Chapter 2

MONETARY POLICY SHOCKS: WHAT HAVE WE LEARNED AND TO WHAT END?

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Abstract

This chapter reviews recent research that grapples with the question: What happens after an exogenous shock to monetary policy? We argue that this question is interesting because it lies at the center of a particular approach to assessing the empirical plausibility of structural economic models that can be used to think about systematic changes in monetary policy institutions and rules.

The literature has not yet converged on a particular set of assumptions for identifying the effects of an exogenous shock to monetary policy. Nevertheless, there is considerable agreement about the qualitative effects of a monetary policy shock in the sense that inference is robust across a large subset of the identification schemes that have been considered in the literature. We document the nature of this agreement as it pertains to key economic aggregates.

Keywords

monetary policy shocks, recursiveness assumption, benchmark analysis

1. Introduction

In the past decade there has been a resurgence of interest in developing quantitative, monetary general equilibrium models of the business cycle. In part, this reflects the importance of ongoing debates that center on monetary policy issues. What caused the increased inflation experienced by many countries in the 1970s? What sorts of monetary policies and institutions would reduce the likelihood of it happening again? How should the Federal Reserve respond to shocks that impact the economy? What are the welfare costs and benefits of moving to a common currency area in Europe? To make fundamental progress on these types of questions requires that we address them within the confines of quantitative general equilibrium models.

Assessing the effect of a change in monetary policy institutions or rules could be accomplished using purely statistical methods. But only if we had data drawn from otherwise identical economies operating under the monetary institutions or rules we are interested in evaluating. We don't. So purely statistical approaches to these sorts of questions aren't feasible. And, real world experimentation is not an option. The only place we can perform experiments is in structural models.

But we now have at our disposal a host of competing models, each of which emphasizes different frictions and embodies different policy implications. Which model should we use for conducting policy experiments? This chapter discusses a literature that pursues one approach to answering this question. It is in the spirit of a suggestion made by R.E. Lucas (1980). He argues that economists

> "... need to test them (models) as useful imitations of reality by subjecting them to shocks for which we are fairly certain how actual economies or parts of economies would react. The more dimensions on which the model mimics the answers actual economies give to simple questions, the more we trust its answers to harder questions." *R.E. Lucas (1980)*

The literature we review applies the Lucas program using monetary policy shocks. These shocks are good candidates for use in this program because different models respond very differently to monetary policy shocks [see Christiano, Eichenbaum and Evans (1997a)].[1] The program is operationalized in three steps:

- First, one isolates monetary policy shocks in actual economies and characterizes the nature of the corresponding monetary experiments.
- Second, one characterizes the actual economy's response to these monetary experiments.
- Third, one performs the same experiments in the model economies to be evaluated and compares the outcomes with actual economies' responses to the corresponding experiments.

These steps are designed to assist in the selection of a model that convincingly

[1] Other applications of the Lucas program include the work of Galí (1997) who studies the dynamic effects of technology shocks, and Rotemberg and Woodford (1992) and Ramey and Shapiro (1998), who study the dynamic effects of shocks to government purchases.

answers the question, "how does the economy respond to an exogenous monetary policy shock?" Granted, the fact that a model passes this test is not sufficient to give us complete confidence in its answers to the types of questions we are interested in. However this test does help narrow our choices and gives guidance in the development of existing theory.

A central feature of the program is the analysis of monetary policy shocks. Why not simply focus on the actions of monetary policy makers? Because monetary policy actions reflect, in part, policy makers' responses to nonmonetary developments in the economy. A given policy action and the economic events that follow it reflect the effects of *all* the shocks to the economy. Our application of the Lucas program focuses on the effects of a monetary policy shock per se. An important practical reason for focusing on this type of shock is that different models respond very differently to the experiment of a monetary policy shock. In order to use this information we need to know what happens in response to the analog experiment in the actual economy. There is no point in comparing a model's response to one experiment with the outcome of a different experiment in the actual economy. So, to proceed with our program, we *must* know what happens in the actual economy after a shock to monetary policy.

The literature explores three general strategies for isolating monetary policy shocks. The first is the primary focus of our analysis. It involves making enough identifying assumptions to allow the analyst to estimate the parameters of the Federal Reserve's *feedback rule*, i.e., the rule which relates policymakers' actions to the state of the economy. The necessary identifying assumptions include functional form assumptions, assumptions about which variables the Fed looks at when setting its operating instrument and an assumption about what the operating instrument is. In addition, assumptions must be made about the nature of the interaction of the policy shock with the variables in the feedback rule. One assumption is that the policy shock is orthogonal to these variables. Throughout, we refer to this as the *recursiveness* assumption. Along with linearity of the Fed's feedback rule, this assumption justifies estimating policy shocks by the fitted residuals in the ordinary least squares regression of the Fed's policy instrument on the variables in the Fed's information set. The economic content of the recursiveness assumption is that the time t variables in the Fed's information set do not respond to time t realizations of the monetary policy shock. As an example, Christiano et al. (1996a) assume that the Fed looks at current prices and output, among other things, when setting the time t value of its policy instrument. In that application, the recursiveness assumption implies that output and prices respond only with a lag to a monetary policy shock.

While there are models that are consistent with the previous recursiveness assumption, it is nevertheless controversial.[2] This is why authors like Bernanke (1986),

[2] See Christiano, Eichenbaum and Evans (1997b) and Rotemberg and Woodford (1997) for models that are consistent with the assumption that contemporaneous output and the price level do not respond to a monetary policy shock.

Sims (1986), Sims and Zha (1998) and Leeper et al. (1996) adopt an alternative approach. No doubt there are some advantages to abandoning the recursiveness assumption. But there is also a substantial cost: a broader set of economic relations must be identified. And the assumptions involved can also be controversial. For example, Sims and Zha (1998) assume, among other things, that the Fed does not look at the contemporaneous price level or output when setting its policy instrument and that contemporaneous movements in the interest rate do not directly affect aggregate output. Both assumptions are clearly debatable. Finally, it should be noted that abandoning the recursiveness assumption doesn't require one to adopt an identification scheme in which a policy shock has a contemporaneous impact on all nonpolicy variables. For example, Leeper and Gordon (1992) and Leeper et al. (1996) assume that aggregate real output and the price level are not affected in the impact period of a monetary policy shock.

The second and third strategies for identifying monetary policy shocks do not involve explicitly modelling the monetary authority's feedback rule. The second strategy involves looking at data that purportedly signal exogenous monetary policy actions. For example, Romer and Romer (1989) examine records of the Fed's policy deliberations to identify times in which they claim there were exogenous monetary policy shocks. Other authors like Rudebusch (1995) assume that, in certain sample periods, exogenous changes in monetary policy are well measured by changes in the federal funds rate. Finally, authors like Cooley and Hansen (1989, 1997), King (1991), Christiano (1991) and Christiano and Eichenbaum (1995) assume that all movements in money reflect exogenous movements in monetary policy.

The third strategy identifies monetary policy shocks by the assumption that they do not affect economic activity in the long run.[3] We will not discuss this approach in detail. We refer the reader to Faust and Leeper (1997) and Pagan and Robertson (1995) for discussions and critiques of this literature.

The previous overview makes clear that the literature has not yet converged on a particular set of assumptions for identifying the effects of an exogenous shock to monetary policy. Nevertheless, as we show, there is considerable agreement about the qualitative effects of a monetary policy shock in the sense that inference is robust across a large subset of the identification schemes that have been considered in the literature. The nature of this agreement is as follows: after a contractionary monetary policy shock, short term interest rates rise, aggregate output, employment, profits and various monetary aggregates fall, the aggregate price level responds very slowly, and various measures of wages fall, albeit by very modest amounts. In addition, there is agreement that monetary policy shocks account for only a very modest percentage of the volatility of aggregate output; they account for even less of the movements in

[3] For an early example of this approach see Galí (1992).

the aggregate price level.[4] The literature has gone beyond this to provide a richer, more detailed picture of the economy's response to a monetary policy shock (see Section 4.6). But even this small list of findings has proven to be useful in evaluating the empirical plausibility of alternative monetary business cycle models [see Christiano et al. (1997a)]. In this sense the Lucas program, as applied to monetary policy shocks, is already proving to be a fruitful one.

Identification schemes do exist which lead to different inferences about the effects of a monetary policy shock than the consensus view just discussed. How should we select between competing identifying assumptions? We suggest one selection scheme: eliminate a policy shock measure if it implies a set of impulse response functions that is inconsistent with every element in the set of monetary models that we wish to discriminate between. This is equivalent to announcing that if none of the models that we are interested in can account for the qualitative features of a set of impulse response functions, we reject the corresponding identifying assumptions, not the entire set of models. In practice, this amounts to a set of sign and shape restrictions on impulse response functions [see Uhlig (1997) for a particular formalization of this argument]. Since we have been explicit about the restrictions we impose, readers can make their own decisions about whether to reject the identifying assumptions in question.

In the end, the key contribution of the monetary policy shock literature may be this: it has clarified the mapping from identification assumptions to inference about the effects of monetary policy shocks. This substantially eases the task of readers and model builders in evaluating potentially conflicting claims about what actually happens after a monetary policy shock.

The remainder of this chapter is organized as follows:

Section 2: We discuss possible interpretations of monetary policy shocks.

Section 3: We discuss the main statistical tool used in the analysis, namely the Vector Autoregression (VAR). In addition we present a reasonably self-contained discussion of the identification issues involved in estimating the economic effects of a monetary policy shock.

Section 4: We discuss inference about the effects of a monetary policy shock using the recursiveness assumption. First, we discuss the link between the recursiveness assumption and identified VAR's. Second, we display the dynamic response of various economic aggregates to a monetary policy shock under three benchmark identification schemes, each of which satisfies the recursiveness assumption. In addition, we discuss related findings in the literature concerning other aggregates not explicitly analyzed here. Third, we discuss the robustness of inference to various perturbations including: alternative identification schemes which also impose the recursiveness assumption, incorporating information from the federal funds futures market into the analysis and varying the subsample over which the analysis is conducted. Fourth, we consider

[4] These latter two findings say nothing about the impact of the systematic component of monetary policy on aggregate output and the price level. The literature that we review is silent on this point.

some critiques of the benchmark identification schemes. Fifth, we consider the implications of the benchmark identification schemes for the volatility of various economic aggregates.

Section 5: We consider other approaches which focus on the monetary authority's feedback rule, but which do not impose the recursiveness assumption.

Section 6: We discuss the difficulty of directly interpreting estimated monetary policy rules.

Section 7: We consider the narrative approach to assessing the effects of a monetary policy shock.

Section 8: We conclude with a brief discussion of various approaches to implementing the third step of the Lucas program as applied to monetary policy shocks. In particular we review a particular approach to performing monetary experiments in model economies, the outcomes of which can be compared to the estimated effects of a policy shock in actual economies. In addition we provide some summary remarks.

2. Monetary policy shocks: some possible interpretations

Many economists think that a significant fraction of the variation in central bank policy actions reflects policy makers' systematic responses to variations in the state of the economy. As noted in the introduction, this systematic component is typically formalized with the concept of a feedback rule, or reaction function. As a practical matter, it is recognized that not all variations in central bank policy can be accounted for as a reaction to the state of the economy. The unaccounted variation is formalized with the notion of a monetary policy shock. Given the large role that the concepts of a feedback rule and a policy shock play in the literature, we begin by discussing several sources of exogenous variation in monetary policy.

Throughout this chapter we identify a monetary policy shock with the disturbance term in an equation of the form

$$S_t = f(\Omega_t) + \sigma_s \varepsilon_t^s. \tag{2.1}$$

Here S_t is the instrument of the monetary authority, say the federal funds rate or some monetary aggregate, and f is a linear function that relates S_t to the information set Ω_t. The random variable, $\sigma_s \varepsilon_t^s$, is a monetary policy shock. Here, ε_t^s is normalized to have unit variance, and we refer to σ_s as the standard deviation of the monetary policy shock.

One interpretation of f and Ω_t is that they represent the monetary authority's feedback rule and information set, respectively. As we indicate in Section 6, there are other ways to think about f and Ω_t which preserve the interpretation of ε_t^s as a shock to monetary policy.

What is the economic interpretation of these policy shocks? We offer three interpretations. The first is that ε_t^s reflects exogenous shocks to the preferences of the monetary authority, perhaps due to stochastic shifts in the relative weight given to unemployment and inflation. These shifts could reflect shocks to the preferences of the members of the Federal Open Market Committee (FOMC), or to the weights by which their views are aggregated. A change in weights may reflect shifts in the political power of individual committee members or in the factions that they represent. A second source of exogenous variation in policy can arise because of the strategic considerations developed in Ball (1995) and Chari, Christiano and Eichenbaum (1998). These authors argue that the Fed's desire to avoid the social costs of disappointing private agents' expectations can give rise to an exogenous source of variation in policy like that captured by ε_t^s. Specifically, shocks to private agents' expectations about Fed policy can be self-fulfilling and lead to exogenous variations in monetary policy. A third source of exogenous variation in Fed policy could reflect various technical factors. For one set of possibilities, see Hamilton (1997). Another set of possibilities, stressed by Bernanke and Mihov (1995), focuses on the measurement error in the preliminary data available to the FOMC at the time it makes its decision.

We find it useful to elaborate on Bernanke and Mihov's suggestion for three reasons. First, their suggestion is of independent interest. Second, we use it in Section 6 to illustrate some of the difficulties involved in trying to interpret the parameters of f. Third, we use a version of their argument to illustrate how the interpretation of monetary policy shocks can interact with the plausibility of alternative assumptions for identifying ε_t^s.

Suppose the monetary authority sets the policy variable, S_t, as an exact function of current and lagged observations on a set of variables, x_t. We denote the time t observations on x_t and x_{t-1} by $x_t(0)$ and $x_{t-1}(1)$, where

$$x_t(0) = x_t + v_t, \qquad x_{t-1}(1) = x_{t-1} + u_{t-1}. \tag{2.2}$$

So, v_t represents the contemporaneous measurement error in x_t, while u_t represents the measurement error in x_t from the standpoint of period $t+1$. If x_t is observed perfectly with a one period delay, then $u_t \equiv 0$ for all t. Suppose that the policy maker sets S_t as follows:

$$S_t = \beta_0 S_{t-1} + \beta_1 x_t(0) + \beta_2 x_{t-1}(1). \tag{2.3}$$

Expressed in terms of correctly measured variables, this policy rule reduces to Equation (2.1) with:

$$f(\Omega_t) = \beta_0 S_{t-1} + \beta_1 x_t + \beta_2 x_{t-1}, \qquad \sigma_s \varepsilon_t^s = \beta_1 v_t + \beta_2 u_{t-1}. \tag{2.4}$$

This illustrates how noise in the data collection process can be a source of exogenous variation in monetary policy actions.

This example can be used to illustrate how one's interpretation of the error term can affect the plausibility of alternative assumptions used to identify ε_t^s. Recall the recursiveness assumption, according to which ε_t^s is orthogonal to the elements of Ω_t. Under what circumstances would this assumption be correct under the measurement error interpretation of ε_t^s?

To answer this, suppose that v_t and u_t are classical measurement errors, i.e. they are uncorrelated with x_t at all leads and lags. If $\beta_0 = 0$, then the recursiveness assumption is satisfied. Now suppose that $\beta_0 \neq 0$. If $u_t \equiv 0$, then this assumption is still satisfied. However, in the more plausible case where $\beta_2 \neq 0$, $u_t \neq 0$ and u_t and v_t are correlated with each other, then the recursiveness condition fails. This last case provides an important caveat to measurement error as an interpretation of the monetary policy shocks estimated by analysts who make use of the recursiveness assumption. We suspect that this may also be true for analysts who do not use the recursiveness assumption (see Section 5 below), because in developing identifying restrictions, they typically abstract from the possibility of measurement error.

3. Vector autoregressions and identification

A fundamental tool in the literature that we review is the vector autoregression (VAR). A VAR is a convenient device for summarizing the first and second moment properties of the data. We begin by defining more precisely what a VAR is. We then discuss the identification problem involved in measuring the dynamic response of economic aggregates to a fundamental economic shock. The basic problem is that a given set of second moments is consistent with many such dynamic response functions. Solving this problem amounts to making explicit assumptions that justify focusing on a particular dynamic response function.

A VAR for a k-dimensional vector of variables, Z_t, is given by

$$Z_t = B_1 Z_{t-1} + \cdots + B_q Z_{t-q} + u_t, \qquad Eu_t u_t' = V. \tag{3.1}$$

Here, q is a nonnegative integer and u_t is uncorrelated with all variables dated $t-1$ and earlier.[5] Consistent estimates of the B_i's can be obtained by running ordinary least squares equation by equation on Equation (3.1). One can then estimate V from the fitted residuals.

Suppose that we knew the B_i's, the u_t's and V. It still would not be possible to compute the dynamic response function of Z_t to the fundamental shocks in the economy. The basic reason is that u_t is the one step ahead forecast error in Z_t. In general, each element of u_t reflects the effects of all the fundamental economic shocks. There is no reason to presume that any element of u_t corresponds to a particular economic shock, say for example, a shock to monetary policy.

[5] For a discussion of the class of processes that VAR's summarize, see Sargent (1987). The absence of a constant term in Equation (3.1) is without loss of generality, since we are free to set one of the elements of Z_t to be identically equal to unity.

To proceed, we assume that the relationship between the VAR disturbances and the fundamental economic shocks, ε_t, is given by $A_0 u_t = \varepsilon_t$. Here, A_0 is an invertible, square matrix and $E\varepsilon_t\varepsilon_t' = D$, where D is a positive definite matrix.[6] Premultiplying Equation (3.1) by A_0, we obtain:

$$A_0 Z_t = A_1 Z_{t-1} + \cdots + A_q Z_{t-q} + \varepsilon_t. \tag{3.2}$$

Here A_i is a $k \times k$ matrix of constants, $i = 0, \ldots, q$ and

$$B_i = A_0^{-1} A_i, \quad i = 1, \ldots, q, \quad \text{and} \quad V = A_0^{-1} D \left(A_0^{-1}\right)'. \tag{3.3}$$

The response of Z_{t+h} to a unit shock in ε_t, γ_h, can be computed as follows. Let $\tilde{\gamma}_h$ be the solution to the following difference equation:

$$\tilde{\gamma}_h = B_1 \tilde{\gamma}_{h-1} + \cdots + B_q \tilde{\gamma}_{h-q}, \quad h = 1, 2, \ldots \tag{3.4}$$

with initial conditions

$$\tilde{\gamma}_0 = I, \quad \tilde{\gamma}_{-1} = \tilde{\gamma}_{-2} = \cdots = \tilde{\gamma}_{-q} = 0. \tag{3.5}$$

Then,

$$\gamma_h = \tilde{\gamma}_h A_0^{-1}, \; h = 0, 1, \ldots. \tag{3.6}$$

Here, the (j, l) element of γ_h represents the response of the jth component of Z_{t+h} to a unit shock in the lth component of ε_t. The γ_h's characterize the "impulse response function" of the elements of Z_t to the elements of ε_t.

Relation (3.6) implies we need to know A_0 as well as the B_i's in order to compute the impulse response function. While the B_i's can be estimated via ordinary least squares regressions, getting A_0 is not so easy. The only information in the data about A_0 is that it solves the equations in (3.3). Absent restrictions on A_0 there are in general many solutions to these equations. The traditional simultaneous equations literature places no assumptions on D, so that the equations represented by $V = A_0^{-1} D \left(A_0^{-1}\right)'$ provide no information about A_0. Instead, that literature develops restrictions on A_i, $i = 0, \ldots, q$ that guarantee a unique solution to $A_0 B_i = A_i$, $i = 1, \ldots, q$.

In contrast, the literature we survey always imposes the restriction that the fundamental economic shocks are uncorrelated (i.e., D is a diagonal matrix), and places no restrictions on A_i, $i = 1, \ldots, q$.[7] Absent additional restrictions on A_0 we can set

$$D = I. \tag{3.7}$$

Also note that without any restrictions on the A_i's, the equations represented by $A_0 B_i = A_i$, $i = 1, \ldots, q$ provide no information about A_0. All of the information about

[6] This corresponds to the assumption that the economic shocks are recoverable from a finite list of current and past Z_t's. For our analysis, we only require that a subset of the ε_t's be recoverable from current and past Z_t's.

[7] See Leeper, Sims and Zha (1996) for a discussion of Equation (3.7).

this matrix is contained in the relationship $V = A_0^{-1}\left(A_0^{-1}\right)'$. Define the set of solutions to this equation by

$$Q_V = \left\{A_0 : A_0^{-1}\left(A_0^{-1}\right)' = V\right\}. \tag{3.8}$$

In general, this set contains many elements. This is because A_0 has k^2 parameters while the symmetric matrix, V, has at most $k(k+1)/2$ distinct numbers. So, Q_V is the set of solutions to $k(k+1)/2$ equations in k^2 unknowns. As long as $k > 1$, there will in general be many solutions to this set of equations, i.e., there is an identification problem.

To solve this problem we must find and defend restrictions on A_0 so that there is only one element in Q_V satisfying them. In practice, the literature works with two types of restrictions: a set of linear restrictions on the elements of A_0 and a requirement that the diagonal elements of A_0 be positive. Suppose that the analyst has in mind l linear restrictions on A_0. These can be represented as the requirement $\tau\text{vec}(A_0) = 0$, where τ is a matrix of dimension $l \times k^2$ and $\text{vec}(A_0)$ is the $k^2 \times 1$ vector composed of the k columns of A_0. Each of the l rows of τ represents a different restriction on the elements of A_0. We denote the set of A_0 satisfying these restrictions by:

$$Q_\tau = \{A_0 : \tau\text{vec}(A_0) = 0\}. \tag{3.9}$$

In the literature that we survey, the restrictions summarized by τ are either zero restrictions on the elements of A_0 or restrictions across the elements of individual rows of A_0. Cross equation restrictions, i.e., restrictions across the elements of different rows of A_0, are not considered.

Next we motivate the sign restrictions that the diagonal elements of A_0 must be strictly positive.[8] If $Q_\tau \cap Q_V$ is nonempty, it can never be composed of just a single matrix. This is because if A_0 lies in $Q_V \cap Q_\tau$, then $\tilde{A}_0$ obtained from A_0 by changing the sign of all elements of an arbitrary subset of rows of A_0 also lies in $Q_\tau \cap Q_V$. To see this, let W be a diagonal matrix with an arbitrary pattern of ones and minus ones along the diagonal. It is obvious that $WA_0 \in Q_\tau$. Also, because W is orthonormal (i.e., $W'W = I$), $WA_0 \in Q_V$ as well.

Suppose we impose the restriction that the diagonal elements of A_0 be strictly positive. This rules out matrices $\tilde{A}_0$ that are obtained from an $A_0 \in Q_\tau \cap Q_V$ by changing the signs of all the elements of A_0. In what follows we only consider A_0 matrices that obey the sign restrictions. That is, we insist that $A_0 \in Q_S$, where

$$Q_S = \{A_0 : A_0 \text{ has strictly positive diagonal elements}\}. \tag{3.10}$$

From Equation (3.2) we see that the ith diagonal of A_0 being positive corresponds to the normalization that a positive shock to the ith element of ε_t represents a positive shock to the ith element of Z_t when the other elements of Z_t are held fixed.

[8] The following discussion ignores the possibility that $Q_\tau \cap Q_V$ contains a matrix with one or more diagonal elements that are exactly zero. A suitable modification of the argument below can accommodate this possibility.

When there is more than one element in the set $Q_V \cap Q_\tau \cap Q_S$ we say that the system is "underidentified", or, "not identified". When $Q_V \cap Q_\tau \cap Q_S$ has one element, we say it is "identified". So, in these terms, solving the identification problem requires selecting a τ which causes the system to be identified.

Note that $Q_V \cap Q_\tau$ is the set of solutions to $k(k+1)/2 + l$ equations in the k^2 unknowns of A_0. In practice, the literature seeks to achieve identification by selecting a full row rank τ satisfying the order condition, $l \geqslant k(k-1)/2$. However, the order and sign conditions are not sufficient for identification. For example, when $l = k(k-1)/2$ underidentification could occur for two reasons. First, a neighborhood of a given $A_0 \in Q_V \cap Q_\tau \cap Q_S$ could contain other matrices belonging to $Q_V \cap Q_\tau \cap Q_S$. This possibility can be ruled out by verifying a simple rank condition, namely that the matrix derivative with respect to A_0 of the equations defining (3.8) is of full rank.[9] In this case, we say we have established *local* identification. A second possibility is that there may be other matrices belonging to $Q_V \cap Q_\tau \cap Q_S$ but which are not in a small neighborhood of A_0.[10] In general, no known simple conditions rule out this possibility. If we do manage to rule it out, we say the system is *globally* identified.[11] In practice, we use the rank and order conditions to verify local identification. Global identification must be established on a case by case basis. Sometimes, as in our discussion of Bernanke and Mihov (1995), this can be done analytically. More typically, one is limited to building confidence in global identification by conducting an ad hoc numerical search through the parameter space to determine if there are other elements in $Q_V \cap Q_\tau \cap Q_S$.

The difficulty of establishing global identification in the literature we survey stands in contrast to the situation in the traditional simultaneous equations context.

[9] Here we define a particular rank condition and establish that the rank and order conditions are sufficient for local identification. Let α be the $k(k+1)/2$ dimensional column vector of parameters in A_0 that remain free after imposing condition (3.9), so that $A_0(\alpha) \in Q_\tau$ for all α. Let $f(\alpha)$ denote the $k(k+1)/2$ dimensional row vector composed of the upper triangular part of $A_0(\alpha)^{-1}\left[A_0(\alpha)^{-1}\right]' - V$. Let $F(\alpha)$ denote the $k(k+1)/2$ by $k(k+1)/2$ derivative matrix of $f(\alpha)$ with respect to α. Let α^* satisfy $f(\alpha^*) = 0$. Consider the following rank condition: $F(\alpha)$ has full rank for all $\alpha \in D(\alpha^*)$, where $D(\alpha^*)$ is some neighborhood of α^*. We assume that f is continuous and that F is well defined. A straightforward application of the mean value theorem (see Bartle (1976), p. 196) establishes that this rank condition guarantees $f(\alpha) \neq 0$ for all $\alpha \in D(\alpha^*)$ and $\alpha \neq \alpha^*$. Let $g_\iota : \left[\underline{\varepsilon}_\iota, \overline{\varepsilon}_\iota\right] \to R^{k(k+1)/2}$ be defined by $g_\iota(\varepsilon) = f(\alpha^* + \iota\varepsilon)$, where ι is an arbitrary non-zero $k(k+1)/2$ column vector, and $\underline{\varepsilon}_\iota$ and $\overline{\varepsilon}_\iota$ are the smallest and largest values, respectively, of ε such that $(\alpha^* + \iota\varepsilon) \in D(\alpha^*)$. Note that $g_\iota'(\varepsilon) = \iota' F(\alpha^* + \iota\varepsilon)$ and $\underline{\varepsilon}_\iota < 0 < \overline{\varepsilon}_\iota$. By the mean value theorem, $g_\iota(\varepsilon) = g_\iota(0) + g_\iota'(\gamma)\varepsilon$ for some γ between 0 and ε. This can be written $g_\iota(\varepsilon) = \iota' F(\alpha^* + \iota\varepsilon)\varepsilon$. The rank condition implies that the expression to the right of the equality is nonzero, as long as $\varepsilon \neq 0$. Since the choice of $\iota \neq 0$ was arbitrary, the result is established.

[10] A simple example is $(x-a)(x-b) = 0$, which is one equation with two isolated solutions, $x = a$ and $x = b$.

[11] We can also differentiate other concepts of identification. For example, asymptotic and small sample identification correspond to the cases where V is the population and finite sample value of the variance covariance matrix of the VAR disturbances, respectively. Obviously, asymptotic identification could hold while finite sample identification fails, as well as the converse.

