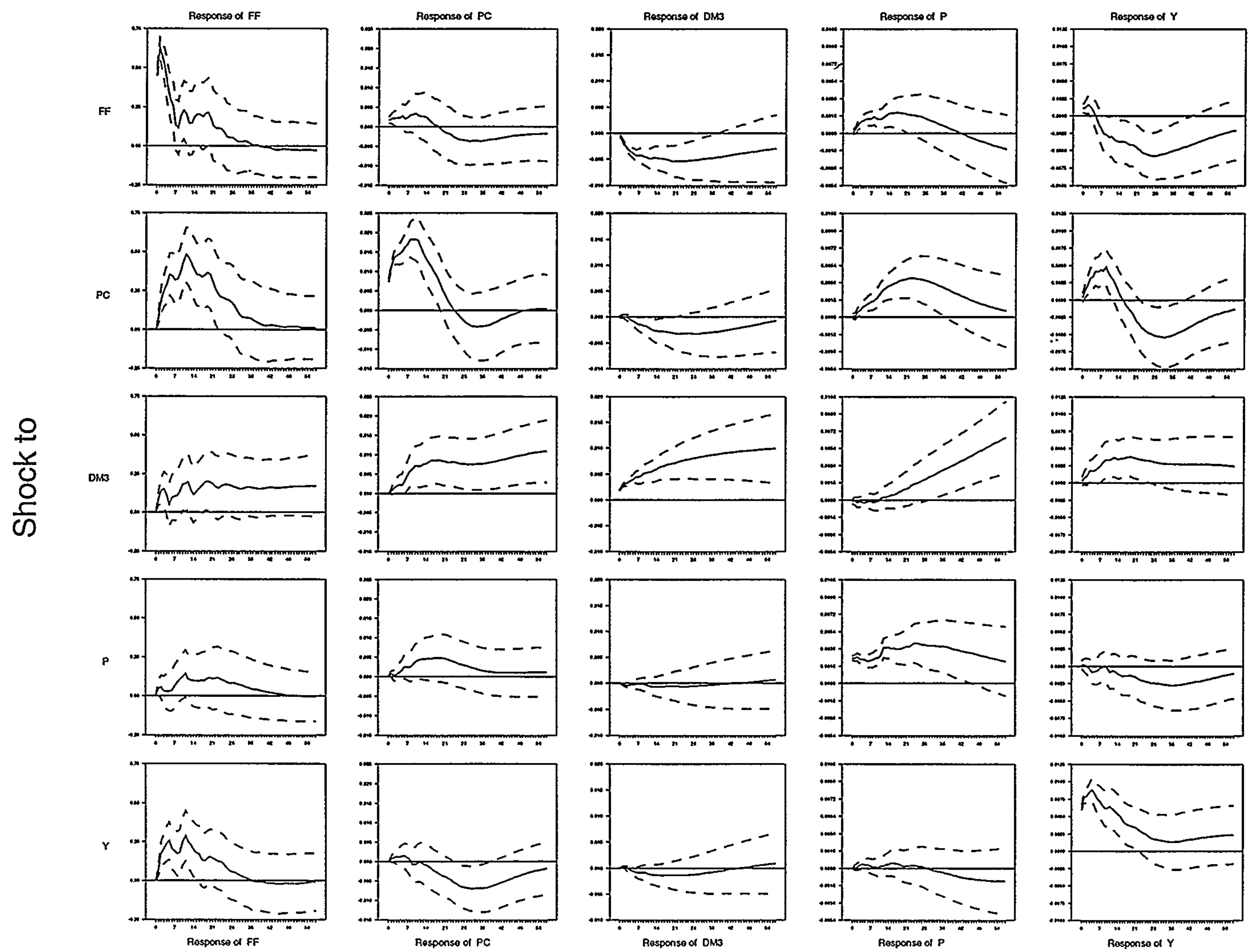

Figure 4.8. Unrestricted VAR Impulse Responses, {FF, PC, DL, P, Y} Model

Monthly data: 1960:1 - 1995:11

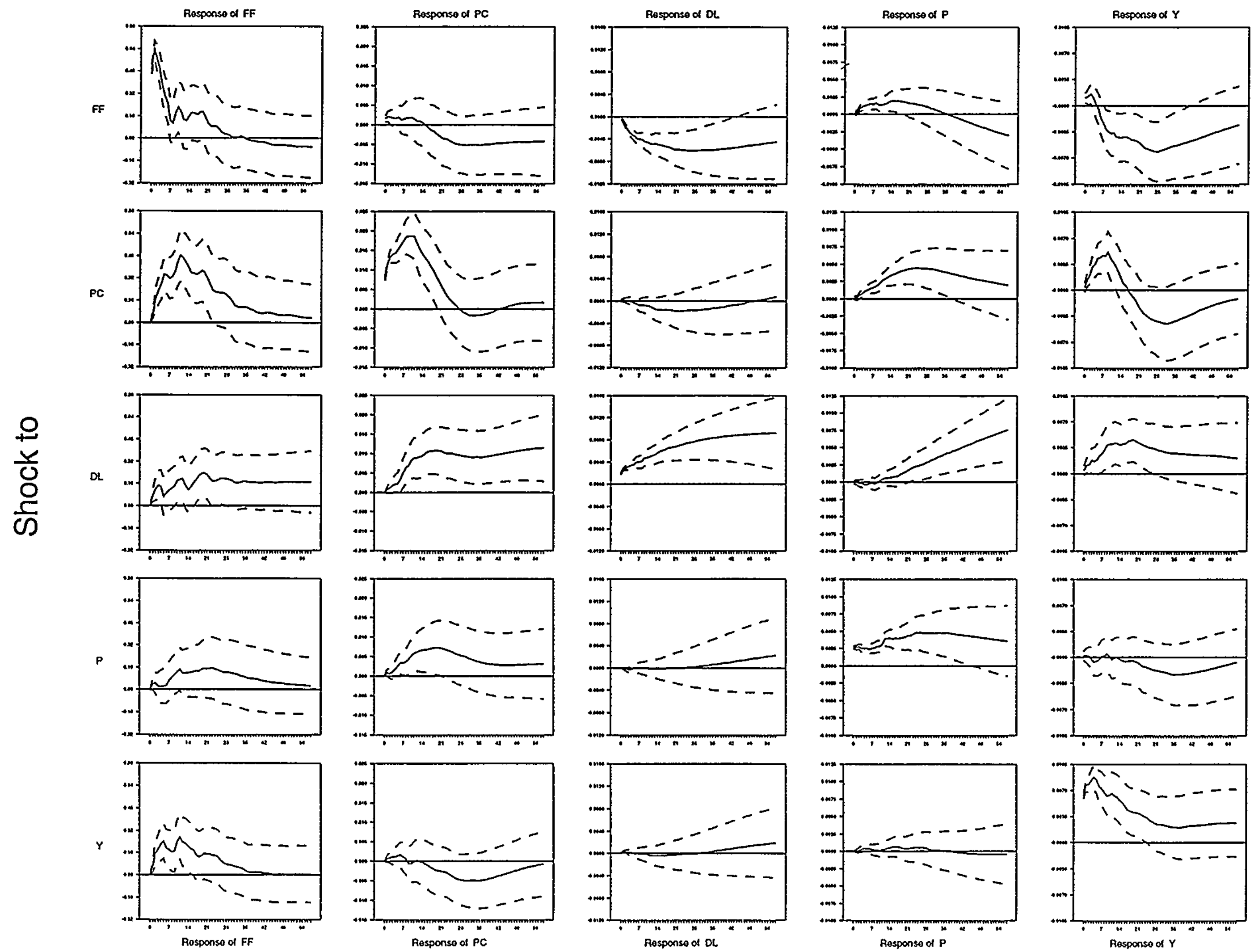

Figure 4.9. Unrestricted VAR Impulse Responses, {FF, PC, CEM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

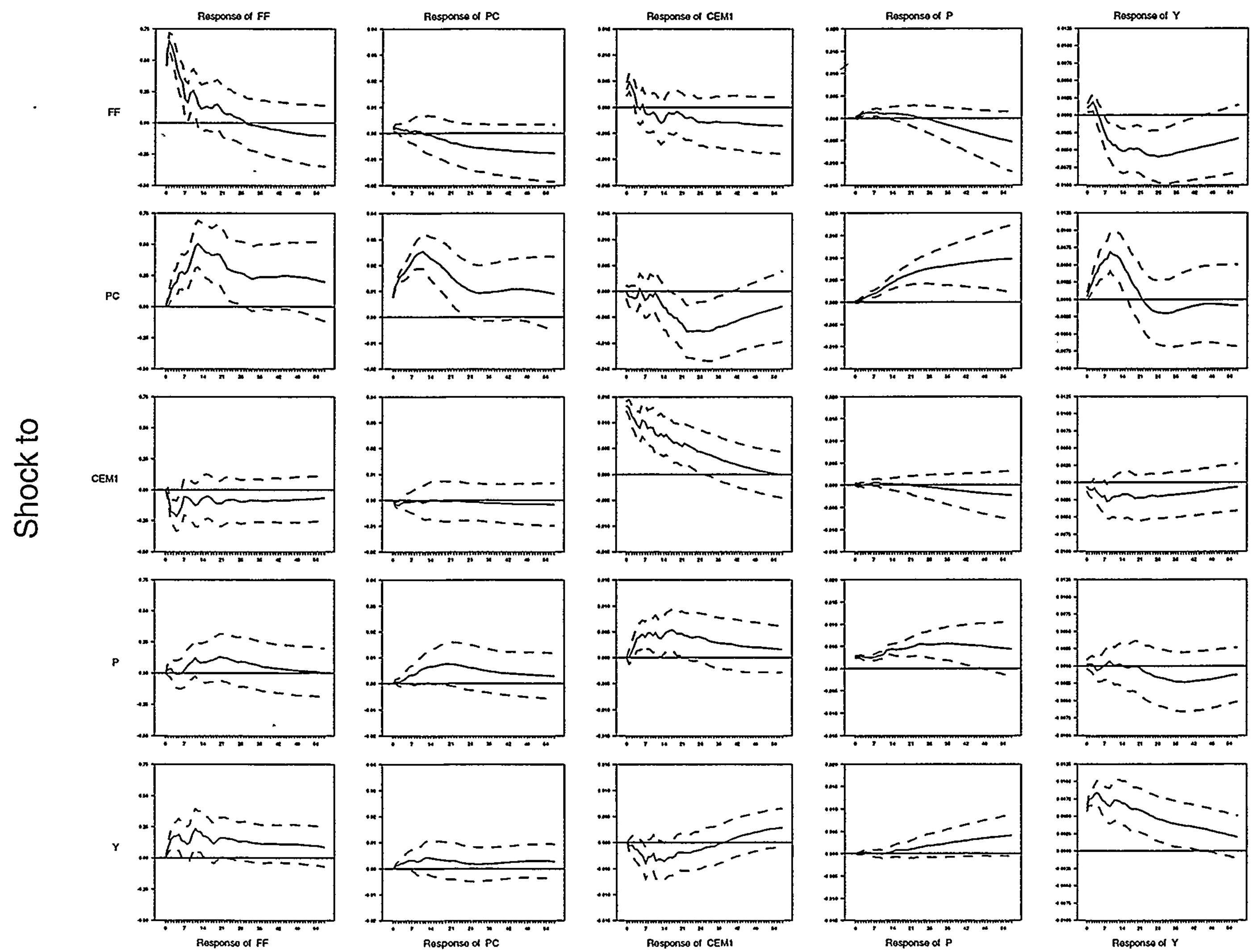

Figure 4.9. Unrestricted VAR Impulse Responses, {FF, PC, CEM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

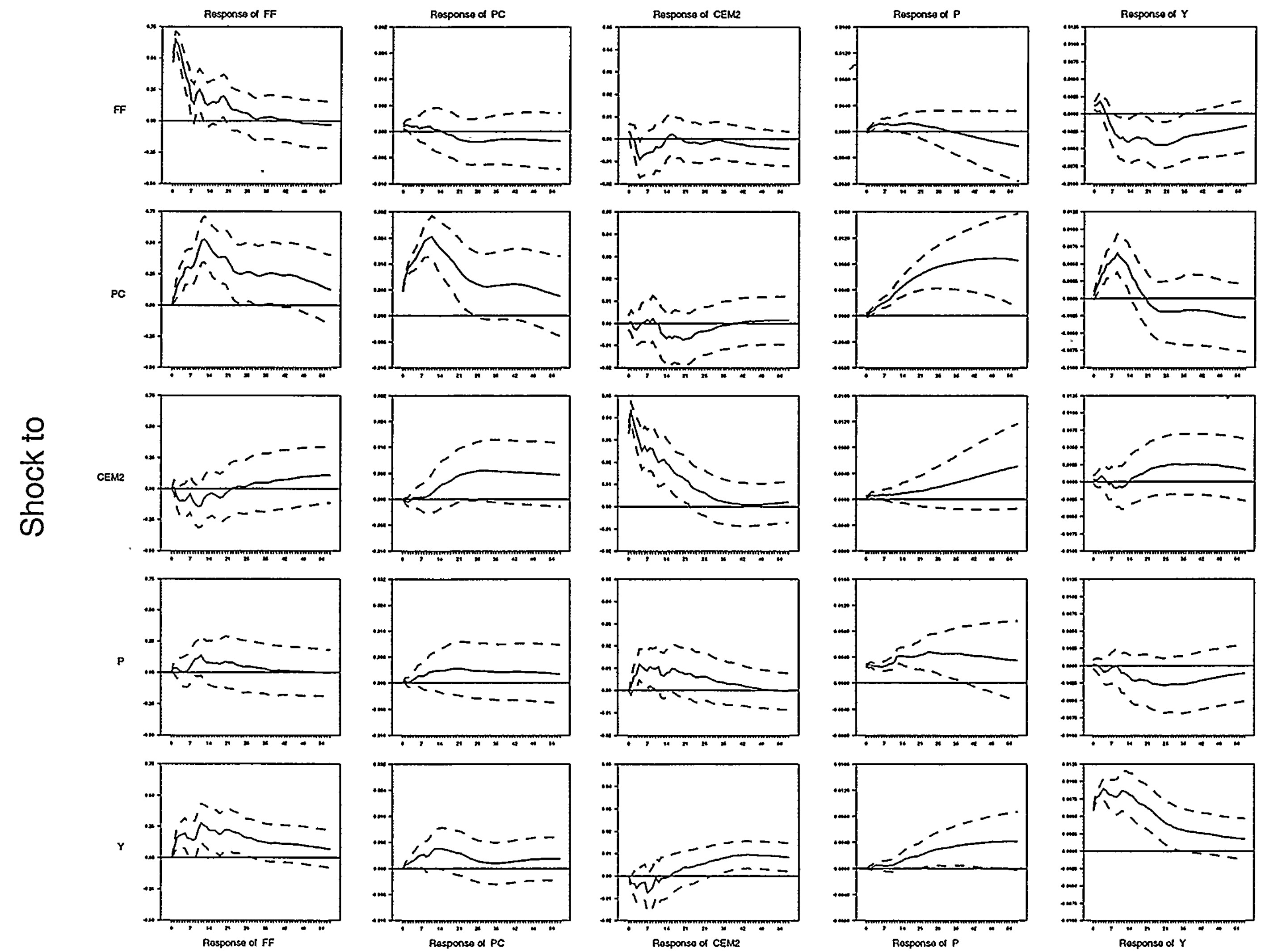

Figure 4.9. Unrestricted VAR Impulse Responses, {FF, PC, CEM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

