What Does Monetary Policy Do?

by Eric M. Leeper, Christopher A. Sims, and Tao Zha[1]

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1. Introduction

There is a long tradition in monetary economics of searching for a single policy variable—perhaps a monetary aggregate, perhaps an interest rate—that is more or less controlled by policy and stably related to economic activity. Whether the variable is conceived as an "indicator of policy" or a "measure of policy stance", correlations between it and macro time series are taken to reflect the effects of monetary policy. Conditions for the existence of such a variable are stringent. Essentially policy choices must evolve autonomously, independently of economic conditions. Even the harshest critics of monetary authorities would not maintain policy decisions are unrelated to the economy. The line of work we extend builds on a venerable econometric tradition to emphasize the need to specify and estimate behavioral relationships for policy. The estimated relationships separate the regular response of policy to the economy from the response of the economy to policy, arriving at a more accurate measure of the effects of policy changes.

One sometimes encounters a presumption that models for "policy analysis" and "forecasting" are sharply distinct. A model useful for policy choice need not fit data well and well-fit models necessarily sacrifice economic interpretability. We do not share this presumption, and aim here to show that it is possible to construct economically interpretable models with superior fit to the data.

As the recent empirical literature on the effects of monetary policy has developed ways of handling more complex, multivariate data sets, a variety of models and approaches has emerged. Researchers have chosen different data sets, made different assumptions, and tended to emphasize the differences between their results and those of others, rather than the commonalities. This paper uses a single time frame and data set to test the robustness of results in this recent literature and to trace the nature and sources of differences in conclusions.

We analyze and interpret the data in ways that do not impose strong economic beliefs. The methods we employ permit estimation of large time series models, allowing more comprehensive analysis of the data. Some of the models integrate policy behavior with the banking system, the demand for a broad monetary aggregate, and a rich array of goods and financial market variables, providing a more complete understanding of the monetary transmission mechanism. Weak economic assumptions and large models combine to reveal difficulties with sorting out policy effects that other approaches fail to bring out.

The size of effects attributed to shifts in monetary policy varies across specifications of economic behavior. We show, though, that most of the specifications imply that only a modest portion (or in some cases, essentially none) of the variance of output or prices in the US since 1960 is attributable to shifts in monetary policy. Furthermore, we point out substantive problems in the models that imply large real effects, and argue that correcting these problems lowers the implied size of the real effects.

Another robust conclusion, common across these models, is that a large fraction of the variation in monetary policy instruments is attributable to systematic reaction by policy authorities to the state of the economy. This is of course what we would expect of good monetary policy, but it is also the reason why using the historical behavior of aggregate time series to uncover the effects of monetary policy is difficult.

2. Method

Our work uses a class of models, called "identified vector autoregressions", that has begun to be widely used only recently. Nonetheless a considerable part of previous empirical research on the effects of monetary policy uses methods that fit within this general framework. In this section we describe the framework itself, summarize its differences from other widely used frameworks, and consider some common criticisms of the framework. In the following section we discuss the ways we and others have put substantive meat on the abstract skeleton of a method we discuss in this section.

2.1 Model Form

We use a class of models called "identified vector autoregressions." These models break up the variation in a list of time series into mutually independent components, according to the following general scheme. If $y(t)$ is a $k \times 1$ vector of time series, we write

$$\sum_{s=0}^{m} A_s y(t-s) = A(L)y(t) = e(t) \ , \tag{1}$$

where the disturbance vector $e(t)$ is uncorrelated with $y(s)$ for $s < t$ and has an identity covariance matrix.[2] We assume A_0 is invertible, which guarantees that we can solve (1) to produce

$$y(t) = \sum_{s=0}^{t-1} C_s e(t-s) + E_0 y(t) \ . \tag{2}$$

The elements of C_s, treated as functions of s, are known as the model's *impulse responses*, as they delineate how each variable in y responds over time to each disturbance in e.[3]

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[2] Note that we have omitted any constant terms in the system. There is no loss of generality if we admit the possibility that one of the equations takes the form $y_k(t) = y_k(t-1)$, with no error term, in which case y_k becomes the constant.

