FINANCIAL SOURCES OF MACROECONOMIC FLUCTUATIONS: AN EMPIRICAL INVESTIGATION

BY

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A Thesis
Submitted to the Faculty of Graduate Students
in Partial Fulfillment of the Requirements
for the Degree of

DOCTOR OF PHILOSOPHY

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THE UNIVERSITY OF MANITOBA

FACULTY OF GRADUATE STUDIES

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ABSTRACT

The idea that financial structure and output determination may be interrelated has gone through several cycles over the past half a century since its inception at the time of the Great Depression. In its latest reincarnation in the theory of *Financial Acceleration*, it considers financial factors as propagation mechanisms for the disturbances originating from the *real* economy, where *agency costs* of credit allocation by the financial intermediaries play a central role.

Financial factors have rarely been studied as potential *sources* of variation in the economy. Our study, however, investigates the *origination* of disturbances from money and bank credit and allows for the *propagation* of disturbances within a relatively simple macro-dynamic system that utilizes the new approach of *Structural Vector Autoregression.*

Our findings for the Canadian as well as British economies indicate that money, but not credit, accounts for a sizable variation in output and other macroeconomic variables over various time horizons. However, bank credit serves as a propagation channel through which money disturbances are exacerbated. The results call for greater attention to monetary, in particular money demand, disturbances by the authorities.

ACKNOWLEDGEMENT

I would like to express my deepest sense of gratitiude and appreciation to my supervisor, Professor Norman Cameron, for his insightful comments and persistent stimulation throughout this research. I would also like to thank Professor Wayne Simpson for his valuable comments and encouragement. Also, my thanks go to Professor David Stangland who spared some of his scarce time and provided me with helpful comments. I am also grateful to Professor John Keating of Kansas University for his enriching comments.

Above all, my special thanks go to my caring wife, Mojegan, and loving children, Samim, Saba, and Yalda, whose understanding and endless support gave me the peace of mind I needed so dearly during this endeavor. It is to them that I dedicate this thesis.

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CHAPTER ONE

INTRODUCTION

The idea that financial structure and output determination may be interrelated has gone through several cycles over the past century.[1] Its origin can be traced back to the time of the Great Depression. Depression-era economists believed that the behavior of the financial system was largely responsible for the extraordinary events of the time. The collapse of the financial system along with real economic activity caught the attention of the period's economists, in particular Fisher (1939), who argued persuasively that the severity of the economic downturn resulted from poorly functioning financial markets. The Keynesian revolution, however, diverted attention from broader financial issues to focus just on money, which was considered to be of primary importance in Keynes' Liquidity Preference theory. This narrowing of focus occurred despite the fact that financial elements did matter to Keynes himself [2]. Later on, the well-known empirical work by Friedman and Schwartz (1963) further propelled the idea that money, and not credit, was the key financial aggregate. They studied the historical relationship between money and output in the United States and established a positive correlation between the two that was particularly strong for the Great Depression period.

Both Liquidity Preference theory and the time series work of Friedman and Schwartz preoccupied the mainstream economists so much that money was the only institutions only commercial banks received attention and that, too, only because they dealt with money. Mainstream macroeconomics thus largely ignored the potential links between output behavior and the performance of credit markets.

Outside the neo-classical synthesis and beginning with Gurley and Shaw (1955), there emerged a counter-movement that emphasized the significance of the financial system and, in particular, the importance of financial intermediaries in the credit supply process. Reflecting on the experience of developed as well as underdeveloped countries, they argued that financial intermediaries play an important role in directing general economic activity by improving the efficiency of inter-temporal trade. Moreover, they noted that as the financial system evolves, the quantity of money both loses its link to the level of economic activity and becomes an endogenous quantity harder to control. Instead, they argued, the economy's overall *financial capacity* - the measure of borrowers' ability to absorb prudent debt - was more relevant to macroeconomic behavior than the money stock. Gurley and Shaw's Intermediaries played the important role of enhancing borrowers' financial capacity by removing the impediments to the flow of funds from savers to investors.

Some of the above ideas were later integrated into mainstream macroeconomics. For example, Kuh and Meyer (1963) linked investment activity to balance sheet variables. Tobin and Dolde (1963) resorted to capital market imperfections to reconcile the Keynesian and life cycle theories of consumption. Brainard and Tobin (1963) and Tobin (1975) elaborated the financial sector of macroeconomic models and formally integrated some of Fisher's and Gurley and Shaw's ideas with conventional theory. Brunner and

Meltzer (1976) extended the IS-LM model to include a credit market. Others like Minsky (1975) and Kindleberger (1978), identified the financial system as the main source of instability and potential crises within the capitalist economy.

The tide in the notion that financial factors could be relevant to macroeconomic behavior was soon to ebb as Modigliani and Miller (1958) introduced their famous formal proposition that real economic decisions of firms were independent of firms' financial structure. Its formal elegance and the justification it provided for abstracting from the complex issues of financial structure appealed to many. The approach was adopted, for example, by Hall and Jorgenson (1967) in their development of the neo-classical theory of investment that ignores financial considerations.

The methodological revolution in macroeconomics in the 1970's which emphasized developing macroeconomic models from individual optimization also helped, in an indirect way, to shift attention away from financial factors that could not easily be motivated from first principles at the time. At the same time, increasing use of vector autoregressions in analyzing macroeconomic time series, pioneered by Sims (1972), rekindled interest in the explanatory power of money, as the key financial aggregate, in output fluctuations. Reduced-form estimations in this approach established a *causal* relationship from money to output. Once again, economists became obsessed with money as an important variable driving output fluctuations, at least in the short run. This has been true for both the *nominal rigidities* and the *rational expectations-equilibrium* schools [3].

A new surge of interest in studying the financial aspects of the business cycle fluctuations followed as further empirical work not only cast doubt on the *causal* relationship between money and output (e.g. Sims (1980), King and Plosser (1984), Litterman and Weiss (1985)), but also provided evidence that financial factors affected output (e.g. Mishkin (1978), Friedman (1980), Bernanke (1983), Greenwald, Stiglitz, and Weiss (1984), and Hamilton (1987) among others). At the same time, techniques useful for formalizing financial market problems became available due to progress in the economics of information and incentives. A basic tenet of information economics relates inefficiencies in trade to asymmetric information of the parties involved. This new approach which in fact owes its origin to the pioneering work by Akerlof (1970) on the "lemons" problem, has been widely adopted in the literature on modeling financial structure and intermediation.

The burgeoning research on financial intermediation stresses the role of these institutions (especially banks) in overcoming *informational imperfections* in credit markets. It applies first principles to explain the endogenous emergence and structure of intermediaries and their allocative consequences. Macroeconomists, however, have been more interested in the study of the nature of interaction between these intermediaries and the real sector of the economy during cyclical fluctuations.

The macroeconomic implications of financial intermediation beyond the conventional monetary channel were explored by Bernanke (1983) in an attempt to explain the depth and persistence of the Great Depression. Increased costs of intermediation (e.g. screening, monitoring, accounting, and default costs) are noted to have been influential in those events. Such costs, generally referred to as *agency costs*, have been more formally studied in competitive equilibrium frameworks by, for example, Willamson (1986, 1987a,1987b) and Bernanke and Gertler (1989), Gertler (1992), Moore (1993), and Bernanke, Gertler, and Gilchrist (1996) among others. The common theme in all these studies has come to be captured in the so-called *financial accelerator* theory as the dominant explanation for the nature of interaction between the financial factors and real economic activity. The theory links the agency costs to the borrowers' balance sheet (net worth) conditions, and the latter tend to move pro-cyclically. During booms borrowers have healthy balance sheets and low agency costs, and therefore have ample access to credit, which in turn stimulates investment and reinforces booms. Conversely, during recessions borrowers have fragile financial positions, high agency costs, and limited access to credit, which discourages economic activity and reinforces recession. The theory, therefore, provides a propagation mechanism through which shocks originating in the real sector are amplified by the financial system or financial intermediaries, in particular [4]. Some empirical implications of the theory have been tested by Fazzari, Hubbard, and Petersen (1988) and Gertler and Gilchrist (1993), among others.

As noted above, studies in the financial accelerator paradigm have largely tended to identify financial factors as merely enhancing or propagating mechanisms through which real disturbances affect output and economic activity. The propagation mechanism in those models hinges upon pro-cyclical agency costs that arise from asymmetric information in loan markets. The empirical macroeconomic significance of pro-cyclical agency costs has not been sufficiently investigated. Initial attempts by Williamson (1987b) and Fuerst (1995) in this regard, however, do not provide strong evidence for empirical relevance of such costs.

If financial factors are relevant to the dynamics of the real sector of the economy, one wonders why should they not be treated as potential independent *sources* of output fluctuations rather than just propagation mechanisms accelerating the effects of non-financial disturbances. As Ramey (1992, p. 191) observes, "... shocks to the banking industry are more plausible as sources of business fluctuations than shocks to the goods industry because of the central role of banks in the economy. Banking services are used by all sectors of the economy whereas, with the notable exception of oil, most goods are an input for only a fraction of other sectors". One would therefore expect shocks to the goods industry to be diversified away in the behavior of aggregate output, but not so for the banking industry. This may particularly be true for the last two decades in which surges of financial innovations have swept through all financial markets and, therefore, affected financing terms and conditions for all sectors of the economy.

The shocks that may hit the intermediation system are numerous. They include : changes in monetary policy, changes in financial regulations (e.g. changes in regulations concerning portfolio composition), shocks to public demand for intermediary liabilities (e.g. flights to quality), financial innovations (e.g. the introduction of money market certificates or new lending instruments), and finally, technical changes (computerization and electronic banking). Such shocks affect the cost and scope of the intermediation process.

In the spirit of the above argument and in view of the relative paucity of work on this account, we study financial factors as potential *sources* of output dynamics within a simple dynamic macroeconomic framework. More specifically, we investigate the impact over time on output and other major macroeconomic variables of shocks or *innovations* in financial variables, and estimate the quantitative contribution of such shocks to variations in output and other macroeconomic variables over various horizons.

A well - known framework for the analysis of the *sources* of shocks or disturbances to the economy and of the resulting dynamics in the major macroeconomic variables is the unrestricted (atheoretical) Vector Auto-Regression (VAR) approach pioneered by Sims (1972, 1980). In this approach, residuals obtained from an estimated reduced form of the system (in which each macroeconomic variable is expressed in terms of lagged values of its own and all the other variables in the system), are orthogonalized into certain "structural" disturbances which are believed to drive the underlying structural system. However, there are problems with this approach[5]. Despite the original assertion that atheoretical VAR does not impose *prior* restrictions on the model for purposes of identification, it is now well known that the approach is, in fact, based on *implicit* prior restrictions that imply a particular and *strictly recursive* structure for the economy. The conventional decomposition of the covariance matrix of the reduced form innovations into orthogonal structural disturbances is thus valid within recursive systems only, and its results depend heavily on the imposed order of recursion. But, as many economists believe, economic structures are not typically recursive. Hence, the conventional method of orthogonalization does not provide primitive time series shocks that can be interpreted as truly structural shocks both in *impulse-response* analysis and in *variance decomposition*.

Recognizing the above problem, some researchers have recently tended to make use of *explicit* economic theory to identify and estimate structural disturbances from the reduced form residuals, and thereby make it possible to discriminate among alternative hypotheses about the economy. This rather new approach has been used by Blanchard and Watson (1986), Bernanke (1986), Sims (1986), Blanchard and Quah (1989), Blanchard (1989), Shapiro and Watson (1988), Keating (1990), and Gali (1992), and has come to be known as the "Structural Vector Auto-Regression" (SVAR) approach.

Current research in the SVAR tradition uses various sets of long run and/or short run theoretical restrictions in order to recover or identify the structural model from the reduced form VAR. In the so-called *long run* SVAR models, restrictions are imposed on the long run multipliers of structural disturbances. In the *contemporaneous* SVAR models, however, restrictions are placed on the contemporaneous (immediate) effects of innovations in the variables of the system[6].

We follow the contemporaneous SVAR approach to study the role of money and credit as major financial variables in *causing* fluctuations in output and other key macroeconomic variables. To this end, we consider several competing models, each of which studies the joint dynamics of output, price, money, credit, and a policy variable (either the monetary base or an interest rate).

Our models are applied to the post-war quarterly data of both the Canadian economy and, for comparison, the United Kingdom economy. The United Kingdom is chosen rather than the United States because the UK is presumed to be subject to shocks that are different from those in North America.

The thesis is organized as follows. Chapter Two provides a detailed formal presentation of the SVAR methodology. In Chapter Three, we examine the stochastic properties of the data for later estimation. Chapter Four deals with various identification schemes and reports the estimations of the structural parameters. Chapter Five presents the dynamic behavior of both the Canadian and UK economies, as captured by the impulse-response functions and forecast error variance decompositions. We present the conclusions in Chapter Six.

CHAPTER NOTES

1. Gertler (1988) provides a fairly thorough review of this literature.

2. Keynes's theory of investment had built into it the *state of credit* which emphasized the lenders' confidence in financing the borrowers' projects; see Minsky (1975).

3. Recently, there has been a surge in literature on the role of money in output fluctuations within the competitive equilibrium paradigm. See Christiano and Eichenbaum (1992) and Fuerst (1992) for examples of such work.

4. A substantial body of literature on the so-called credit channel of monetary policy also draws on information imperfections in the credit markets.

5. A thorough critique of this approach can be found in Cooley and LeRoy (1985).

6. The classification of SVAR models into long run and short run is due to Keating (1992).

CHAPTER TWO

THE METHODOLOGY OF

STRUCTURAL VECTOR AUTOREGRESSION

The Structural Vector Autoregression (SVAR) approach has emerged in response to the shortcomings of the standard (atheoretical) Vector Autoregression (VAR). It blends the empiricism of the latter approach with theoretical priors furnished by macroeconomic theory. The SVAR approach is proving a promising vehicle for dynamic analysis of the macroeconomy.

The SVAR approach is best understood by starting with the standard VAR. After all, the SVAR approach grew as an extension and refinement of the standard VAR methodology. Therefore, in the following, we begin with a formal presentation of the standard VAR that provides us with much of the terminology and many of the statistical constructs that are being used in the SVAR approach. Then, after a detailed description of the SVAR methodology, we present theoretical asymptotic measures of sampling distribution for all the estimates embodied in the SVAR approach. Such measures are being used to establish statistical significance for the estimates in the following chapters.

The Standard Vector Auto-Regression[1]

Consider a p^{th}-order vector autoregression, denoted as VAR(p), of the form

$$x_t = C + B_1 x_{t-1} + B_2 x_{t-2} + \cdots + B_p x_{t-p} + \varepsilon_t \qquad (2.1)$$

Where $x = (x_1, x_2, \ldots, x_n)$, C denotes an (nx1) vector of constants, and B_i is an (nxn) matrix of autoregressive coefficients, for i = 1,2,...,p. The (nx1) vector ε_t is a white noise vector, that is,

$$E(\varepsilon_t) = 0$$

$$E(\varepsilon_t \varepsilon'_\tau) = \Sigma_\varepsilon \qquad \text{for } t = \tau$$

$$= 0 \qquad \text{otherwise}$$

with Σ_ε an (nxn) symmetric positive definite matrix. The process VAR(p) is taken to be covariance – stationary, which requires that all the roots of the following determinantal equation lie inside the unit circle (i.e. $|\lambda_i| < 1$ for all i):

$$\left| I_n \lambda^p - B_1 \lambda^{p-1} - B_2 \lambda^{p-2} - \cdots - B_p \right| = 0$$

where I_n is the identity matrix of dimension n, and the solution vector λ has nxp elements.

The VAR system (2.1) is efficiently and consistently estimated by the Ordinary Least Squares (OLS) method[2]. This (first stage) estimation provides us with estimates of B_i matrices and the vector of reduced form residuals that are used to calculate the Impulse-Response functions and Variance Decompositions to be discussed below.

Impulse – Response Functions

Any VAR(p) process such as (2.1) can be transformed into a convergent infinite moving average, MA(∞), of the white noise vector ε_t :

$$\begin{aligned} x_t &= \mu + \Theta_0\varepsilon_t + \Theta_1\varepsilon_{t-1} + \Theta_2\varepsilon_{t-2} + \Theta_3\varepsilon_{t-3} + \cdots \\ &= \mu + \Theta(L)\varepsilon_t \end{aligned} \tag{2.2}$$

where $\Theta(L)$ is a matrix polynomial in the lag operator L. that is.

$$\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \Theta_3 L^3 + \cdots$$

with $\Theta_0 = I_n$. an identity matrix of dimension n, and Θ_h given by

$$\Theta_h = \sum_{i=1}^{h} \Theta_{h-i} B_i \qquad \text{for } h = 1, 2, \ldots .$$

μ is the mean of x_t. The matrix Θ_h can be interpreted as the following partial derivative :

$$\Theta_h = \partial x_{t+h} / \partial \varepsilon_t' \tag{2.3}$$

That is, the row i, column j element of matrix Θ_h identifies the consequences of a one-time shock in the j^{th} variable's innovation at date t (ε_{jt}) for the value of the i^{th} variable at time t+h ($x_{i,t+h}$), holding all other innovations at all dates constant.

A plot of the row i, column j element of Θ_h ($\Theta_{i,j,h}$) for each date h is called the *impulse – response* function. It describes the response of $x_{i,t+h}$ to a one-time impulse in x_{jt} with all other variables dated t or earlier held constant.

In the standard VAR approach, the reduced form residuals from the VAR system (ε_t) are orthogonalized into a set of independent disturbances (shocks) that are the ultimate sources of dynamism in the system. Such orthogonalization amounts to triangularizing the real symmetric positive definite matrix of covariances of the reduced form residuals (Σ_ε). That is, calculating the matrix A in

$$\Sigma_\varepsilon = ADA' \qquad (2.4)$$

where A is a unique lower triangular matrix with 1's along the principal diagonal, and D is a unique diagonal matrix with positive entries along the principal diagonal.

Once the lower triangular matrix A is obtained, the vector of independent (fundamental) disturbances, denoted by u_t, is constructed from

$$u_t = A^{-1}\varepsilon_t \qquad (2.5)$$

Since ε_t is uncorrelated with its own lags or with lagged values of x, it follows that u_t is also uncorrelated with its own lags or with lagged values of x. Moreover, the elements of u_t are uncorrelated with each other :

$$\begin{aligned} E(u_t u_t') &= A^{-1}E(\varepsilon_t\varepsilon_t')A^{-1'} \\ &= A^{-1}\Sigma_\varepsilon A^{-1'} \\ &= A^{-1}(ADA')A^{-1'} \\ &= D \end{aligned}$$

Since D is a diagonal matrix by definition, the elements of u_t are mutually uncorrelated. The (j,j) element of D gives the variance of u_{jt}. In most applications the matrix D is normalized to an identity matrix (I_n) and the decomposition reduces to

$$\Sigma_\varepsilon = PP'$$

where $P = AD^{1/2}$. This is the well-known Cholesky decomposition. The matrix P differs from A in having the standard deviations of u_t along the main diagonal in place of 1's. The vector of fundamental disturbances is then defined as

$$\begin{aligned} v_t &= P^{-1}\varepsilon_t = D^{-1/2}A^{-1}\varepsilon_t \\ &= D^{-1/2}u_t. \end{aligned}$$

Therefore, a one unit increase in v_{jt} is the same as a one standard deviation increase in u_{jt}. Equation (2.5) may be rewritten as

$$\varepsilon_t = Au_t\,. \tag{2.6}$$

The above equation together with equation (2.3), allow us to formulate the responses of the vector x to a one standard deviation impulse in the variables of the vector, h periods ahead, by the following :

$$\begin{aligned} \frac{\partial x_{t+h}}{\partial u_t'} &= \frac{\partial x_{t+h}}{\partial \varepsilon_t'} \cdot \frac{\partial \varepsilon_t}{\partial u_t'} \\ &= \Theta_h A \end{aligned} \tag{2.7}$$

A plot of the (i,j) element of the matrix $\Theta_h A$ as a function of h is known as an orthogonalized impulse – response function, because it reflects response of x_{t+h} to only the orthogonal component of the reduced-form impulse ε_t

Variance Decomposition Functions

The error in forecasting a VAR h periods into the future can be identified as

$$x_{t+h} - \hat{x}_{t+h} \mid t = \varepsilon_{t+h} + \Theta_1 \varepsilon_{t+h-1} + \Theta_2 \varepsilon_{t+h-2} + \cdots + \Theta_{h-1} \varepsilon_{t+1}.$$

which reflects the accumulated impact of all the unforecastable reduced-form shocks from date t+1 to date t+h. The Mean Squared Error (MSE) of this h-period-ahead forecast is thus,

$$\begin{aligned} \mathrm{MSE}(x_{t+h} \mid t) &= E\left[(x_{t+h} - \hat{x}_{t+h} \mid t)(x_{t+h} - \hat{x}_{t+h} \mid t)'\right] \\ &= \Sigma_\varepsilon + \Theta_1 \Sigma_\varepsilon \Theta_1' + \Theta_2 \Sigma_\varepsilon \Theta_2' + \cdots + \Theta_{h-1} \Sigma_\varepsilon \Theta_{h-1}' \end{aligned} \tag{2.8}$$

The variance decomposition technique associated with VAR seeks to determine how each of the orthogonalized disturbances ($u_{1t}, u_{2t}, \ldots, u_{nt}$) contribute to this MSE. Writing equation (2.6) as

$$\varepsilon_t = Au_t = a_1 u_{1t} + a_2 u_{2t} + \cdots + a_n u_{nt}.$$

where a_j denotes the j^{th} column of the matrix A, and recalling that the u'_js are uncorrelated, we will have

$$\begin{aligned} \Sigma_\varepsilon &= E(\varepsilon_t \varepsilon_t') \\ &= a_1 a_1' \operatorname{Var}(u_{1t}) + a_2 a_2' \operatorname{Var}(u_{2t}) + \cdots + a_n a_n' \operatorname{Var}(u_{nt}) \end{aligned} \tag{2.9}$$

where $\operatorname{Var}(u_{jt})$ is the variance of u_{jt}, the (j,j) element of the diagonal matrix D in equation (2.4). Substitution of (2.9) into (2.8) gives the MSE of the h–period-ahead forecast as the sum of n terms, one arising from each of the disturbances u_{jt}:

$$\mathrm{MSE}(\hat{x}_{t+h} \mid t) = \sum_{j=1}^{n} \left\{ \operatorname{Var}(u_{jt}) \cdot \left[a_j a_j' + \Theta_1 a_j a_j' \Theta_1' + \Theta_2 a_j a_j' \Theta_2' + \cdots + \Theta_{h-1} a_j a_j' \Theta_{h-1}' \right] \right\}.$$

The contribution of the j^{th} orthogonalized innovation to the MSE of the h-period-ahead forecast would then be

$$\mathrm{Var}(u_{jt})\cdot\left[a_j a_j' + \Theta_1 a_j a_j'\Theta_1' + \Theta_2 a_j a_j'\Theta_2' + \cdots + \Theta_{h-1} a_j a_j'\Theta_{h-1}'\right].$$

The variance decomposition function for variable k, denoted by $w_{kj,h}$, gives the proportion of the MSE of the h-period-ahead forecast of variable k that is accounted for by orthogonalized innovations in variable j. It can be written as :

$$w_{kj,h} = \frac{\sum_{i=0}^{h-1} (\Theta A)^2_{kj,i}}{MSE_k(h)}$$

Structural Vector Autoregression[3]

Impulse-response and variance decomposition functions are the parts of VAR analysis that illustrate dynamic characteristics of empirical models. In the standard VAR such characterization is achieved without, apparently, resorting to any structural economic theory – hence the name " atheoretical " economics. However, as Cooley and LeRoy (1985) have extensively argued, if the Choleski decomposition technique is in fact atheoretical, the estimated shocks are not structural and will generally be linear combinations of the (true) structural disturbances. In this case, standard VAR analysis is difficult to interpret because the impulse responses and variance decompositions for the Choleski shocks will be complicated functions of the dynamic effects of all the structural disturbances. Moreover, they reject the claim that Choleski decompositions are atheoretical. The approach, as noted before, actually implies a particular economic structure that is often difficult to reconcile with most economic theories. More specifically, the mechanical orthogonalization technique, in effect, imposes a fully *recursive* contemporaneous structure on the system which is often difficult to justify.

Another troubling feature of the standard VAR is that, in general, the impulse-response and variance decomposition results are sensitive to the specific *ordering* of the variables in vector $\mathbf{x}$. The ordering of variables in the $\mathbf{x}$ vector matters because it changes the order of recursiveness in the model. In the absence of a strong prior with regard to the ordering of the variables, it becomes very difficult, in general, to interpret the dynamic behavior of any impulse-response or variance decomposition from a VAR system.

The above criticisms have encouraged the development of the so-called Structural Vector Autoregression (SVAR) approach which relies on economic theory to provide structural interpretations for the system dynamism.

The SVAR approach was initiated, almost simultaneously, by the pioneering works of Bernanke (1986), Blanchard and Watson (1986), and Sims (1986). It has been further developed by Keating (1990,1992), Gali (1992), and Giannini (1992) among others. The approach allows the researcher to use economic theory to transform the reduced form VAR model back into a system of structural equations. More specifically, it replaces the mechanical triangular decomposition of the variance-covariance matrix of the reduced-form residuals (Σ_ε) with a different decomposition built upon theoretical restrictions. These theoretical restrictions are imposed on the *contemporaneous* or *long run* relationships among the variables of the system.

To derive the relationships between the reduced form residuals and the structural disturbances, we need to start with the VAR representation of the structural model of the economy. For convenience, let the structural model be a linear dynamic simultaneous equations system such as :

$$Ax_t = C(L)x_{t-1} + Dz_t \ , \qquad (2.10)$$

where x_t is a vector of endogenous variables and z_t is a vector of exogenous variables (including residuals) with the same dimension as x_t. The elements of the square matrix, A, are the structural parameters on the contemporaneous endogenous variables, and C(L) is a p^{th} degree matrix polynomial in the lag operator L. The matrix D measures the contemporaneous responses of endogenous variables to the exogenous variables. Since observable exogenous variables are not allowed in a VAR framework, let vector z_t consist of only unobservable exogenous variables which are assumed to be disturbances to the structural equations.

The reduced form for the system in (2.10) is

$$x_t = A^{-1}C(L)x_{t-1} + A^{-1}Dz_t \, . \qquad (2.11)$$

Once the stochastic properties of the disturbance term z is specified, equation (2.11) can be represented as a VAR system. Disturbances are usually assumed to have either temporary or permanent effects[4]. In the case of temporary effects, z_t is taken to be a serially uncorrelated white noise vector, $z_t = u_t$. A VAR representation of the structural model would then be

$$\begin{aligned} x_t &= A^{-1}C(L)x_{t-1} + A^{-1}Du_t \\ &= B(L)x_{t-1} + \varepsilon_t \end{aligned} \qquad (2.12)$$

where $B(L) = A^{-1}C(L)$ is a nonlinear function of the contemporaneous and dynamic structural parameters , and $\varepsilon_t = A^{-1}Du_t$ is the vector of serially uncorrelated reduced form residuals.

Alternatively, when shocks have permanent effects, z_t is considered a unit root process, that is, $z_t - z_{t-1} = u_t$.[5] Here, z_t equals the sum of all past and present realisations of u_t. Applying the first difference operator to equation (2.12) and inserting the relationship $z_t - z_{t-1} = u_t$ into the resulting expression would give us the following VAR representation :

$$\Delta x_t = B(L)\Delta x_{t-1} + \varepsilon_t \tag{2.13}$$

with $B(L)$ and ε_t previously defined. The VAR representation (2.12) or (2.13), as we noted before, can be consistently and efficiently estimated by the ordinary least squares (OLS) method .

Contemporaneous SVAR

Equation (2.12) shows that the contemporaneous relationship between the reduced form residuals (ε_t) and the structural disturbances (u_t) is captured in the following equation :

$$\varepsilon_t = A^{-1}Du_t \tag{2.14}$$

where reduced form residuals are expressed as a linear combination of the structural disturbances. A knowledge of the parameters in the matrices A and D would enable us to retrieve the structural disturbances from the reduced form residuals. In contrast to the standard VAR approach, the contemporaneous SVAR identifies the structural parameters in A and D through imposition of theoretical restrictions on the parameters of these two matrices. Some of the restrictions are exclusion (zero) restrictions that are necessary to reduce the number of structural parameters to be less than or equal to the number of unique estimated elements of the variance-covariance matrix of the reduced fom residuals (Σ_{ε}). Using (2.12) or (2.13),

$$\begin{aligned} \Sigma_{\varepsilon} &= E(\varepsilon\varepsilon_t') = A^{-1}DE(u_t u_t')D'A'^{-1} \\ &= A^{-1}D\Sigma_u D'A'^{-1} \end{aligned} \tag{2.15}$$

where E is the unconditional expectation operator, and Σ_u is the variance –covariance matrix for the structural disturbances.

An OLS estimation of the VAR provides an estimate of Σ_{ε} that can be used with equation (2.15) to obtain estimates of A, D, and Σ_u. There are, in general, n^2 parameters in A, n^2 parameters in D, and $n(n+1)/2$ unique elements in Σ_u. That is a total of $2n^2 + n(n+1)/2$ parameters. However, the number of unique elements in Σ_{ε} is only $n(n+1)/2$. Hence, identification of the structural parameters requires at least $2n^2$ restrictions to be imposed on A, D, and Σ_u.

Usually, Σ_u is specified as a diagonal matrix, because the primitive structural disturbances are assumed to originate from independent sources. This provides $(n^2-n)/2$ restrictions on the unique elements of Σ_u. Furthermore, the diagonal elements of A are set to unity, because each structural equation is normalized on a particular endogenous variable. A further simplification typically adopted in the literature, takes D as an identity matrix, implying that each equation of the system is subject to only one structural disturbance. This leaves at least $n(n-1)/2$ additional identifying restrictions to be imposed on A. When D is not taken as an identity matrix to allow certain structural disturbances to affect more than one equation – as is the case with one of our two identifications – the remaining n(n-1)/2 restrictions must be shared between A and D matrices.

Therefore, the methodology consists of a two-step procedure. First, the reduced form VAR with sufficient lags of each variable is estimated with OLS. Next, by imposing a sufficient number of restrictions, equation (2.15) which is a nonlinear system of equations, is solved for the estimates of structural parameters.

The solution to equation (2.15) could be obtained through maximization of the likelihood function with respect to the structural parameters[6]. Bernanke (1986) has offered an alternative solution based on the General Method of Moments (GMM). This approach, which is followed in the present study, consists of equating the *sample* variance-covariance matrix of structural disturbances to that of the *population*, which follows directly from the maintained hypothesis of the GMM. More specifically, given the assumptions on Σ_u, the method entails setting the symmetric elements on either side of the main diagonal of the sample variance-covariance matrix of structural disturbances equal to zero. This produces a nonlinear system of equations of lower dimension that is solved for estimates of the structural parameters in A and D. Given the latter estimates, the variances of the structural disturbances – the diagonal elements of Σ_u – are read off the main diagonal of the sample variance-covariance matrix of the structural disturbances.

The structural parameters – the nonzero elements of A, D, and Σ_u – will generally be identified under two conditions. First, the number of estimated parameters must not exceed the number of unique elements in Σ_ε, which is an *order* condition[7]. The second condition is that the system of nonlinear equations (2.15) have at least one solution.

This is a *rank* condition that requires the matrix of partial derivatives of the distinct population covariances with respect to unknown parameters to be of full column rank[8].

For a system of 5 variables and thus 5 equations, the estimated variance-covariance matrix of reduced form residuals has 5(5+1)/2=15 unique elements. Hence, *just-identification* of the parameters in the matrix A would require exactly 10 restrictions on the off-diagonal elements of that matrix[9]. A detailed description of the contemporaneous identification schemes and structural parameters estimates of various models specified in this study appears in chapter Four.

Before turning to the measures of confidence for the SVAR estimates, a brief review of the *long run* SVAR approach is in order.

Long run SVAR

As indicated before, one could impose theoretical restrictions on the long run behavior of the structural disturbances to identify the structural parameters of the underlying system. If each shock has a permanent effect on at least one of the variables, and if the variables in x are not cointegrated, the relevant VAR to be estimated would be equation (2.13) :

$$\Delta x_t = B(L)\Delta x_{t-1} + \varepsilon_t .$$

The moving average (MA) representation of the above VAR is

$$\Delta x_t = \Theta(L)\varepsilon_t .$$

where $\Theta(L) = [\, I - B(L)L\,]^{-1}$. The response of x_t, rather than Δx_t, is usually of greater interest. Such responses can be generated from forward iterations of the following relationship :

$$x_t = x_{t-1} + \Theta(L)\varepsilon_t \ ,$$

starting at t =1 and assuming all the elements of ε at time zero and earlier to be zero. The result would be

$$x_t = x_0 + \sum_{i=0}^{t-1} \Gamma_i \varepsilon_{t-i} = x_0 + \Gamma(L)\varepsilon_t \ ,$$

where $\Gamma_i = \sum_{j=0}^{i} \Theta_j$. The response of x_{t+h} to ε_t - or the long run multiplier of the reduced form "innovation" – is Γ_i which is the sum of coefficients in $\Theta(L)$. The assumption that Δx is stationary ensures that Γ_i is a convergent sum. Γ_i is conveniently represented by $\Theta(1)$, that is, the matrix polynomial $\Theta(L)$ evaluated at $L = 1$.

Given the relationship between the reduced form residuals and the structural disturbances implied by (2.12), the structural MA representation (SMA) of VAR can be written as

$$\begin{aligned} \Delta X &= \Theta(L)\varepsilon_t \\ &= \Theta(L)A^{-1}D\,u_t \\ &= \Phi(L)\,u_t \end{aligned}$$

where the SMA parameters are now given by

$$\Phi(L) = \left[I - B(L)L \right]^{-1} A^{-1} D \ ,$$

and the long run structural multipliers by

$$\Phi(1) = [I - B(1)]^{-1} A^{-1} D. \qquad (2.16)$$

Solving (2.16) for $A^{-1}D$ and substituting the result into (2.15) yields

$$[I - B(1)]^{-1} \Sigma_{\varepsilon} [I - B(1)]^{-1'} = \Theta(1) \Sigma_u \Theta(1)' \qquad (2.17)$$

where the matrix $B(1)$ is the sum of the VAR coefficients. Equation (2.17) can be used to identify the parameters in $\Theta(1)$ and Σ_u. Estimates of the matrices on the left-hand side of this equation are obtained directly from the first stage (unconstrained) VAR. Since $\Theta(1)$ has n^2 elements and Σ_u has $n(n+1)/2$ unique elements, at least n^2 identifying restrictions must be imposed on $\Theta(1)$ and Σ_u to get the number of free parameters in these matrices at most equal to the number of unique elements in the symmetric matrix of the left-hand side of (2.17).