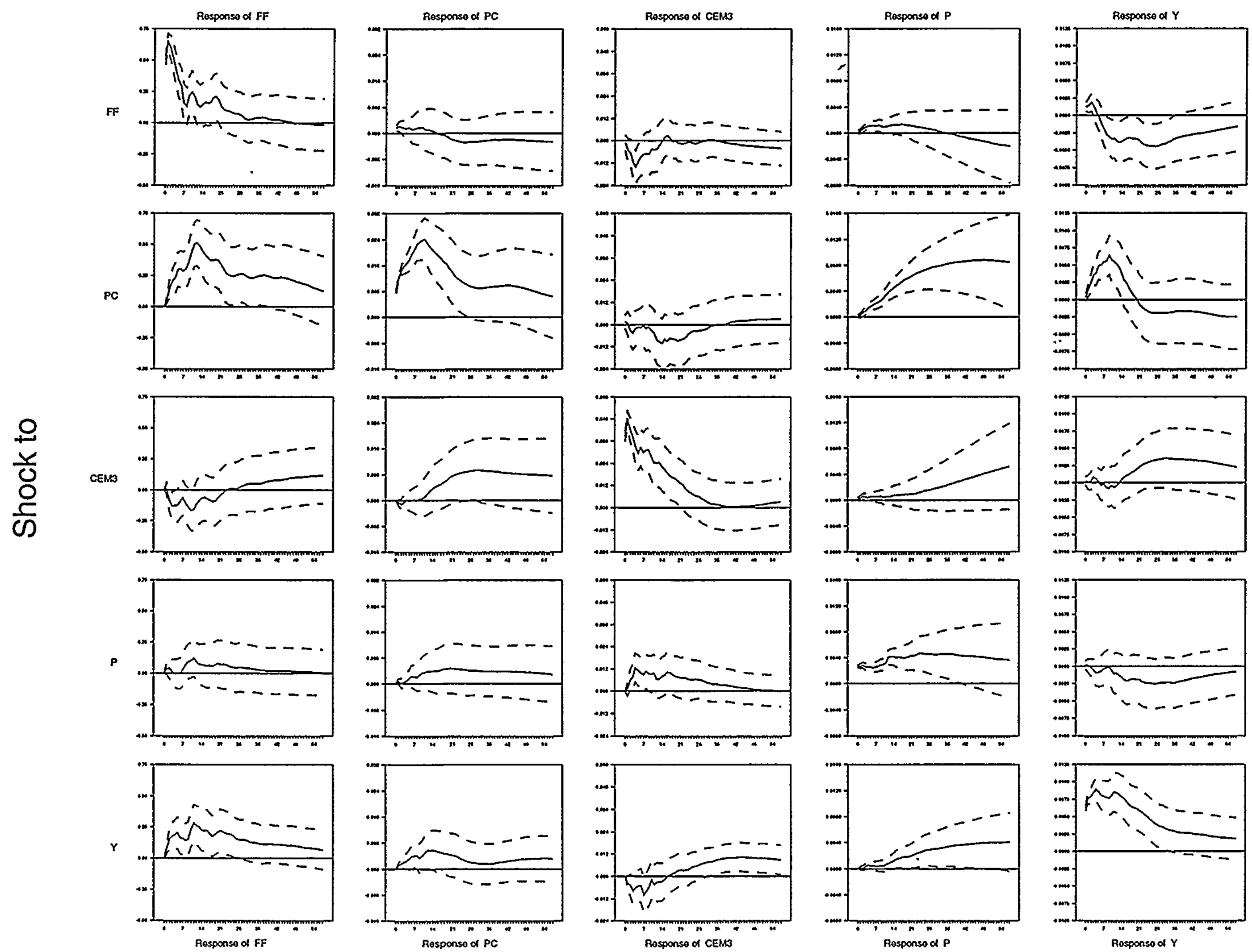

Figure 4.9. Unrestricted VAR Impulse Responses, {FF, PC, CEL, P, Y} Model

Monthly data: 1960:1 - 1995:11

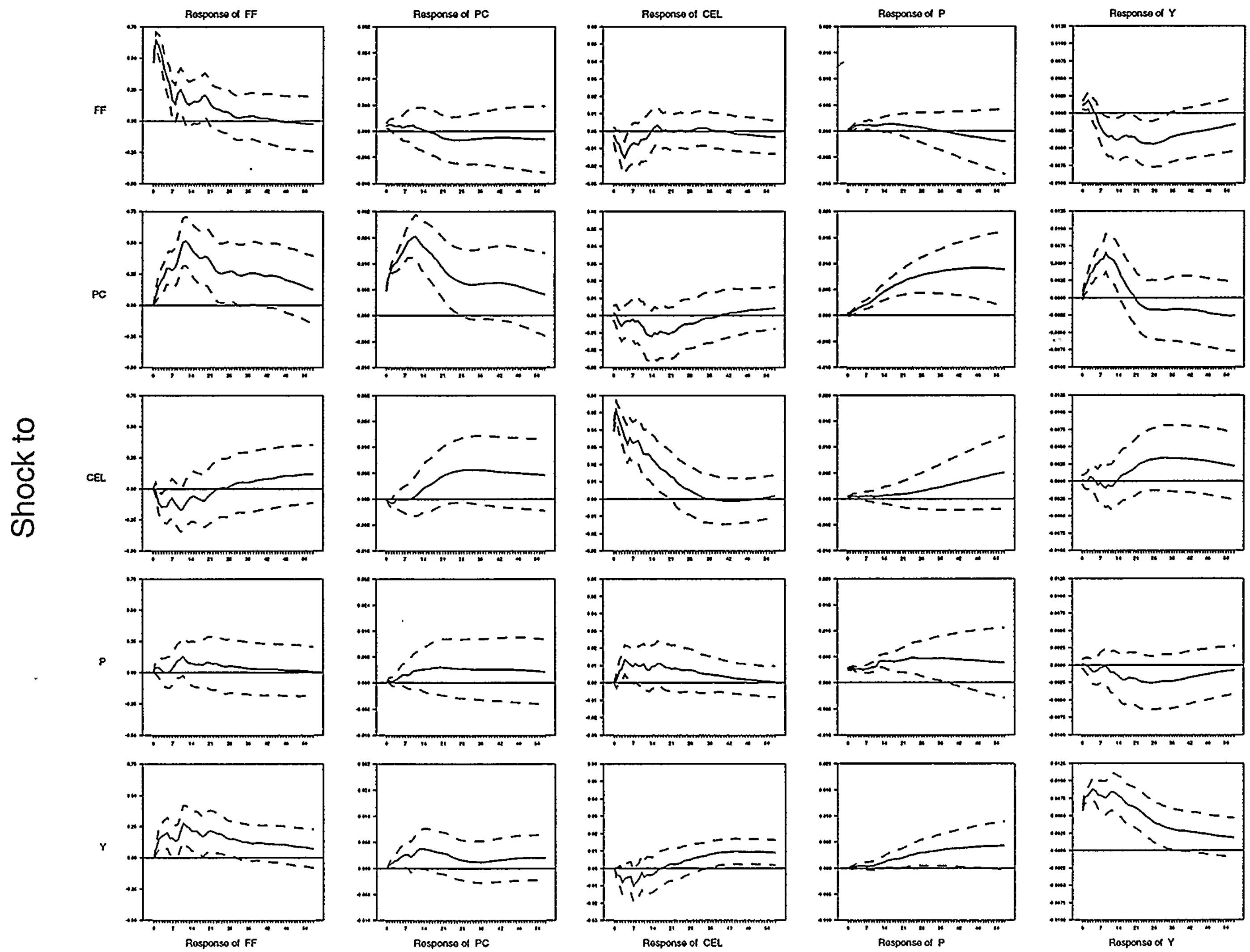

Figure 4.10. Unrestricted VAR Impulse Responses, {FF, PC, M1, P, Y} Model

Monthly data: 1960:1 - 1995:11

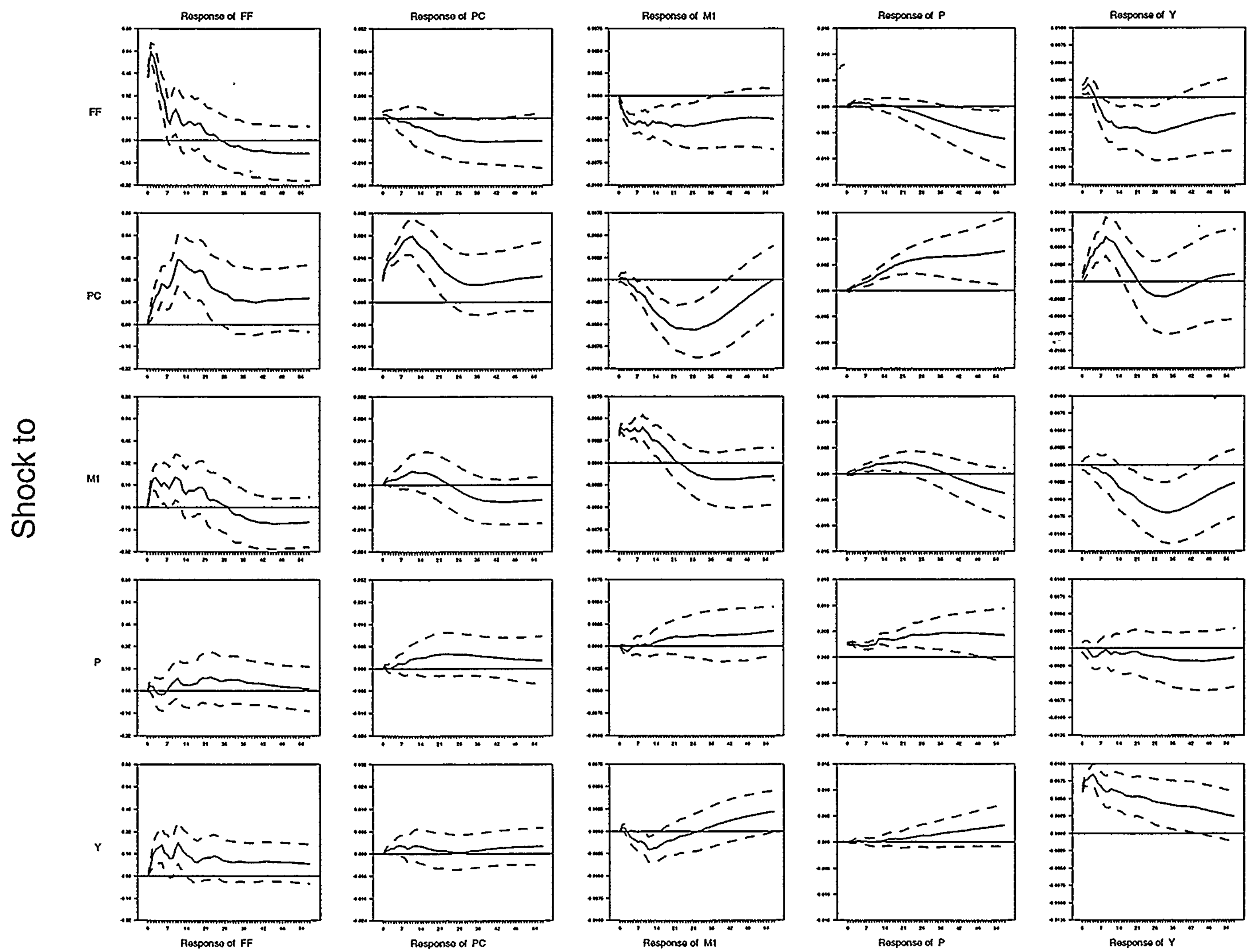

Figure 4.10. Unrestricted VAR Impulse Responses, {FF, PC, M2, P, Y} Model

Monthly data: 1960:1 - 1995:11

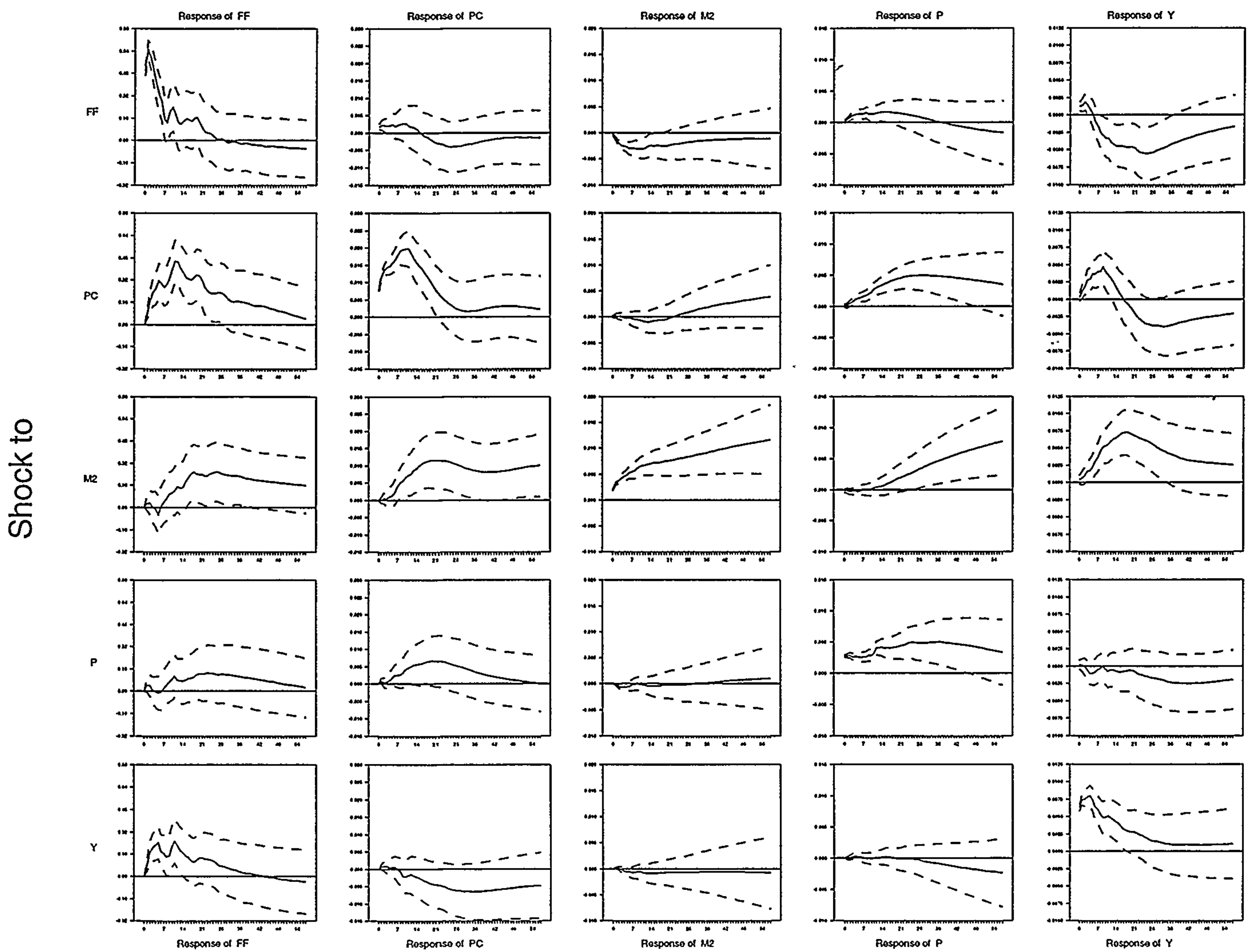

Figure 4.10. Unrestricted VAR Impulse Responses, {FF, PC, M3, P, Y} Model

Monthly data: 1960:1 - 1995:11

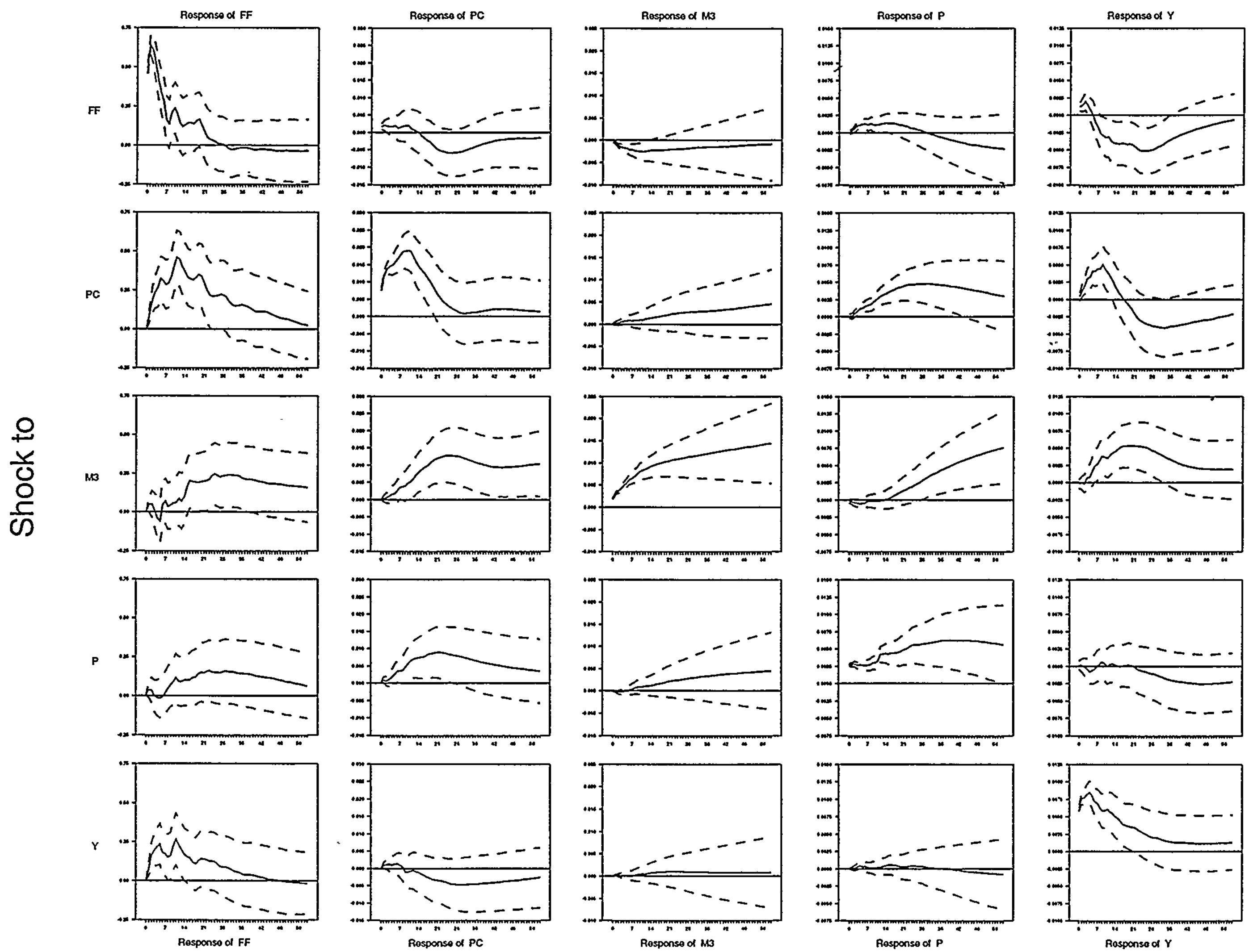

Figure 4.10. Unrestricted VAR Impulse Responses, {FF, PC, L, P, Y} Model

Monthly data: 1960:1 - 1995:11

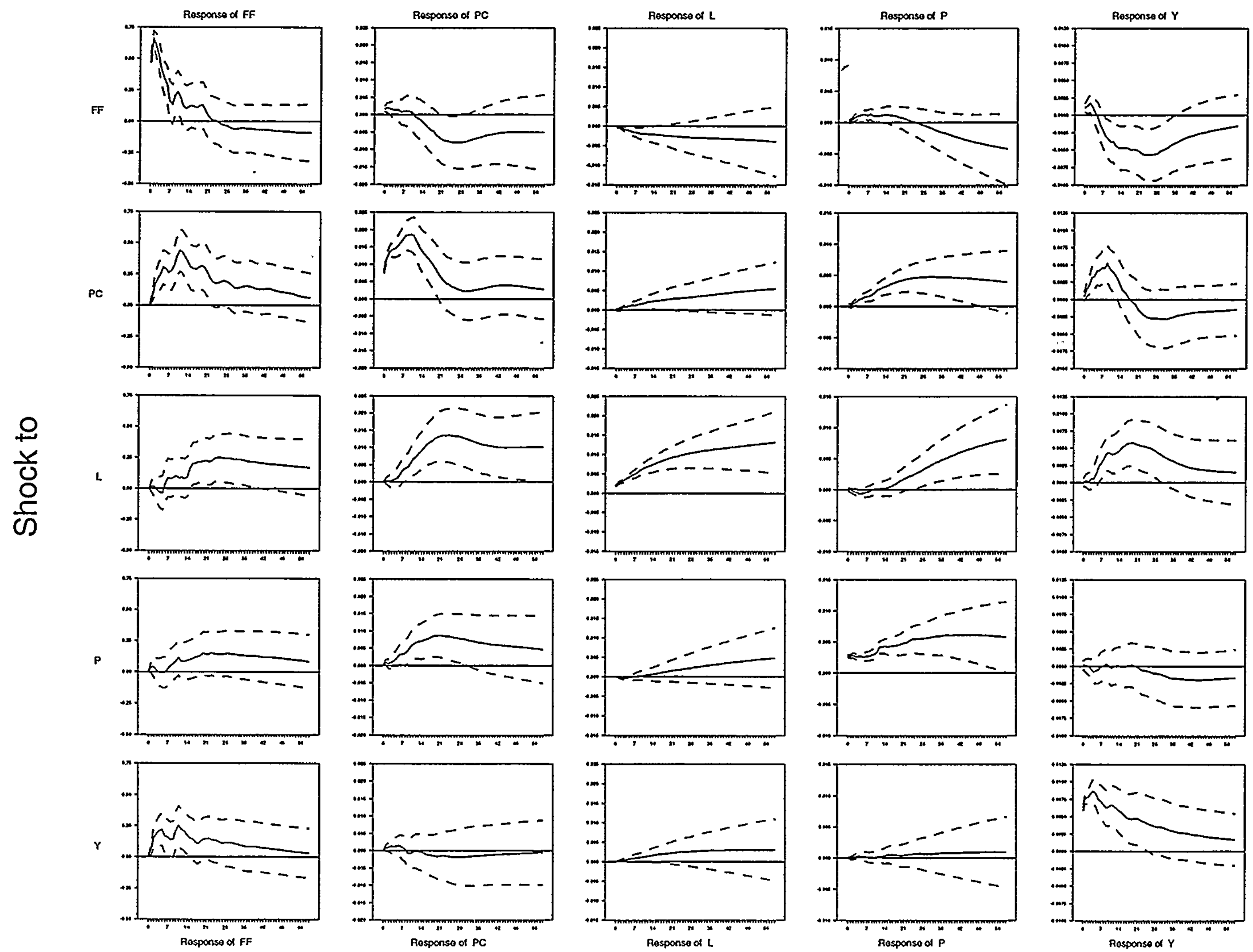

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*DM*	*FF*	*P*	*Y*	*DM*	*FF*	*P*	*Y*	*DM*	*FF*	*P*	*Y*
Panel 1: Divisia M1												
DM	1.000				.000	.000	.023	.000	20.793	65.223	4.523	9.461
FF	-.057	1.000			.000	.000	.058	.000	8.380	40.390	15.233	35.996
P	-.032	.054	1.000		.247	.006	.000	.693	4.560	3.397	70.390	21.654
Y	-.029	.211	.053	1.000	.783	.112	.386	.000	26.590	27.149	2.460	43.801
Panel 2: Divisia M2												
DM	1.000				.000	.000	.402	.202	76.337	13.211	4.587	5.865
FF	-.229	1.000			.001	.000	.094	.000	10.308	57.405	5.613	26.674
P	-.079	.088	1.000		.053	.001	.000	.636	34.826	23.385	37.740	4.048
Y	.028	.209	.053	1.000	.053	.381	.638	.000	30.711	29.050	13.736	26.502

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*DM*	*FF*	*P*	*Y*	*DM*	*FF*	*P*	*Y*	*DM*	*FF*	*P*	*Y*
Panel 3: Divisia M3												
DM	1.000				.000	.000	.658	.363	86.657	11.312	.883	1.148
FF	-.266	1.000			.000	.000	.124	.001	13.259	52.225	7.619	26.896
P	-.059	.087	1.000		.081	.004	.000	.810	35.131	15.266	46.801	2.801
Y	-.007	.211	.055	1.000	.167	.583	.637	.000	28.701	30.352	11.617	29.329
Panel 4: Divisia L												
DM	1.000				.000	.000	.648	.119	79.351	18.160	.733	1.756
FF	-.211	1.000			.013	.000	.246	.007	16.478	46.407	9.962	27.152
P	-.018	.087	1.000		.084	.007	.000	.886	39.903	9.603	46.330	4.163
Y	.031	.200	.055	1.000	.125	.458	.691	.000	23.186	36.176	6.670	33.968

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*DM*	*DUAL*	*P*	*Y*	*DM*	*DUAL*	*P*	*Y*	*DM*	*DUAL*	*P*	*Y*
Panel 5: Divisia M1												
DM	1.000				.000	.004	.053	.001	61.613	10.013	12.228	16.145
DUAL	-.220	1.000			.112	.000	.021	.008	6.372	30.971	22.857	39.799
P	-.074	.099	1.000		.326	.126	.000	.022	3.313	6.506	48.584	41.596
Y	-.004	.072	.048	1.000	.822	.024	.611	.000	4.140	9.167	18.938	67.754
Panel 6: Divisia M2												
DM	1.000				.000	.000	.095	.002	67.440	12.379	1.634	18.546
DUAL	-.171	1.000			.173	.000	.041	.003	2.324	55.509	26.109	16.058
P	-.110	.097	1.000		.729	.856	.000	.399	16.798	.652	75.644	6.906
Y	-.019	.122	.048	1.000	.027	.096	.231	.000	30.203	9.836	30.450	29.510

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*DM*	*DUAL*	*P*	*Y*	*DM*	*DUAL*	*P*	*Y*	*DM*	*DUAL*	*P*	*Y*
Panel 7: Divisia M3												
DM	1.000				.000	.000	.158	.031	65.795	20.785	1.705	11.715
DUAL	-.058	1.000			.490	.000	.160	.004	1.188	63.657	23.200	11.954
P	-.105	.076	1.000		.485	.784	.000	.291	17.599	1.115	74.556	6.730
Y	-.009	.037	.012	1.000	.048	.222	.108	.000	24.537	18.972	25.391	31.100
Panel 8: Divisia L												
DM	1.000				.000	.000	.190	.193	65.378	27.379	1.881	5.361
DUAL	-.070	1.000			.742	.000	.195	.008	1.093	61.010	22.198	15.700
P	-.061	.063	1.000		.303	.759	.000	.211	24.990	1.551	67.132	6.327
Y	-.002	.082	.051	1.000	.032	.184	.108	.000	21.078	27.360	20.813	30.748

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*CEM*	*FF*	*P*	*Y*	*CEM*	*FF*	*P*	*Y*	*CEM*	*FF*	*P*	*Y*
					Panel 9: CEM1							
CEM	1.000				.000	.010	.302	.023	61.911	33.922	1.206	2.961
FF	.263	1.000			.000	.000	.301	.000	7.697	43.753	16.240	32.309
P	.067	.078	1.000		.068	.015	.000	.169	8.063	3.395	68.741	19.801
Y	-.021	.212	.084	1.000	.059	.011	.513	.000	13.559	31.965	3.755	50.720
					Panel 10: CEM2							
CEM	1.000				.000	.245	.122	.002	76.955	9.984	1.513	11.547
FF	.100	1.000			.097	.000	.169	.000	1.693	43.521	15.281	39.503
P	.081	.087	1.000		.721	.031	.000	.481	1.090	4.407	65.090	29.413
Y	.090	.230	.076	1.000	.113	.074	.635	.000	6.162	23.412	10.106	60.319

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*CEM*	*FF*	*P*	*Y*	*CEM*	*FF*	*P*	*Y*	*CEM*	*FF*	*P*	*Y*
					Panel 11: CEM3							
CEM	1.000				.000	.293	.128	.002	81.703	4.967	.961	12.368
FF	-.031	1.000			.044	.000	.167	.000	4.488	41.917	14.993	38.601
P	.058	.089	1.000		.855	.044	.000	.471	1.006	4.895	65.520	28.578
Y	.041	.237	.078	1.000	.073	.063	.634	.000	13.854	19.215	9.848	57.083
					Panel 12: CEL							
CEM	1.000				.000	.333	.153	.004	83.084	4.162	.990	11.763
FF	-.057	1.000			.0459	.000	.177	.001	6.329	40.012	15.571	38.089
P	.050	.088	1.000		.905	.047	.000	.418	.421	4.437	66.435	28.707
Y	.031	.234	.077	1.000	.049	.042	.643	.000	13.871	18.855	8.722	58.551

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*M*	*FF*	*P*	*Y*	*M*	*FF*	*P*	*Y*	*M*	*FF*	*P*	*Y*
Panel 13: Sum M1												
M	1.000				.000	.000	.007	.000	20.222	61.809	6.818	11.151
FF	-.057	1.000			.000	.000	.021	.000	9.317	41.342	14.476	34.865
P	-.038	.055	1.000		.206	.006	.000	.724	4.447	3.630	71.211	20.712
Y	-.017	.213	.054	1.000	.790	.118	.387	.000	28.256	26.533	1.828	43.382
Panel 14: Sum M2												
M	1.000				.000	.000	.185	.374	94.343	3.348	1.657	.651
FF	-.157	1.000			.170	.000	.167	.000	18.827	45.127	12.705	23.341
P	-.078	.081	1.000		.514	.006	.000	.829	28.698	10.784	59.087	4.430
Y	.029	.229	.054	1.000	.034	.141	.568	.000	42.914	22.625	12.344	22.116

TABLE 4.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*M*	*FF*	*P*	*Y*	*M*	*FF*	*P*	*Y*	*M*	*FF*	*P*	*Y*
					Panel 15: Sum M3							
M	1.000				.000	.158	.568	.674	93.132	.572	4.360	1.935
FF	-.121	1.000			.006	.000	.235	.001	20.515	42.383	13.751	23.350
P	-.056	.077	1.000		.605	.007	.000	.886	30.422	4.830	61.896	2.851
Y	-.032	.223	.052	1.000	.049	.078	.604	.000	28.978	24.791	14.783	31.447
					Panel 16: Sum L							
M	1.000				.000	.165	.432	.249	84.953	2.175	4.666	8.205
FF	-.056	1.000			.242	.000	.371	.004	28.166	35.660	12.494	23.680
P	.004	.067	1.000		.258	.007	.000	.888	38.808	3.809	51.499	5.884
Y	.027	.202	.051	1.000	.043	.100	.619	.000	23.270	29.793	10.322	36.615

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*FF*	*DM*	*P*	*Y*	*FF*	*DM*	*P*	*Y*	*FF*	*DM*	*P*	*Y*
Panel 1: Divisia M1												
FF	1.000				.000	.000	.058	.000	38.894	9.877	15.233	35.996
DM	-.057	1.000			.000	.000	.231	.000	66.246	19.769	4.523	9.461P
P	.054	-.032	1.000		.006	.247	.000	.693	2.977	4.979	70.340	21.654
Y	.211	-.029	.053	1.000	.112	.783	.386	.000	24.188	29.551	2.460	43.801
Panel 2: Divisia M2												
FF	1.000				.000	.001	.094	.000	50.499	17.214	5.613	26.674
DM	-.229	1.000			.000	.000	.402	.202	28.794	60.754	4.587	5.865P
P	.088	-.079	1.000		.001	.053	.000	.636	17.774	40.438	37.740	4.048
Y	.209	.028	.053	1.000	.381	.053	.638	.000	41.391	18.370	13.736	26.502

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

Equation	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
	FF	*DM*	*P*	*Y*	*FF*	*DM*	*P*	*Y*	*FF*	*DM*	*P*	*Y*
Panel 3: Divisia M3												
FF	1.000				.000	.000	.124	.001	45.131	20.353	7.619	26.896
DM	-.266	1.000			.000	.000	.658	.363	31.609	66.359	.883	1.148
P	.087	-.059	1.000		.004	.081	.000	.081	12.579	37.818	46.802	2.801
Y	.211	-.007	.055	1.000	.583	.167	.637	.000	44.665	14.388	11.617	29.329
Panel 4: Divisia L												
FF	1.000				.000	.013	.246	.007	40.822	22.063	9.962	27.152
DM	-.211	1.000			.000	.000	.647	.119	36.128	61.383	.733	1.756
P	.087	-.018	1.000		.007	.084	.000	.886	8.763	40.743	46.331	4.163
Y	.200	.031	.055	1.000	.458	.125	.691	.000	46.926	12.435	6.670	33.968

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*FF*	*CEM*	*P*	*Y*	*FF*	*CEM*	*P*	*Y*	*FF*	*CEM*	*P*	*Y*
					Panel 5: CEM1							
FF	1.000				.000	.000	.301	.000	39.150	12.300	16.240	32.309
CEM	.263	1.000			.010	.000	.302	.023	19.337	76.496	1.206	2.961
P	.078	.068	1.000		.015	.068	.000	.169	3.807	7.651	68.741	19.801
Y	.212	-.021	.084	1.000	.011	.059	.513	.000	40.810	4.715	3.754	50.720
					Panel 6: CEM2							
FF	1.000				.000	.097	.169	.000	42.505	2.710	15.281	39.503
CEM	.100	1.000			.245	.000	.122	.002	6.008	80.931	1.513	11.547
P	.087	.081	1.000		.031	.721	.000	.481	4.675	.823	65.090	29.413
Y	.230	.090	.076	1.000	.074	.113	.635	.000	21.620	7.954	10.106	60.319

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

Equation	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
	FF	*CEM*	*P*	*Y*	*FF*	*CEM*	*P*	*Y*	*FF*	*CEM*	*P*	*Y*
Panel 7: CEM3												
FF	1.000				.000	.044	.167	.000	42.498	3.907	14.993	38.601
CEM	-.031	1.000			.293	.000	.128	.002	6.148	80.522	.961	12.368
P	.089	.058	1.000		.044	.855	.000	.471	4.835	1.066	65.520	28.578
Y	.237	.041	.077	1.000	.063	.073	.634	.000	20.034	13.035	9.848	57.083
Panel 8: CEL												
FF	1.000				.000	.046	.177	.001	41.319	5.022	15.571	38.087
CEM	-.057	1.000			.333	.000	.153	.004	6.211	81.035	.990	11.763
P	.088	.050	1.000		.047	.905	.000	.418	4.436	.421	66.435	28.707
Y	.234	.031	.077	1.000	.042	.049	.643	.000	20.262	12.464	8.722	58.551

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*FF*	*M*	*P*	*Y*	*FF*	*M*	*P*	*Y*	*FF*	*M*	*P*	*Y*
Panel 9: Sum M1												
FF	1.000				.000	.000	.021	.000	39.640	11.019	14.476	34.865
M	-.057	1.000			.000	.000	.007	.000	62.313	19.718	6.818	11.151
P	.055	-.038	1.000		.006	.206	.000	.724	3.195	4.882	71.211	20.712
Y	.213	-.017	.054	1.000	.118	.790	.387	.000	23.543	31.247	1.828	43.382
Panel 10: Sum M2												
FF	1.000				.000	.170	.167	.000	41.598	22.355	12.705	23.341
M	-.157	1.000			.000	.000	.185	.374	3.506	94.185	1.657	.651
P	.081	-.077	1.000		.006	.514	.000	.829	7.409	32.074	59.087	1.430
Y	.229	.029	.054	1.000	.142	.034	.568	.000	32.083	33.456	12.344	22.116

TABLE 4.2

UNRESTRICTED VAR RESULTS FOR INTEREST RATE RULE

	Correlation matrices for innovations				Marginal significance levels for exclusion of lags				Forecast error variance decomposition (60 month horizon)			
Equation	*FF*	*M*	*P*	*Y*	*FF*	*M*	*P*	*Y*	*FF*	*M*	*P*	*Y*
Panel 11: Sum M3												
FF	1.000				.000	.006	.235	.001	39.846	23.052	13.752	23.351
M	-.068	1.000			.158	.000	.568	.674	1.224	92.481	4.360	1.935
P	.067	-.021	1.000		.007	.605	.000	.886	4.094	31.159	61.896	2.851
Y	.223	-.003	.054	1.000	.078	.049	.604	.000	30.955	22.815	14.783	31.447
Panel 12: Sum L												
FF	1.000				.000	.242	.371	.004	35.026	28.799	12.494	23.680
M	-.056	1.000			.165	.000	.432	.249	3.963	83.165	4.666	8.205
P	.066	.004	1.000		.007	.258	.000	.888	4.564	38.052	51.500	5.884
Y	.202	.027	.051	1.000	.100	.043	.619	.000	32.557	20.506	10.322	36.615

Table 4.3: Summary Results for Four-variable system with Money Supply rule			
Model	Liqudity Puzzle	Price Puzzle	Output Puzzle
{DM1, FF, P, Y}	yes	yes	yes
{DM2, FF, P, Y}	yes	no	no
{DM3, FF, P, Y}	yes	no	no
{DL, FF, P, Y}	yes	no	no
{DM1, DUALM1, P, Y}	yes	no	no
{DM2, DUALM2, P, Y}	yes	no	no
{DM3, DUALM3, P, Y}	yes	no	no
{DL, DUALL, P, Y}	yes	no	no
{CEM1, FF, P, Y}	no	yes	yes
{CEM2, FF, P, Y}	no	no	yes
{CEM3, FF, P, Y}	no	yes	yes
{CEL, FF, P, Y}	no	yes	yes
{M1, FF, P, Y}	yes	yes	yes
{M2, FF, P, Y}	yes	no	no
{M3, FF, P, Y}	yes	no	no
{L, FF, P, Y}	yes	no	no

Table 4.4: Summary Results for Four-variable system with Interest Rate rule

Model	Price Puzzle	Output Puzzle
{FF, DM1, P, Y}	yes	no
{FF, DM2, P, Y}	yes	no
{FF, DM3, P, Y}	yes	no
{FF, DL, P, Y}	yes	no
{FF, CEM1, P, Y}	yes	no
{FF, CEM2, P, Y}	yes	no
{FF, CEM3, P, Y}	yes	no
{FF, CEL, P, Y}	yes	no
{FF, M1, P, Y}	yes	no
{FF, M2, P, Y}	yes	no
{FF, M3, P, Y}	yes	no
{FF, L, P, Y}	yes	no

Table 4.5: Summary Results for Five-variable system with Interest Rate rule

Model	Price Puzzle	Output Puzzle
{FF, PC, DM1, P, Y}	no	no
{FF, PC, DM2, P, Y}	yes	no
{FF, PC, DM3, P, Y}	yes	no
{FF, PC, DL, P, Y}	yes	no
{FF, PC, CEM1, P, Y}	no	no
{FF, PC, CEM2, P, Y}	yes	no
{FF, PC, CEM3, P, Y}	yes	no
{FF, PC, CEL, P, Y}	yes	no
{FF, PC, M1, P, Y}	no	no
{FF, PC, M2, P, Y}	yes	no
{FF, PC, M3, P, Y}	yes	no
{FF, PC, L, P, Y}	yes	no

CHAPTER 5

EMPIRICAL RESULTS OF STRUCTURAL VARs

5.1 Introduction

The structural VAR approach, M-rule ordering, used in this section is based on Gordon and Leeper (1994) in identifying the contemporaneous monetary policy. This is a seven-variable VAR system consisting of {M, R, P, Y, U, R10, PC} where the objective is to use structural identification scheme to specify "economically" meaningful contemporaneous interactions among specific variables.[27]

In the unrestricted approach, placing the monetary policy variable first in the Wold ordering assumes that the Federal Reserve does not respond to within-period values of the other variables in the VAR system or that those other variables only respond to within-period values of the policy variable. However, this type of monetary policy identification scheme has been criticized for being theoretically implausible. Recently, Sims (1996) and others recognize that monetary policy actions are rarely random shifts in policy and are usually a response to economic conditions. The Gordon and Leeper structural VAR is used to overcome some of those problems.