[3] We write here as if we were sure that a correct model can be constructed in the form of (1) and (2) with our list of variables. Of course if we have omitted some important variable, this assumption may be incorrect. A related, but technically more subtle, point has been made by Sargent [1984], who points out that a representation of the form (2) may exist for the variable list, yet the corresponding form (1) may not be available. This occurs when C in (2) is not what engineers call a "minimum delay filter". Intuitively, it occurs when the variables in y do not respond quickly enough to e. While this is an important point, it is really a special case of the point that we can obtain misleading results by not having the right variable list.

2.2 Identification

To use this mathematical structure for economic policy analysis we have to *identify* it, meaning we have to give its elements economic interpretations.[4]   The mathematical model explains all variation in the data as arising from the independent disturbances *e*. Since in this paper we are studying the effects of monetary policy, we need to specify an element of the *e* vector, or a list of its elements, that represents disturbances to monetary policy. The equation system (1) contains one equation for each element of the *e* vector, defining it as a function of current and past values of $y(t)$. So specifying the element or elements of *e* that correspond to monetary policy is equivalent to specifying an equation or set of equations that characterizes monetary policy behavior. These equations can be thought of as describing relations among current and past *y*'s that hold exactly when there are no disturbances to policy. They are, in other words, policy rules or reaction functions. The remaining equations of the system describe the non-policy part of the economy, and their disturbances are non-policy sources of variation in the economy.

While representations of the behavior of the *y* time series in the form (1) and (2) exist under fairly general conditions, they are not unique. That is, models in this form with different *A* and (therefore) *C* coefficients may imply exactly the same behavior of *y*. Because the implications of the model for the effects of a change in monetary policy are determined by *A* and *C*, this means that models with different policy implications may be indistinguishable on the basis of their fit to the data. When this is true, the model is said to be *unidentified*. The nature of the non-uniqueness is as follows. Given any matrix *W* satisfying $W'W = I$, i.e. any *orthonormal* matrix, we can replace *e* by We, $A(L)$ by $WA(L)$, and $C(L)$ by $C(L)W'$, arriving at a new representation of the same form. Since the new version of the model is just a linear transformation of the old one, it implies the same time series properties for the data *y*. Only if we know enough about the form of *A* (or, equivalently, *C*) to rule out some transformed *WA*'s or CW''s as implausible or impossible will the data be able to lead us to the most likely form of *A*.

We use three sorts of restrictions in order to pin down the connection between *A* and the implied behavior of *y*. That is, we use three sorts of identifying restrictions. One is exact linear restrictions on the elements of A_0, usually setting certain elements to zero. If we rely entirely on these, we know that we will need at least $k \cdot (k-1)/2$ of them, because a $k \times k$ orthonormal matrix has this many free parameters. Once we have this number of restrictions on the elements of A_0, the restriction equations, together with the $k \cdot (k+1)/2$ independent restrictions in the

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[4] "Identified" is used in various senses in economics. Sometimes an identified model means, as in this paragraph, a model that has an economic interpretation, as opposed to a "reduced form" model that merely summarizes the statistical properties of the data. But in other contexts a model is said to be identified only when data to be used in fitting it are informative about its behavioral interpretation.   Often, but not always, this is a situation where more than one behavioral interpretation can be given to the same reduced form. We follow common practice in using the word in both ways, depending on the context.

W′W = *I* requirement, are enough equations to make *W* unique.[5]   Another sort of identifying restriction is probabilistic assertions about elements of *A* – assertions that certain values or relations among values of elements of *A* are more likely than others. And the third is informal restrictions on the reasonableness of the impulse responses, the *C*'s in (2). The first two types are easy to handle mathematically, while the latter is difficult mathematically. It is used informally, in that we focus attention on results that do not produce implausible impulse responses. Our criterion for plausibility is loose. We do not expect to see strongly positive responses of prices, output, or monetary aggregates, or strongly negative responses of interest rates, to monetary contraction. The fact that we use this sort of identifying information informally may give the impression that we are doing undisciplined data mining. But we could have done the same thing, at much more computational cost, by imposing our beliefs in the forms of impulse responses as precise mathematical restrictions. This would not have been any more "disciplined" than our actual procedure. Our procedure differs from what empirical researchers in economics always do only in being possibly less apologetic. Economists adjust their models until they both fit the data and give "reasonable" results. There is nothing unscientific or dishonest about this. What would be unscientific or dishonest would be hiding results for models that fit much better than the one displayed (even if the hidden model seemed unreasonable) or for models that fit about as well as those reported and that support other interpretations of the data that some readers might regard as reasonable. We are doing nothing of this sort.