There, the identification problem only involves systems of linear equations. Under these circumstances, local identification obtains if and only if global identification obtains. The traditional simultaneous equations literature provides a simple set of rank and order conditions that are necessary and sufficient for identification. These conditions are only sufficient to characterize local identification for the systems that we consider.[12] Moreover, they are neither necessary nor sufficient for global identification.

We now describe two examples which illustrate the discussion above. In the first case, the order and sign conditions are sufficient to guarantee global identification. In the second, the order condition and sign conditions for identification hold, yet the system is not identified.

In the first example, we select τ so that all the elements above (alternatively, below) the diagonal of A_0 are zero. If, in addition, we impose the sign restriction, then it is well known that there is only one element in $Q_V \cap Q_\tau \cap Q_S$, i.e., the system is globally identified. This result is an implication of the uniqueness of the Cholesky factorization of a positive definite symmetric matrix. This example plays a role in the section on identification of monetary policy shocks with a recursiveness assumption.

For our second example, consider the case $k = 3$ with the following restricted A_0 matrix:

$$A_0 = \begin{bmatrix} a_{11} & 0 & a_{13} \\ 0 & a_{22} & a_{23} \\ 0 & a_{32} & a_{33} \end{bmatrix},$$

where $a_{ii} > 0$ for $i = 1, 2, 3$. Since there are three zero restrictions, the order condition is satisfied. Suppose that $A_0 \in Q_V$, so that $A_0 \in Q_V \cap Q_\tau \cap Q_S$. Let W be a block diagonal matrix with unity in the $(1,1)$ element and an arbitrary 2×2 orthonormal matrix in the second diagonal block. Let W also have the property that WA_0 has positive elements on the diagonal. Then, $WW' = I$, and $WA_0 \in Q_V \cap Q_\tau \cap Q_S$.[13] In this case we do not have identification, even though the order and sign conditions are satisfied. The reason for the failure of local identification is that the rank condition does not hold. If it did hold, then identification would have obtained. The failure of the rank condition in this example reflects that the second and third equations in the system are indistinguishable.

[12] To show that the rank condition is not necessary for local identification, consider $f(x) = (x - a)^2$. For this function there is a globally unique zero at $x = a$, yet $f'(a) = 0$.

[13] To see that this example is non empty, consider the case $a_{11} = 0.70$, $a_{13} = 0.40$, $a_{22} = 0.38$, $a_{23} = 0.50$, $a_{32} = 0.83$, $a_{33} = 0.71$ and let the 2×2 lower block in W be

$$\begin{bmatrix} 0.4941 & 0.8694 \\ 0.8694 & -0.4941 \end{bmatrix}.$$

It is easy to verify that WA_0 satisfies the zero and sign restrictions on A_0.

It is easy to show that every element in $Q_V \cap Q_\tau \cap Q_S$ generates the same dynamic response function to the first shock in the system. To see this, note from Equation (3.5) that the first column of A_0^{-1} is what characterizes the response of all the variables to the first shock. Similarly, the first column of $(WA_0)^{-1}$ controls the response of the transformed system to the first shock. But, the result $(WA_0)^{-1} = A_0^{-1}W'$, and our definition of W imply that the first columns of $(WA_0)^{-1}$ and of A_0^{-1} are the same. So, if one is only interested in the dynamic response of the system to the first shock, then the choice of the second diagonal block of W is irrelevant. An extended version of this observation plays an important role in our discussion of nonrecursive identification schemes below.

4. The effects of a monetary policy shock: a recursiveness assumption

In this section we discuss one widely used strategy for estimating the effects of a monetary policy shock. The strategy is based on the recursiveness assumption, according to which monetary policy shocks are orthogonal to the information set of the monetary authority. Section 4.1 discusses the relationship between the recursiveness assumption and VARs. Section 4.2 describes three benchmark identification schemes which embody the recursiveness assumption. In addition, we display estimates of the dynamic effects of a monetary policy shock on various economic aggregates, obtained using the benchmark identification schemes. Section 4.3 reviews some results in the literature regarding the dynamic effects of a monetary policy shock on other economic aggregates, obtained using close variants of the benchmark schemes. Section 4.4 considers robustness of the empirical results contained in Section 4.2. Section 4.5 discusses various critiques of the benchmark identification schemes. Finally, Section 4.6 investigates the implications of the benchmark schemes for the volatility of various economic aggregates.

4.1. The recursiveness assumption and VARs

The recursiveness assumption justifies the following two-step procedure for estimating the dynamic response of a variable to a monetary policy shock. First, estimate the policy shocks by the fitted residuals in the ordinary least squares regression of S_t on the elements of Ω_t. Second, estimate the dynamic response of a variable to a monetary policy shock by regressing the variable on the current and lagged values of the estimated policy shocks.

In our analysis we find it convenient to map the above two-step procedure into an asymptotically equivalent VAR-based procedure. There are two reasons for this. First, the two-step approach implies that we lose a number of initial data points equal to the number of dynamic responses that we wish to estimate, plus the number of lags, q, in Ω_t. With the VAR procedure we only lose the latter. Second, the VAR methodology provides a complete description of the data generating process for the elements of Ω_t.

This allows us to use a straightforward bootstrap methodology for use in conducting hypothesis tests.

We now indicate how the recursiveness assumption restricts A_0 in Equation (3.2). Partition Z_t into three blocks: the k_1 variables, X_{1t}, whose contemporaneous values appear in Ω_t, the k_2 variables, X_{2t}, which only appear with a lag in Ω_t, and S_t itself. Then, $k = k_1 + k_2 + 1$, where k is the dimension of Z_t. That is:

$$Z_t = \begin{pmatrix} X_{1t} \\ S_t \\ X_{2t} \end{pmatrix}.$$

We consider $k_1, k_2 \geq 0$. To make the analysis interesting we assume that if $k_1 = 0$, so that X_{1t} is absent from the definition of Z_t, then $k_2 > 1$. Similarly, if $k_2 = 0$, then $k_1 > 1$. The recursiveness assumption places the following zero restrictions on A_0 :

$$A_0 = \begin{bmatrix} \underset{(k_1 \times k_1)}{a_{11}} & \underset{(k_1 \times 1)}{0} & \underset{(k_1 \times k_2)}{0} \\ \underset{(1 \times k_1)}{a_{21}} & \underset{(1 \times 1)}{a_{22}} & \underset{(1 \times k_2)}{0} \\ \underset{(k_2 \times k_1)}{a_{31}} & \underset{(k_2 \times 1)}{a_{32}} & \underset{(k_2 \times k_2)}{a_{33}} \end{bmatrix}. \tag{4.1}$$

Here, expressions in parentheses indicate the dimension of the associated matrix and $a_{22} = 1/\sigma_s$, where $\sigma_s > 0$.

The zero block in the middle row of this matrix reflect the assumption that the policy maker does not see X_{2t} when S_t is set. The two zero blocks in the first row of A_0 reflect our assumption that the monetary policy shock is orthogonal to the elements in X_{1t}. These blocks correspond to the two distinct channels by which a monetary policy shock could in principle affect the variables in X_{1t}. The first of these blocks corresponds to the direct effect of S_t on X_{1t}. The second block corresponds to the indirect effect that operates via the impact of a monetary policy shock on the variables in X_{2t}.

We now show that the recursiveness assumption is not sufficient to identify all the elements of A_0. This is not surprising, in light of the fact that the first k_1 equations are indistinguishable from each other, as are the last k_2 equations. Significantly, however, the recursiveness assumption *is* sufficient to identify the object of interest: the dynamic response of Z_t to a monetary policy shock. Specifically, we establish three results. The first two are as follows: (i) there is a nonempty family of A_0 matrices, one of which is lower triangular with positive terms on the diagonal, which are consistent with the recursiveness assumption [i.e., satisfy Equation (4.1)] and satisfy $A_0^{-1}\left(A_0^{-1}\right)' = V$; and (ii) each member of this family generates precisely the same dynamic response function of the elements of Z_t to a monetary policy shock. Result (iii) is that if we adopt the normalization of always selecting the lower triangular A_0 matrix identified in (i), then the dynamic response of the variables in Z_t are invariant to the ordering of variables in X_{1t} and X_{2t}.

To prove (i)–(iii) it is useful to establish a preliminary result. We begin by defining some notation. Let the $((k_1+1)k_2+k_1) \times k^2$ matrix τ summarize the zero restrictions on A_0 in Equation (4.1). So, Q_τ is the set of A_0 matrices consistent with the recursiveness assumption. Let Q_V be the set of A_0 matrices defined by the property that $A_0^{-1}(A_0^{-1})'$ [see Equation (3.8)]. In addition, let

$$W = \begin{bmatrix} W_{11} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & W_{33} \end{bmatrix}, \tag{4.2}$$

where W is partitioned conformably with A_0 in Equation (4.1) and W_{11} and W_{33} are arbitrary orthonormal matrices. Define

$$Q_{\bar{A}_0} = \left\{A_0 : A_0 = W\bar{A}_0, \text{ for some } W \text{ satisfying (4.2)}\right\}.$$

Here $\bar{A}_0$ is a matrix conformable with W.

We now establish the following result:

$$Q_{\bar{A}_0} = Q_V \cap Q_\tau, \tag{4.3}$$

where $\bar{A}_0$ is an arbitrary element of $Q_V \cap Q_\tau$. It is straightforward to establish that $A_0 \in Q_{\bar{A}_0}$ implies $A_0 \in Q_V \cap Q_\tau$. The result, $A_0 \in Q_V$ follows from orthonormality of W and the fact, $\bar{A}_0 \in Q_V$. The result, $A_0 \in Q_\tau$, follows from the block diagonal structure of W in Equation (4.2). Now consider an arbitrary $A_0 \in Q_V \cap Q_\tau$. To show that $A_0 \in Q_{\bar{A}_0}$, consider the candidate orthonormal matrix $W = A_0\bar{A}_0^{-1}$, where invertibility of $\bar{A}_0$ reflects $\bar{A}_0 \in Q_V$. Since W is the product of two block-lower triangular matrices, it too is block-lower triangular. Also, it is easy to verify that $WW' = I$. The orthonormality of W, together with block-lower triangularity imply that W has the form (4.2). This establishes $A_0 \in Q_{\bar{A}_0}$ and, hence, Equation (4.3).

We now prove result (i). The fact that $Q_V \cap Q_\tau$ is not empty follows from the fact that we can always set A_0 equal to the inverse of the lower triangular Cholesky factor of V. The existence and invertability of this matrix is discussed in Hamilton (1994, p. 91).[14] To see that there is more than one element in $Q_V \cap Q_\tau$, use the characterization result (4.3), with $\bar{A}_0$ equal to the inverse of the Cholesky factor of V. Construct the orthonormal matrix $W \neq I$ by interchanging two of either the first k_1 rows or the last k_2 rows of the k-dimensional identity matrix.[15] Then, $W\bar{A}_0 \neq \bar{A}_0$. Result (i) is established because $W\bar{A}_0 \in Q_V \cap Q_\tau$.

[14] The Cholesky factor of a positive definite, symmetric matrix, V, is a lower triangular matrix, C, with the properties (i) it has positive elements along the diagonal, and (ii) it satisfies the property, $CC' = V$.

[15] Recall, orthonormality of a matrix means that the inner product between two different columns is zero and the inner product of any column with itself is unity. This property is obviously satisfied by the identity matrix. Rearranging the rows of the identity matrix just changes the order of the terms being added in the inner products defining orthonormality, and so does not alter the value of column inner products. Hence a matrix obtained from the identity matrix by arbitrarily rearranging the order of its rows is orthonormal.

We now prove result (ii). Consider any two matrices, A_0, $\tilde{A}_0 \in Q_V \cap Q_\tau$. By Equation (4.3) there exists a W satisfying Equation (4.2), with the property $\tilde{A}_0 = WA_0$, so that

$$\tilde{A}_0^{-1} = A_0^{-1} W'.$$

In conjunction with Equation (4.2), this expression implies that the $(k_1 + 1)$th column of $\tilde{A}_0^{-1}$ and A_0^{-1} are identical. But, by Equation (3.6) the implied dynamic responses of Z_{t+i}, $i = 0, 1, \ldots$ to a monetary policy shock are identical too. This establishes result (ii).

We now prove (iii) using an argument essentially the same as the one used to prove (ii). We accomplish the proof by starting with a representation of Z_t in which A_0 is lower triangular with positive diagonal elements. We then arbitrarily reorder the first k_1 and the last k_2 elements of Z_t. The analog to A_0 in the resulting system need not be lower triangular with positive elements. We then apply a particular orthonormal transformation which results in a lower triangular system with positive diagonal elements. The response of the variables in Z_t to a monetary policy shock is the same in this system and in the original system.

Consider $\tilde{Z}_t = DZ_t$, where D is the orthonormal matrix constructed by arbitrarily reordering the columns within the first k_1 and the last k_2 columns of the identity matrix.[16] Then, $\tilde{Z}_t$ corresponds to Z_t with the variables in X_{1t} and X_{2t} reordered arbitrarily. Let B_i, $i = 1, \ldots, q$ and V characterize the VAR of Z_t and let A_0 be the unique lower triangular matrix with positive diagonal terms with the property $A_0^{-1}\left(A_0^{-1}\right)' = V$. Given the B_i's, A_0 characterizes the impulse response function of the Z_t's to ε_t [see Equations (3.4)–(3.6)]. The VAR representation of $\tilde{Z}_t$, obtained by suitably reordering the equations in (3.1), is characterized by DB_iD', $i = 1, \ldots, q$, and DVD'.[17] Also, it is easily verified that $(A_0D')^{-1}\left[(A_0D')^{-1}\right]' = DVD'$, and that given the DB_iD''s, A_0D' characterizes the impulse response function of the $\tilde{Z}_t$'s to ε_t. Moreover, these responses coincide with the responses of the corresponding variables in Z_t to ε_t. Note that A_0D' is not in general lower triangular. Let $\tilde{A}_0 = A_0D'$:

$$\tilde{A}_0 = \begin{bmatrix} \tilde{a}_{11} & 0 & 0 \\ \tilde{a}_{21} & \tilde{a}_{22} & 0 \\ \tilde{a}_{31} & \tilde{a}_{32} & \tilde{a}_{33} \end{bmatrix},$$

where $\tilde{a}_{ii}$ is full rank, but not necessarily lower triangular, for $i = 1, 3$. Let the QR decomposition of these matrices be $\tilde{a}_{ii} = Q_iR_i$, where Q_i is a square, orthonormal

[16] The type of reasoning in the previous footnote indicates that permuting the columns of the identity matrix does not alter orthonormality.

[17] To see this, simply premultiply Equation (3.1) by D on both sides and note that $B_iZ_{t-i} = B_iD'DZ_{t-i}$, because $D'D = I$.

matrix, and R_i is lower triangular with positive elements along the diagonal. This decomposition exists as long as $\tilde{a}_{ii}$, $i = 1, 3$, is nonsingular, a property guaranteed by the fact $A_0 \in Q_V \cap Q_\tau$ [see Strang (1976), p. 124].[18] Let

$$W = \begin{bmatrix} Q_1' & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & Q_3' \end{bmatrix}.$$

Note that $WW' = I$, $\left(W\tilde{A}_0\right)^{-1}\left[\left(W\tilde{A}_0\right)^{-1}\right]' = DVD'$, and $W\tilde{A}_0$ is lower triangular with positive elements along the diagonal. Since $\left(W\tilde{A}_0\right)^{-1} = \tilde{A}_0^{-1}W'$, the $(k_1 + 1)$th columns of $\tilde{A}_0^{-1}W'$ and $\tilde{A}_0^{-1}$ coincide. We conclude that, under the normalization that A_0 is lower diagonal with positive diagonal terms, the response of the variables in Z_t to a monetary policy shock is invariant to the ordering of variables in X_{1t} and X_{2t}. This establishes (iii).

We now summarize these results in the form of a proposition.

Proposition 4.1. Consider the sets Q_V and Q_τ.

(i) The set $Q_V \cap Q_\tau$ is nonempty and contains more than one element.

(ii) The $(k_1 + 1)$th column of γ_i, $i = 0, 1, \ldots$ in Equation (3.6) is invariant to the choice of $A_0 \in Q_V \cap Q_\tau$.

(iii) Restricting $A_0 \in Q_V \cap Q_\tau$ to be lower triangular with positive diagonal terms, the $(k_1 + 1)$th column of γ_i, $i = 0, 1, \ldots$ is invariant to the ordering of the elements in X_{1t} and X_{2t}.

We now provide a brief discussion of (i)–(iii). According to results (i) and (ii), under the recursiveness assumption the data are consistent with an entire family, $Q_V \cap Q_\tau$, of A_0 matrices. It follows that the recursiveness assumption is not sufficient to pin down the dynamic response functions of the variables in Z_t to every element of ε_t. But, each $A_0 \in Q_V \cap Q_\tau$ does generate the same response to one of the ε_t's, namely the one corresponding to the monetary policy shock. In this sense, the recursiveness assumption identifies the dynamic response of Z_t to a monetary shock, but not the response to other shocks.

In practice, computational convenience dictates the choice of some $A_0 \in Q_V \cap Q_\tau$. A standard normalization adopted in the literature is that the A_0 matrix is lower triangular with nonnegative diagonal terms. This still leaves open the question of how to order the variables in X_{1t} and X_{2t}. But, according to result (iii), the dynamic response of the variables in Z_t to a monetary policy shock is invariant to this ordering. At

[18] Actually, it is customary to state the QR decomposition of the $(n \times n)$ matrix A as $A = QR$, where R is *upper* triangular. We get it into lower triangular form by constructing the orthonormal matrix E with zeros everywhere and 1's in the $(n+1-i, i)$th entries, $i = 1, 2, \ldots, n$, and writing $A = (QE)\left(E'R\right)$. The orthonormal matrix to which we refer in the text is actually QE.

the same time, the dynamic impact on Z_t of the nonpolicy shocks is sensitive to the ordering of the variables in X_{1t} and X_{2t}. The recursiveness assumption has nothing to say about this ordering. Absent further identifying restrictions, the nonpolicy shocks and the associated dynamic response functions simply reflect normalizations adopted for computational convenience.

4.2. Three benchmark identification schemes

We organize our empirical discussion around three benchmark recursive identification schemes. These correspond to different specifications of S_t and Ω_t. In our first benchmark system, we measure the policy instrument, S_t, by the time t federal funds rate. This choice is motivated by institutional arguments in McCallum (1983), Bernanke and Blinder (1992) and Sims (1986, 1992). Let Y_t, P_t, $PCOM_t$, FF_t, TR_t, NBR_t, and M_t denote the time t values of the log of real GDP, the log of the implicit GDP deflator, the smoothed change in an index of sensitive commodity prices (a component in the Bureau of Economic Analysis' index of leading indicators), the federal funds rate, the log of total reserves, the log of nonborrowed reserves plus extended credit, and the log of either $M1$ or $M2$, respectively. Here all data are quarterly. Our benchmark specification of Ω_t includes current and four lagged values of Y_t, P_t, and $PCOM_t$, as well as four lagged values of FF_t, NBR_t, TR_t and M_t. We refer to the policy shock measure corresponding to this specification as an *FF* policy shock.

In our second benchmark system we measure S_t by NBR_t. This choice is motivated by arguments in Eichenbaum (1992) and Christiano and Eichenbaum (1992) that innovations to nonborrowed reserves primarily reflect exogenous shocks to monetary policy, while innovations to broader monetary aggregates primarily reflect shocks to money demand. We assume that Ω_t includes current and four lagged values of Y_t, P_t, and $PCOM_t$, as well as four lagged values of FF_t, NBR_t, TR_t and M_t. We refer to the policy shock measure corresponding to this specification as an *NBR* policy shock.

Note that in both benchmark specifications, the monetary authority is assumed to see Y_t, P_t and $PCOM_t$, when choosing S_t.[19] This assumption is certainly arguable because quarterly real GDP data and the GDP deflator are typically known only with a delay. Still, the Fed does have at its disposal monthly data on aggregate employment, industrial output and other indicators of aggregate real economic activity. It also has substantial amounts of information regarding the price level. In our view the assumption that the Fed sees Y_t and P_t when they choose S_t seems at least as plausible as assuming that they don't.[20] Below we document the effect of deviating from this benchmark assumption.

[19] Examples of analyses which make this type of information assumption include Christiano and Eichenbaum (1992), Christiano et al. (1996a, 1997a), Eichenbaum and Evans (1995), Strongin (1995), Bernanke and Blinder (1992), Bernanke and Mihov (1995), and Gertler and Gilchrist (1994).

[20] See for example the specifications in Sims and Zha (1998) and Leeper et al. (1996).

Notice that under our assumptions, Y_t, P_t and $PCOM_t$ do not change in the impact period of either an *FF* or an *NBR* policy shock. Christiano et al. (1997b) present a dynamic stochastic general equilibrium model which is consistent with the notion that prices and output do not move appreciably in the impact period of a monetary policy shock. The assumption regarding $PCOM_t$ is more difficult to assess on theoretical grounds absent an explicit monetary general equilibrium model that incorporates a market for commodity prices. In any event, we show below that altering the benchmark specification to exclude the contemporaneous value of $PCOM_t$ from Ω_t has virtually no effect on our results.[21]

In the following subsection we display the time series of the two benchmark policy shock estimates. After that, we study the dynamic response of various economic time series to these shocks. At this point, we also consider our third benchmark system, a variant of the *NBR* policy shocks associated with Strongin (1995). Finally, we consider the contribution of different policy shock measures to the volatility of various economic aggregates.

4.2.1. *The benchmark policy shocks displayed*

We begin by discussing some basic properties of the estimated time series of the *FF* and *NBR* policy shocks. These are obtained using quarterly data over the sample period 1965:3–1995:2. Figure 1 contains two time series of shocks. The dotted line depicts the quarterly *FF* policy shocks. The solid line depicts the contemporaneous changes in the federal funds rate implied by contractionary *NBR* policy shocks. In both cases the variable M_t was measured as $M1_t$.

Since the policy shock measures are by construction serially uncorrelated, they tend to be noisy. For ease of interpretation we report the centered, three quarter moving average of the shock, i.e., we report $(\varepsilon^s_{t+1} + \varepsilon^s_t + \varepsilon^s_{t-1})/3$. Also, for convenience we include shaded regions, which begin at a National Bureau of Economic Research (NBER) business cycle peak, and end at a trough. The two shocks are positively correlated, with a correlation coefficient of 0.51. The estimated standard deviation of the *FF* policy shocks is 0.71, at an annual rate. The estimated standard deviation of the *NBR* is 1.53% and the standard deviation of the implied federal funds rate shock is 0.39, at an annual rate.

In describing our results, we find it useful to characterize monetary policy as "tight" or "contractionary", when the smoothed policy shock is positive, and "loose" or "expansionary" when it is negative. According to the *FF* policy shock measure, policy was relatively tight before each recession, and became easier around the time of the trough.[22] A similar pattern is observed for the movements in the federal funds rate

[21] This does not mean that excluding lagged values from Ω_t has no effect on our results.

[22] In Figure 1, the beginning of the 1973–74 recession appears to be an exception to the general pattern. To some extent this reflects the effects of averaging since there was a 210 basis point *FF* policy shock in 1973Q3.

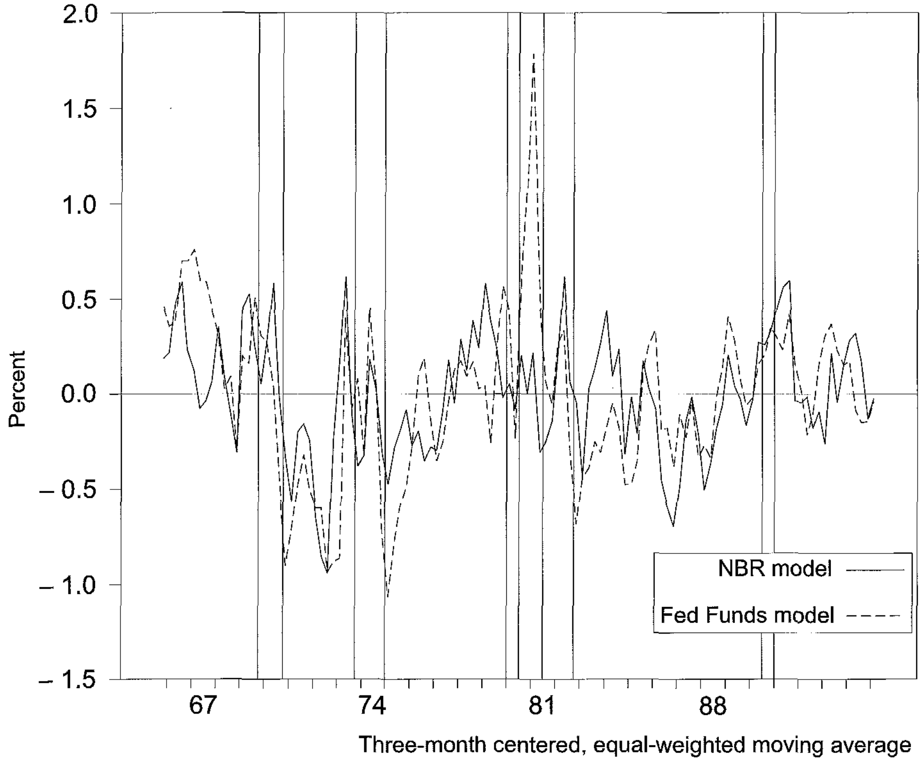


Fig. 1. Contractionary benchmark policy shocks in units of federal funds rate. The dotted line depicts the quarterly *FF* policy shocks. The solid line depicts the contemporaneous changes in the federal funds rate implied by contractionary *NBR* policy shocks. In both cases the variable M_t was measured as $M1_t$.

implied by the *NBR* shocks, except that in the 1981–1982 period, policy was loose at the start, very tight in the middle, and loose at the end of the recession.