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[27]The variable M corresponds to the 12 different monetary policy variables while R reflects either FF or DUAL.

5.2 The Gordon and Leeper (1994) Structural VAR

The contemporaneous restrictions in the seven-variable system are stated below:

$$M = a_1R + a_2P + a_3Y + e^m \qquad (5.1)$$

$$R = a_4M + a_5R10 + a_6PC + e^r \qquad (5.2)$$

$$P = a_7Y + a_8U + e^p \qquad (5.3)$$

$$Y = a_9U + e^y \qquad (5.4)$$

$$U = e^u \qquad (5.5)$$

$$R10 = a_{10}P + a_{11}Y + a_{12}U + e^{r10} \qquad (5.6)$$

$$PC = a_{13}P + a_{14}Y + a_{15}U + a_{16}R10e^d \qquad (5.7)$$

The above also implies the following restriction in the contemporaneous matrix A_0:

$$A(L)x_t = \varepsilon_t$$
$$(A_0 - A_1L - A_2L^2 \ldots)x_t = \varepsilon_t$$
$$where$$
$$A_0 = \begin{bmatrix} 1 & a_1 & a_2 & a_3 & 0 & 0 & 0 \\ a_4 & 1 & 0 & 0 & 0 & a_5 & a_6 \\ 0 & 0 & 1 & a_7 & a_8 & 0 & 0 \\ 0 & 0 & 0 & 1 & a_9 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & a_{10} & a_{11} & a_{12} & 1 & 0 \\ 0 & 0 & a_{13} & 1 & a_{14} & a_{15} & 1 \end{bmatrix}, \quad x_t = \begin{bmatrix} M \\ R \\ P \\ Y \\ U \\ R10 \\ PC \end{bmatrix}$$

where (5.1) and (5.2) are money demand and money supply equations respectively. In (5.1) the demand for money is related to interest rate, price level and income, and in (5.2) the money supply is related to interest rates and commodity prices. The model also makes the assumption that money market variables (M, R) do not affect variables in both the financial (R10, PC) and goods markets (U, Y, P). In fact, a triangularized pattern is formed in the order U, Y, P, R10 and PC. This means that in the Choleski-type block, U is assumed to contemporaneously affect Y, P, R10 and PC.

Based on the above assumptions, the structural VAR model assumes that the Federal Reserve responds to current money and financial market variables but not to current goods market variables. That is, R, R10 and CP are observed by the Federal Reserve within the month while U, Y and P are observed with a one month lag. To avoid some of the problems associated with policy endogeneity, it is further assumed that the Federal Reserve treats R, R10 and CP as informational rather than behavioural. This means that the Federal Reserve does not necessarily influence or responds to those variables.

Table 5.1 presents the results for the estimated contemporaneous coefficients and standard errors for both equations (5.1) and (5.2) to determine if the estimated structural parameters for the money demand and supply equations have reasonable economic interpretations. For example, the expected sign for contemporaneous interest elasticity of money demand in equation (5.1) should be negative. Moreover, the interest elasticity of money supply in equation (5.2) should be positive indicating that the Federal Reserve increases money supply to offset high interest rates while the commodity price elasticity should be negative indicating that the Federal Reserve is sensitive to information about future inflation and will decrease the money supply to fight inflation.

In testing for the overidentifying restrictions, the likelihood ratio χ^2 test statistics are used but they are not reported here since the null hypothesis is strongly rejected for all the models.[28] The impulse responses are presented in Figures 5.1 to 5.4. In addition to studying the response of FF, P and Y as in Chapter 4, two additional responses which are of interest here involve U and R10. According to Gordon and Leeper (1994), following a monetary policy shock, the expected impulse responses for U should fall initially and then rise over time. Furthermore, R10 should increase based on the expectation theory of the term structure due to higher future short rates.

5.2.1 Empirical Results

Figure 5.1 reports the impulse responses for the following models: {DM1, FF, P, Y, U, R10, PC}, {DM2, FF, P, Y, U, R10, PC}, {DM3, FF, P, Y, U, R10, PC}, and {DL, FF, P, Y, U, R10, PC}. The liquidity puzzle is present in all the models where FF increases following shocks to DM1, DM2, DM3 and DL. However, the correct responses for P and Y are observed following shocks to DM2, DM3 and DL. This is consistent

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[28]There are a total of 5 overidentifying restrictions in the contemporaneous structure and no restrictions are placed on lagged variables. In the 7-variable system, the necessary number of restrictions needed for identification is $(7^2 - 7)/2 = 21$. Here, the contemporaneous matrix A_0 contains 26 zero restrictions. However, in all the models, the χ^2 test statistics are highly significant leading to the rejecting of the null hypothesis stating the acceptance of those 5 overidentifying restrictions. See Enders (1995) and Doan (1995) for detailed description of the testing procedures.

with the standard IS-LM model showing that an expansionary policy causes a persistent rise in P and a short term increase in Y. In those three cases, the response of U declines initially but increases overtime. Similarly, there is a steady increase in R10 following expansionary monetary policy shocks.

In Table 5.1, panel 1 shows that the interest elasticity of money demand for DM1 is negative and statistically significant which is economically reasonable. This implies that money demand decreases as interest rate increases. As expected also, the price and output elasticities are both positive but are not statistically significant individually. On the money supply side, the interest elasticity is positive for DM2 and DL in panels 2 and 4. This is consistent with the view that the Federal Reserve increases the money supply in order to offset high interest rates. The responsiveness between money supply and commodity prices is negative for DM2 and DL indicating that the Federal Reserve is sensitive to information about future inflationary pressures.

The estimated impulse responses for {DM1, DUALM1, P, Y, U, R10, PC}, {DM2, DUALM2, P, Y, U, R10, PC}, {DM3, DUALM3, P, Y, U, R10, PC}, {DL, DUALL, P, Y, U, R10, PC} models are reported in Figure 5.2. There is strong evidence of the liquidity puzzle following shocks to DM1. A small but insignificant decline in FF is observed after about six months following shocks to DM2, DM3 and DL. The price puzzle is also observed after DM1 shocks but not for the rest. In those three cases, both U and R10 display the correct impulse responses.

Panel 7 shows a negative and significant interest elasticity of money demand for DM3. The correct price and output elasticities are observed for DM1 and DM2 in panels

5 and 6. As for the money supply, a positive interest elasticity is found for DM2 in panel 6. Overall, the structural interpretation for both the money demand and supply equations are somewhat inconsistent throughout.

Figure 5.3 shows that following a positive monetary policy shock, there is a decline in FF indicating a liquidity effect and is especially strong for {CEM1, FF, P, Y, U, R10, PC} model. However, in all cases, P, U, and R10 display impulse responses which are inconsistent.

Looking at panels 10 and 11, the interest elasticities for CEM2 and CEM3 are both negative and significant. However, only panel 11 display a positive price and output elasticities. In the money supply function, the correct interest and commodity price elasticities are observed for CEM1 and CEL in panels 9 and 12.

Lastly, the estimated responses for {M1, FF, P, Y, U R10, PC}, {M2, FF, P, Y, U, R10, PC}, {M3, FF, P, Y, U, R10, PC} and {L, FF, P, Y, U, R10, PC} are shown in Figure 5.4. There is some weak evidence of the liquidity effect in models with M2 and M3 where expansionary monetary policy shocks cause a short decline in FF after 6 months or so. Except for the model with M1, the other three models show consistent impulse responses for P, Y, U and R10.

The interest elasticities of money demand for M1, M2, M3 and L are all positive which is inconsistent with theory. However, the correct sign for price and output elasticities is found for M1, M3 and L in panels 13, 15 and 16, respectively. As for the money supply, only panels 13 and 14 display positive interest and commodity price elasticities.

5.3 Conclusion

The results for the structural VARs are summarized in Table 5.2. Using the Currency Equivalence monetary aggregates seem to be most successful in solving the liquidity puzzle but not the price and output puzzles. The overall results for the estimated contemporaneous coefficients for the money demand and money supply equations do not have reasonable economic interpretation. None of the twelve monetary aggregates are able to show the correct signs for the specific elasticities associated with money demand and supply.

The Gordon and Leeper structural VAR has a total of 5 overidentifying restrictions being placed on the contemporaneous matrix. However, the test for those overidentifying restrictions are strongly rejected in all cases. This suggests that the results here are not very significant. This could be attributed to the different monetary aggregates and sample period used in this study.

Figure 5.1. Structural VAR Impulse Responses, {DM1, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

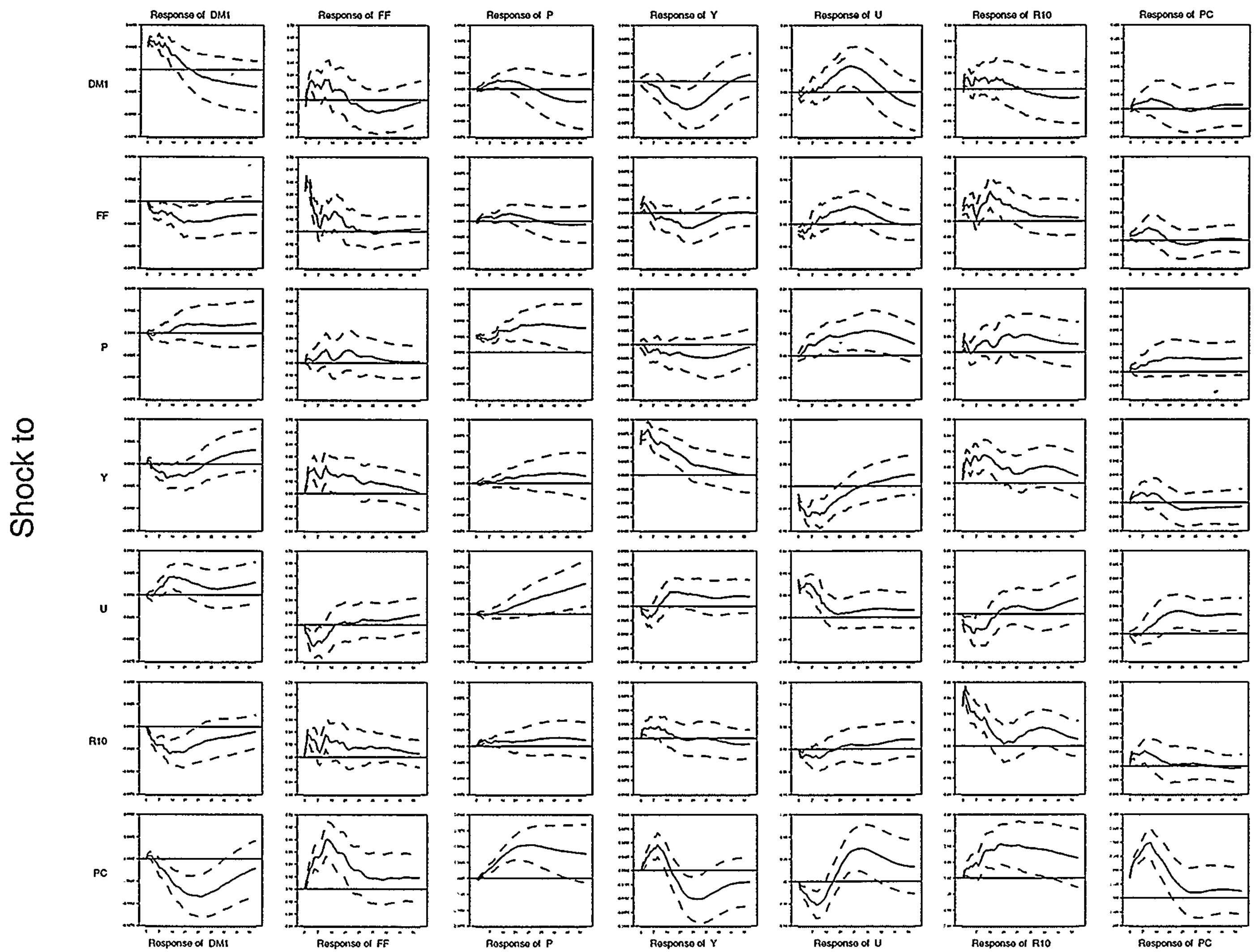

Figure 5.1. Structural VAR Impulse Responses, {DM2, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

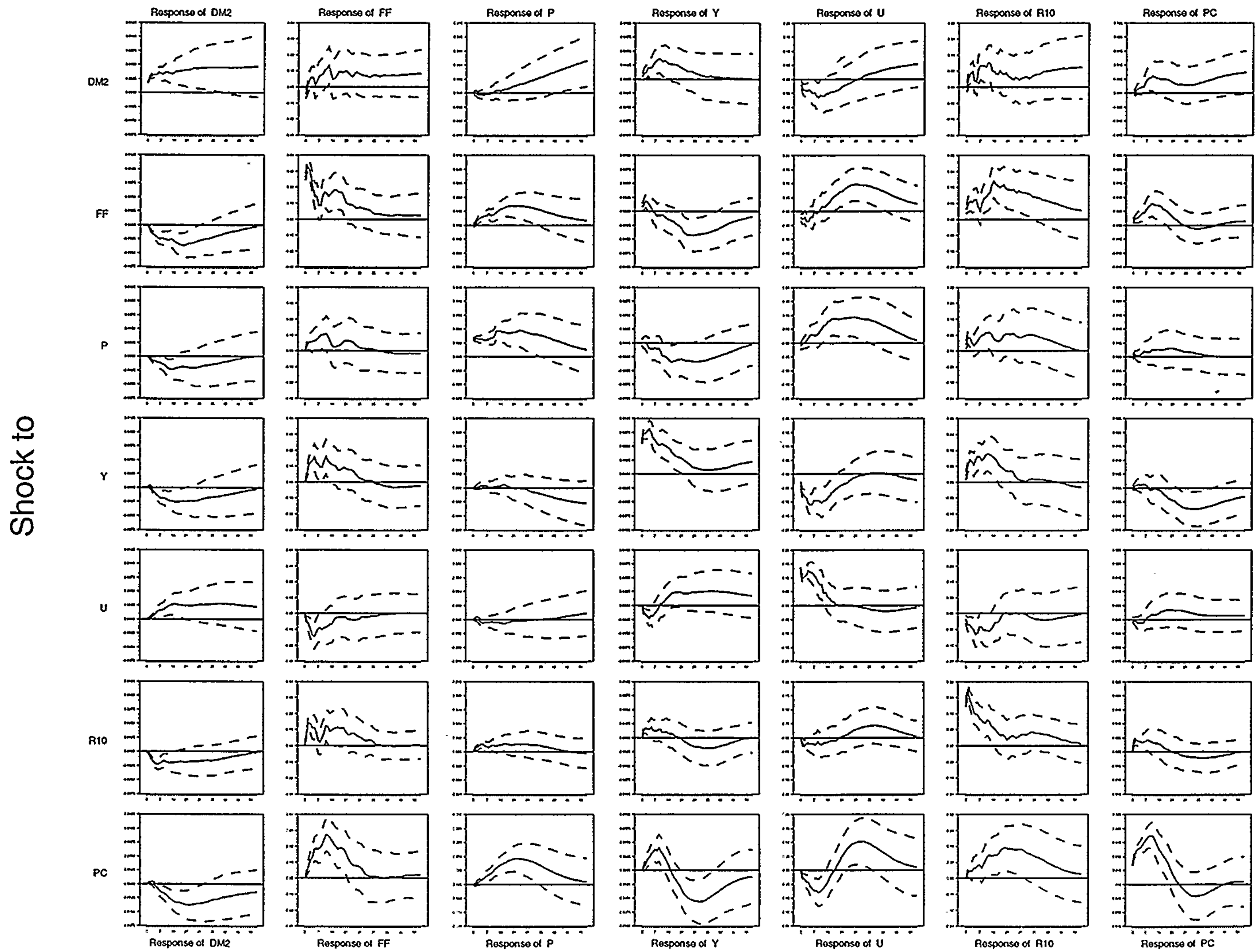

Figure 5.1. Structural VAR Impulse Responses, {DM3, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

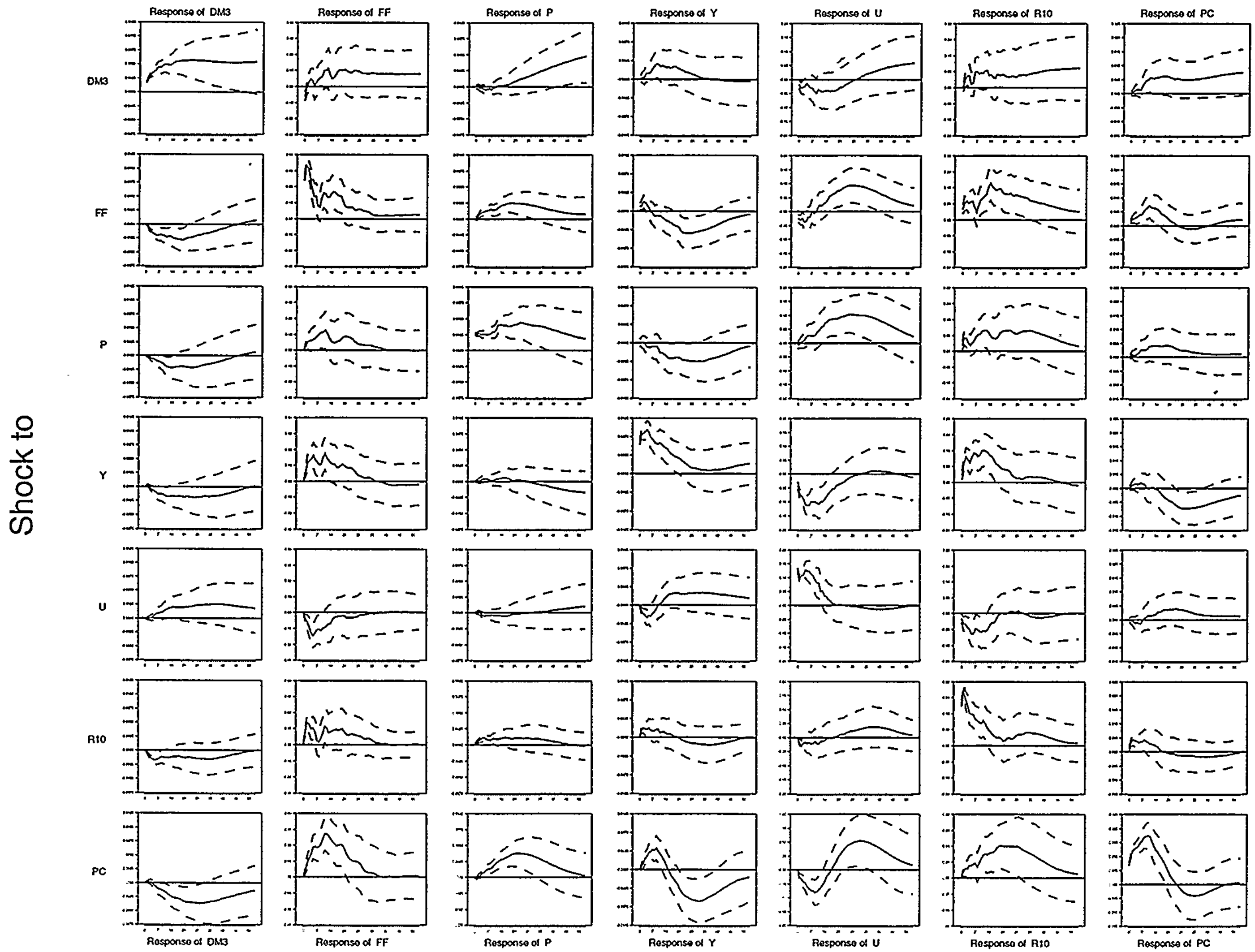

Figure 5.1. Structural VAR Impulse Responses, {DL, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

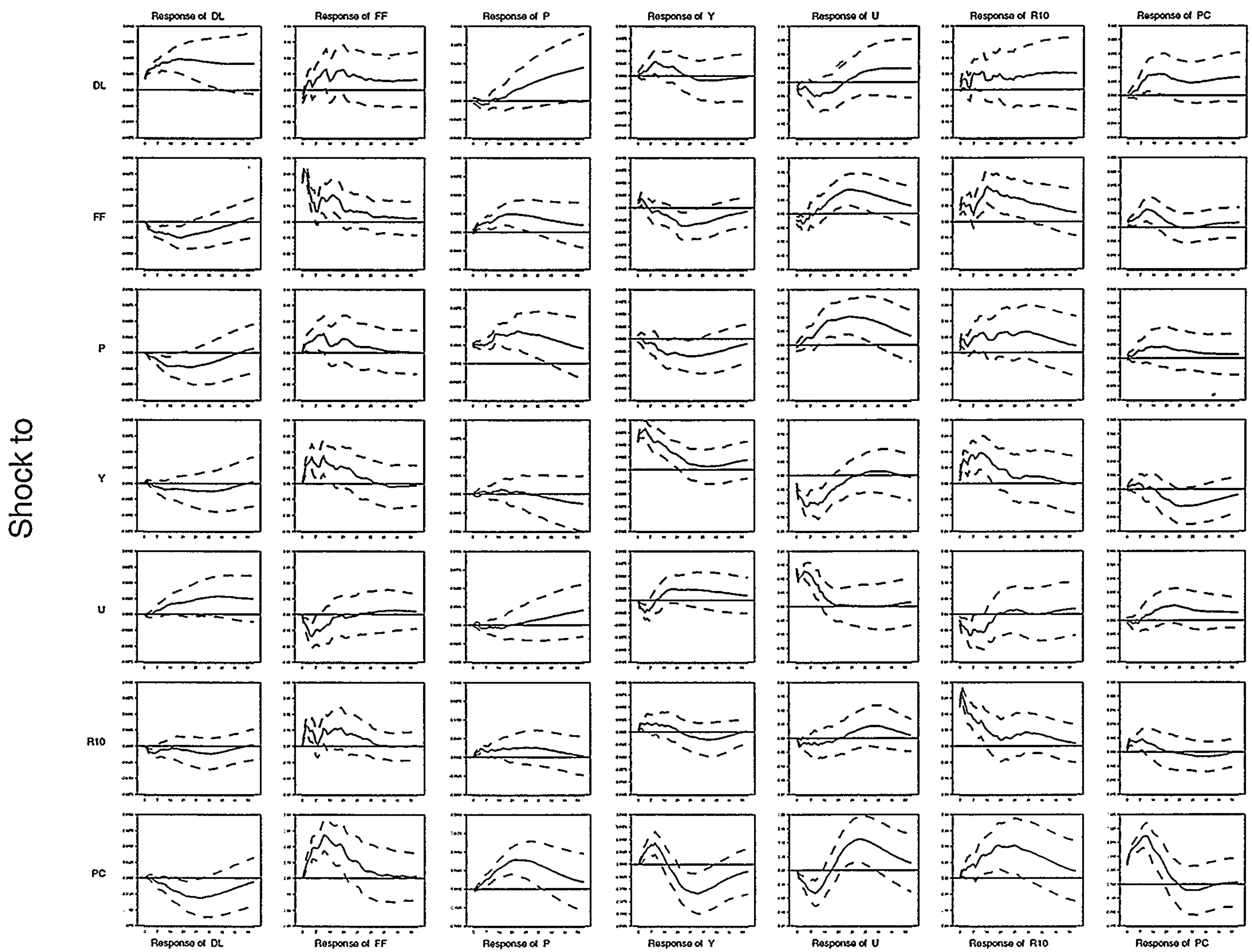

Figure 5.2. Structural VAR Impulse Responses, {DM1, DUALM1, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

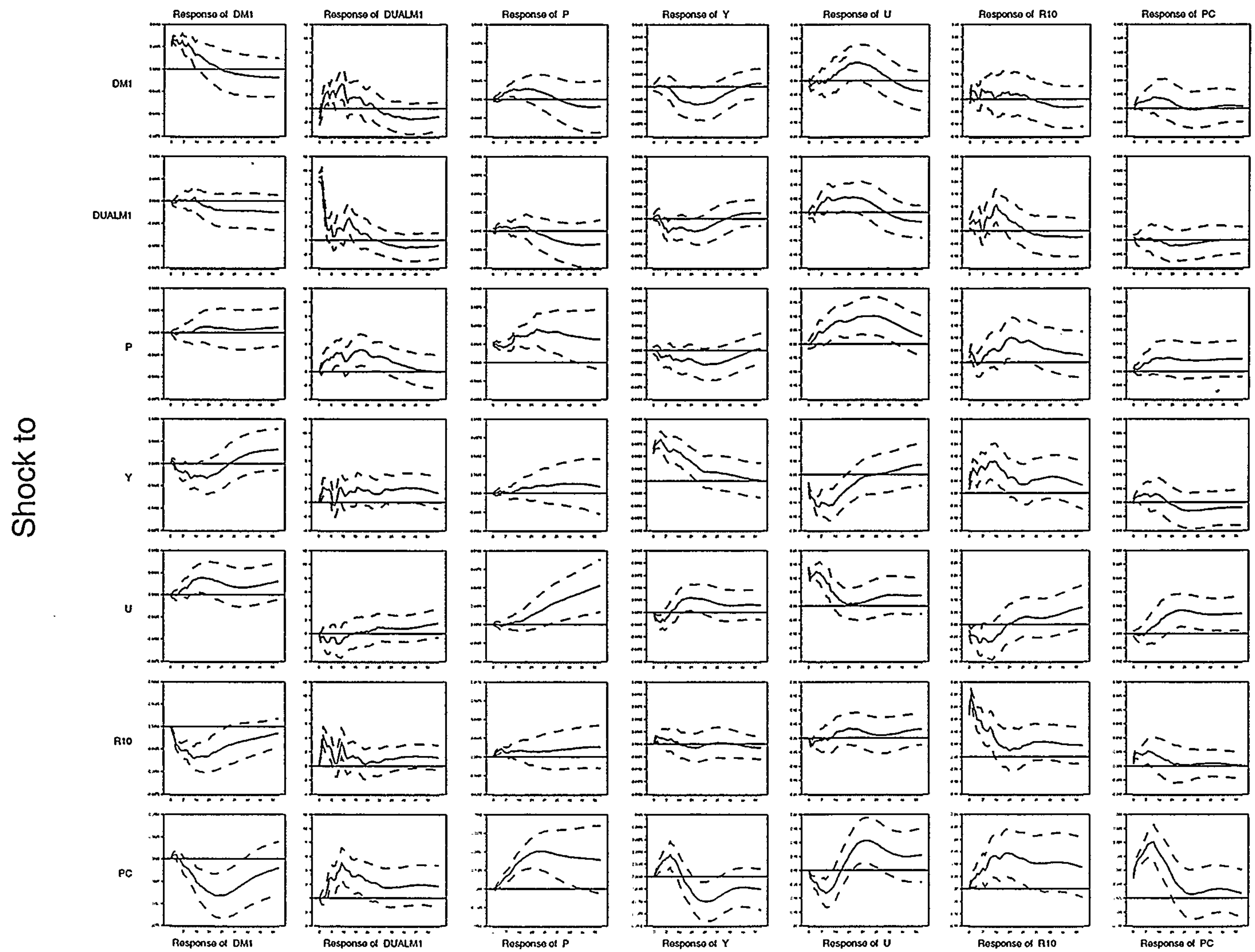

Figure 5.2. Structural VAR Impulse Responses, {DM2, DUALM2, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