Several long run SVAR models have been identified and estimated with different estimation techniques. They are typically low dimension (2 or 3 variables) models mostly concerned with identification of demand versus supply shocks in output fluctuations[10].

Measures of Confidence in SVAR Estimations

The variances of the structural parameter estimates, the impulse-response functions, and the variance decompositions have usually been derived from simulation experiments like the Monte Carlo approach of Renkle (1987), or bootstrapping method of Sims (1986). Recently, the *asymptotic* distributions of the above statistical measures have been *analytically* obtained by Baillie (1987) and Lutkepohl (1989, 1990). While the resulting estimators of the variances share the unknown small sample properties with those obtained by Monte Carlo or bootstrapping methods, they reduce the computational burden to a great extent. Our calculations of the variances of the estimations are all based on the corresponding asymptotic formulas. In what follows, we describe the asymptotic variances of the structural parameters, impulse-responses, and variance decompositions drawing on Amisano and Giannini's (1997) exposition.

The Asymptotic Variances of the Contemporaneous Structural Parameters

The contemporaneous relationship between the vector of reduced form residuals and structural disturbances was already specified in equation (2.14) and is reformulated below for the special case of $D = I_n$

$$A\varepsilon_t = u_t . \qquad (2.18)$$

The structural parameters to be estimated are the nonrestricted or *free* elements of the matrix A, denoted by α. The standard errors of these estimates are analytically derived from the asymptotic *information matrix* of such parameters which enables us to write the asymptotic distribution of the estimated vector of these free parameters as

$$\hat{\alpha} \sim AN\left[\alpha, \frac{1}{T} I(\alpha)^{-1}\right], \qquad (2.19)$$

where α is the vector of free parameters in A, AN stands for asymptotic normal distribution, and T is the number of sample observations. $I(\alpha)$ is the asymptotic information matrix of α, and is obtained from the asymptotic information matrix of the *vectorized* elements of matrix A, $\mathrm{vec}A$, according to the following formula [11] :

$$I(\alpha) = S' I(\text{vecA})\, S, \qquad (2.20)$$

where S is the so called *elimination* matrix that transforms vecA into the vector of free parameters, α. The asymptotic information matrix of vecA has the form

$$I(\text{vecA}) = \left[(A^{-1} \otimes I)(I_{n^2} + ©)(A'^{-1} \otimes I) \right., \qquad (2.21)$$

where the symbol $\otimes$ represents the Kronecker multiplication, I is the identity matrix of the same order as A, I_{n^2} is the identity matrix of order n^2, and © is the *commutation* matrix that transforms the column-wise vectorization of a matrix (e.g. vecA) into a row-wise vectorization of that matrix (e.g. vecA$'$).

Substituting (2.21) into (2.20) and the result back into (2.19), gives us the variance-covariance matrix of the estimated free structural parameters as

$$\Sigma_{\alpha} = \frac{1}{T}\left\{ S' \left[(A^{-1} \otimes I)(I_{n^2} + ©)(A'^{-1} \otimes I) \right] S \right\}^{-1}.$$

The vector of variances of the estimated structural parameters would then consist of the elements of the principal diagonal of the above variance-covariance matrix, that is,

$$\text{Var}(\hat{\alpha}) = \left[\text{diag}(\Sigma_{\alpha}) \right],$$

where Var stands for variance and the operator diag refers to the principal diagonal of the relevant matrix.

For the general form of the contemporaneous relationship between the reduced form residuals and the structural shocks, equation (2.18) will change to

$$A\varepsilon_t = D\, u_t . \qquad (2.22)$$

Now, the free structural parameters that need to be estimated come from both matrices A and D. We denote these parameters as α and δ, respectively. The formulas for the standard errors of the estimated structural parameters in this case are basically the same as in the special case above, except that they are now a bit more involved.

The asymptotic distribution of the estimated vector of free parameters is now

$$\begin{pmatrix} \hat{\alpha} \\ \hat{\delta} \end{pmatrix} \sim AN\left[\begin{pmatrix} \alpha \\ \delta \end{pmatrix}, \frac{1}{T} I \begin{pmatrix} \alpha \\ \delta \end{pmatrix}^{-1}\right], \tag{2.23}$$

where the vector $\begin{pmatrix} \hat{\alpha} \\ \hat{\delta} \end{pmatrix}$ stacks together the free parameters of matrix A and D in a column vector. The asymptotic distribution of this vector can be written as

$$I\begin{pmatrix} \alpha \\ \delta \end{pmatrix} = \begin{bmatrix} S'_a & [0] \\ [0] & S'_d \end{bmatrix} I\begin{bmatrix} \mathrm{vecA} \\ \mathrm{vecD} \end{bmatrix} \begin{bmatrix} S_a & [0] \\ [0] & S_d \end{bmatrix}, \tag{2.24}$$

where S_a and S_d are the elimination matrices associated with vecA and vecB, the vectorized elements of the matrices A and D, respectively. [0] is a zero matrix of appropriate dimensions. $I\begin{pmatrix} \alpha \\ \delta \end{pmatrix}$, the asymptotic information matrix of the vectorized elements A and D, is obtained from

$$I\begin{bmatrix} \mathrm{vecA} \\ \mathrm{vecD} \end{bmatrix} = \begin{bmatrix} K^{-1} \otimes D'^{-1} \\ -(I \otimes D'^{-1}) \end{bmatrix} (I_{n^2} + ©) \left[(K'^{-1} \otimes D^{-1}) \;\; -(I \otimes D^{-1}) \right], \tag{2.25}$$

where $K = D^{-1}A$, the first square bracket on the right-hand side of the equation is a vertical stacking of the two constituent matrices, and the last square bracket on the same side is a horizontal stacking of the two given matrices. $\otimes$, ©, I, and I_{n^2} are defined as before.

Sequential substitution of (2.25) into (2.24) and the latter into (2.23) allows us to write the estimated asymptotic variance-covariance matrix of estimated structural parameters as follows

$$\Sigma_{\binom{\alpha}{\delta}} = \frac{1}{T}\left\{ \begin{bmatrix} S'_{\alpha} & [0] \\ [0] & S'_{d} \end{bmatrix} \begin{bmatrix} K^{-1} \otimes D'^{-1} \\ -(I \otimes D'^{-1}) \end{bmatrix} (I_{n^2} + ©) \left[(K'^{-1} \otimes D^{-1}) \quad -(I \otimes D^{-1}) \right] \begin{bmatrix} S_{\alpha} & [0] \\ [0] & S_{d} \end{bmatrix} \right\}^{-1}$$

The vector of variances of the estimated structural parameters is, once again, calculated as the elements of the main diagonal of the above variance-covariance matrix. Therefore,

$$\mathrm{Var}\begin{pmatrix} \bar{\alpha} \\ \bar{\delta} \end{pmatrix} = \left[\mathrm{diag}(\Sigma_{\binom{\alpha}{\delta}}) \right],$$

with Var and diag as defined before.

The Asymptotic Variances of the Impulse-Responses

Given the relationship between the vector of reduced form residuals and the vector of structural disturbances as specified in (2.18) above, the structural moving average (SMA) representation of the autoregressive (VAR) system (2.12) would be

$$x_t = \Theta(L)\varepsilon_t = \Theta(L)A^{-1}u_t$$

$$= \Phi(L)\, u_t$$

$$= \sum_{i=0}^{\infty} \Phi_i u_{t-i}$$

where $\Phi(L) = \Theta(L)A^{-1}$ is a matrix polynomial in the lag operator with $\Phi_0 = A^{-1}$ and Φ_i given by

$$\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} B_j \ .$$

As before, B_j's are the coefficient matrices of the autoregressive system. Now, using the following notations

$$\phi_i = \operatorname{vec} \Phi_i \qquad \phi_i \ \text{is}\ n^2 \times 1$$

$$\phi_h = \operatorname{vec}\left[\Phi_0, \Phi_1, \cdots, \Phi_h\right] \quad \phi_h \ \text{is}\ [(n+1)\,n^2 \times 1] \ , \tag{2.26}$$

$$\pi = \operatorname{vec} \Pi = \operatorname{vec}\left[B_1, B_2, \cdots, B_p\right]$$

the asymptotic distribution of the estimated vector of impulse-responses up to horizon h is shown by Lutkepohl (1989) to be

$$\phi_h \sim AN\left[[0]\, ,\ \Sigma(h)\right] \ , \tag{2.27}$$

where, again, AN stands for asymptotic normal, [0] is a vector of zeros, and $\Sigma(h)$ is an $(h+1)n^2 \times (h+1)n^2$ matrix of the variance-covariance of the impulse-response coefficients with the ii^{th} $n^2 \times n^2$ block

$$\Sigma(h)_{ii} = G_i \Sigma_\pi G_i' + (I_n \otimes J\beta' J')\Sigma(0)(I_n \otimes J\beta' J')' \tag{2.28}$$

where the G_i matrices are of $n^2 \times n^2 p$ order (p is the order of autoregression) such that

$$\begin{aligned} G_0 &= [\,0\,] \\ G_i &= \sum_{k=0}^{i-1}\left\{\left[\Phi_0' J(\beta')^{i-1-k}\right] \otimes J\beta^k J'\right\} \quad \text{for } i > 0 \end{aligned} \tag{2.29}$$

The matrices β and J in (2.28) and (2.29) are defined as

$$\beta = \begin{bmatrix} B_1 & B_2 & \cdots & B_{p-1} & B_p \\ I_n & 0 & \cdots & 0 & 0 \\ 0 & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & I_n & 0 \end{bmatrix} \qquad (np \times np)$$

$$J = \begin{bmatrix} I_n & 0 & \cdots & 0 \end{bmatrix} \qquad (n \times np) \qquad (2.30)$$

where I_n and 0 are identity and zero matrices, respectively, of the appropriate dimensions.

Σ_π is the estimated variance-covariance matrix of the vector π, the vectorized elements of the autoregressive coefficients (Π), and is calculated from

$$\Sigma_\pi = Q^{-1} \otimes \Sigma_\varepsilon \; . \qquad (2.31)$$

where Q is a positive definite matrix defined as

$$Q = \underset{T \to \infty}{\text{plim}} \; \frac{XX'}{T}$$

with X being the matrix of the lagged observations of all the variables in the VAR system which has dimensions of $np \times T$.

Finally, $\Sigma(0)$ in (2.28) is the estimated variance-covariance matrix of the impulse-response coefficients in the first (current) period and is obtained from the following formula

$$\Sigma(0) = \left(A'^{-1} \otimes A^{-1}\right)\Sigma_a\left(A^{-1} \otimes A'^{-1}\right).$$

Σ_a in the above equation is, in turn, calculated from

$$\Sigma_a = S\ I(\tilde{\alpha})^{-1}S'$$

with the information matrix $I(\alpha)$ and elimination matrix S previously defined in (2.19) and (2.20) above.

The variances of the impulse-response coefficients for any particular horizon are eventually read off the main diagonal of the corresponding block of the $\Sigma(h)$ matrix. The variances of the impulse-responses are , therefore, calculated as

$$\mathrm{Var}(\Phi_i) = \left[\mathrm{diag}(\hat{\Sigma}(h)_{ii})\right]. \qquad (2.32)$$

For the more general contemporaneous relationship between the reduced form residuals and the structural disturbances given in (2.22), the SMA representation of the system is

$$\begin{aligned} x_t &= \Theta(L)\varepsilon_t = \Theta(L)A^{-1}D\,u_t \\ &= \Phi(L)\,u_t \\ &= \sum_{i=0}^{\infty}\Phi_i u_{t-i} \end{aligned}$$

with $\Phi_0 = A^{-1}D$ and Φ_i as defined earlier. The asymptotic distribution of the estimated vector of impulse-responses would be the same as in (2.27), except that $\Sigma(0)$ in (2.28) is now of the following form

$$\Sigma(0) = (K'^{-1} \otimes K^{-1})\left[I \otimes D^{-1} \quad -(A'D^{-1} \otimes D^{-1})\right]\Sigma_{ad}\begin{bmatrix} I \otimes D'^{-1} \\ -(D^{-1}A \otimes D'^{-1}) \end{bmatrix}(K^{-1} \otimes K'^{-1}).$$

where, again, $K = D^{-1}A$ and Σ_{ad} is defined as

$$\Sigma_{ad} = \begin{bmatrix} S_a & 0 \\ 0 & S_d \end{bmatrix} \left\{ I \begin{pmatrix} \alpha \\ \delta \end{pmatrix} \right\}^{-1} \begin{bmatrix} S_a' & 0 \\ 0 & S_d' \end{bmatrix} .$$

with $I\begin{pmatrix} \alpha \\ \delta \end{pmatrix}$, S_a, and S_d as defined in (2.24) above. The estimated asymptotic variances of the impulse-responses are obtained upon substitution of the relevant estimated parameter values with their true values in the variance equation (2.32).

The Asymptotic Variances of the Forecast Error Variance Decompositions

The proportion of the h-step ahead forecast error variance of variable k, accounted for by innovations in variable j, denoted by $w_{kj,h}$, was shown to be

$$w_{kj,h} = \sum_{i=0}^{h-1} \Phi^2_{kj,i} \Big/ MSE(h)$$

$$= \sum_{i=0}^{h-1} (e_k' \Phi_i e_j)^2 \Big/ MSE(h)$$

where as before, $\Phi_{kj,h}$, is the kjth element of Φ_i, e_k is the kth column of I_n, and

$$MSE_k(h) = \sum_{i=0}^{h-1} e_k' \Phi_i \Sigma_\varepsilon \Phi_i' e_k .$$

is the mean squared error (forecast error variance) of a h-step ahead forecast of variable k.

The asymptotic distribution of the estimated variance decompositions, $\hat{w}_{kj,h}$, is shown by Lutkepohl (1990) to be[12]

$$\hat{w}_{kj,h} \sim AN\left[w_{kj,h} , \sigma^2_{w_{kj,h}} \right] \qquad k,j = 1, \dots, n; \quad h = 1, 2, \dots$$

where $\sigma^2_{w_{kj,h}}$ is the variance of $w_{kj,h}$ and is defined as

$$\sigma^2_{w_{kj,h}} = \frac{1}{T}(d_{kj,h} \Sigma_\pi d'_{kj,h} + \bar{d}_{kj,h} \Sigma_\sigma \bar{d}'_{kj,h})$$

Σ_π has already been defined in (2.31) and Σ_σ is the variance-covariance matrix of the vectorized lower-triangular elements of the matrix Σ_ε, that is, σ = vech(Σ_ε).[13] $d_{kj,h}$ and $\bar{d}_{kj,h}$ are obtained from the following formulas

$$d_{kj,h} = 0 \qquad \text{for } h = 1$$

$$\begin{aligned} d_{kj,h} = 2\sum_{i=1}^{h-1}\Big[& MSE_k(h)(e'_k \Phi_i A^{-1} e_j)(e'_j A'^{-1} \otimes e'_k) G_i \\ & - (e'_k \Phi_i A^{-1} e_j)^2 \sum_{m=1}^{h-1} (e'_k \Phi_m \Sigma_\varepsilon \otimes e'_k) G_m \Big] \Big/ MSE_k(h)^2 \qquad \text{for } h > 1 \end{aligned} \tag{2.33}$$

$$\begin{aligned} \bar{d}_{kj,h} = \sum_{i=0}^{h-1}\Big[& 2MSE_k(h)(e'_k \Phi_i A^{-1} e_j)(e'_j \otimes e'_k \Phi_i) H \\ & - (e'_k \Phi_i A^{-1} e_j)^2 \sum_{m=0}^{h-1} (e'_k \Phi_m \otimes e'_k \Phi_m) D_k \Big] \Big/ MSE_k(h)^2 \qquad \text{for } h = 1, 2, \dots \end{aligned} \tag{2.34}$$

The G_i matrix in the equation (2.33) consists of the partial derivatives of the moving average coefficients with respect to the autoregressive coefficients in the VAR, that is,

$$G_i = \partial \operatorname{vec}(\Phi_i) / \partial \pi' = \sum_{m=0}^{i-1} J(\beta')^{i-1-m} \otimes \Phi_m ,$$

with π defined in (2.26), and J and β as defined in (2.30). The matrix H in the equation (2.34) contains the partial derivatives of the vectorized elements of the structural matrix A^{-1} with respect to the vectorized unique elements of the matrix Σ_{ε}. Therefore,

$$H = \partial \, vec(A^{-1}) / \partial \sigma' = L'_n \left[L_n (I_{n^2} + ©) (A^{-1} \otimes I_n) L'_n \right]^{-1}$$

where L_n is the elimination matrix of dimension $[n(n+1)/2 \times n^2]$ that transforms the vectorized elements of a symmetric matrix to a vector consisting of the unique elements of that matrix.

Finally, the matrix D_k in (2.34) is a duplication matrix that transforms the vectorized unique elements of a symmetric matrix to a vector made up of all the elements of that matrix.

Once the estimated parameters are plugged into equation for $\sigma^2_{w_{k,i,h}}$, the estimated asymptotic variances of the variance decompositions ($\hat{\sigma}^2_{w_{k,i,h}}$) would be obtained.

CHAPTER NOTES

1. This section borrows from Hamilton's (1994) presentation of the approach.
2. Zellner (1962) has shown that when all the explanatory variables of a simultaneous system of regression equations are the same, the OLS is just as efficient and consistent as other simultaneous methods.
3. We have drawn on Keating (1992) for presentation of this approach.
4. Autoregressive shocks can also be accommodated within an expanded VAR, without having any effect on the identification procedure of the structural parameters.
5. The unit root could also result from parameters in the dynamic structural model.
6. See Hamilton (1992), page 332.
7. In the case of just-identification, the number of estimated parameters must be exactly equal to the number of unique covariances in Σ_{ε}, that is, n(n+1)/2, where n is the number of variables in x_t.
8. See Hamilton (1992), page 334.
9. Five of the unique elements of Σ_{ε} are needed for identification of the variances of the structural disturbances.
10. See, for example, Shapiro and Watson (1986), Blanchard and Quah (1989), and Gali (1992).
11. A matrix is vectorized by stacking its columns one after another to obtain a column vector.

12. A more compact version of these relationships is presented in Amisano and Giannini (1997). We use their version to calculate the asymptotic standard errors of the variance decompositions.

13. The operator vech varies from vec in that it only stacks the elements on and below the main diagonal from each column of the matrix. This operator is used for symmetric matrices.

CHAPTER THREE

STOCHASTIC PROPERTIES OF THE DATA

Before embarking on the specification of the models and identification and estimation of the structural parameters and other statistics, we need to examine the stochastic properties of the sample data to make sure that our VAR systems are specified properly.

When the individual time series in the VAR process are all stationary, the system as whole will be stationary, for each of the equations in the system is merely a linear combination of stationary variables. However, in case one or more of the series are non-stationary, stationarity of the system requires suitable transformation of the series.

We consider two classes of models each of which consists of five variables presumed to capture the macroeconomic behavior of the economy. In each class, the joint dynamics of output, price, money stock, credit, and a monetary policy variable is studied. For the first class, the monetary policy variable is the monetary base (b). Therefore, the models in this class are referred to as "monetary-base" models (or class-B models). The policy variable in the second class of models is the interest rate (r) . Hence, such models are referred to as "interest-rate" models (or class-R models). The models in each class differ in terms of the particular credit measure included. We work with three narrow to broad measures of bank credit. This makes for three models in each of the two classes. For ease of reference, we label the monetary-base models as B1, B2, and B3, where the numerical modifiers correspond to narrow, semi-broad, and broad measures of bank credit, respectively. Similarly, the interest-rate models are labeled as R1, R2, and R3.

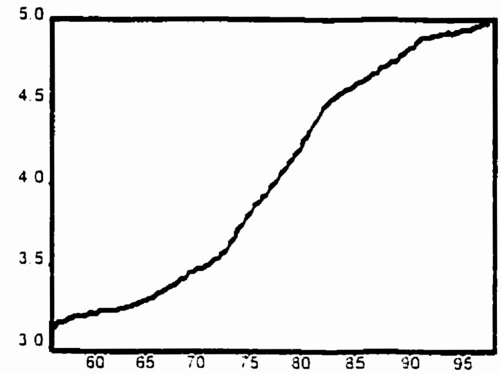
We have focused on bank credit because banks play a major role in financial intermediation both in Canada and the United Kingdom, and they are considered "special" by many borrowers who find alternative sources of borrowing more costly[1].

Our time series for both Canada and the United Kingdom (U.K.) are seasonally adjusted quarterly observations on real gross domestic product (y), the consumer price index (p), the monetary base (b), nominal short term interest rate (r) narrow money stock (m), and three measures of credit, namely, bank credit to persons (c1), bank credit to businesses (c2), and total bank credit (c3). The short term interest rate for Canada is the bank rate, but for the United Kingdom it is the rate on three- month treasury bills. The variables are all measured in natural logarithms, except for the rates of interest that are in percentages. Our sample covers the period 1956I to 1997II for Canada, and the period 1967I to 1995IV for the U.K. See Appendix I at the end of chapter for details and sources of data.

The first step in the examination of the properties of the data is the simple visual inspection of the time paths of the relevant variables. We have plotted the series for both countries in Figures 3.1 and 3.2 below.

Figure 3.1 : Plots of Canadian Time Series

3.1a - Log of real output (y)



3.1b - Log of consumer price index (p)

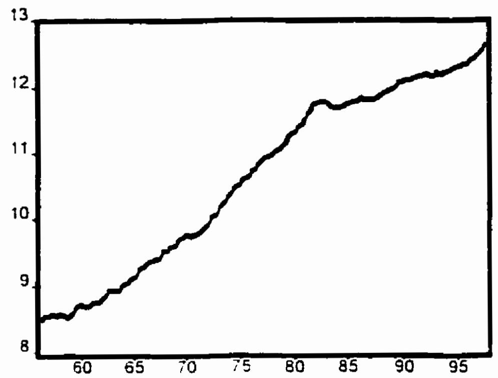
3.1c - Log of monetary base (b)

3.1d - Log of money stock (m)

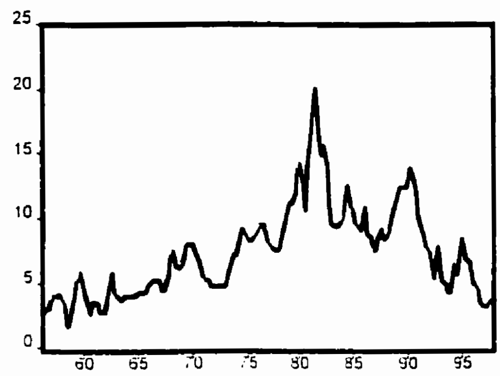
3.1e - Log of bank credit to persons (c1)

3.1f - Log of bank credit to business (c2)

Figure 3.1 continued



3.1g - Log of total bank credit (c3)



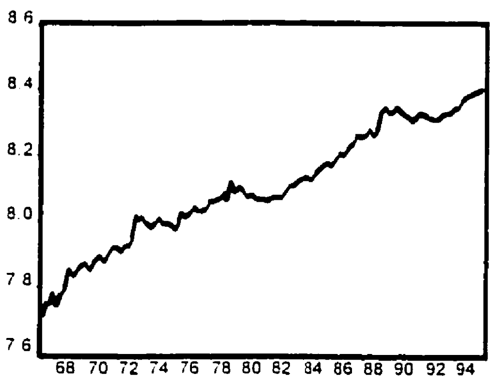
3.1h - The bank rate in percentage (r)

As we can see from Figure 3.1, the recessions Of 1981-83 and 1990-91 are reflected in the time paths of all the series. Real output (y), monetary base (b), money stock (m), and credit measures (c1, c2, and c3) stagnate or even drop during these episodes. Prices continue to grow at, more or less, the same rate in the first recession, but taper off during the second. Overall the series, with the exception of the bank rate, show rising trends over the sample period. The bank rate (r) shows a rising trend up to 1986, thereafter it shows a declining trend. Real output and money stock seem to have a single deterministic linear trend. The remaining series, however, do not exhibit deterministic trends. The plots clearly indicate that none of the series are stationary. Whether they are stationary around a linear trend can not be told from the plots themselves.

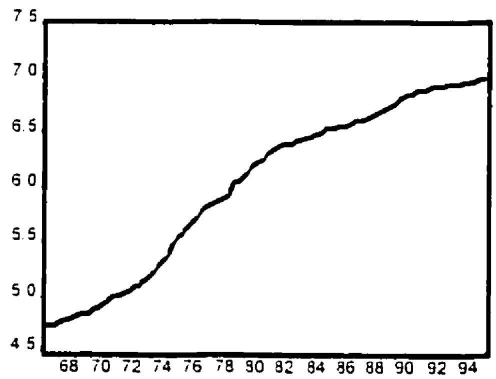
For the U.K., Figure 3.2 reflects rising trends throughout the sample period for all the series but the interest rate. Real output and credit measures seem to have linear trends, whereas the other series are more likely to contain stochastic trends. The interest rate follows a pattern very similar to that of the bank rate in Canada. Despite wide fluctuations, it appears to trend upward till the late eighties where it reverts to a sharply declining trend.

The overall picture here is the same as that for the Canadian series. No time series appears to be stationary, and the nature of the trend component can not be revealed by the naked eye.

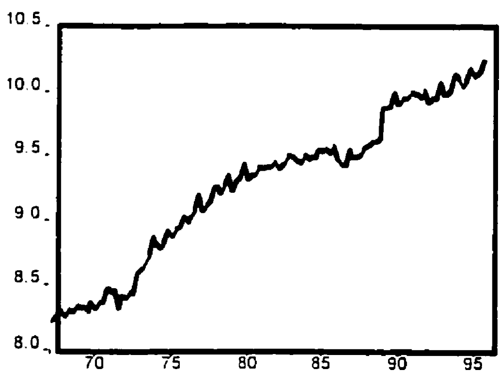
Figure 3.2 : Plots of the U.K. Time Series



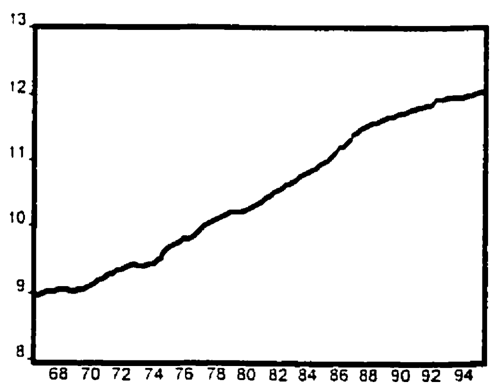
3.2a - Log of real output (y)



3.2b - Log of consumer price index (p)

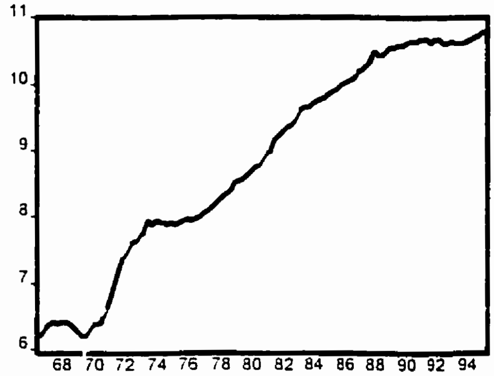


3.2c - Log of monetary base (b)

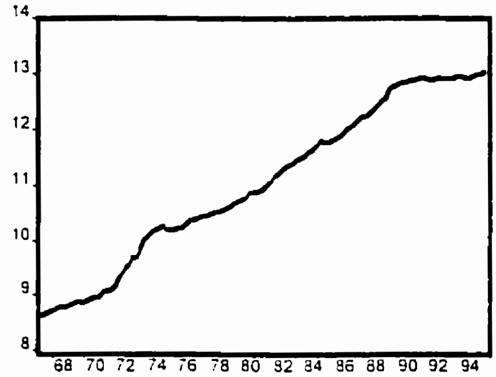


3.2d - Log of money stock (m)

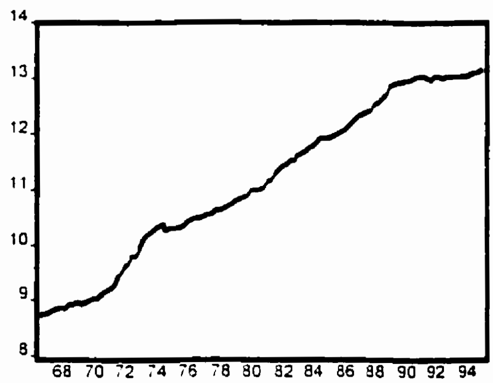
Figure 3.2 continued



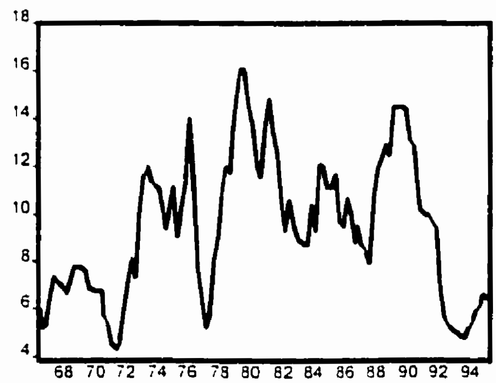
3.2e - Log of bank credit to consumers (c1)



3.2f - Log of bank credit to business (c2)



3.2g - Log of total bank credit (c3)



3.2h - Treasury bill rate in percentage (r)

Although the above visual examinations are useful in shedding some light on the stochastic properties of the time series involved, such properties must be formally examined by the relevant statistical tests. The existing statistical tests enable us to determine if a series is stationary, and also check for the degree of integration or the number of unit roots in the case of non-stationary series. The results of a number of such tests for our time series are presented in the following section.

Univariate Unit Root Tests

To determine whether our variables are stationary around deterministic or stochastic trends, we have done two standard unit root tests on the series. Panel (a) of Table 3.1 contains the results of the Augmented Dicky-Fuller, ADF(τ), and the non-parametric Phillips-Perron tests, PP(τ), for the Canadian time series in levels[2]. The null hypothesis of a unit root in series is tested against the alternative hypothesis of stationarity around a deterministic linear trend[3]. The number of lags for the ADF(τ) test was chosen on the basis of the Durbin-Watson and Schwartz criteria to purge serial correlation to the extent possible. For the PP(τ) test, the truncation lag was set at 4 as suggested by Newey-West[4].

Table 3.1 : Unit root tests for Canadian series

(a) – series in levels

Variable	ADF(τ)	PP(τ)
real output (y)	-0.32	-0.30
price index (p)	-1.89	-1.45
monetary base (b)	-0.76	-0.16
bank rate (r)	-2.14	-2.16
money stock (m)	-2.40	-2.41
bank credit to persons (c1)	-0.08	0.03
bank credit to businesses (c2)	-1.56	-1.14
bank credit to persons and businesses (c3)	-1.37	-0.75

Note: The asymptotic critical values at 5 and 10 percent significance are –3.43 and –3.14, respectively. The null hypothesis of a unit root is rejected if the test statistic exceeds (in absolute terms) the critical value.

It is clear from panel (a) that the various test statistics cannot reject the null hypothesis of a unit root in all of the series in levels, even at 10 percent level of significance[5].

To see if the non-stationary series are first difference stationary, that is, they have only one unit root, we have repeated the same tests for the first differences of such variables. The latter results are reported in panel b of Table 3.1. In this case, the alternative hypothesis is that of stationarity around a constant term. The results strongly indicate that all the series are first-difference stationary. In fact, the null of non-stationarity is rejected at 1 percent significance level for all the variables.

Table 3.1 : Unit root tests for Canadian series

(b) – series in first differences

Variable	ADF(τ)	PP(τ)
real output (y)	-10.00	-10.13
price index (p)	-3.48	-4.10
monetary base (b)	-4.74	-7.18
bank rate (r)	-9.19	-9.98
money stock (m)	-9.49	-9.57
bank credit to persons (c1)	-4.99	-9.69
bank credit to businesses (c2)	-5.37	-6.81
bank credit to persons and businesses (c3)	-4.37	-6.72

Note: The asymptotic critical values at 1 and 5 percent significance are –3.47 and –2.88, respectively. The null hypothesis of a unit root is rejected if the test statistic exceeds (in absolute terms) the critical value.

Table 3.2 reports the results of the same exercise as in Table 3.1 for the United Kingdom. Again, the unit root tests for the series in levels are presented in panel a, and those for the first differences in panel b.

Table 3.2 : Unit root tests for the U.K. series

(a) – series in levels

Variable	ADF(τ)	PP(τ)
real output (y)	-2.99	-2.91
price index (p)	-0.86	0.42
monetary base (b)	-1.93	-2.52
treasury bill rate (r)	-2.69	-2.46
money stock (m)	-1.72	-1.89
bank credit to persons (c1)	-2.09	-0.82
bank credit to businesses (c2)	-1.20	-0.84
bank credit to persons and businesses (c3)	-2.18	-0.72

Note: The asymptotic critical values at 5 and 10 percent significance are −3.43 and −3.14, respectively. The null hypothesis of a unit root is rejected if the test statistic exceeds (in absolute terms) the critical value.

Here, too, the results in panel (a) strongly suggest the presence of unit roots in all the series in level form. The null hypothesis of a unit root can not be rejected even at the modest significance level of 10 percent.

As was the case with the Canadian data, panel (b) of Table 3.2 suggests that the U.K. series all stationary in first differences at the stringent significance level of 1 percent.

Table 3.2 : Unit root tests for the U.K. series

(b) – series in first differences

Variable	ADF(τ)	PP(τ)
real output (y)	-7.21	-14.72
price index (p)	-4.23	-6.75
monetary base (b)	-4.11	-15.96
treasury bill rate (r)	-6.85	-8.48
money stock (m)	-4.42	-8.74
bank credit to persons (c1)	-3.75	-6.55
bank credit to businesses (c2)	-4.91	-7.48
bank credit to persons and businesses (c3)	-3.76	-7.21

Note: The asymptotic critical values at 1 and 5 percent significance are -3.47 and -2.88, respectively. The null hypothesis of a unit root is rejected if the test statistic exceeds (in absolute terms) the critical value.