Our approach to identification here is very similar to that of the rest of the identified VAR literature, but it differs from some other approaches to quantitative macroeconomics. The differences correspond in some cases to criticisms that those taking other approaches often make of the identified VAR approach.

2.3 Comparison to Other Approaches

Traditional econometric simultaneous equations (SE) modeling works with systems quite similar in form to those we deal with. It begins with a system in the form (1), usually with our assumption that the **e** vector is uncorrelated across time, and always without our assumption that **e** has an identity covariance matrix. With an unrestricted Ω as covariance matrix for **e**, the mathematical structure is subject to a wider range of transformations that leave the implications of the model for data unchanged. While the identified VAR framework admits an arbitrary orthonormal *W* as a transformation matrix, the standard simultaneous equations framework admits an arbitrary non-singular matrix *V* in the same role. So in order to pin down the mapping between **e** and the data, stronger a priori restrictions on *A* are required in the SE approach. Traditionally these take two forms.   One form is block triangularity restrictions on contemporaneous interactions among variables (A_0 from (1)) that are linked to conformable block diagonality restrictions on Ω.   Such a combination of restrictions breaks the variable list into two components, one usually labeled "predetermined", the other labeled "endogenous".   The second

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[5] This is an order conditions, analogous to the order condition for identification in SE modeling. As in SE modeling, there is always a possibility that there are enough equations, but they fail to be independent, so that a rank condition fails while an order condition holds.

form of traditional restriction then adds linear constraints (again, often simply setting coefficients to zero) on the elements of the rows of A corresponding to the endogenous variables.

To get a feeling for the difference in requirements for identification between identified VAR's and traditional simultaneous equations, it may help to consider the simplest possible model. In a two-equation system with no lags, a single zero restriction on A_0 suffices for identification in the identified VAR framework. That is, the system

$$a_{11}y_1(t) + a_{12}y_2(t) = \mathbf{e}_1(t)$$
$$a_{22}y_2(t) = \mathbf{e}_2(t) \quad , \tag{3}$$

in which we have imposed the single constraint $a_{21} = 0$, has a unique mapping from A to the stochastic properties (here just the covariance matrix) of y. The y vector is implied to have a covariance matrix $\Omega = A_0 A_0'$, and A_0 can be found from Ω as its unique upper triangular square root, or Choleski decomposition. If (3) is interpreted as a traditional simultaneous equations system, however, it is not identified – arbitrary linear combinations of the two equations satisfy all the restrictions (since there are none) on the form of the first equation, while leaving the implications of the system for the behavior of y unchanged. A nonsingular linear transformation of the system can replace the first equation by a linear combination of the two equations, while leaving the second equation unchanged. An orthonormal linear transformation must change both equations at once, in order to preserve the lack of correlation of the disturbances. This is why the system is not identified as a standard SE model, while it is identified as our type of identified VAR model. This kind of system, called recursive, is a well-recognized special case in the simultaneous equations literature.[6] In this two-variable version, a single linear restriction on any of the four coefficients in A_0, together with the usual identified VAR restriction that the $\mathbf{e}$'s are uncorrelated, is equivalent to the traditional SE modeling assumption that one of the variables in the system is predetermined.

Impulse responses can be computed for traditional SE models as well as for identified VAR's. The restriction that in an identified VAR we have $\mathrm{Var}(\mathbf{e}) = I$, though, means that in some circumstances conclusions about model behavior are less dependent on identifying assumptions on A in identified VAR's than in SE models. Consider an example that arises in our discussion below. We might find that the rows of $C(L)$ corresponding to prices and interest rates (the first and second rows, say) mostly show prices and interest rates moving in the same direction when they show any substantial movement – $c_{1j}(s)$ and $c_{2j}(s)$ of the same sign for most j and s when either $c_{1j}(s)$ or $c_{2j}(s)$ is large. We might expect that the response to a monetary policy shock should show the opposite sign pattern, with $c_{1j}(s)$ and $c_{2j}(s)$ moving in opposite directions. Then we can conclude that monetary policy disturbances cannot account for much of the observed variation in prices and interest rates, regardless of what identifying restrictions we may invoke. It is true that linear transformations of the system will correspond to linear transformations of the disturbances. Some linear transformations, differences for example, of responses that have $c_{1j}(s)$ and $c_{2j}(s)$ of the same sign could easily show $c_{1j}(s)$ and $c_{2j}(s)$ of