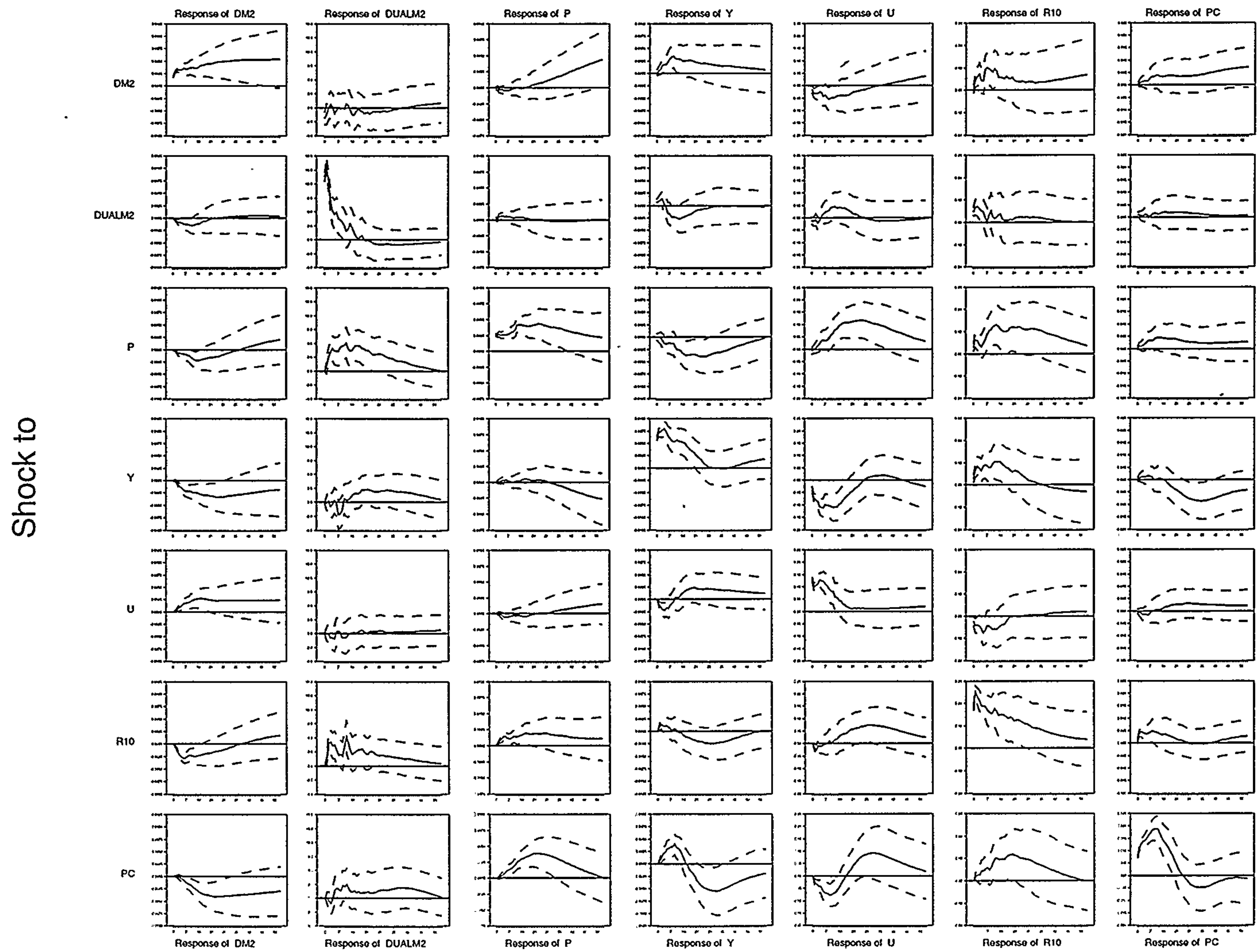

Figure 5.2. Structural VAR Impulse Responses, {DM3, DUALM3, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

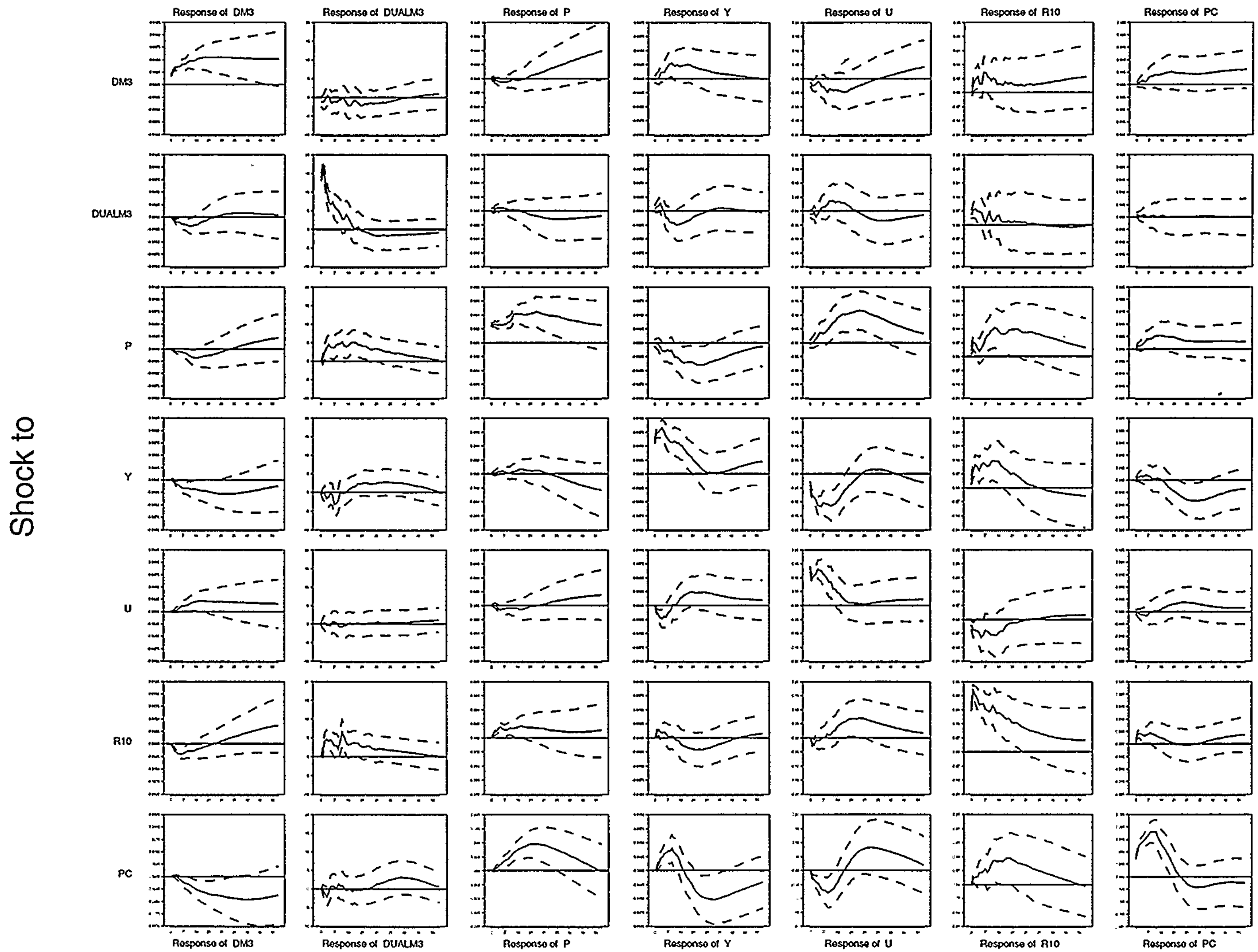

Figure 5.2. Structural VAR Impulse Responses, {DL, DUALL, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

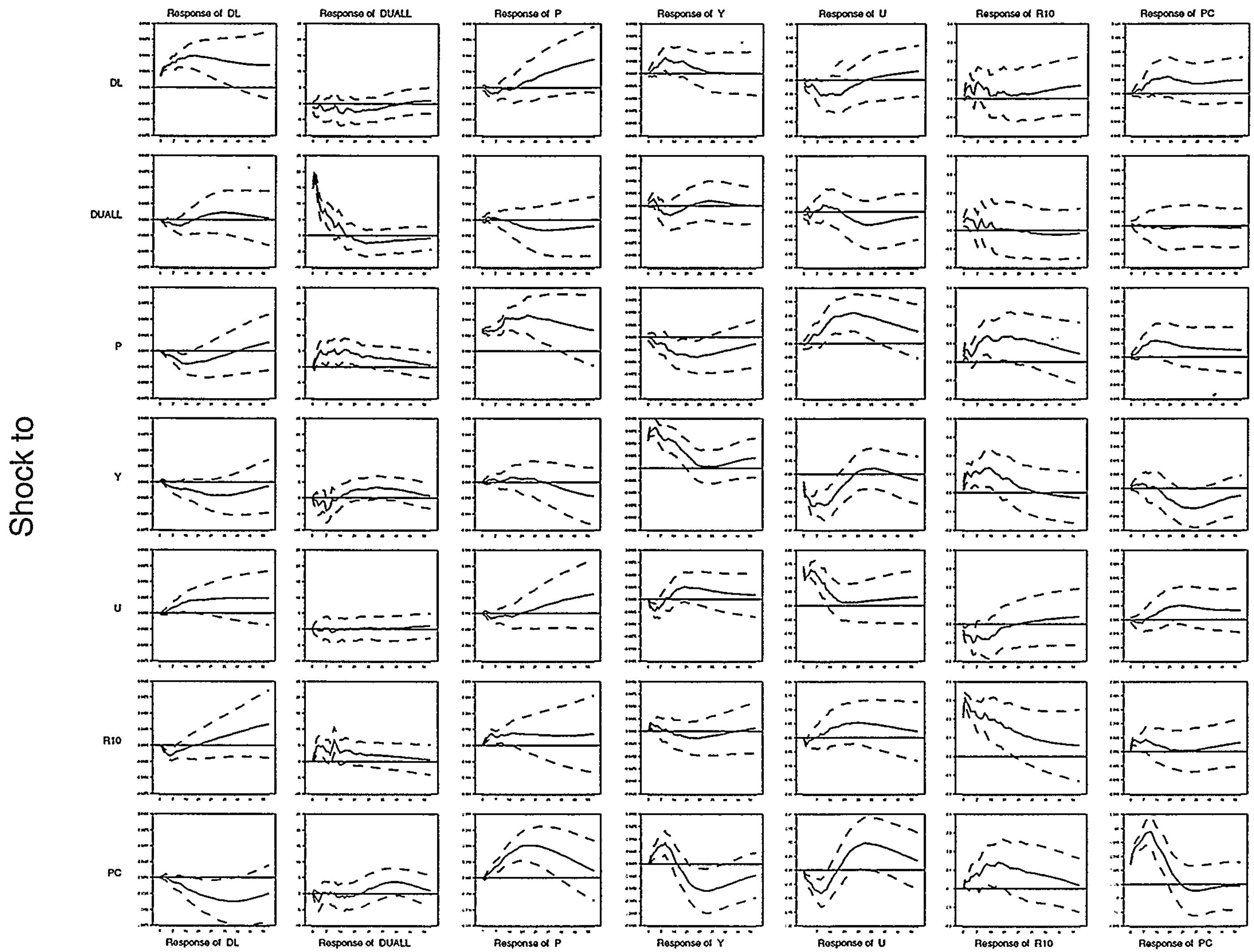

Figure 5.3. Structural VAR Impulse Responses, {CEM1, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

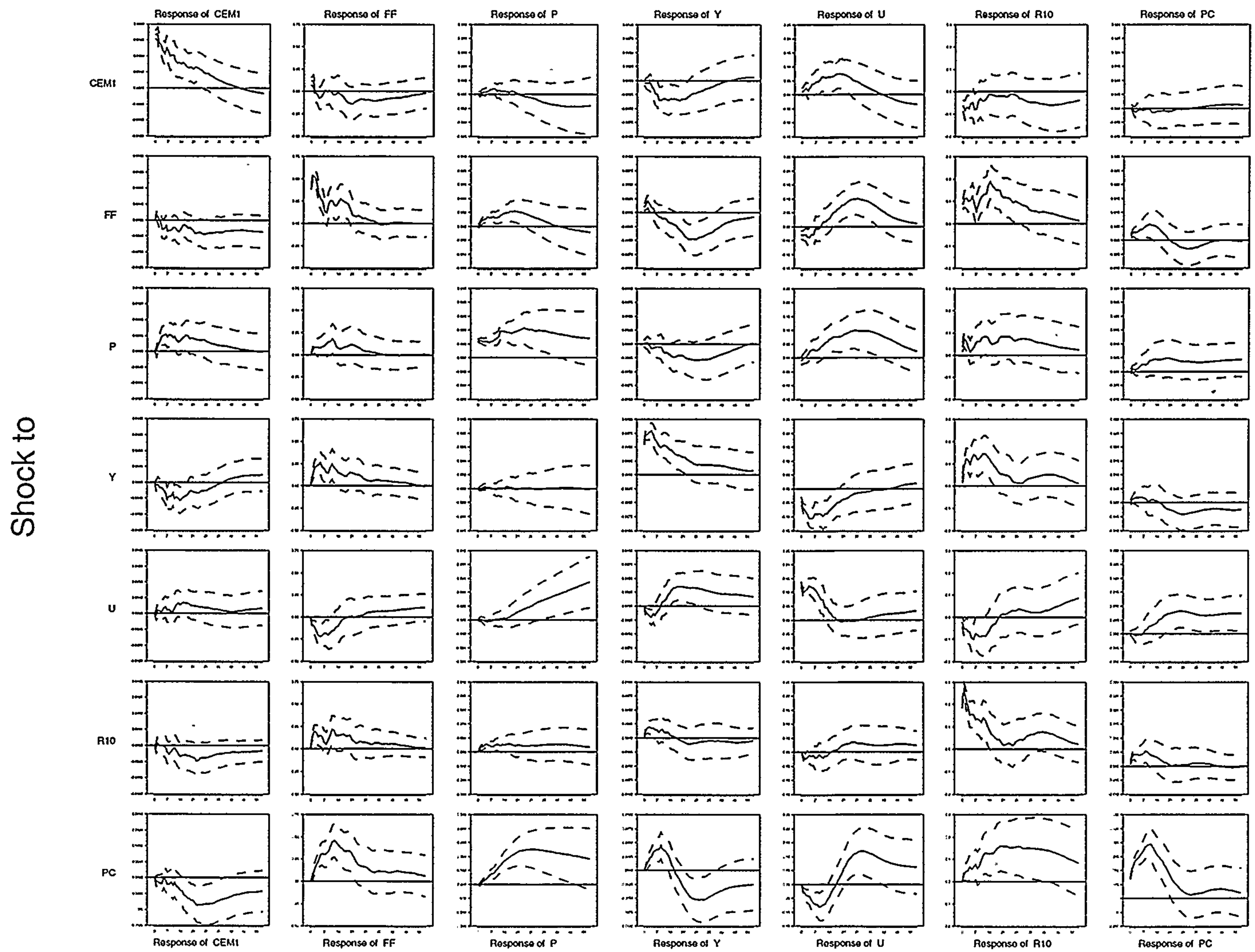

Figure 5.3. Structural VAR Impulse Responses, {CEM2, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

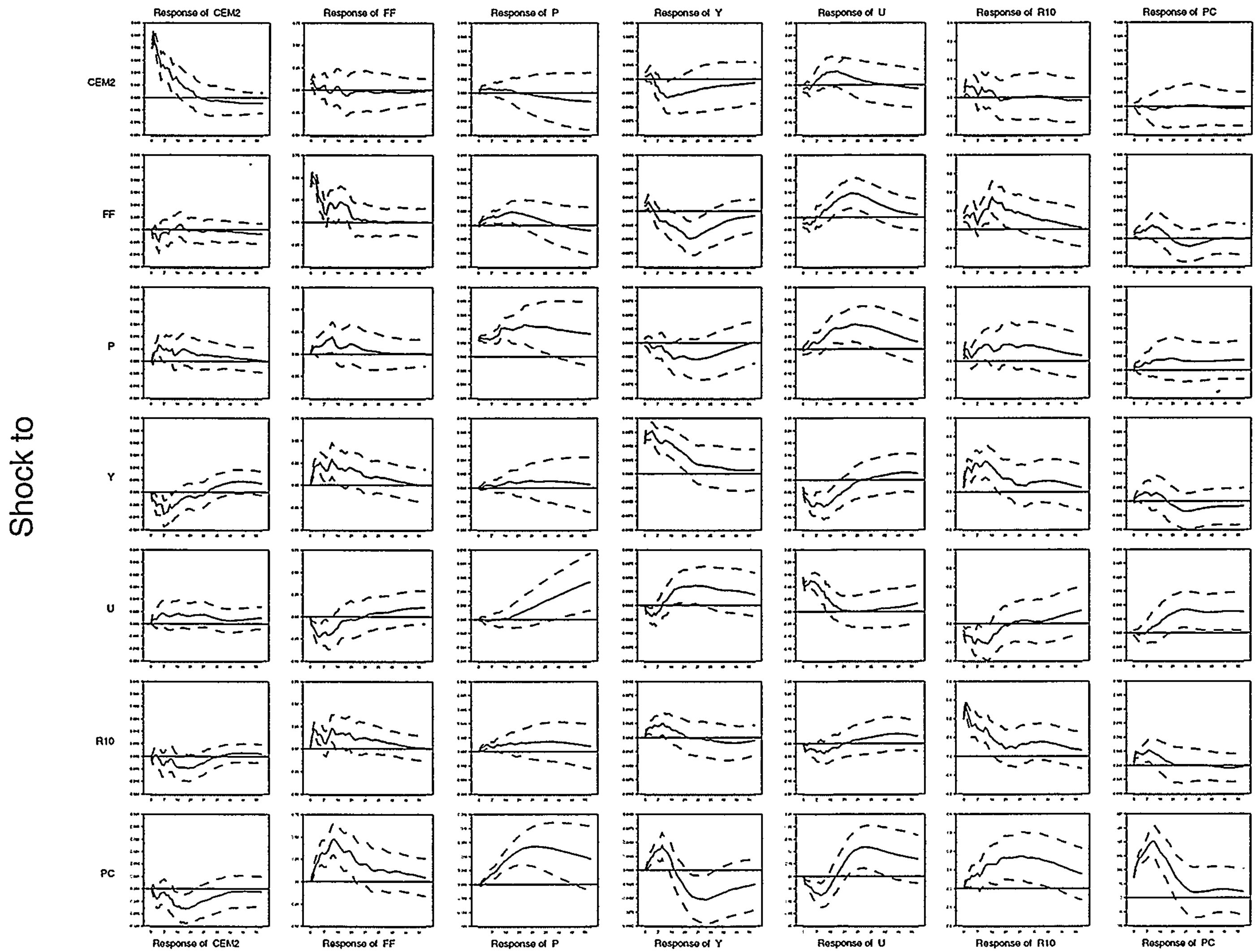

Figure 5.3. Structural VAR Impulse Responses, {CEM3, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

Shock to

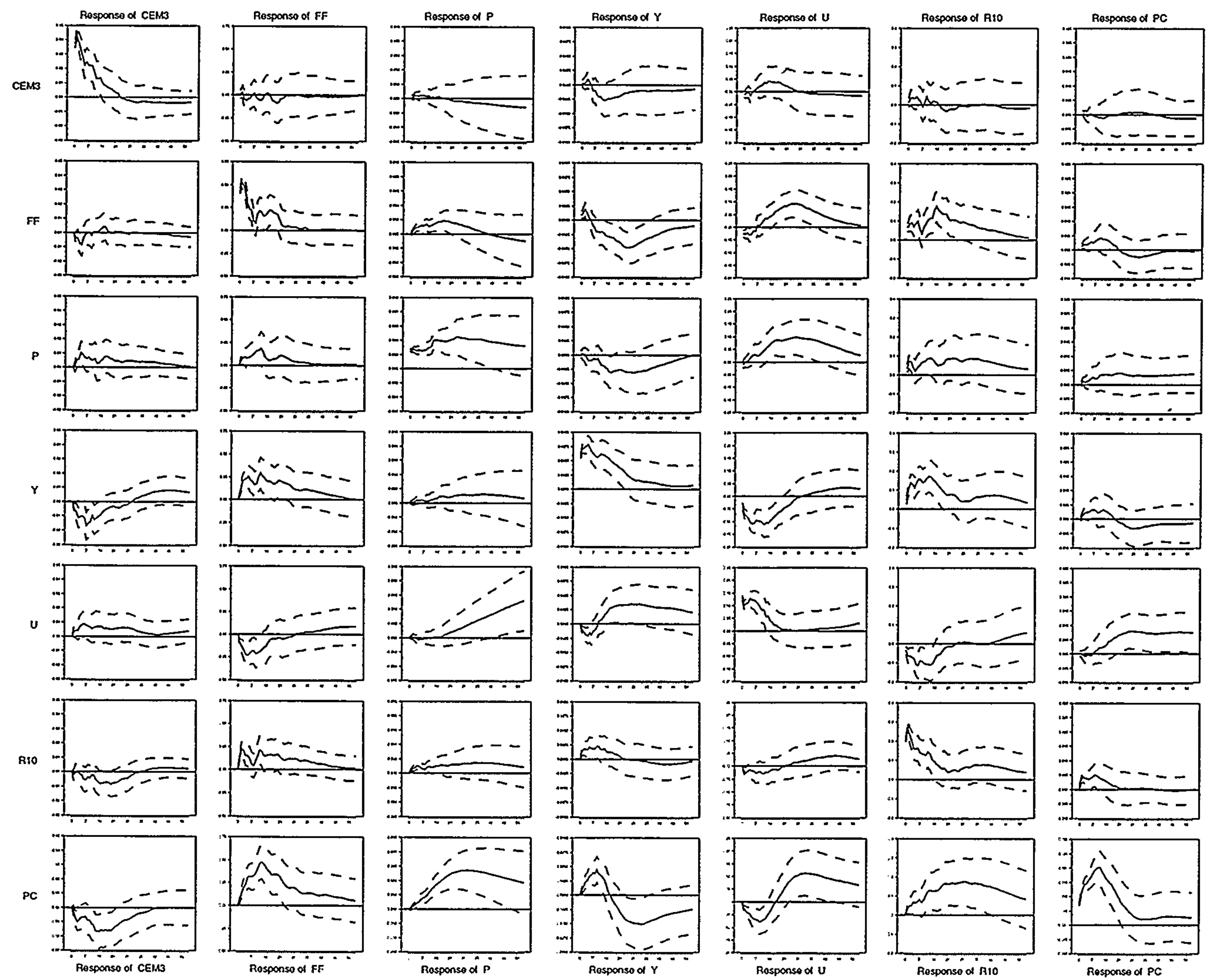

Figure 5.3. Structural VAR Impulse Responses, {CEL, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

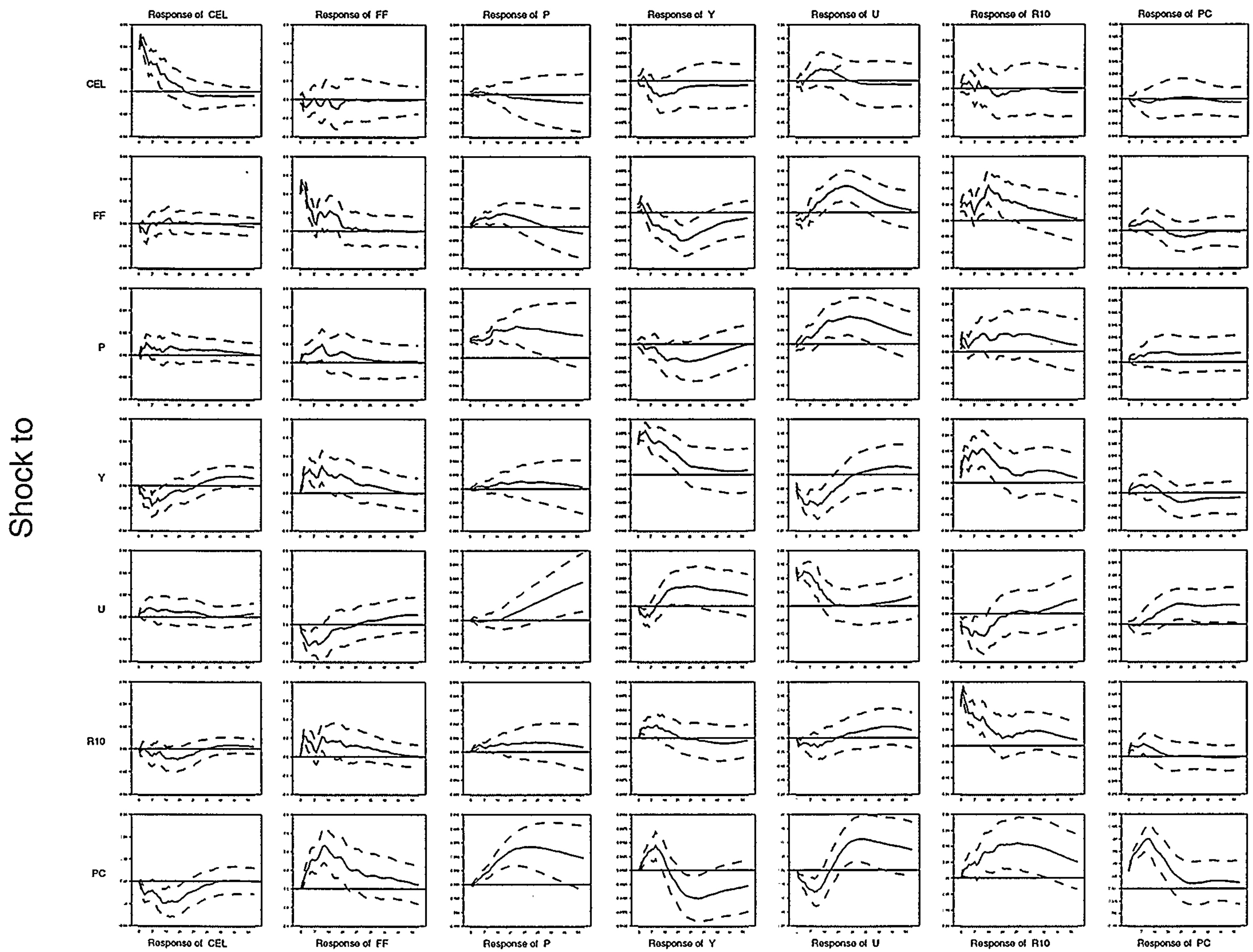

Figure 5.4. Structural VAR Impulse Responses, {M1, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