4.2.2. *What happens after a benchmark policy shock?*

4.2.2.1. Results for some major economic aggregates. Figure 2 displays the estimated impulse response functions of contractionary benchmark *FF* and *NBR* policy shocks on various economic aggregates included in Ω_t. These are depicted in columns 1 and 2, respectively. Column 3 reports the estimated impulse response functions from a third policy shock measure which we refer to as an *NBR/TR* policy shock. This shock measure was proposed by Strongin (1995) who argued that the demand for total reserves is completely interest inelastic in the short run, so that a monetary policy shock initially only rearranges the composition of total reserves between nonborrowed and borrowed reserves. Strongin argues that, after controlling for movements in certain variables that are in the Fed's information set, a policy shock should be measured as the

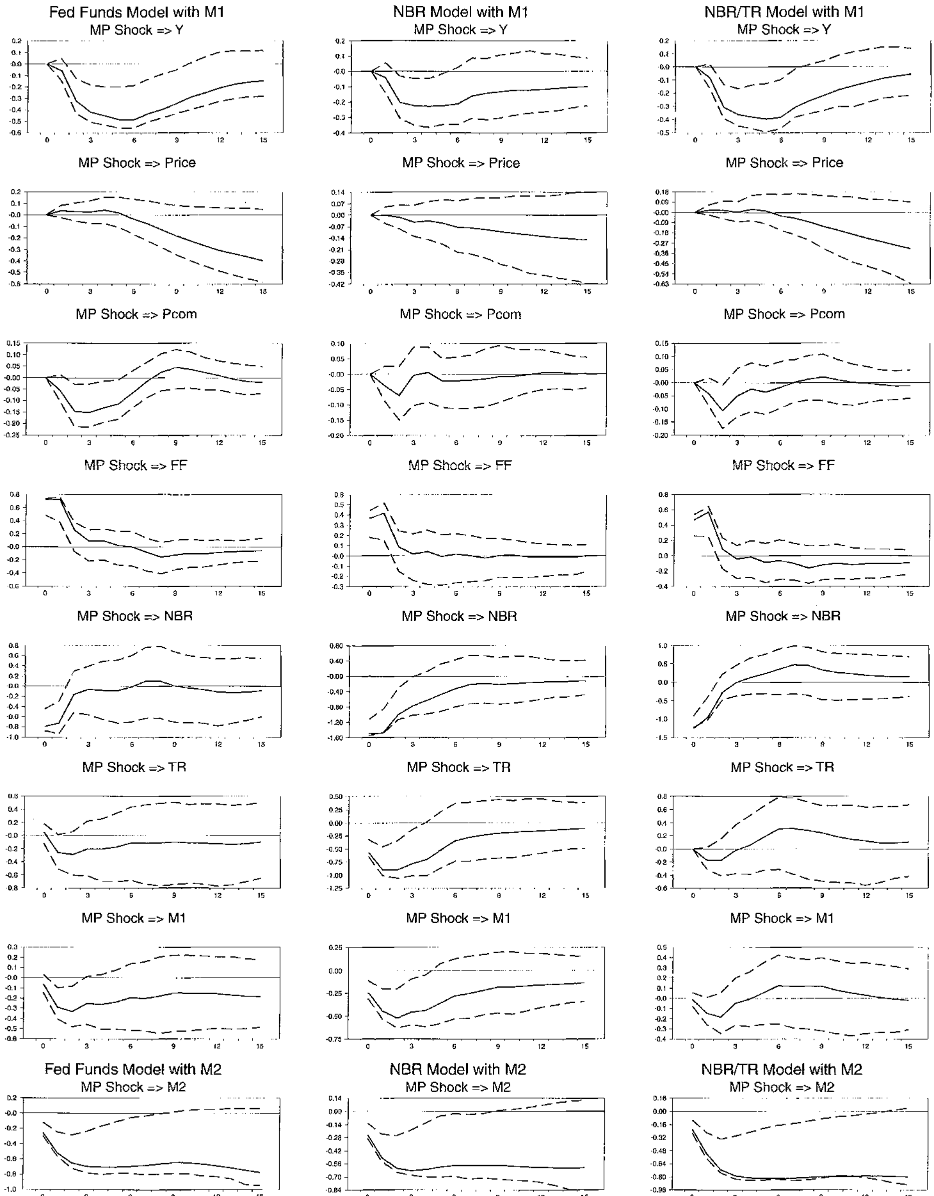


Fig. 2. The estimated impulse response functions of contractionary benchmark *FF* and *NBR* policy shocks on various economic aggregates included in Ω_t (columns 1 and 2). Column 3 reports the estimated impulse response functions from a third policy shock measure which we refer to as an *NBR/TR* policy shock. The solid lines in the figure report the point estimates of the different dynamic response functions. Dashed lines denote a 95% confidence interval for the dynamic response functions.

innovation to the ratio of nonborrowed to total reserves. We capture this specification by measuring S_t as *NBR* and assuming that Ω_t includes the current value of *TR*. With this specification, a shock to ε_t^s does not induce a contemporaneous change in *TR*.

All three identification schemes were implemented using $M1$ and $M2$ as our measure of money. This choice turned out to have very little effect on the results. The results displayed in Figure 2 are based on a system that included $M1$. The last row of Figure 2 depicts the impulse response function of $M2$ to the different policy shock measures, obtained by replacing $M1$ with $M2$ in our specification of Ω_t. The solid lines in the figure report the point estimates of the different dynamic response functions. Dashed lines denote a 95% confidence interval for the dynamic response functions.[23]

The main consequences of a contractionary *FF* policy shock can be summarized as follows. First, there is a persistent rise in the federal funds rate and a persistent drop in nonborrowed reserves. This finding is consistent with the presence of a strong liquidity effect. Second, the fall in total reserves is negligible initially. But eventually total reserves fall by roughly 0.3 percent. So according to this policy shock measure, the Fed insulates total reserves in the short run from the full impact of a contraction in nonborrowed reserves by increasing borrowed reserves.[24] This is consistent with the arguments in Strongin (1995). Third, the response of $M1$ is qualitatively similar to the response of *TR*. In contrast, for the $M2$ system, the *FF* policy shock leads to an immediate and persistent drop in $M2$. Fourth, after a delay of 2 quarters, there is a sustained decline in real GDP. Notice the 'hump shaped' response function with the maximal decline occurring roughly a year to a year and a half after the policy shock. Fifth, after an initial delay, the policy shock generates a persistent decline in the index of commodity prices. The GDP deflator is flat for roughly a year and a half after which it declines.

[23] These were computed using a bootstrap Monte Carlo procedure. Specifically, we constructed 500 time series on the vector Z_t as follows. Let $\{\widehat{u}_t\}_{t=1}^T$ denote the vector of residuals from the estimated VAR. We constructed 500 sets of new time series of residuals, $\{\widehat{u}_t(j)\}_{t=1}^T, j = 1, \dots, 500$. The tth element of $\{\widehat{u}_t(j)\}_{t=1}^T$ was selected by drawing randomly, with replacement, from the set of fitted residual vectors, $\{\widehat{u}_t\}_{t=1}^T$. For each $\{\widehat{u}_t(j)\}_{t=1}^T$, we constructed a synthetic time series of Z_t, denoted $\{Z_t(j)\}_{t=1}^T$, using the estimated VAR and the historical initial conditions on Z_t. We then re-estimated the VAR using $\{Z_t(j)\}_{t=1}^T$ and the historical initial conditions, and calculated the implied impulse response functions for $j = 1, \dots, 500$. For each fixed lag, we calculated the 12th lowest and 487th highest values of the corresponding impulse response coefficients across all 500 synthetic impulse response functions. The boundaries of the confidence intervals in the figures correspond to a graph of these coefficients. In many cases the point estimates of the impulse response functions are quite similar to the mean value of the simulated impulse response functions. But there is some evidence of bias, especially for Y, $M2$, *NBR* and *FF*. The location of the solid lines inside the confidence intervals indicates that the estimated impulse response functions are biased towards zero in each of these cases. See Killian (1998) and Parekh (1997) for different procedures for accommodating this bias.

[24] A given percentage change in total reserves corresponds roughly to an equal dollar change in the total and nonborrowed reserves. Historically, nonborrowed reserves are roughly 95% of total reserves. Since 1986, that ratio has moved up, being above 98% most of the time.

Before going on, it is of interest to relate these statistics to the interest elasticity of the demand for *NBR* and *M*1. Following Lucas (1988, 1994), suppose the demand for either of these two assets has the following form:

$$M_t = f_M(\Omega_t) - \varphi FF_t + \varepsilon_t^d,$$

where ε_t^d denotes the money demand disturbance and M denotes the log of either $M1$ or *NBR*. Here, φ is the short run, semi-log elasticity of money demand. A consistent estimate of φ is obtained by dividing the contemporaneous response of M_t to a unit policy shock by the contemporaneous response of FF_t to a unit policy shock. This ratio is just the instrumental variables estimate of φ using the monetary policy shock. The consistency of this estimator relies on the assumed orthogonality of ε_t^s with ε_t^d and the elements of Ω_t.[25] Performing the necessary calculations using the results in the first column of Figure 2, we find that the short run money demand elasticities for $M1$ and *NBR* are roughly −0.1 and −1.0, respectively. The $M1$ demand elasticity is quite small, and contrasts sharply with estimates of the long run money demand elasticity. For example, the analogous number in Lucas (1988) is −8.0. Taken together, these results are consistent with the widespread view that the short run money demand elasticity is substantially smaller than the long run elasticity [see Goodfriend (1991)].

We next consider the effect of an *NBR* policy shock. As can be seen, with two exceptions, inference is qualitatively robust. The exceptions have to do with the impact effect of a policy shock on *TR* and $M1$. According to the *FF* policy shock measure, total reserves are insulated, roughly one to one, contemporaneously from a monetary policy shock. According to the *NBR* policy shock measure, total reserves fall by roughly one half of a percent. Consistent with these results, an *NBR* policy shock leads to a substantially larger contemporaneous reduction in $M1$, compared to the reduction induced by an *FF* policy shock. Interestingly, $M2$ responds in very similar ways to an *FF* and an *NBR* policy shock.

[25] To see this, note first the consistency of the instrumental variables estimator:

$$-\varphi = \frac{\mathrm{Cov}(M_t, \varepsilon_t^s)}{\mathrm{Cov}(FF_t, \varepsilon_t^s)}.$$

Note too that:

$$\mathrm{Cov}(M_t, \varepsilon_t^s) = \varphi_M \sigma_\varepsilon^2, \ \mathrm{Cov}(FF_t, \varepsilon_t^s) = \varphi_R \sigma_\varepsilon^2,$$

where φ_M and φ_R denote the contemporaneous effects of a unit policy shock on M_t and FF_t, respectively, and σ_ε^2 denotes the variance of the monetary policy shock. The result, that the instrumental variable estimator coincides with φ_M/φ_R, follows by taking the ratio of the above two covariances. These results also hold if M_t, FF_t, and Ω_t are nonstationary. In this case, we think of the analysis as being conditioned on the initial observations.

From column 3 of Figure 2 we see that, aside from *TR* and $M1$, inference is also qualitatively similar to an *NBR/TR* policy shock. By construction *TR* does not respond in the impact period of a policy shock. While not constrained, $M1$ also hardly responds in the impact period of the shock but then falls. In this sense the *NBR/TR* shock has effects that are more similar to an *FF* policy shock than an *NBR* policy shock.

A maintained assumption of the *NBR*, *FF* and *NBR/TR* policy shock measures is that the aggregate price level and output are not affected in the impact period of a monetary policy shock. On a priori grounds, this assumption seems more reasonable for monthly rather than quarterly data. So it seems important to document the robustness of inference to working with monthly data. Indeed this robustness has been documented by various authors.[26] Figure 3 provides such evidence for the benchmark policy shocks. It is the analog of Figure 2 except that it is generated using monthly rather than quarterly data. In generating these results we replace aggregate output with nonfarm payroll employment and the aggregate price level is measured by the implicit deflator for personal consumption expenditures. Comparing Figures 2 and 3 we see that qualitative inference is quite robust to working with the monthly data.

To summarize, all three policy shock measures imply that in response to a contractionary policy shock, the federal funds rate rises, monetary aggregates decline (although some with a delay), the aggregate price level initially responds very little, aggregate output falls, displaying a hump shaped pattern, and commodity prices fall. In the next subsection, we discuss other results regarding the effects of a monetary policy shock.

We conclude this subsection by drawing attention to an interesting aspect of our results that is worth emphasizing. The correlations between our three policy shock measures are all less than one (see, for example, Figure 1).[27] Nevertheless, all three lead to similar inference about qualitative effects of a disturbance to monetary policy. One interpretation of these results is that all three policy shock measures are dominated by a common monetary policy shock. Since the bivariate correlations among the three are less than one, at least two must be confounded by nonpolicy shocks as well. Evidently, the effects of these other shocks is not strong enough to alter the qualitative characteristics of the impulse response functions. It is interesting to us just how low the correlation between the shock measures can be without changing the basic features of the impulse response functions.

A similar set of observations emerges if we consider small perturbations to the auxiliary assumptions needed to implement a particular identification scheme. For example, suppose we implement the benchmark *FF* model in two ways: measuring M_t by the growth rate of $M2$ and by the log of $M1$. The resulting policy shock measures

[26] See for example Geweke and Runkle (1995), Bernanke and Mihov (1995) and Christiano et al. (1996b).

[27] Recall, the estimated correlation between an *FF* and *NBR* shock is 0.51. The analog correlation between an *NBR / TR* shock and an *FF* shock is 0.65. Finally, the correlation between an *NBR/TR* shock and an *NBR* shock is 0.82.

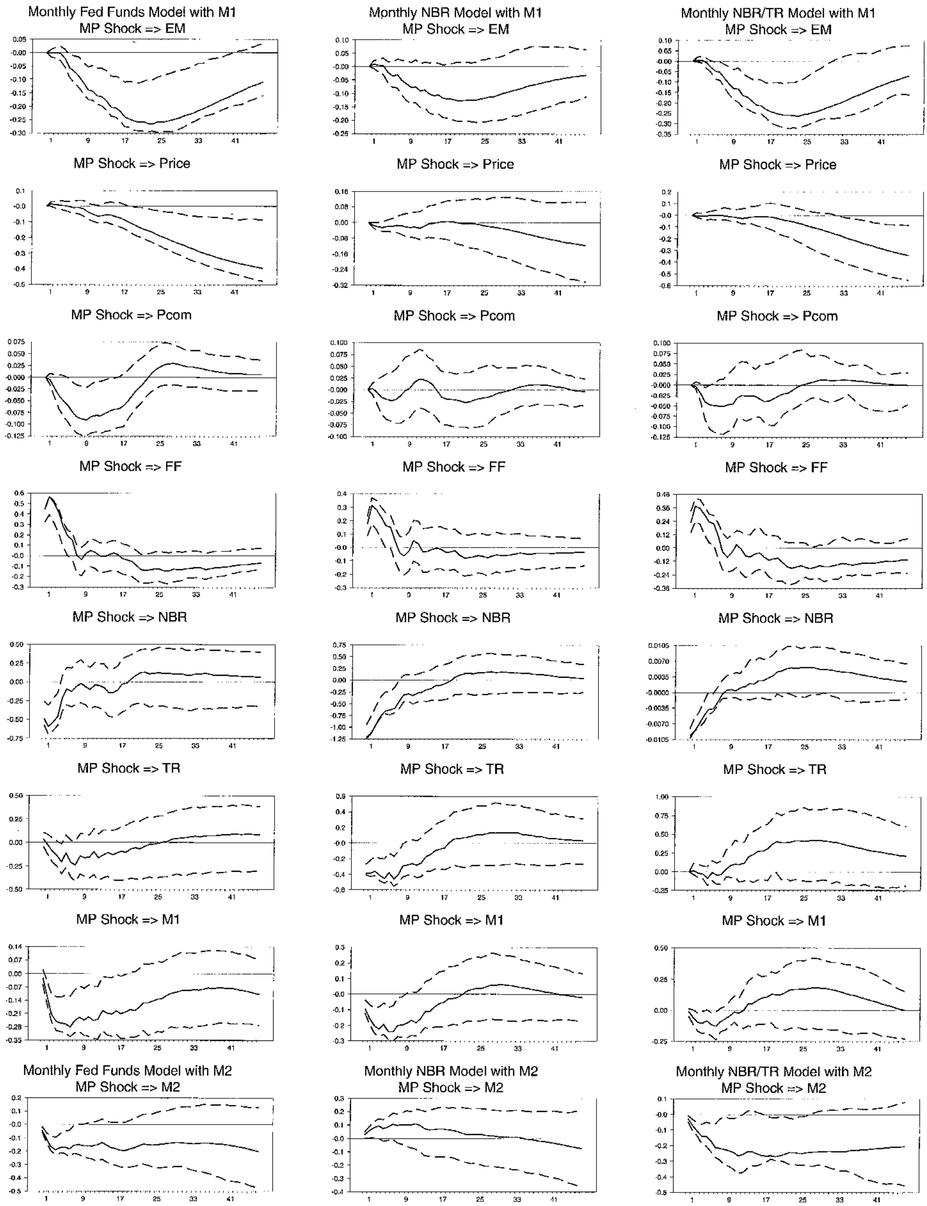


Fig. 3. Evidence for benchmark policy shocks. Analog of Figure 2, but using monthly rather than quarterly data.

have a correlation coefficient of only 0.85. This reflects in part that in several episodes the two shock measures give substantially different impressions about the state of monetary policy. For example in 1993Q4, the $M1$ based shock measure implies a 20 basis point contractionary shock. The $M2$ growth rate based shock measure implies an 80 basis point contractionary shock. These types of disagreements notwithstanding, both versions of the benchmark *FF* model give rise to essentially the same inference about the effect of a given monetary policy shock.

We infer from these results that while inference about the qualitative effects of a monetary policy shock appears to be reliable, inference about the state of monetary policy at any particular date is not.

4.3. Results for other economic aggregates

In the previous section we discussed the effects of the benchmark policy shocks on various economic aggregates. The literature has provided a richer, more detailed picture of the way the economy responds to a monetary policy shock. In this section we discuss some of the results that have been obtained using close variants of the benchmark policy shocks. Rather than provide an exhaustive review, we highlight a sample of the results and the associated set of issues that they have been used to address. The section is divided into two parts. The first subsection considers the effects of a monetary policy shock on domestic US economic aggregates. In the second subsection, we discuss the effects of a monetary policy shock on exchange rates. The papers we review use different sample periods as well as different identifying assumptions. Given space constraints, we refer the reader to the papers for these details.

4.3.1. US domestic aggregates

The work in this area can be organized into two categories. The first category pertains to the effects of a monetary policy shock on different measures of real economic activity, as well as on wages and profits. The second category pertains to the effects of a monetary policy shock on the borrowing and lending activities of different agents in the economy.

4.3.1.1. Aggregate real variables, wages and profits. In Section 4.2.2 we showed that aggregate output declines in response to contractionary benchmark *FF* and *NBR* policy shocks. Christiano et al. (1996a) consider the effects of a contractionary monetary policy shock on various other quarterly measures of economic activity. They find that after a contractionary benchmark *FF* policy shock, unemployment rises after a delay of about two quarters.[28] Other measures of economic activity respond more quickly to the policy shock. Specifically, retail sales, corporate profits in retail trade

[28] Working with monthly data Bernanke and Blinder (1992) also find that unemployment rises after a contractionary monetary policy shock. The shock measure which they use is related to our benchmark *FF* policy shock measure in the sense that both are based on innovations to the Federal Funds rate and both impose a version of the recursiveness assumption.

and nonfinancial corporate profits immediately fall while manufacturing inventories immediately rise.[29]

Fisher (1997) examines how different components of aggregate investment respond to a monetary policy shock [see also Bernanke and Gertler (1995)]. He does so using shock measures that are closely related to the benchmark *FF* and *NBR* policy measures. Fisher argues that all components of investment decline after a contractionary policy shock. But he finds important differences in the timing and sensitivity of different types of investment to a monetary policy shock. Specifically, residential investment exhibits the largest decline, followed by equipment, durables, and structures. In addition he finds a distinctive lead–lag pattern in the dynamic response functions: residential investment declines the most rapidly, reaching its peak response several quarters before the other variables do. Fisher uses these results to discuss the empirical plausibility of competing theories of investment.

Gertler and Gilchrist (1994) emphasize a different aspect of the economy's response to a monetary policy shock: large and small manufacturing firms' sales and inventories.[30] According to Gertler and Gilchrist, small firms account for a disproportionate share of the decline in manufacturing sales that follows a contractionary monetary policy shock. In addition they argue that while small firms' inventories fall immediately after a contractionary policy shock, large firms' inventories initially rise before falling. They use these results, in conjunction with other results in their paper regarding the borrowing activities of large and small firms, to assess the plausibility of theories of the monetary transmission mechanism that stress the importance of credit market imperfections.

Campbell (1997) studies a different aspect of how the manufacturing sector responds to a monetary policy shock: the response of total employment, job destruction and job creation. Using a variant of the benchmark *FF* policy shock measure, Campbell finds that, after a contractionary monetary policy shock, manufacturing employment falls immediately, with the maximal decline occurring roughly a year after the shock. The decline in employment primarily reflects increases in job destruction as the policy shock is associated with a sharp, persistent rise in job destruction but a smaller, transitory fall in job creation. Campbell argues that these results are useful as a guide in formulating models of cyclical industry dynamics.

We conclude this subsection by discussing the effects of a contractionary monetary policy shock on real wages and profits. Christiano et al. (1997a) analyze various measures of aggregate real wages, manufacturing real wages, and real wages for ten 2 digit SIC level industries. In all cases, real wages decline after a contractionary benchmark *FF* policy shock, albeit by modest amounts. Manufacturing real wages

[29] The qualitative results of Christiano et al. (1996a) are robust to whether they work with benchmark *NBR*, *FF* policy shocks or with Romer and Romer (1989) shocks.

[30] Gertler and Gilchrist (1994) use various monetary policy shock measures, including one that is related to the benchmark *FF* policy shock as well as the onset of Romer and Romer (1989) episodes.

fall more sharply than economy-wide measures. Within manufacturing, real wages fall more sharply in durable goods industries than in nondurable good industries. Christiano et al. (1997a) argue that these results cast doubt on models of the monetary transmission mechanism which stress the effects of nominal wage stickiness per se. This is because those types of models predict that real wages should rise, not fall, after a contractionary monetary policy shock.

To study the response of real profits to a monetary policy shock, Christiano et al. (1997a) consider various measures of aggregate profits as well as before tax profits in five sectors of the economy: manufacturing, durables, nondurables, retail and transportation and utilities. In all but two cases, they find that a contractionary *FF* policy shock leads to a sharp persistent drop in profits.[31] Christiano et al. (1997a) argue that these results cast doubt on models of the monetary transmission mechanism which stress the effects of sticky prices per se but don't allow for labor market frictions whose effect is to inhibit cyclical movements in marginal costs. This is because those types of models predict that profits should rise, not fall, after a contractionary monetary policy shock.

Finally, we note that other authors have obtained similar results to those cited above using policy shock measures that are not based on the recursiveness assumption. For example, policy shock measures based on the identifying assumptions in Sims and Zha (1998) lead to a qualitatively similar impact on wages, profits and various measures of aggregate output as the benchmark *FF* policy shock. Similarly, Leeper, Sims and Zha's (1996) results regarding the response of investment are quite similar to Fisher's.

4.3.1.2. Borrowing and lending activities. Various authors have investigated how a monetary policy shock affects borrowing and lending activities in different sectors of the economy. In an early contribution, Bernanke and Blinder (1992) examined the effects of a contractionary monetary policy shock on bank deposits, securities and loans. Their results can be summarized as follows. A contractionary monetary policy shock (measured using a variant of the benchmark *FF* policy shock) leads to an immediate, persistent decline in the volume of bank deposits as well as a decline in bank assets. The decline in assets initially reflects a fall in the amount of securities held by banks. Loans are hardly affected. Shortly thereafter security holdings begin climbing back to their preshock values while loans start to fall. Eventually, securities return to their pre-shock values and the entire decline in deposits is reflected in loans. Bernanke and Blinder (1992) argue that these results are consistent with theories of the monetary transmission mechanism that stress the role of credit market imperfections.

Gertler and Gilchrist (1993, 1994) pursue this line of inquiry and argue that a monetary policy shock has different effects on credit flows to small borrowers (consumers and small firms) versus large borrowers. Using a variant of the benchmark *FF* policy

[31] The two exceptions are nondurable goods and transportation and utilities. For these industries they cannot reject the hypothesis that profits are unaffected by contractionary policy shock.

shock, they find that consumer and real estate loans fall after a contractionary policy shock but commercial and industrial loans do not [Gertler and Gilchrist (1993)]. In addition, loans to small manufacturing firms decline relative to large manufacturing firms after a contractionary monetary policy shock. In their view, these results support the view that credit market imperfections play an important role in the monetary transmission mechanism.

Christiano et al. (1996a) examine how net borrowing by different sectors of the economy responds to a monetary policy shock. Using variants of the *FF* and *NBR* benchmark policy shocks, they find that after a contractionary shock to monetary policy, net funds raised in financial markets by the business sector increases for roughly a year. Thereafter, as the decline in output induced by the policy shock gains momentum, net funds raised by the business sector begin to fall. Christiano et al. (1996a) argue that this pattern is not captured by existing monetary business cycle models.[32] Christiano et al. (1996a) also find that net funds raised by the household sector remains unchanged for several quarters after a monetary policy shock. They argue that this response pattern is consistent with limited participation models of the type discussed in Christiano et al. (1997a,b). Finally, Christiano et al. (1996a) show that the initial increase in net funds raised by firms after a contractionary benchmark *FF* policy shock coincides with a temporary reduction in net funds raised (i.e., borrowing) by the government. This reduction can be traced to a temporary increase in personal tax receipts. After about a year, though, as output declines further and net funds raised by the business and household sectors falls, net funds raised by the government sector increases (i.e., the government budget deficit goes up).

Taken together, the above results indicate that a contractionary monetary policy shock has differential effects on the borrowing and lending activities of different agents in the economy. Consistent with the version of the Lucas program outlined in the introduction to this survey, these findings have been used to help assess the empirical plausibility of competing theories of the monetary transmission mechanism.

4.3.2. Exchange rates and monetary policy shocks

Various papers have examined the effects of a monetary policy shock on exchange rates. Identifying exogenous monetary policy shocks in an open economy can lead to substantial complications relative to the closed economy case. For example, in some countries, monetary policy may not only respond to the state of the domestic economy but also to the state of foreign economies, including foreign monetary policy actions. At least for the USA, close variants of the benchmark policy shock measures continue to give reasonable results. For example, Eichenbaum and Evans (1995) consider variants of the benchmark *FF* and *NBR/TR* policy shock measures in which some

[32] Christiano et al. (1996a) and Gertler and Gilchrist (1994) discuss possible ways to account for this response pattern.

foreign variables appear in the Fed's reaction function. A maintained assumption of their analysis is that the Fed does not respond contemporaneously to movements in the foreign interest rate or the exchange rate. Eichenbaum and Evans use their policy shock measures to study the effects of a contractionary US monetary policy shock on real and nominal exchange rates as well as domestic and foreign interest rates.[33] They find that a contractionary shock to US monetary policy leads to (i) persistent, significant appreciations in US nominal and real exchange rates and (ii) persistent decreases in the spread between foreign and US interest rates, and (iii) significant, persistent deviations from uncovered interest rate parity in favor of US investments.[34] Under uncovered interest rate parity, the larger interest rate differential induced by a contractionary US monetary policy shock should be offset by expected future depreciations in the dollar. Eichenbaum and Evans' empirical results indicate that the opposite is true: the larger return is actually magnified by expected future appreciations in the dollar. Eichenbaum and Evans discuss the plausibility of alternative international business cycle models in light of their results.

While variants of the benchmark *FF* identification scheme generate results that are consistent with traditional monetary analyses when applied to the USA, this is generally not the case when they are used to identify foreign monetary policy shocks. For example, Grilli and Roubini (1995) consider policy shock measures for non-US G7 countries that are closely related to Eichenbaum and Evans' measures. Using these measures, they find that a contractionary shock to a foreign country's monetary policy leads initially to a depreciation in the foreign country's currency. Grilli and Roubini argue that this result reflects that the measured policy shocks are confounded by the systematic reaction of foreign monetary policy to US monetary policy and expected inflation. This motivates them to construct an alternative policy shock measure which is based on the recursiveness assumption and a measure of S_t equal to the spread between foreign short term and long term interest rates. With this measure, they find that a contractionary shock to foreign monetary policy leads to a transitory appreciation in the foreign exchange rate and a temporary fall in output.

In contrast to Grilli and Roubini, authors like Cushman and Zha (1997), Kim and Roubini (1995), and Clarida and Gertler (1997) adopt identification schemes that do not employ the recursiveness assumption. In particular, they abandon the assumption that the foreign monetary policy authority only looks at predetermined variables when setting its policy instrument. Cushman and Zha (1997) assume that Bank of Canada officials look at contemporaneous values of the Canadian money supply, the exchange rate, the US foreign interest rate and an index of world commodity prices when setting a short term Canadian interest rate. Kim and Roubini (1995) assume that the reaction

[33] The foreign countries which they look at are Japan, Germany, Italy, France and Great Britain.

[34] Sims (1992) and Grilli and Roubini (1995) also analyze the effect of a monetary policy shock on US exchange rates using close variants of the *FF* benchmark policy shock. They too find that a contractionary policy shock leads to an appreciation of the US exchange rate.

function of foreign central bankers includes contemporaneous values of the money supply, the exchange rate and the world price of oil (but not the federal fund rate). Clarida and Gertler (1997) assume that the Bundesbank's reaction function includes current values of an index of world commodity prices, the exchange rate, as well as the German money supply (but not the US federal funds rate).[35] In all three cases, it is assumed that the money supply and the exchange rate are not predetermined relative to the policy shock. As a consequence, monetary policy shocks cannot be recovered from an ordinary least squares regression. Further identifying assumptions are necessary to proceed.