Cointegration Tests

Testing for the stationarity of the time series is necessary, but not sufficient, for adequate specification of the VAR models. In addition, we must check for cointegration among the variables of the system. If the variables of the system turn out to be cointegrated[6], their joint process could be stationary. In this case, a modified version of VAR, namely, the Vector Error Correction (VEC) model must be specified. The VEC uses the long-run relationships among the levels of the variables to obtain more efficient estimates of short-run dynamic relationships among them.

The first cointegration test applied to our various sets of variables is the standard Engle-Granger test, which in effect, performs the univariate unit root tests on the residuals from an unlagged linear regression relationship among the variables. The results of this test for various sets of variables are reported in Tables 3.3 and 3.4 for Canada and the U.K., respectively.

Table 3.3 : Engle-Granger Cointegration tests for Canada

Model (Variable set)	ADF(τ)	PP(τ)
Model B1 : y, p, b, m.c1	-3.55	-4.98
Model B2 : y, p, b, m.c2	-1.47	-1.52
Model B3 : y, p, b, m.c3	-1.33	-1.61
Model R1 : y, p, r, m.c1	-3.40	-4.43
Model R2 : y, p, r, m.c2	-1.19	-1.32
Model R3 : y, p, r, m.c3	-1.55	-1.80

Note : The critical value at 5 percent significance is –4.42 according to Davidson and Mackinnon (1993).

The results of the Engle-Granger cointegration tests for Canada do not support the presence of cointegration among the variables for all the six models (variable sets) as far as ADF(τ) is concerned. There is, however, some evidence of cointegration for the first and fourth variable sets (models B1 and R1) according to the PP(τ) test. The ADF(τ) test cannot reject the null hypothesis of no cointegration among the variables of these two groups at 5 percent level of statistical significance. These results should be treated cautiously as we will see below.

Table 3.4 : Engle-Granger Cointegration tests for the U.K.

Model (Variable set)	ADF(τ)	PP(τ)
Model B1 : y, p, b, m,c1	-3.93	-4.37
Model B2 : y, p, b, m,c2	-3.75	-4.27
Model B3 : y, p, b, m,c3	-3.77	-4.28
Model R1 : y, p, r, m,c1	-3.07	-3.61
Model R2 : y, p, r, m,c2	-3.21	-3.88
Model R3 : y, p, r, m,c3	-3.17	-3.82

Note :. The critical value at 5 percent significance is -4.42 according to Davidson and Mackinnon (1993).

The results for the U.K. are unanimous. Neither the ADF(τ) nor the PP(τ) tests support cointegration among the variables of any of the six models at 5 percent significance level. In other words, there seems to be little evidence of cointegration among the variables in any of the variable sets. However, the proximity of test statistics, especially the PP(τ)'s for the monetary-base models, to the critical value together with the low power of such tests should warn us not to rely much on these results.

We have also performed two multivariate cointegration tests for the above sets of variables. These tests are based on Johansen's (1988) maximum likelihood procedures and are known as *trace* and *maximal eigenvalue* tests. The summary results of such tests for Canada are presented in table 3.5, and those for the United Kingdom in Table 3.6 below. The complete tests results are reported in Tables 3A.1 and 3A.2 in Appendix II of this chapter.

Table 3.5 : Summary of Johansen Cointegration Tests for Canada

Model : Variable set	Trace test	Max. eigenvalue test
B1 : (y, p, b, m, c1)	1	1
B2 : (y, p, b, m, c2)	2	2
B3 : (y, p, b, m, c3)	2	0
R1 : (y, p, r, m, c1)	3	2
R2 : (y, p, r, m, c2)	3	3
R2 : (y, p, r, m, c2)	3	3

Note : The entries in the table are the numbers of cointegrating vectors (ranks) at 5% significance level.

Table 3.6 : Summary of Johansen Cointegration Tests for the U.K.

Model : Variable set	Trace test	Max. eigenvalue test
B1 : (y, p, b, m, c1)	5	1
B2 : (y, p, b, m, c2)	2	1
B3 : (y, p, b, m, c3)	2	1
R1 : (y, p, r, m, c1)	2	1
R2 : (y, p, r, m, c2)	1	1
R2 : (y, p, r, m, c2)	1	1

Note : The entries in the table are the numbers of cointegrating vectors (ranks) at 5% significance level.

It can be gleaned from the tests in Table 3.5 that the variables in each of the six groups are cointegrated, although the number of cointegrating vectors vary from group to group and from one test to the other. In a majority of cases, the results from the *trace* tests, indicate the existence of a higher number of cointegrating relationships than the *Max. eigenvalue* tests. Johansen and Juselious (1990), however, suggest that *Max. eigenvalue* test has greater power than the *trace* test. Thus, by a conservative account, the results in Table 3.5 do support the existence of one to two cointegrating vectors for each of the variable groups.

The Johansen cointegration tests reported in Table 3.6 above show a bit different for the U.K. time series especially for the first group of variables. For the first variable group, the *trace* test indicates five cointegration relationships. The series in this group, therefore, are suggested to be stationary in levels at 5 percent significance, a result that is not supported by the unit root tests on these same variables. In fact, the results in Table 3.2 panel (a) strongly support the existence of a unit root in all these five variables against the alternative hypothesis of stationarity around a linear trend. The *Max. eigenvalue test,* however, suggests only one cointegration vector. For the rest of the variable groups, we have basically the same results as for Canada. That is, the *trace* test suggests either one or two cointegrating vectors, whereas the *Max. eigenvalue* test supports only one cointegartion vector.

The multivariate cointegration results reported in Tables 3.5 and 3.6 above, however, contradict our previous results based on the univariate Engle-

Granger cointegration tests that did not support cointegration among the same group of variables, both for Canada and the U.K[7]. The apparent inconsistency might be blamed, in part, on the low power of the univariate cointegration tests. As Davidson and MacKinnon (1993) indicate, these tests are severely biased against rejecting the null hypothesis when they are used with seasonally adjusted data.

When there is evidence of cointegration among the variables of a VAR system, such information can be incorporated into the VAR system. Therefore, as mentioned above, a modified version of VAR which is known as the Vector Error Correction (VEC) model must be estimated. In the VEC model the lagged cointegration vector(s) are added to the list of explanatory terms on the right-hand side of the VAR equations that are specified in first differences. The cointegration vectors are presumed to be the long run "equilibrium" relationships among the variables. Upon closer examination of the Johansen cointegration vectors, however, we have found in most cases that none of the coefficients in the cointegration relationships are statistically significant. This could possibly be due to a high degree of collinearity among the variables.

In view of the ambiguity over the existence of cointgration among the variables of our various models, we experimented with both the VAR and the VEC specifications of all our models. However, the estimation results from the VEC versions of models were too implausible to believe. That is why we have focused on the VAR specification, and present the estimation results only for our VAR models in the next two chapters.

As a further step to make sure that our various VAR systems are covariance-stationary, we have tested the stability of these systems in the following section.

Testing the Stability of the VAR systems

A systemic examination of the covariation of the variables in a VAR system is achieved by observing the characteristic roots of the determinantal equation introduced on page 2 in the previous chapter. As indicated there, covariance-stationarity of a multivariate process requires all the characteristic roots to be within the unit circle. We have calculated these roots for the first difference specification of each of our six VAR systems that consist of the six variable groups specified in Tables 3.5 and 3.6 above. The results for Canada are presented in Table 3.7, and those for the U.K. in Table 3.8. There are np characteristic roots in each system, where n is the number of variables and p is the lag order of the system. With five variables and three lags in each model, there are fifteen characteristic roots for each model.

Table 3.7 : Characteristic roots of the determinantal equations of the "monetary-base" VAR models (in first differences) for Canada

B1	B2	B3
-0.487	-0.327	-0.371
-0.296 + 0.6i	-0.303 – 0.607i	-0.303 + 0.618i
-0.296 – 0.6i	-0.303 + 0.607i	-0.303 – 0.618i
-0.23 – 0.525i	-0.207 + 0.31i	-0.244 – 0.36i
-0.23 + 0.525i	-0.207 – 0.31i	-0.244 + 0.36i
-0.179 – 0.258i	-0.17 + 0.37i	-0.145 – 0.549i
-0.179 + 0.258i	-0.17 – 0.37i	-0.145 + 0.549i
-0.046 + 0.707i	-0.15 + 0.55i	-0.092 – 0.285i
-0.046 - 0.707i	-0.15 – 0.55i	-0.092 + 0.285i
0.235 – 0.282i	-0.02	0.119
0.235 + 0.282i	0.582	0.508 – 0.11i
0.526	0.635 – 0.23i	0.508 + 0.11i
0.684 + 0.179i	0.635 + 0.23i	0.683 + 0.176i
0.684 - 0.179i	0.675	0.683 – 0.176i
0.897	0.899	0.898

Table 3.8 : Characteristic roots of the determinantal equations of the "interest-rate" VAR models (in first differences) for Canada

(b) Models including the bank rate		
R1	R2	R3
-0.366 + 0.624i	-0.363 – 0.622i	-0.391 – 0.434i
-0.366 – 0.624i	-0.363 + 0.622i	-0.391 + 0.434i
-0.339 – 0.317i	-0.363 - 0.431i	-0.362 – 0.627i
-0.339 + 0.317i	-0.363 + 0.431i	-0.362 + 0.627i
-0.243 – 0.510i	-0.258 – 0.411i	-0.240 + 0.390i
-0.243 + 0.510i	-0.258 + 0.411i	-0.240 – 0.390i
-0.053 + 0.705i	-0.162 – 0.565i	-0.157 + 0.570i
-0.053 - 0.705i	-0.162 + 0.565i	-0.157 – 0.570i
0.047 – 0.500i	0.144 – 0.441i	0.165 – 0.503i
0.047 + 0.500i	0.144 + 0.441i	0.165 + 0.503I
0.443 + 0.307i	0.494	0.574
0.443 - 0.307i	0.594 – 0.351i	0.578 – 0.378i
0.668 - 0.186i	0.594 + 0.351i	0.578 – 0.378i
0.668 + 0.186i	0.770	0.762
0.894	0.887	0.876

Table 3.9 : Characteristic roots of the determinantal equations of the "monetary-base" VAR models (in first differences) for the U.K.

B1	B2	B3
-0.808	-0.829	-0.835
-0.463 + 0.205i	-0.516 – 0.236i	-0.462
-0.463 – 0.205i	-0.516 + 0.236i	-0.441 – 0.223i
-0.409	-0.268 + 0.518i	-0.441 + 0.223i
-0.262 + 0.521i	-0.268 – 0.518i	-0.24 + 0.514i
-0.262 – 0.521i	-0.204	-0.24 – 0.514i
0.012 + 0.799i	0.003 – 0.795i	-0.0008 + 0.797i
0.012 – 0.799i	0.003 + 0.795i	-0.0008 – 0.797i
0.069 + 0.539i	0.031 – 0.594i	0.069 – 0.559i
0.069 – 0.539i	0.031 + 0.594i	0.069 + 0.559i
0.267 + 0.342i	0.224 + 0.265i	0.225 + 0.329i
0.267 – 0.342i	0.224 – 0.265i	0.225 – 0.329i
0.717 + 0.011i	0.733 + 0.151i	0.748 + 0.151i
0.717 – 0.011i	0.733 – 0.151i	0.748 – 0.151i
0.925	0.873	0.881

Table 3.10 : Characteristic roots of the determinantal equations of the "interest-rate" VAR models (in first differences) for the U.K.

R1	R2	R3
-0.593	-0.634 – 0.278i	-0.63
0.514	-0.634 + 0.278i	-0.419
-0.451 – 0.207i	-0.582	-0.337 – 0.277i
-0.451 + 0.207i	-0.324 + 0.428i	-0.337 + 0.277i
-0.14 + 0.439i	-0.324 – 0.428i	-0.262 + 0.331i
-0.14 – 0.439i	-0.226 + 0.411i	-0.262 – 0.331i
-0.117 + 0.609i	-0.226 – 0.411i	-0.209 + 0.522i
-0.117 – 0.609i	-0.039	-0.209 – 0.522i
0.091	0.175 – 0.821i	0.09 – 0.597i
0.161 – 0.469i	0.175 + 0.821i	0.09 + 0.597i
0.161 + 0.469i	0.356 + 0.432i	0.385 + 0.327i
0.49	0.356 – 0.432i	0.385 – 0.327i
0.706 + 0.175i	0.812	0.709 – 0.169i
0.706 – 0.175i	0.822 – 0.066i	0.709 + 0.169i
0.863	0.822 + 0.066i	0.87

A glance at the results in Tables 3.7 through 3.10 reveals that all the characteristic roots for all our VAR models are indeed within the unit circle as required by a stationary process, and therefore, our VAR models are stable over time. As we will see later on, stability of a model ensures that the impact of given shocks will fade away over time and, as a result, the system converges to its finite long-run equilibrium.

APPENDIX I

Data definitions and Sources

The Canadian time series were taken from the Statistics Canada database (CANSIM) and various issues of the Review of Bank of Canada. Following is the list of the series with their identification labels in CANSIM:

Series	CANSIM label
y : Gross Domestic Product (GDP) at 1986 prices	D20463
p : Consumer Price Index (CPI), 1986 = 100	P100298
b : The Monetary base	B1646
r : The Bank Rate	B14006
m : Money Supply (Currency and Demand deposits)	B1627
c1: Chartered Banks Total Personal Loans	B109
c2: Chartered Banks Business Loans	B1623
c3: Chartered Banks Total Loans	B1605

The U.K. time series were obtained from the OECD Main Indicators (OECDMI) series, the Bank of England Quarterly Bulletin (BEQB), and various issues of the International financial Statistics (IFS) series. The series are described below:

Series	Source
Y : Gross Domestic Product (GDP) at 1985 prices	OECDMI
P : Consumer Price Index (CPI), 1963 = 100	OECDMI
B : Monetary Base (Reserve Money)	IFS
R : The 3 – month Treasury Bill rate	IFS
M : Money Supply (narrow definition, M1)	IFS
C1: Banks credit to consumers	BEQB
C2 : Banks credit to Businesses	BEQB
C3 : Banks Total credit	BEQB

APPENDIX II

Extensive Results of the Johansen Cointegration Tests

Table 3A.1 : Johansen Cointegration Tests for Canada
Model B1 - Variable set : y, p, b, m, and c1

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	83.75	68.90	65.06
r ≤1	r > 1	41.55	47.18	43.96
r ≤2	r > 2	20.88	29.51	26.79
r ≤3	r > 3	5.30	15.19	13.33
r ≤4	r > 4	0.21	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	42.19	33.17	30.77
r = 1	r = 2	20.66	27.17	24.71
r = 2	r = 3	15.58	20.77	18.69
r = 3	r = 4	5.09	14.03	12.10
r = 4	r = 5	.21	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.1 : Johansen Cointegration Tests for Canada
Model B2 - Variable set : y, p, b, m, and c2

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	90.23	68.90	65.06
r ≤1	r > 1	57.13	47.18	43.96
r ≤2	r > 2	27.20	29.51	26.79
r ≤3	r > 3	8.30	15.19	13.33
r ≤4	r > 4	3.26	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	33.10	33.17	30.77
r = 1	r = 2	29.93	27.17	24.71
r = 2	r = 3	18.89	20.77	18.69
r = 3	r = 4	5.04	14.03	12.10
r = 4	r = 5	3.26	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.1 : Johansen Cointegration Tests for Canada
Model B3 - Variable set : y, p, b, m, and c3

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	86.20	68.90	65.06
r ≤1	r > 1	54.53	47.18	43.96
r ≤2	r > 2	27.24	29.51	26.79
r ≤3	r > 3	8.15	15.19	13.33
r ≤4	r > 4	2.79	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	30.90	33.17	30.77
r = 1	r = 2	26.63	27.17	24.71
r = 2	r = 3	18.63	20.77	18.69
r = 3	r = 4	5.23	14.03	12.10
r = 4	r = 5	2.79	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.1 : Johansen Cointegration Tests for Canada
Model R1 - Variable set : y, p, r, m, and c1

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	108.56	68.90	65.06
r ≤1	r > 1	59.70	47.18	43.96
r ≤2	r > 2	29.88	29.51	26.79
r ≤3	r > 3	12.90	15.19	13.33
r ≤4	r > 4	0.53	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	48.86	33.17	30.77
r = 1	r = 2	29.82	27.17	24.71
r = 2	r = 3	16.98	20.77	18.69
r = 3	r = 4	12.37	14.03	12.10
r = 4	r = 5	0.53	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.1 : Johansen Cointegration Tests for Canada
Model R2 – Variable set : y, p, r, m, and c2

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	116.12	68.90	65.06
r ≤1	r > 1	70.11	47.18	43.96
r ≤2	r > 2	32.36	29.51	26.79
r ≤3	r > 3	9.21	15.19	13.33
r ≤4	r > 4	0.00	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	46.01	33.17	30.77
r = 1	r = 2	37.75	27.17	24.71
r = 2	r = 3	23.15	20.77	18.69
r = 3	r = 4	9.21	14.03	12.10
r = 4	r = 5	0.00	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.1 : Johansen Cointegration Tests for Canada
Model R3 - Variable set : y, p, r, m, and c3

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	117.65	68.90	65.06
r ≤1	r > 1	71.45	47.18	43.96
r ≤2	r > 2	35.87	29.51	26.79
r ≤3	r > 3	10.92	15.19	13.33
r ≤4	r > 4	0.07	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	46.20	33.17	30.77
r = 1	r = 2	35.58	27.17	24.71
r = 2	r = 3	24.95	20.77	18.69
r = 3	r = 4	10.85	14.03	12.10
r = 4	r = 5	0.07	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model B1 – Variable set : y, p, b, m, and c1

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
$r = 0$	$r > 0$	90.20	68.90	65.06
$r \leq 1$	$r > 1$	56.73	47.18	43.96
$r \leq 2$	$r > 2$	36.41	29.51	26.79
$r \leq 3$	$r > 3$	19.47	15.19	13.33
$r \leq 4$	$r > 4$	7.08	3.96	2.81
Max. eigenvalue test:				
$r = 0$	$r = 1$	33.47	33.17	30.77
$r = 1$	$r = 2$	20.32	27.17	24.71
$r = 2$	$r = 3$	16.94	20.77	18.69
$r = 3$	$r = 4$	12.38	14.03	12.10
$r = 4$	$r = 5$	7.06	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model B2 - Variable set : y, p, b, m, and c2

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
$r = 0$	$r > 0$	90.75	68.90	65.06
$r \leq 1$	$r > 1$	53.20	47.18	43.96
$r \leq 2$	$r > 2$	33.01	29.51	26.79
$r \leq 3$	$r > 3$	15.00	15.19	13.33
$r \leq 4$	$r > 4$	4.71	3.96	2.81
Max. eigenvalue test:				
$r = 0$	$r = 1$	37.55	33.17	30.77
$r = 1$	$r = 2$	20.19	27.17	24.71
$r = 2$	$r = 3$	18.01	20.77	18.69
$r = 3$	$r = 4$	10.28	14.03	12.10
$r = 4$	$r = 5$	4.72	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model B3 - Variable set : y, p, b, m, and c3

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	84.24	68.90	65.06
r ≤1	r > 1	49.75	47.18	43.96
r ≤2	r > 2	29.42	29.51	26.79
r ≤3	r > 3	12.24	15.19	13.33
r ≤4	r > 4	4.42	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	33.30	33.17	30.77
r = 1	r = 2	19.62	27.17	24.71
r = 2	r = 3	16.58	20.77	18.69
r = 3	r = 4	7.56	14.03	12.10
r = 4	r = 5	4.27	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model R1 - Variable set : y, p, r, m, and c1

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
r = 0	r > 0	90.23	68.90	65.06
r ≤1	r > 1	48.66	47.18	43.96
r ≤2	r > 2	23.61	29.51	26.79
r ≤3	r > 3	10.08	15.19	13.33
r ≤4	r > 4	2.75	3.96	2.81
Max. eigenvalue test:				
r = 0	r = 1	41.57	33.17	30.77
r = 1	r = 2	25.05	27.17	24.71
r = 2	r = 3	13.53	20.77	18.69
r = 3	r = 4	7.33	14.03	12.10
r = 4	r = 5	2.75	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model R2 - Variable set : y, p, r, m, and c2

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
$r = 0$	$r > 0$	91.46	68.90	65.06
$r \leq 1$	$r > 1$	39.28	47.18	43.96
$r \leq 2$	$r > 2$	20.44	29.51	26.79
$r \leq 3$	$r > 3$	10.52	15.19	13.33
$r \leq 4$	$r > 4$	3.37	3.96	2.81
Max. eigenvalue test:				
$r = 0$	$r = 1$	52.18	33.17	30.77
$r = 1$	$r = 2$	18.83	27.17	24.71
$r = 2$	$r = 3$	9.92	20.77	18.69
$r = 3$	$r = 4$	7.15	14.03	12.10
$r = 4$	$r = 5$	3.37	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

Table 3A.2 : Johansen Cointegration Tests for the U.K.
Model R3 - Variable set : y, p, r, m, and c3

Null Hypothesis	Alternative Hypothesis	Test Value	95% Critical Value	90% Critical Value
Trace test:				
$r = 0$	$r > 0$	85.74	68.90	65.06
$r \leq 1$	$r > 1$	39.85	47.18	43.96
$r \leq 2$	$r > 2$	17.71	29.51	26.79
$r \leq 3$	$r > 3$	7.96	15.19	13.33
$r \leq 4$	$r > 4$	2.99	3.96	2.81
Max. eigenvalue test:				
$r = 0$	$r = 1$	44.31	33.17	30.77
$r = 1$	$r = 2$	21.38	27.17	24.71
$r = 2$	$r = 3$	9.41	20.77	18.69
$r = 3$	$r = 4$	4.80	14.03	12.10
$r = 4$	$r = 5$	2.89	3.96	2.81

Note: The tests allow for a linear trend in the data. The letter r indicates the rank or the number of the cointegrating vectors under different hypotheses. The critical values are from Johansen and Juselius (1990), table A1. The null hypothesis is rejected when the test value exceeds the critical value.

CHAPTER NOTES

1. On the special nature of bank loans see Fama (1985) and Bernanke (1986), for example.
2. There are numerous unit root tests available in the literature. However, the Augmented Dicky-Fuller test and the Phillips-Perron test are the most popular. These two test are based on the null hypothesis of non-stationarity (unit root). Recently, other tests have been developed that take stationarity as the null hypothesis. See Tanaka (1990) and Leybourne and McCabe (1994) for examples of such tests.
3. Perron (1989, 1997) has initiated tests that allow for kinks in the linear trend. His approach increases the chance of identifying series as stationary. We have avoided using kinks because the choice of the kink point(s) involves some arbitrariness.
4. Experiments with less than 4 truncation lags did not change the results.
5. The interest rate was not found to be stationary around a constant term either.
6. According to Engle and Granger (1987), when each of a set of variables is integrated of order one (has a unit root) and a linear combination of those variables is integrated of order zero (is stationary), the variables are said to be cointegrated.
7. In fact, there was some weak evidence of cointegration for the first variable set in the case of Canada.

CHAPTER FOUR

SPECIFICATION AND ESTIMATION OF STRUCTURAL VAR MODELS

Following our results on the stochastic properties of the sample observations in the previous chapter, we begin this chapter by specification of our various VAR models for Canada and the United Kingdom. Then, we turn to alternative specifications of the contemporaneous structural relationships that comprise our various SVAR models. Finally, we report and analyze estimations of structural models for the two countries under alternative scenarios.

Specification of VAR models

We have seen in chapter two that a structural dynamic macroeconomic model can be cast in terms of a VAR model where each variable is a function of the lagged values of all the variables. Thus, if the structural model is

$$\mathbf{A}\mathbf{x}_t = \mathbf{C}(L)\mathbf{x}_{t-1} + \mathbf{D}\,\mathbf{u}_t \,, \tag{4.1}$$

then the reduced or VAR form of the model would be

$$\begin{aligned} \mathbf{x}_t &= \mathbf{A}^{-1}\mathbf{C}(L)\mathbf{x}_{t-1} + \mathbf{A}^{-1}\mathbf{D}\,\mathbf{u}_t \\ &= \mathbf{B}(L)\mathbf{x}_{t-1} + \varepsilon_t \end{aligned} \tag{4.2}$$

It is recalled that $\mathbf{x}_t$ is the vector of endogenous variables. The elements of the square matrix $\mathbf{A}$ are the structural parameters on the contemporaneous endogenous variables. $\mathbf{C}(L)$ is a matrix polynomial in the lag operator L. $\mathbf{u}_t$ is the vector of structural disturbances assumed to be white noises, and $\mathbf{D}$ is a square matrix with 1's along its main diagonal that adds different structural disturbances to different equations.

The dimension of the VAR models is, of course, dictated by the number of variables included in the system. Despite being quite general dynamic specifications, the VAR models cannot handle large sets of variables. This is because there would be too many parameters to estimate and, therefore, the available data set would leave too few degrees of freedom. Consequently, empirical applications have usually been restricted to relatively small-dimension VARs.

As indicated in chapter three, we consider two classes of models, both of which are based on sets of five variables. The models in the first class include real output (y), average consumer price level (p), the monetary base (b) as the monetary policy variable, narrow money stock (m), and a credit variable (c_i). In order to test the sensitivity of our results to different measures of credit, we experiment with three measures of bank credit – credit to persons (c1), credit to businesses (c2), and total bank credit (c3). Therefore, there are three models in this class, one model for each credit variable. They have been labeled as models B1, B2 and B3.

The models in the second class contain the rate of interest (r) as the monetary policy variable in place of the monetary base. Here, too, there are three models corresponding to our three credit variables. We have labeled them as R1, R2, and R3.

The above variations provide us with six different VAR models for each of the two countries. All the variables in these VAR models appear in first difference form because each of the variables was shown to be non-stationary in level. Since there was some evidence of cointegration among the variables of various models, we also specified the models in VEC form. The estimation results from these versions turned out to be generally the same, but some of the estimated coefficients were too implausible to believe. Therefore, we do not report the VEC results here. Since the variables are measured in natural logs, the VAR models are cast in terms of the rate of growth of variables[2]. Therefore, y denotes the rate of growth of real output, p stands for the rate of inflation and so on.

The number of lags in all the VAR models is set at three. This appeared to be the optimal number of lags as suggested by various criteria such as Akaike Information Criterion (AIC), Schwartz Criterion (SC), and the adjusted R^2. Three lags is sufficient to render the VAR residuals serially uncorrelated.

Specification of Structural Relationships

In order to retrieve the structural model (4.1) from the VAR model (4.2), we need to identify matrices $\mathbf{A}$ and $\mathbf{D}$. As described in the methodology of the SVAR in chapter two (p. 20), the problem is reduced to identifying the following relationship between the reduced form residuals (ε_t) coming from the first stage estimation of the VAR model and the structural disturbances ($\mathbf{u}_t$) from the structural model,

$$\mathbf{A}\varepsilon_t = \mathbf{D}\,\mathbf{u}_t \,, \qquad (4.3)$$

with $\mathbf{A}$ and $\mathbf{D}$ matrices defined previously. Given the limited $n(n+1)/2$ unique elements in the estimated variance-covariance matrix of the reduced form residuals (Σ_ε), identification restrictions must be imposed on the elements of $\mathbf{A}$ and $\mathbf{D}$. All our models have five variables, so $n = 5$. Thus, there are 15 unique elements in Σ_ε, 5 of which are used to identify the variances of the structural disturbances (σ^2_u). Although overidentified models can be estimated by maximum likelihood methods, we restrict our study to "just-identified" or "exactly identified" models for reasons explained by Bernanke (1986). An exact identification of the parameters in $\mathbf{A}$ and $\mathbf{D}$, therefore, requires 10 and only 10 unrestricted parameters in these two matrices. That is, there is just enough information to solve for 10 parameters in those matrices.

In what follows we describe two alternative identification schemes that are applied to all our VAR models. In the first scheme we set $\mathbf{D} = \mathbf{I}$ (the identity matrix), so that we need to solve for 10 parameters from the matrix $\mathbf{A}$. In the second scheme, however, we allow one of the off-diagonal elements in $\mathbf{D}$ to be non-zero. In this slight variation, we must solve for 9 parameters from $\mathbf{A}$ and a single parameter from $\mathbf{D}$. Aside from the *order* condition (i.e. the equality of the number of estimated parameters and the number of distinct covariances in Σ_ε), a *rank* condition must also be satisfied to ensure identification. The latter condition, in our framework, requires that the system solving for estimates of the structural parameters have at least one solution (see equation 4.14 below).

The First Identification Scheme

Equation (4.3) above, in essence, orthogonalizes the reduced form residuals into a set of uncorrelated structural disturbances. This transformation, however, is to be based on economic theory. We use conventional economic theory to determine the contemporaneous relationships among the reduced form residuals and structural disturbances. For the monetary-base models the contemporaneous theoretical relationships are presented in equations (4.4) to (4.8) below. The time subscripts have been ignored for clearer presentation.

$$\underset{}{\varepsilon_y} = \underset{(+)}{a1}(\varepsilon_{ci} - \varepsilon_p) + u_y \qquad (4.4)$$

$$\varepsilon_p = \underset{(+)}{a2}\,\varepsilon_y + u_p \qquad (4.5)$$

$$\varepsilon_b = \underset{(+)}{a3\,\varepsilon_y} + \underset{(-)}{a4\,\varepsilon_p} + \underset{(?)}{a5\,\varepsilon_m} + u_b \qquad (4.6)$$

$$\varepsilon_m = \underset{(+)}{a6\,\varepsilon_y} + \underset{(+)}{a7\,\varepsilon_p} + u_m \qquad (4.7)$$

$$\varepsilon_{ci} = \underset{(+)}{a8\,\varepsilon_p} + \underset{(+)}{a9\,\varepsilon_b} + \underset{(?)}{a10\varepsilon_m} + u_{ci} \qquad (4.8)$$

In the above equations, ε_y, ε_p, ε_b, ε_m, and ε_{ci} represent the reduced form errors or "innovations" in the corresponding variables, and ci refers to one of $c1$, $c2$, or $c3$. Likewise, u_y, u_p, u_b, u_y, u_m, and u_{ci}, indicate the structural disturbances or shocks to the equations describing the corresponding variables. The coefficients $a1$, $a2$, ..., $a10$ are the structural parameters that specify the contemporaneous relationships among the innovations in variables or, equivalently, among the variables themselves. All other possible linkages have been restricted to zero.

Equation (4.4) may be conceived as an "aggregate demand" relationship. It is assumed that real output growth is demand determined as autonomous real demand shocks – namely, IS shocks (u_y) - affect the rate of growth of real output. This assumption belongs to the Keynesian paradigm and has been utilized in many empirical applications[3]. However, we also allow innovations in output growth to be explicitly driven by innovations in the rate of growth of real credit (ε_{cl} - ε_p). Including credit in this equation is motivated by the idea that major components of aggregate demand depend on the availability of credit. The vast literature on financial market imperfections underlines the importance of credit constraints in determining the level of economic activity and output[4]. Equation (4.5) reflects behavior of inflation and is interpreted as the short term "aggregate supply" function. Innovations in aggregate demand are allowed to affect inflation in a way consistent with the Phillips curve idea. Inflation's "own" innovations, (i.e. u_p). capture shocks that might conveniently be thought of as cost or supply shocks. Such shocks might originate from technology, labour supply, or the tax regime. Equation (4.6) embodies a policy reaction function on the part of the monetary authority. The nominal monetary base reacts to real output growth, inflation, and the rate of growth of money balances. It is also driven by its own innovations, which should be interpreted as transitory monetary policy shocks. Monetary base responses to foreign exchange market disturbances are examples of monetary policy shocks. Innovations in the rate of growth of money in equation (4.7) are affected by innovations in output growth and inflation, as in a simple quantity theory of money.

Exogenous shocks to money growth due to, for example, technological or institutional innovations are captured in money's own innovations (u_m). Moreover, money's own innovations would contain interest rate innovations that are not explicitly represented in equation (4.7). Finally, equation (4.8) may be considered as a "credit supply" function. It specifies nominal credit growth shocks (u_{ci}), arising from exogenous financial innovations or regulatory shocks, as credit 's own shocks. In addition, credit innovations are influenced by innovations in inflation, nominal monetary base, and money demand. Expansion or contraction of the monetary base affect the availability of funds to the banking system and, consequently, the availability of bank credit to the borrowers. This is a rather convenient way to incorporate the so called "credit view" of monetary policy transmission mechanism expounded mainly by Bernanke (1986 and 1992)[5]. The presence of money demand in the credit supply equation could also be justified by the idea that money innovations affect the supply of deposits into the banks and, therefore, the flow of credit to borrowers. The expected signs for the structural parameters consistent with the proposed theories are indicated in brackets below the coefficients[6].