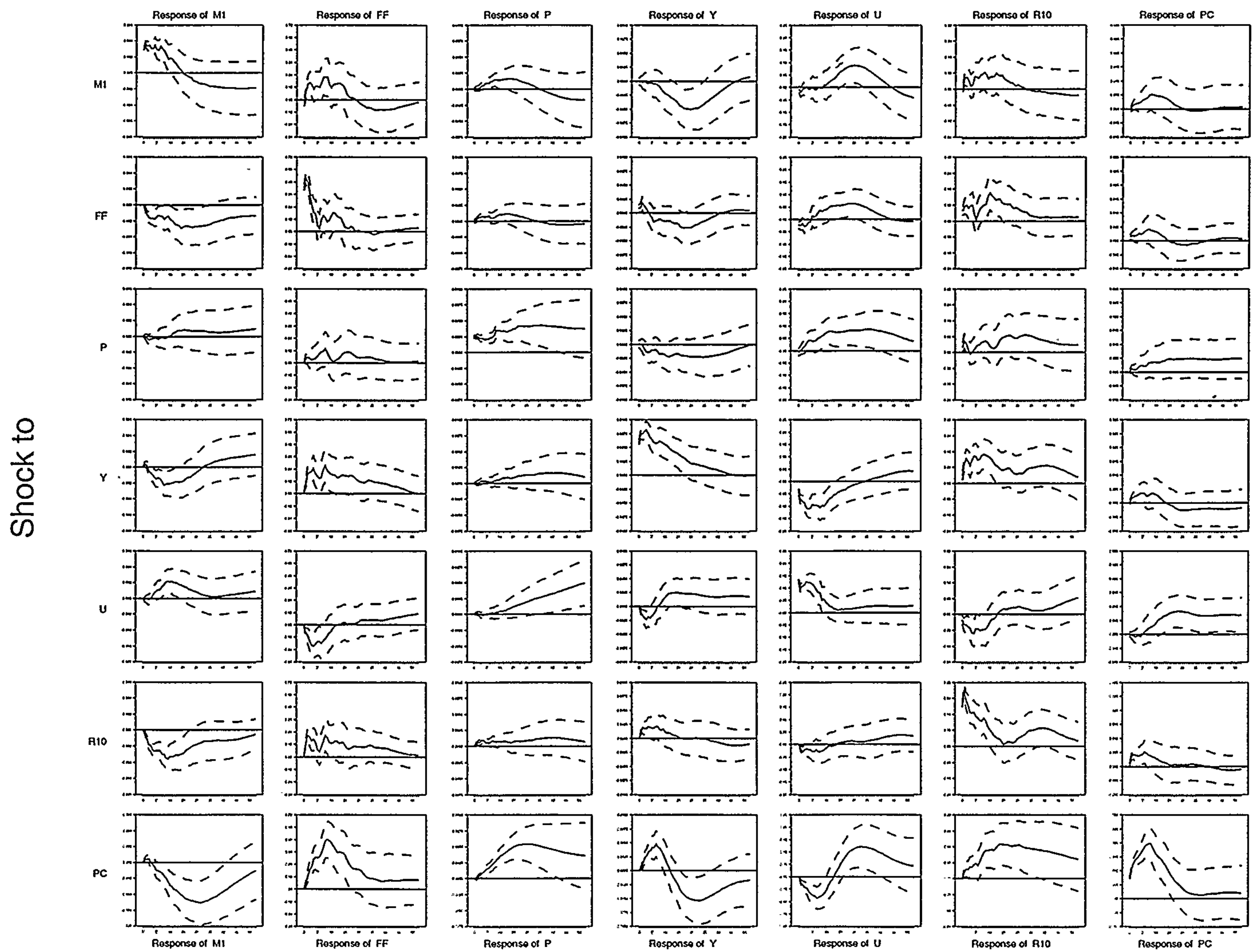

Figure 5.4. Structural VAR Impulse Responses, {M2, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

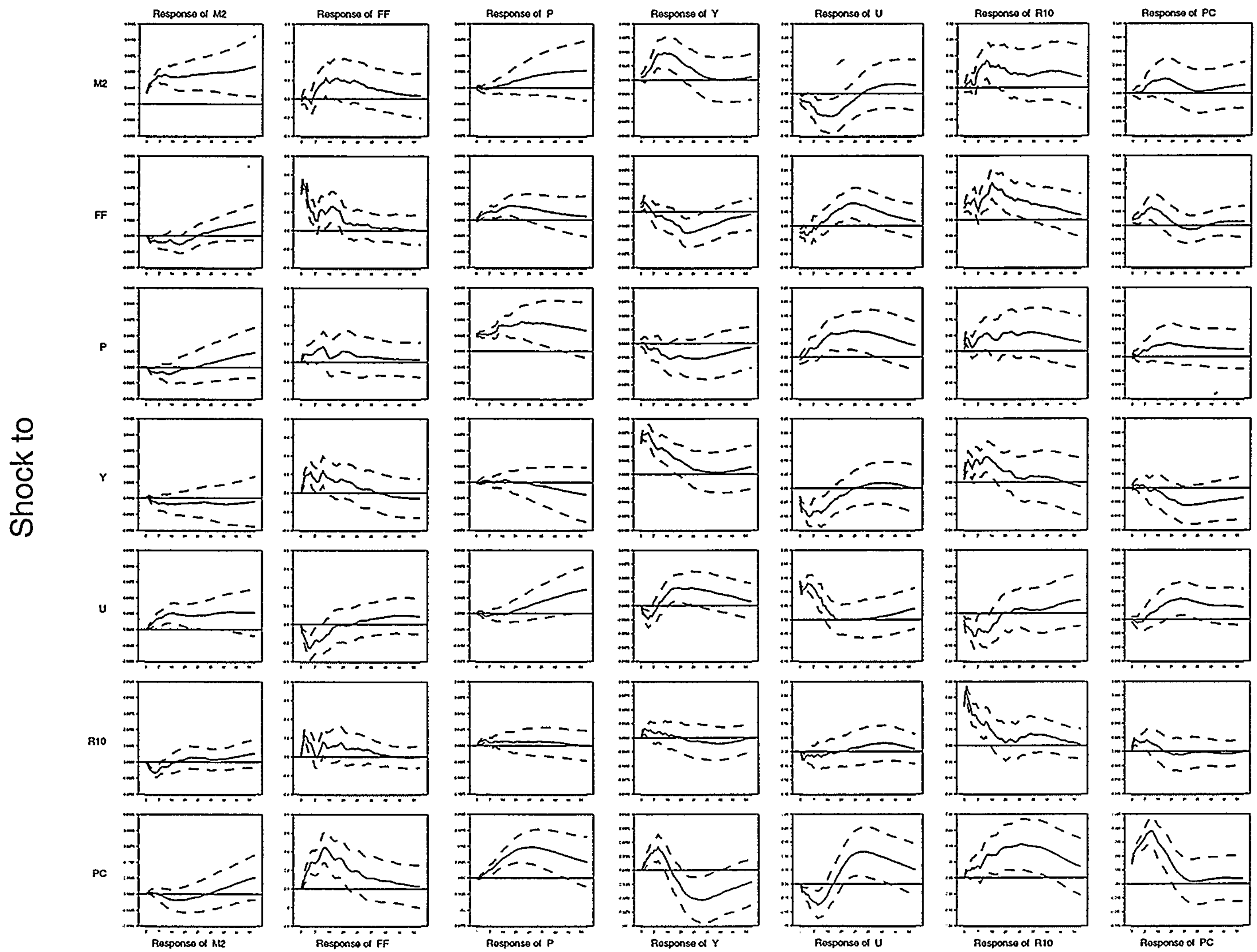

Figure 5.4. Structural VAR Impulse Responses, {M3, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

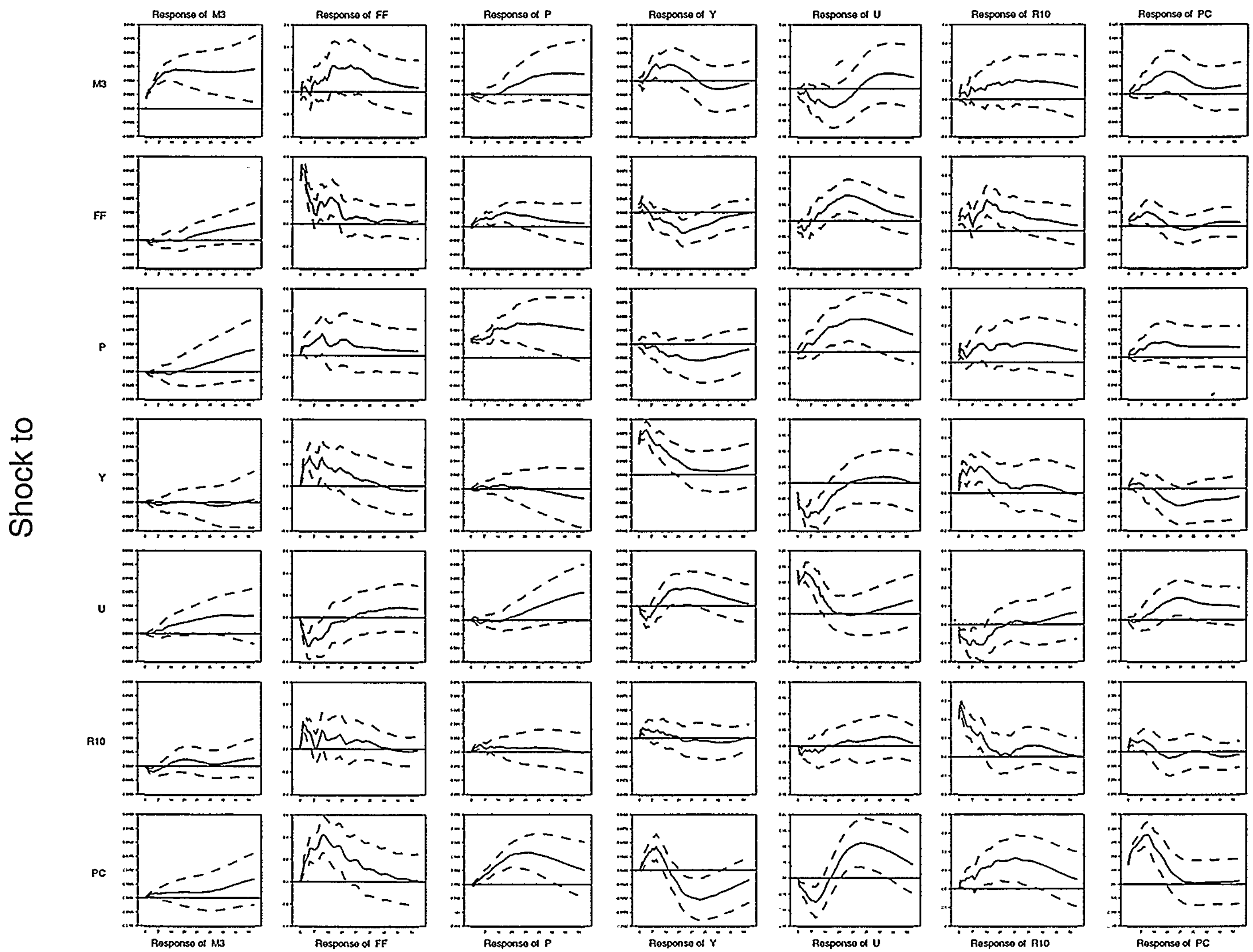

Figure 5.4. Structural VAR Impulse Responses, {L, FF, P, Y, U, R10, PC}

Monthly data: 1960:1 - 1995:11

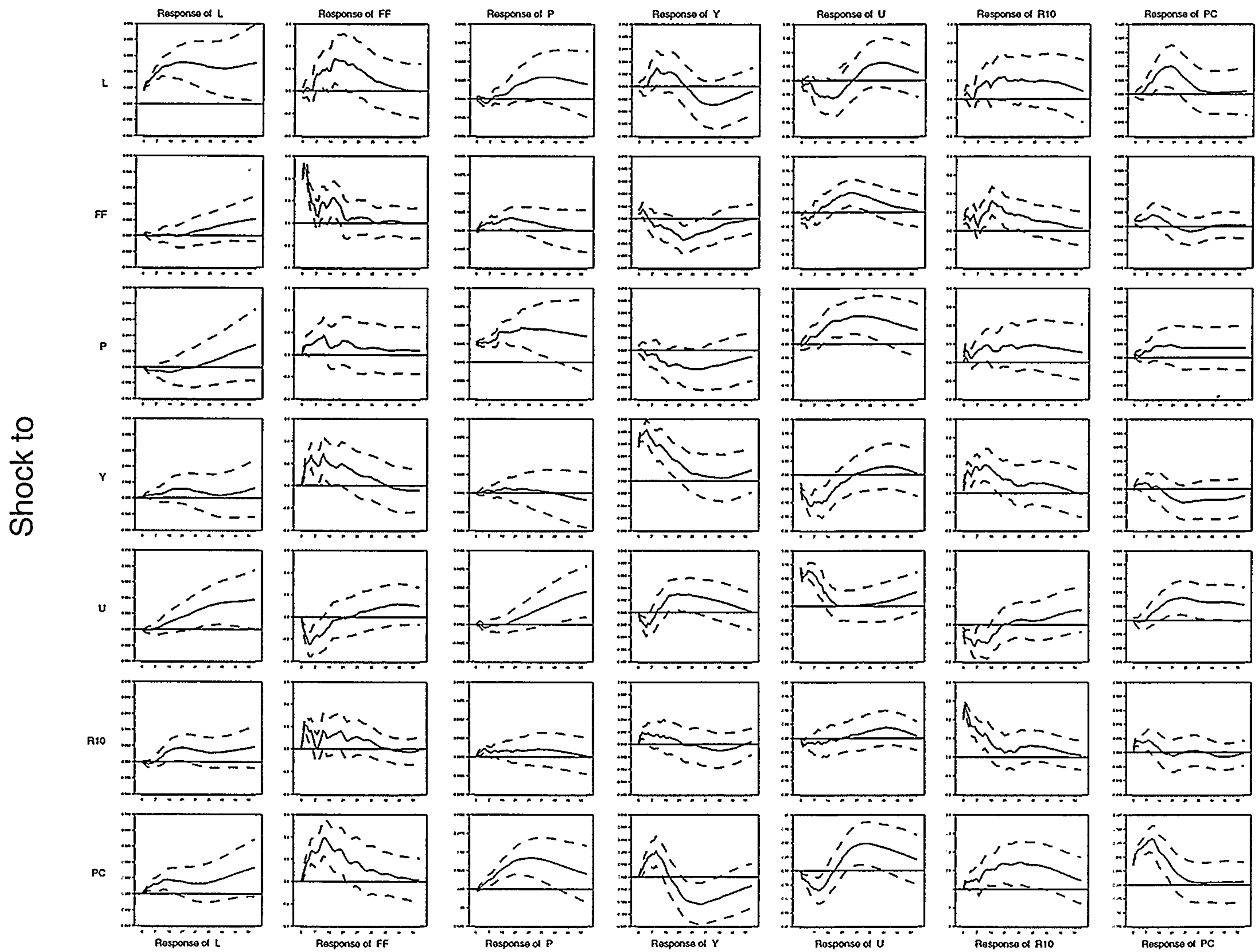

Table 5.1: Estimated Contemporaneous Coefficients

					Panel 1					
Money Demand	DM1	=	-1.567 FF	+	0.086 P	+	0.332 Y	+	e^d	
(standard error)			(0.155)		(12.857)		(5.650)			
Money Supply	FF	=	-5.545 DM1	+	0.409 R10	+	1.027 PC	+	e^s	
(standard error)			(0.247)		(0.091)		(2.681)			
					Panel 2					
Money Demand	DM2	=	2.459 FF	+	0.188 P	-	1.903 Y	+	e^d	
(standard error)			(0.299)		(19.920)		(8.833)			
Money Supply	FF	=	5.177 DM2	+	0.407 R10	+	1.038 PC	+	e^s	
(standard error)			(0.236)		(0.094)		(2.780)			
					Panel 3					
Money Demand	DM3	=	0.954 FF	+	0.059 P	-	0.460 Y	+	e^d	
(standard error)			**		(0.376)		(0.164)			
Money Supply	FF	=	-0.509 DM3	+	0.399 R10	+	0.926 PC	+	e^s	
(standard error)			(0.746)		(0.092)		(2.759)			
					Panel 4					
Money Demand	DL	=	2.172 FF	+	0.249 P	+	0.601 Y	+	e^d	
(standard error)			(0.176)		(17.620)		(7.773)			
Money Supply	FF	=	3.009 DL	+	0.416 R10	+	0.890 PC	+	e^s	
(standard error)			(0.127)		(0.092)		(2.771)			

Note: ** indicates standard error is negligible

Table 5.1: Estimated Contemporaneous Coefficients

		Panel 5			
Money Demand	DM1 =	0.621 DUALM1	+ 4.897 P	+ 3.006 Y	+ e^d
(standard error)		**	(128.509)	(53.635)	
Money Supply	DUALM1 =	-1.221 DM1	+ 0.656 R10	+ 13.100 PC	+ e^s
(standard error)		(0.106)	(2.025)	(58.690)	
		Panel 6			
Money Demand	DM2 =	2.533 DUALM2	+ 0.010 P	+ 0.010 Y	+ e^d
(standard error)		(0.209)	(655.515)	(288.802)	
Money Supply	DUALM2 =	5.088 DM2	+ 0.148 R10	+ 0.101 PC	+ e^s
(standard error)		(0.231)	(3.094)	(87.567)	
		Panel 7			
Money Demand	DM3 =	-2.185 DUALM3	- 10.900 P	- 7.467 Y	+ e^d
(standard error)		(0.179)	(573.061)	(247.347)	
Money Supply	DUALM3 =	-3.300 DM3	+ 0.951R10	+ 9.182 PC	+ e^s
(standard error)		(0.136)	(3.111)	(90.094)	
		Panel 8			
Money Demand	DL =	0.166 DUALL	- 0.321 P	- 0.221 Y	+ e^d
(standard error)		**	(49.460)	(21.214)	
Money Supply	DUALL =	-0.254 DL	+ 0.283 R10	+ 2.100 PC	+ e^s
(standard error)		(0.220)	(3.433)	(101.676)	

Note: ** indicates standard error is negligible

Table 5.1: Estimated Contemporaneous Coefficients

Panel 9

Money Demand (standard error)	$CEM1 = 2.125\,FF + 0.101\,P + 0.094\,Y + e^d$ (0.228) (17.380) (7.890)
Money Supply (standard error)	$FF = 4.753\,CEM1 + 0.588\,R10 + 0.140\,PC + e^s$ (0.206) (0.084) (2.586)

Panel 10

Money Demand (standard error)	$CEM2 = -1.897\,FF - 0.038\,P - 0.668\,Y + e^d$ (0.106) (15.477) (7.025)
Money Supply (standard error)	$FF = -2.054\,CEM2 + 0.527\,R10 + 0.646\,PC + e^s$ (0.075) (0.092) (2.801)

Panel 11

Money Demand (standard error)	$CEM3 = -0.854\,FF + 0.105\,P + 0.110\,Y + e^d$ ** (1.368) (0.604)
Money Supply (standard error)	$FF = -0.463\,CEM3 + 0.516\,R10 + 0.127\,PC + e^s$ (0.181) (0.090) (2.725)

Panel 12

Money Demand (standard error)	$CEL = 2.201\,FF + 0.116\,P - 0.326\,Y + e^d$ (0.229) (17.943) (8.340)
Money Supply (standard error)	$FF = 4.335\,CEL + 0.499\,R10 + 1.579\,PC + e^s$ (0.186) (0.097) (2.917)

Note: ** indicates standard error is negligible

Table 5.1: Estimated Contemporaneous Coefficients

Panel 13

Money Demand (standard error)

$$M1 = \underset{**}{0.091\,FF} + \underset{(3.749)}{0.099\,P} + \underset{(1.580)}{0.099\,Y} + e^d$$

Money Supply (standard error)

$$FF = \underset{(0.102)}{0.606\,M1} + \underset{(0.093)}{0.414\,R10} + \underset{(2.732)}{0.130\,PC} + e^s$$

Panel 14

Money Demand (standard error)

$$M2 = \underset{(0.210)}{0.210\,FF} - \underset{(16.210)}{0.018\,P} + \underset{(7.433)}{0.501\,Y} + e^d$$

Money Supply (standard error)

$$FF = \underset{(0.211)}{4.718\,M2} + \underset{(0.091)}{0.452\,R10} + \underset{(2.699)}{2.278\,PC} + e^s$$

Panel 15

Money Demand (standard error)

$$M3 = \underset{**}{0.493\,FF} + \underset{(5.212)}{0.092\,P} + \underset{(2.259)}{0.427\,Y} + e^d$$

Money Supply (standard error)

$$FF = \underset{(0.078)}{-0.561\,M3} + \underset{(0.089)}{0.411\,R10} + \underset{(2.712)}{0.882\,PC} + e^s$$

Panel 16

Money Demand (standard error)

$$L = \underset{**}{0.259\,FF} + \underset{(5.603)}{0.099\,P} + \underset{(2.418)}{0.102\,Y} + e^d$$

Money Supply (standard error)

$$FF = \underset{(0.041)}{-0.031\,L} + \underset{(0.089)}{0.448\,R10} + \underset{(2.743)}{0.134\,PC} + e^s$$

Note: ** indicates standard error is negligible

Table 5.2: Summary Results for Seven-variable system with Money Supply rule

Model	Liqudity Puzzle	Price Puzzle	Output Puzzle
{DM1, FF, P, Y, U, R10, PC}	yes	yes	yes
{DM2, FF, P, Y, U, R10, PC}	yes	no	no
{DM3, FF, P, Y, U, R10, PC}	yes	no	no
{DL, FF, P, Y, U, R10, PC}	yes	no	no
{DM1, DUALM1, P, Y, U, R10, PC}	yes	yes	yes
{DM2, DUALM2, P, Y, U, R10, PC}	yes	no	no
{DM3, DUALM3, P, Y, U, R10, PC}	yes	no	no
{DL, DUALL, P, Y, U, R10, PC}	yes	no	no
{CEM1, FF, P, Y, U, R10, PC}	no	yes	yes
{CEM2, FF, P, Y, U, R10, PC}	yes	yes	yes
{CEM3, FF, P, Y, U, R10, PC}	yes	yes	yes
{CEL, FF, P, Y, U, R10, PC}	yes	yes	yes
{M1, FF, P, Y, U, R10, PC}	yes	yes	yes
{M2, FF, P, Y, U, R10, PC}	yes	no	no
{M3, FF, P, Y, U, R10, PC}	yes	no	no
{L, FF, P, Y, U, R10, PC}	yes	no	no

CHAPTER 6

SOLVING THE PUZZLES

6.1 Introduction

This chapter attempts to solve some of the puzzles mentioned in this study namely the liquidity, output, and price puzzles. Instead of using innovations to the twelve monetary aggregates or the federal funds rate, the non-borrowed monetary base is used instead. The use of monetary base seems appropriate as it represents the Federal Reserve's operating target and has long been viewed as a centerpiece of monetary policy.

Haslag and Hein (1995) state that early studies by Brunner (1981), Meltzer (1984), Friedman (1984) and McCallum (1988) all share the view that monetary base is the most useful single sufficient statistic for summarizing the impact of monetary policy actions. Cecchetti (1995) also states that monetary base is viewed as outside money meaning that it is imperfectly substitutable with all other assets thus making it a better choice as a policy indicator. However, recent VAR studies do not share this view and argue that there are some endogenous components in the monetary base arising from legal requirements such as reserve requirements. They argue that changes in it are associated with changes in those legal requirements. This is similar to the problem faced by using traditional broad monetary aggregates such as M1 and M2.

To overcome some of those problems here, some adjustment is made where the borrowed reserves are subtracted from the monetary base which gives rise to non-borrowed monetary base.[29] This reduces some of the endogenous components arising from the demand for borrowed reserves.[30]

Following Mishkin (1995), the non-borrowed monetary base is defined as

$$NBMB = MB - BR$$

where NBMB is non-borrowed reserves, MB is monetary base, and BR is borrowed reserves. According to Mishkin, the non-borrowed monetary base (NBMB) is distinguished as such because of the superior ability of the Federal Reserve to control it through open market operations than the borrowed reserves which is influenced by the discount rate. Although the Federal Reserve sets the discount rate, the individual bank's decision plays a strong role in determining the level of borrowed reserves. Furthermore, Mishkin also offers evidence that over the period 1980 to 1993, the primary determinant of movements in M1 is non-borrowed monetary based.

In the VAR analysis, a five-variable system is used with M rule ordering {NBMB, M, FF, P, Y}. The M variable represents each of the twelve different monetary aggregates. Following an increase in NBMB, M should also increase. The reason is that

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[29]To adjust for changes in reserve requirements, McCallum (1996) subtracts the predicted growth in the permanent component of the base velocity from the monetary base (velocity-adjusted monetary base).

[30]Interestingly, this study experimented with the monetary base and found that innovations in it produce the liquidity puzzle. These results are not be presented here as the focus is on using non-borrowed monetary base as policy instrument.

an increase in NBMB arising from open market purchase also increases the money supply. As expected, FF should fall while P and Y should both increase following an expansionary monetary policy

6.2 Empirical Results

In Figures 6.1 to 6.4, the top row of each graph presents the estimated impulse responses of the variables to an innovation in NBMB. This should provide a useful comparison with the impulse responses found in Chapter 4 regarding the appearance of the different puzzles. Table 6.1 contains the results from the correlation matrices for innovations, Granger-causality tests, and forecast error variance decompositions for a 60-month horizon.

Figure 6.1 corresponds to the models {NBMB, DM1, FF, P, Y}, {NBMB, DM2, FF, P, Y}, {NBMB, DM3, FF, P, Y}, and {NBMB, DL, FF, P, Y}. Following shocks to NBMB, all the Divisia monetary aggregates increase. There is an immediate and significant decrease in FF indicating the liquidity effect. This is the correct response which is missing from the M-rule VARs in Chapter 4. Furthermore, P increases in all the models except for {NBMB, DM2, FF, P, Y}.[31] The correct response of Y is observed in all cases.

In Table 6.1, panels 1 to 4 show that DM1, DM2, DM3 and DL account for greater fluctuation in Y compared to NBMB. Over 18 percent of the fluctuation in Y is

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[31]The price effect, however, does not appear to be statistically significant. This study has also experimented with the inclusion of PC but the results yielded similar responses.

explained by those monetary aggregates compared to less that 17 percent by NBMB. On the contrary, NBMB is found to Granger-cause Y at the 10 percent significance level compared the monetary aggregates. In all cases, FF fails to show any strong predictive value for Y. However, due to the significant correlation matrices for innovations, the estimated impulse responses and forecast error variance decompositions are not robust. Further examination with different Wold orderings is required in this case.

Next, FF is replaced by DUAL which is the user costs associated with the Divisia aggregates. The estimated impulse responses are presented in Figure 6.2. Except for {NBMB, DM1, DUALM1, P, Y}, the liquidity puzzle is present in the other models. Like before, the price puzzle is also observed in the case when DM2 is used. Interestingly, the variance decompositions show that DM2, DM3, and DL still account for greater fluctuation in Y compared to NBMB. However, NBMB innovations are able to account for 28 percent of Y variance compared to 7 percent by DM1. The Granger-causality test show that NBMB continues to dominate in every case.

Figure 6.3 present the impulse responses for the following models with the Currency Equivalence aggregates: {NBMB, CEM1, FF, P, Y}, {NBMB, CEM2, FF, P, Y}, {NBMB, CEM3, FF, P, Y}, and {NBMB, CEL, FF, P, Y}. There is no evidence of the liquidity puzzle in all the models. Similarly, both the price and output puzzles also disappear. The forecast error variance decompositions show that over 38 percent of the variance in Y is explained by FF innovations. Less than 19 percent is accounted for by NBMB and the Currency Equivalence aggregates individually. The Granger-causality tests show that CEM1 and CEL are found to have the highest explanatory power for Y.

The last model considers the use of NBMB together with the Simple Sum aggregates. The estimated impulse responses for {NBMB, M1, FF, P, Y}, {NBMB, M2, FF, P, Y}, {NBMB, M3, FF, P, Y}, and {NBMB, L, FF, P, Y} models are presented in Figure 6.4. The impulse responses show that all of the puzzles including liquidity, price and output puzzles are no longer present. The Granger-causality tests indicate that M2, M3 and L are able to capture most of the predictive value for output. Moreover, the forecast error variance decompositions show that most of the variance in Y is explained by M1, M2, M3 compared to NBMB.