The precise identifying assumptions which these authors make differ. But in all cases, they assume the existence of a group of variables that are predetermined relative to the policy shock.[36] These variables constitute valid instruments for estimating the parameters in the foreign monetary policy maker's reaction function. We refer the reader to the papers for details regarding the exact identifying assumptions.[37]

With their preferred policy shocks measures, all three of the above papers find that a contractionary foreign monetary policy shock causes foreign exchange rates to appreciate and leads to a rise in the differential between the foreign and domestic interest rate.[38] In this sense, their results are consistent with Eichenbaum and Evans' evidence regarding the effects of a shock to monetary policy. In addition, all three papers provide evidence that a contractionary foreign monetary policy shock drives foreign monetary aggregates and output down, interest rates up and affects the foreign price level only with a delay. In this sense, the evidence is consistent with the evidence in Section 4.2.2 regarding the effect of a benchmark *FF* policy shock on the US economy.

4.4. Robustness of the benchmark analysis

In this subsection we assess the robustness of our benchmark results to various perturbations. First, we consider alternative identification schemes which also impose the recursiveness assumption. Second, we consider the effects of incorporating information from the federal funds futures market into the analysis. Finally, we analyze the subsample stability of our results.

[35] Clarida et al. (1998) provide a different characterization of the Bundesbank's reaction function as well as the reaction functions of five other central banks.

[36] For example in all these cases it is assumed that a measure of commodity prices, foreign industrial production, the foreign price level and the federal funds rate are predetermined relative to the foreign monetary policy shock.

[37] Clarida and Gali (1994) use long run identifying restrictions to assess the effects of nominal shocks on real exchange rates.

[38] Consistent with the evidence in Eichenbaum and Evans (1995), Cushman and Zha (1997) find that a contractionary foreign monetary policy shock induces a persistent, significant deviation from uncovered interest parity in favor of foreign investments.

4.4.1. Excluding current output and prices from Ω_t

The estimated one-step-ahead forecast errors in Y_t and FF_t are positively correlated (.38), while those in Y_t and NBR_t are negatively correlated (–.22). Any identification scheme in which S_t is set equal to either the time t federal funds rate or nonborrowed reserves must come to terms with the direction of causation underlying this correlation: Does it reflect (a) the endogenous response of policy to real GDP via the Fed's feedback rule, or (b) the response of real GDP to policy? Our benchmark policy measures are based on the assumption that the answer to this question is (a). Under this assumption we found that a contractionary monetary policy shock drives aggregate output down. Figure 4 displays the results when the answer is assumed to be (b). Specifically, columns 1 and 3 report the estimated impulse response functions of various economic aggregates to policy shock measures that were computed under the same identification assumptions as those underlying the *FF* and *NBR* policy shocks except that Y_t is excluded from Ω_t. The key result is that under these identifying assumptions, a contractionary policy shock drives aggregate output *up* before driving it down. In other respects, the results are unaffected.

It might be thought that the initial response pattern of output could be rationalized by monetary models which stress the effects of an inflation tax on economic activity, as in Cooley and Hansen (1989). It is true that in these models a serially correlated decrease in the money supply leads to an increase in output. But, in these models this happens via a reduction in anticipated inflation and in the interest rate. Although the candidate policy shock is associated with a serially correlated decrease in the money supply, it is also associated with a rise in the interest rate and virtually no movement in the price level. This response pattern is clearly at variance with models in which the key effects of monetary policy shocks are those associated with the inflation tax. We do not know of other models which can rationalize a rise in output after a contractionary monetary policy shock. Absent *some* coherent model that can account for the response functions in columns 1 and 3 of Figure 4, we reject the underlying identifying assumptions as being implausible. We suspect that the resulting shock measures confound policy and nonpolicy disturbances.

Columns 2 and 4 of Figure 4 report the estimated impulse response functions to policy shock measures computed under the same identification assumptions as those underlying the *FF* and *NBR* policy shocks except that P_t is excluded from Ω_t. As can be seen, the benchmark results are virtually unaffected by this perturbation.

4.4.2. Excluding commodity prices from Ω_t: The price puzzle

On several occasions in the postwar era, a rise in inflation was preceded by a rise in the federal funds rate and in commodity prices. An example is the oil price shock in 1974. Recursive identification schemes that set S_t equal to FF_t and do not include the commodity prices in Ω_t as leading indicators of inflation in the Fed's feedback rule sometimes imply that contractionary monetary policy shocks lead to a sustained rise in

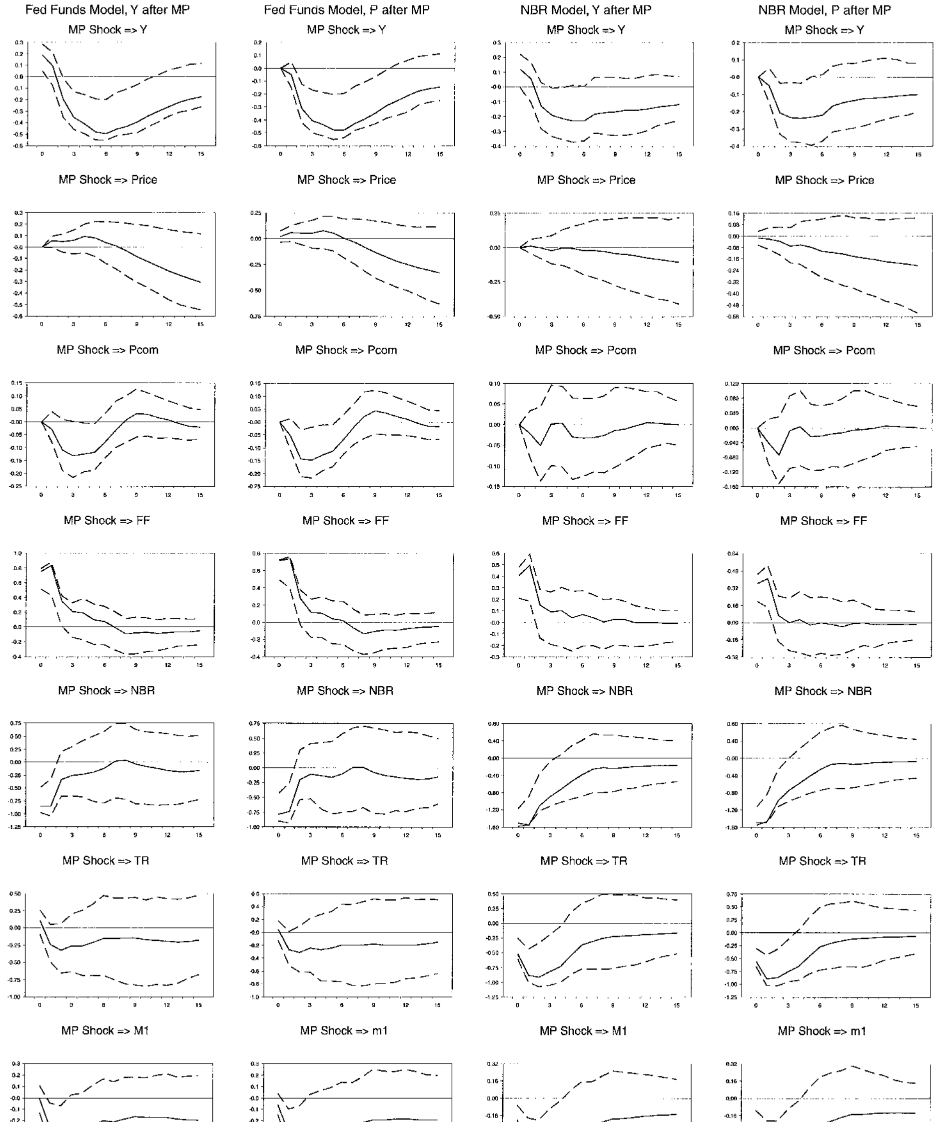


Fig. 4. Results when the answer is assumed to be the response of real GDP to policy. Columns 1 and 3 report the estimated impulse response functions of various economic aggregates to policy shock measures that were computed under the same identification assumptions as those underlying the *FF* and *NBR* policy shocks except that Y_t is excluded from Ω_t. Columns 2 and 4 report the estimated impulse response functions to policy shock measures computed under the same identification assumptions as those underlying the *FF* and *NBR* policy shocks except that P_t is excluded from Ω_t. As can be seen, the benchmark results are virtually unaffected by this perturbation.

the price level.[39] Eichenbaum (1992) viewed this implication as sufficiently anomalous relative to standard theory to justify referring to it as "the price puzzle".[40] Sims (1992) conjectured that prices appeared to rise after certain measures of a contractionary policy shock because those measures were based on specifications of Ω_t that did not include information about future inflation that was available to the Fed. Put differently, the conjecture is that policy shocks which are associated with substantial price puzzles are actually confounded with nonpolicy disturbances that signal future increases in prices. Christiano et al. (1996a) and Sims and Zha (1998) show that when one modifies such shock measures by including current and lagged values of commodity prices in Ω_t, the price puzzle often disappears. It has now become standard practice to work with policy shock measures that do not generate a price puzzle.

To document both the nature of the puzzle and the resolution, Figure 5 displays the impulse response of P_t to eight different contractionary monetary policy shock measures. The top and bottom rows display the effects of shocks to systems in which S_t is measured by FF_t and NBR_t, respectively. Columns 1–4 correspond to policy shock measures in which (i) the current value of P_t, Y_t and current and lagged values of $PCOM_t$ are omitted from Ω_t, (ii) current and lagged values of $PCOM_t$ are omitted from Ω_t, (iii) the current value of $PCOM_t$ is omitted from Ω_t, and (iv) Ω_t is given by our benchmark specification, respectively.

A number of interesting results emerge here. First, policy shock measures based on specifications in which current and lagged values of *PCOM* are omitted from Ω_t imply a rise in the price level that lasts several years after a contractionary policy shock. Second, according to the point estimates, the price puzzle is particularly pronounced for the specification in which the current values of Y_t and P_t are also excluded from Ω_t (column 1). Recall that deleting P_t from Ω_t had virtually no effect on our results. These findings suggest that current Y and current and past *PCOM* play a similar role in purging policy shock measures of nonpolicy disturbances. Third, the 95% confidence intervals displayed in Figure 5 indicate that the price puzzle is statistically significant for the Fed Funds based shock measures associated with columns 1 and 2 in Figure 5.[41]

[39] The first paper that documents the "price puzzle" for the USA and several other countries appears to be Sims (1992).

[40] There do exist some models that predict a temporary rise in the price level after a contraction. These models stress the role of self fulfilling shocks to expectations in the monetary transmission mechanism. See for example Beaudry and Devereux (1995). Also there exist some limited participation models of the monetary transmission mechanism in which the impact effect of contractionary monetary policy shocks is so strong that prices rise in the impact period of the policy shock. See for example Fuerst (1992) and Christiano et al. (1997a).

[41] We used the artificial data underlying the confidence intervals reported in Figure 5 to obtain a different test of the price puzzle. In particular, we computed the number of times that the average price response over the first 2, 4 and 6 quarters was positive. For the *FF* model underlying the results in column 1 the results were 96.4%, 97.2%, and 98.0%, respectively. Thus, at each horizon, the price puzzle is significant at the 5% significance level. For the *FF* model underlying the second column, the results are 95.6%, 94.6%, and 89.8%, so that there is a marginally significant price puzzle over the first year. Regardless

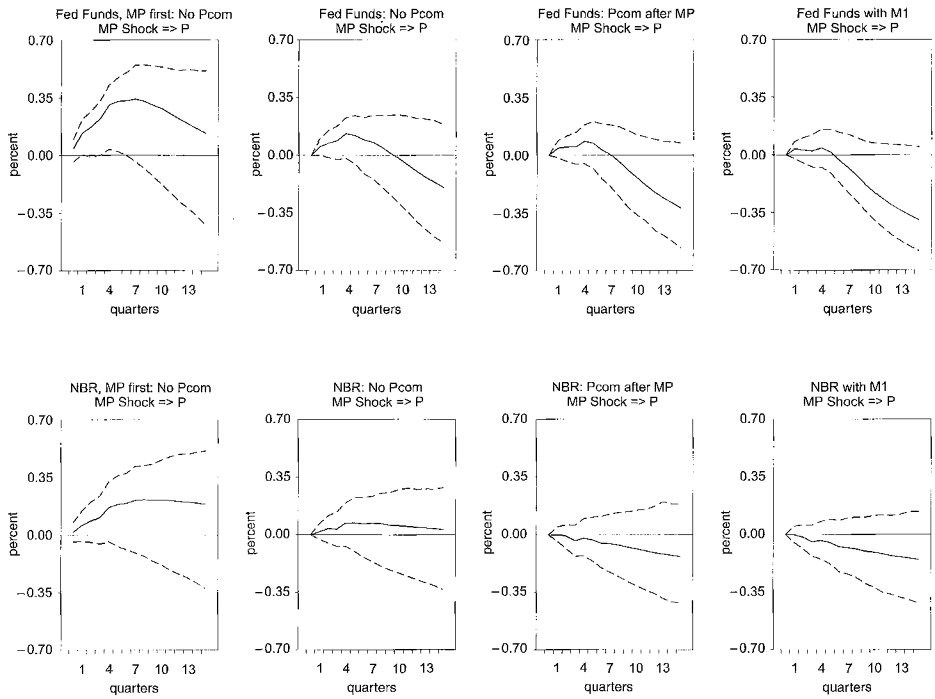


Fig. 5. The impulse response of P_t to eight different contractionary monetary policy shock measures. The top and bottom rows display the effects of shocks to systems in which S_t is measured by FF_t and NBR_t, respectively. Columns 1–4 correspond to policy shock measures in which (i) the current value of P_t, Y_t and current and lagged values of $PCOM_t$ are omitted from Ω_t, (ii) current and lagged values of $PCOM_t$ are omitted from Ω_t, (iii) the current value of $PCOM_t$ is omitted from Ω_t, and (iv) Ω_t is given by our benchmark specification, respectively.

Fourth, consistent with results in Eichenbaum (1992), the price puzzle is less severe for the *NBR* based policy shocks. Fifth, little evidence of a price puzzle exists for the benchmark *FF* and *NBR* policy shocks.

We conclude this section by noting that, in results not reported here, we found that the dynamic responses of nonprice variables to monetary policy shocks are robust to deleting current and lagged values of *PCOM* from Ω_t.

4.4.3. *Equating the policy instrument, S_t, with $M0$, $M1$ or $M2$*

There is a long tradition of identifying monetary policy shocks with statistical innovations to monetary aggregates like the base ($M0$), $M1$ and $M2$. Indeed this was

of the horizon, the price puzzle was not significant at even the 10% significance level for the other specifications in Figure 5.

the standard practice in the early literature on the output and interest rate effects of an unanticipated shock to monetary policy.[42] This practice can be thought of as setting S_t equal to a monetary aggregate like $M0$, $M1$ or $M2$ and using a particular specification of Ω_t. We refer the reader to Leeper, Sims and Zha (1996) and Cochrane (1994) for critical reviews of this literature.

Here we discuss the plausibility of identification schemes underlying M based policy shock measures by examining the implied response functions to various economic aggregates. Figure 6 reports estimated response functions corresponding to six policy measures. Columns 1 and 2 pertain to policy shock measures in which S_t is set equal to $M0_t$. Column 1 is generated assuming that Ω_t consists of 4 lagged values of Y_t, P_t, $PCOM_t$, FF_t, NBR_t and $M0_t$. For column 2, we add the current value of Y_t, P_t, and $PCOM_t$ to Ω_t. Columns 3 and 4 are the analogs of columns 1 and 2 except that $M0_t$ is replaced by $M1_t$. Columns 5 and 6 are the analogs of columns 1 and 2 except that $M0_t$ is replaced by $M2$.

We begin by discussing the dynamic response functions corresponding to the $M0$ based policy shock measures. Notice that the responses in column 1 are small and estimated very imprecisely. Indeed, it would be difficult to reject the hypotheses that Y, P, $PCOM$, and FF are all unaffected by the policy shock. Once we take sampling uncertainty into account, it is hard to argue that these response functions are inconsistent with the benchmark policy shock measure based response functions. In this limited sense, inference is robust. Still, the point estimates of the response functions are quite different from our benchmark results. In particular, they indicate that a contractionary policy shock drives P_t and FF_t down. The fall in P_t translates into a modest decline in the rate of inflation.[43] After a delay of one or two periods, Y_t rises by a small amount. The delay aside, this response pattern is consistent with a simple neoclassical monetary model of the sort in which there is an inflation tax effect on aggregate output [see for example Cooley and Hansen (1989)].

The response functions in column 2 are quite similar to those in column 1. As before, they are estimated with sufficient imprecision that they can be reconciled with various models. The point estimates themselves are consistent with simple neoclassical monetary models. Compared to column 1, the initial decline in Y_t after a contractionary policy shock is eliminated, so that the results are easier to reconcile with a simple neoclassical monetary model.

The impulse response functions associated with the $M1$ based policy shocks in columns 3 and 4 are similar to those reported in columns 1 and 2, especially when sampling uncertainty is taken into account. The point estimates themselves seem harder to reconcile with a simple monetary neoclassical model. For example, according to

[42] See for example Barro (1977), Mishkin (1983), S. King (1983) and Reichenstein (1987). For more recent work in this tradition see King (1991) and Cochrane (1994).

[43] The fall in P_t translates into an initial .20 percent decline in the annual inflation rate. The maximal decline in the inflation rate is about .25 percent which occurs after 3 periods. The inflation rate returns to its preshock level after two years.

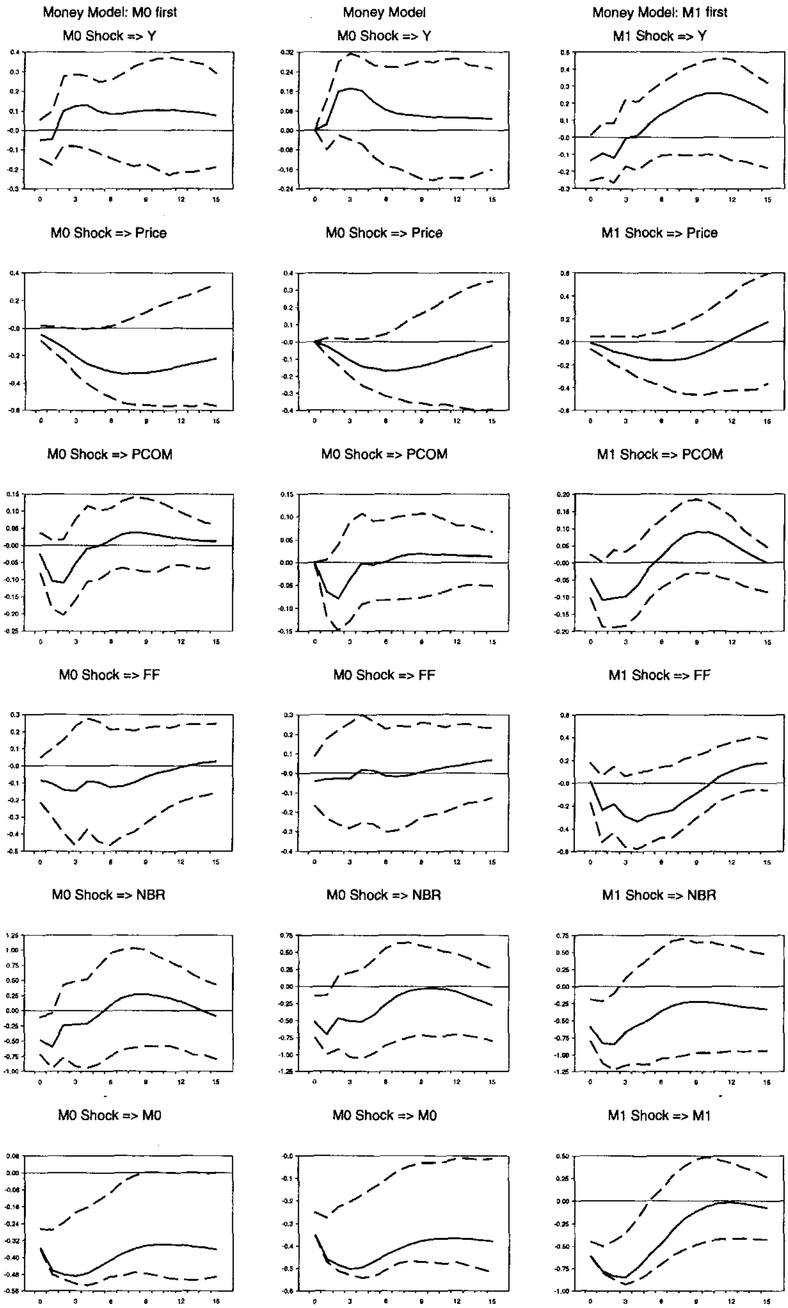
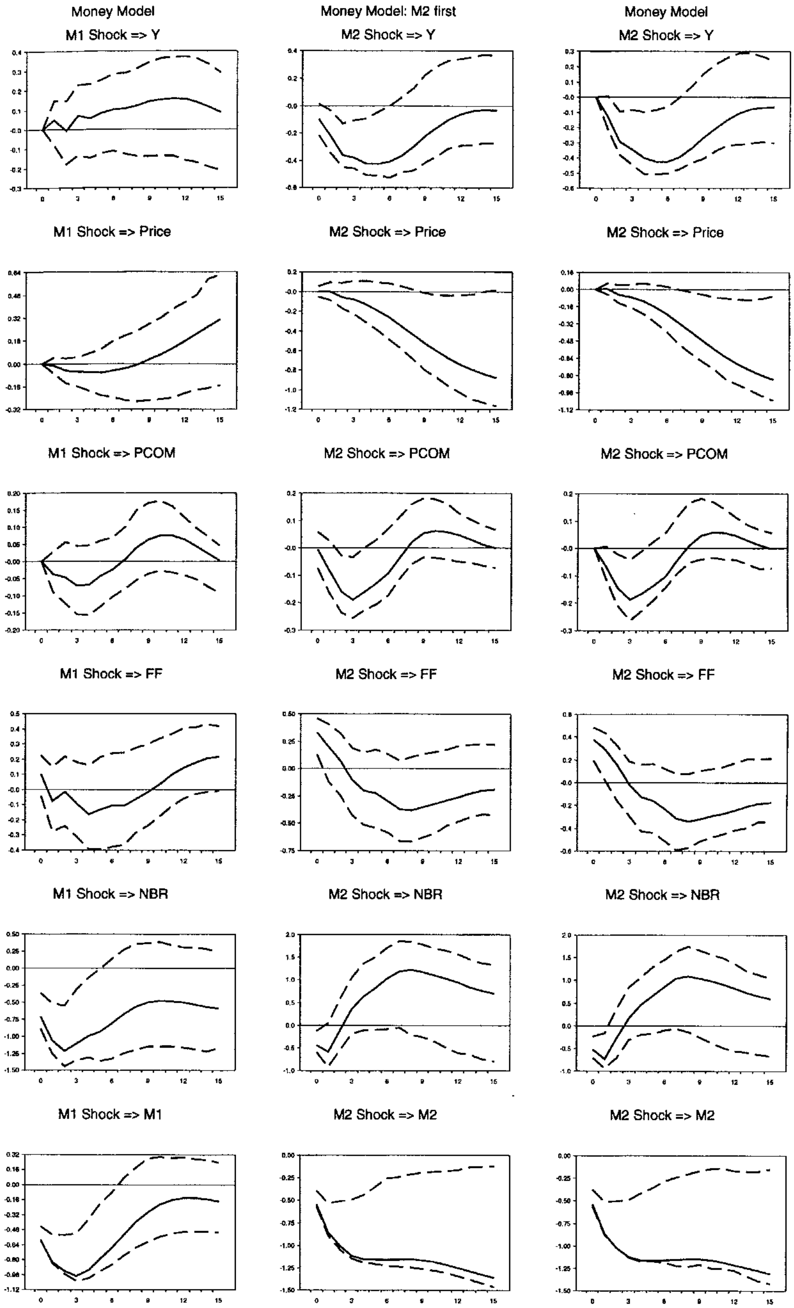


Fig. 6. Estimated response functions corresponding to six policy measures.


Money Model
M1 Shock => Y
Money Model: M2 first
M2 Shock => Y
Money Model
M2 Shock => Y
M1 Shock => Price
M2 Shock => Price
M2 Shock => Price
M1 Shock => PCOM
M2 Shock => PCOM
M2 Shock => PCOM
M1 Shock => FF
M2 Shock => FF
M2 Shock => FF
M1 Shock => NBR
M2 Shock => NBR
M2 Shock => NBR
M1 Shock => M1
M2 Shock => M2
M2 Shock => M2

column 3, output falls for over two quarters after a contractionary policy shock. The fact that output eventually rises seems difficult to reconcile with limited participation or sticky wage/price models. This is also true for the results displayed in column 4. Moreover, the results in that column also appear to be difficult to reconcile with the neoclassical monetary model. For example, initially inflation is hardly affected by a monetary contraction, after which it actually rises. Sampling uncertainty aside, we conclude that the $M1$ based policy shock measures are difficult to reconcile with known (at least to us) models of the monetary transmission mechanism.

Finally, consider the $M2$ based policy shock measures. Here a number of interesting results emerge. First, the impulse response functions are estimated more precisely than those associated with the $M0$ and $M1$ based policy shock measures. Second, the impulse response functions share many of the qualitative properties of those associated with the benchmark policy shocks measures. In particular, according to both columns 5 and 6, a contractionary monetary policy shock generates a prolonged decline in output and a rise in FF_t. Also the price level hardly changes for roughly 3 quarters. This is true even for the policy shock measure underlying column 5 where the price level is free to change in the impact period of the shock. There is one potentially important anomaly associated with the $M2$ based policy shock measures: after a delay, NBR and $M2$ move in opposite directions.

In sum, the M based policy shock measures provide mixed evidence on the robustness of the findings associated with our benchmark policy shocks. The response functions associated with the $M0$ and $M1$ policy shock measures are estimated quite imprecisely. In this sense they do not provide evidence against robustness. The point estimates of the response functions associated with the $M1$ based policy shock measures are hard to reconcile with existing models of the monetary transmission mechanism. But the point estimates associated with the $M0$ based policy shock measures are consistent with simple neoclassical monetary models. If one wants evidence that is not inconsistent with simple neoclassical monetary models, this is where to look. Finally, apart from the anomalous response of NBR, qualitative inference about the effects of a monetary policy shock are robust to whether we work with the $M2$ based policy shock measure or the benchmark policy shock measures.

4.4.4. Using information from the federal funds futures market

An important concern regarding the benchmark policy shock measures is that they may be based on a smaller information set than the one available to the monetary authority or private agents. Rudebusch (1996) notes that one can construct a market-based measure of the one-month ahead unanticipated component of the federal funds rate. He does so using data from the federal funds futures market, which has been active since late 1988.[44] He recognizes that a component of the unanticipated move in the

[44] See Brunner (1994), Carlson et al. (1995), and Krueger and Kuttner (1996) for further discussion and analysis of the federal funds futures market.

federal funds rate reflects the Federal Reserve's endogenous response to the economy. To deal with this problem, he measures the exogenous shock to monetary policy as the part of the unanticipated component of the federal funds rate which is orthogonal to a measure of news about employment. In Rudebusch's view, the correlation between the resulting measure and our *FF* benchmark policy shock measure is sufficiently low to cast doubt upon the latter.[45] But policy shock measures can display a low correlation, while not changing inference about the economic effects of monetary policy shocks. We now investigate whether and how inference is affected by incorporating federal funds futures market data into the analysis.