For the interest-rate models, we have basically the same theoretical relationships as are specified above. However, the policy variable in the reaction function (4.6) is now the rate of interest which responds contemporaneously to inflation and money growth, but not to output growth. The latter is partially imposed by the just-identification of the model. However, we could assume that within the quarter, information on real output is not as available as for inflation and money growth. Also, the money equation (4.7) is now expanded to include innovations in the rate of interest. Moreover, the credit supply is now responding to innovations in the rate of interest instead of the monetary base. With these alterations, the interest-rate models are presented in equations (4.9) to (4.13) below.

$$\varepsilon_y = \underset{(+)}{a1}(\varepsilon_{ci} - \varepsilon_p) + u_y \tag{4.9}$$

$$\varepsilon_p = \underset{(+)}{a2}\,\varepsilon_y + u_p \tag{4.10}$$

$$\varepsilon_r = \underset{(+)}{a3}\,\varepsilon_p + \underset{(?)}{a4}\,\varepsilon_m + u_r \tag{4.11}$$

$$\varepsilon_m = \underset{(+)}{a5}\,\varepsilon_y + \underset{(+)}{a6}\,\varepsilon_p + \underset{(-)}{a7}\,\varepsilon_r + u_m \tag{4.12}$$

$$\varepsilon_{ci} = \underset{(+)}{a8}\,\varepsilon_p + \underset{(-)}{a9}\,\varepsilon_r + \underset{(?)}{a10}\,\varepsilon_m + u_{ci} \quad (i = 1,2,3) \tag{4.13}$$

The Second Identification Scheme

To allow for the possible contemporaneous impact of monetary policy shocks on the innovations in credit supply, we have slightly modified the first identification : in the credit supply equations of both the monetary-base and interest-rate models, we have replaced the (reduced form) innovations in money growth (ε_m) with the (structural) monetary policy shocks, u_b and u_r, respectively. This identification calls for changing **D** from an identity matrix to a matrix which differs from **I** in having a non-zero element in its fifth row, third column. Now, there are 9 parameters (a1 to a9) from matrix **A** and 1 parameter (d) from matrix **D** to be identified. The resulting version of the contemporaneous system from this second identification appears in equations (4.4)' to (4.8)' for the monetary-base models.

$$\varepsilon_y = \underset{(+)}{a1}(\varepsilon_{ci} - \varepsilon_p) + u_y \tag{4.4'}$$

$$\varepsilon_p = \underset{(+)}{a2}\,\varepsilon_y + u_p \tag{4.5'}$$

$$\varepsilon_b = \underset{(+)}{a3}\,\varepsilon_y + \underset{(-)}{a4}\,\varepsilon_p + \underset{(?)}{a5}\,\varepsilon_m + u_b \tag{4.6'}$$

$$\varepsilon_m = \underset{(+)}{a6}\,\varepsilon_y + \underset{(+)}{a7}\,\varepsilon_p + u_m \tag{4.7'}$$

$$\varepsilon_{ci} = \underset{(+)}{a8}\,\varepsilon_p + \underset{(+)}{a9}\,\varepsilon_b + \underset{(+)}{d}\,u_b + u_{ci} \quad (i = 1.2.3) \tag{4.8'}$$

Similarly, the corresponding version for the interest-rate models under the second identification is represented in the following equation system

$$\varepsilon_y = \underset{(+)}{a1}(\varepsilon_{ci} - \varepsilon_p) + u_y \tag{4.9'}$$

$$\varepsilon_p = \underset{(+)}{a2}\,\varepsilon_y + u_p \tag{4.10'}$$

$$\varepsilon_r = \underset{(+)}{a3}\,\varepsilon_p + \underset{(?)}{a4}\,\varepsilon_m + u_r \tag{4.11'}$$

$$\varepsilon_m = \underset{(+)}{a5}\,\varepsilon_y + \underset{(+)}{a6}\,\varepsilon_p + \underset{(-)}{a7}\,\varepsilon_r + u_m \tag{4.12'}$$

$$\varepsilon_{ci} = \underset{(+)}{a8}\,\varepsilon_p + \underset{(-)}{a9}\,\varepsilon_r + \underset{(-)}{d}\,u_r + u_{ci} \quad (i = 1.2.3) \tag{4.13'}$$

The above alternative specifications should provide us the opportunity to test the robustness of our results. Sarte (1997) has warned that the SVAR results could be dependent on the particular identifying assumptions, especially when the system is estimated by the Instrumental Variables method. Our estimation method is not based on the Instrumental Variables. However, Sarte's warning is still to be heeded.

Estimation of Structural Relationships

As indicated in chapter two, the estimation technique adopted in this study follows that of Bernanke (1986) which is based on the Method of Moments. The method is computationally easy, and provides the same numerical results as the maximum likelihood estimates if one assumes normality of the structural disturbances as well as just-identification[7].

The Method of Moments equates the sample moments with the corresponding population moments, and then solves a nonlinear system of equations for the estimates of the structural parameters in matrices $\mathbf{A}$ and $\mathbf{D}$. More specifically, the sample variance-covariance matrix of structural disturbances is set equal to that of the population, that is, Σ_u. Given the assumption that Σ_u is diagonal, our task becomes one of finding coefficient values in the identification schemes above that will yield zero values for the symmetric elements on either side of the main diagonal of the sample variance-covariance matrix of structural disturbances[8].

Given equation (4.3) above, the sample variance-covariance matrix of structural disturbances can be written as

$$\Sigma_{\hat{u}} = \mathbf{D}^{-1}\mathbf{A}\,\Sigma_{\hat{\varepsilon}}\mathbf{D}'^{-1}\mathbf{A}' \ , \qquad (4.14)$$

where the symbol (^) indicates the estimated (sample) magnitudes. The matrices on both sides of equation (4.14) are square and of dimension 5 for all our models. Therefore, this equation system contains 10 nonlinear (quadratic) equations to be solved simultaneously for estimates of the free parameters in $\mathbf{A}$ and $\mathbf{D}$[9].

Once the estimates of the parameters in $\mathbf{A}$ and $\mathbf{D}$ are obtained, the variances of the structural disturbances (σ^2_u) – the diagonal elements of Σ_u – are "read off" from the main diagonal of $\Sigma_{\hat{u}}$. The system of 10 nonlinear equations must, of course, have at least one solution to ensure the identification of the structural parameters. In fact, all the models we have considered, give either one or two solutions. So, the rank condition is always met. In cases of two solutions, usually, one solution could be given preference to the other on theoretical grounds.

In what follows we report our estimation results for various models under alternative identifications. The results for Canada appear first, and those for the U.K. follow afterwards.

We begin with the monetary-base models for which the results under each of the two identification schemes are reported in Tables 4.1 and 4.2, respectively.

Table 4.1 : Estimated Structural Relationships for Canada (Class-B models under the First Identification)

Model B1 :

$$\varepsilon_v = \underset{(0.027)}{0.050}\,(\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = \underset{(0.045)}{-0.073}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.085)}{0.054}\,\varepsilon_v + \underset{(0.148)}{0.046}\,\varepsilon_p + \underset{(0.044)}{0.242}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.147)}{0.153}\,\varepsilon_v + \underset{(0.264)}{0.278}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c1} = \underset{(0.379)}{1.068}\,\varepsilon_p + \underset{(0.184)}{0.324}\,\varepsilon_h + \underset{(0.112)}{0.151}\,\varepsilon_m + u_{c1} \qquad \sigma(u_{c1}) = 0.023$$

Model B2 :

$$\varepsilon_v = \underset{(0.033)}{-0.016}\,(\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = \underset{(0.044)}{-0.053}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.083)}{0.099}\,\varepsilon_v + \underset{(0.148)}{0.043}\,\varepsilon_p + \underset{(0.044)}{0.236}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.147)}{0.145}\,\varepsilon_v + \underset{(0.264)}{0.283}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c2} = \underset{(0.330)}{0.467}\,\varepsilon_p + \underset{(0.160)}{0.172}\,\varepsilon_h - \underset{(0.98)}{0.274}\,\varepsilon_m + u_{c2} \qquad \sigma(u_{c2}) = 0.020$$

Model B3 :

$$\varepsilon_v = \underset{(0.041)}{-0.009}\,(\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = \underset{(0.043)}{-0.059}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.082)}{0.106}\,\varepsilon_v + \underset{(0.149)}{0.044}\,\varepsilon_p + \underset{(0.044)}{0.236}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.146)}{0.123}\,\varepsilon_v + \underset{(0.264)}{0.285}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c3} = \underset{(0.264)}{0.470}\,\varepsilon_p + \underset{(0.128)}{0.229}\,\varepsilon_h - \underset{(0.078)}{0.189}\,\varepsilon_m + u_{c3} \qquad \sigma(u_{c3}) = 0.016$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

Table 4.2 : Estimated Structural Relationships for Canada (Class-B models under the Second Identification)

Model B1 :

$$\varepsilon_y = \underset{(0.036)}{0.046}(\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.045)}{-0.072}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.094)}{0.056}\,\varepsilon_y + \underset{(0.149)}{0.046}\,\varepsilon_p + \underset{(0.044)}{0.242}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.157)}{0.157}\,\varepsilon_y + \underset{(0.266)}{0.278}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c1} = \underset{(0.457)}{1.039}\,\varepsilon_p - \underset{(0.548)}{0.946}\,\varepsilon_h - \underset{(0.228)}{0.623}\,u_h + u_{c1} \qquad \sigma(u_{c1}) = 0.023$$

Model B2 :

$$\varepsilon_y = \underset{(0.049)}{0.004}(\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.045)}{-0.049}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.076)}{0.095}\,\varepsilon_y + \underset{(0.149)}{0.043}\,\varepsilon_p + \underset{(0.044)}{0.236}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.153)}{0.161}\,\varepsilon_y + \underset{(0.265)}{0.283}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c2} = \underset{(0.511)}{0.517}\,\varepsilon_p - \underset{(0.637)}{0.987}\,\varepsilon_h + \underset{(0.297)}{1.154}\,u_h + u_{c2} \qquad \sigma(u_{c2}) = 0.020$$

Model B3 :

$$\varepsilon_y = \underset{(0.052)}{0.013}(\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.044)}{-0.055}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_h = \underset{(0.075)}{0.101}\,\varepsilon_y + \underset{(0.150)}{0.044}\,\varepsilon_p + \underset{(0.044)}{0.236}\,\varepsilon_m + u_h \qquad \sigma(u_h) = 0.009$$

$$\varepsilon_m = \underset{(0.148)}{0.134}\,\varepsilon_y + \underset{(0.266)}{0.285}\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.016$$

$$\varepsilon_{c3} = \underset{(0.430)}{0.505}\,\varepsilon_p - \underset{(0.534)}{0.572}\,\varepsilon_h + \underset{(0.253)}{0.801}\,u_h + u_{c3} \qquad \sigma(u_{c3}) = 0.016$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

The estimation results for B1, B2, and B3 models in Table 4.1 are fairly similar. So, the following remarks by and large apply to all three models. The results, in general, reflect the disappointing feature of low t – ratios. However, as noted in chapter two, this has become inevitable in a majority of the standard as well as structural VAR estimations, mostly because these models contain too many parameters. An alternative explanation could be a weak covariation in the data at high frequencies. As for the signs of the coefficients, most of them comply with our theoretical assumptions. The negative, but insignificant coefficient of credit in the aggregate demand equation of models B2 and B3 is unexpected. The insignificant coefficient of output in the aggregate supply equation, though not of the right sign, implies a flat supply curve within the quarter. This finding supports the rigidity of prices in the very short run of a quarter. Also, the positive insignificant coefficient of inflation in the policy reaction function gives no indication of inflation targeting by the monetary authority. However, most of the coefficients are of the expected signs. Monetary base responds positively to output, and changes directly with money demand in a way that implies accommodating liquidity shocks, presumably with the aim of interest rate targeting. Money demand grows in response to output growth as well as inflation. And finally, credit supply increases with inflation and the monetary base. The positive response of credit to the monetary base confirms the "credit view" of monetary policy transmission mechanism. The ambiguity of the impact of money demand innovations on the credit supply is echoed in our estimates. Model B1 suggests a positive impact, but both B2 and B3 models indicate a negative effect.

The estimation results under the second identification in Table 4.2 are, again, similar for the three models B1, B2, and B3. Here, too, the estimated coefficients are mostly insignificant. However, the credit coefficient in the aggregate demand equation is now of the right sign for all three models. Aggregate supply remains flat, and Inflation retains its unexpected positive sign in the policy reaction functions. Money demand equations have the appropriate signs on output growth and inflation as under the first identification. What is different here, as far as the credit supply function is concerned, is an unwelcome change of sign in the parameter of the monetary base innovations in models B2 and B3. This parameter is not statistically significant in either case, however.

What distinguishes the second identification from the first, is the replacement of innovations in money demand (ε_m) by the shocks to monetary base - monetary policy shocks – (u_b) in the credit supply function. Both B2 and B3 models reflect a significant positive impact of monetary policy shocks on credit. This is expected to happen, since the expansion of the monetary base enhances the reserve position of the banks and provides for expansion of credit. Such a result, however, is not born out in model B1.

Overall, our results are more or less the same for different credit measures (designating our monetary-base models) and under the two alternative identifications. In other words, our estimation results are reasonably robust across models and identification schemes.

We now turn to the interest-rate models for which the estimation results under the first and second identifications are reported in Tables 4.3 and 4.4, respectively.

Table 4.3 : Estimated Structural Relationships for Canada (Class-R models under the First Identification)

Model R1 :

$$\varepsilon_v = \underset{(0.027)}{0.045}(\varepsilon_{c1} - \varepsilon_p) + u_v \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = \underset{(0.045)}{-0.075}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_r = \underset{(0.329)}{-0.322}\,\varepsilon_p + \underset{(0.077)}{1.063}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.020$$

$$\varepsilon_m = \underset{(0.220)}{0.437}\,\varepsilon_v + \underset{(0.378)}{1.036}\,\varepsilon_p - \underset{(0.163)}{2.485}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.023$$

$$\varepsilon_{c1} = \underset{(0.378)}{1.058}\,\varepsilon_p - \underset{(0.206)}{0.277}\,\varepsilon_r + \underset{(0.118)}{0.337}\,\varepsilon_m + u_{c1} \qquad \sigma(u_{c1}) = 0.023$$

Model R2 :

$$\varepsilon_v = -\underset{(0.034)}{0.032}(\varepsilon_{c2} - \varepsilon_p) + u_v \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = -\underset{(0.042)}{0.053}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.004$$

$$\varepsilon_r = -\underset{(0.257)}{0.172}\,\varepsilon_p + \underset{(0.061)}{0.722}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.015$$

$$\varepsilon_m = \underset{(0.174)}{0.474}\,\varepsilon_v + \underset{(0.325)}{1.587}\,\varepsilon_p - \underset{(0.145)}{1.985}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.019$$

$$\varepsilon_{c2} = \underset{(0.325)}{0.139}\,\varepsilon_p + \underset{(0.174)}{0.530}\,\varepsilon_r + \underset{(0.099)}{0.031}\,\varepsilon_m + u_{c2} \qquad \sigma(u_{c2}) = 0.019$$

Model R3 :

$$\varepsilon_v = -\underset{(0.043)}{0.017}(\varepsilon_{c3} - \varepsilon_p) + u_v \qquad \sigma(u_v) = 0.008$$

$$\varepsilon_p = \underset{(0.044)}{-0.058}\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_r = -\underset{(0.231)}{0.147}\,\varepsilon_p + \underset{(0.059)}{0.675}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.014$$

$$\varepsilon_m = \underset{(0.176)}{0.424}\,\varepsilon_v + \underset{(0.314)}{0.919}\,\varepsilon_p - \underset{(0.149)}{1.927}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.019$$

$$\varepsilon_{c3} = \underset{(0.248)}{0.261}\,\varepsilon_p + \underset{(0.141)}{0.403}\,\varepsilon_r - \underset{(0.081)}{0.050}\,\varepsilon_m + u_{c3} \qquad \sigma(u_{c3}) = 0.015$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

**Table 4.4 : Estimated Structural Relationships for Canada
(Class-R models under the Second Identification)**

Model R1 :

$$\varepsilon_y = \underset{(0.028)}{0.045} (\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.046)}{-0.075} \varepsilon_y + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_r = \underset{(0.331)}{-0.322} \varepsilon_p + \underset{(0.078)}{1.063} \varepsilon_m + u_r \qquad \sigma(u_r) = 0.020$$

$$\varepsilon_m = \underset{(0.227)}{0.437} \varepsilon_y + \underset{(0.383)}{1.036} \varepsilon_p - \underset{(0.167)}{2.485} \varepsilon_r + u_m \qquad \sigma(u_m) = 0.023$$

$$\varepsilon_{c1} = \underset{(0.408)}{1.160} \varepsilon_p + \underset{(0.271)}{0.594} \varepsilon_r - \underset{(0.104)}{0.317} u_r + u_{c1} \qquad \sigma(u_{c1}) = 0.023$$

Model R2 :

$$\varepsilon_y = \underset{(0.036)}{-0.032} (\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.043)}{-0.053} \varepsilon_y + u_p \qquad \sigma(u_p) = 0.004$$

$$\varepsilon_r = \underset{(0.261)}{-0.172} \varepsilon_p + \underset{(0.064)}{0.722} \varepsilon_m + u_r \qquad \sigma(u_r) = 0.015$$

$$\varepsilon_m = \underset{(0.179)}{0.474} \varepsilon_y + \underset{(0.332)}{1.587} \varepsilon_p - \underset{(0.153)}{1.985} \varepsilon_r + u_m \qquad \sigma(u_m) = 0.019$$

$$\varepsilon_{c2} = \underset{(0.346)}{0.146} \varepsilon_p + \underset{(0.267)}{0.573} \varepsilon_r - \underset{(0.117)}{0.043} u_r + u_{c2} \qquad \sigma(u_{c2}) = 0.019$$

Model R3 :

$$\varepsilon_y = \underset{(0.042)}{-0.017} (\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.008$$

$$\varepsilon_p = \underset{(0.043)}{-0.058} \varepsilon_y + u_p \qquad \sigma(u_p) = 0.005$$

$$\varepsilon_r = \underset{(0.241)}{-0.147} \varepsilon_p + \underset{(0.061)}{0.675} \varepsilon_m + u_r \qquad \sigma(u_r) = 0.014$$

$$\varepsilon_m = \underset{(0.179)}{0.424} \varepsilon_y + \underset{(0.328)}{0.919} \varepsilon_p - \underset{(0.156)}{1.927} \varepsilon_r + u_m \qquad \sigma(u_m) = 0.019$$

$$\varepsilon_{c3} = \underset{(0.262)}{0.272} \varepsilon_p + \underset{(0.212)}{0.477} \varepsilon_r - \underset{(0.117)}{0.074} u_r + u_{c3} \qquad \sigma(u_{c3}) = 0.015$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

The estimation results look very similar for the three models R1, R2, and R3 under both identifications. For the first identification, the results in Table 4.3 support the positive role of credit in output innovations in model R1. But, as in the monetary-base models, they indicate a negative response of output to credit innovations. Such responses are not different from zero, however. Also, the findings once again reflect the insignificant contemporaneous effect of aggregate demand innovations on inflation. The interest rate, which is the policy variable in this class, responds negatively (though insignificantly) to inflation in all three models. Such a response implies that the monetary authority is not reacting to control inflation within the quarter. Interestingly, interest rate responds positively, and very significantly so, to innovations in money demand in all three models. That is, the monetary authority appears to stabilize the money stock at the expense of interest rate instability. This finding is in contrast to what we observed in the monetary-base models. The money equation in all three models supports the theoretically expected positive relationships between money demand and output as well as money demand and inflation. Moreover, in this extended equation money demand shows a significant negative response to the rate of interest as the standard theory would predict.

The results for the credit supply equation are in accord with our theoretical priors. Credit innovations change positively with changes in inflation. Contrary to the monetary-base models, however, there is no ambiguity over the impact of money demand innovations on credit supply in these interest-rate models. These models all reflect a positive impact, though not significant, from money demand innovations on the credit supply. As more money is deposited to the banks, they can afford to extend more loans.

Unexpectedly, credit supply responds positively to innovations in the monetary policy variable (i.e. the rate of interest). In other words, higher interest rates or tighter monetary policy, induces banks to lend more. A possible justification is that because of the close co-movement of the interest rates, the banks are able to offer higher rates on deposits and thereby attract more funds to lend. Credit to persons appears less responsive to interest rate innovations. however. as the corresponding coefficient in model R1 is not significant.

Let us now turn to Table 4.4 for the estimation results under the second identification. Here, too, the results are comparable for the three models. The positive response of output to credit innovations in model R1and its negative response to the same in models R2 and R3 are once again echoed under the second identification scheme. Aggregate supply remains flat as in the first identification. The interest rate responds to inflation and money demand innovations in the same way it did under the first identification. That is, it does not respond to inflation within the quarter, but moves to stabilize the money stock. As for the money equation, the results are the same as in the first identification. In particular, they share the significant negative response of money demand innovations to the rate of interest. Finally, the credit supply responds positively to inflation and the rate of interest as before. As in the case of the monetary-base models the presence of monetary policy shocks , here shocks to the interest rate, differentiates the second identification scheme from the first. In confirmation of the "credit view", credit supply responds negatively to interest rate disturbances (monetary policy shocks). That is, higher interest rates diminish the bank reserves and thus available funds for credit.

For all the models and identifications, the estimated standard errors of the structural disturbances reported in the above tables appear to be very small. This should not be surprising, given the fact the residuals from which they are extracted are errors on the rate of growth of variables that are themselves very small numbers.

Overall, despite the now familiar problem of low t-ratios, the results in Tables 4.1 through 4.4 above are encouraging. Most of the estimated coefficients are consistent with our theoretical presumptions. Moreover, the results stand relatively robust under alternative identifications and for different credit measures.

Estimations of the structural models for the United Kingdom are reported in Tables 4.5 through 4.8 below. The tables are arranged in the same order as for Canada. Therefore, Tables 4.5 and 4.6 contain the results for the monetary-base models for the first and second identifications, whereas Tables 4.7 and 4.8 report the results for the interest-rate models under the two alternative specifications.

Table 4.5 : Estimated Structural Relationships for the U.K.
(Class-B models under the First Identification)

<u>Model B1 :</u>

$$\underset{}{\varepsilon_v = -\,0.007\,(\varepsilon_{c1} - \varepsilon_p) + u_v} \qquad \sigma(u_v) = 0.015$$
$$(0.039)$$

$$\varepsilon_p = -\,0.023\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.011$$
$$(0.069)$$

$$\varepsilon_b = 0.834\,\varepsilon_v + 0.389\,\varepsilon_p - 0.092\,\varepsilon_m + u_b \qquad \sigma(u_b) = 0.046$$
$$(0.284) \quad (0.387) \quad (0.224)$$

$$\varepsilon_m = 0.014\,\varepsilon_v - 0.048\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.019$$
$$(0.120) \quad (0.163)$$

$$\varepsilon_{c1} = -\,0.482\,\varepsilon_p - 0.033\,\varepsilon_b - 0.037\,\varepsilon_m + u_{c1} \qquad \sigma(u_{c1}) = 0.040$$
$$(0.275) \quad (0.064) \quad (0.159)$$

<u>Model B2 :</u>

$$\varepsilon_v = -\,0.013\,(\varepsilon_{c2} - \varepsilon_p) + u_v \qquad \sigma(u_v) = 0.015$$
$$(0.039)$$

$$\varepsilon_p = -\,0.027\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.011$$
$$(0.069)$$

$$\varepsilon_b = 0.920\,\varepsilon_v + 0.176\,\varepsilon_p - 0.228\,\varepsilon_m + u_b \qquad \sigma(u_b) = 0.045$$
$$(0.284) \quad (0.387) \quad (0.224)$$

$$\varepsilon_m = -\,0.028\,\varepsilon_v - 0.062\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.019$$
$$(0.120) \quad (0.163)$$

$$\varepsilon_{c2} = -\,0.516\,\varepsilon_p + 0.088\,\varepsilon_b - 0.306\,\varepsilon_m + u_{c2} \qquad \sigma(u_{c2}) = 0.032$$
$$(0.275) \quad (0.064) \quad (0.159)$$

<u>Model B3 :</u>

$$\varepsilon_v = -\,0.015\,(\varepsilon_{c3} - \varepsilon_p) + u_v \qquad \sigma(u_v) = 0.015$$
$$(0.007)$$

$$\varepsilon_p = -0.023\,\varepsilon_v + u_p \qquad \sigma(u_p) = 0.011$$
$$(0.837)$$

$$\varepsilon_b = 0.942\,\varepsilon_v + 0.180\,\varepsilon_p - 0.247\,\varepsilon_m + u_b \qquad \sigma(u_b) = 0.045$$
$$(1.155) \quad (0.128) \quad (0.816)$$

$$\varepsilon_m = -\,0.040\,\varepsilon_v - 0.074\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.019$$
$$(0.117) \quad (0.013)$$

$$\varepsilon_{c3} = -\,0.524\,\varepsilon_p + 0.075\,\varepsilon_b - 0.031\,\varepsilon_m + u_{c3} \qquad \sigma(u_{c3}) = 0.031$$
$$(0.021) \quad (0.015) \quad (0.135)$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

Table 4.6 : Estimated Structural Relationships for the U.K.
(Class-B models under the Second Identification)

Model B1 :

$$\varepsilon_y = -0.054\,(\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$
$$\quad (0.114)$$

$$\varepsilon_p = -0.060\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.011$$
$$\quad (0.117)$$

$$\varepsilon_b = 0.820\,\varepsilon_y + 0.390\,\varepsilon_p - 0.092\,\varepsilon_m + u_b \qquad \sigma(u_b) = 0.046$$
$$\quad (0.297) \quad (0.396) \quad (0.215)$$

$$\varepsilon_m = 0.011\,\varepsilon_y - 0.048\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.019$$
$$\quad (0.122) \quad (0.164)$$

$$\varepsilon_{c1} = -0.671\,\varepsilon_p + 0.374\,\varepsilon_b - 0.407\,u_b + u_{c1} \qquad \sigma(u_{c1}) = 0.040$$
$$\quad (0.637) \quad (0.995) \quad (1.152)$$

Model B2 :

$$\varepsilon_y = -0.380\,(\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.021$$
$$\quad (0.049)$$

$$\varepsilon_p = -0.316\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.012$$
$$\quad (0.086)$$

$$\varepsilon_b = 1.123\,\varepsilon_y + 0.030\,\varepsilon_p - 0.296\,\varepsilon_m + u_b \qquad \sigma(u_b) = 0.045$$
$$\quad (0.327) \quad (0.396) \quad (0.175)$$

$$\varepsilon_m = -0.114\,\varepsilon_y - 0.003\,\varepsilon_p + u_m \qquad \sigma(u_m) = 0.019$$
$$\quad (0.135) \quad (0.166)$$

$$\varepsilon_{c2} = -1.319\,\varepsilon_p + 1.349\,\varepsilon_b - 1.218\,u_b + u_{c2} \qquad \sigma(u_{c2}) = 0.040$$
$$\quad (0.567) \quad (0.365) \quad (0.472)$$

Model B3 :

$$\varepsilon_y = -0.039\,(\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma^2(u_y) = 0.021$$
$$\quad (0.053)$$

$$\varepsilon_p = -0.317\,\varepsilon_y + u_p \qquad \sigma^2(u_p) = 0.012$$
$$\quad (0.085)$$

$$\varepsilon_b = 1.113\,\varepsilon_y + 0.043\,\varepsilon_p - 0.314\,\varepsilon_m + u_b \qquad \sigma^2(u_b) = 0.046$$
$$\quad (0.328) \quad (0.406) \quad (0.180)$$

$$\varepsilon_m = -0.129\,\varepsilon_y - 0.012\,\varepsilon_p + u_m \qquad \sigma^2(u_m) = 0.019$$
$$\quad (0.134) \quad (0.166)$$

$$\varepsilon_{c3} = -1.292\,\varepsilon_p + 1.246\,\varepsilon_b - 1.137\,u_b + u_{c3} \qquad \sigma^2(u_{c3}) = 0.034$$
$$\quad (0.463) \quad (0.296) \quad (0.453)$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

Table 4.7 : Estimated Structural Relationships for the U.K. (Class-R models under the First Identification)

<u>Model R1 :</u>

$$\varepsilon_y = -0.011\,(\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$
$$(0.032)$$

$$\varepsilon_p = -0.052\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$
$$(0.082)$$

$$\varepsilon_r = -0.102\,\varepsilon_p + 0.137\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.011$$
$$(0.080)\quad(0.051)$$

$$\varepsilon_m = 0.019\,\varepsilon_y + 0.037\,\varepsilon_p - 0.919\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.018$$
$$(0.113)\quad(0.131)\quad(0.165)$$

$$\varepsilon_{c1} = -0.466\,\varepsilon_p - 0.117\,\varepsilon_r - 0.089\,\varepsilon_m + u_{c1} \qquad \sigma(u_{c1}) = 0.040$$
$$(0.290)\quad(0.375)\quad(0.205)$$

<u>Model R2 :</u>

$$\varepsilon_y = -0.002\,(\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$
$$(0.037)$$

$$\varepsilon_p = -0.050\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$
$$(0.082)$$

$$\varepsilon_r = 0.026\,\varepsilon_p - 1.114\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.020$$
$$(0.145)\quad(0.077)$$

$$\varepsilon_m = -0.079\,\varepsilon_y - 0.727\,\varepsilon_p + 7.557\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.087$$
$$(0.548)\quad(0.632)\quad(0.558)$$

$$\varepsilon_{c2} = -0.463\,\varepsilon_p + 0.686\,\varepsilon_r - 0.156\,\varepsilon_m + u_{c2} \qquad \sigma(u_{c2}) = 0.032$$
$$(0.232)\quad(0.286)\quad(0.163)$$

<u>Model R3 :</u>

$$\varepsilon_y = -0.008\,(\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$
$$(0.040)$$

$$\varepsilon_p = -0.056\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$
$$(0.082)$$

$$\varepsilon_r = 0.227\,\varepsilon_p - 3.164\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.056$$
$$(0.407)\quad(0.204)$$

$$\varepsilon_m = 0.260\,\varepsilon_y - 1.006\,\varepsilon_p - 12.41\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.126$$
$$(0.795)\quad(0.915)\quad(0.802)$$

$$\varepsilon_{c3} = -0.476\,\varepsilon_p + 0.592\,\varepsilon_r - 0.168\,\varepsilon_m + u_{c3} \qquad \sigma(u_{c3}) = 0.028$$
$$(0.203)\quad(0.250)\quad(0.143)$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

Table 4.8 : Estimated Structural Relationships for the U.K. (Class-R models under the Second Identification)

Model R1 :

$$\varepsilon_y = -\underset{(0.036)}{0.011}(\varepsilon_{c1} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$

$$\varepsilon_p = -\underset{(0.091)}{0.052}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$

$$\varepsilon_r = -\underset{(0.080)}{0.102}\,\varepsilon_p + \underset{(0.076)}{0.137}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.011$$

$$\varepsilon_m = \underset{(0.114)}{0.019}\,\varepsilon_y + \underset{(0.133)}{0.037}\,\varepsilon_p - \underset{(0.249)}{0.919}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.018$$

$$\varepsilon_{c1} = -\underset{(0.394)}{0.533}\,\varepsilon_p - \underset{(2.172)}{0.765}\,\varepsilon_r + \underset{(0.564)}{0.649}\,u_r + u_{c1} \qquad \sigma(u_{c1}) = 0.040$$

Model R2 :

$$\varepsilon_y = -\underset{(0.044)}{0.002}(\varepsilon_{c2} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$

$$\varepsilon_p = -\underset{(0.097)}{0.050}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$

$$\varepsilon_r = \underset{(0.145)}{0.026}\,\varepsilon_p - \underset{(0.077)}{1.114}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.020$$

$$\varepsilon_m = -\underset{(0.568)}{0.079}\,\varepsilon_y + \underset{(0.634)}{0.727}\,\varepsilon_p + \underset{(0.560)}{7.557}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.087$$

$$\varepsilon_{c2} = -\underset{(0.236)}{0.467}\,\varepsilon_p + \underset{(0.294)}{0.826}\,\varepsilon_r - \underset{(0.097)}{0.140}\,u_r + u_{c2} \qquad \sigma(u_{c2}) = 0.032$$

Model R3 :

$$\varepsilon_y = -\underset{(0.050)}{0.008}(\varepsilon_{c3} - \varepsilon_p) + u_y \qquad \sigma(u_y) = 0.015$$

$$\varepsilon_p = -\underset{(0.101)}{0.056}\,\varepsilon_y + u_p \qquad \sigma(u_p) = 0.013$$

$$\varepsilon_r = \underset{(0.407)}{0.227}\,\varepsilon_p - \underset{(0.204)}{3.164}\,\varepsilon_m + u_r \qquad \sigma(u_r) = 0.056$$

$$\varepsilon_m = \underset{(0.817)}{0.260}\,\varepsilon_y - \underset{(0.918)}{1.006}\,\varepsilon_p - \underset{(0.804)}{12.41}\,\varepsilon_r + u_m \qquad \sigma(u_m) = 0.126$$

$$\varepsilon_{c3} = -\underset{(0.205)}{0.488}\,\varepsilon_p + \underset{(0.254)}{0.645}\,\varepsilon_r - \underset{(0.095)}{0.053}\,u_r + u_{c3} \qquad \sigma(u_{c3}) = 0.028$$

Note : The numbers in brackets are asymptotic standard errors. σ_u's are the estimated standard errors of the structural disturbances.

As expected, the estimation results for the U.K. share the general problem of statistical imprecision with those for Canada. On a positive note, however, they share the important feature of being relatively robust across the models. Also, the results do support our theoretical expectations in majority of cases. We do not intend to discuss the above results for the U.K. equation by equation for various models and identifications. Instead, in what follows, we concentrate on the differences in results that might point to any potential structural dissimilarities between the two economies.

The first difference to note is the negative, though insignificant, contribution of credit innovations to output growth. This is a robust result across all models and under alternative identifications. Therefore, output appears to be less sensitive to broad credit than narrow credit. A second difference is the negative response of the monetary base to money innovations in the monetary-base models. Here, the monetary authority appears to have aimed at controlling the money stock rather than targeting the interest rate. Substantial volatility in the rate of interest over the sample period provides some evidence for such an inference. This tentative inference is also supported by model R1 under both identifications, where the rate of interest responds positively to money demand innovations. Again, implying that the monetary authority aims at controlling the money stock. This conjecture, however, is negated in models R2 and R3, where the negative coefficient on money suggests an accommodating behaviour on the part of the monetary authority.

Another contrast is the negative response of money growth to inflation in the monetary-base models under both identifications. The situation is somewhat different for the interest-rate models. Model R3 shares the negative response of money to inflation with the monetary-base models, whereas R1 and R2 do not. The impact of output on money demand is mixed. For the most part, it is negative in Class-B models, and positive in the interest-rate models. Once again, the low precision of estimated coefficients should remind us to be cautious about such results.

We should also mention the rather peculiar negative response of credit supply to inflation, which is common to all models for the U.K.. Expectations of future inflation could reduce the supply of credit at existing nominal interest rates. However, our models tend to capture the contemporaneous (within the quarter) relationships, and do not allow for expectations. So, we might think of this result as another anomalous finding.

Yet another contrast is the negative impact of money demand innovations on credit supply across all models. For the U.K. Increased demand for money appears to have diminished the flow of deposits into the banks.

Finally, we must take note of the relatively larger magnitudes of estimated standard errors of the structural disturbances compared to those for Canada. A shorter sample period might provide a partial answer. However, it could also be related to the different nature and intensity of shocks buffeting the two economies.

We close this chapter on the positive note that in spite of overall imprecise estimations of the structural models and the presence of certain anomalies and idiosyncrasies across the models, the results do provide reasonable support for our theoretical specifications and create sufficient ground for proceeding with the other statistical practices. Thus, In the next chapter, we present the impulse response analyses and variance decompositions which are based on our structural results.