6.3 Conclusion

The VAR models in this chapter are by far the best in terms of producing consistent dynamic responses of key macro variables when compared to the ones presented in previous two chapters. In all cases, the liquidity puzzle is solved except when the user costs are used. Furthermore, the price puzzle no longer appears except in only two cases. Lastly, the output puzzle is completely solved. A summary of the results is reported in Table 6.1.

However, the innovation accounting analysis undertaken here is not robust due to the significant correlation matrices for innovations found in all the VARs. The Granger-causality tests do not lend support to previous VAR studies that FF predicts Y better than monetary aggregates. On the contrary, in most of the cases here NBMB is found to Granger cause Y. In summary, the use of non-borrowed monetary base seems to be the most promising policy indicator than the twelve monetary aggregates and federal funds rate.

Figure 6.1. Unrestricted VAR Impulse Responses, {NBMB, DM1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

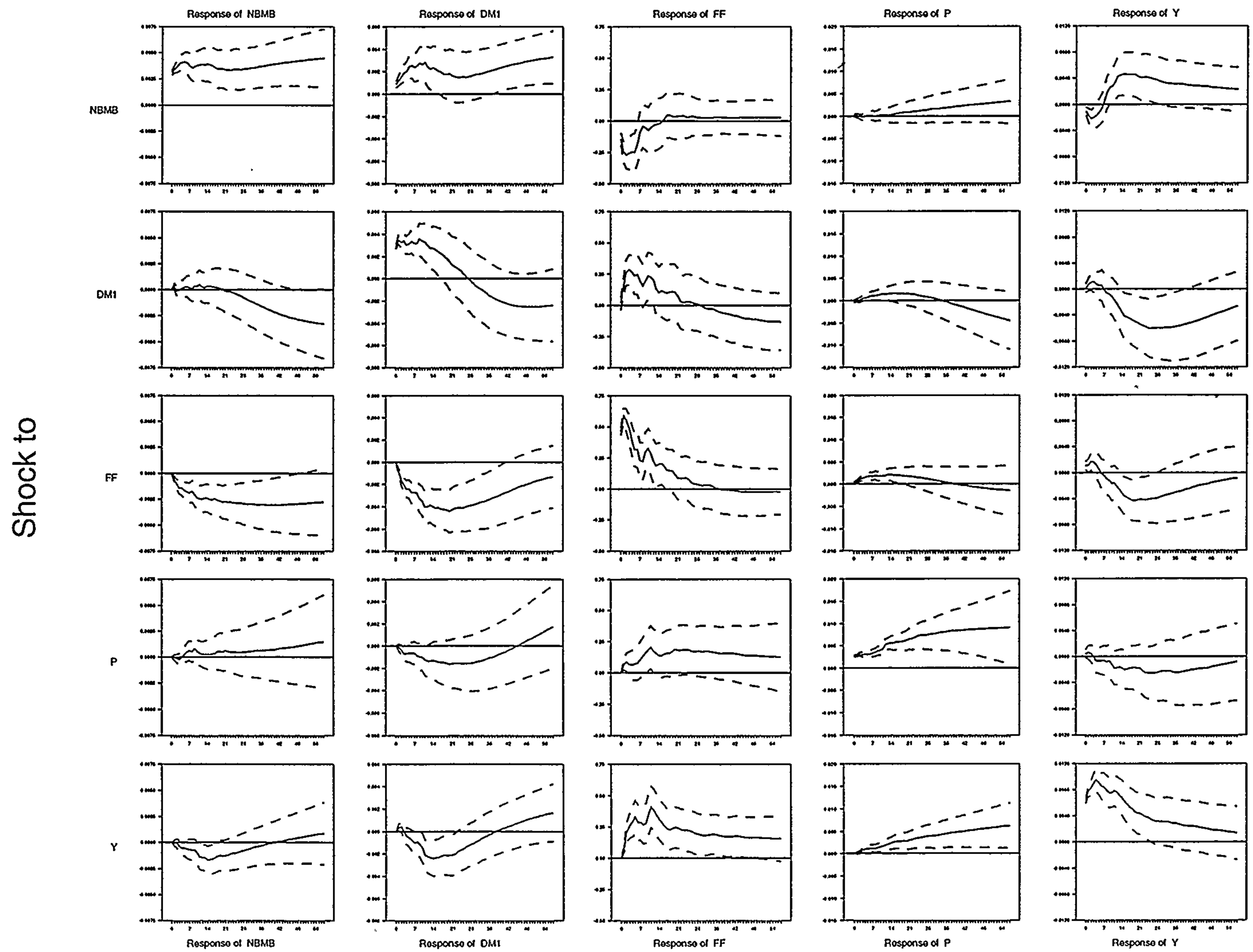

Figure 6.1. Unrestricted VAR Impulse Responses, {NBMB, DM2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

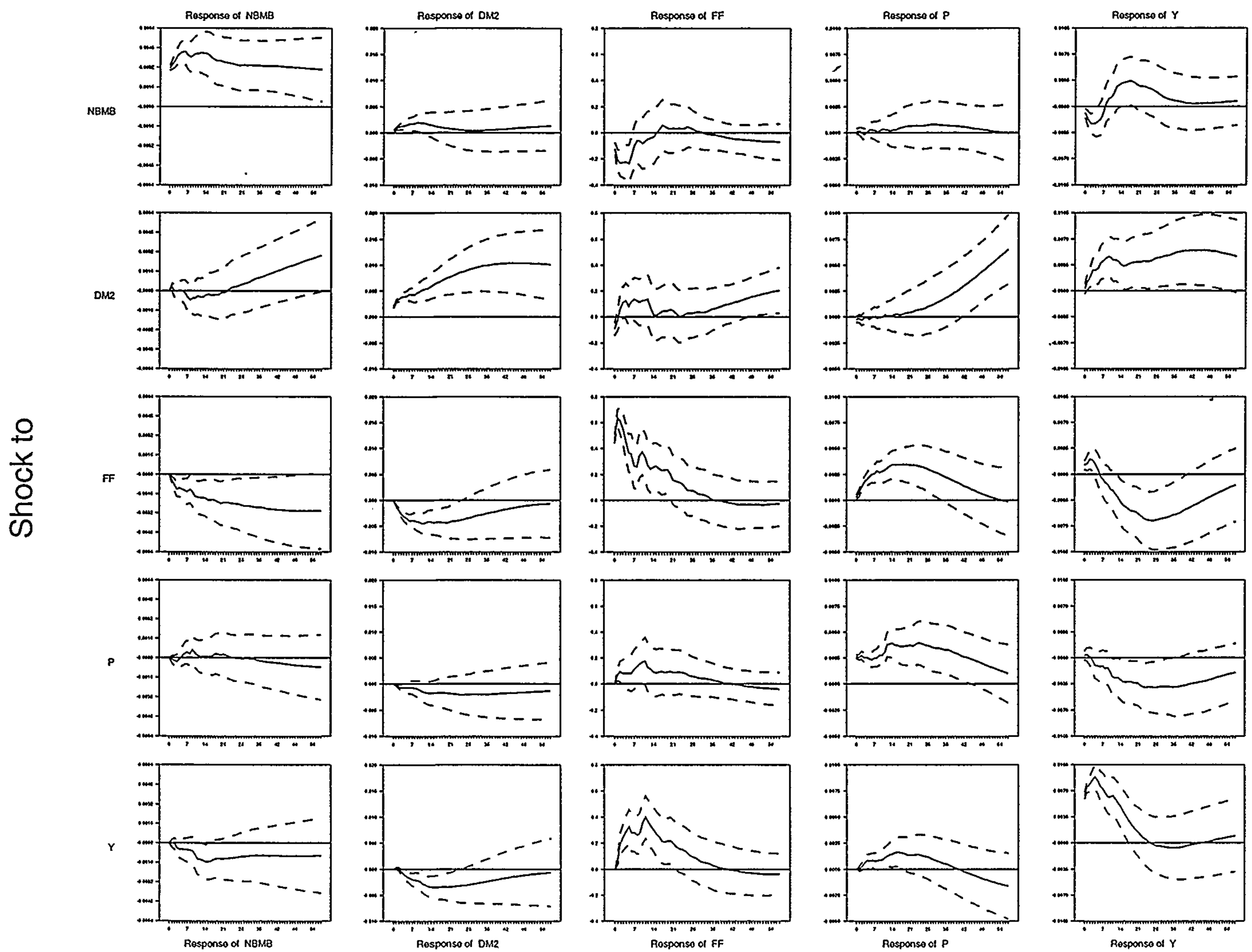

Figure 6.1. Unrestricted VAR Impulse Responses, {NBMB, DM3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

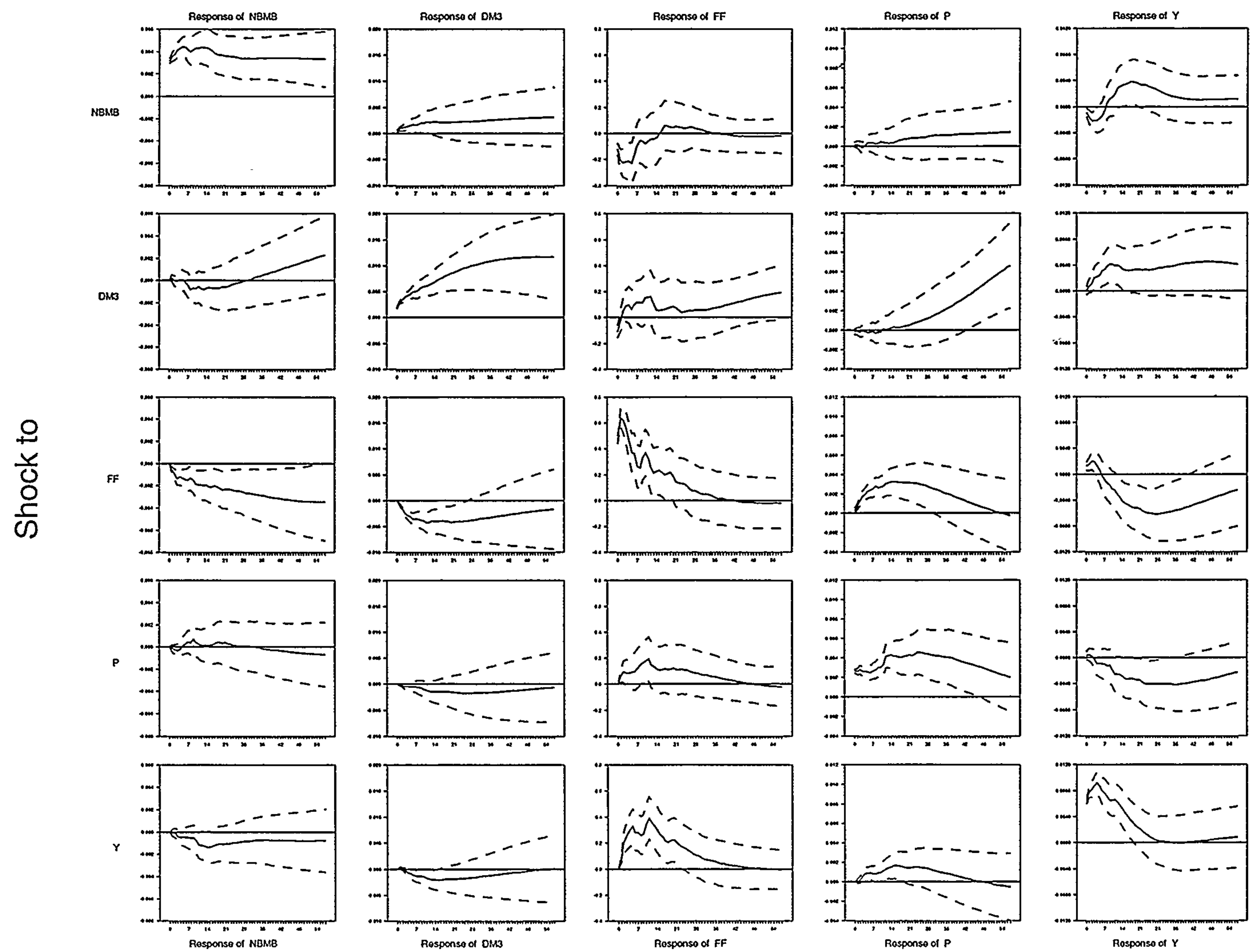

Figure 6.1. Unrestricted VAR Impulse Responses, {NBMB, DL, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