To study this question, we repeated the benchmark *FF* analysis, replacing FF_t with $FF_t - FM_{t-1}$ in the underlying monthly VAR.[46] Here FM_{t-1} denotes the time $t-1$ futures rate for the average federal funds rate during time t.[47] We refer to the orthogonalized disturbance in the $FF_t - FM_{t-1}$ equation as the *FM* policy shock. In addition, because of data limitations, we redid the analysis for what we refer to as the Rudebusch sample period, 1989:04–1995:03. Because of the short sample period, we limit the number of lags in the VAR to six. Before considering impulse response functions to the policy shocks, we briefly discuss the shocks themselves. Panel *A* of Figure 7 displays the *FM* policy shocks for the period 1989:10–1995:03. In addition, we display *FF* policy shocks for the same period. These were computed using our benchmark, monthly VAR model, estimated over the whole sample period, using six lags in the VAR. Panel *B* is the same as Panel *A*, except that the VAR underlying the benchmark *FF* policy shocks is estimated using data only over the Rudebusch sample period.

A few features of Figure 7 are worth noting. First, the shock measures in Panel *A* are of roughly similar magnitude, with a standard deviation of the benchmark and *FM* policy shocks being 0.22 and 0.16, respectively. Consistent with the type of findings reported by Rudebusch, the correlation between the two shock measures is relatively low, 0.34.[48] Second, when we estimate the VARs underlying the benchmark *FF* and *FM* policy shocks over the same sample period, the correlations rise to approximately 0.45. Interestingly, the *FF* policy shocks now have a smaller standard deviation than the *FM* policy shocks.[49]

We now proceed to consider robustness of inference regarding the effects of monetary policy shocks. The dynamic response functions to an *FM* policy shock, together with 95% confidence intervals, are displayed in column 1 of Figure 8. There

[45] See Sims (1996) for a critique of Rudebusch's analysis.

[46] Evans and Kuttner (1998) find that small, statistically insignificant deviations from futures market efficiency partially account for the low correlations between variants of the *FF* benchmark policy shocks and $FF_t - FM_{t-1}$.

[47] These data were taken from Krueger and Kuttner (1996).

[48] Rudebusch actually reports the R^2 in the regression relation between the two shocks. This is the square of the correlation between the two variables. So, our correlation translates into an R^2 of 0.12.

[49] Given the short sample, it is important to emphasize that the standard deviations have been adjusted for degrees of freedom.

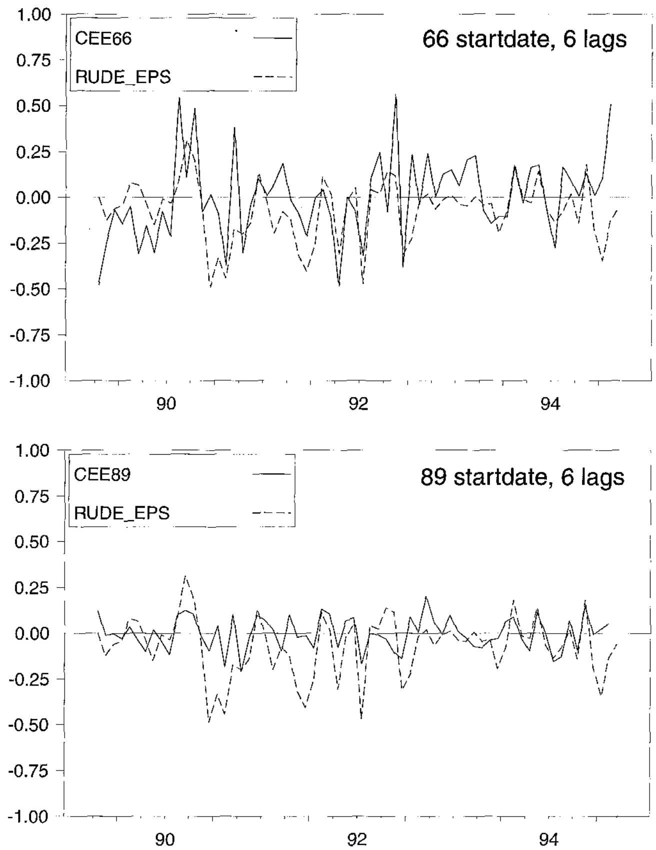


Fig. 7. Top: the *FM* policy shocks for the period 1989:10–1995:03. In addition, we display *FF* policy shocks for the same period. These were computed using our benchmark, monthly VAR model, estimated over the whole sample period, using six lags in the VAR. Bottom: the same as top, except that the VAR underlying the benchmark *FF* policy shocks is estimated using data only over the Rudebusch sample period.

are two obvious features to these results. First, the policy shock itself is very small (a little over 10 basis points). Second, with the exception of $FF_t - FM_{t-1}$, the response of the other variables is not significantly different from zero at all lags.

To compare these results with those based on the benchmark *FF* policy shocks, we need to control for the difference in sample periods and lag lengths. To this end, we report the impulse response functions and standard errors of the 6 lag benchmark *FF* model estimated over the Rudebusch sample period. These are displayed in column 2 of Figure 8. We see that the same basic message emerges here as in column 1: over the Rudebusch sample period, the shocks are small and the impulse response functions are imprecisely estimated. We conclude that there is no evidence to support

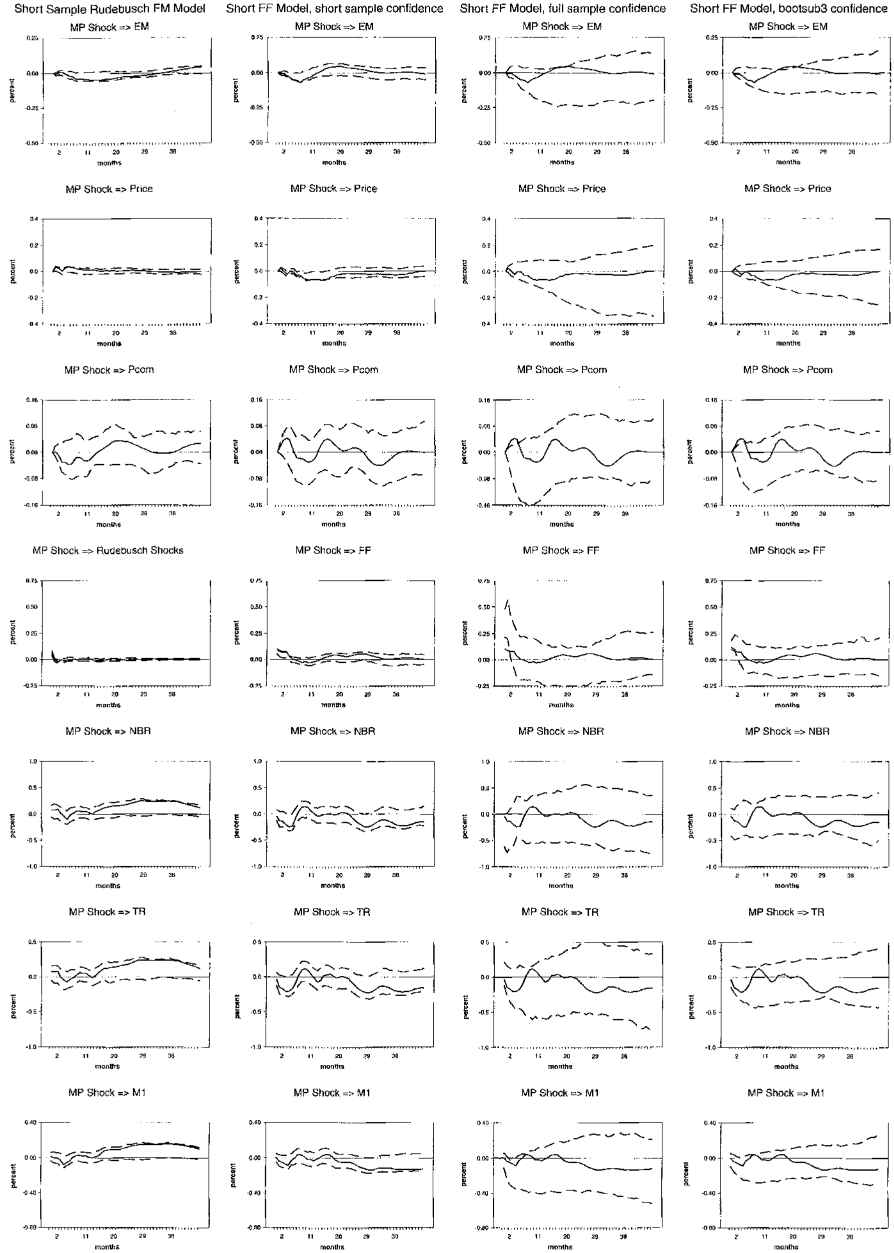


Fig. 8. The dynamic response functions to an *FM* policy shock, together with 95% confidence intervals, are displayed in column 1. There are two obvious features to these results. First, the policy shock itself is very small (a little over 10 basis points). Second, with the exception of $FF_t - FM_{t-1}$, the response of the other variables is not significantly different from zero at all lags.

the notion that inference is sensitive to incorporating federal funds market data into the analysis. This conclusion may very well reflect the limited data available for making the comparison.

4.4.5. Sample period sensitivity

Comparing the results in Figure 8 with our full sample, benchmark *FF* results (see column 1, Figure 2) reveals that the impulse response functions are much smaller in the Rudebusch sample period. A similar phenomenon arises in connection with our benchmark *NBR* model. Pagan and Robertson (1995) characterize this phenomenon as the "vanishing liquidity effect". Wong (1996) also documents this phenomenon for various schemes based on the recursiveness assumption. These findings help motivate the need to study the robustness of inference to different sample periods.

We now proceed to investigate subsample stability. Our discussion is centered around two general questions. First, what underlies the difference in impulse response functions across subsamples? Here, we distinguish between two possibilities. One possibility is that the difference reflects a change in the size of the typical monetary policy shock. The other possibility is that it reflects a change in the dynamic response to a shock of a given magnitude. We will argue that, consistent with the findings in Christiano's (1995) discussion of the vanishing liquidity effect, the evidence is consistent with the hypothesis that the first consideration dominates. Second, we discuss robustness of qualitative inference. Not surprisingly in view of our findings regarding the first question, we find that qualitative inference about the effects of a monetary policy shock is robust across subsamples. This last finding is consistent with results in Christiano et al. (1996b). In the analysis that follows, we focus primarily on results for the benchmark *FF* policy shocks. We then briefly show that our conclusions are robust to working with the *NBR* policy shocks.

To begin our analysis of subsample stability, we test the null hypothesis that there was no change at all in the data generating mechanism for the Rudebusch sample period. To this end, we constructed confidence intervals for the impulse response functions in column 2 of Figure 8 under the null hypothesis that the true model is the one estimated using data over the full sample.[50] The resulting confidence intervals are reported in column 3. In addition, that column reports for convenience the estimated response functions from column 2. We see that the estimated impact effect of a one standard deviation policy shock on the federal funds rate (see the

[50] These confidence intervals were computed using a variant of the standard bootstrap methodology employed in this paper. In particular, we generated 500 artificial time series, each of length equal to that of the full sample, using the six lag, benchmark full sample *FF* VAR and its fitted disturbances. In each artificial time series we estimated a six lag, benchmark *FF* VAR model using artificial data over the period corresponding to the Rudebusch sample period. The 95% confidence intervals are based on the impulse response functions corresponding to the VARs estimated from the artificial data.

fourth row of column 3) lies well below the 95% confidence interval. So, we reject the null hypothesis that there was no change at all in the data generating mechanism in the Rudebusch sample.[51] Next, we modified the null hypothesis to accommodate the notion that the only thing which changed in the Rudebusch sample was the nature of the monetary policy shocks. In all other respects, the data generating mechanism is assumed to remain unchanged. Under this null hypothesis, we generated 95% confidence intervals for the estimated impulse response functions in column 2 of Figure 8.[52] These confidence intervals are reported in column 4 of Figure 8, which also repeats for convenience the point estimates from column 2. Notice that, with one exception, all of the estimated impulse response functions lie within the plotted confidence intervals.[53] The exception is that the impulse response function of *PCOM* lies just outside the plotted confidence intervals for roughly the first six periods. Based on these results, we conclude that there is little evidence against the joint hypothesis that (i) the response of the aggregates to a given policy shock is the same in the two sample periods and (ii) the size of the shocks was smaller in the post 1988:10 period. For any particular subsample, we refer to these two conditions as the modified subsample stability hypothesis.

We now consider the stability of impulse response functions in other subsamples. Figure 9 reports response functions to monthly benchmark *FF* policy shocks, estimated over four subsamples: the benchmark sample, and the periods 1965:1–1979:9, 1979:10–1994:12, and 1984:2–1994:12. In each case, the method for computing confidence intervals is analogous to the one underlying the results in column 4 of Figure 8.[54] From Figure 9 we see that the estimated response functions for

[51] The procedure we have used to reject the null hypothesis of no change versus the alternative of a change in 1989 implicitly assumes the choice of break date is exogenous with respect to the stochastic properties of the data. There is a large literature (see Christiano (1992) and the other papers in that Journal of Business and Economic Statistics volume) which discusses the pitfalls of inference about break dates when the choice of date is endogenous. In this instance our choice was determined by the opening of the Federal Funds Futures Market. Presumably, this date can be viewed as exogenous for the purpose of our test.

[52] With one exception, these confidence intervals were computed using the procedure described in the previous footnote. The exception has to do with the way the shocks were handled. In particular, the artificial data were generated by randomly sampling from the orthogonalized shocks, rather than the estimated VAR disturbances. Residuals other than the policy shocks were drawn, with replacement, from the full sample period set of residuals. The policy shocks were drawn from two sets. Shocks for periods prior to the analog of the Rudebusch sample period were drawn, with replacement, from the pre-Rudebusch sample fitted policy shocks. Shocks for periods during the analog of the Rudebusch sample period were drawn, with replacement, from the Rudebusch sample fitted policy shocks.

[53] In this manuscript, we have adopted the extreme assumption that the stochastic properties of the policy shock changed abruptly on particular dates. An alternative is that the changes occur smoothly in the manner captured by an ARCH specification for the policy shocks. Parekh (1997) pursues this interpretation. He modifies our bootstrap procedures to accommodate ARCH behavior in the shocks.

[54] That is, they are computed under the assumption that the data generating mechanism is the six lag, full sample estimated VAR with policy shocks drawn only from the relevant subsample. All other shocks are drawn randomly from the full sample of fitted shocks.

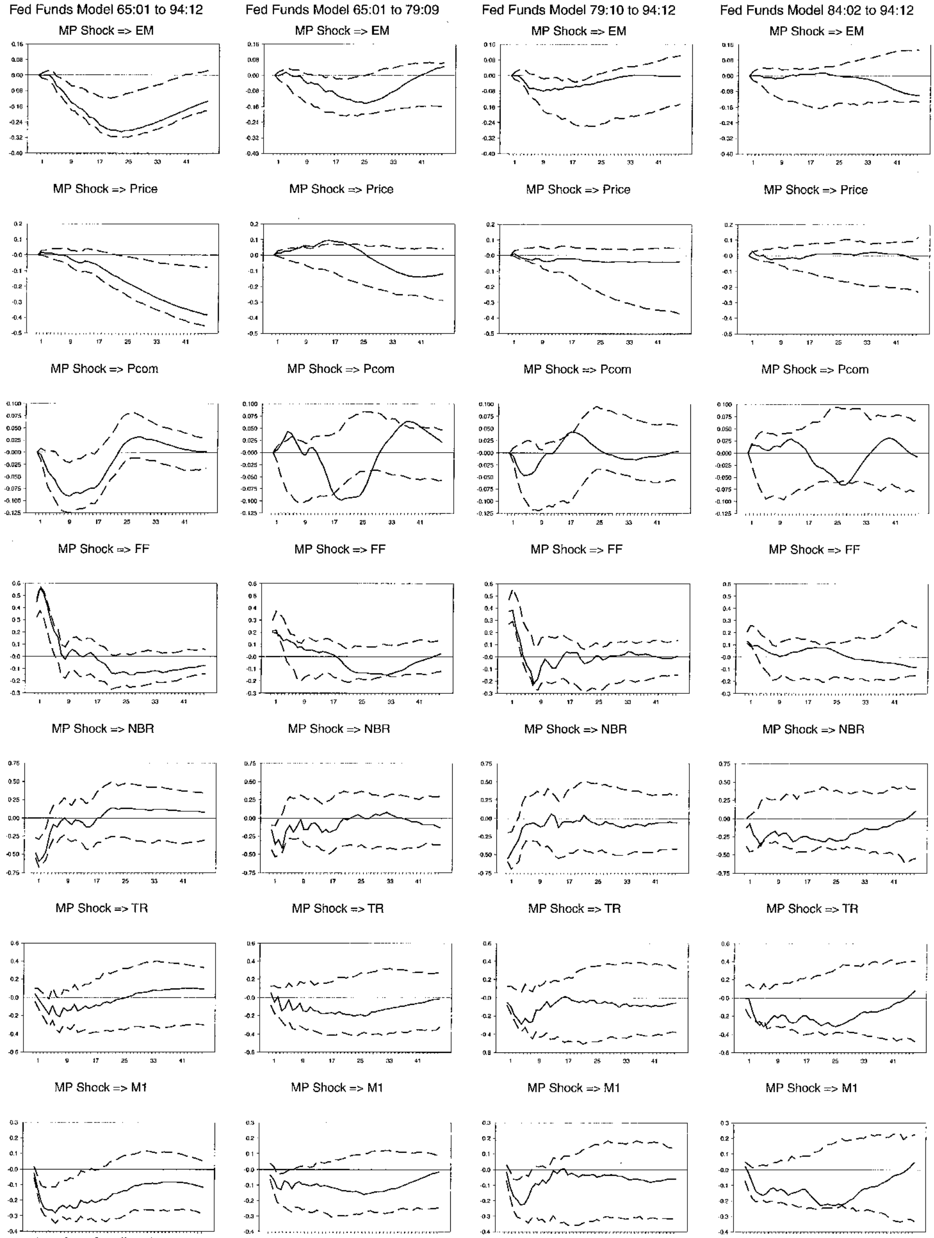


Fig. 9. Response functions to monthly benchmark *FF* policy shocks, estimated over four subsamples: the benchmark sample, and the periods 1965:1–1979:9, 1979:10–1994:12, and 1984:2–1994:12.

employment, $P, PCOM$, and $M1$ almost always lie within the confidence intervals. For the third and fourth sample periods there is no evidence against the modified subsample stability hypothesis. There is some marginal evidence against the hypothesis in the first subsample. In particular, the *PCOM* and price level responses lie outside the plotted confidence interval at some horizons. We find these results somewhat troubling, since they may indicate that the benchmark *FF* policy shocks are contaminated by other shocks to which the Fed responds. Despite this, the overall impression one gets from these results is that the modified subsample stability hypothesis is not rejected for the benchmark *FF* policy shocks.

At the same time, there is strong evidence that the variance of the policy shocks changed over the sample. One interpretation is that the early 1980s were a period in which policy shocks were very large, but that the shocks were of comparable magnitude and substantially smaller size throughout the rest of the post-war period. One bit of evidence in favor of this view is that the estimated policy shocks in the second and fourth sample periods are reasonably similar in size, 20 basis points versus 12 basis points, respectively.

We now briefly point out that qualitative inference is robust across subsamples. For each subsample we find evidence consistent with a liquidity effect. Specifically, a policy-induced rise in the federal funds rate is associated with a decline in nonborrowed reserves, total reserves and $M1$. In addition, the contractionary policy shock is associated with a delayed response of employment and a very small change in the price level.

We now consider the results for the benchmark *NBR* policy shocks, reported in Figure 10. The overall impression conveyed here is similar to what we saw in Figure 9. There is relatively little evidence against the modified subsample sensitivity hypothesis. For the most part, the point estimates all lie within the plotted confidence intervals. Note that the impulse response functions are qualitatively robust across subsamples.

We now turn to a complementary way of assessing subsample stability, which focuses on the magnitude of the liquidity effect. Panels A and B of Table 1 report summary statistics on the initial liquidity effect associated with the benchmark *FF* and *NBR* identification schemes, respectively. In that table, *FF/NBR* denotes the average of the first three responses in the federal funds rate, divided by the average of the first three responses in nonborrowed reserves. These responses are taken from the appropriate entries in Figure 9. As a result, *FF/NBR* denotes the percentage point change in the federal funds rate resulting from a policy-induced one percent change in *NBR*. $FF/M1$ denotes the corresponding statistic with the policy-induced change in $M1$ in the denominator. Because of the shape of the impulse response function in $M1$, we chose to calculate this statistic by averaging the first six responses in *FF* and $M1$. The statistics are reported for the four sample periods considered in Figure 9. In addition, the 95% confidence intervals are computed using the appropriately modified version of the bootstrap methodology used to compute confidence intervals in Figure 9. Panel B is the exact analog of Panel A, except that the results are based on the *NBR* policy shocks.

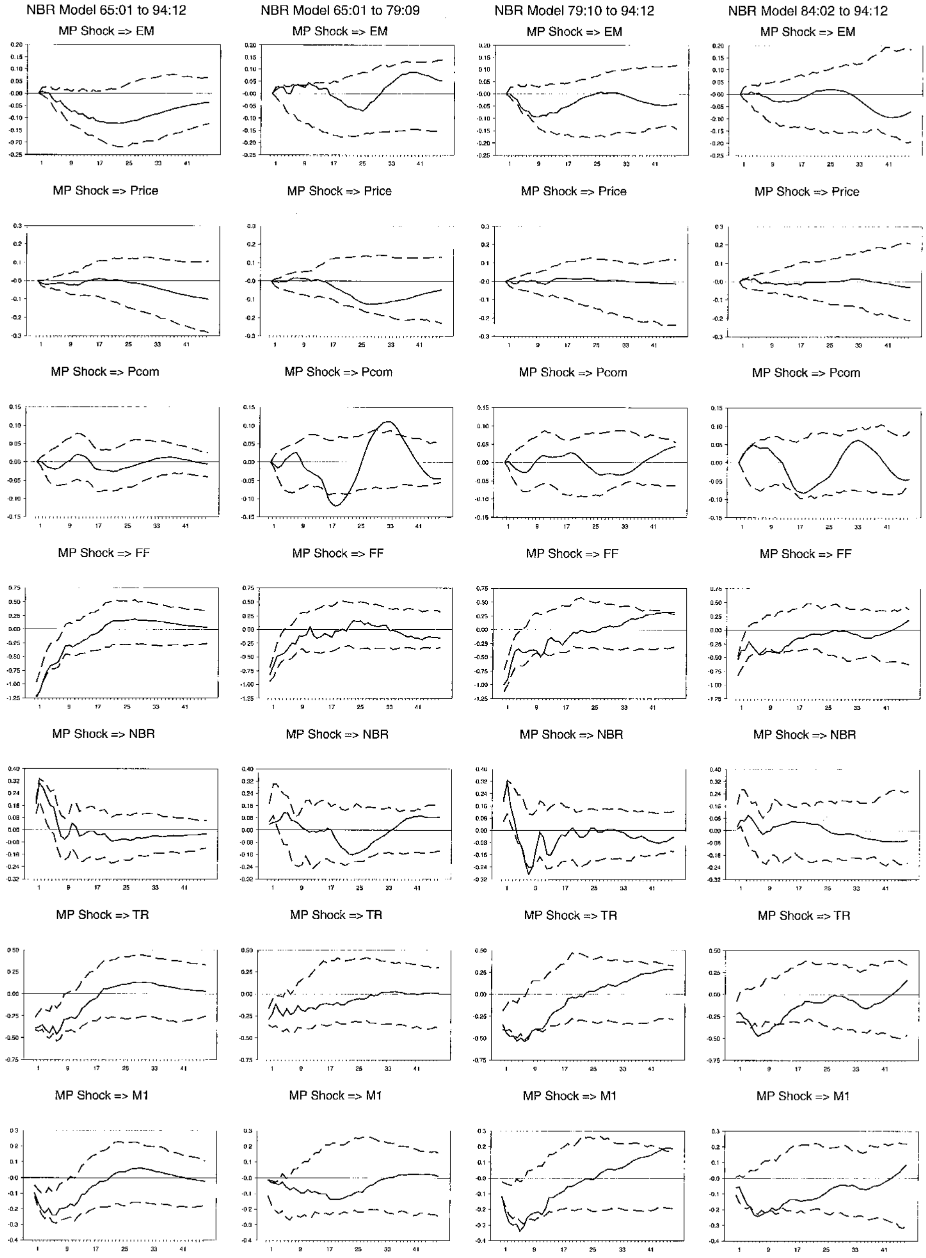


Fig. 10. Results for the benchmark *NBR* policy shocks.

Table 1
The liquidity effect, sample period sensitivity

Subsample	*FF/NBR*	*FF/M*1
Panel A: *FF* Policy Shock		
65:01–94:12	−0.94 (−1.30, −0.73)	−2.17 (−3.61, −1.36)
65:01–79:09	−0.70 (−2.64, −0.55)	−1.88 (−8.32, −0.72)
79:10–94:12	−0.71 (−1.95, −0.64)	−1.13 (−4.48, −0.82)
84:02–94:12	−0.69 (−5.52, 1.86)	−0.97 (−13.92, 13.39)
Panel B: *NBR* Policy Shocks		
65:01–94:12	−0.23 (−0.29, −0.17)	−1.14 (−2.10, −0.59)
65:01–79:09	−0.07 (−0.36, −0.11)	−2.08 (−4.86, −0.14)
79:10–94:12	−0.27 (−0.35, −0.13)	−0.37 (−3.56, −0.15)
84:02–94:12	−0.13 (−0.45, −0.04)	−0.47 (−10.12, 5.35)

We begin our discussion by reviewing the results in panel A. The full sample results indicate that a one percent policy-shock induced increase in nonborrowed reserves results in roughly a one percentage point reduction in the federal funds rate. A one percent policy-shock induced increase in $M1$ results in roughly a two percentage point decline in the federal funds rate. The point estimates do vary across the subsamples. However, the evidence suggests that the differences in estimated responses can be accounted for by sampling uncertainty. In particular, there is little evidence against the null hypothesis that the true responses are the same in the subsamples. This is evident from the fact that the confidence intervals in the subsamples include the point estimates for the full sample.

Turning to panel B, we see that, using the *NBR* identification scheme, we obtain point estimates of the responses that are generally smaller. Again, there is little evidence against subsample stability.

We now summarize our findings regarding subsample stability. We have two basic findings. First, there is evidence that the variance of the policy shocks is larger in the early 1980s than in the periods before or after. Second, we cannot reject the view that the response of economic variables to a shock of given magnitude is stable over the different subsamples considered.

We conclude this section by noting that other papers have also examined the subsample stability question. See, for example Balke and Emery (1994), Bernanke and Mihov (1995) and Strongin (1995). These papers focus on a slightly different question than we do. They investigate whether the Fed adopted different operating procedures in different subperiods, and provide some evidence that different specifications of the policy rule in Equation (2.1) better characterize different subsamples. At the same time, Bernanke and Mihov (1995) and Strongin (1995) do not find that the dynamic response functions to a monetary policy shock are qualitatively different over the different subsample periods that they consider. In this sense, their results are consistent with ours.

4.5. Discriminating between the benchmark identification schemes

In the introduction we sketched a strategy for assessing the plausibility of different identification schemes. The basic idea is to study the dynamic response of a broad range of variables to a monetary policy shock. We dismiss an identification scheme if it implies a set of dynamic response functions that is inconsistent with every model we are willing to consider.