CHAPTER NOTES

1. On the special nature of bank loans see, for example, Fama (1985).
2. Interest rates are measured in percentages, so their first differences are simply changes in the levels of these variables.
3. See, for example, Blanchard (1989), Turner (1993), and Karras (1994).
4. See Jaffee and Russel (1976), Blinder and Stiglitz (1983), and Greenwald and Stiglitz (1993) among others.
5. In his examination of the "credit view" of the monetary policy transformation mechanism, Bernanke (1986) considers a SVAR model that includes credit. However, his specification of credit equation suggests a passive role for credit. This does not seem to reflect the essence of the "credit view" which tends to underline the importance of credit supply versus credit demand.
6. A question mark (?) under a coefficient indicates theoretical ambiguity.
7. See Bernanke (1986), page 58.
8. Recall that the matrix Σ_u is diagonal by assumption.
9. The number of elements above or below the main diagonal of a symmetric matrix of dimension n is equal to n(n-1)/2, which is 10 when n = 5.

CHAPTER FIVE

DYNAMIC SIMULATIONS : IMPULSE-RESPONSES AND VARIANCE DECOMPOSITIONS

Having obtained the structural parameters estimates for various models, we are now able to study the dynamic behavior of the macroeconomic system embodied in those models. More specifically, we seek to find out how a given system reacts over time to a particular *one-time* structural shock occurring at a certain point in time. Such an experiment involves simulation of the future behavior of the system once it has been hit by a shock. Impulse-response analysis, a prominent feature of the VAR approach, is in fact such a simulation exercise. The related variance decomposition analysis in this approach provides us with the additional information on the relative contribution of each of the shocks to the forecast error variances of each of the variables in the system. The latter analysis is known, following Sims (1980), as "innovation accounting".

Thus, we begin this chapter by reporting the estimated impulse-responses for our selected models. There follows a discussion of how well the results correspond to our theoretical presumptions. In fact, consistency of the patterns of responses with theoretical predictions is a serious test of the theory-based restrictions imposed on the contemporaneous structural relationships. Then, we turn to the estimated variance decompositions that quantify the relative significance of various structural shocks in the overall variations of each of the variables of the system. Such results are critical to the main objective of our investigation. They will tell us how important, if at all, financial variables are in causing fluctuations in real output and other macroeconomic variables.

Estimated Impulse-Responses

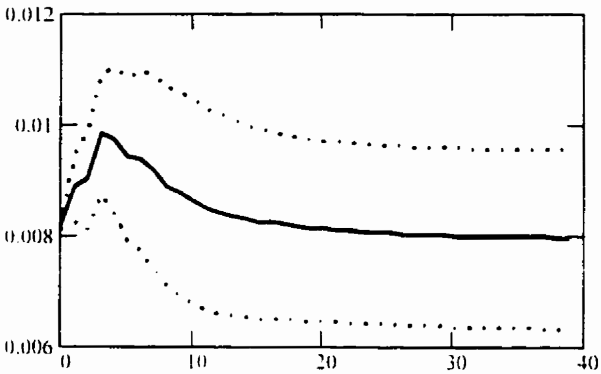
We have estimated the impulse-responses for each of the models discussed in the previous chapter. For each class of models, the results for each of the two identification strategies are strikingly similar. Therefore, we only report the results for the first identification. Our structural results in chapter four imply that a policy reaction function based on the monetary base is more appropriate for Canada, whereas one based on the interest rate is more appropriate for the United Kingdom. The idea that the United Kingdom must have been more concerned with interest rate control because of having a fixed exchange rate regime during most of the sample period (while Canada had a flexible exchange rate system), lends some credence to this inference. To further economize in reporting the results, we restrict ourselves to the monetary-base models for Canada and interest-rate models for the United Kingdom. To save still more space, we do not present the results for the models B2 and R2, because they resemble those for B3 and R3, respectively.

Although our VAR models are cast in the first differences of variables, we have calculated the impulse-responses for the (log) levels of variables. For the interest rate, however, they have been calculated for the level of this variable. A one standard deviation confidence band has also been estimated for each of the responses, using the asymptotic standard errors of the responses. The latter have been calculated through fairly complicated formulas that were presented in chapter two. The responses are plotted for a time horizon of up to 40 quarters (10 years) for all cases. For a model with 5 variables, there are 25 impulse-response functions.

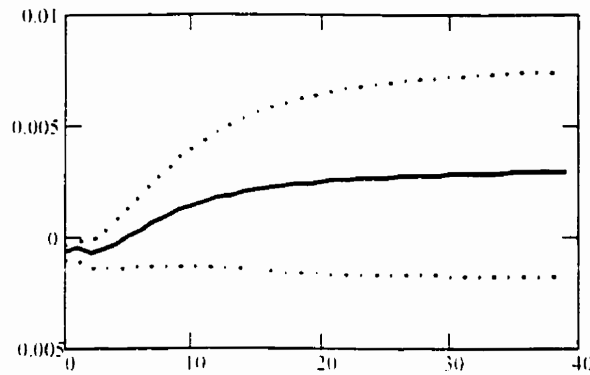
Estimated Impulse-Responses for Canada

We begin with the impulse-responses of the model B1, and report the results for the model B3 next. For Canada, Figures 5.1 through 5.5 present the impulse-responses of the variables in B1 to each of the 5 structural shocks namely, real aggregate demand or IS shocks, aggregate supply (AS) shocks, monetary policy shocks, money demand shocks, and credit shocks, respectively, over the 40 quarters following each shock. Figures 5.6 through 5.10 present the same for model B3. The figures show the responses of variables to a unit (one standard deviation) shock to structural disturbances. Structural shocks have been normalized to have a unit variance. The vertical axes reflect changes in the (log) levels of variables from their base values, which are assumed to be zero for simplicity.

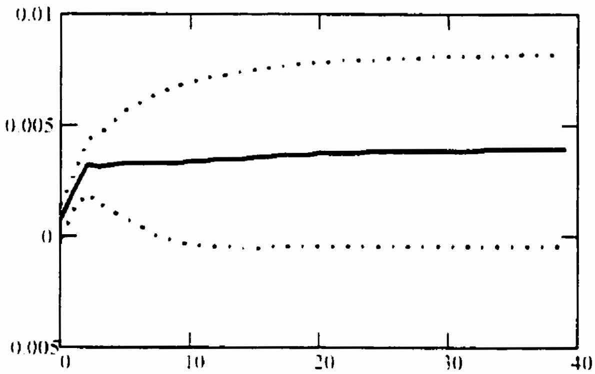
Figure 5.1 : Responses to IS shocks / model B1 – Canada



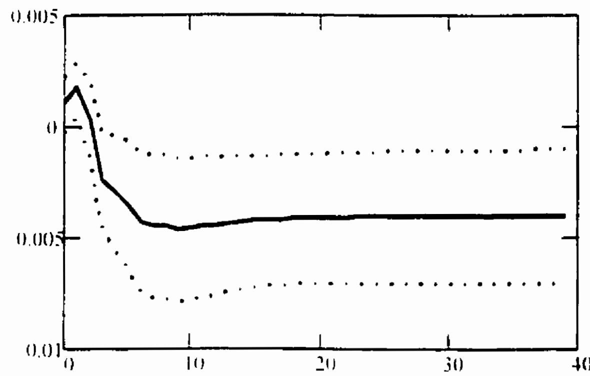
5.1a - real output response



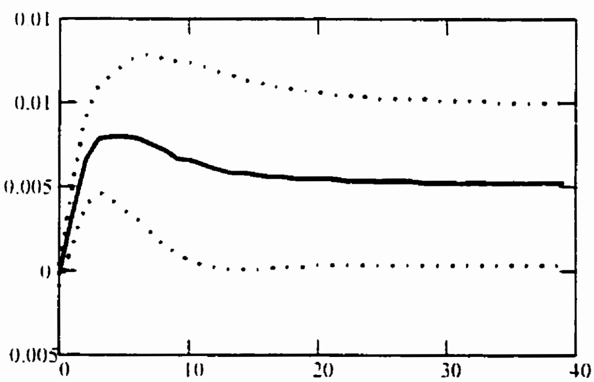
5.1b - price response



5.1c - monetary base response



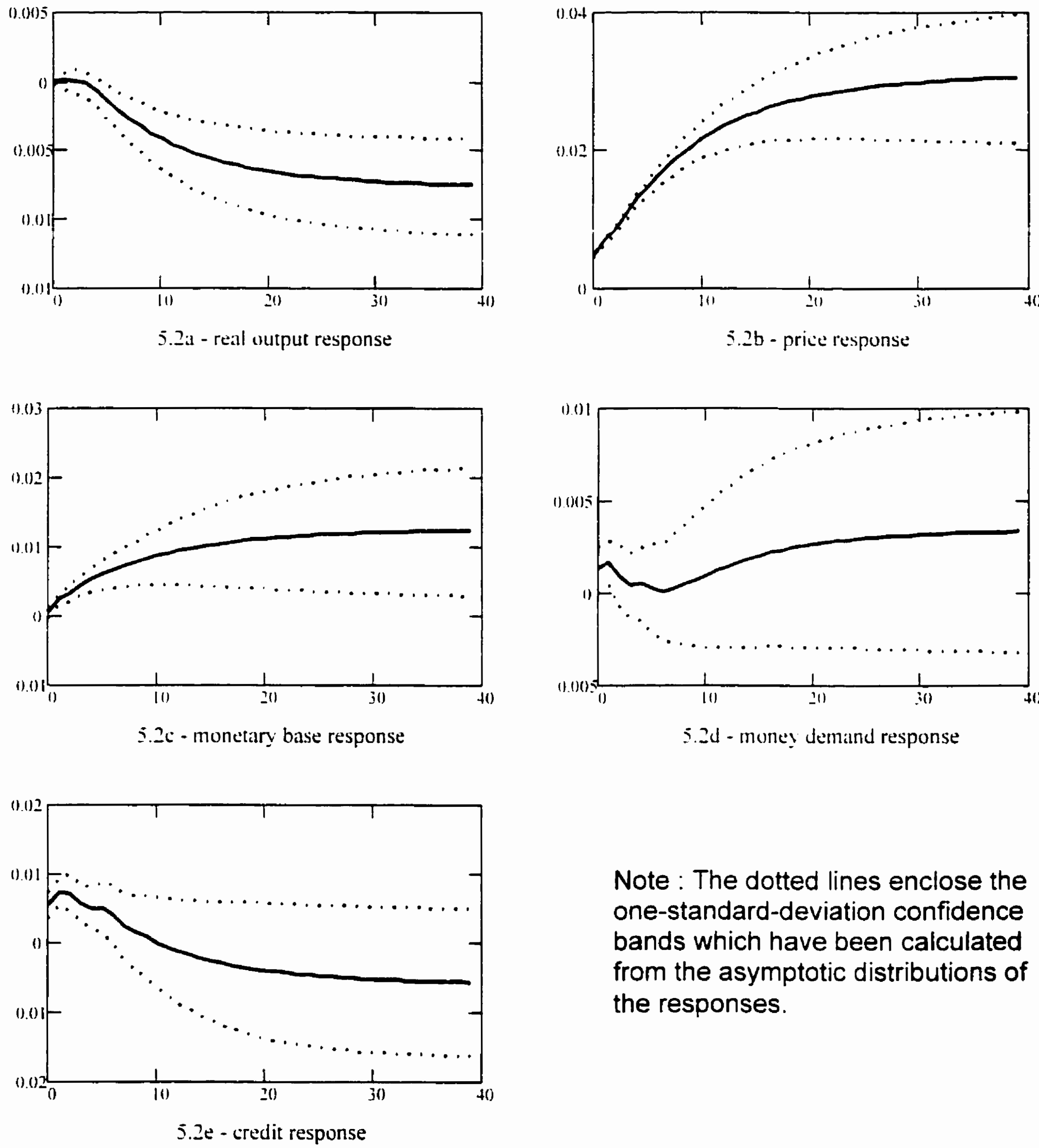
5.1d - money demand response



5.1e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

Figure 5.2 : Responses to negative AS shocks / model B1 - Canada



5.2a - real output response

5.2b - price response

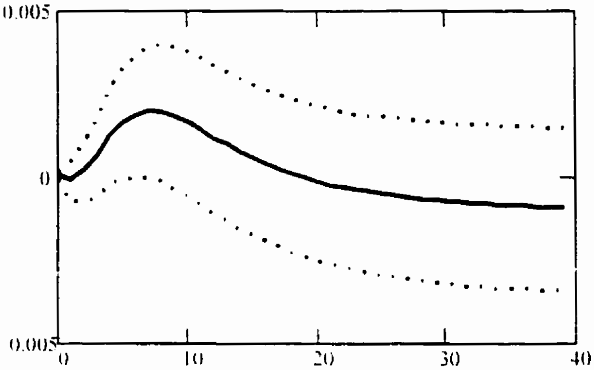
5.2c - monetary base response

5.2d - money demand response

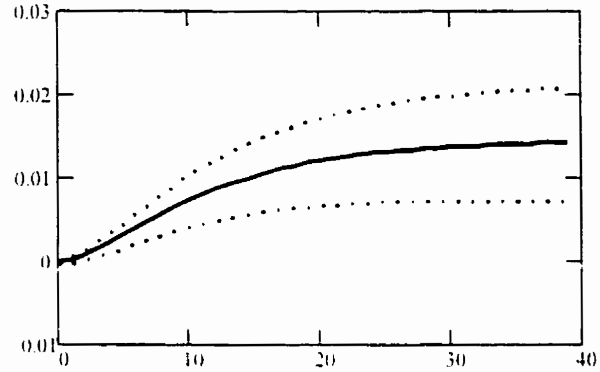
5.2e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

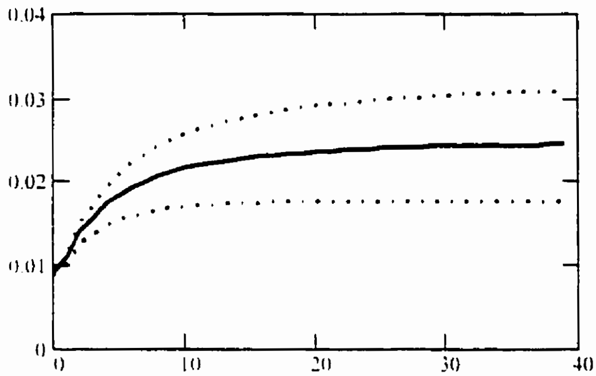
Figure 5.3 : Responses to monetary policy shocks / model B1 – Canada



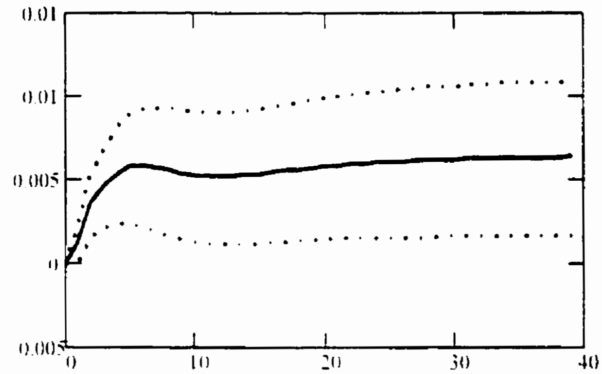
5.3a - real output response



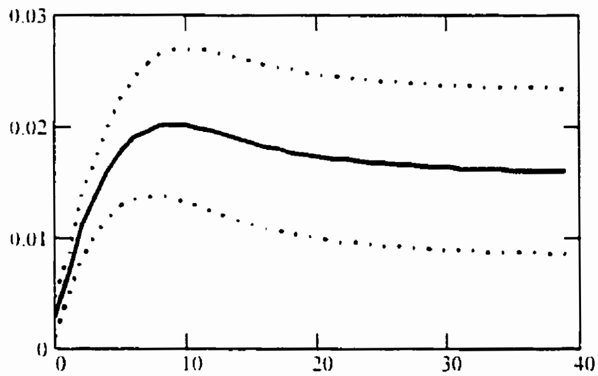
5.3b - price response



5.3c - monetary base response



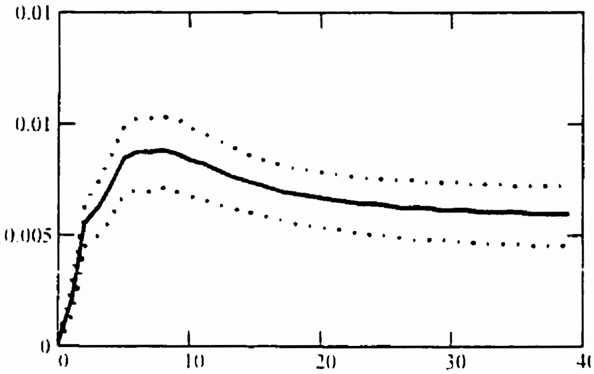
5.3d - money demand response



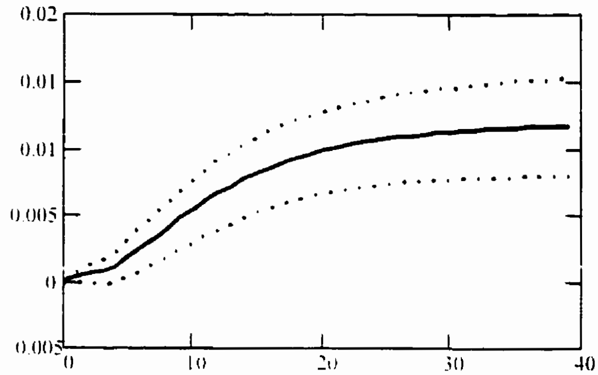
5.3e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

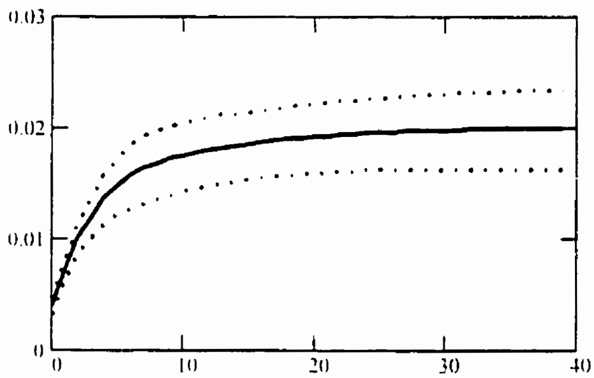
Figure 5.4 : Responses to money demand shocks / model B1 – Canada



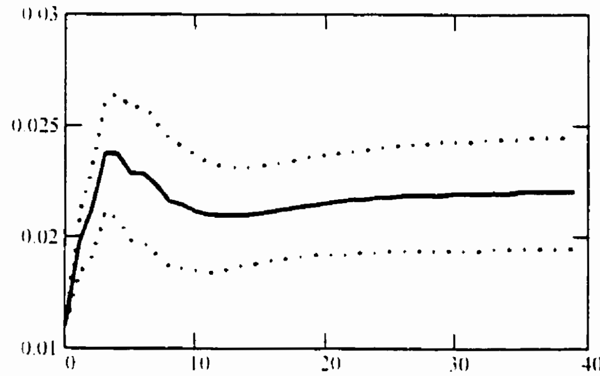
5.4a - real output response



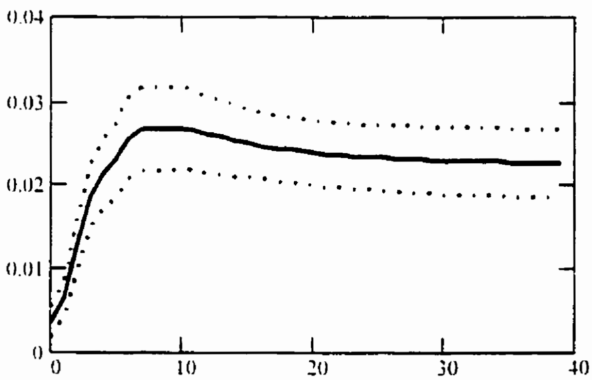
5.4b - price response



5.4c - monetary base response



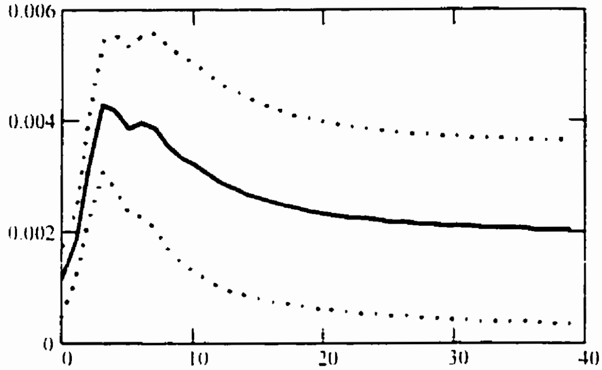
5.4d - money demand response



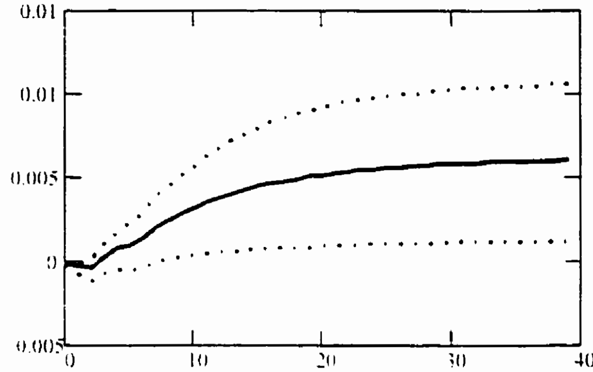
5.4e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

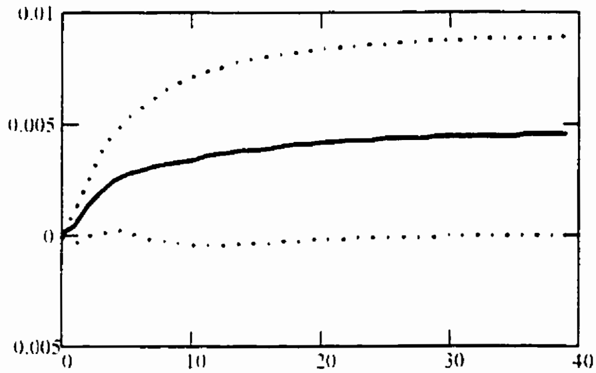
Figure 5.5 : Responses to credit shocks / model B1 – Canada



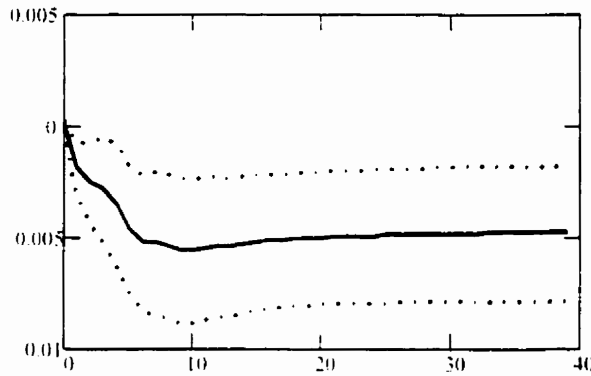
5.5a - real output response



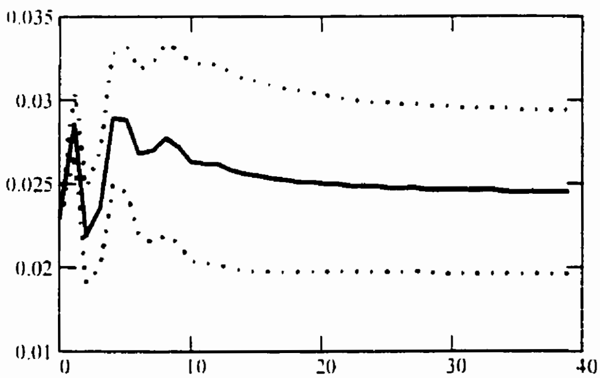
5.5b - price response



5.5c - monetary base response



5.5d - money demand response



5.5e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

Figure 5.1 shows the responses of real output, price, monetary base, money demand, and credit supply to IS shock. Real output increases contemporaneously and continues to rise in the following quarters. It reaches its peak in the third to fourth quarter. It loses much of its gain afterwards and settles at the same level as in the first quarter within 4 years. Therefore, the impact of IS shock is highest in the short run of one year. The impact, however, persists to be significantly different from zero even in the long run horizon of 10 years. Since we have not separated real IS shocks from nominal IS shocks, the shocks must be thought of as the combined real and nominal IS shocks. The permanent impact of IS shocks on real output has also been documented by several other researchers. See, for example, Diamond (1984), Yoshikawa and Ohtake (1987), and Keating (1992) among others.

Price does not respond to an IS shock within the first 5 to 6 quarters. It gradually increases beyond the 6^{th} quarter and converges to its long run level. The response, however, is not statistically different from zero throughout the forecast horizon. This result is consistent with the permanent effect of an IS shock on real output. If an IS shock contributes to the long run level of real output, it must have a negligible impact on the price level. These findings seem to support a strong and long-lived version of sticky prices as in the traditional Keynesian paradigm.

The monetary base responds positively in the first 3 quarters and remains steady afterwards as the nominal output stabilizes. The response of money demand is unexpected. One would expect money demand to increase with the level of output. However, despite a small increase in the first 2 quarters, money demand declines through the 6^{th} quarter where it settles at its long run level. This unexpected reduction in money demand could perhaps be related to some missing variable form our demand for money function. Credit supply responds positively to IS shock in the first 4 quarters and stays at its peak for another 3 quarters. It gradually declines to a small extent and attains a permanent level (not significantly different from zero, though) beyond the 4th year. This favorable response of credit to IS shock could have resulted from the positive response of monetary base to IS shock, because credit supply is directly related to the monetary base according to the "credit view" of monetary policy transmission mechanism. It could also be the case that credit supply is accommodating increased credit demand due to IS shock.

The responses of variables to a unit AS shock are shown in various panels of Figure 5.2. Since output (supply) and price are inversely related for a given demand, a positive shock to price may be perceived as a negative supply shock. Therefore, all the responses in this figure are considered reactions to a negative AS shock. Real output does not respond to AS shock in the first year, but declines for much of the time horizon to settle at a steady level beyond the 6th year. As expected, price rises in the current period and continues to rise for most of the time. It eventually converges to a level toward the end of the time horizon. Monetary base shows a positive, though weak, response which is all over by the end of the 2nd year. Such a response is also expected, because a declining real output together with a faster rising price level imply a slow growing nominal output to which monetary base responds. Money demand initially declines for 2 years. It then rises to catch up with the rising price level. The wide confidence band around this response, however, indicates that it is not statistically different from zero. Credit responds positively in the first few quarters as the monetary base and prices go up. It declines afterwards and bottoms to a level not different from zero.

The five panels of Figure 5.3 contain the responses of variables to a unit monetary policy shock in the form of expansion in the monetary base. Real output is not affected for the first 3 quarters. It begins to rise in the 4^{th} quarter and attains its peak toward the end of the 8^{th} quarter. This lagged response of real output to monetary policy is well known in the literature. Output, however, declines gradually to lose all the gain by the end of the 4^{th} year. There is no significant long run impact of monetary policy on real output, a finding that is compatible with much of the perceived theory in this regard. Price shows inertia in the first few quarters before monetary expansion gets translated into higher aggregate demand. It then increases monotonically for most of the time until it stabilizes toward the end of the 10-year horizon. As expected, monetary base jumps up in the current quarter and continues to rise well into the 3^{rd} year where it converges to its long run level. Money demand shows a response similar to that of the monetary base, with stronger initial response presumably due to increase in real output. Credit supply shows a positive and strong response to monetary policy shock for the first 4 to 5 quarters that slows down by the end of the 10^{th} quarter. It remains high for the rest of the time, however. The finding, once again, supports the "credit view" of the monetary policy transmission mechanism.

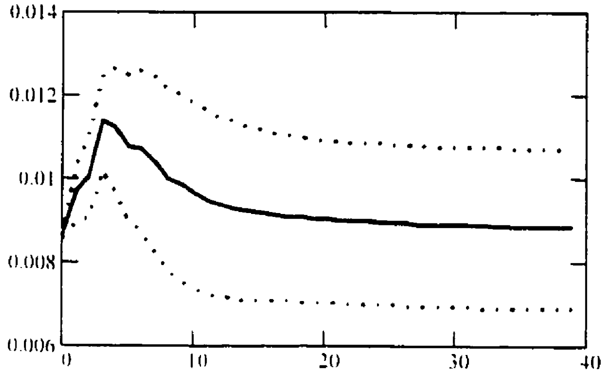
Responses to money demand shocks are reported in Figure 5.4. Money demand shocks appear to have a positive and lasting impact on real output. Much of the impact occurs during the 2^{nd} to 5^{th} quarters, however. It is not clear why money demand shock should increase real output. Our conjecture is that an accommodative monetary authority responds to money demand shock by increasing the monetary base, which is evident from panel 5.4c. Increased monetary base, in turn, enhances credit supply that helps increase real output. In fact, panels 5.4a and 5.4e show a striking similarity in the patterns of responses of real output and credit supply. This tends to reinforce our conjecture in this regard. The response of the price level is trivial in the first 4 quarters, but it is positive afterwards. Much of the rise in price happens during the 2nd and 3rd year. As expected, money demand responds positively to its own shock and attains its peak value about the same time that real output is at its highest.

Finally, Figure 5.5 presents responses to credit shocks. Panel 5.5a shows that real output increases sharply in the first 3 quarters and declines thereafter before converging to its long run level. Therefore, credit shock appears to have much of its impact on real output in the short run of 8 quarters, leaving no significant impact in the long run. As before, price shows stickiness in the short run of 4 to 6 quarters. It rises gradually in the long run, however. The monetary base has its typical behavior as it responds to real output and price. It rises over the course of 8 quarters and soon converges to its long run level. The anomaly here is the response of money demand to credit shocks. We would expect money demand to move in tandem with the real output and price. However, money demand declines for the first 6 quarters and remains steady for the rest of the time horizon. Although credit might be considered as a substitute for money, there is no such relationship specified in our structural model to justify that. Once again, the suspicion is that our money demand function is too simple to capture the full dynamics of money demand. Credit response to its own shock is as expected. It rises in the short run of 4 quarters and retains much of this impact over the long run. Its short run behavior is rather erratic, however.

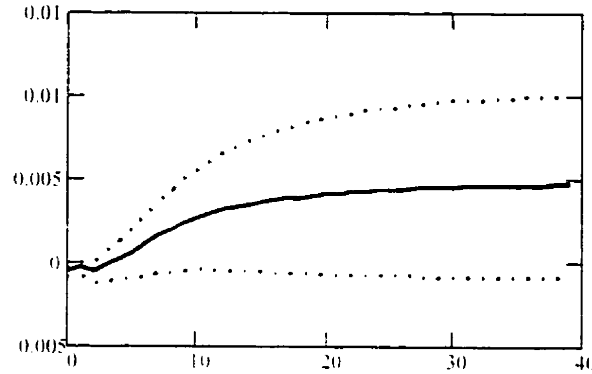
In summary, most of the responses of variables to various structural shocks seem to be consistent with the perceived economic theory and, therefore, validate our earlier estimation results on the underlying structural model.

We now turn to model B3 for which the impulse-responses are reported in Figures 5.6 through 5.10 below.