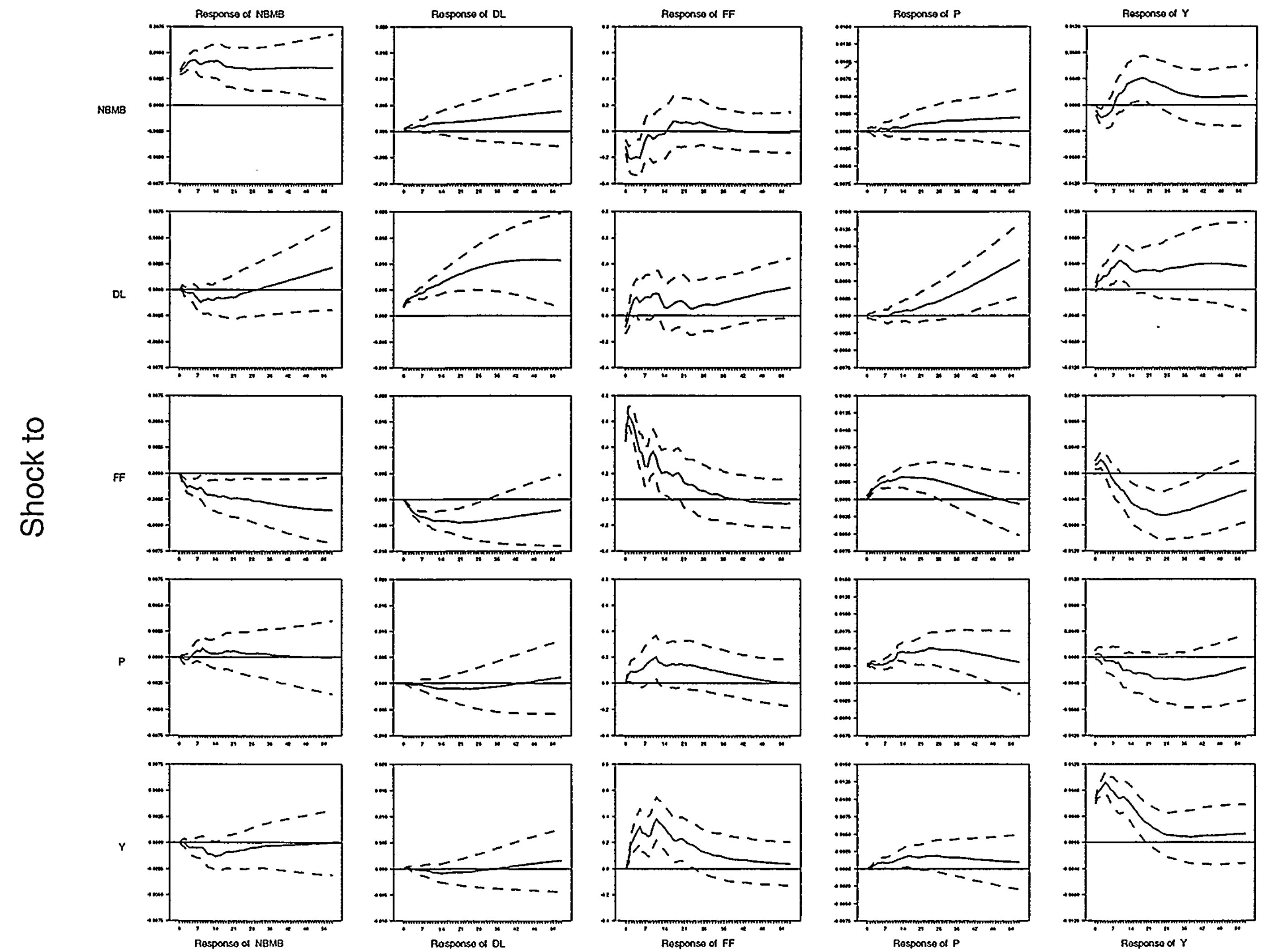

Figure 6.2. Unrestricted VAR Impulse Responses, {NBMB, DM1, DUALM1, P, Y} Model

Monthly data: 1960:1 - 1995:11

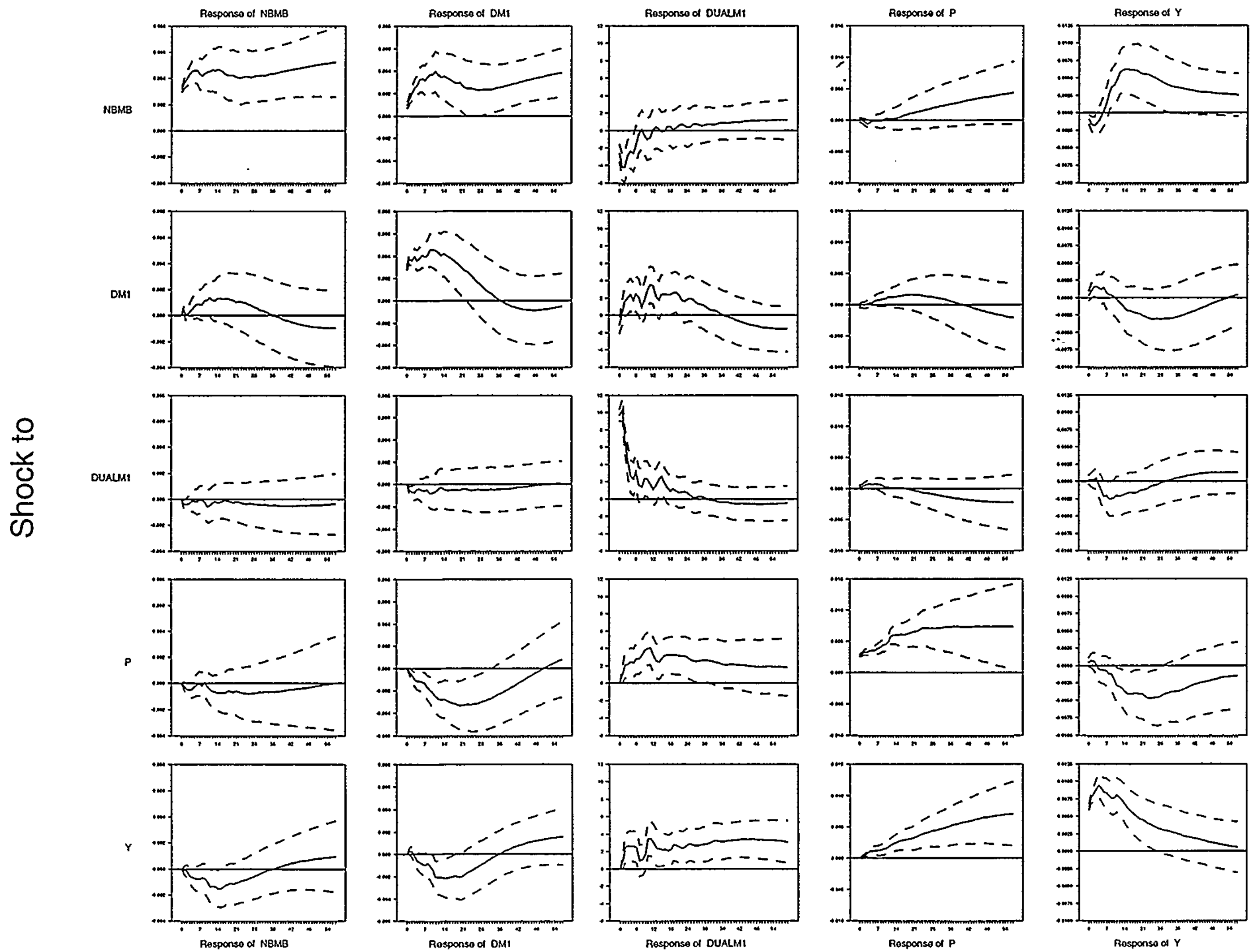

Figure 6.2. Unrestricted VAR Impulse Responses, {NBMB, DM2, DUALM2, P, Y} Model

Monthly data: 1960:1 - 1995:11

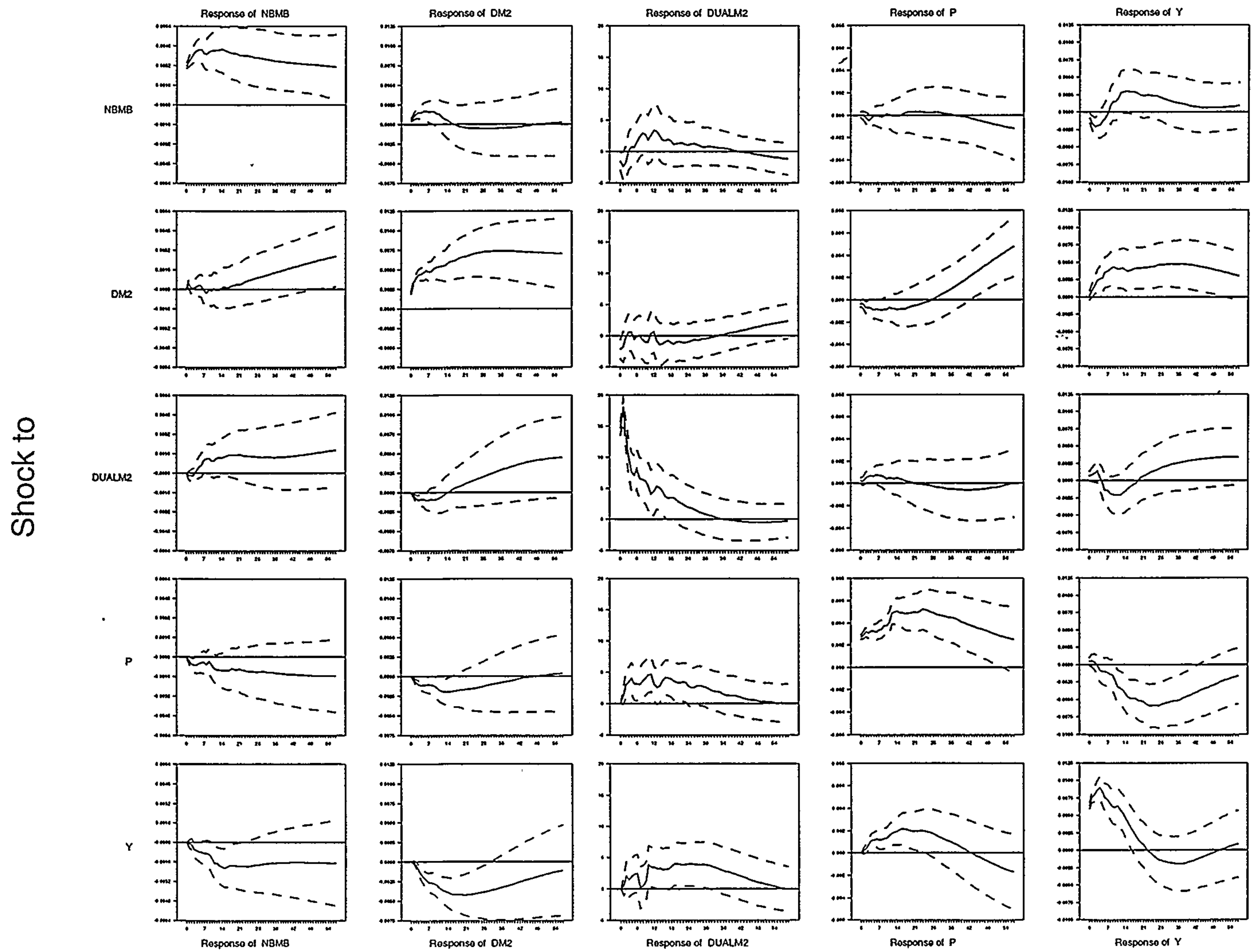

Figure 6.2. Unrestricted VAR Impulse Responses, {NBMB, DM3, DUALM3, P, Y} Model

Monthly data: 1960:1 - 1995:11

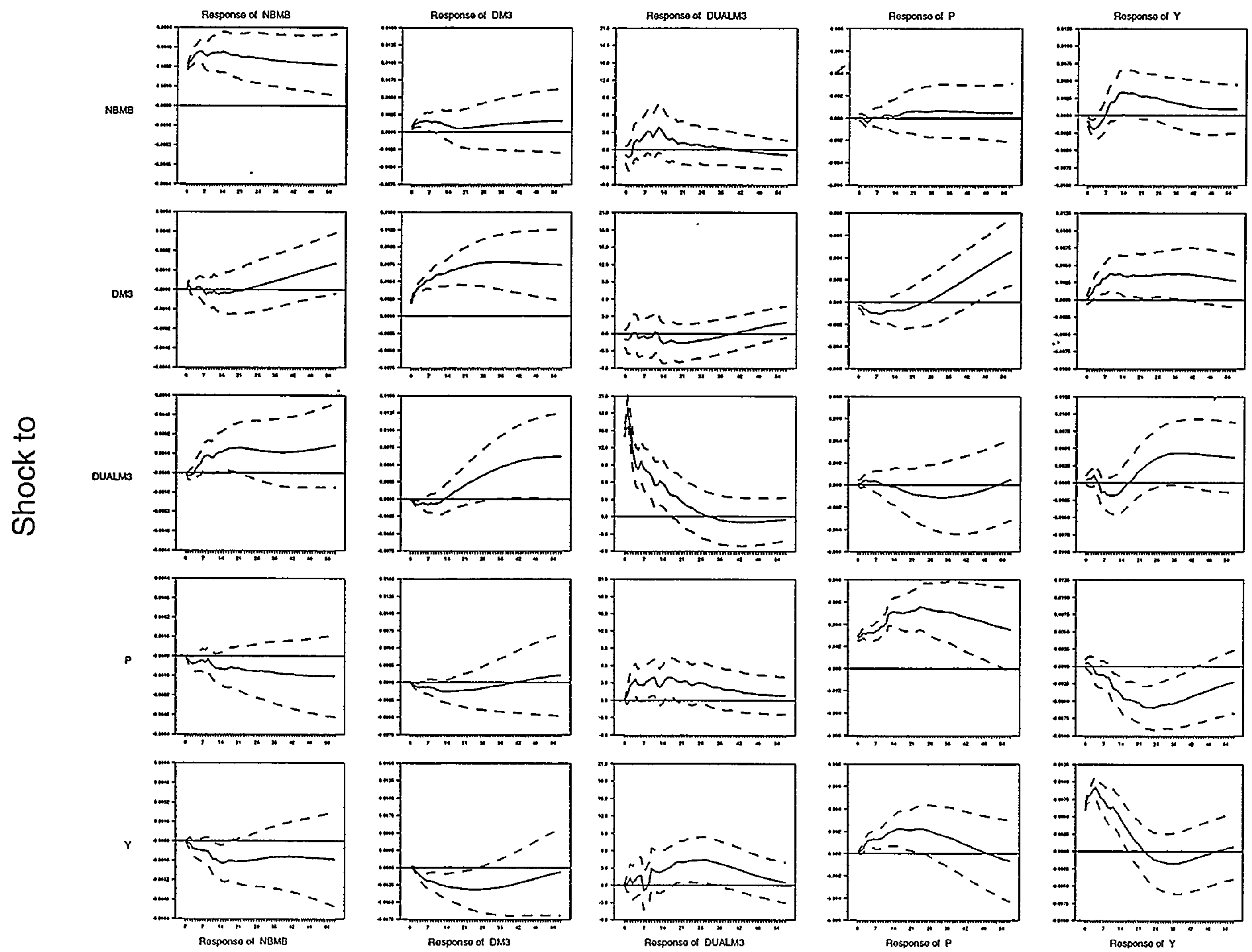

Figure 6.2. Unrestricted VAR Impulse Responses, {NBMB, DL, DUALL, P, Y} Model

Monthly data: 1960:1 - 1995:11

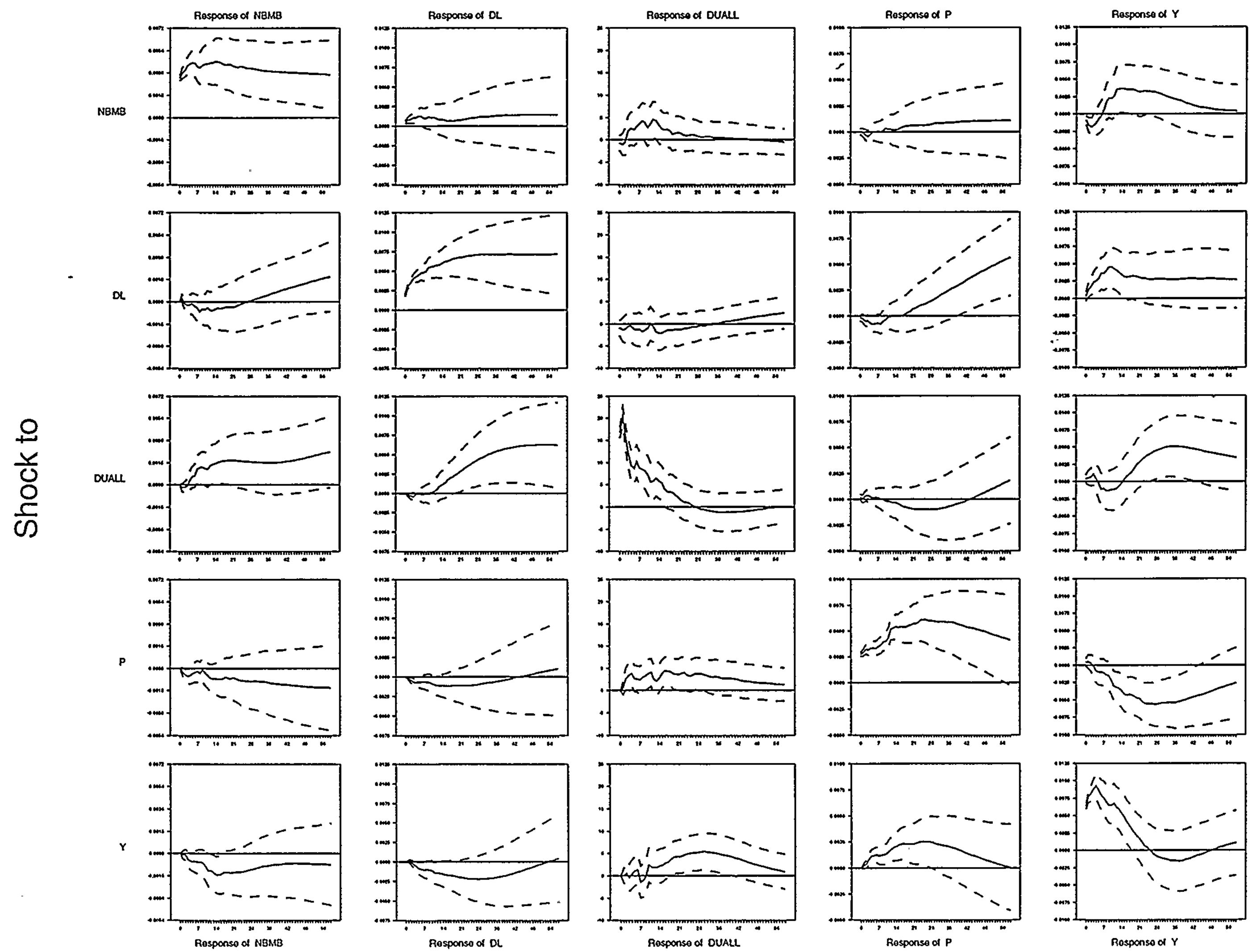

Figure 6.3. Unrestricted VAR Impulse Responses, {NBMB, CEM1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

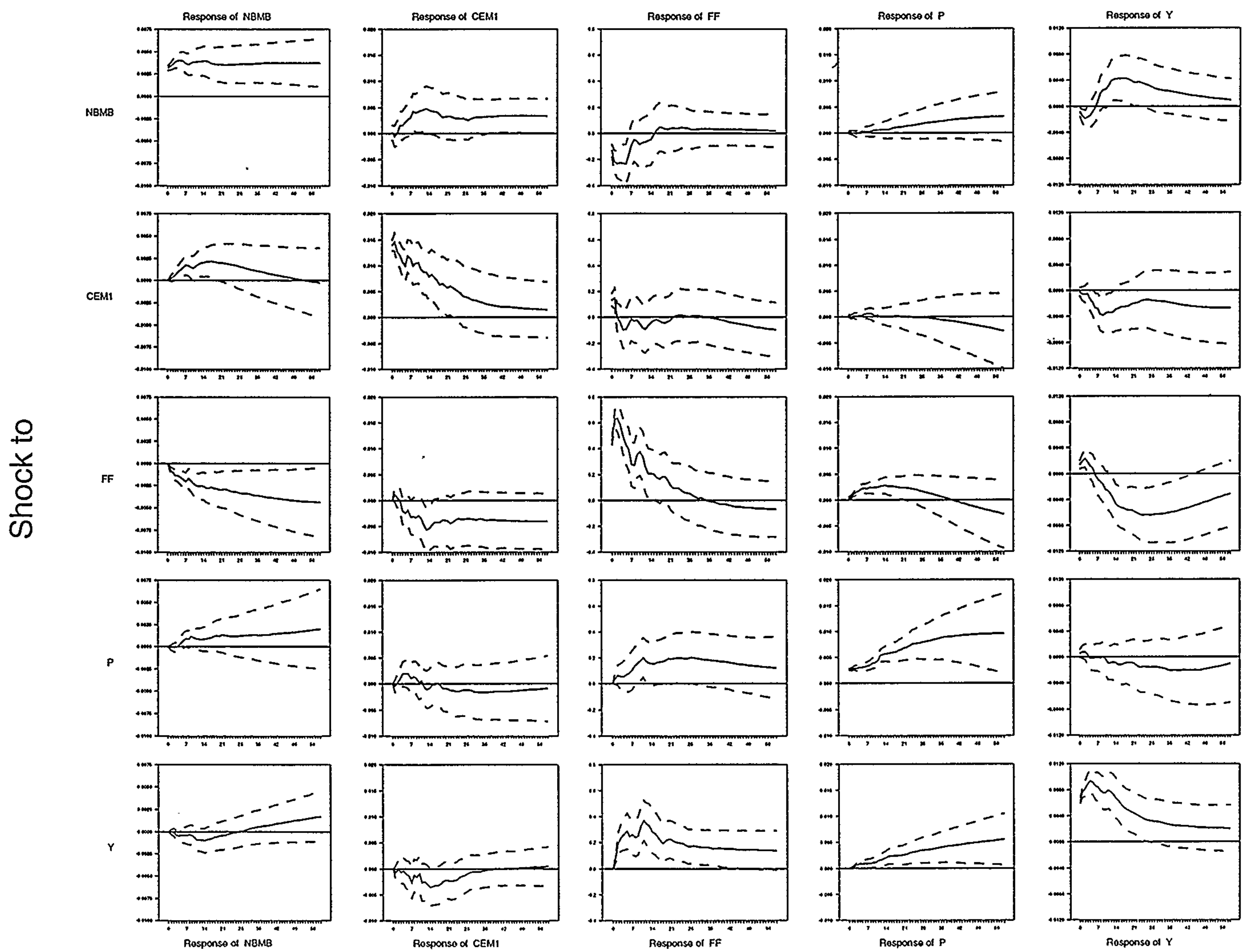

Figure 6.3. Unrestricted VAR Impulse Responses, {NBMB, CEM2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

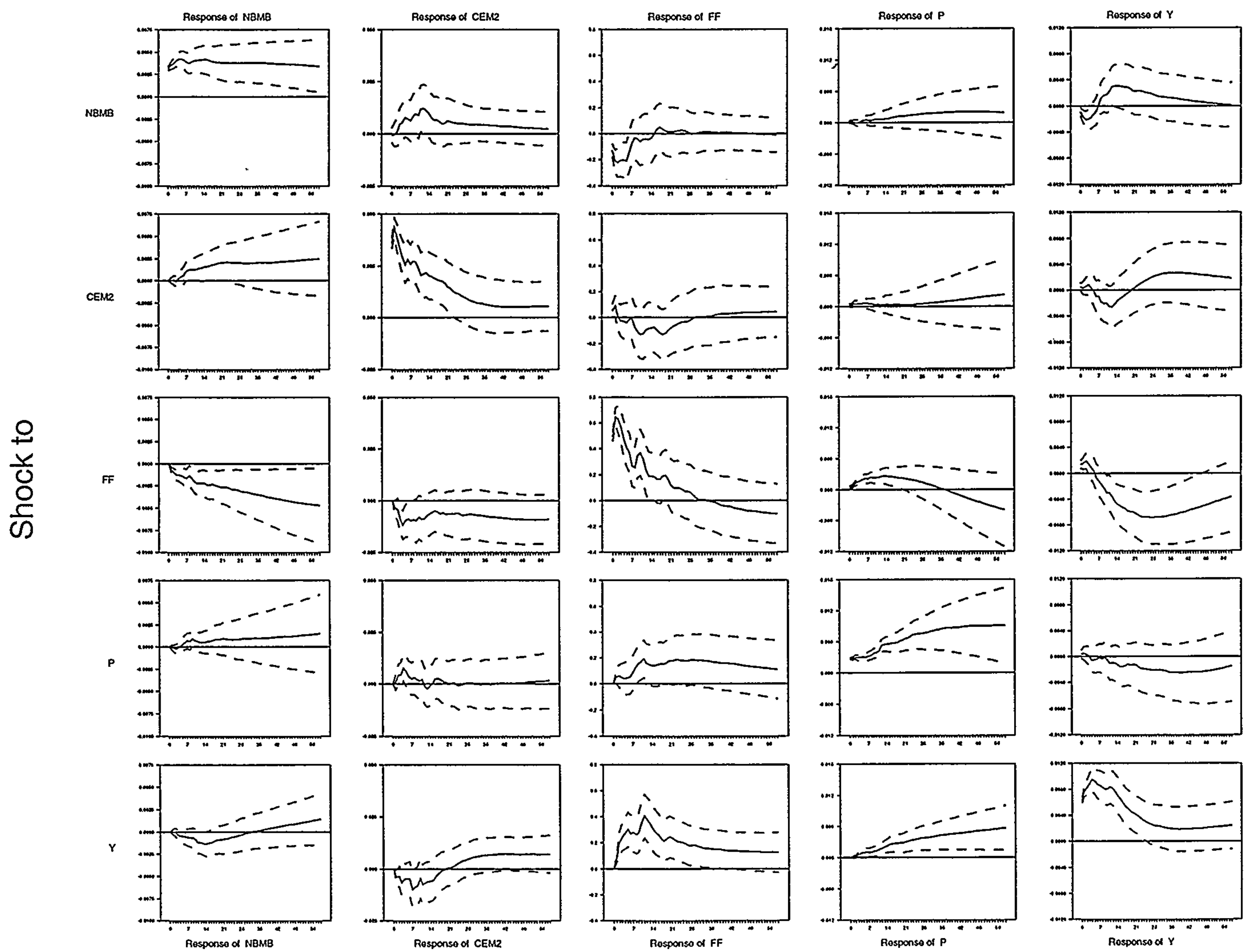

Figure 6.3. Unrestricted VAR Impulse Responses, {NBMB, CEM3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

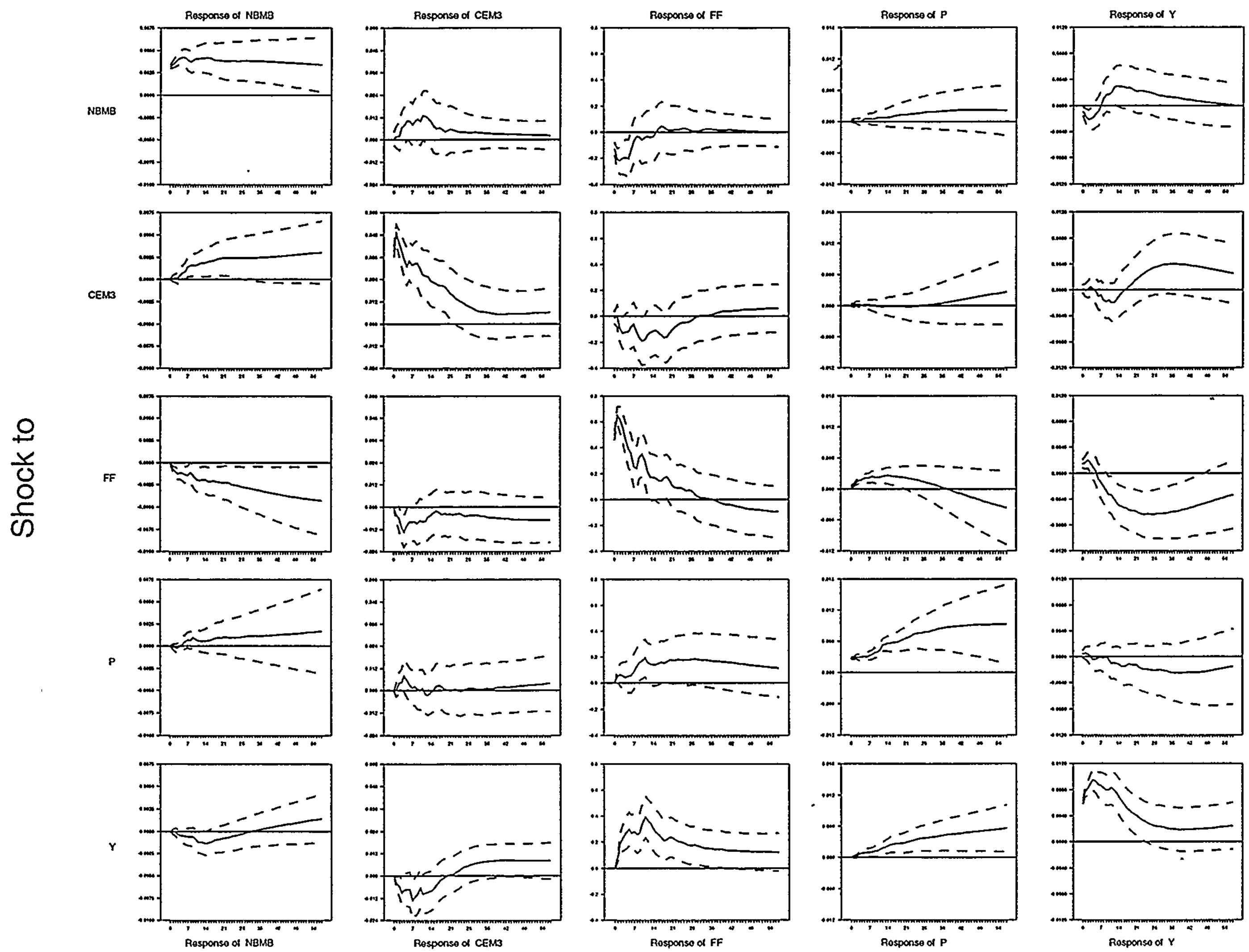

Figure 6.3. Unrestricted VAR Impulse Responses, {NBMB, CEL, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

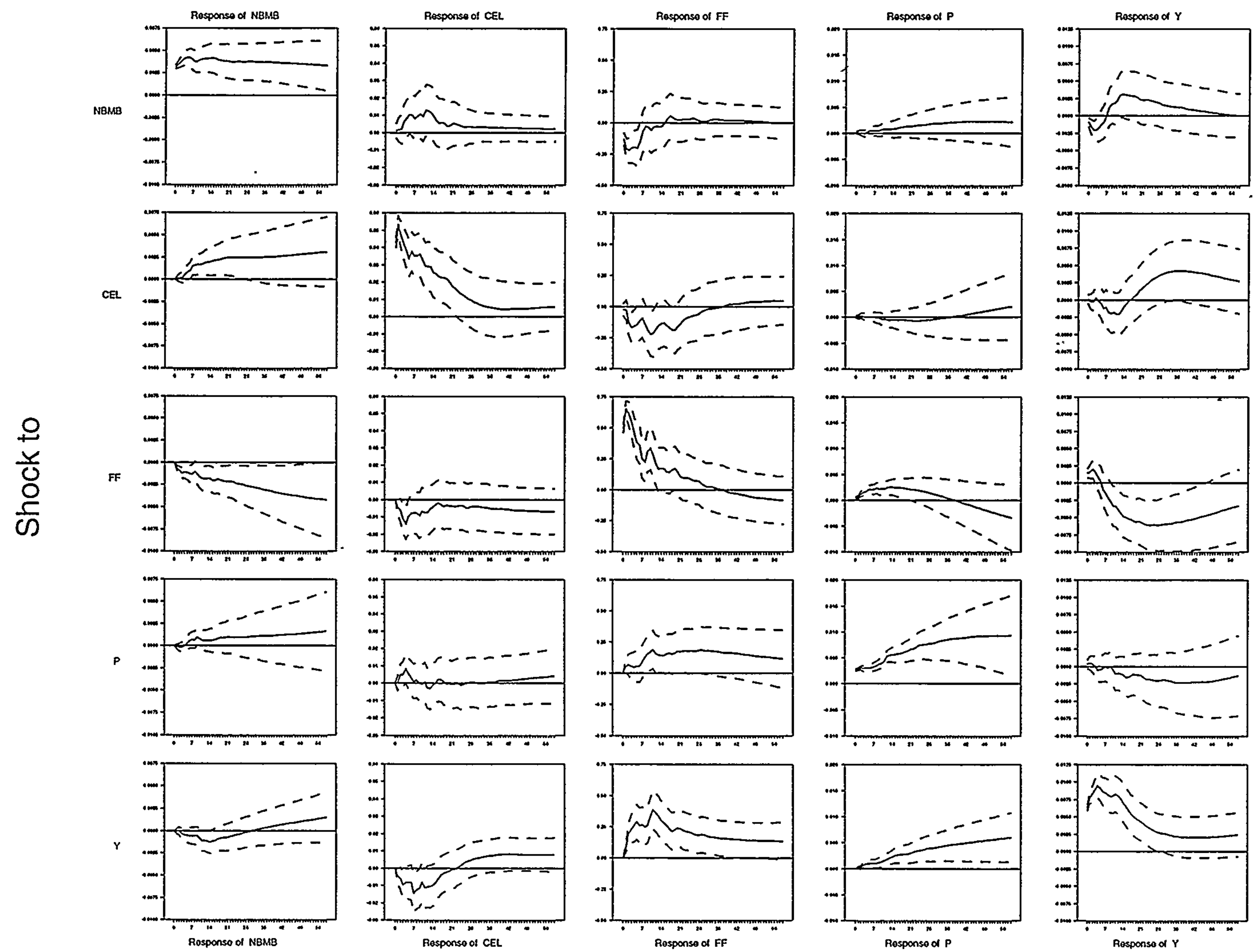

Figure 6.4. Unrestricted VAR Impulse Responses, {NBMB, M1, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

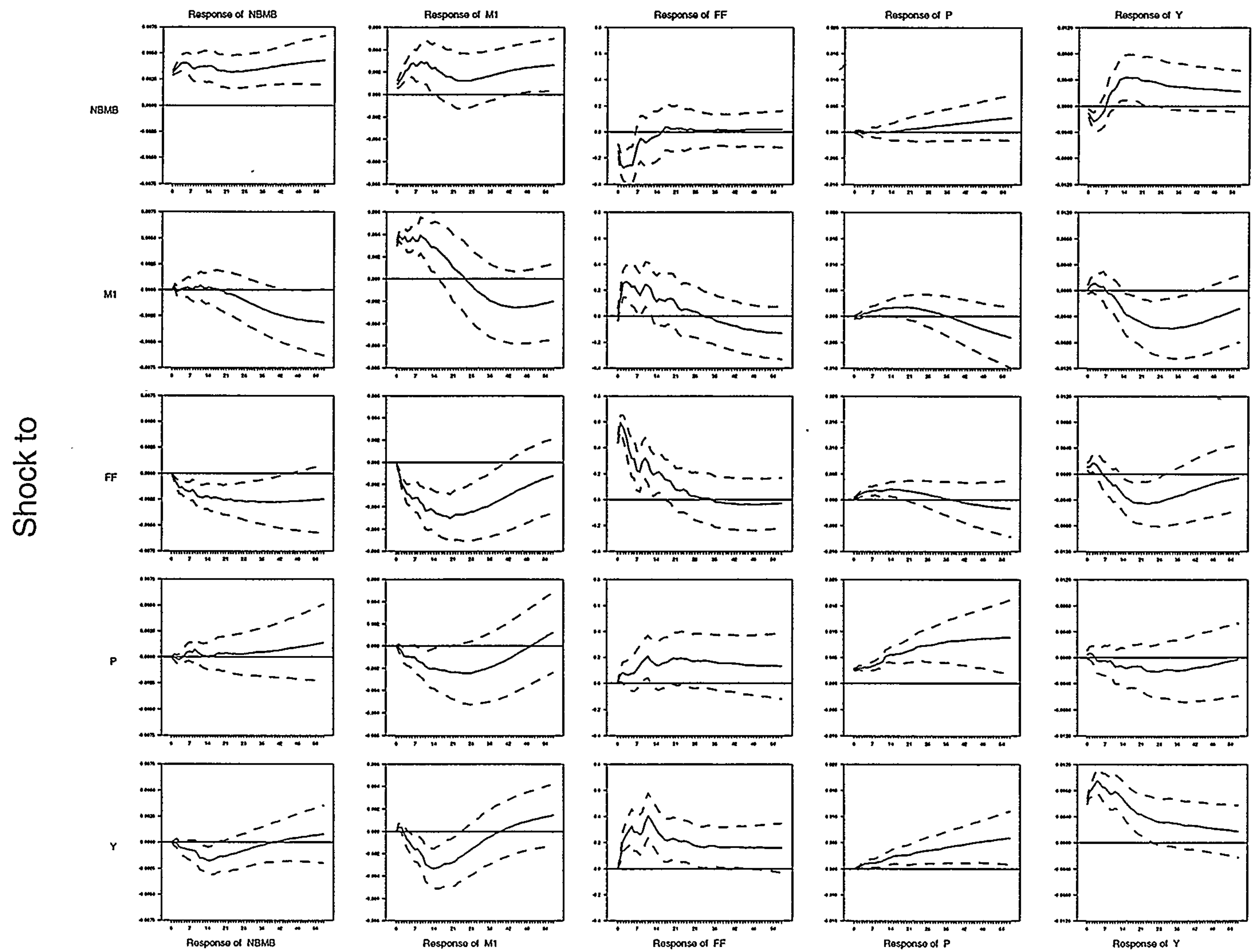

Figure 6.4. Unrestricted VAR Impulse Responses, {NBMB, M2, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

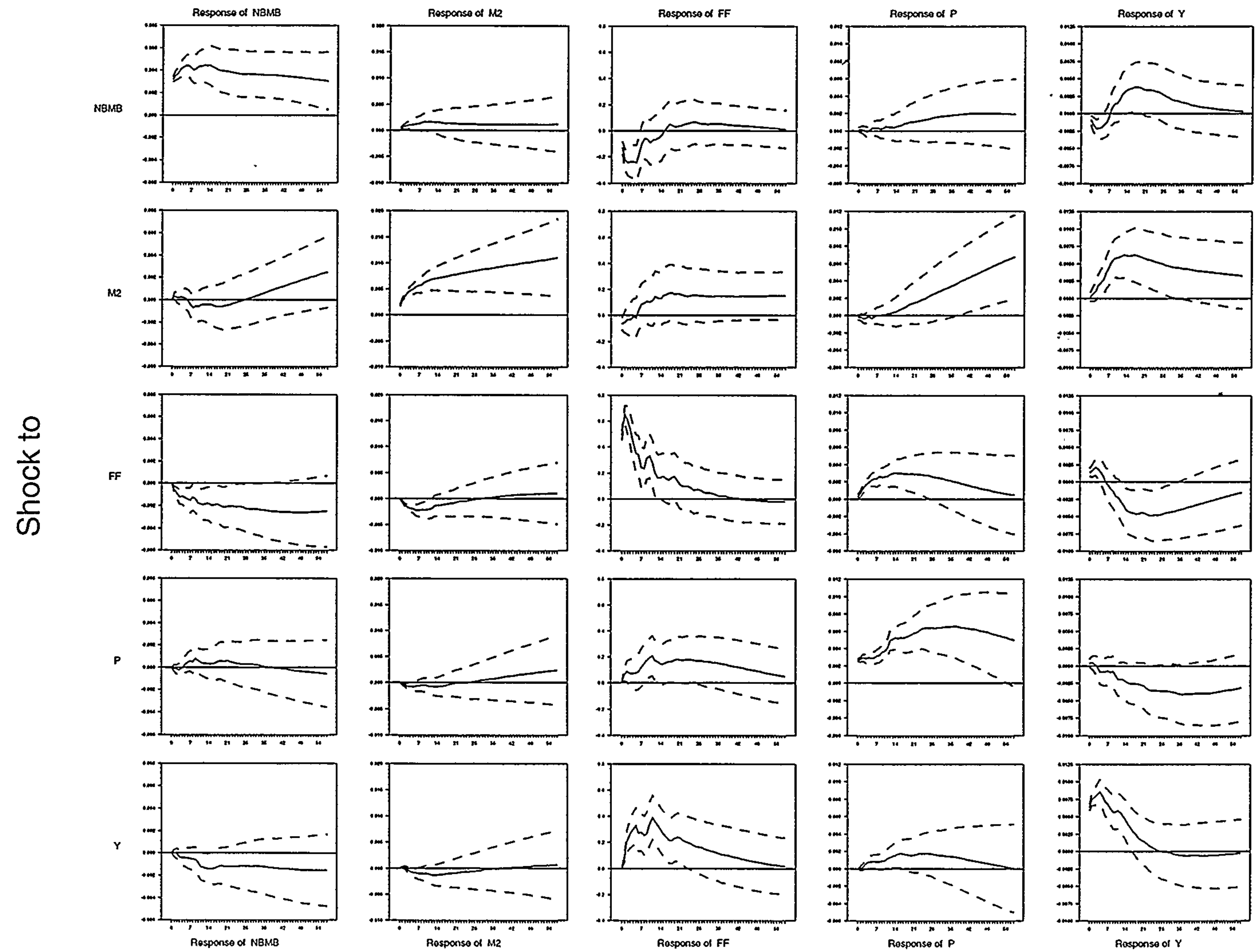

Figure 6.4. Unrestricted VAR Impulse Responses, {NBMB, M3, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