The first subsection illustrates our approach by comparing the plausibility of two interpretations of an orthogonalized shock to *NBR*. These amount to two alternative identification schemes. The first corresponds to the benchmark *NBR* identification scheme described in Section 4. Under this scheme, an orthogonalized contractionary shock to *NBR* is interpreted as a negative money supply shock. The second scheme, recently proposed by Coleman, Gilles and Labadie (1996), interprets the same shock as either a positive shock to money demand, or as news about a future monetary expansion. When we use our strategy to assess their identification scheme, we find that we can dismiss it as implausible. [55]

The second subsection contrasts our approach to discriminating among identification schemes with one recently proposed in Bernanke and Mihov (1995). We review their methodology and explain why we think our approach is more likely to be fruitful.

4.5.1. The Coleman, Gilles and Labadie identification scheme

According to Coleman, Gilles and Labadie (1996), understanding why an *NBR* policy shock may not coincide with an exogenous contractionary shock to monetary policy requires understanding the technical details about the way the Fed allocates the different tasks of monetary policy between the discount window and the Federal Open Market Committee. They argue, via two examples that a contractionary *NBR* shock may correspond to other types of shocks.

[55] The discussion presented here summarizes the analysis in Christiano (1996).

In their first example, they argue that a negative *NBR* shock may actually correspond to a positive shock to the demand for money. The argument goes as follows. Suppose that there was a shock to either the demand for *TR*, $M1$ or $M2$ that drove up the interest rate. Absent a change in the discount rate, this would lead to an increase in Borrowed Reserves via the discount window. Suppose in addition that the FOMC believes that the managers of the discount window always over accommodate shocks to the demand for money, and respond by pulling nonborrowed reserves out of the system. An attractive feature of this story is that it can potentially account for the fact that the federal funds rate is negatively correlated with nonborrowed reserves and positively correlated with borrowed reserves [see Christiano and Eichenbaum (1992)]. Unfortunately, the story has an important problem: it is hard to see why a *positive* shock to money demand would lead to a sustained *decline* in total reserves, $M1$ or $M2$. But this is what happens after an *NBR* policy shock (see Figure 2). In light of this fact, the notion that a negative *NBR* policy shock really corresponds to a positive money demand shock seems unconvincing.

In their second example, Coleman, Gilles and Labadie argue that a negative *NBR* shock may actually correspond to a positive *future* shock to the money supply. The basic idea is that the Fed signals policy shifts in advance of actually implementing them, and that a signal of an imminent increase in total reserves produces an immediate rise in the interest rate. Such a rise would occur in standard neoclassical monetary economies of the type considered by Cooley and Hansen (1989). Suppose that the rise in the interest rate results in an increase in borrowed reserves. If the Fed does not wish the rise in borrowed reserves to generate an immediate rise in total reserves, it would respond by reducing nonborrowed reserves.

This interpretation of the rise in the interest rate after an *NBR* policy shock is particularly interesting because it does not depend on the presence of a liquidity effect. Indeed, this interpretation presumes that the interest rate rises in anticipation of a future increase in the money supply. To the extent that the interpretation is valid, it would constitute an important attack on a key part of the evidence cited by proponents of the view that plausible models of the monetary transmission mechanism ought to embody strong liquidity effects. Again there is an important problem with this interpretation of the evidence: the anticipated rise in the future money supply that the contractionary *NBR* policy shock is supposed to be proxying for never happens: *TR*, $M1$ and $M2$ *fall* for over two years after a contractionary *NBR* policy shock. In light of this, the notion that a contractionary *NBR* policy shock is proxying for expansionary future money supply shocks seems very unlikely.

4.5.2. The Bernanke–Mihov critique

The preceding subsection illustrates our methodology for assessing the plausibility of different identification schemes. Bernanke and Mihov (BM) propose an alternative approach. Under the assumption that the policy function is of the form of Equation (2.1), they develop a particular test of the null hypothesis that ε_t^s is a monetary policy shock against the alternative that ε_t^s is confounded by nonmonetary policy shocks to the market for federal funds.

To implement their test, Bernanke and Mihov develop a model of the federal funds market which is useful for interpreting our benchmark identification schemes. These schemes are all exactly identified, so that each fits the data equally well. To develop a statistical test for discriminating between these schemes, BM impose a particular overidentifying restriction: the amount that banks borrow at the discount window is not influenced by the total amount of reserves in the banking system. BM interpret a rejection of a particular overidentified model as a rejection of the associated *NBR*, *FF* or *NBR/TR* identification scheme. But a more plausible interpretation is that it reflects the implausibility of their overidentifying restriction. This is because that restriction is not credible in light of existing theory about the determinants of discount window borrowing and the empirical evidence presented below.

4.5.2.1. A model of the federal funds market. BM assume that the demand for total reserves is given by

$$TR_t = f_{TR}(\Omega_t) - \alpha FF_t + \sigma_d \varepsilon_t^d, \tag{4.4}$$

where $f_{TR}(\Omega_t)$ is a linear function of the elements of Ω_t, $\alpha, \sigma_d > 0$, and ε_t^d is a unit variance shock to the demand for reserves which is orthogonal to Ω_t. According to Equation (4.4), the demand for total reserves depends on the elements of Ω_t and responds negatively to the federal funds rate. The demand for borrowed reserves is:

$$BR_t = f_{BR}(\Omega_t) + \beta FF_t - \gamma NBR_t + \sigma_b \varepsilon_t^b, \tag{4.5}$$

where $f_{BR}(\Omega_t)$ is a linear function of the elements of Ω_t and $\sigma_b > 0$. The unit variance shock to borrowed reserves, ε_t^b, is assumed to be orthogonal to Ω_t. BM proceed throughout under the assumption that $\gamma = 0$. Below, we discuss in detail the rationale for specification (4.5).[56] Finally, they specify the following Fed policy rule for setting NBR_t:

$$NBR_t = f_{NBR}(\Omega_t) + e_t, \tag{4.6}$$

where

$$e_t = \phi^d \sigma_d \varepsilon_t^d + \phi^b \sigma_b \varepsilon_t^b + \sigma_s \varepsilon_t^s \tag{4.7}$$

Here, ε_t^s is the unit variance exogenous shock to monetary policy. By assumption, ε_t^d, ε_t^b, ε_t^s are mutually orthogonal, both contemporaneously and at all leads and lags.

[56] We follow BM in not including the interest rate charged at the discount window (the discount rate) as an argument in Equation (4.5). BM rationalize this decision on the grounds that the discount rate does not change very often.

The parameters ϕ^d and ϕ^b control the extent to which Fed responds contemporaneously to shocks in the demand for total reserves and borrowed reserves.

Using the fact that $TR = NBR + BR$, and solving Equations (4.4)–(4.7), we obtain

$$\begin{bmatrix} TR_t \\ NBR_t \\ FF_t \end{bmatrix} = F(\Omega_t) + u_t,\ u_t = B\varepsilon_t, \tag{4.8}$$

where

$$F(\Omega_t) = \begin{bmatrix} \frac{\beta}{\beta+\alpha} & -\alpha\frac{\gamma-1}{\beta+\alpha} & \frac{\alpha}{\beta+\alpha} \\ 0 & 1 & 0 \\ \frac{1}{\beta+\alpha} & \frac{\gamma-1}{\beta+\alpha} & -\frac{1}{\beta+\alpha} \end{bmatrix} \begin{bmatrix} f_{TR}(\Omega_t) \\ f_{NBR}(\Omega_t) \\ f_{BR}(\Omega_t) \end{bmatrix} \tag{4.9}$$

and

$$B = \begin{bmatrix} \sigma_d\frac{\beta-\phi^d\alpha\gamma+\phi^d\alpha}{\beta+\alpha} & -\alpha\sigma_s\frac{\gamma-1}{\beta+\alpha} & -\alpha\sigma_b\frac{-1+\phi^b\gamma-\phi^b}{\beta+\alpha} \\ \sigma_d\phi^d & \sigma_s & \sigma_b\phi^b \\ \sigma_d\frac{\phi^d\gamma-\phi^d+1}{\beta+\alpha} & \sigma_s\frac{\gamma-1}{\beta+\alpha} & \sigma_b\frac{-1+\phi^b\gamma-\phi^b}{\beta+\alpha} \end{bmatrix}, \tag{4.10}$$

$$\varepsilon_t = \begin{bmatrix} \varepsilon_t^d \\ \varepsilon_t^s \\ \varepsilon_t^b \end{bmatrix},\ E\varepsilon_t\varepsilon_t' = I. \tag{4.11}$$

4.5.2.2. Identifying the parameters of the model. We now turn to the problem of identifying the parameters of the money market model. As in Section 3, we first estimate u_t using the fitted disturbances, $\hat{u}_t$, in a linear regression of the money market variables on Ω_t, and then estimate ε_t from $\hat{\varepsilon}_t = B^{-1}\hat{u}_t$ using a sample estimate of B. The latter can be obtained by solving

$$V = BB', \tag{4.12}$$

where V is the Gaussian maximum likelihood estimate of Eu_tu_t' which respects the restrictions, if any, implied by Equation (4.12) and the structure of B in Equation (4.10). The estimate, V, is obtained by maximizing

$$-\frac{T}{2}\left\{\log|V| + tr\left(SV^{-1}\right)\right\}, \quad \text{where} \quad S = \frac{1}{T}\sum_{t=1}^{T}\hat{u}_t\hat{u}_t', \tag{4.13}$$

subject to conditions (4.10)–(4.12). When the latter restrictions are not binding, the solution to this maximization problem is $V = S$.[57]

[57] BM use a slightly different estimation strategy. See the appendix in BM.

Denote the model's eight structural parameters by

$$\psi = [\alpha, \beta, \gamma, \phi^d, \phi^b, \sigma_d^2, \sigma_b^2, \sigma_s^2]. \tag{4.14}$$

Let $\hat{\psi}_T$ denote a value of ψ which implies a B that satisfies condition (4.12). The model is underidentified if there exist other values of ψ that have this property too. The model is exactly identified if $\hat{\psi}_T$ is the only value of ψ with this property. Finally, the model is overidentified if the number of structural parameters is less than six, the number of independent elements in S.

Given the symmetry of V, condition (4.12) corresponds to six equations in eight unknown parameters: α, β, γ, ϕ^d, ϕ^b, σ_d^2, σ_b^2, σ_s^2. To satisfy the order condition discussed in Section 3, at least two more restrictions must be imposed.

Recall that the *FF*, *NBR* and *NBR/TR* identification schemes analyzed in the previous section correspond to a particular orthogonality condition on the monetary policy shock. These conditions are satisfied in special cases of the federal funds market model described above. Each special case corresponds to a different set of two restrictions on the elements of ψ. In each case, the estimation procedure described above reduces to first setting $V = S$ and then solving the inverse mapping from V to the free elements of ψ in condition (4.12). The uniqueness of this inverse mapping establishes global identification.

When $S_t = NBR_t$, relations (4.8)–(4.10) imply that the measured policy shock is given by Equation (4.7). So, from the perspective of this framework, our *NBR* system assumes:

$$\phi^d = \phi^b = 0. \tag{4.15}$$

The free parameters in ψ are uniquely recovered from V as follows:

$$\alpha = -\frac{V_{21}}{V_{32}}, \qquad \sigma_s^2 = V_{22}, \tag{4.16}$$

$$\beta = \frac{V_{11} + \alpha V_{31}}{V_{31} + \alpha V_{33}}, \qquad \sigma_d^2 = (\beta + \alpha)\,[V_{31} + \alpha V_{33}], \tag{4.17}$$

$$\gamma = 1 - \frac{V_{21}(\beta + \alpha)}{\alpha \sigma_s^2}, \qquad \sigma_b^2 = V_{33}(\alpha + \beta)^2 - \sigma_d^2 - (1-\gamma)^2 \sigma_s^2. \tag{4.18}$$

where V_{ij} refers to the (i,j) element of V.

When $S_t = FF_t$ then

$$e_t = \frac{\phi^d(\gamma - 1) + 1}{\beta + \alpha}\varepsilon_t^d + \frac{-1 + \phi^b(\gamma - 1)}{\beta + \alpha}\varepsilon_t^b + \frac{\gamma - 1}{\beta + \alpha}\varepsilon_t^s. \tag{4.19}$$

From the perspective of this framework, the benchmark *FF* system assumes:

$$\phi^d = \frac{1}{1-\gamma}, \qquad \phi^b = -\phi^d. \tag{4.20}$$

The free parameters in ψ are recovered from V as follows:

$$c = \frac{\gamma - 1}{\beta + \alpha}, \qquad \sigma_s^2 = \frac{V_{32}^2}{V_{33}}, \qquad \alpha = -\frac{V_{31}}{V_{33}}, \tag{4.21}$$

$$\sigma_d^2 = V_{11} - \alpha^2 c^2 \sigma_s^2, \qquad \gamma = 1 - \left[\frac{\sigma_d^2}{V_{21} + \alpha c \sigma_s^2}\right], \tag{4.22}$$

$$\sigma_b^2 = (1-\gamma)^2 \left[V_{22} - \frac{\sigma_d^2}{(1-\gamma)^2} - \sigma_s^2\right], \qquad \beta = (\gamma - 1)\frac{V_{32}}{V_{33}} - \alpha. \tag{4.23}$$

The *NBR/TR* system assumes:

$$\alpha = \phi^b = 0. \tag{4.24}$$

Under these conditions, it is easy to verify that the error of the regression of NBR_t on Ω_t and TR_t is ε_t^s. The free parameters of the money model are recovered from V as follows:

$$\sigma_d^2 = V_{11}, \qquad \phi^d = \frac{V_{21}}{V_{11}}, \qquad \sigma_s^2 = V_{22} - \left(\phi^d\right)^2 \sigma_d^2, \tag{4.25}$$

$$c_1 = \frac{V_{32} - \phi^d V_{31}}{\sigma_s^2}, \qquad c_2 = \frac{V_{31}}{\sigma_d^2}, \qquad \beta = \left[c_2 - \phi^d c_1\right]^{-1}, \tag{4.26}$$

$$\sigma_b^2 = \beta^2 \left[V_{33} - c_2^2 \sigma_d^2 - c_1^2 \sigma_s^2\right], \qquad \gamma = \beta c_1 + 1. \tag{4.27}$$

Restrictions (4.15), (4.20), (4.24) guarantee that the benchmark *NBR*, *FF* and *NBR/TR* policy shock measures are not polluted by nonmonetary policy shocks, respectively.

4.5.2.3. The Bernanke–Mihov test. Recall that the basic purpose of the money market model discussed above is to help assess whether different monetary policy shock measures are polluted by nonpolicy shocks to the money market. In the case of the *NBR* policy system this amounts to testing restriction (4.15). For the *FF* and *NBR/TR* systems this corresponds to testing restrictions (4.20) and (4.24), respectively. The problem is that, since each of these systems is exactly identified, the restrictions cannot be tested using standard statistical procedures. From this perspective, the money market model is not helpful. As the model stands, to assess the different identification schemes, one must revert to the strategy laid out in the previous section. Namely, one must examine the qualitative properties of the impulse response functions.

Instead BM impose an *additional* maintained assumption on the model. Specifically, they assume $\gamma = 0$, i.e., the demand for borrowed reserves does not depend on the level of nonborrowed reserves. With this additional restriction, the *NBR*, *FF* and *NBR/TR* models have only five structural parameters, so each is overidentified. Consequently, each can be tested using standard likelihood ratio methods. An important limitation of this approach is that we can always interpret a rejection as evidence against the maintained hypothesis, $\gamma = 0$, rather than as evidence against the *NBR*, *FF* or *NBR/TR* identification schemes. A rejection would be strong evidence against one of these identification schemes *only* to the extent that one had overwhelmingly sharp priors that γ really is zero. In fact, there are no compelling reasons to believe that γ is zero. Just the opposite is true. Standard dynamic models of the market for reserves suggest that γ is not zero.

Consider for example Goodfriend's (1983) model of a bank's demand for borrowed reserves. Goodfriend highlights two factors that affect a bank's decision to borrow funds from the Federal Reserve's discount window. The first factor is the spread between the federal funds rate and the Fed's discount rate (here assumed constant). The higher this spread is, the lower is the cost of borrowing funds from the discount window, relative to the cost of borrowing in the money market. The second factor is the existence of nonprice costs of borrowing at the Federal Reserve discount window. These costs rise for banks that borrow too much or too frequently, or who are perceived to be borrowing simply to take advantage of the spread between the federal funds rate and the discount rate.

Goodfriend writes down a bank objective function which captures both of the aforementioned factors and then derives a policy rule for borrowed reserves that is of the following form:

$$BR_t = \lambda_1 BR_{t-1} - \lambda_2 hFF_t - h\sum_{i=2}^{\infty} \lambda_2^i E_t(FF_{t-1+i}), \quad -1 < \lambda_1,\ \lambda_2 < 0,\ h > 0. \tag{4.28}$$

Here E_t denotes the conditional expectation based on information at time t. Reflecting the presence of the first factor in banks' objective functions, the current federal funds rate enters the decision rule for BR with a positive coefficient. The variable, BR_{t-1}, enters this expression with a negative coefficient because of the second factor. The presence of the expected future federal funds rate in the policy rule reflects both factors. For example, when E_tFF_{t+1} is high, banks want BR_t to be low so that they can take full advantage of the high expected funds rate in the next period without having to suffer large nonprice penalties at the discount window.

The crucial thing to note from Equation (4.28) is that any variable which enters $E_t\,(FF_{t-1+i})$ also enters the "demand for borrowed reserves" (4.5). So, if nonborrowed reserves help forecast future values of the federal funds rate, γ should not equal zero. To assess the empirical importance of this argument we proceeded as follows. We regressed FF_t on 12 lagged values (starting with month $t-1$) of data on employment, P, $PCOM$, FF, NBR, and TR. The estimation period for the regression is the same as for our monthly benchmark VAR's. We computed an F-statistic for testing the null hypothesis that all the coefficients on NBR in this equation are equal to zero. The value of this statistic is 3.48 which has a probability value of less than 0.001 percent using conventional asymptotic theory.

Given our concerns about the applicability of conventional asymptotic theory in this context we also computed the probability value of the F-statistic using an appropriately modified version of the bootstrap methodology used throughout this chapter. Specifically, we estimated a version of our benchmark monthly VAR in which all values of *NBR* were excluded from the federal funds equation.[58] Using the estimated version of this VAR, we generated 500 synthetic time series by drawing randomly, with replacement, from the set of fitted residuals. On each synthetic data set, we computed an F-statistic using the same procedure that was applied in the actual data. Proceeding in this way, we generated a distribution for the F-statistic under the null hypothesis that lagged values of *NBR* do not help forecast the federal funds rate. We find that none of the simulated F-statistics exceed the empirical value of 3.48. This is consistent with the results reported in the previous paragraph which were based on conventional asymptotic distribution theory. Based on this evidence, we reject the null hypothesis that lagged values of *NBR* are not useful for forecasting future values of *FF* and the associated hypothesis that *NBR* is not an argument of the demand for *BR*.

The argument against the BM exclusion restriction ($\gamma = 0$), is a special case of the general argument against exclusion restrictions presented in Sargent (1984) and Sims (1980). In fact, this argument suggests that none of the parameters of BM's money market model are identified since even exact identification relies on the exclusion of *NBR* and *BR* from total reserves demand (4.4), and *TR* from the borrowed reserves function (4.5).

There is another reason not to expect $\gamma = 0$. The second factor discussed above suggests that a bank which is not having reserve problems, but still borrows funds at the discount window, may suffer a higher nonprice marginal cost of borrowing. This would happen if the discount window officer suspected such a bank were simply trying to profit from the spread between the federal funds rate and discount rate.[59] Presumably a bank that possesses a large amount of nonborrowed reserves could be viewed as having an "ample supply of federal funds". The appropriate modification to the analysis in Goodfriend (1983) which reflects these considerations leads to the conclusion that NBR_t should enter on the right hand side of Equation (4.28) with a negative coefficient. We conclude that what we know about the operation of the discount window and the dynamic decision problems of banks provides no support for the BM maintained hypothesis that γ is equal to zero.

4.5.2.4. Empirical results. To make concrete the importance of BM's maintained assumption that $\gamma = 0$, we estimated both the restricted and unrestricted *NBR*, *FF* and *NBR/TR* models, as discussed above. The results are reported in Tables 2a and 2b. Each table reports results based on two data sets, the BM monthly data and the quarterly data used in the rest of this chapter. For the BM data, we used their estimated S matrix, which they kindly provided to us. The column marked "restricted" reports results for the model with $\gamma = 0$. These correspond closely to those reported by BM.[60] The

[58] Each equation in this VAR was estimated separately using OLS and 12 lags of the right hand side variables.

[59] Regulation A, the regulation which governs the operation of the discount window, specifically excludes borrowing for this purpose.

[60] The small differences between the two sets of results reflect different estimation methods.

Table 2a
Estimation results for money market models

	NBR model			*FF* model		
	B-M Data, 1965:1–1994:12		1965:Q3–1995:Q2	B-M Data, 1965:1–1994:12		1965:Q3–1995:Q2
	restricted	unrestricted	unrestricted	restricted	unrestricted	unrestricted
α	0.009	0.035	0.022	−0.003	−0.003	−0.001
	(0.00763)	(0.00763)	(0.00550)	(0.00099)	(0.00070)	(0.00104)
β	0.031	0.012	0.012	0.012	0.012	0.012
	(0.00269)	(0.00129)	(0.00151)	(0.00106)	(0.00091)	(0.00107)
γ	0	0.481	0.279	0	−0.103	−0.073
		(0.03229)	(0.05599)		(0.04849)	(0.05864)
ϕ^d	0	0	0	1	1	1
σ_d	0.011	0.020	0.022	0.009	0.009	0.013
	(0.00065)	(0.00333)	(0.00387)	(0.00033)	(0.00023)	(0.00058)
σ_s	0.013	0.013	0.018	0.004	0.004	0.008
	(0.00048)	(0.00048)	(0.00114)	(0.00070)	(0.00047)	(0.00107)
σ_b	0.013	0.007	0.009	0.009	0.010	0.011
	(0.00100)	(0.00033)	(0.00070)	(0.00035)	(0.00053)	(0.00077)
p-value	0.000			0.052		

columns marked "unrestricted" report the analog results when the restriction, $\gamma = 0$, is not imposed. The bottom row of Tables 2a and 2b reports the p-values for testing the monthly restricted versus unrestricted model.[61]

Several results in these tables are worth noting. To begin with, according to column 1 of Table 2a, BM's restricted *NBR* model is strongly rejected. Recall, they interpret this rejection as reflecting that ϕ^d and/or ϕ^b are nonzero. As we have stressed, one can just as well infer that γ is not zero. In fact, from column 2 we see that the estimated value of γ is positive and highly statistically significant. Of course, this result would not be particularly interesting if the estimated values of the other parameters in the unrestricted model violated BM's sign restrictions. But, this is not the case. All the parameter values satisfy BM's sign restrictions. This is the case whether we use monthly or quarterly data. Taken together, our results indicate that BM's claim to have rejected the benchmark *NBR* model is unwarranted.

[61] We use a likelihood ratio statistic which, under the null hypothesis, has a chi-square distribution with 1 degree of freedom.

Table 2b
Estimation results, restricted and unrestricted models

	NBR/TR model		
	B-M Data, 1965:1–1994:12		1965:Q3–1995:Q2
	restricted	unrestricted	unrestricted
α	0	0	0
β	0.046	0.038	0.026
	(0.00424)	(0.00422)	(0.00358)
γ	0	0.200	–0.011
		(0.07836)	(0.10371)
ϕ^d	0.802	0.802	0.886
	(0.06350)	(0.06350)	(0.09664)
σ_d	0.009	0.009	0.013
	(0.00033)	(0.00033)	(0.00082)
σ_s	0.011	0.011	0.014
	(0.00040)	(0.00040)	(0.00087)
σ_b	0.019	0.016	0.015
	(0.00188)	(0.00181)	(0.00234)
p-value	0.032		

Next, from column 4 of Table 2a, we see that, consistent with BM's results, the *FF* model cannot be rejected on the basis of the likelihood ratio test. Notice, however, that the estimated value of α is negative. Indeed, the null hypothesis, $\alpha \geqslant 0$, is strongly rejected. This calls into question the usefulness of their model for interpreting the benchmark *FF* identification scheme for the sample period as a whole.[62] Finally, note from Table 2b that the *NBR/TR* model is not strongly rejected by BM's likelihood ratio test and the parameter values are consistent with all of BM's sign restrictions.

In sum, BM have proposed a particular way to test whether the policy shock measures associated with different identification schemes are polluted by nonpolicy shocks. The previous results cast doubt on the effectiveness of that approach.

4.6. Monetary policy shocks and volatility

Up to now we have focussed on answering the question, what are the dynamic effects of a monetary policy shock? A related question is: How have monetary policy

[62] BM actually argue that this model is most suitable for the pre-1979 period. Here too, their point estimate of α is negative and significantly different from zero.

shocks contributed to the volatility of various economic aggregates? The answer to this question is of interest for two reasons. First, it sheds light on the issue of whether policy shocks have been an important independent source of impulses to the business cycle. Second, it sheds light on identification strategies which assume that the bulk of variations in monetary aggregates reflect exogenous shocks to policy. For example, this is a maintained assumption in much of the monetized real business cycle literature. [63]

Table 3 summarizes the percentage of the variance of the k step ahead forecast errors in P, Y, $PCOM$, FF, NBR, TR and $M1$ that are attributable to quarterly benchmark FF, NBR and NBR/TR policy shocks. Analog results for policy shock measures based on $M0$, $M1$, and $M2$ are reported in Table 4.

We begin by discussing the results based on the benchmark policy measures. First, according to the benchmark FF measure, monetary policy shocks have had an important impact on the volatility of aggregate output, accounting for 21%, 44% and 38% of the variance of the 4, 8 and 12 quarter ahead forecast error variance in output, respectively. However, these effects are smaller when estimated using the NBR/TR policy shock measures and smaller still for the benchmark NBR policy shocks. Indeed, the latter account for only 7%, 10% and 8% of the 4, 8 and 12 quarter ahead forecast error variance of output. Evidently, inference about the importance of monetary policy shocks depends sensitively on which policy shock measure is used. In addition, conditioning on the policy shock measure, there is substantial sampling uncertainty regarding how important policy shocks are in accounting for the variance of the k step forecast error.

Second, none of the policy shock measures account for much of the volatility of the price level, even at the three year horizon. In addition, only the FF benchmark policy shock measure accounts for a nontrivial portion of the variability of $PCOM$. Evidently, monetary policy shocks are not an important source of variability in prices, at least at horizons of time up to three years in length.

Third, regardless of whether we identify S_t with the federal funds rate or NBR, policy shocks account for a large percent of the volatility of S_t at the two quarter horizon. However, their influence declines substantially over longer horizons. Fourth, according to the benchmark FF and NBR/TR measures, monetary policy shocks play a very minor role in accounting for the variability in TR and $M1$. Policy shocks play a more important role according to the benchmark NBR measure. Even here, most of the volatility in TR and $M1$ arises as a consequence of nonpolicy shocks. Identification strategies which assume that monetary aggregates are dominated by shocks to policy are inconsistent with these results. Finally, policy shocks are more important in explaining the volatility in $M2$ than for TR or $M1$. This is true regardless of which benchmark policy measure we consider. Still, the variation in $M2$ due to policy shocks never exceeds 50%.

[63] See Cooley and Hansen (1989), Chari et al. (1996) and Christiano and Eichenbaum (1995).