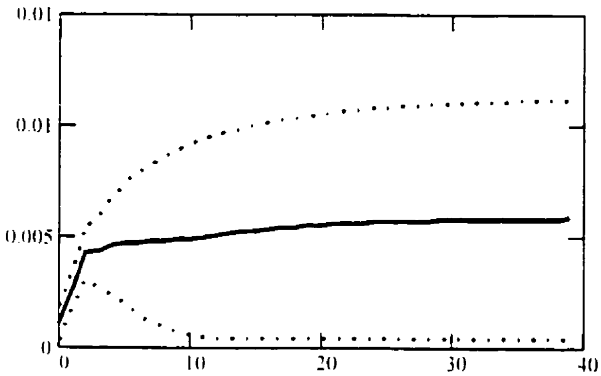
Figure 5.6 : Responses to IS shocks – model B3 / Canada



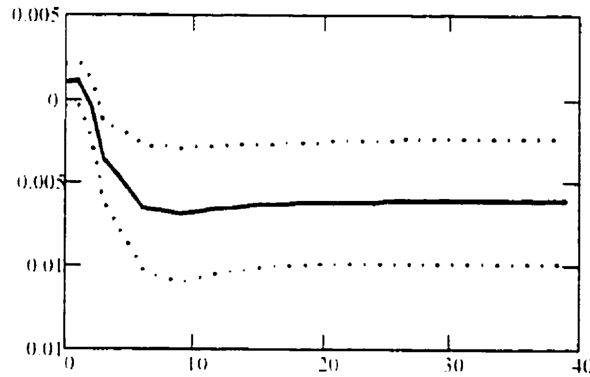
5.6a - real output response



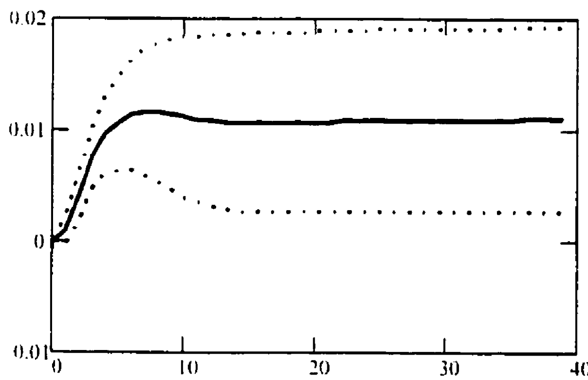
5.6b - price response



5.6c - monetary base response



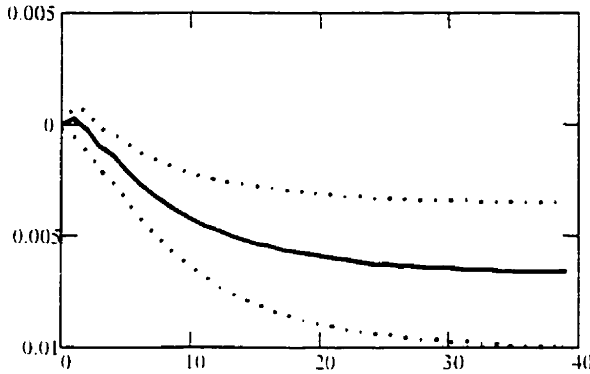
5.6d - money demand response



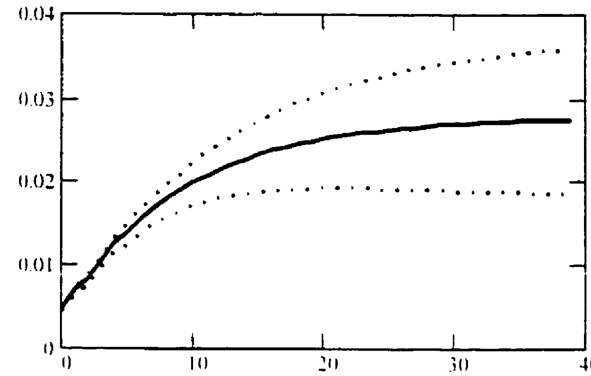
5.6e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

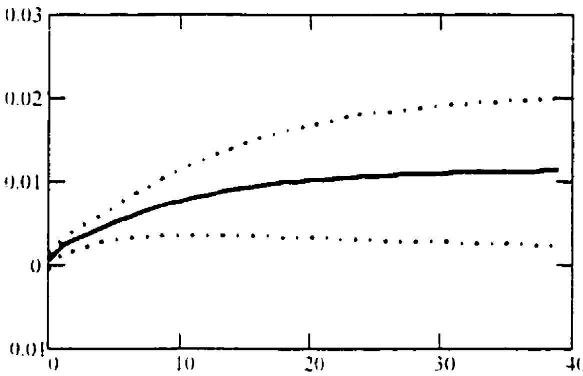
Figure 5.7 : Responses to negative AS shocks – model B3 / Canada



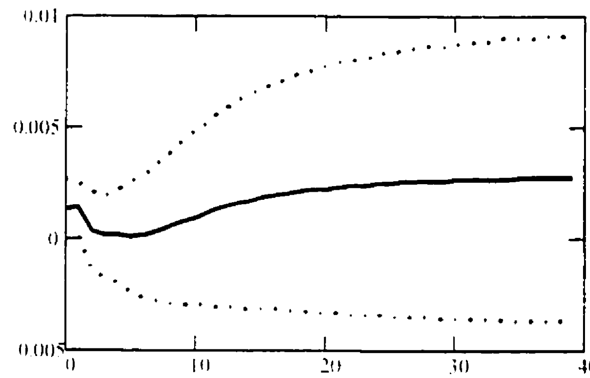
5.7a - real output response



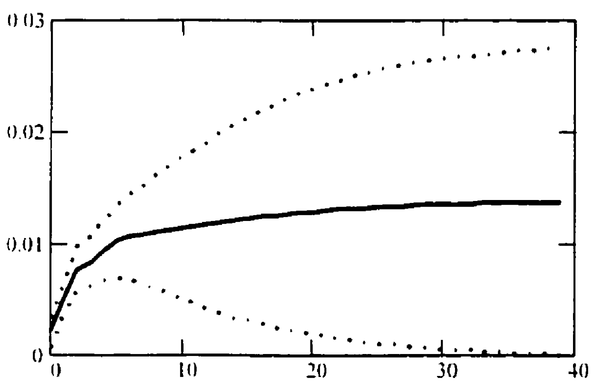
5.7b - price response



5.7c - monetary base response



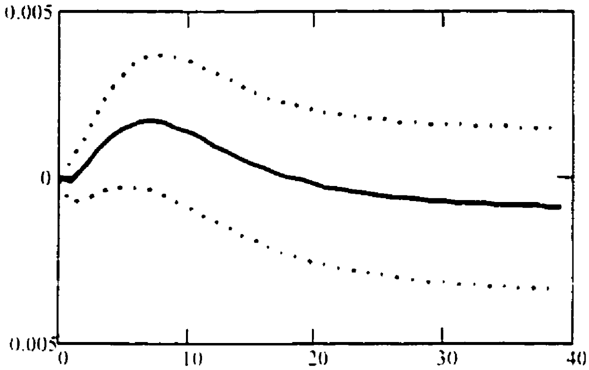
5.7d - money demand response



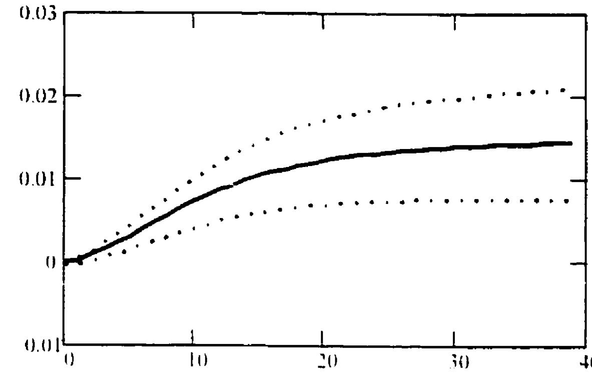
5.7e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

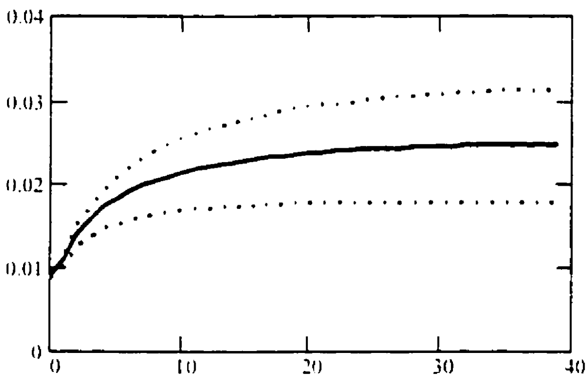
Figure 5.8 : Responses to monetary policy shock – model B3 / Canada



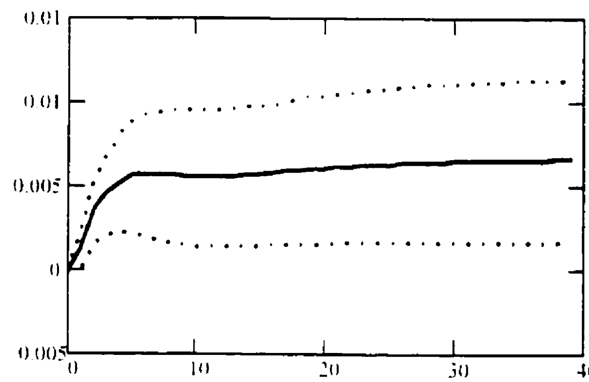
5.8a - real output response



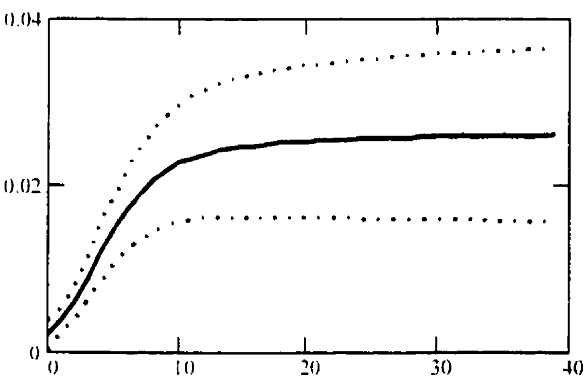
5.8b - price response



5.8c - monetary base response



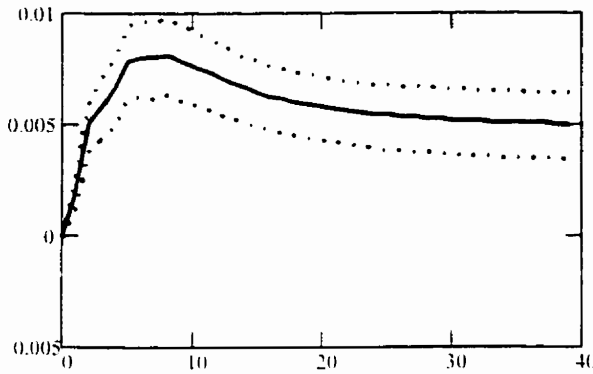
5.8d - money demand response



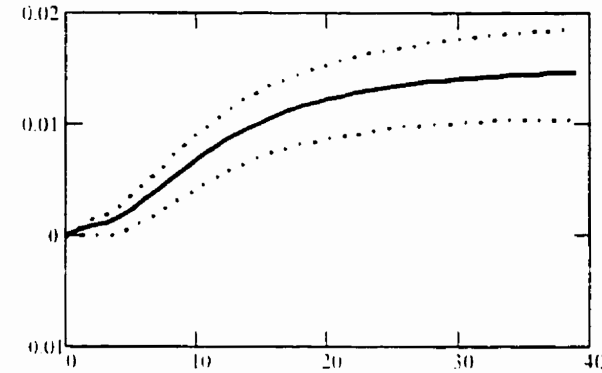
5.8e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

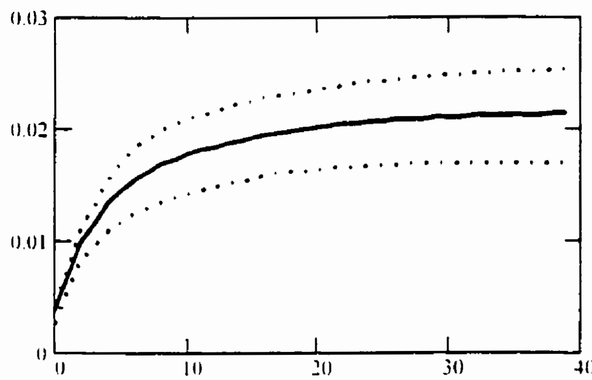
Figure 5.9 : Responses to money demand shock - model B3 / Canada



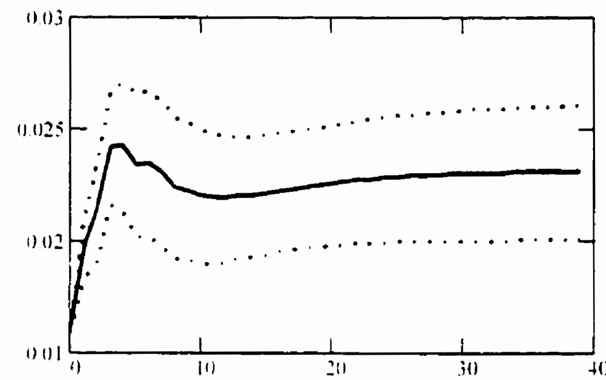
5.9a - real output response



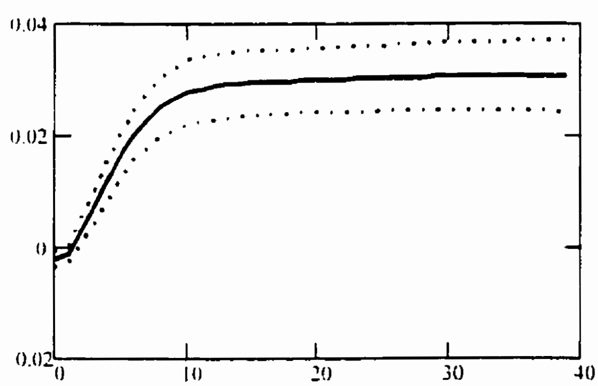
5.9b - price response



5.9c - monetary base response



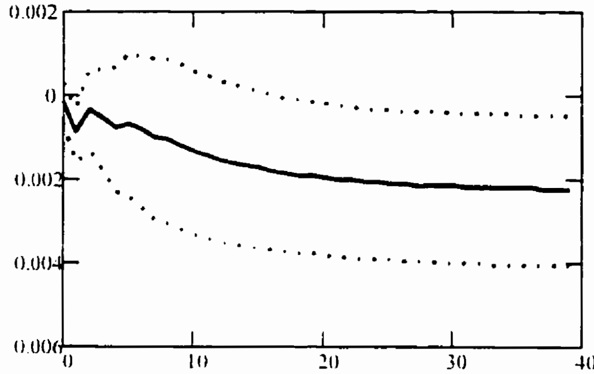
5.9d - money demand response



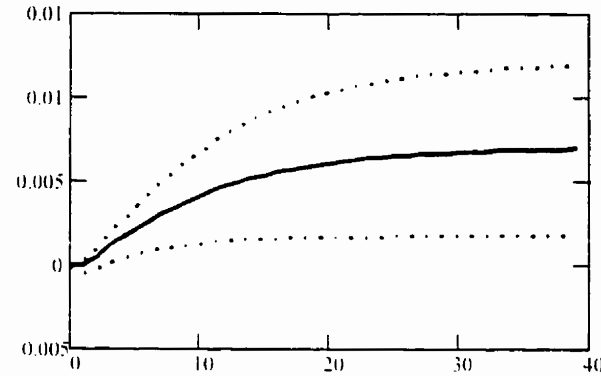
5.9e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

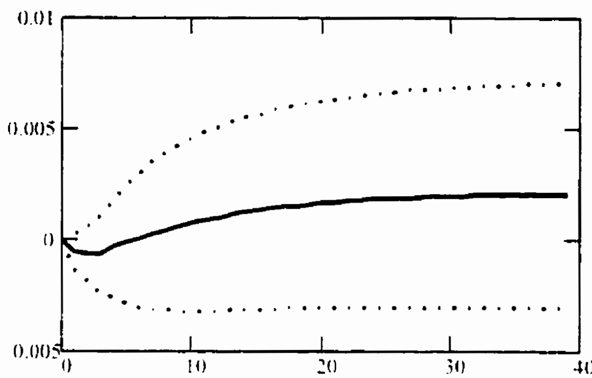
Figure 5.10 : Responses to credit shock - model B3 / Canada



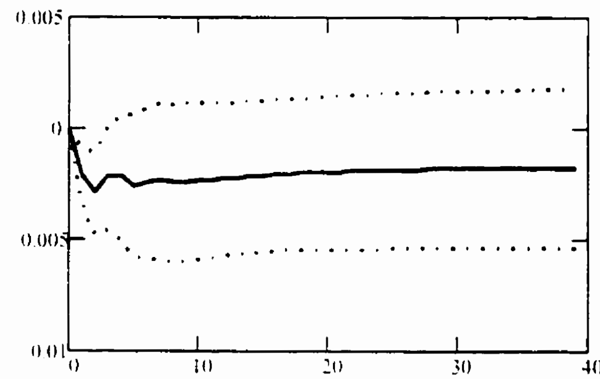
5.10a - real output response



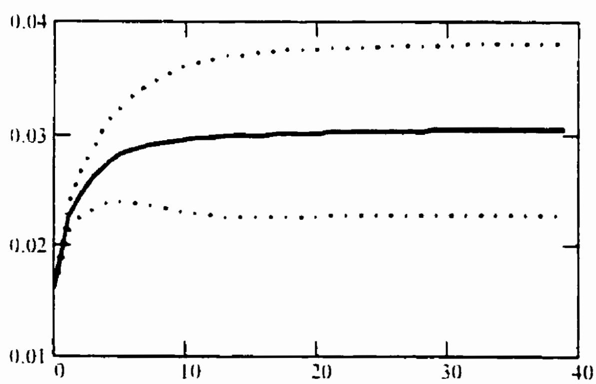
5.10b - price response



5.10c - monetary base response



5.10d - money demand response



5.10e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

A glance at Figures 5.6 through 5.10 reveals that the impulse-responses of the model B3 which is based on the broad measure of credit (i.e. total bank credit) are generally of the same pattern as those for the model B1, which is based on the narrow measure of credit to persons. There are, however, a few instances in which the two models behave differently. The first one to note, is the different responses of the two credit measures to AS shock. For the narrow measure, the response as reflected in panel 5.2e of Figure 5.2 is positive and lasts only for 9 to 10 quarters. Whereas for the broad measure, the response persists over the long run. The latter response, however, is less precisely estimated. The positive responses of both credit measures to (negative) AS shock arise from increasing monetary base and prices.

The two models also differ in terms of the response of real output to credit shock. As depicted in panel 5.5a of Figure 5.5, real output response to narrow credit shock is positive and retains much of its short run gain over the long run. However, panel 5.10a of Figure 5.10 shows that real output response to broad credit shock is overall negative and trivial in the short run.

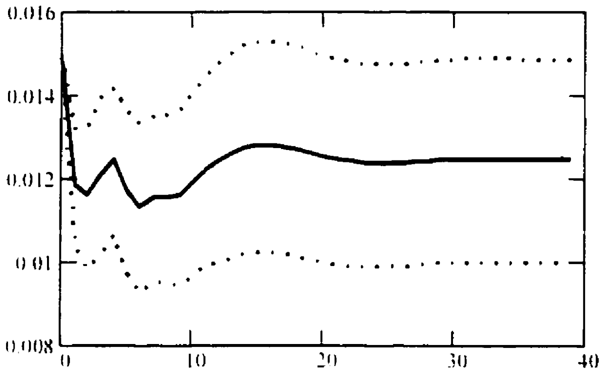
The last difference to observe is the response pattern of credit to its own shock. The narrow credit shows a volatile response in the short run, whereas the response pattern of broad credit is smooth at all times. The two credit measures begin to converge to their long run level at the same time, however.

We are left with the impression that the various impulse-response results for Canada are relatively robust to the choice of credit measure. However, as far as the impact on real output is concerned, the result based on the narrow credit (model B1) is more consistent with our structural theory.

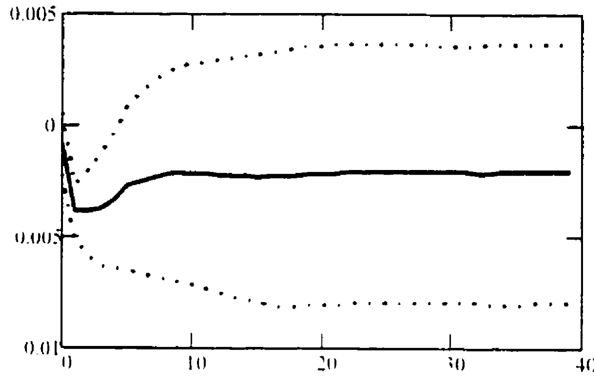
Estimated Impulse-Responses for the U.K.

In what follows, we describe the impulse-response patterns for the United Kingdom. Figures 5.11 through 5.15 report such patterns for the model R1 which has the rate of interest as its policy variable and corresponds to the narrow measure of credit. Impulse-responses for the model R3 which is based on the broad measure of credit are presented in Figures 5.16 through 5.20. The structural shocks are the same as those for Canada and, as before, the figures show the responses to a unit shock (impulse).

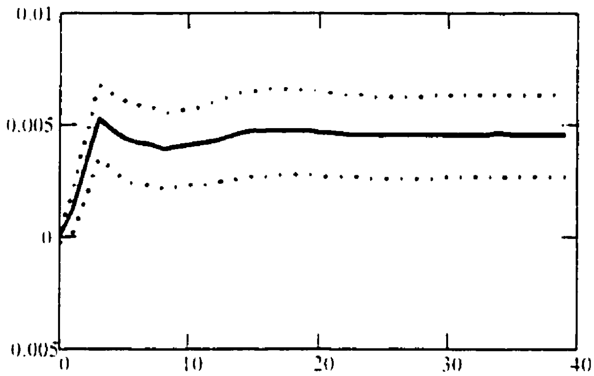
Figure 5.11 : Responses to IS shock - model R1 / U.K.



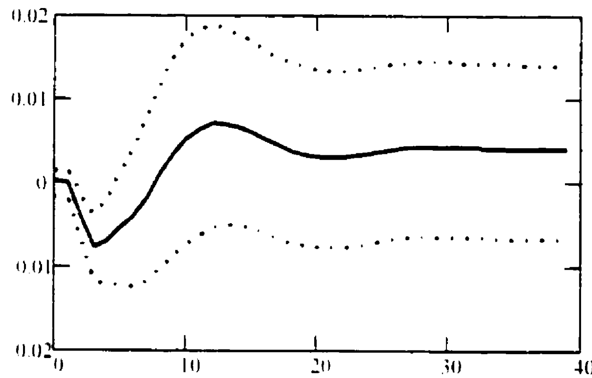
5.11a - real output response



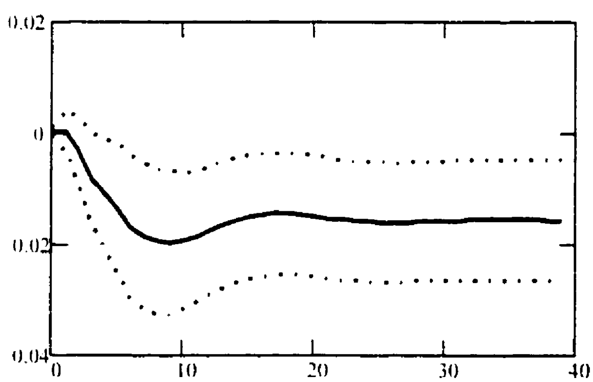
5.11b - price response



5.11c - interest rate response



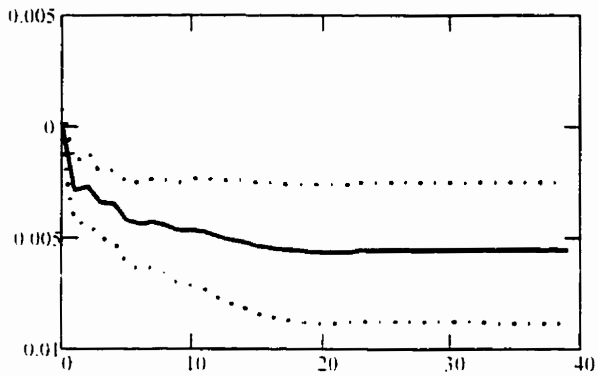
5.11d - money demand response



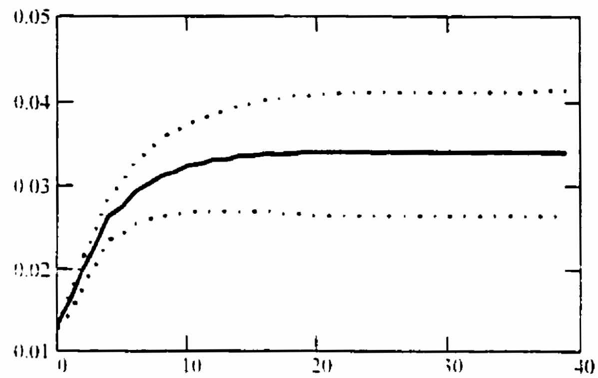
5.11e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

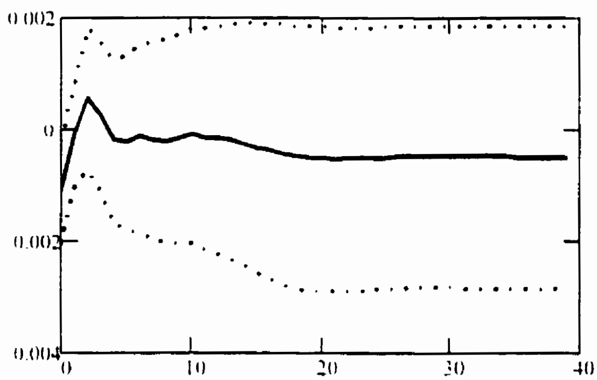
Figure 5.12 : Responses to negative AS shocks - model R1 / U.K.



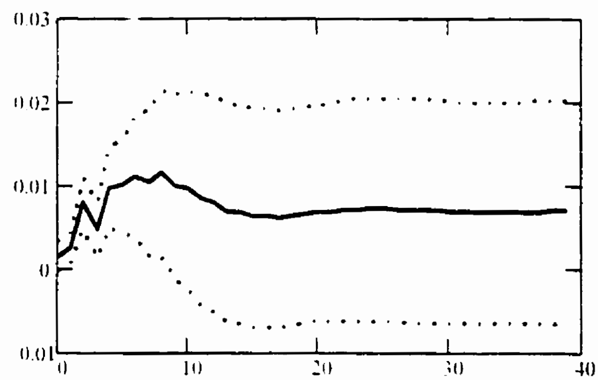
5.12a - real output response



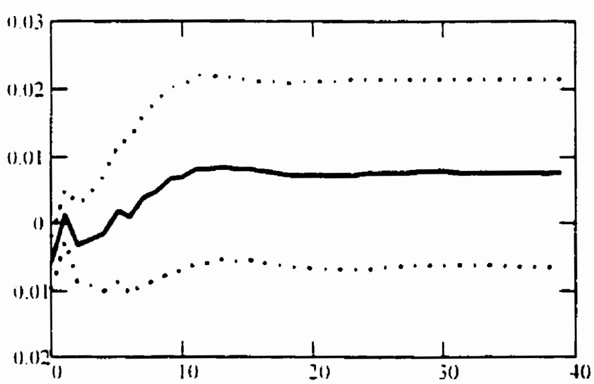
5.12b - price response



5.12c - interest rate response



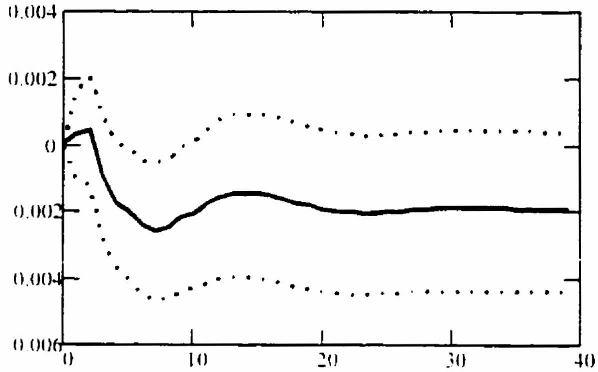
5.12d - money demand response



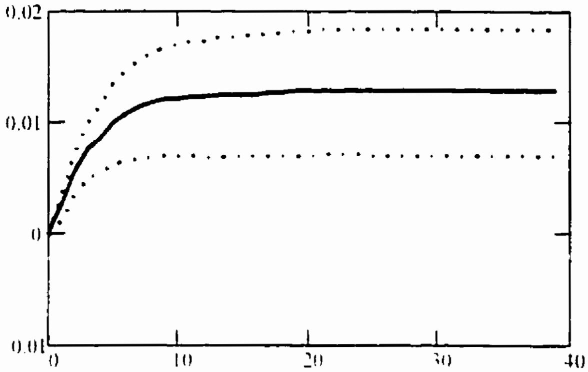
5.12e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

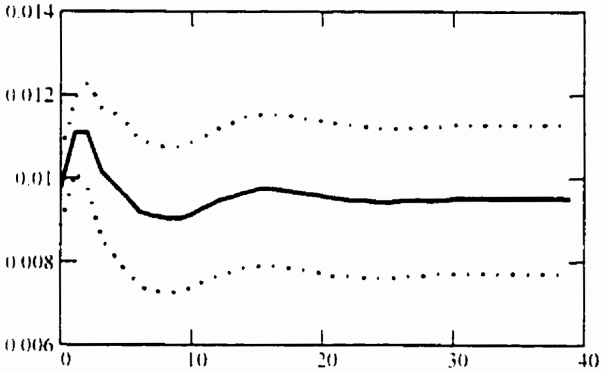
Figure 5.13 : Responses to monetary policy shock - model R1 / U.K.



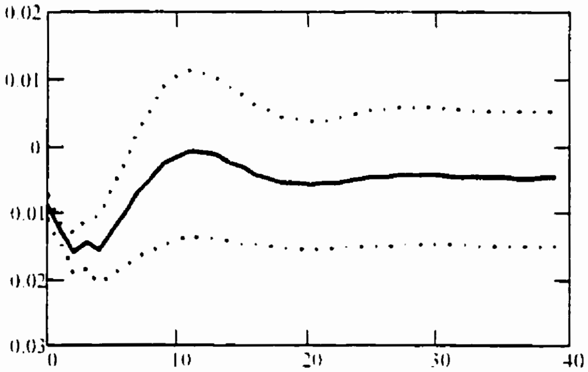
5.13a - real output response



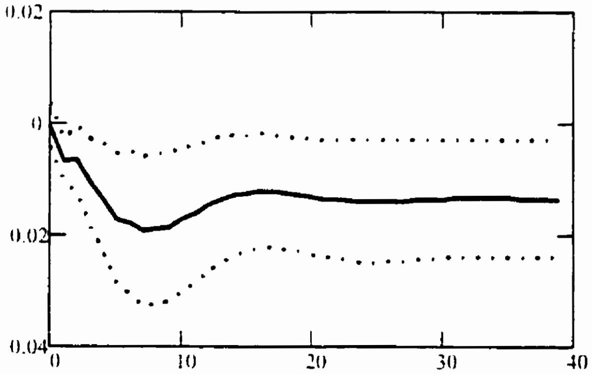
5.13b - price response



5.13c - interest rate response



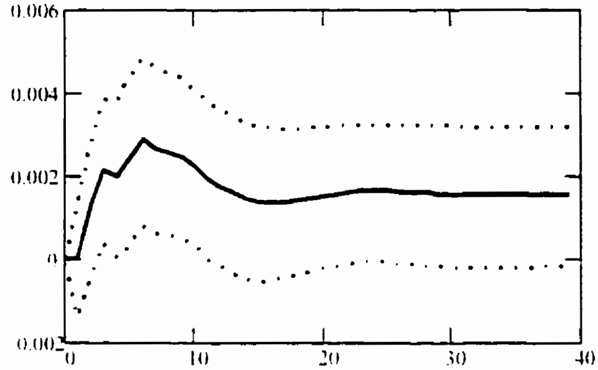
5.13d - money demand response



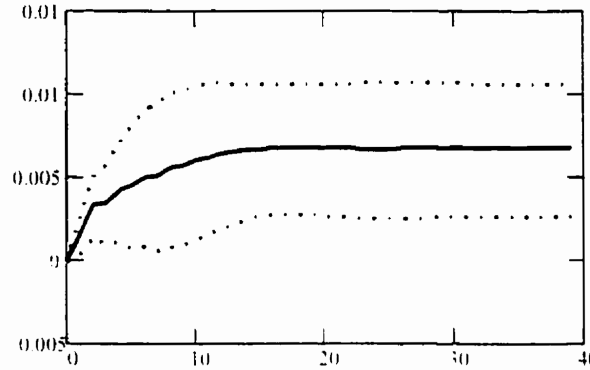
5.13e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

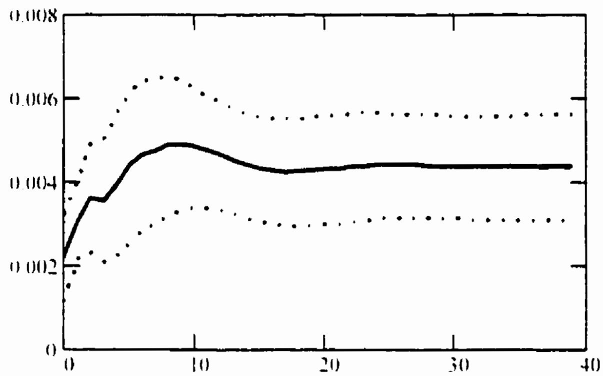
Figure 5.14 : Responses to money demand shock - model R1 / U.K.



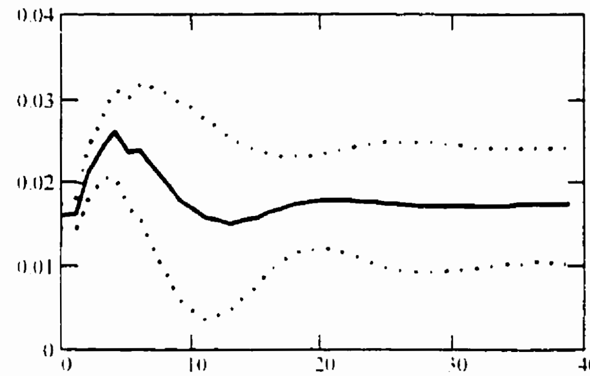
5.14a - real output response



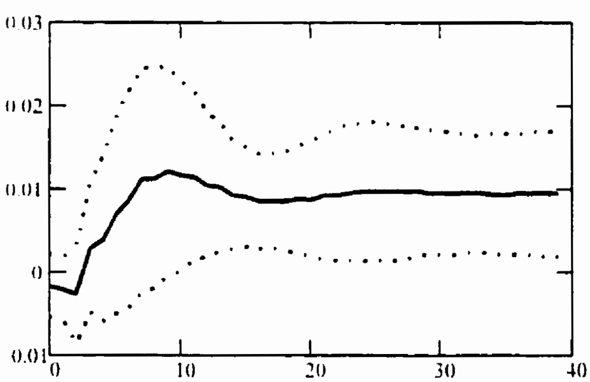
5.14b - price response



5.14c - interest rate response



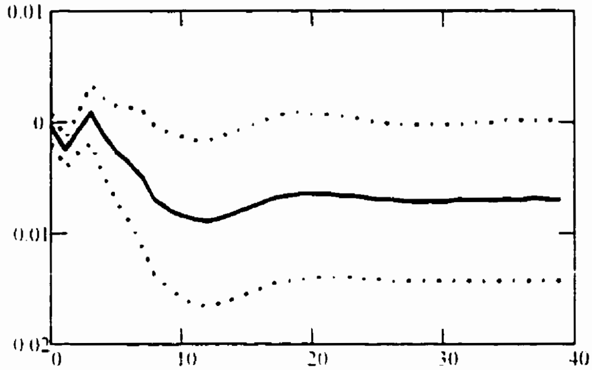
5.14d - money demand response



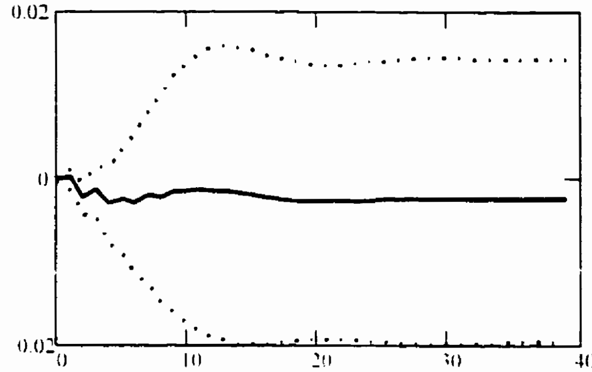
5.14e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

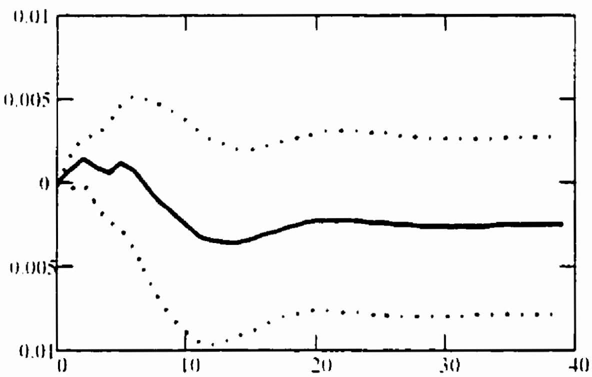
Figure 5.15 : Responses to credit shock - model R1 / U.K.