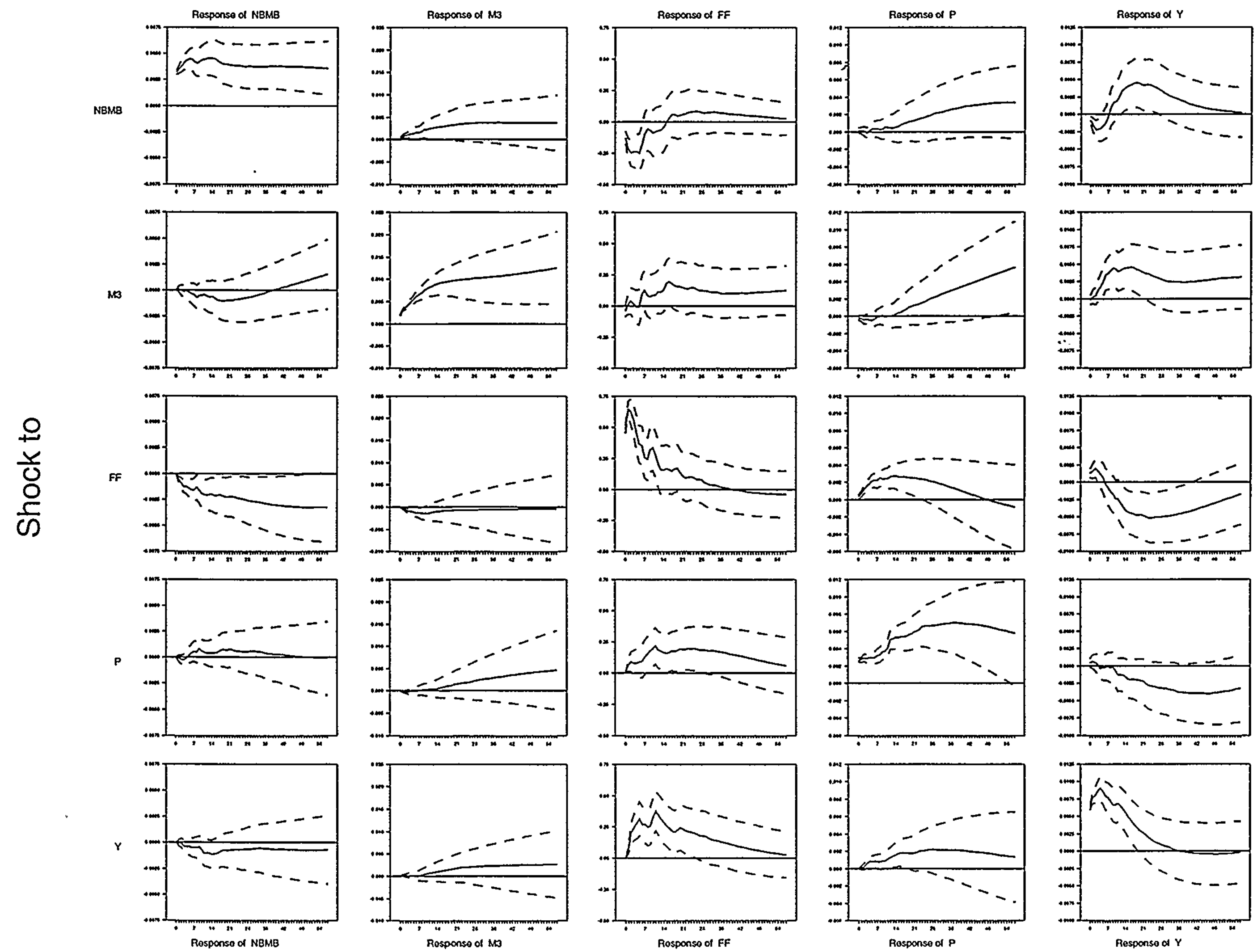

Figure 6.4. Unrestricted VAR Impulse Responses, {NBMB, L, FF, P, Y} Model

Monthly data: 1960:1 - 1995:11

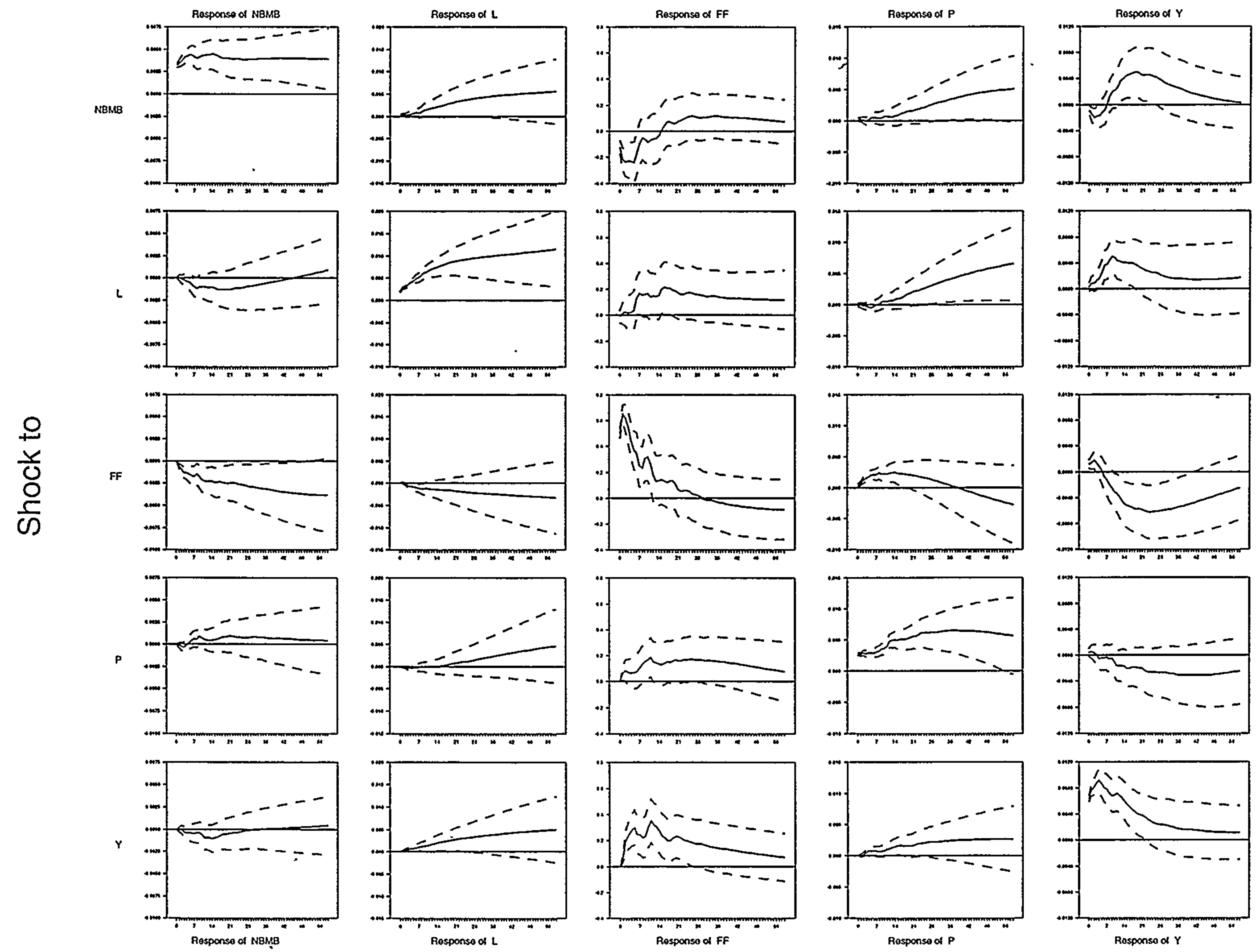

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*DM*	*FF*	*P*	*Y*	*NBMB*	*DM*	*FF*	*P*	*Y*	*NBMB*	*DM*	*FF*	*P*	*Y*
							Panel 1: DM1								
NBMB	1.000					.000	.006	.004	.132	.680	55.940	11.952	27.900	1.343	2.864
DM	.283	1.000				.487	.000	.000	.090	.000	22.047	23.079	41.049	5.760	8.063
FF	-.294	-.056	1.000			.011	.000	.000	.008	.000	5.890	12.582	28.507	16.164	36.856
P	.028	-.037	.078	1.000		.363	.512	.024	.000	.611	4.864	5.286	2.403	66.021	21.425
Y	-.154	-.026	.204	.066	1.000	.006	.183	.764	.315	.000	16.354	29.188	11.763	5.798	36.896
							Panel 2: DM2								
NBMB	1.000					.000	.096	.074	.379	.652	56.602	8.784	28.807	.799	5.007
DM	.250	1.000				.388	.000	.000	.516	.216	1.087	79.604	9.876	3.707	5.725
FF	-.245	-.244	1.000			.508	.001	.000	.307	.000	6.861	11.198	48.447	5.079	28.415
P	.044	-.069	.104	1.000		.083	.027	.001	.000	.368	.924	33.992	23.238	37.258	4.588
Y	-.134	.009	.203	.061	1.000	.060	.044	.661	.489	.000	4.743	31.029	26.723	15.406	22.099

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*DM*	*FF*	*P*	*Y*	*NBMB*	*DM*	*FF*	*P*	*Y*	*NBMB*	*DM*	*FF*	*P*	*Y*
							Panel 3: DM3								
NBMB	1.000					.000	.054	.015	.293	.804	59.442	4.828	31.706	.703	3.320
DM	.245	1.000				.153	.000	.000	.792	.390	5.371	81.965	9.693	1.580	1.390
FF	-.241	-.273	1.000			.433	.000	.000	.241	.001	5.780	11.702	46.917	6.852	28.749
P	.046	-.050	.105	1.000		.092	.047	.001	.000	.496	3.088	32.042	17.639	43.535	3.696
Y	-.135	-.024	.209	.063	1.000	.120	.255	.926	.478	.000	7.188	22.239	30.171	16.077	24.324
							Panel 4: DL								
NBMB	1.000					.000	.044	.004	.233	.611	59.847	4.387	33.527	.500	1.739
DM	.202	1.000				.257	.000	.000	.819	.182	6.796	78.425	13.405	.561	.812
FF	-.232	-.217	1.000			.586	.015	.000	.390	.005	5.246	15.294	42.813	8.848	27.799
P	.051	-.010	.101	1.000		.125	.068	.002	.000	.589	4.517	38.547	12.029	40.583	4.322
Y	-.135	.026	.204	.063	1.000	.060	.105	.914	.523	.000	8.210	18.149	35.429	10.897	27.315

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*DM*	*DUAL*	*P*	*Y*	*NBMB*	*DM*	*DUAL*	*P*	*Y*	*NBMB*	*DM*	*DUAL*	*P*	*Y*
Panel 5: DM1															
NBMB	1.000					.000	.010	.308	.390	.772	91.663	3.292	.652	1.356	3.037
DM	.310	1.000				.089	.000	.013	.049	.002	41.176	29.540	.797	20.613	7.873
DUAL	-.254	-.192	1.000			.016	.002	.000	.000	.004	7.069	11.901	23.164	23.581	34.284
P	-.006	-.068	.096	1.00		.379	.302	.343	.000	.020	8.496	2.059	2.638	54.719	32.088
Y	-.138	-.005	.071	.067	1.000	.001	.176	.092	.475	.000	28.473	6.678	3.350	17.281	44.218
Panel 6: DM2															
NBMB	1.000					.000	.002	.165	.167	.400	63.814	9.910	7.587	7.504	11.185
DM	.268	1.000				.551	.000	.000	.053	.005	.837	70.083	12.720	2.274	14.086
DUAL	-.108	-.166	1.000			.793	.209	.000	.081	.004	4.188	3.295	58.080	15.643	18.794
P	.015	-.116	.105	1.00		.176	.328	.899	.000	.313	.773	18.820	.689	71.718	7.998
Y	-.131	-.008	.103	.062	1.000	.027	.105	.124	.428	.000	5.544	29.053	9.969	29.656	25.777

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*DM*	*DUAL*	*P*	*Y*	*NBMB*	*DM*	*DUAL*	*P*	*Y*	*NBMB*	*DM*	*DUAL*	*P*	*Y*
Panel 7: DM3															
NBMB	1.000					.000	.002	.084	.099	.636	66.254	5.060	12.001	7.945	8.741
DM	.273	1.000				.352	.000	.000	.167	.069	1.892	68.196	21.074	1.017	7.821
DUAL	-.061	-.077	1.000			.661	.495	.000	.133	.003	4.252	2.575	62.685	12.447	18.040
P	.023	-.093	.082	1.00		.244	.255	.789	.000	.199	.651	16.843	1.917	72.742	7.85
Y	-.132	-.037	.071	.059	1.000	.038	.296	.265	.268	.000	7.345	18.952	17.232	30.511	25.959
Panel 8: DL															
NBMB	1.000					.000	.007	.088	.158	.604	67.981	4.619	16.297	5.481	5.621
DM	.221	1.000				.493	.000	.001	.245	.379	1.973	64.064	29.794	1.005	3.164
DUAL	-.045	-.068	1.000			.573	.690	.000	.111	.006	5.135	3.087	58.535	14.036	19.206
P	.023	-.064	.068	1.00		.351	.222	.767	.000	.183	1.483	22.79	1.809	66.852	7.078
Y	-.135	.013	.064	.057	1.000	.012	.100	.219	.265	.000	8.126	15.113	22.227	28.790	25.743

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					**Marginal significance levels for exclusion of lags**					**Forecast error variance decomposition (60 month horizon)**				
Equation	*NBMB*	*CEM*	*FF*	*P*	*Y*	*NBMB*	*CEM*	*FF*	*P*	*Y*	*NBMB*	*CEM*	*FF*	*P*	*Y*
								Panel 9: CEM1							
NBMB	1.000					.000	.078	.001	.086	.047	48.004	5.238	38.913	5.109	2.735
CEM	.015	1.000				.780	.000	.155	.593	.171	15.492	59.469	18.924	2.720	3.395
FF	-.260	.264	1.000			.831	.000	.000	.367	.001	5.434	2.481	40.205	19.764	32.115
P	.062	.070	.092	1.000		.345	.202	.006	.000	.618	5.408	1.649	4.558	70.598	17.787
Y	-.131	-.028	.220	.088	1.000	.062	.051	.458	.640	.000	11.069	8.638	38.530	2.959	38.804
								Panel 10: CEM2							
NBMB	1.000					.000	.365	.001	.214	.344	46.804	11.296	36.804	2.636	2.458
CEM	-.017	1.000				.722	.000	.536	.172	.012	6.899	67.845	14.775	.857	9.623
FF	-.249	.109	1.000			.764	.181	.000	.290	.001	4.003	2.853	41.277	17.786	34.081
P	.057	.075	.103	1.000		.223	.816	.007	.000	.545	3.189	1.537	5.947	68.771	20.556
Y	-.136	.077	.240	.075	1.000	.071	.110	.536	.385	.000	4.185	6.343	45.577	5.235	38.659

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*CEM*	*FF*	*P*	*Y*	*NBMB*	*CEM*	*FF*	*P*	*Y*	*NBMB*	*CEM*	*FF*	*P*	*Y*
							Panel 11: CEM3								
NBMB	1.000					.000	.265	.001	.250	.388	47.297	18.086	29.237	2.925	2.455
CEM	.015	1.000				.632	.000	.479	.154	.007	5.915	74.324	7.462	.913	11.386
FF	-.249	-.028	1.000			.777	.095	.000	.284	.001	3.960	6.287	38.386	17.756	33.611
P	.057	.051	.105	1.000		.195	.890	.009	.000	.544	3.604	1.326	5.299	69.239	20.532
Y	-.137	.027	.246	.075	1.000	.076	.077	.476	.402	.000	4.451	12.807	39.213	5.223	38.305
							Panel 12: CEL								
NBMB	1.000					.000	.252	.001	.266	.357	47.993	18.760	27.496	3.150	2.601
CEM	.023	1.000				.703	.000	.480	.197	.011	5.395	76.992	5.649	1.009	10.954
FF	-.251	-.054	1.000			.775	.097	.000	.284	.001	4.033	8.181	36.707	18.382	32.696
P	.057	.041	.104	1.000		.166	.900	.009	.000	.538	3.879	.869	5.256	69.703	20.292
Y	-.137	.017	.244	.074	1.000	.067	.047	.401	.418	.000	4.814	13.455	38.469	4.482	38.780

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*M*	*FF*	*P*	*Y*	*NBMB*	*M*	*FF*	*P*	*Y*	*NBMB*	*M*	*FF*	*P*	*Y*
								Panel 13: M1							
NBMB	1.000					.000	.005	.004	.149	.716	56.973	13.017	25.404	1.304	3.302
M	.267	1.000				.724	.000	.000	.046	.000	15.267	21.607	43.697	9.031	10.397
FF	-.288	-.057	1.000			.023	.000	.000	.006	.000	5.459	13.265	28.799	16.757	35.720
P	.022	-.042	.079	1.000		.353	.436	.031	.000	.632	3.078	4.761	2.705	68.577	20.877
Y	-.157	-.017	.206	.068	1.000	.012	.295	.738	.376	.000	14.376	28.410	14.119	4.358	38.737
								Panel 14: M2							
NBMB	1.000					.000	.85	.090	.448	.762	65.854	6.064	21.234	.641	6.206
M	.200	1.000				.527	.000	.000	.191	.397	1.885	93.500	1.867	2.013	.735
FF	-.253	-.171	1.000			.571	.172	.000	.111	.000	6.244	15.125	35.342	15.345	27.944
P	.056	-.070	.099	1.000		.172	.533	.002	.000	.673	3.952	24.639	9.381	59.469	2.558
Y	-.135	.008	.235	.069	1.000	.286	.163	.914	.549	.000	7.743	35.331	18.859	16.868	21.199

TABLE 6.1

UNRESTRICTED VAR RESULTS FOR MONEY SUPPLY RULE

	Correlation matrices for innovations					Marginal significance levels for exclusion of lags					Forecast error variance decomposition (60 month horizon)				
Equation	*NBMB*	*M*	*FF*	*P*	*Y*	*NBMB*	*M*	*FF*	*P*	*Y*	*NBMB*	*M*	*FF*	*P*	*Y*
								Panel 15: M3							
NBMB	1.000					.000	.916	.012	.302	.723	67.427	2.372	27.686	.910	1.605
M	.192	1.000				.442	.000	.239	.681	.764	8.819	80.398	.527	6.693	3.563
FF	-.250	-.121	1.000			.357	.003	.000	.160	001.	7.542	11.028	35.637	17.282	28.515
P	.066	-.051	.100	1.000		.213	.697	.004	.000	.708	10.212	16.989	5.585	62.074	5.140
Y	-.132	-.042	.222	.072	1.000	.255	.191	.861	.623	.000	11.404	17.119	26.228	15.864	29.385
								Panel 16: L							
NBMB	1.000					.000	.718	.002	.201	.453	62.401	2.735	32.382	1.711	.771
M	.143	1.000				.378	.000	.070	.633	.415	12.095	68.225	4.001	5.750	9.899
FF	-.238	-.054	1.000			.484	.191	.000	.238	.002	9.649	15.098	33.065	15.389	26.798
P	.061	-.004	.087	1.000		.242	.375	.004	.000	.752	14.981	22.609	4.511	50.647	7.252
Y	-.139	.267	.208	.066	1.000	.136	.088	.875	.600	.000	12.461	10.552	33.579	9.953	33.454

Table 6.2: Summary Results for Five-variable system with Money Supply rule			
Model	Liqudity Puzzle	Price Puzzle	Output Puzzle
{NBMB, DM1, FF, P, Y}	no	no	no
{NBMB, DM2, FF, P, Y}	no	yes	no
{NBMB, DM3, FF, P, Y}	no	no	no
{NBMB, DL, FF, P, Y}	no	no	no
{NBMB, DM1, DUALM1, P, Y}	no	no	no
{NBMB, DM2, DUALM2, P, Y}	yes	yes	no
{NBMB, DM3, DUALM3, P, Y}	yes	no	no
{NBMB, DL, DUALL, P, Y}	yes	no	no
{NBMB, CEM1, FF, P, Y}	no	no	no
{NBMB, CEM2, FF, P, Y}	no	no	no
{NBMB, CEM3, FF, P, Y}	no	no	no
{NBMB, CEL, FF, P, Y}	no	no	no
{NBMB, M1, FF, P, Y}	no	no	no
{NBMB, M2, FF, P, Y}	no	no	no
{NBMB, M3, FF, P, Y}	no	no	no
{NBMB, L, FF, P, Y}	no	no	no

CHAPTER 7

SUMMARY AND CONCLUSIONS

Using the vector autoregression (VAR) approach, the investigation in this study shows that using the twelve monetary aggregates and the federal funds rate to identify monetary policy shocks fail to produce dynamic responses fully consistent with traditional Keynesian IS-LM model. According to that model, an expansionary (contractionary) monetary policy should cause interest rates to fall (rise), and prices and output to rise (fall). The VAR evidence fails to rationalize this view. However, a more successful attempt is made when using the non-borrowed monetary base as policy indicator. The main findings in this study are summarized below.

The unrestricted VAR approach by Sims (1980) is used in Chapter 4 to investigate the dynamic effects of monetary policy shocks on interest rates, prices and output. Two identification schemes are applied namely the money supply rule (M-rule) and the interest rate rule (R-rule). In the former, positive innovations to each of the twelve monetary aggregates are identified as expansionary monetary policy shocks while the latter treats positive innovations to the federal funds rate as contractionary policy shocks. Under the M-rule, the results show that innovations in the Divisia and Simple Sum aggregates are associated with the liquidity puzzle. For instance, the federal funds rate increases rather than decreases following an expansionary monetary policy shock. Although weaker evidence of the liquidity puzzle is found when using the Currency Equivalence aggregates, the price and output puzzles are observed in turn. When switching to the R-rule VARs, the price puzzle is observed in all cases. In the attempt to solve this problem, the commodity prices (PC) is added following Sims (1992). The price puzzle disappears in VAR models with DM1, CEM1, and M1. More importantly, however, the innovation accounting analysis is found to be sensitive to the ordering of the variables. This is gathered from the significant correlation matrices for innovations. The concern, of course, is whether reordering of the variables in the VAR system will produce drastically different results from those obtained here. Further investigation will be needed in order to address this question.

The analysis is carried on in Chapter 5 using the structural VAR approach based on Gordon and Leeper (1994). Restrictions are placed on the contemporaneous relationship between money and the other macro variables. The results show that all the models fail to produce the correct estimated contemporaneous coefficients associated with the money supply and demand equations. In terms of the impulse response functions, the Currency Equivalence aggregates are found to best solve the liquidity puzzle but not the price and output puzzles. Since the overidentifying restrictions are rejected for all the structural VAR models, the findings here are not significant. Although the structural identification schemes are derived from economic theory, they cannot be justified econometrically.

The puzzling evidence found in Chapters 4 and 5 is not be too surprising as it merely reinforces what is known from previous VAR studies. As discussed in Chapter 2, there are many factors that can account for a diversity of outcomes ranging from the different definitions of money used, the sample period, and, most importantly, the different VAR approaches used. Twelve different definitions of the money supply are used in this study including four Divisia aggregates, four Currency Equivalence aggregates, and four Simple Sum aggregates. The conclusion is that different monetary aggregates tend to produce different puzzles.

The data sample used in this study starts from 1960:1 to 1995:11. Due to changing Federal Reserve operating procedures, there may be structural breaks in the data which are ignored in this study. For instance, it is only between 1979 and 1982 that the Federal Reserve actually targeted the growth of monetary aggregates. The M-rule VARs used here assume that such policy lasts from 1960 to 1995. However, this may be justified on the ground that they represent the intermediate targets of the Federal Reserve although some other operating targets may be used at the same time. In view of the current Federal Reserve operating procedures, researchers are using actual operating targets most notably non-borrowed reserves and the federal funds rate. Recently, Bernanke and Mihov (1995) found support for Bernanke and Blinder's (1992) use of the federal funds rate for the period prior to 1979, and Strongin's (1995) use of non-borrowed reserves and total reserves for the period after 1979.

Perhaps the most interesting findings in this study is found in Chapter 6 where the non-borrowed monetary base is used as the monetary policy indicator. It is defined by subtracting borrowed reserves from the monetary base in order to overcome some of the problems associated with endogenous movement caused by the demand for reserves. According to Haslag and Hein (1995), the monetary base has long been regarded as the centerpiece for monetary policy by early studies. In this chapter, the unrestricted VAR approach is used following the M-rule ordering where non-borrowed monetary base is ordered first followed by monetary aggregates, and macroeconomic variables. The estimated impulse responses show that the liquidity puzzle is no longer present in all the models using the federal funds rate. Following positive shocks to the non-borrowed monetary base, the federal funds rate decreases indicating the liquidity effect. Furthermore, the price puzzle is solved except in two cases only while the output puzzle is completely solved.

The scope of this study remains modest since more sophisticated VAR techniques are available. For instance, long run restrictions can be imposed on the model where monetary policy shocks only affects the price level. This approach is introduced by Blanchard and Quah (1989) where shocks are separated into temporary and permanent components. Another promising approach is the semi-structural VARs proposed by Bernanke and Mihov (1995). Since this study focuses primarily on the money market and ignores the reserves market completely, it is possible to incorporate variables from both markets using the approach proposed. Perhaps it is worth mentioning again that the VARs here are based in a closed economy setting thus foreign shocks are not taken into account. Nevertheless, this study serves as a good survey of the different monetary measures and provides a good idea regarding which of those twelve measures can be selectively incorporated into future VAR studies.

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APPENDIX A

Monetary Aggregates

1. Simple Sum (M1, M2, M3, L) - The simple sum, also known as traditional broad monetary aggregates, are the typical monetary aggregation constructed by central banks. They are widely used in early VAR studies to indicate monetary policy stance. However, this method of aggregation has been criticized for assigning equal weight to each of the component assets thus treating them as perfect substitutes. It is said to be distortive. Barnett, Fisher and Serletis (1992) argue that different weights should be assigned to different assets based on the value of the monetary services that they each provide. The simple sum index is defined as:

$$M_t = \sum_{i=1}^{n} x_{it}$$

where x_i is the i^{th} monetary component.

2. Divisia (DM1, DM2, DM3, DL) - Barnett (1980) considers the Divisia aggregates to be more meaningful than the Simple Sum aggregates because they are based on utility maximizing behaviour, thus providing a stronger theoretical foundation than the conventional simple sum index. The demand function for the different Divisia monetary assets are derived together with the user cost of those assets. The user cost measures the

opportunity cost of the monetary services provided by each asset and is defined as DUAL in this study. For instance, DUALM1 refers to the user cost of DM1, and so forth. Basically, the Divisia index is defined as:

$$\frac{D_t}{D_{t-1}} = \prod_{i=1}^{n} \left(\frac{x_{it}}{x_{i,t-1}} \right)^{(1/2)(s_{it}+s_{i,t-1})}$$

where D_t = the Divisia quantity at time t

x_i = monetary assets i

π_i = user cost of x_i

$s_i = (\pi_i x_i / \Sigma \pi_i x_i)$

The user cost is defined as:

$$\pi_i = \left(\frac{R - r_i}{1 + R} \right)$$

where r_i = yield on i^{th} asset

R = yield on benchmark asset

3. Currency Equivalence (CEM1, CEM2, CEM3, CEL) - According to Rotemberg, the difference between the Currency Equivalence and Divisia aggregates is the principle underlying the derivation of those aggregates. The former is more theoretically stringent

because of the stronger assumption about the aggregator function (separability conditions), giving a central role to currency. The weights of the Currency Equivalence aggregates depend on the moneyness or liquidity of each assets. For instance, currency has a weight of unity, being the most liquid, while those assets with a lower yield receive smaller weights. Without going into details, the Currency Equivalence aggregate is defined as:

$$CE_t \equiv \sum_{i=1}^{N} \frac{r_{b,t} - r_{i,t}}{r_{b,i}} x_{i,t}$$

where r_b = return on prime-grade commercial paper

r_i = return on i^{th} monetary asset

x_i = monetary asset i