Table 3
Percent of k-period ahead forecast error variance due to policy shock: quarterly results

	FF policy shock				*NBR* policy shock				*NBR/TR* policy shock			
	2	4	8	12	2	4	8	12	2	4	8	12
Y	0.4	21	44	38	0	7	10	8	0	17	30	22
	(0, 5)	(7, 41)	(18, 56)	(15, 50)	(0, 3)	(1, 21)	(1, 28)	(2, 12)	(0, 7)	(5, 36)	(9, 47)	(7, 42)
P	0.5	0.3	0.4	2.5	0	0	1	1	0	0	0	1
	(0, 3)	(0, 6)	(0, 8)	(0, 17)	(0, 2)	(0, 5)	(0, 9)	(0, 12)	(0, 3)	(0, 6)	(0, 8)	(0, 14)
PCOM	1.0	10	13	11	0	1	1	1	1	3	3	2
	(0, 5)	(1, 26)	(3, 26)	(2, 27)	(0, 3)	(0, 10)	(0, 11)	(1, 12)	(0, 4)	(0, 16)	(1, 16)	(1, 15)
FF	65	35	19	17	19	10	5	5	34	18	10	9
	(43, 81)	(211, 51)	(12, 38)	(11, 36)	(7, 34)	(4, 23)	(3, 19)	(3, 19)	(17, 48)	(9, 21)	(5, 25)	(5, 25)
NBR	22	9	3	2	85	46	19	13	47	19	8	6
	(8, 38)	(4, 21)	(2, 15)	(1, 17)	(64, 92)	(27, 63)	(10, 38)	(7, 33)	(29, 61)	(11, 31)	(5, 23)	(4, 21)
TR	2	2	1	1	37	29	12	8	1	1	1	1
	(0, 11)	(0, 15)	(0, 15)	(0, 17)	(20, 52)	(11, 47)	(4, 33)	(2, 29)	(0, 5)	(0, 7)	(0, 10)	(0, 16)
M1	8	9	5	4	25	25	13	9	2	2	1	1
	(2, 23)	(2, 27)	(1, 24)	(1, 25)	(10, 40)	(7, 44)	(2, 34)	(3, 29)	(0, 11)	(0, 12)	(0, 10)	(0, 13)
M2	36	39	35	30	34	34	28	24	35	46	45	41
	(16, 54)	(17, 57)	(10, 56)	(5, 52)	(17, 51)	(14, 53)	(7, 50)	(4, 46)	(17, 51)	(22, 62)	(15, 60)	(10, 58)

Table 4
Percent of k-period ahead forecast error variance due to policy shocks quarterly results

	$M0$ policy shock				$M1$ policy shock				$M2$ policy shock			
	2	4	8	12	2	4	8	12	2	4	8	12
Y	0	5	5	3	0	0	3	6	2	14	29	24
	(0, 3)	(0, 17)	(1, 17)	(1, 15)	(0, 3)	(0, 7)	(1, 14)	(2, 19)	(0, 7)	(1, 29)	(3, 43)	(3, 39)
P	0	3	4	2	0	0	0	0	0	1	6	15
	(0, 4)	(0, 11)	(0, 16)	(0, 18)	(0, 2)	(0, 6)	(0, 11)	(0, 12)	(0, 2)	(0, 9)	(0, 25)	(0, 43)
$PCOM$	1	1	1	1	0	2	2	4	2	22	26	26
	(0, 5)	(0, 9)	(0, 9)	(1, 12)	(0, 4)	(0, 12)	(0, 13)	(0, 20)	(0, 8)	(3, 39)	(3, 41)	(4, 42)
FF	0	0	0	0	15	3	3	3	13	9	8	11
	(0, 6)	(0, 9)	(0, 11)	(0, 12)	(0, 7)	(0, 11)	(1, 17)	(1, 17)	(4, 26)	(3, 22)	(3, 27)	(3, 33)
NBR	6	2	1	1	24	22	12	10	30	18	9	11
	(0, 19)	(0, 13)	(0, 15)	(0, 16)	(9, 39)	(7, 38)	(3, 31)	(3, 33)	(14, 45)	(7, 33)	(4, 23)	(3, 33)
TR	22	11	4	3	61	56	27	18	18	14	6	9
	(7, 39)	(3, 27)	(2, 19)	(1, 16)	(40, 74)	(28, 71)	(10, 51)	(7, 44)	(6, 36)	(3, 30)	(2, 20)	(2, 30)
$M0$	85	69	48	39	–	–	–	–	–	–	–	–
	(66, 91)	(39, 83)	(18, 71)	(12, 66)								
$M1$	–	–	–	–	91	79	41	27	–	–	–	–
					(71, 94)	(49, 87)	(17, 63)	(11, 56)				
$M2$	–	–	–	–	–	–	–	–	94	84	73	67
									(77, 95)	(53, 89)	(30, 82)	(20, 80)

Next we consider the results obtained for policy shock measures based on $M0$, $M1$, and $M2$. The VAR's underlying these results correspond to the ones underlying the results reported in columns 2, 4 and 6 in Figure 6. In each case, S_t is equated to either $M0$, $M1$ or $M2$, and the information set, Ω_t, includes current and past values of Y_t, P_t, $PCOM_t$ as well as lagged values of FF_t, TR_t and S_t. A number of results are interesting to note here. First, the $M0$ and $M1$-based policy shock measures account for only a trivial fraction of the fluctuations in output. In contrast, at horizons greater than a year, $M2$-based policy measures account for a noticeably larger fraction of output variations. While they account for a smaller fraction of output volatility than do the *FF* policy shocks, they are similar on this dimension to the *NBR/TR* policy shock measures. Second, neither the $M0$ or $M1$-based policy shock measures account for more than a trivial part of the volatility of P and *PCOM*. Policy shock measures based on $M2$ play a somewhat larger role at horizons of a year or longer. However, there is considerable sampling uncertainty about these effects. Finally, at horizons up to a year, $M0$, $M1$, and $M2$-based policy shocks account for sizeable percentages of $M0$, $M1$, and $M2$, respectively. At longer horizons the percentages are lower.

Viewed across both sets of identification strategies that we have discussed, there is a great deal of uncertainty about the importance of monetary policy shocks in aggregate fluctuations. The most important role for these shocks emerged with the FF-based measure of policy shocks. The smallest role is associated with the $M0$ and $M1$-based policy shock measures.

We conclude this subsection by noting that even if monetary policy shocks have played only a very small role in business fluctuations, it does not follow that the systematic component, f in Equation (2.1), of monetary policy has played a small role. The same point holds for prices. A robust feature of our results is that monetary policy shocks account for a very small part of the variation in prices. This finding does not deny the proposition that systematic changes in monetary policy, captured by f, can play a fundamental role in the evolution of prices at all horizons of time.

5. The effects of monetary policy shocks: abandoning the recursiveness approach

In this section we discuss an approach to identifying the effects of monetary policy shocks that does not depend on the recursiveness assumption. Under the recursiveness assumption, the disturbance term, ε_t^s, in the monetary authority's reaction function [see Equation (2.1)] is orthogonal to the elements of their information set Ω_t. As discussed above [see Equation (4.1)] this assumption corresponds to the notion that economic variables within the quarter are determined in a block recursive way: first, the variables associated with goods markets (prices, employment, output, etc.) are determined; second, the Fed sets its policy instrument (i.e., *NBR* in the case of the benchmark *NBR* system, and *FF* in the case of the benchmark *FF* system); and third, the remaining variables in the money market are determined.

To help compare the recursiveness assumption with alternative identifying assumptions, it is convenient to decompose it into two parts. First, it posits the existence of a set of variables that is predetermined relative to the policy shock. Second, it posits that the Fed only looks at predetermined variables in setting its policy instrument. Together, these assumptions imply that monetary policy shocks can be identified with the residuals in the ordinary least squares regression of the policy instrument on the predetermined variables.

The papers discussed in this section abandon different aspects of the recursiveness assumption. All of them drop the assumption that the Fed only looks at variables that are predetermined relative to the monetary policy shock. This implies that ordinary least squares is not valid for isolating the monetary policy shocks. Consequently, all these papers must make further identifying assumptions to proceed. The papers differ in whether they assume the existence of variables which are predetermined relative to the monetary policy shock. Sims and Zha (1998) assume there are no variables with this property. In contrast, papers like Sims (1986), Gordon and Leeper (1994), and Leeper, Sims and Zha (1996) assume that at least a subset of goods market variables are predetermined. Under their assumptions, these variables constitute valid instruments for estimating the parameters of the Fed's policy rule.

The section is organized as follows. First, we discuss the identifying assumptions in the paper by Sims and Zha (1998). We then compare their results with those obtained using the benchmark identification schemes. Finally, we briefly consider the analyses in the second group of papers mentioned above.

5.1. *A fully simultaneous system*

This section is organized as follows. In the first subsection we discuss the specification of the Sims and Zha (1998) (SZ) model and corresponding identification issues. In the second subsection, we compare results obtained with a version of the SZ model to those obtained using the benchmark policy shocks.

5.1.1. *Sims–Zha: model specification and identification*

We begin our discussion of the SZ model by describing their specification of the money supply equation. It is analogous to our policy function (2.1), with S_t identified with a short term interest rate, R_t. Sims and Zha (1998) assume that the only contemporaneous variables which the Fed sees when setting S_t are a producer's price index for crude materials (*Pcm*) and a monetary aggregate (*M*). In addition, the Fed is assumed to see a list of lagged variables to be specified below. Note that unlike the benchmark systems, Ω_t does not contain the contemporaneous values of the aggregate price level and output. As Sims and Zha (1998) point out, this is at best only a reasonable working hypothesis.[64] The reaction function in the SZ model can be summarized as follows:

$$R_t = \text{const.} + a_1 M_t + a_2 Pcm_t + f_S(Z_{t-1}, \ldots, Z_{t-q}) + \sigma \varepsilon_t^s, \tag{5.1}$$

where $f_S(Z_{t-1}, \ldots, Z_{t-q})$ is a linear function of past values of all the variables in the system, $q > 0$, $\sigma > 0$, and ε_t^S is a serially uncorrelated monetary policy shock.

Sims and Zha (1998) assume that Pcm and M are immediately affected by a monetary policy shock. As noted above, this rules out ordinary least squares as a method to estimate Equation (5.1). Instrumental variables would be a possibility if they made the identifying assumption that there exists a set of variables predetermined relative to the monetary policy shock. However, they are unwilling to do so. They make other identifying assumptions instead.

First, they postulate a money demand function of the form:

$$M_t - P_t - Y_t = \text{const.} + b_1 R_t + f_M(Z_{t-1}, \ldots, Z_{t-q}) + \sigma_M \varepsilon_t^M. \tag{5.2}$$

Here, $f_M(Z_{t-1}, \ldots, Z_{t-q})$ is a linear function of past values of all the variables in the system, $\sigma_M > 0$, and ε_t^M is a serially uncorrelated shock to money demand. Recall, Y_t and P_t denote aggregate output and the price level. Note that the coefficients on Y_t and P_t are restricted to unity. Sims and Zha display a model which rationalizes a money demand relationship like Equation (5.2).[65]

Second, they assume that Pcm_t responds contemporaneously to all shocks in the system. They motivate this assumption from the observation that crude materials prices are set in auction markets. Third, as noted above, they are not willing to impose the assumption that goods market variables like P and Y are predetermined relative to the monetary policy shock. Clearly, they cannot allow P and Y to respond to all shocks in an unconstrained way, since the system would then not be identified. Instead, they limit the channels by which monetary policy and other shocks have a contemporaneous effect on P and Y. To see how they do this, it is convenient to define a vector of variables denoted by X_t, which includes P_t and Y_t. Sims and Zha impose the restriction that X_t does not respond directly to M_t or R_t, but that it does respond to Pcm_t. A monetary

[64] This is because the Fed does have at its disposal various indicators of price and output during the quarter. For example, the Fed has access to weekly reports on unemployment claims and retail sales. Also, two weeks prior to each FOMC meeting, policymakers have access to the "Beige Book", which is compiled from nationwide surveys of business people. In addition, FOMC members are in constant contact with members of the business community. Moreover, the Fed receives, with a one month lag, various monthly measures of output and prices (e.g. employment, wages and the consumer price level).

[65] Their model rationalizes a relationship between the contemporaneous values of M_t, P_t, Y_t and S_t. One can rationalize the lagged terms in the money demand equation if there is a serially correlated shock to the marginal product of money in their model economy. Ireland (1997) and Kim (1998) rationalize similar relationships with Y replaced by consumption.

policy shock has a contemporaneous impact on the variables in X_t via its impact on Pcm_t.

To see this, first let

$$X_t = \begin{bmatrix} P_t \\ Y_t \\ W_t \\ Pim_t \\ Tbk_t \end{bmatrix}, \qquad Z_t = \begin{bmatrix} Pcm_t \\ M_t \\ R_t \\ X_t \end{bmatrix}.$$

where Pim denotes the producer price index of intermediate materials, W denotes average hourly earnings of nonagricultural workers, Tbk denotes the number of personal and business bankruptcy filings. The assumptions stated up to now imply the following restrictions on the matrix A_0 in representation (3.2) of Z_t:

$$A_0 = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} & a_{17} & a_{18} \\ 0 & a_{22} & a_{23} & -a_{22} & -a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 & 0 \\ a_{41} & 0 & 0 & a_{44} & a_{45} & a_{46} & a_{47} & a_{48} \\ a_{51} & 0 & 0 & a_{54} & a_{55} & a_{56} & a_{57} & a_{58} \\ a_{61} & 0 & 0 & a_{64} & a_{65} & a_{66} & a_{67} & a_{68} \\ a_{71} & 0 & 0 & a_{74} & a_{75} & a_{76} & a_{77} & a_{78} \\ a_{81} & 0 & 0 & a_{84} & a_{85} & a_{86} & a_{87} & a_{88} \end{bmatrix} \tag{5.3}$$

The first row of A_0 corresponds to the Pcm equation. The second and third rows correspond to the money demand equation (5.2), and to the monetary policy rule (5.1), respectively. The next five rows correspond to X_t. The second and third elements of ε_t in Equation (3.2) correspond to ε_t^M and ε_t^s.

It is evident from Equation (5.3) that the impact of a monetary policy shock operates on X_t via its influence on Pcm. Specifically, this reflects the fact that the $(4, 1)$ to $(8, 1)$ elements of A_0 are potentially nonzero. If we impose that these elements are zero, then, given the other zero restrictions in the second and third columns of A_0, the variables in X_t are predetermined relative to a monetary policy shock.

We now consider identification of the SZ model. Notice that the last five rows in A_0 have the same restrictions, suggesting that Equation (3.2) is not identified. To see that this is in fact the case, consider the following orthonormal matrix:

$$W = \begin{bmatrix} \underset{(3\times3)}{I} & \underset{(3\times5)}{0} \\ \underset{(5\times3)}{0} & \underset{(5\times5)}{\widetilde{W}} \end{bmatrix}, \tag{5.4}$$

where the dimensions are indicated in parentheses and $\widetilde{W}$ is an arbitrary orthonormal matrix. Note that if A_0 satisfies (i) the restrictions in Equation (5.3) and (ii) the relation

$A_0^{-1}\left(A_0^{-1}\right)' = V$, then WA_0 does too. Here, V denotes the variance covariance matrix of the fitted residuals in the VAR (3.1), for Z_t. By the identification arguments in Section 3, representation (3.2) with A_0 and with WA_0 are equivalent from the standpoint of the data. That is, there is a family of observationally equivalent representations (3.2), for the data. Each corresponds to a different choice of A_0.

We now discuss the implications of this observational equivalence result for impulse response functions. Recall from Equation (3.6) that, conditional on the B_i's characterizing the VAR of Z_t, the dynamic response functions of Z_t to ε_t are determined by A_0^{-1}. Also, note that $(WA_0)^{-1} = A_0^{-1}W'$. Two important conclusions follow from these observations. First, the impulse response functions of Z_t to the first three elements of ε_t are invariant to the choice of A_0 belonging to the set of observational equivalent A_0's defined above, i.e., generated using $W's$ of the form given by Equation (5.4). Second, the dynamic response functions to the last five elements of ε_t are not. To the extent that one is only interested in the response functions to the first three elements of ε_t, the precise choice of $\widetilde{W}$ is irrelevant. Sims and Zha choose to work with the A_0 satisfying Equation (5.3) and the additional restriction that the square matrix formed from the bottom right 5×5 matrix in A_0 is upper triangular.[66] The corresponding dynamic response functions of Z_t to the last five shocks in ε_t simply reflect this normalization.

We now make some summary remarks regarding identification of the SZ model. In Section 3 we discussed an order condition which, in conjunction with a particular rank condition, is sufficient for local identification. According to that order condition, we need at least 28 restrictions on A_0. The restrictions in Equation (5.3), along with the normalization mentioned in the previous paragraph, represent 31 restrictions on A_0. So, we satisfy one of the sufficient conditions for identification. The rank condition must be assessed at the estimated parameter values. Finally, to help guarantee global identification, Sims and Zha impose the restriction that the diagonal element of A_0 are positive.

5.1.2. Empirical results

We organize our discussion of the empirical results around three major questions. First, what are the effects of a contractionary monetary policy shock using the SZ identification scheme? Second, how do these effects compare to those obtained using the benchmark identification scheme? Third, what is the impact on Sims and Zha's (1998) results of their assumption that the variables in X_t respond contemporaneously to a monetary policy shock?

[66] The A_0 matrix is contained in the set of observationally equivalent A_0's as long as that set is non-empty. To see this, suppose there is some A_0 that satisfies (i) Equation (5.3) and (ii) the relation $A_0^{-1}\left(A_0^{-1}\right)' = V$. Let QR denote the QR decomposition of the lower right 5×5 part of this matrix $\tilde{a}$. The 5×5 matrix Q is orthonormal and R is upper triangular. Then, form the orthonormal matrix W as in Equation (5.4), with $\widetilde{W} = Q'$. The matrix WA_0 satisfies (i) and (ii) with the additional restriction on Equation (5.3) that the lower right 5×5 matrix in A_0W is upper triangular. This establishes the result sought.

To answer these questions, we employ a version of the SZ model in which M_t corresponds to $M2$ growth and R_t corresponds to the 3 month Treasury Bill Rate.[67] The four-lag VAR model was estimated using data over the period 1965Q3–1995Q2.[68] Our results are presented in column 1 of Figure 11. The solid lines correspond to our point estimates of the dynamic response of the variables in Z_t to a contractionary monetary policy shock. The dotted lines represent 95% confidence intervals about the mean of the impulses.[69] The main consequences of a contractionary SZ policy shock can be summarized as follows. First, there is a persistent decline in the growth rate of M2 and a rise in the interest rate. Second, there is a persistent decline in the GDP deflator and the prices of intermediate goods and crude materials. Third, after a delay, the shock generates a persistent decline in real GDP. Finally, note that the real wage is basically unaffected by the SZ policy shock. Comparing these results with those in Figure 2, we see that the qualitative response of the system to an SZ policy shock is quite similar to those in the benchmark *FF* and *NBR* systems. It is interesting to note that the estimated SZ policy shocks are somewhat smaller than the estimated benchmark *FF* policy shocks. For example, the impact effect of a benchmark *FF* policy shock on the federal funds rate is about 70 basis points, while the impact of a SZ policy shock on the three-month Treasury bill rate is about 40 basis points. At the same time, the SZ policy shock measure is roughly of the same order of magnitude as an *NBR* policy shock. In both cases a policy shock is associated with a forty basis point move in the federal funds rate.

We now turn to the third question posed above. We show that Sims and Zha's insistence that X_t is not predetermined relative to a monetary policy shock has essentially no impact on their results. To do this, we simply shut down the coefficients in A_0 which allow a monetary policy shock to have a contemporaneous impact on X_t and reestimate the system. Column 2 in Figure 11 reports the results. Comparing columns 1 and 2, we see that inference is virtually unaffected.

It is interesting to compare the SZ model with the analysis in Leeper et al. (1996). They work with a system that contains more variables. But, the fundamental difference is that they impose the assumption that goods market variables are predetermined

[67] The variable, *Tbk*, is not used in our analysis. Also, *SZ* measure M as the log level of $M2$. Comparing the estimated dynamic response functions to a monetary shock in our version of *SZ* with those in *SZ* it can be verified that these two perturbations make essentially no difference to the results.

[68] The variable, *Pcm*, was measured as the log of the producer price index for crude materials, SA; *Pim* is the logged producer price index for intermediate materials, SA; Y is logged GDP in fixed-weight 1987 dollars, SA; P is the logged GDP deflator derived from nominal GDP and GDP in fixed-weight 1987 dollars, SA; R is the three-month Treasury bill rate; and the change in the log of M2, SA. These data series are taken from the Federal Reserve Board's macroeconomic database. Logged average hourly earnings of private nonagricultural production workers are divided by the GDP deflator, SA, and are derived from the Citibase data set.

[69] These were computed using the procedure described in Sims and Zha (1995).

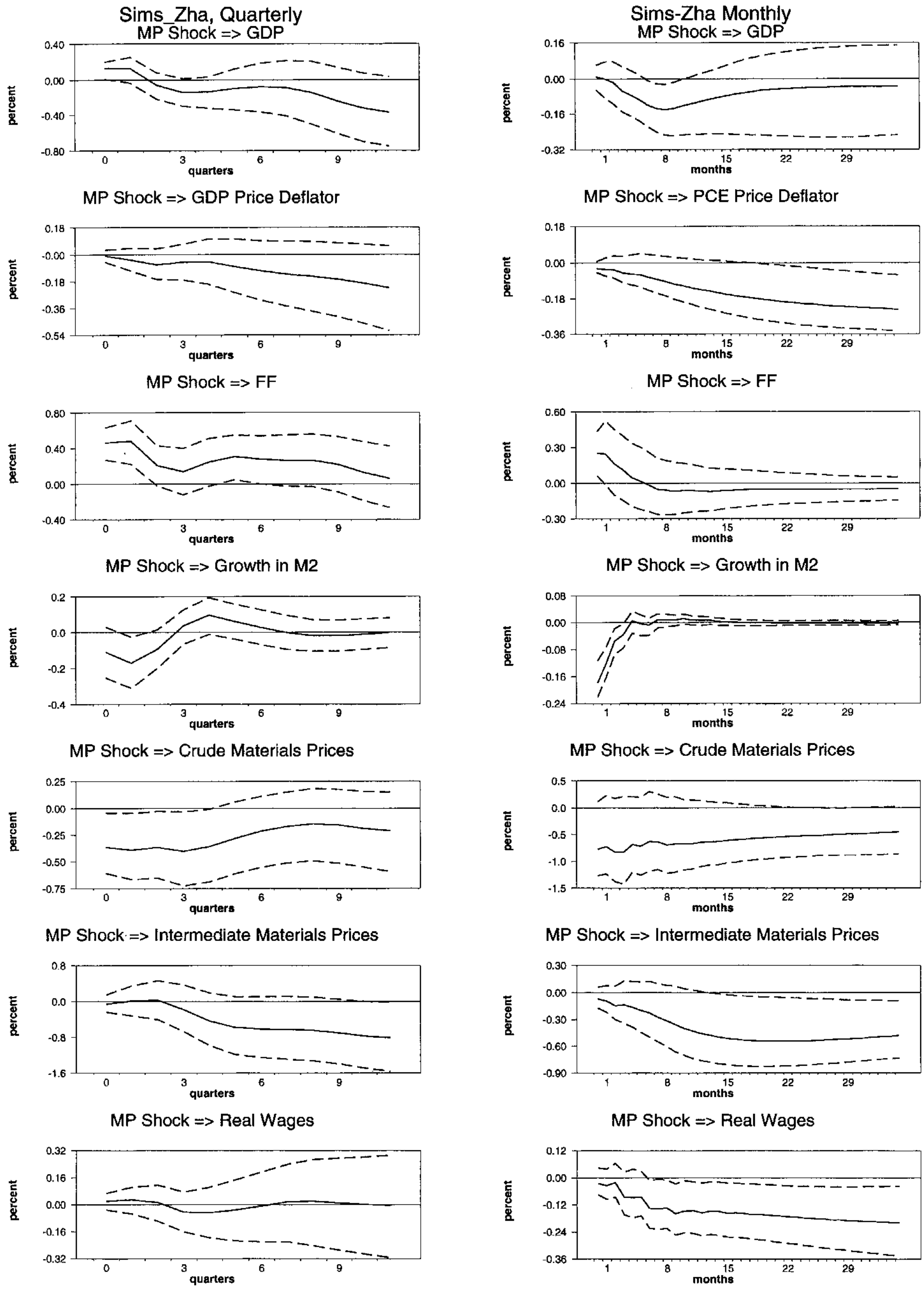

Sims_Zha, Quarterly
MP Shock => GDP
0.40
0.00
-0.40
-0.80
percent
0 3 6 9
quarters
Sims-Zha Monthly
MP Shock => GDP
0.16
0.00
-0.16
-0.32
percent
1 8 15 22 29
months
MP Shock => GDP Price Deflator
0.18
-0.00
-0.18
-0.36
-0.54
MP Shock => PCE Price Deflator
0.18
0.00
-0.18
-0.36
MP Shock => FF
0.80
0.40
0.00
-0.40
MP Shock => FF
0.60
0.30
0.00
-0.30
MP Shock => Growth in M2
0.2
0.0
-0.2
-0.4
MP Shock => Growth in M2
0.08
0.00
-0.08
-0.16
-0.24
MP Shock => Crude Materials Prices
0.25
0.00
-0.25
-0.50
-0.75
MP Shock => Crude Materials Prices
0.5
0.0
-0.5
-1.0
-1.5
MP Shock => Intermediate Materials Prices
0.8
0.0
-0.8
-1.6
MP Shock => Intermediate Materials Prices
0.30
0.00
-0.30
-0.60
-0.90
MP Shock => Real Wages
0.32
0.16
0.00
-0.16
-0.32
MP Shock => Real Wages
0.12
0.00
-0.12
-0.24
-0.36

Fig. 11.

relative to a monetary policy shock.[70] The response to a monetary policy shock of the variables that these analyses have in common is very similar. This is consistent with our finding that the absence of predeterminedness of good market variables in the SZ model is not important.

A number of other studies also impose predeterminedness of at least some goods market variables. These include Sims (1986), who assumes predeterminedness of investment, and Gordon and Leeper (1994), who assume all goods market variables and the 10 year Treasury rate are predetermined. Inference about the dynamic response of economic aggregates is very similar across these papers, Sims and Zha (1998), Leeper et al. (1996) and the benchmark systems.

6. Some pitfalls in interpreting estimated monetary policy rules

In Sections 4 and 5 we reviewed alternative approaches for identifying the effects of a monetary policy shock. A common feature of these different approaches is that they make enough identifying assumptions to enable the analyst to estimate the parameters of the Federal Reserves's feedback rule. A natural question is: why did we not display or interpret the parameter estimate? The answer is that these parameters are not easily interpretable.

In this section we describe three examples which illustrate why the estimated policy rules are difficult to interpret in terms of the behavior of the monetary authority. We emphasize, however, that the considerations raised here need not necessarily pose a problem for the econometrician attempting to isolate monetary policy shocks and their consequences.

The central feature of our examples is that the policy maker reacts to data that are different from the data used by the econometrician. In the first example, the decision maker uses error-corrupted data, while the econometrician uses error-free data. In the second and third examples the decision maker reacts to a variable that is not in the econometrician's data set. The policy rule parameters estimated by the econometrician are a convolution of the parameters of the rule implemented in real time by the policy maker and the parameters of the projection of the missing data onto the econometrician's data set. It is the convolution of these two types of parameters which makes it difficult to assign behavioral interpretations to the econometrician's estimated policy rule parameters.