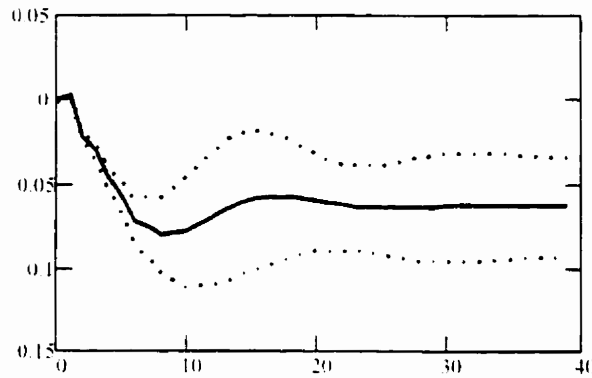
5.15a - real output response



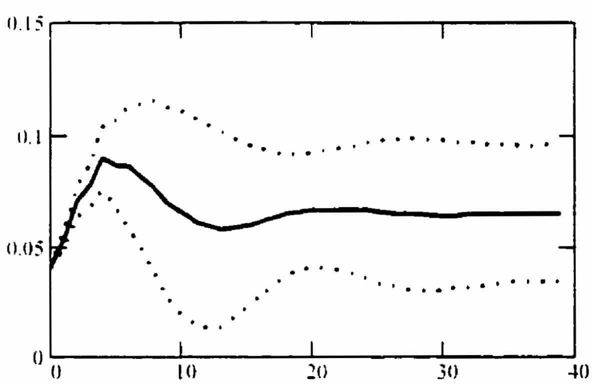
5.15b - price response



5.15c - interest rate response



5.15d - money demand response



5.15e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

Figure 5.11 shows the responses of our set of five variables - real output, price, rate of interest, money demand, and credit supply - to real aggregate demand (IS) shock. Real output rises contemporaneously, but loses about a quarter of the gain in the second quarter and stays more or less at this level for the rest of the time horizon. So, here too, IS shock leaves a permanent impact on real output. Price does not respond in the current quarter, but declines in the second quarter where it remains sticky for another two quarters before a slight increase in the following quarters. It remains below its initial level over the long run. The negative response of price to IS shock is not theoretically plausible. However, its wide band of confidence signifies the statistical insignificance of such response. IS shock has no contemporaneous impact on the rate of interest. However, interest increases during the 2nd to 4th quarters and stabilizes thereafter for the long run. Money demand begins to decline in the 3rd quarter as price declines and the interest rate rises. It increases from the 4th quarter on and settles at a small positive level over the long run. Credit supply declines during the 3rd to 10th quarter and converges to its long run level after a modest increase. This negative response is presumably caused by the higher interest rate that adversely affects the available funds for lending according to the "credit view" argument.

Responses to a negative aggregate supply (AS) shock are reported in Figure 5.12. As before, a positive price shock is taken to be a negative supply shock. Thus, real output declines persistently beyond the current quarter and settles to its long run level after about 3 years. As expected, negative supply shock has a permanent negative impact on real output. Negative shocks to labor supply, input price hikes, and productivity slow down as instances of negative supply shocks could account for a lasting decline in the real output. Supply shock increases price over the short run of 10 quarters. Price remains at its highest over the long run. Interest rate drops contemporaneously, but increases in the next two quarters in response to increasing price level as the monetary authority attempts at curbing the inflation. It declines in the 3rd and 4th quarters to sit around zero for the rest of the time as both output and price stabilize. Money demand increases over the short run, though not quite smoothly. This rise in money demand must have resulted from increased nominal output. Money demand stabilizes beyond the 3rd year. concurrent with real output and price. For the first 7 quarters. the credit supply response is nil. However, it shows a modest rise over the course of the next 3 quarters and settles at a long run level not distinct from zero. So, AS shock does not appear to impact credit supply. This is mainly because the rate of interest remains pretty stable over the whole time horizon.

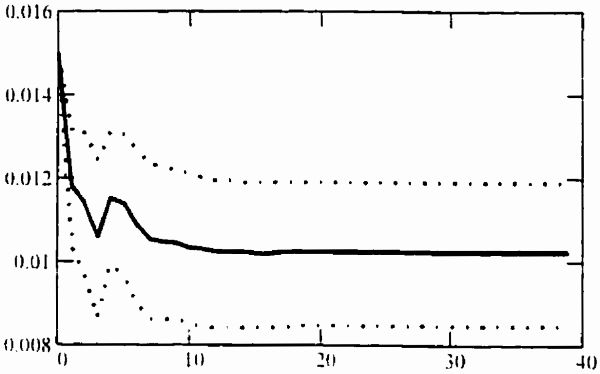
A shock to the rate of interest, which is perceived as the monetary policy shock, causes responses that are depicted in various panels of Figure 5.13. In contrast to the Class-B models, a positive monetary policy shock here is a *contractionary* measure on the part of the monetary authority. Therefore, real output starts to decline after a lag of 3 quarters. The maximum negative impact occurs during the 6th to 7th quarters. Real output retains much of the loss towards the end of the time horizon. This reduction in real output might be caused by the reduction in credit supply. The similar patterns of real output and credit supply responses to monetary policy shock bear on this observation. The reduction in credit supply, in turn, is resulted from higher rates of interest as predicted by the "credit view" of monetary policy transmission mechanism. Money demand declines during the first 4 quarters in response to lower output and higher interest rate. However, it rebounds afterwards due to rising prices and rests close to zero beyond the 10th quarter.

Figure 5.14 presents the responses to money demand shock. Despite the inertia in the first two quarters, real output increases sharply in the 3rd and 4th quarters and reaches a peak by the end of 6^{th} quarter. The similarity of the pattern and timing (with a lag of a quarter) of output and money demand responses imply that money is moving output, which is consistent with the vast literature on real balance and liquidity effect. *As* panel 5.14b indicates, money demand shocks increase the price rather sharply in the first 3 quarters. Price continues to grow only gradually for another 8 quarters before stabilizing at its long run level. Positive impulses to money demand push up the rate of interest contemporaneously. The rate of interest increases up to the 8^{th} quarter and declines slowly to settle at a long run level above the initial rise. Money demand responds positively to its own shock and peaks by the end of the 4^{th} quarter. It declines thereafter and converges to the its long run level. Credit Supply sluggishly declines during the first 3 quarters as higher interest rates constrain the bank reserves and thus loanable funds. It rebounds in the 4^{th} quarter and increases, possibly due to higher prices, till the 9^{th} quarter where it subsides to a long run positive level.

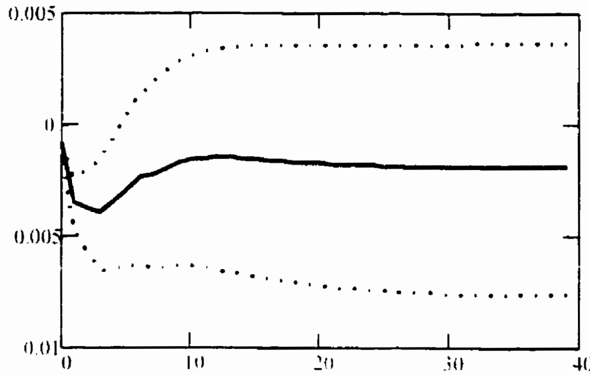
Finally, we discuss the responses to credit shock which are reported in Figure 5.15. Credit increases in response to its own shock and attains a maximum by the end of the 4^{th} quarter. It declines for the next 8 quarters and stabilizes just over the initial response over the long run. We would expect real output to follow the credit pattern, However, counter to our expectation, real output shows an overall declining pattern. Price is hardly affected at any time horizon. The interest rate shows a trivial positive response in the first 6 quarters, but declines below zero and remains so in the long run. Declining real output and the stable price level call for a declining response of money demand as reflected in panel 5.15d of this figure.

Overall, despite a few anomalies in the responses to various shocks, the impulse-responses in model R1 are, for the most part, consistent with the underlying structural theory. To find out if our results vary with the change of narrow credit to broad credit, we now turn to model R3 for which the impulse-responses estimates are presented in Figures 5.16 through 5.20 below.

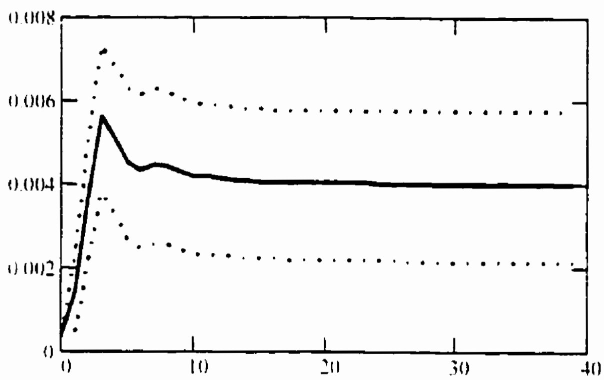
Figure 5.16 : Responses to IS shock - model R3 / U.K.



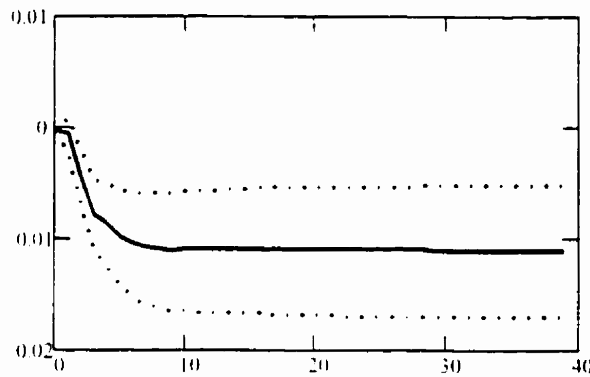
5.16a - real output response



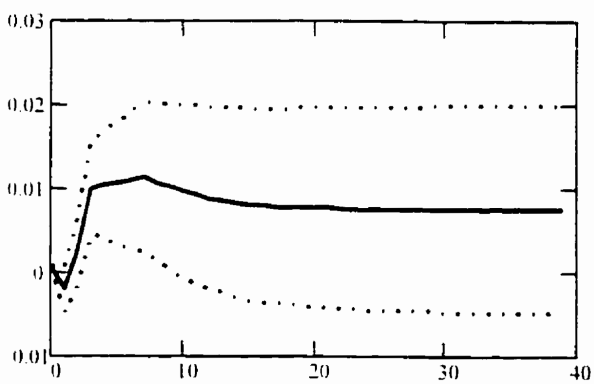
5.16b - price response



5.16c - interest rate response



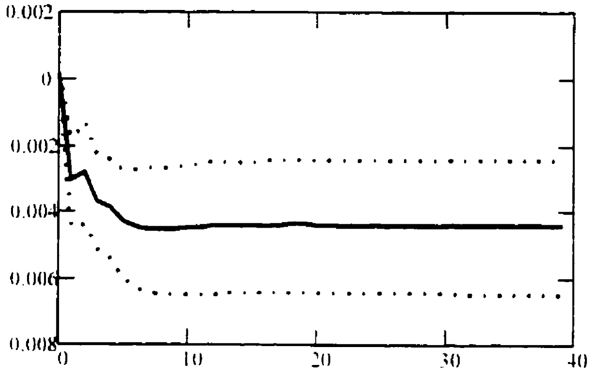
5.16d - money demand response



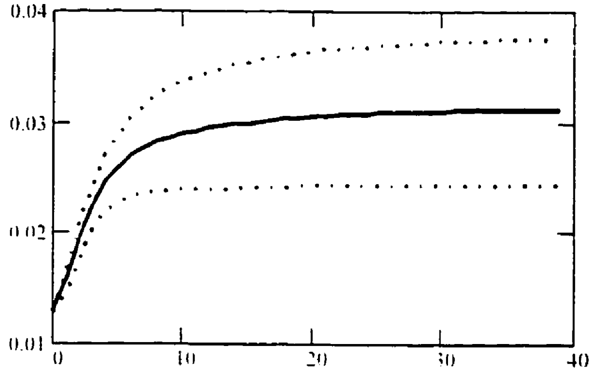
5.16e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

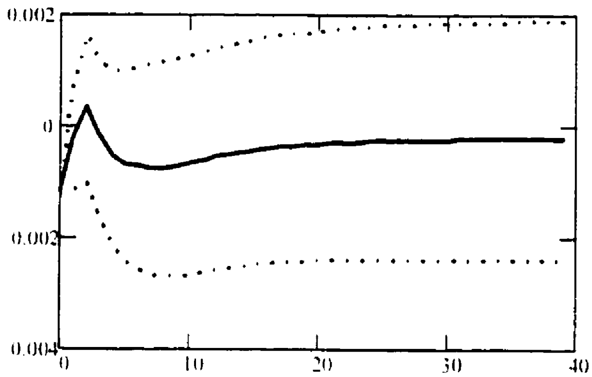
Figure 5.17 : Responses to negative AS shock - model R3 / U.K.



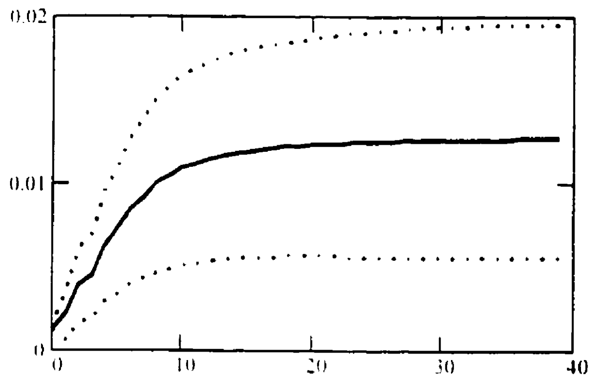
5.17a - real output response



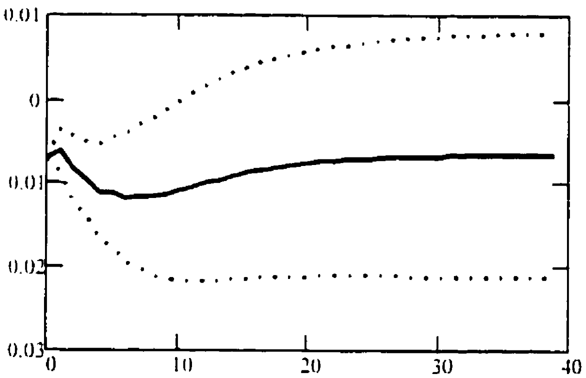
5.17b - price response



5.17c - interest rate response



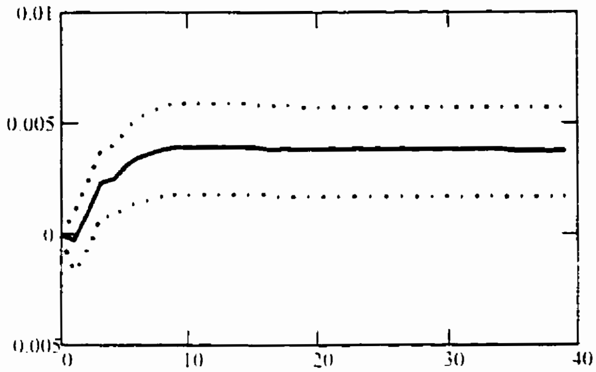
5.17d - money demand response



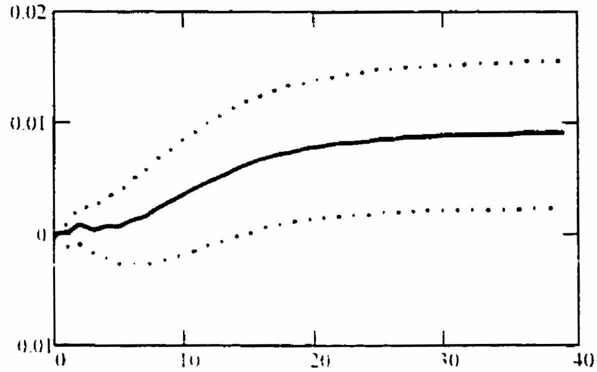
5.17e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

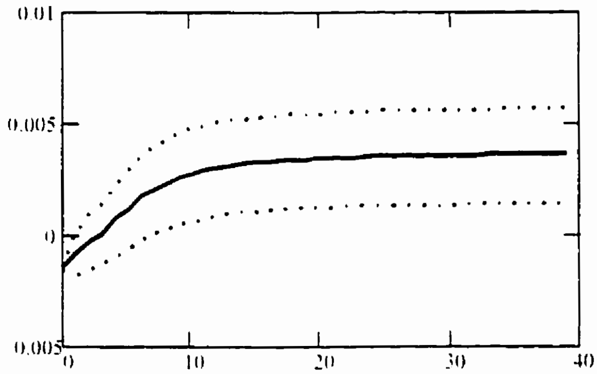
Figure 5.18 : Responses to monetary policy shock - model R3 / U.K.



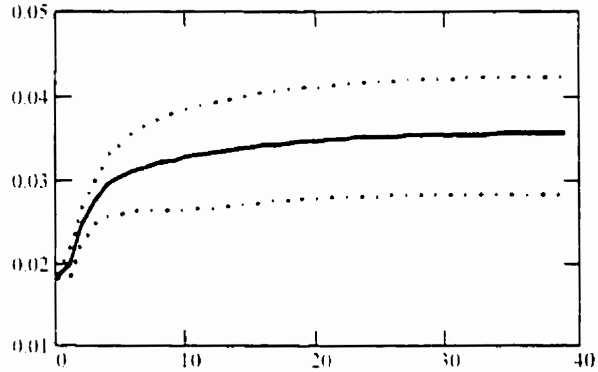
5.18a - real output response



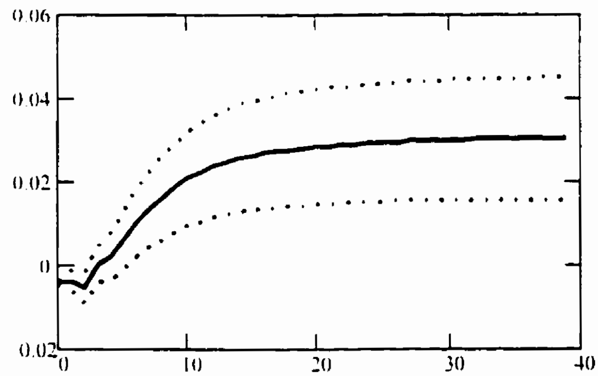
5.18b - price response



5.18c - interest rate response



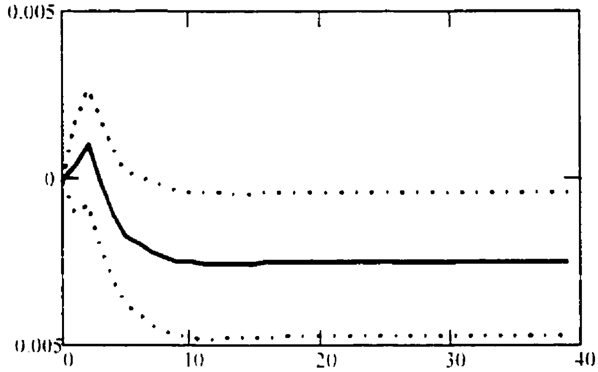
5.18d - money demand response



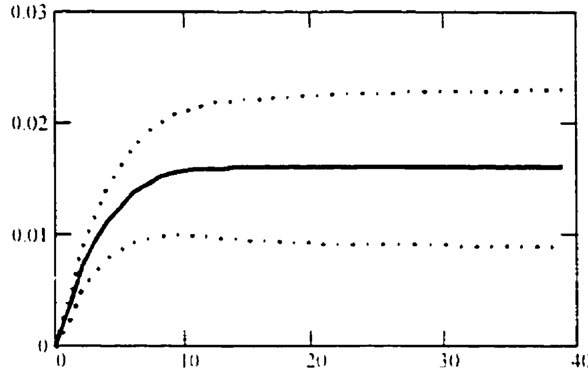
5.18e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

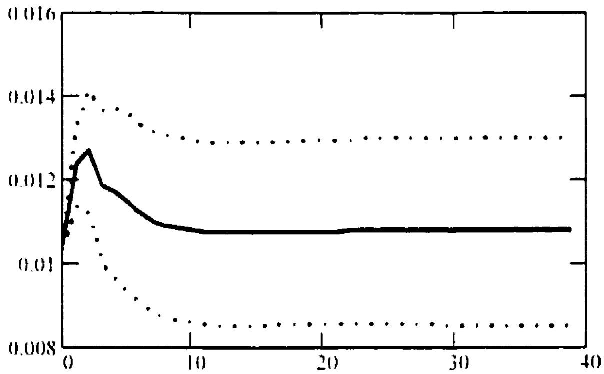
Figure 5.19 : Responses to money demand shock - model R3 / U.K.



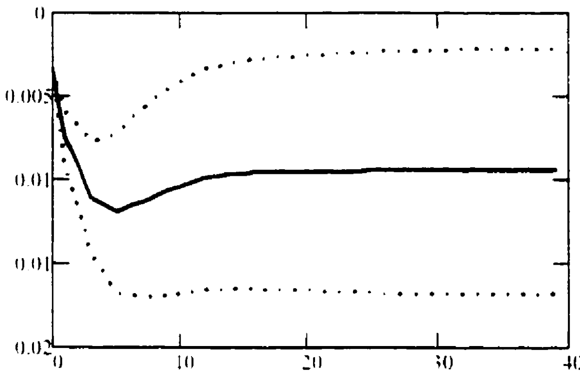
5.19a - real output response



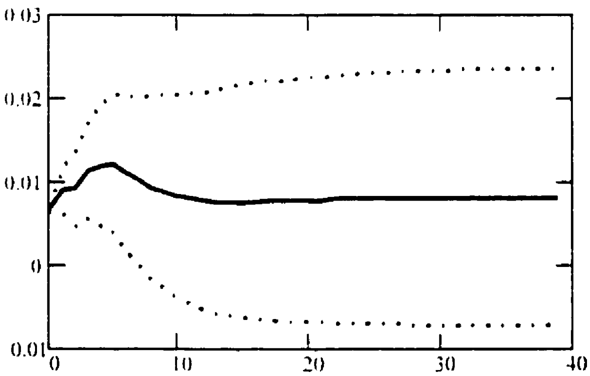
5.19b - price response



5.19c - interest rate response



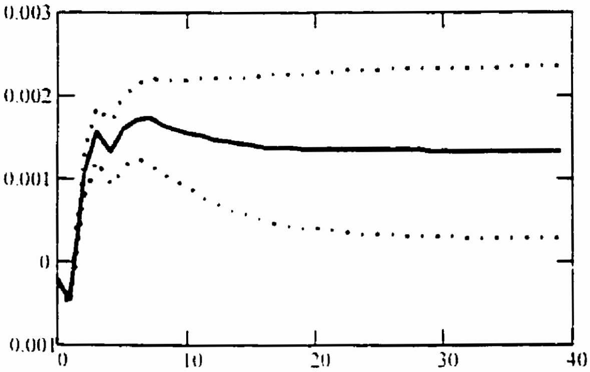
5.19d - money demand response



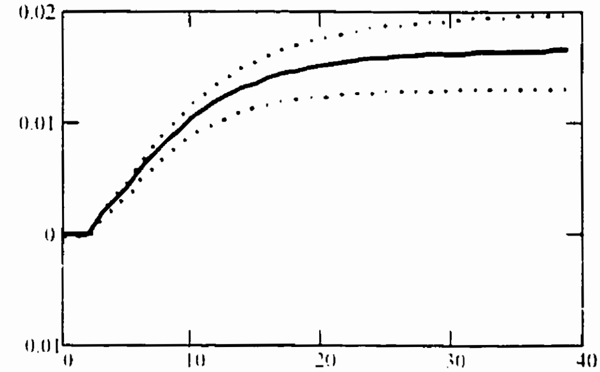
5.19e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

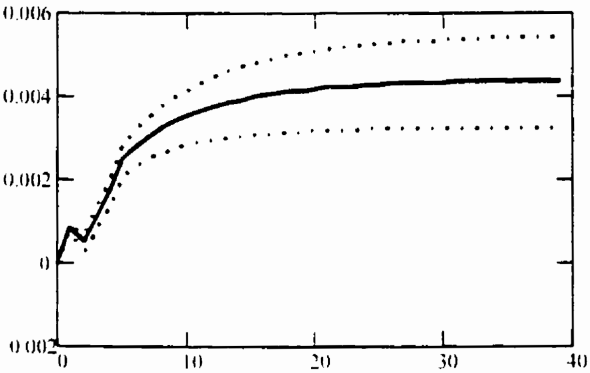
Figure 5.20 : Responses to credit shock - model R3 / U.K.



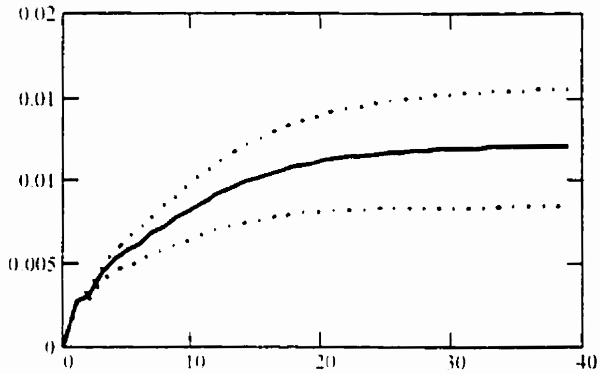
5.20a - real output response



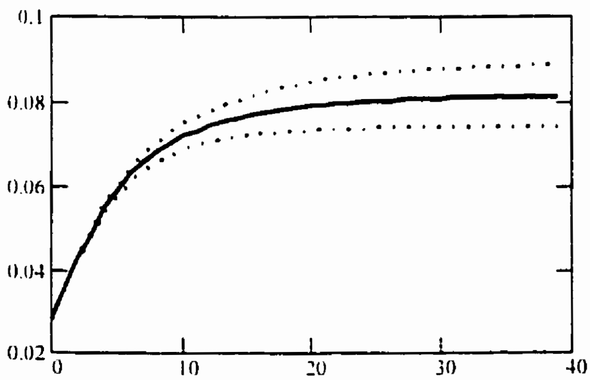
5.20b - price response



5.20c - interest rate response



5.20d - money demand response



5.20e - credit response

Note : The dotted lines enclose the one-standard-deviation confidence bands which have been calculated from the asymptotic distributions of the responses.

Contrary to what we found for Canada, it seems that the choice of credit measure has significant implications for the patterns of responses in the U.K. economy. There are more cases of disagreement between the results of model R1 and R3 that are based on the narrow and broad measures of credit, respectively.

The patterns of responses to IS shock are the same for real output, price, and the interest rate in the two models. However, in model R3, money demand shows a continuous negative response that starts in the second quarter and converges to its long run level after 8 quarters. This contrasts the result in model R1 where money demand shows a negative response in the short run , but a modest positive response over the long run. Also, credit response to IS shock in model R3 is positive for the whole time horizon, except for the first 2 to 3 quarters. This differs from the negative response of credit to the same shock in model R1.

Responses to AS shock are basically the same for the two models. Yet, credit response is negative throughout in models R3, which differs from the insignificant positive response in model R1. A weaker price increase to AS shock in model R3 might account for the difference.

Greater discrepancies show up for the patterns of responses to monetary policy shock. Unexpectedly, in model R3 contractionary policy through higher rates of interest have positive and lasting impact on real output. Price response is more sluggish during the short run in model R3 than in model R1. Also, money demand response in model R3 is strong and positive compared to the (short run) negative response in model R1. The interest rate response to its own shock is weaker in R1 than in R3. Moreover, credit response to contractionary monetary policy is overall positive in model R3 that contrasts the negative response in model R1.

Money demand shock also elicits different responses in the two models. While the long run response of real output to money demand shock is positive under R1, it is negative for R3. Responses of price and the interest rate are both stronger for R3 than R1. Furthermore, money demand response to its own shock is negative throughout in R3 in contrast to the positive response in R1.

Yet, the greatest discrepancies concern the responses to credit shock. Despite a trivial negative response in the short run of 2 quarters, real output increases over time in response to a credit shock in model R3. Such a finding contrasts with the negative response obtained for model R1. In model R3, aside from the initial inertia, price continues to rise persistently over the long run. Whereas in model R1, price remains stable for the entire time horizon. In addition, the long run positive response of the interest rate in model R3 differs from the long run negative response of this variable in model R1. Credit supply responses are also a bit different, but they share the same long run pattern.

Overall, we are less confident about our impulse-response results for the U.K. economy. The different patterns of responses in the two alternative models R1 and R3 indicate that such results are not as robust as those obtained for Canada.

The analysis of the impulse-response functions was to delineate the future time paths of the variables of the system in response to a shock in each of the variables. In order to measure the relative importance of different structural shocks in the overall variations in variables, however, we need to decompose such variations into components attributed to each of the structural shocks. This is the well-known Variance Decomposition analysis which is the subject of the next section.

Estimated Variance Decompositions

As we saw in chapter two, variance decompositions or "innovation accounting" introduced by Sims (1980), allocates each variable's forecast error variance to the individual shocks. It is a technique that provides complementary information for a better understanding of the relationships between the variables of a VAR model. It allows us to compare the role played by different variables in causing variations in the variables of the system as reflected in the impulse-responses.

We have estimated the variance decompositions of the models B1 and B3 for Canada, and those of the models R1 and R3 for the United Kingdom. The standard errors associated with these estimates have been calculated from the asymptotic formulas presented in chapter two. The decompositions are reported for selected time horizons. They indicate the proportion of each variable 's forecast error variance that is explained by a particular shock. It is obvious that the sum of these proportions for each variable must be equal to one (or, a 100 per cent) at any forecast horizon.

Estimated Variance Decompositions for Canada

For Canada, Tables 5.1 and 5.2 present the variance decompositions of the models B1 and B3, respectively. The variance decompositions for the U.K. are reported in Tables 5.3 and 5.4 for the models R1 and R3, respectively.

Table 5.1 : Variance Decompositions – model B1 / Canada

5.1a - Proportion of total variance of real output due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	97.97 (0.82)	0.001 (0.01)	0.031 (0.05)	0.049 (0.07)	1.94 (2.14)
2	93.93 (1.21)	0.011 (0.10)	0.018 (0.06)	2.978 (2.03)	3.06 (1.90)
3	82.09 (3.29)	0.007 (0.09)	0.033 (0.15)	12.66 (5.06)	5.21 (2.96)
4	75.07 (4.66)	0.009 (0.04)	0.113 (0.43)	17.24 (6.51)	7.56 (4.17)
8	58.98 (8.43)	1.240 (1.76)	1.120 (2.22)	30.37 (10.5)	8.28 (11.4)
12	52.72 (9.66)	4.160 (4.31)	1.340 (2.85)	34.36 (11.4)	7.41 (5.83)
24	47.21 (9.09)	13.79 (10.8)	0.762 (1.76)	32.62 (10.5)	5.61 (5.27)
40	44.47 (7.11)	21.29 (14.9)	0.593 (0.55)	29.12 (9.26)	4.51 (4.64)

Note: The asymptotic standard errors are in brackets

5.1b – Proportion of total variance of price due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	1.57 (1.91)	98.40 (0.70)	0.00 (0.00)	0.00 (0.00)	0.03 (0.50)
2	0.76 (0.92)	98.76 (0.25)	0.11 (0.27)	0.23 (0.44)	0.12 (0.27)
3	0.69 (0.89)	98.22 (0.16)	0.49 (0.82)	0.43 (0.81)	0.16 (0.43)
4	0.48 (0.79)	97.67 (0.56)	1.28 (1.56)	0.45 (0.93)	0.11 (0.11)
8	0.15 (0.19)	92.97 (2.49)	4.54 (4.34)	1.71 (2.55)	0.62 (1.31)
12	0.26 (0.91)	87.63 (4.61)	7.41 (6.44)	3.70 (4.22)	1.29 (2.38)
24	0.49 (1.81)	77.96 (8.52)	11.93 (9.51)	7.43 (6.65)	2.17 (3.84)
40	0.57 (2.16)	74.26 (10.3)	13.72 (10.7)	8.96 (7.53)	2.47 (4.45)

Note: The asymptotic standard errors are in brackets

5.1c – Proportion of total variance of monetary base due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.47 (1.08)	0.30 (0.85)	83.53 (3.13)	15.68 (4.80)	0.01 (0.02)
2	1.54 (1.34)	2.30 (1.53)	71.92 (2.98)	24.15 (4.02)	0.08 (0.24)
3	2.43 (1.92)	3.01 (2.03)	65.84 (4.08)	28.38 (5.20)	0.33 (0.66)
4	2.36 (2.16)	3.69 (2.49)	62.67 (5.07)	30.70 (6.21)	0.57 (1.09)
8	1.85 (2.70)	5.68 (4.51)	57.07 (7.50)	34.33 (8.90)	1.05 (2.10)
12	1.59 (2.88)	7.03 (6.35)	55.28 (8.35)	34.89 (9.85)	1.20 (2.55)
24	1.39 (3.05)	9.64 (10.1)	52.93 (9.23)	34.61 (10.6)	1.42 (3.08)
40	1.34 (3.17)	11.07 (12.3)	51.74 (9.72)	34.29 (11.1)	1.55 (3.34)

Note: The asymptotic standard errors are in brackets

5.1d – Proportion of total variance of money demand due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.45 (1.05)	0.67 (1.27)	0.00 (0.00)	98.86 (0.45)	0.01 (0.02)
2	0.64 (0.90)	0.71 (0.92)	0.27 (0.44)	97.89 (0.39)	0.48 (0.57)
3	0.38 (0.62)	0.49 (0.75)	1.37 (1.43)	96.89 (0.49)	0.85 (1.14)
4	0.59 (0.50)	0.33 (0.57)	2.13 (2.11)	95.95 (0.63)	0.99 (1.47)
8	1.68 (2.45)	0.15 (0.38)	4.04 (4.31)	91.60 (2.01)	2.52 (3.29)
12	2.41 (3.41)	0.15 (0.68)	4.51 (5.14)	89.34 (1.54)	3.57 (4.33)
24	2.84 (4.02)	0.60 (2.63)	5.20 (6.17)	87.13 (1.69)	4.22 (4.98)
40	2.83 (4.12)	1.07 (4.29)	5.87 (6.89)	86.07 (0.37)	4.14 (5.01)

Note: The asymptotic standard errors are in brackets

5.1e – Proportion of total variance of credit due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.05)	5.08 (3.36)	1.45 (1.79)	2.32 (2.25)	91.13 (1.88)
2	0.67 (0.80)	5.37 (2.44)	3.63 (1.93)	3.65 (2.03)	86.66 (1.75)
3	2.29 (2.11)	5.64 (2.78)	7.34 (3.46)	8.93 (4.19)	75.79 (3.36)
4	3.24 (2.81)	4.69 (2.56)	10.16 (4.55)	15.67 (6.16)	66.22 (5.00)
8	3.38 (3.61)	2.25 (2.04)	15.82 (7.24)	27.20 (9.62)	51.34 (8.67)
12	2.95 (3.74)	1.34 (1.34)	18.15 (8.69)	31.56 (10.8)	45.98 (10.4)
24	2.44 (3.69)	1.01 (1.40)	19.24 (10.2)	34.47 (11.2)	42.83 (11.8)
40	2.24 (3.66)	1.33 (3.52)	18.93 (10.8)	35.06 (11.3)	42.43 (12.4)

Note: The asymptotic standard errors are in brackets

Panel 5.1a of Table 5.1 shows that IS shock is the dominant source of variation in real output for the whole forecast horizon. As expected, it is much more significant in the short run of 4 quarters. Yet, it remains significant even after 40 quarters. Aggregate supply shock, on the other hand, is not contributing to the real output variation during the first 4 quarters. It begins to play a role after 8 quarters and gains significance towards the end of the time horizon, accounting for only 21 per cent of total variation in real output. This contribution is well below the findings by other studies. For example, Keating (1992) finds aggregate supply contributing about 50 percent to output variation after 40 quarters. Others like Blanchard and Quah (1989), Gali (1992), and Shapiro and Watson (1988) have found supply contributions in the order of 60 to 86 percent. The latter studies, however, are based on the prior assumption that aggregate demand shocks have no long run impact on output. Therefore, by construction, aggregate supply shocks prevail in the long run. Our finding in this regard is compatible with that of Blanchard and Watson (1986). Surprisingly, monetary policy shocks do not contribute to real output variation at any forecast horizon. Its peak contribution that occurs in the 12th quarter is even less than 1.5 per cent. Money demand shock, however, is an important contributor. It accounts for over 17 per cent of the output variation in the 4th quarter, reaches a peak of 34 per cent in the 12th quarter, and retains that significance by the end of the forecast horizon. This finding is consistent with Keating's (1992) results from his "contemporaneous" model. Credit shock makes a modest contribution in the early quarters and achieves it maximum contribution in the 8th quarter. Its long run contribution falls to a level of 4.5 percent which is not statistically significant.