Our first example builds on the measurement error example discussed in Section 2. We assume there is measurement error in the data used by real time policy makers, while the econometrician uses final revised data. We suppose $x_t + \upsilon_t$ corresponds to the

[70] In their description of the model, monetary policy shocks impact on the analog of X via a limited set of variables. In practice, however, they set the coefficients on these variables equal to zero. So, all their estimated systems have the property that the goods market variables are predetermined relative to the monetary policy shock.

raw data received by the primary data collection agency and that v_t reflects classical reporting and transmission errors that are uncorrelated with the true variable, x_t, at all leads and lags. In addition, we suppose that the reporting errors are discovered in one period, so that u_t in Equation (2.2) is zero. We assume that the data collection agency (or, the staff of the policy maker) reports its best guess, $\hat{x}_t$, of the true data, x_t, using its knowledge of the underlying data generating mechanism and the properties of the measurement error process.[71] Finally, suppose that x_t evolves according to

$$x_t = \rho_1 S_{t-1} + \rho_2 x_{t-1} + \omega_t,$$

where ω_t is uncorrelated with all variables dated $t-1$ and earlier. Suppose the data collection authority computes $\hat{x}_t$ as the linear projection of x_t on the data available to it. Then,

$$\hat{x}_t = P[x_t | S_{t-1}, x_t + v_t, x_{t-1}] = a_0 S_{t-1} + a_1(x_t + v_t) + a_2 x_{t-1}, \tag{6.1}$$

where the a_i's are functions of ρ_1, ρ_2, and the variances of ω_t and v_t. Now, suppose that the policy authority is only interested in responding to x_t, and that it attempts to do so by setting

$$S_t = \alpha \hat{x}_t \tag{6.2}$$

in real time. Substituting Equation (6.1) into this expression, we see that Equation (6.2) reduces to Equations (2.1) and (2.4) with

$$\beta_0 = \alpha a_0, \ \beta_1 = \alpha a_1, \ \beta_2 = \alpha a_2. \tag{6.3}$$

Notice how different the econometrician's estimated policy rule, (2.4) and (6.3), is from the real time policy rule (6.2). The β's in the estimated policy rule are a convolution of the behavioral parameter, α, the measurement error variance, and the parameters governing the data generating mechanism underlying the variables that interest the policy maker.[72] Also notice that an econometrician who estimates the policy rule using the recursiveness assumption will, in population, correctly identify the monetary policy shock with $\alpha a_1 v_t$.

This example shows how variables might enter f, perhaps even with long lags, despite the fact that the policy maker does not care about them *per se*. In the example, the variables S_{t-1} and x_{t-1} enter *only* because they help solve a signal extraction problem. Finally, the example illustrates some of the dangers involved in trying to give

[71] For a discussion of the empirical plausibility of this model of the data collection agency, see Mankiw et al. (1984), and Mankiw and Shapiro (1986).

[72] See Sargent (1989), for a discussion of how to econometrically unscramble parameters like this in the presence of measurement error.

a structural interpretation to the coefficients in f. Suppose a_0 and α are positive. An analyst might be tempted to interpret the resulting positive value of β_0 as reflecting a desire to minimize instrument instability. In this example, such an interpretation would be mistaken. Significantly, even though the estimated policy rule has no clear behavioral interpretation, the econometrician in this example correctly identifies the exogenous monetary policy shock.

For our second example, we assume that the policy maker responds only to the current innovation in some variable, for example, output. In particular suppose that,

$$S_t = \alpha e_t + \sigma_s \varepsilon_t^s,$$

where e_t is the innovation to which the policy maker responds, α is the policy parameter, and ε_t^s is the exogenous policy shock. Suppose that e_t is related to data in the following way, $e_t = \sum_{i=0}^{\infty} \beta_i x_{t-i}$, so that in Equation (2.1),

$$f(\Omega_t) = \alpha \sum_{i=0}^{\infty} \beta_i x_{t-i}.$$

Suppose the econometrician makes the correct identification assumptions and recovers $f(\Omega_t)$ exactly. An analyst with sharp priors about the number of lags in the policy maker's decision rule, or about the pattern of coefficients in that rule, might be misled into concluding that fundamental specification error is present. In fact, there is not. The disturbance recovered by the econometrician, $S_t - f(\Omega_t)$, corresponds exactly to the exogenous monetary policy shock.

Our final example is taken from Clarida and Gertler (1997) and Clarida et al. (1997, 1998). They consider the possibility that the rule implemented by the policy authority has the form $S_t = \alpha E_t x_{t+1} + \sigma_s \varepsilon_t^s$. In this case, $f(\Omega_t) = \alpha E_t x_{t+1}$, and Ω_t contains all the variables pertinent to the conditional expectation, $E_t x_{t+1}$. Assuming there is substantial persistence in x_t, f will contain long lags and its coefficients will be hard to interpret from the standpoint of the behavior of policy makers.[73]

These examples suggest to us that direct interpretation of estimated policy rules is fraught with pitfalls. This is why we did not discuss or report the estimated policy rules. Instead, we focused on dynamic response functions of economic aggregates to monetary policy shocks.

7. The effects of a monetary policy shock: the narrative approach

In the previous sections, we have discussed formal statistical approaches to identifying exogenous monetary policy shocks and their effects on the economy. The central

[73] Clarida et al. (1997, 1998) estimate the parameters of forward looking policy rules, so that in principle they can uncover interpretable parameters like α.

problem there lies with the identification of the exogenous monetary policy shock itself. As we discussed above, there are many reasons why shocks measured in this way may not be exogenous. These include all the reasons that policy rules, like (2.1), might be misspecified. For example, there may be subsample instability in the monetary policy rule, policymakers' information sets may be misspecified. In addition, the various auxiliary assumptions that must be made in practice, e.g., the specification of lag lengths, are always subject to question. Romer and Romer motivate what they call the narrative approach as a way of identifying monetary policy shocks that avoids these difficulties.[74]

This section is organized as follows. First, we discuss the specific identifying assumptions in Romer and Romer's analysis. Second, we contrast results obtained under their assumptions with the benchmark results reported above.[75]

Any approach that wishes to assess the effects of a monetary policy action on the economy must grapple with the endogeneity problem. Romer and Romer (1989) do so by identifying episodes (p. 134) "... when the Federal Reserve specifically intended to use the tools it had available to attempt to create a recession to cure inflation." They select such episodes based on records pertaining to policy meetings of the Federal Reserve. They interpret the behavior of output in the wake of these episodes as reflecting the effects of monetary policy actions and not some other factors. To justify this interpretation, they make and attempt to defend two identifying assumptions. First, in these episodes, inflation did not exert a direct effect on output via, say, the anticipated inflation tax effects emphasized in Cooley and Hansen (1989). Second, in these episodes inflation was not driven by shocks which directly affected output, such as supply shocks. These two assumptions underlie their view that the behavior of output in the aftermath of a Romer and Romer episode reflected the effects of the Fed's actions.

The Romer and Romer (1989) episodes are: December 1968; April 1974; August 1978; October 1979. We follow Kashyap et al. (1993) by adding the 1966 credit crunch (1966:2) to the index of monetary contractions. In addition, we add the August 1988 episode identified by Oliner and Rudebusch (1996) as the beginning of a monetary contraction.[76] For ease of exposition, we refer to all of these episodes as Romer and Romer episodes.

It is difficult to judge on a priori grounds whether the narrative approach or the strategy discussed in the previous sections is better. The latter approach can lead to misleading results if the wrong identifying assumptions are made in specifying the Fed's policy rule. A seeming advantage of Romer and Romer's approach is that one is not required formally to specify a Fed feedback rule. But there is no free lunch.

[74] They attribute the narrative approach to Friedman and Schwartz (1963).

[75] See Christiano et al. (1996b), Eichenbaum and Evans (1995) and Leeper (1997) for a similar comparison.

[76] In a later paper, Romer and Romer (1994) also add a date around this time.

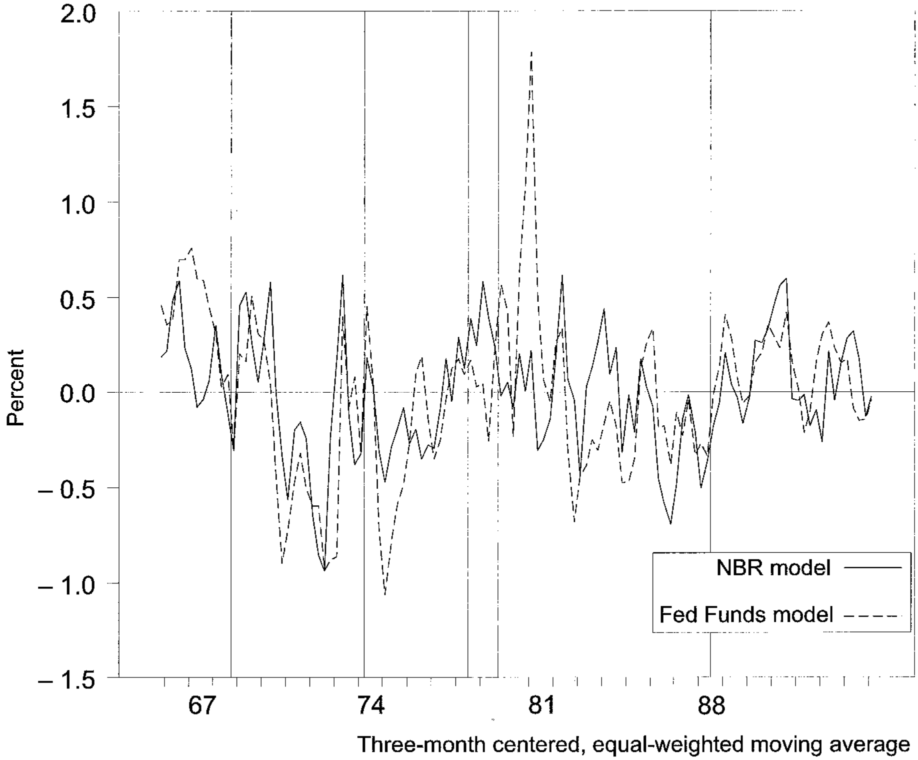


Fig. 12. Contractionary benchmark policy shocks in units of federal funds rate; three-month centered, equal-weighted moving average, with Romer dates.

As we pointed out, they too must make identifying assumptions which are subject to challenge. Shapiro (1994) for example challenges the usefulness of these dates on the grounds that they do not reflect an exogenous component of monetary policy. In his view, they reflect aspects of monetary policy that are largely forecastable using other macro variables. An additional shortcoming of the Romer and Romer approach, at least as applied to postwar monetary policy, is that it delivers only a few episodes of policy actions, with no indications of their relative intensity. In contrast, the strategy discussed in the previous section generates many "episodes", one for each date in the sample period, and a quantitative measure of the intensity of the exogenous shock for each date. So in principle, this approach can generate more precise estimates of the effects of a monetary policy shock.

It is of interest to compare the Romer and Romer episodes with the benchmark *FF* and *NBR* shocks. According to Figure 12, with one exception each Romer and Romer episode is followed, within one or two quarters, by a contractionary *FF* and *NBR* policy contraction. The exception is October 1979, which is not followed by a contractionary *NBR* policy shock.[77] At the same time, we identify several contractionary policy shocks which are not associated with a Romer and Romer episode.

We now turn to the issue of how qualitative inference is affected by use of the Romer and Romer index. To determine the impact of a Romer and Romer episode on the set of variables, Z_t, we proceed as follows. First, we define the dummy variable, d_t, to be one during a Romer and Romer episode, and zero otherwise. Second, we modify the benchmark VAR to include current and lagged values of d_t:

$$Z_t = A(L)\, Z_{t-1} + \beta(L)\, d_t + u_t. \tag{7.1}$$

Here, $\beta(L)$ is a finite ordered vector polynomial in nonnegative powers of L. We estimate Equation (7.1) using equation-by-equation least squares. For calculations based on quarterly data, the highest power of L in $A(L)$ and in $\beta(L)$ are 5 and 6, respectively. For calculations based on monthly data, the corresponding figures are 11 and 12. The response of Z_{t+k} to a Romer and Romer episode is given by the coefficient on L^k in the expansion of $[I - A(L)L]^{-1}\,\beta(L)$. To obtain confidence intervals for the dynamic response function of Z_t, we apply a version of the bootstrap Monte Carlo procedure used above which accommodates the presence of d_t in Equation (7.1). In principle, the right way to proceed is to incorporate into the bootstrap simulations a model of how the Fed and then Romer and Romer process the data in order to assign values to d_t. This task is clearly beyond the scope of this analysis. In our calculations, we simply treat d_t as fixed in repeated samples.

We also report results obtained using the monetary policy index constructed by Boschen and Mills (1991). Based on their reading of the FOMC minutes, Boschen and Mills rate monetary policy on a discrete scale, $\{-2, -1, 0, 1, 2\}$ where -2 denotes very tight and $+2$ denotes very loose. To look at the effects of this policy measure, we include it in our definition of Z_t and calculate the dynamic response of the variables in Z_t to an innovation in the Boschen and Mills index.

Figure 13 reports the monthly data based estimates of the dynamic response of various aggregates to a Romer and Romer shock and an innovation in the Boschen and Mills index. To facilitate comparisons, column 1 reproduces the dynamic response functions associated with our monthly benchmark *FF* policy shocks.

According to our point estimates, the qualitative responses to an *FF* policy shock and a Romer and Romer episode shock are quite similar: the federal funds rate rises, the price level is not much affected, at least initially, employment falls with a delay, *PCOM* falls, and all the monetary aggregates (*NBR*, *M*1 and *M*2) fall. It is interesting that the initial impacts of a Romer and Romer episode on employment

[77] We cannot estimate benchmark shocks for 1966:2 because of data limitations.

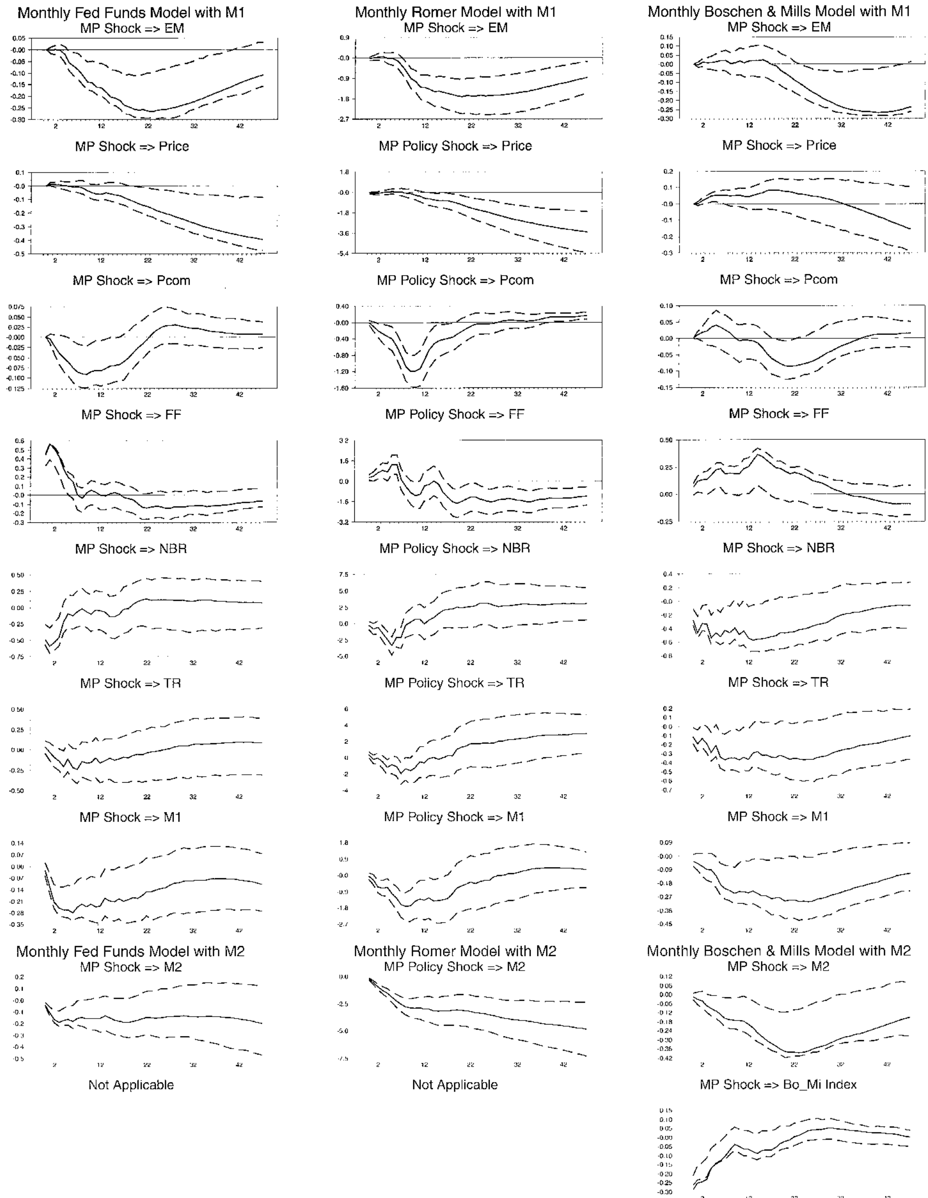


Fig. 13. The monthly data based estimates of the dynamic response of various aggregates to a Romer and Romer shock and an innovation in the Boschen and Mills index. To facilitate comparisons, column 1 reproduces the dynamic response functions associated with our monthly benchmark *FF* policy shocks.

and the price level are quite small. Unlike the identification schemes underlying the benchmark shock measures, this is not imposed by the Romer and Romer procedure. There are some differences between the estimated effects of the two shock measures. These pertain to the magnitude and timing of the responses. Romer and Romer episodes coincide with periods in which there were large rises in the federal funds rate. The maximal impact on the federal funds rate after a Romer and Romer episode is roughly 100 basis points. In contrast, the maximal impact on the federal funds rate induced by an *FF* policy shock is roughly 60 points. Consistent with this difference, the maximal impact of a Romer and Romer shock on employment, *PCOM*, *NBR*, *TR*, $M1$ and $M2$ is much larger than that of a *FF* policy shock. Finally, note that the response functions to a Romer and Romer shock are estimated less precisely than the response functions to an *FF* policy shock. Indeed, there is little evidence against the hypothesis that output is unaffected by a Romer and Romer shock.[78]

While similar in some respects, the estimated response functions to an innovation in the Boschen and Mills results do differ in some important ways from both the *FF* and Romer and Romer shocks. First, the impact of a Boschen and Mills shock is delayed compared to the impact of the alternative shock measures. For example the maximal increase in the federal funds rate occurs 14 months after a Boschen and Mills shock. In contrast, the maximal increase of the federal funds rate occurs 1 and 3 periods after an *FF* and Romer and Romer shock, respectively. Another anomaly associated with the Boschen and Mills response functions is the presence of a price puzzle: both *PCOM* and the price level rise for a substantial period of time after a contraction.

Figure 14 reports the quarterly data based estimates of the dynamic response of various aggregates to a Romer and Romer shock and an innovation in the Boschen and Mills index. The key finding here is that the qualitative properties of the estimated impulse response functions associated with the three policy shock measures are quite similar. Unlike the monthly results where employment initially rises in response to a Romer and Romer episode, there is no initial rise in aggregate output. The only major difference is that, as with the monthly data, the maximal impact of a Boschen and Mills shock measure on the federal funds rate is substantially delayed relative to the other two shock measures. Integrating over the monthly and quarterly results, we conclude that qualitative inference about the effects of a monetary policy shock is quite robust to the different shock measures discussed in this section.

[78] Romer and Romer report statistically significant effects on output. This difference could arise for two reasons. First, we include more variables in our analysis than do Romer and Romer. Second, we compute standard errors using a different method than they do.

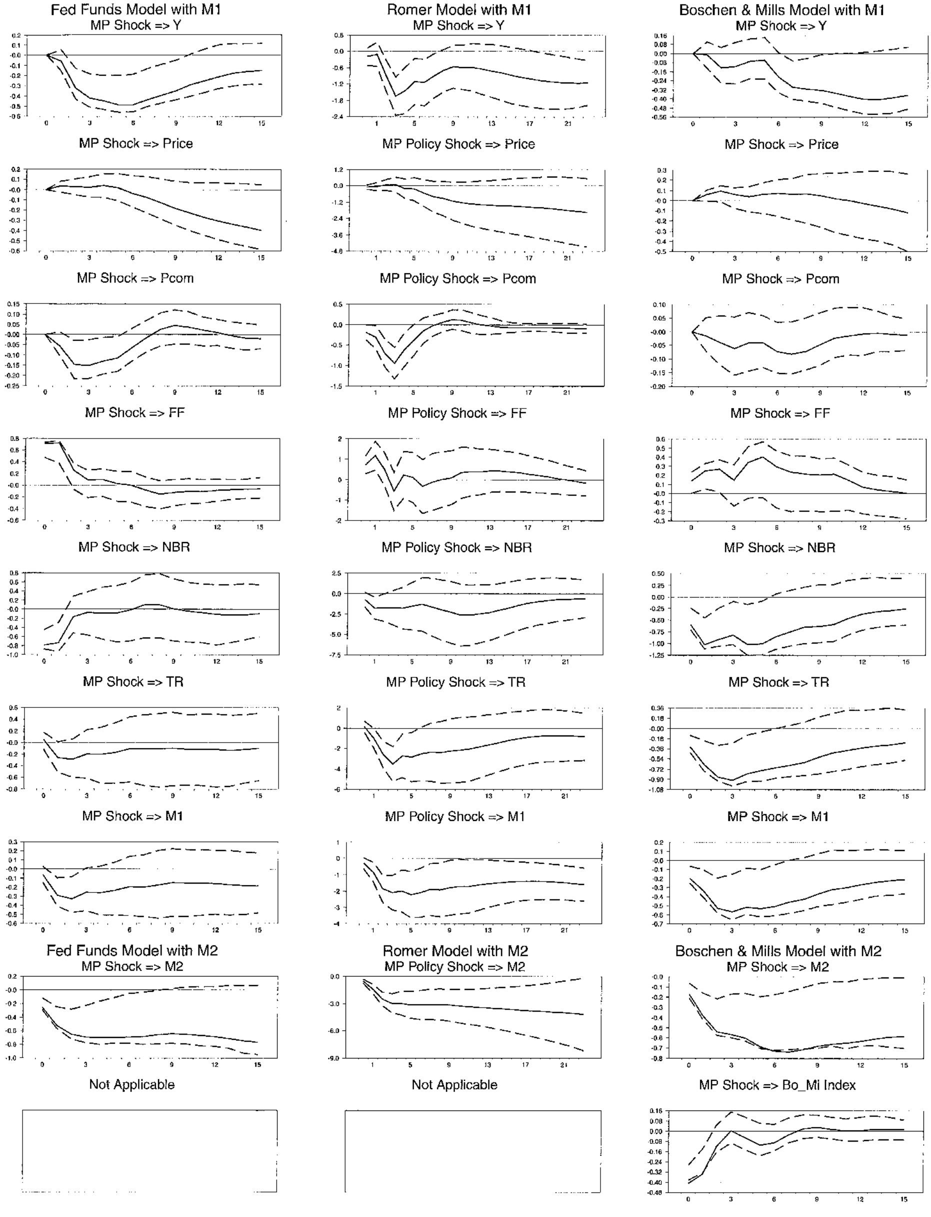


Fig. 14. The quarterly data based estimates of the dynamic response of various aggregates to a Romer and Romer shock and an innovation in the Boschen and Mills index.

8. Conclusion

In this chapter we have reviewed the recent literature that grapples with the question: What happens after a shock to monetary policy? This question is of interest because it lies at the center of the particular approach to model evaluation that we discussed: the Lucas program applied to monetary economics. The basic step in that program involves subjecting monetary models to a particular experiment: a monetary policy shock. Since alternative models react very differently to such a shock, this experiment can, in principle, be the basis of a useful diagnostic test. But to be useful in practice, we need to know how the actual economy responds to the analog experiment. Isolating these data based experiments requires identifying assumptions. We argued that qualitative inference about the effects of a monetary policy shock is robust across many, but not all the sets of identifying assumptions that have been pursued in the literature.

A key question remains: How can the results of the literature we reviewed be used to quantitatively assess the performance of a particular model? Much of the empirical literature on monetary policy shocks proceeds under the assumption that monetary policy is highly reactive to the state of the economy. In sharp contrast, analyses of quantitative general equilibrium models often proceed under much simpler assumptions about the nature of the monetary authority's reaction function. This leads to an obvious problem: unless the monetary policy rule has been specified correctly, the nature of the monetary experiment being conducted in the model is not the same as the experiment in the data.

One way to deal with the problem is to solve theoretical models using estimated reaction functions taken from the policy shock literature. There are two potential problems associated with this approach. First, and most importantly, it is often the case that models have multiple equilibria when policy is specified as a relationship between endogenous variables. Second, the complexity of estimated reaction functions makes it difficult (at least for us) to gain intuition for the way a monetary policy shock impacts on a model economy.

Christiano et al. (1997b) suggest an alternative approach to ensuring the consistency between model and data based experiments. The basic idea is to calculate the dynamic effects of a policy shock in a model economy under the following representation of monetary policy: the growth rate of money depends only on current and past shocks to monetary policy. Formally such a specification represents the growth rate of money as a univariate, exogenous stochastic process. However this representation *cannot* be developed by examining the univariate time series properties of the growth rate of money, say by regressing the growth rate of money on its own lagged values. Instead the representation must be based on the estimated impulse response function of the growth rate of money to a monetary policy shock.

The rationale underlying the proposal by Christiano et al. (1997b) is as follows. To actually implement a particular monetary policy rule, the growth rate of money *must* (if only implicitly) respond to current and past exogenous shocks in an appropriate way. This is true even when the systematic component of policy is thought of as a relationship between endogenous variables, like the interest rate, output and inflation. The literature on monetary policy shocks provides an estimate of the way the growth rate of money actually does respond to a particular shock – a monetary policy shock. For concreteness we refer to the estimated impulse response function of the growth rate of money to a policy shock as "the exogenous monetary policy rule".[79]

Suppose that an analyst solves a monetary model under the assumption that policy is given by the exogenous policy rule. In addition, suppose that the model has been specified correctly. In this case, the dynamic responses of the model variables to a policy shock should be the same as the dynamic response functions of the corresponding variables to a policy shock in the VAR underlying the estimate of exogenous policy rule [see Christiano et al. (1997b)]. This is true even if the monetary policy shock was identified in the VAR assuming a policy rule that was highly reactive to the state of the economy. So, the empirical plausibility of a model can be assessed by comparing the results of an exogenous policy shock in the model to the results of a policy shock in a VAR.

It is often the case that a model economy will have multiple equilibria when policy is represented as a relationship between endogenous variables. Each may be supported by a different rule for the way the growth rate of money responds to fundamental economic shocks. Yet, for any given rule relating the growth rate of money to these shocks, it is often (but not always) the case that there is a unique equilibrium [see Christiano et al. (1997b) for examples]. Under these circumstances the proposal by Christiano et al. (1997b) for evaluating models is particularly useful. The monetary policy shock literature tells us which exogenous policy rule the Fed did adopt and how the economy did respond to a policy shock. These responses can be compared to the unique prediction of the model for what happens after a shock to monetary policy. However, it is unclear how to proceed under a parameterization of monetary policy in which there are multiple equilibria.

We conclude by noting that we have stressed one motivation for isolating the effects of a monetary policy shock: the desire to isolate experiments in the data whose outcomes can be compared with the results of analog experiments in models. Authors like Sims and Zha (1998) and Bernanke et al. (1997) have pursued a different motivation. These authors argue that if the analyst has made enough assumptions to isolate another fundamental shock to the economy, then it is possible to understand the consequences of a change in the systematic way that monetary policy responds to that shock, even in the absence of a structural model. Their arguments depend in a critical way on ignoring the Lucas critique. This may or may not be reasonable in their particular applications. We are open minded but skeptical. For now we rest our

[79] Christiano et al. (1997b) argue that a good representation for the exogenous monetary policy rule relating the growth rate of $M1$ to current and past policy shocks is a low order MA process with a particular feature: the contemporaneous effect of a monetary policy shock is small while the lagged effects are much larger. In contrast, the dynamic response function of the growth rate of $M2$ to current and past policy shocks is well approximated by an $AR(1)$ process.

case for the usefulness of the monetary policy shock literature on the motivation we have pursued: the desire to build structural economic models that can be used to think about systematic changes in policy institutions and rules.

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