Panel 5.1b of Table 5.1 contains the variance decompositions for the price (forecast error) variance. Price's own shock (aggregate supply shock) explains, almost entirely, the variation in price over the short run of 4 quarters. None of the other shocks appear to contribute to this variation. Contrary to perceived theory, monetary policy and money demand shocks appear to play a role only after 8 quarters. Credit shock plays no significant role at any forecast interval.

Monetary base variation is mainly explained by its own shock (i.e. monetary policy shock). The shock accounts for over 83 per cent of total variation in the first quarter, which declines to 52 per cent in the 40th quarter. IS shock has only a trivial role in the 3rd and 4th quarters. Once again, credit contribution is close to zero for all horizons. Aggregate supply shock increases over time and reaches a peak of 11 per cent by the end of the forecast period. Money demand shock, however, is a significant contributor to the monetary base variations both in the short and long runs. It explains over 15 per cent of the variation in the first quarter and twice as much in the 4^{th} quarter. It peaks to over 34 per cent in the 8^{th} quarter and remains at that level over the long run.

The major contributor to money demand variations throughout the forecast period is the money demand's own shock. Even after 12 quarters 40 per cent of variation is due to money demand shock. Neither IS nor aggregate supply shocks play a significant role in money demand variation. The small long run contributions of monetary policy and credit shocks are not statistically significant either.

Finally, variance decompositions for credit supply in panel 5.1e of the above table indicate that credit supply variations arise from its own shock for the most part. IS shock plays no role, and aggregate supply shock has a small contribution in the first 4 quarters. Monetary policy shock explains a relatively small portion of credit variation in the short run. In the long run, however, a fifth of variation in credit is due to this shock. Here, too, money demand shock plays a significant role. By the 4^{th} quarter over 15 per cent of credit variance is due to money demand shock. Its contribution increases over time and reaches a third of total variation at the end of the forecast horizon.

The picture that emerges from the above decompositions shows a clear dominant role for the IS shock in real output variation at all forecast horizons. It also indicates that the contribution of aggregate supply shock is relatively small and restricted to the long run. Furthermore, money demand shock appears to be a significant source of variation in most of the variables of the system. And interestingly, credit shock does not seem to be a significant factor in causing variations in other variables.

We now turn to the variance decompositions for the model B3 that are reported in Table 5.2 below. Once again, we will have a chance to test the robustness of our results as we switch from the narrow measure of credit to the broad measure.

Table 5.2 : Variance Decompositions – model B3 / Canada

5.2a – Proportion of total variance of real output due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	99.97 (0.02)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.03 (0.17)
2	97.66 (0.52)	0.04 (0.20)	0.005 (0.07)	1.85 (1.62)	0.44 (0.65)
3	90.00 (2.60)	0.04 (0.10)	0.04 (0.19)	9.62 (4.94)	0.29 (0.54)
4	85.93 (3.89)	0.23 (0.43)	0.16 (0.54)	13.42 (6.55)	0.24 (0.59)
8	72.01 (8.73)	2.00 (2.34)	0.84 (1.98)	24.82 (11.6)	0.31 (1.13)
12	65.42 (10.7)	4.75 (4.71)	0.96 (2.44)	28.33 (13.0)	0.53 (1.68)
24	59.34 (10.8)	12.35 (10.2)	0.55 (1.44)	26.42 (12.7)	1.33 (2.85)
40	56.24 (9.41)	18.27 (13.6)	0.47 (0.40)	22.95 (11.7)	2.01 (3.60)

Note: The asymptotic standard errors are in brackets

5.2b - Proportion of total variance of price due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	1.15 (1.17)	98.85 (0.38)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
2	0.44 (0.51)	99.03 (0.06)	0.17 (0.34)	0.35 (0.56)	0.00 (0.03)
3	0.36 (0.55)	98.19 (0.41)	0.66 (0.96)	0.66 (1.10)	0.12 (0.38)
4	0.21 (0.40)	97.00 (0.79)	1.46 (1.68)	0.76 (1.33)	0.56 (0.95)
8	0.39 (1.06)	89.93 (3.10)	4.81 (4.46)	2.89 (3.48)	1.97 (2.74)
12	0.94 (2.31)	82.10 (5.74)	7.95 (6.60)	6.23 (5.72)	2.77 (3.80)
24	1.52 (3.72)	69.60 (10.4)	12.97 (9.63)	12.40 (8.89)	3.51 (5.02)
40	1.66 (4.20)	64.64 (12.3)	15.01 (10.7)	14.96 (9.92)	3.71 (5.50)

Note: The asymptotic standard errors are in brackets

5.2c – Proportion of total variance of monetary base due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	1.27 (1.75)	0.29 (1.09)	83.64 (3.63)	14.79 (5.59)	0.00 (0.00)
2	2.86 (1.82)	2.03 (1.56)	72.22 (3.10)	22.77 (4.21)	0.11 (0.28)
3	4.27 (2.59)	2.43 (1.91)	66.31 (4.16)	26.87 (5.52)	0.11 (0.36)
4	4.38 (3.05)	2.77 (2.20)	63.43 (5.12)	29.31 (6.61)	0.10 (0.41)
8	3.79 (4.34)	4.19 (3.93)	57.94 (7.69)	34.03 (9.61)	0.03 (0.12)
12	3.35 (4.82)	5.39 (5.69)	55.85 (8.64)	35.35 (10.7)	0.04 (0.26)
24	2.99 (5.28)	7.67 (9.07)	52.94 (9.55)	36.24 (11.5)	0.15 (0.88)
40	2.88 (5.50)	8.90 (10.9)	51.46 (9.99)	36.52 (11.9)	0.24 (1.20)

Note: The asymptotic standard errors are in brackets

5.2d – Proportion of total variance of money demand due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.32 (0.88)	0.70 (1.43)	0.00 (0.00)	98.97 (0.46)	0.00 (0.00)
2	0.31 (0.63)	0.57 (0.86)	0.25 (0.43)	98.24 (0.22)	0.62 (0.76)
3	0.20 (0.29)	0.34 (0.58)	1.34 (1.44)	97.01 (0.33)	1.09 (1.33)
4	0.87 (1.04)	0.22 (0.40)	2.06 (2.13)	95.86 (0.53)	0.97 (1.38)
8	3.57 (4.38)	0.10 (0.25)	3.81 (4.33)	91.58 (0.86)	0.93 (1.88)
12	5.10 (6.02)	0.12 (0.63)	4.41 (5.24)	89.42 (1.77)	0.94 (2.12)
24	5.97 (7.04)	0.43 (2.21)	5.26 (6.34)	87.51 (1.84)	0.82 (2.12)
40	5.98 (7.23)	0.73 (3.38)	5.92 (7.04)	86.66 (1.38)	0.69 (1.99)

Note: The asymptotic standard errors are in brackets

5.2e – Proportion of total variance of credit due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.04)	1.61 (1.94)	1.57 (2.64)	1.73 (2.21)	95.07 (1.09)
2	0.12 (0.31)	4.01 (2.10)	2.46 (1.91)	0.73 (0.97)	92.66 (1.32)
3	1.07 (1.25)	6.00 (3.01)	3.55 (2.33)	0.92 (0.91)	88.45 (1.98)
4	2.96 (2.52)	6.56 (3.37)	5.53 (3.35)	3.01 (2.52)	81.92 (3.04)
8	6.09 (5.40)	6.54 (4.40)	12.96 (6.88)	16.36 (7.55)	58.05 (7.27)
12	5.74 (6.16)	6.02 (5.34)	17.06 (8.80)	23.90 (9.18)	47.27 (9.13)
24	5.84 (6.66)	5.96 (7.72)	21.01 (10.9)	29.65 (9.78)	38.45 (10.8)
40	4.55 (6.88)	6.23 (9.25)	22.27 (11.6)	31.29 (9.79)	35.65 (11.7)

Note: The asymptotic standard errors are in brackets

The results in Table 5.2 look very similar to those reported in Table 5.1. Therefore, the change of the credit variable has no significant impact on the overall pattern of decompositions. There are, however, a few minor differences that are discussed below.

IS shock contribution to real output variation is even stronger in model B3 than it is in model B1. As a result, the contributions of aggregate supply and money demand shocks to output variation are somewhat reduced. Moreover, money demand shock appears to play a less important role in the broad credit variation in the first 3 quarters than it does in the narrow credit variation. Also, broad credit shock makes no contribution to real out put variation at any forecast interval. This contrasts the modest contribution of narrow credit shock in real output variance reported in Table 5.1.

The results in Table 5.2 reinforce our previous conclusion that IS shock and money demand shock are the major sources of variation in real output and other macroeconomic variables. As far as financial variables are concerned, money demand and not credit supply appears to be the important source of macroeconomic fluctuations.

Estimated Variance Decompositions for the U.K.

In the rest of the chapter we analyze the variance decompositions for the United Kingdom. As before, we begin with the results for model R1 which is based on the narrow measure of credit. These results are reported in Table 5.3. The results for model R3 are discussed afterwards.

Table 5.3 : Variance Decompositions – model R1 / U.K.

5.3a – Proportion of total variance of real output due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	99.89 (0.09)	0.02 (0.13)	0.00 (0.00)	0.00 (0.00)	0.08 (0.54)
2	96.04 (0.75)	2.12 (1.95)	0.02 (0.20)	0.00 (0.02)	1.81 (1.82)
3	95.25 (0.97)	2.87 (2.60)	0.05 (0.37)	0.33 (0.89)	1.48 (1.77)
4	93.73 (0.93)	3.89 (3.00)	0.17 (0.35)	0.93 (1.81)	1.27 (1.18)
8	85.64 (3.41)	6.71 (5.02)	1.50 (2.04)	2.25 (3.73)	3.89 (8.53)
12	75.16 (11.4)	7.66 (6.11)	1.68 (2.60)	2.27 (3.68)	13.22 (21.0)
24	69.18 (18.0)	10.05 (8.45)	1.43 (2.91)	1.54 (2.83)	17.78 (27.6)
40	67.20 (20.1)	11.20 (9.58)	1.49 (3.22)	1.33 (2.61)	18.76 (29.4)

Note: The asymptotic standard errors are in brackets

5.3b – Proportion of total variance of price due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.36 (1.23)	99.64 (0.30)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
2	3.38 (2.08)	94.40 (0.68)	1.71 (1.46)	0.50 (0.82)	0.00 (0.08)
3	3.33 (2.44)	90.42 (1.11)	4.18 (2.79)	1.50 (1.80)	0.56 (0.90)
4	2.88 (2.57)	88.64 (1.88)	6.32 (3.80)	1.70 (2.16)	0.44 (0.99)
8	1.39 (2.24)	85.99 (3.65)	9.79 (5.86)	2.21 (3.65)	0.61 (2.84)
12	0.91 (2.02)	85.19 (4.66)	10.93 (6.53)	2.54 (4.37)	0.42 (3.19)
24	0.57 (2.02)	84.40 (6.28)	11.59 (7.33)	3.03 (4.87)	0.40 (4.39)
40	0.45 (2.03)	84.09 (6.89)	11.86 (7.69)	3.17 (5.08)	0.41 (4.93)

Note: The asymptotic standard errors are in brackets

5.3c – Proportion of total variance of the Interest rate due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.05)	1.23 (1.99)	94.03 (3.06)	4.72 (6.19)	0.00 (0.00)
2	0.53 (0.89)	0.53 (0.89)	92.60 (2.18)	6.12 (4.06)	0.20 (0.54)
3	3.09 (2.72)	0.41 (0.65)	88.65 (2.49)	7.19 (4.20)	0.65 (1.31)
4	7.44 (4.90)	0.31 (0.56)	83.94 (3.10)	7.64 (4.64)	0.66 (1.58)
8	11.12 (7.30)	0.17 (0.24)	76.63 (5.28)	11.52 (7.88)	0.56 (2.20)
12	11.67 (7.82)	0.12 (0.21)	72.69 (6.76)	13.75 (7.68)	1.76 (6.04)
24	13.50 (8.87)	0.12 (0.66)	68.88 (6.49)	13.63 (6.07)	3.86 (13.8)
40	14.21 (9.38)	0.14 (0.98)	67.66 (6.66)	13.79 (5.72)	4.19 (15.9)

Note: The asymptotic standard errors are in brackets

5.3d – Proportion of total variance of money demand due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.14)	0.67 (1.55)	23.81 (4.57)	75.50 (3.22)	0.00 (0.00)
2	0.00 (0.07)	1.10 (1.35)	32.38 (1.55)	66.05 (0.56)	0.45 (0.83)
3	0.74 (1.00)	3.58 (2.78)	24.79 (4.29)	46.94 (3.62)	23.95 (3.39)
4	1.87 (1.97)	2.49 (2.13)	18.50 (4.57)	39.72 (3.17)	37.41 (4.92)
8	0.69 (1.34)	2.25 (2.09)	5.36 (3.70)	15.98 (3.09)	75.71 (4.51)
12	0.49 (0.12)	1.88 (1.40)	2.62 (2.52)	10.12 (1.31)	84.87 (5.04)
24	0.54 (1.58)	1.50 (1.60)	1.55 (2.96)	8.41 (5.24)	88.00 (6.91)
40	0.47 (1.91)	1.34 (1.75)	1.11 (3.03)	7.71 (5.36)	89.36 (6.58)

Note: The asymptotic standard errors are in brackets

5.3e – Proportion of total variance of credit due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.03)	2.24 (2.73)	0.01 (0.16)	0.17 (0.77)	97.57 (1.07)
2	0.01 (0.09)	0.82 (0.95)	1.00 (1.05)	0.15 (0.51)	98.02 (0.40)
3	0.10 (0.36)	0.51 (0.63)	0.90 (1.16)	0.15 (0.53)	98.33 (0.42)
4	0.50 (1.07)	0.34 (0.53)	1.27 (1.58)	0.14 (0.18)	97.74 (0.61)
8	2.12 (2.55)	0.15 (0.27)	2.88 (2.50)	0.60 (2.76)	94.24 (1.65)
12	3.59 (1.85)	0.35 (1.13)	3.78 (1.02)	1.19 (5.41)	91.07 (4.89)
24	4.33 (3.15)	0.75 (1.94)	3.81 (1.84)	1.50 (6.27)	89.60 (6.04)
40	4.66 (2.85)	0.91 (2.47)	3.84 (2.50)	1.66 (6.84)	88.92 (7.03)

Note: The asymptotic standard errors are in brackets

The results in panel 5.3a of Table 5.3 indicate that IS shock plays the largest role in real output variation at all times. Its contribution is even greater than that obtained for Canada. Greater contribution of IS shock, per force, reduces the role of aggregate supply shock in out variation to a low level of 11 per cent in the long run. Neither monetary policy shock nor money demand shock play a sizeable role in output variance. The long run contribution of the credit shock is not statistically significant either.

Price variation at all forecast horizons is mainly explained by itself. Yet, monetary policy (interest rate) shock is contributing close to 12 per cent of total variation towards the end of the time horizon. IS shock plays a very modest role in the 2nd to 4th quarter. Both money demand and credit shocks have no significant role at any forecast interval.

Variation in the rate of interest is also mostly explained by its own shock, that is, monetary policy shock throughout the forecast horizon. Money demand is the next important contributor, accounting for over 7 per cent after the 4th quarter and up to 14 per cent over the long run. IS shock contribution begins in the 3rd quarter and rises over time to more than 14 per cent after 40 quarters. There is no role for aggregate supply and credit shocks in the interest rate variance at any forecast interval.

Variance decompositions of money demand in panel 5.3d of Table 5.3 show interesting results. While most of the variation in the first 4 quarters is due to money demand's own shock, credit shock assumes a substantial role in the long run variation of money demand. Such a result is not paralleled in any of the two models for Canada. The monetary policy shock is also an important source of variation in money demand in the short run of up to 4 quarters. IS and aggregate supply shocks do not contribute to money demand variance.

As for the credit supply variance, credit's own shock is by far the most important source. Short run variation is almost entirely due to credit's own shock. In the long run, however, IS shock and monetary policy shock appear to contribute a very modest proportion. The small contribution of monetary policy shock to credit variance casts doubt over the existence of a "credit channel" for monetary policy transmission.

Before we get to an overall comparison of the results for Canada vis a vis the U.K., we need to examine the variance decompositions of the model R3 as reported in Table 5.4 below.

Table 5.4 : Variance Decompositions – model R3 / U.K.

5.4a – Proportion of total variance of real output due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	99.96 (0.00)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.02 (0.01)
2	97.33 (0.65)	2.54 (2.06)	0.02 (0.21)	0.03 (0.24)	0.07 (0.02)
3	95.91 (0.95)	3.40 (2.75)	0.19 (0.56)	0.22 (0.80)	0.27 (0.19)
4	93.41 (1.05)	4.82 (3.28)	1.00 (1.65)	0.18 (0.58)	0.60 (0.42)
8	85.83 (0.81)	8.28 (5.39)	3.70 (4.90)	1.08 (1.68)	1.09 (0.67)
12	81.01 (2.65)	9.93 (6.56)	5.74 (7.03)	2.04 (3.00)	1.27 (0.81)
24	76.18 (4.42)	11.52 (7.92)	7.85 (9.21)	3.14 (4.44)	1.29 (1.10)
40	74.32 (5.10)	12.20 (8.61)	8.62 (10.1)	3.58 (5.02)	1.27 (1.33)

Note: The asymptotic standard errors are in brackets.

5.4b – Proportion of total variance of price due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.41 (0.03)	99.58 (0.01)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
2	2.90 (1.71)	94.43 (0.34)	0.00 (0.09)	2.65 (1.86)	0.00 (0.00)
3	3.07 (2.23)	89.83 (1.69)	0.10 (0.41)	7.00 (3.76)	0.00 (0.00)
4	2.83 (2.49)	86.78 (2.73)	0.07 (0.36)	10.05 (5.15)	0.26 (0.18)
8	1.43 (2.20)	79.86 (5.46)	0.12 (0.84)	16.35 (8.31)	2.22 (1.17)
12	0.86 (1.75)	75.17 (6.74)	0.52 (2.09)	18.33 (9.21)	5.11 (2.30)
24	0.43 (1.40)	68.01 (8.14)	2.40 (5.27)	18.14 (9.39)	11.01 (3.59)
40	0.33 (1.38)	64.74 (8.79)	3.65 (6.84)	17.39 (9.32)	13.87 (3.92)

Note: The asymptotic standard errors are in brackets.

5.4c – Proportion of total variance of the interest rate due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.14 (0.01)	1.19 (0.05)	1.91 (0.02)	96.76 (0.03)	0.00 (0.00)
2	0.80 (1.01)	0.51 (0.12)	1.04 (0.51)	97.36 (0.23)	0.26 (0.12)
3	3.35 (2.86)	0.34 (0.17)	0.64 (0.41)	95.43 (1.15)	0.22 (0.09)
4	7.51 (5.06)	0.24 (0.08)	0.46 (0.26)	91.42 (2.52)	0.35 (0.16)
8	10.53 (7.02)	0.26 (0.59)	0.97 (1.97)	85.92 (4.16)	2.30 (1.01)
12	10.93 (7.62)	0.27 (0.81)	2.17 (4.08)	82.46 (5.02)	4.15 (1.35)
24	10.59 (8.11)	0.18 (0.77)	4.62 (6.97)	77.32 (6.09)	7.28 (1.56)
40	10.26 (8.35)	0.12 (0.65)	5.95 (8.30)	74.65 (6.64)	9.01 (1.81)

Note: The asymptotic standard errors are in brackets.

5.4d – Proportion of total variance of money demand due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.01 (0.00)	0.50 (0.02)	96.33 (0.02)	3.16 (0.05)	0.00 (0.00)
2	0.04 (0.22)	0.83 (0.95)	89.91 (1.08)	8.31 (2.52)	0.91 (0.27)
3	1.24 (1.52)	1.45 (1.69)	86.13 (1.52)	10.07 (3.46)	1.10 (0.13)
4	3.20 (2.87)	1.72 (2.09)	82.57 (2.04)	11.02 (4.38)	1.47 (0.16)
8	6.27 (5.12)	3.87 (4.89)	76.64 (1.13)	10.78 (6.37)	2.43 (0.29)
12	7.13 (5.93)	5.58 (7.07)	74.60 (3.61)	9.37 (6.97)	3.31 (0.93)
24	7.22 (6.43)	7.59 (9.41)	72.63 (6.46)	7.14 (7.14)	5.41 (2.33)
40	7.06 (6.55)	8.27 (10.2)	71.84 (7.42)	6.19 (7.07)	6.63 (3.11)

Note: The asymptotic standard errors are in brackets.

5.4e – Proportion of total variance of credit due to various shocks

Quarter(s) ahead	IS shock	Aggregate supply shock	Monetary policy shock	Money demand shock	Credit supply shock
1	0.05 (0.00)	5.61 (0.04)	1.71 (0.13)	5.04 (0.48)	87.58 (0.21)
2	0.19 (0.46)	3.78 (1.34)	1.23 (0.82)	5.38 (1.99)	89.41 (0.64)
3	0.22 (0.30)	3.63 (2.06)	1.28 (1.25)	4.83 (2.60)	90.04 (0.75)
4	1.55 (1.70)	3.57 (2.37)	0.80 (0.71)	4.86 (3.24)	89.22 (1.24)
8	2.47 (3.20)	3.29 (3.25)	1.70 (1.99)	3.65 (3.91)	88.88 (1.26)
12	2.12 (3.30)	2.75 (3.48)	4.21 (4.37)	2.50 (3.53)	88.42 (1.21)
24	1.36 (2.91)	1.63 (3.03)	8.37 (7.36)	1.46 (2.99)	87.17 (3.28)
40	1.07 (2.73)	1.14 (2.65)	10.11 (8.43)	1.18 (2.84)	86.50 (4.19)

Note: The asymptotic standard errors are in brackets.

The variance decompositions of real output forecast error variance in model R3 are basically the same as those reported for model R1. The IS shock assumes yet greater importance in the long run in model R3 than that in model R1. Also, monetary policy shock appears to have some long run contribution, which is not statistically significant.

Price variance is still dominated by its own shock as in model R1. However, money demand shock is now contributing to price variance from the second quarter on. Its contribution reaches 10 per cent in the 4th quarter and increases to 18 per cent over the long run. The other difference in model R3 is the sizable long run contribution of credit shock to price variance. The latter shock did not play a role in price variance in model R1.

The most contrasting results, however, concern the interest rate and money demand variations. In sharp contrast to model R1, interest rate variation in model R3 is strongly dominated by money demand shock at all forecast horizons so that, even in the short run, there is little contribution from the interest rate's own shock. In addition, credit shock is contributing to the long run variation of the interest rate, a finding not supported in model R1.

Short run money demand variation in model R1 was mainly due to its own shock. Its long run variation was largely from the credit shock. In model R3, however, the main contributor to money demand variation, both in the short and long runs, is the interest rate (monetary policy) shock.

The patterns of decompositions of interest rate and money demand variations in model R3 seem to be more consistent with the behaviour of a monetary authority which is using the rate of interest as a tool to stabilize (target) the money stock. Such behaviour received some support from our structural estimates as well as impulse-response analysis for the U.K. economy. Nonetheless, once again, the U.K. results seem to be dependent on the choice of the credit variable, and as such, echo our previous concern about the reliability of our results for this economy.

Credit variance is decomposed by and large the same way as in model R1. But, now both money demand and aggregate supply shocks have a modest contribution in the first 4 quarters. There is also some contribution from the monetary policy shock towards the end of the forecast horizon.

Overall, the variance decomposition results reinforce our findings in the impulse-response analyses. These simulations, in most cases, lend support to our theoretical identifications. Yet, as is the case with other studies, they are marred with statistical imprecision. That is why they should be dealt with due caution. The results for the U.K. are found to be less robust with respect to the choice of the credit variable. Moreover, there are more cases of disagreement between the empirical findings and the accepted theory for this economy. While the shorter sample size might be a partial culprit, we do not rule out the possibility of model misspecification for the U.K.

In spite of the above uncertainties, the results for both Canada and the U.K. point to the prominence of real aggregate demand (IS) shocks in real output fluctuations at all forecast horizons. More pertinent to the focus of our investigation, however, is the role of the financial variables in macroeconomic variations. Of the two financial variables, money emerges as a major *source* of fluctuation in real output and other variables, whereas credit does not. However, credit appears to *propagate* the disturbances from money through the so called "credit channel" of monetary policy transmission.

CHAPTER SIX

CONCLUSION

This study has investigated the empirical significance of money and bank credit as financial factors in the overall fluctuations of real output and other macroeconomic variables in the economies of Canada and the United Kingdom within a structural VAR framework. The structural VAR approach, which avoids the theoretical as well as practical problems of the standard VAR, has enabled us to study financial variables as *sources* of macroeconomic variation. We have made use of simple economic theory to identify our structural models. Two classes of models have been studied. In one class, the joint behavior of output, price, money stock, and bank credit was investigated along with the monetary base as the monetary policy variable. In the other class, the joint behavior of the same non-policy variables was studied along with the rate of interest as the policy variable. In each class we experimented with three measures of bank credit, that is, bank credit to persons, bank credit to businesses, and total bank credit to persons and businesses. This resulted in a set of six models for each country. In addition, we applied two slightly different identification schemes to each of the six models.

Our empirical methodology consisted, in the first stage, of the unrestricted reduced-form estimation of VAR models. All the VAR models were specified in first differences of variables to ensure stationarity. This followed from examination of the stochastic properties of the series in chapter three. The variance-covariance matrices of the reduced-form residuals from the first stage were then used by the Method of Moments to identify the structural parameters of the models.

Estimates of our structural models were reported in chapter four. Despite overall imprecise estimates of the structural parameters and the presence of certain anomalies and idiosyncrasies across models, the results for Canada as well as the U.K. provided reasonable support for our theoretical specifications. In particular, they supported the rigidity of prices in the short run. They lent support to the existence of a monetary reaction function for Canada that accommodates innovations in money demand in favor of interest rate stability, and a reaction function for the U.K. that stabilizes the quantity of money. Also, they showed that credit supply is directly affected by monetary policy innovations, giving credence to the "credit view" of the monetary policy transmission mechanism.

Using the structural parameter estimates, the VAR representations were transformed to structural Moving Average representations in order to calculate the impulse-response functions and forecast error variance decompositions over a time horizon of 40 quarters. The results of such dynamic simulations were presented in chapter five.

The impulse-responses of the monetary-base models for Canada were found, for the most part, to be consistent with our theoretical presumptions. All the variables were seen to converge to their long run levels relatively soon after being shocked by the structural disturbances. There seemed to be little variation in results for different bank credit measures. That is, the results appeared robust to the choice of credit measure. However, narrow credit behavior was found to be more theoretically sensible than broad credit. Long lasting favorable response of real output to positive aggregate demand shocks and its permanent decline in response to negative supply shocks, short term positive contribution of monetary policy shocks to real output, short run price inertia to various structural shocks, and positive contribution of narrow bank credit shock to real output are among the highlights of the impulse-response patterns for Canada. We found less plausible impulse-response patterns for the U.K. economy. The results were also more sensitive to the choice of credit measure. Nevertheless, they showed some plausible patterns like those for Canada.

Variance decompositions served to measure the relative importance of different structural shocks in the overall variations in variables. The relative contribution of each of the five structural shocks in total variation of each variable was calculated over a forecast horizon of up to 40 quarters. The decomposition patterns for Canada remained fairly robust when narrow credit was replaced with broad credit. Here, too, the results for the U.K. showed less robustness. However, the general decomposition patterns were very similar to those for Canada.

The calculations for Canada showed a clear dominant role for aggregate demand shocks in real output fluctuations at all forecast horizons. Aggregate supply shocks' contribution to real output variations, however, were found to be relatively small and restricted to the long run. More pertinent to the focus of our investigation, was the role of the financial variables in macroeconomic fluctuations. Of the two financial variables, money emerged as a major source of fluctuation in real output and other variables, whereas bank credit did not. However, credit appeared to *propagate* the disturbances from money through the so-called "credit channel" of monetary transmission.

Overall, our empirical findings provide some insights into the dynamics of the Canadian as well as the British economies and shed some light on the nature of the structural shocks causing these dynamics. Among other things, they call for aggregate demand management policies to guide the economy both in the short and long runs. Moreover, they imply a more comprehensive approach to monetary management. Given the prominence of money demand shocks versus the money supply shocks in originating fluctuations in output and other variables as our results suggest, a closer examination of the money demand shocks on the part of the monetary authority seems necessary. To the extent that the money demand shocks arise from technological breakthroughs and financial innovations in the intermediation industry, the monetary authority is well advised to attend to such developments more earnestly.

Let us now turn to some of the limitations of the study. There are many potential sources of error in any empirical investigation, and ours is no exception. As far as the structural VAR methodology is concerned, we might refer to several sources of error. The discretionary choice of the variables in a VAR system, the assumption of linear VAR relationships as a proxy for the more complicated data generating processes and the related assumption of linear *symmetric* impulse-response functions, and inability to capture the economy's lag structure in the contemporaneous structural VAR models are among the potential sources of misspecification and error in results. Moreover, there is the important issue of identification. Identification assumptions are theoretical conjectures that can only be improved upon in the light of empirical findings. This signifies the tentative nature of our findings that are based on a particular set of identification assumptions. In particular, the identification or, more precisely, "labeling" of structural shocks which is crucial to the interpretation of impulse-responses patterns and forecast error variance decompositions in the structural VAR approach is somewhat arbitrary and based on oversimplification. This problem is more pronounced in models of lower dimension, where several independent shocks are bunched together and labeled as a single structural shock. Also, when the structural equations relating the reduced-form residuals and structural disturbances do not sufficiently capture the "true" relationships, the structural shocks as "innovations" in such relationships are not appropriately isolated.

We should now refer to some possible refinements and extensions of the study that would set the stage for future studies. The present investigation has been concerned with money and bank credit as two financial variables. It is worth, however, to investigate the behavior of still broader measures of credit and their significance in originating and propagating fluctuations in output and other key macroeconomic variables. Credit measures may be broadened in two directions. One is to consider measures that encompass the whole financial intermediation industry. The other is to expand the bank credit to include the advances to the public sector, given the importance of the government in the economies of Canada and the United Kingdom. Also, to study the role of credit in particular junctures of time (as in the Great Depression or later "credit crunch" episodes), we might restrict the sample period to those specific events. This, however, would require data of higher frequency to avoid the statistical problems.

As mentioned above, the identification of structural relationships and shocks has important bearing on theoretical interpretations of the resulting propagation mechanisms. Therefore, experimenting with further identification schemes is a worthwhile venture that may resolve some of our implausible findings or, at least, provide additional evidence on the sensitivity of our results to other potential identification schemes.

Further investigation of the interactions between the financial sector and the real economy could also be helped by considering other financial variables. Measures of asset prices (like stock price indices) and the nominal foreign exchange rate are two other important financial variables that capture much of what is going on in financial markets. It is only after experimenting with all the financial variables that one might possibly reach a firm conclusion on the role of non-monetary financial variables in causing macroeconomic fluctuations.

Another possible extension of the study would be to identify the structural parameters of the models by imposing *long run* theoretical restrictions instead of *contemporaneous* restrictions. This would allow for a richer short term dynamism at the expense of a more limited long term evolution of the economy.

Finally, applying our theoretical apparatus to the post war American data should serve further testing of our models and the robustness of our results for the Canadian economy, which is broadly similar to the United States' economy. It should also provide us with insights into the sources and nature of business fluctuations in the United States economy.

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