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[6] See Theil [1971] Chapter 9.

opposite signs. But orthonormal transformations of responses that all show large, same-signed movements of $c_{1j}(s)$ and $c_{2j}(s)$ cannot produce transformed responses that are both opposite-signed and large. In other words, if most disturbances that produce substantial responses of interest rates show substantial prices in the same direction, then it is characteristic of the data that these two variables tend to move in the same direction. A monetary policy disturbance, which moves the two variables in opposite directions, cannot then be accounting for more than a small part of overall variance in interest rates. In a traditional SE model we could not reach the same conclusion, because we would have to admit the possibility that there could be a monetary policy shock with large variance, offset by another shock that also moves prices and interest rates in opposite directions but is negatively correlated with the monetary disturbance.

This brings out what we see as an advantage of insisting that a well-specified model accounts for all correlations among disturbances, so that they end up with an identity covariance matrix. When the historical record shows a very strong pattern of positive co-movement between interest rates and prices, then if we believe that monetary policy disturbances would generate negative co-movements, it is reasonable to conclude that monetary policy disturbances have not been a major source of variation in the data. Insistence that it could be true that monetary policy disturbances were important, but that they tend to be systematically offset by private sector disturbances that occur at the same time, seems strained. If this is the actual situation, it raises questions about the model. Do the offsetting private sector shocks occur because of an effect of monetary policy on the private sector shocks? If so, then in effect our model implies that once the full effects of a monetary policy disturbance are accounted for, it does not move interest rates and prices in opposite directions, which is suspicious. Do the offsetting shocks arise because of an effect of the private sector on policy-making? Then we ought to account for this as part of the model of policy behavior.

2.3.1 Objections to Identified VAR Modeling

It is sometimes suggested that disturbances are what is "omitted from the theory", and that therefore we cannot claim to know much about their properties. Note, though, that traditional predeterminedness assumptions make assertions about lack of correlation among sources of variation of just the sort made in identified VAR models. If we really know nothing about the stochastic properties of disturbance terms, we will not be able to distinguish disturbances from systematic components of variation. Furthermore, any actual use of models for policy analysis makes correlation among disturbances a serious embarrassment. If disturbances to the monetary policy reaction function are strongly correlated with private sector disturbances, how are we to use the system to simulate the effects of variations in monetary policy? The usual answer in practice is that simulations of the effects of paths of policy variables or of hypothetical policy rules are conducted under the assumption that such policy changes can be made without producing any change in disturbance terms in other equations, even if the estimated covariance matrix of disturbances shows strong correlations. This is not logically inconsistent, but it amounts to the claim that the true policy disturbance is that part of the reaction function residual that is not correlated with other disturbances in the system. This in turn is equivalent to the claim that the true reaction function is a linear combination of what the model labels as the reaction function and the other equations in the system whose disturbances are correlated with it. Our view is that if

one is going to do this in the end, the assumptions on the model that justify it should be explicit from the beginning.

Traditional SE modelers also sometimes find puzzling the focus on "policy shocks" in the identified VAR approach. This is largely a semantic confusion. As we have already pointed out, identifying policy shocks is equivalent to identifying equations for policy reaction functions. Also, distinguishing these shocks from other sources of disturbance to the system is equivalent to identifying the non-policy equations of the model, which determine the response of the system to policy actions or to changes in the policy rule. The prominent role given to discussion of shocks in presentations of identified VAR results just reflects a sharp focus on the model's characteristics as a probability model of the data. In practice traditional SE approaches often focus on the equations, with the remainder of the stochastic structure treated casually. Identified VAR results are often presented as tables or charts of "responses to shocks", the C's in (2). But these carry exactly the same information about the model as the A's in (1), the "equation coefficients" that are more commonly presented in traditional SE modeling approaches. Of course presentations of SE models also often include simulations of the model with various kinds of perturbations fed into it. The C's can be thought of as a systematic set of simulations, of responses to a range of types of disturbance wide enough to display all aspects of the model's behavior

Another branch of quantitative macroeconomics, the dynamic stochastic general equilibrium (DSGE) approach,[7] criticizes identified VAR modeling for resembling traditional SE modeling too closely. Traditional SE models in practice generally contain expectational terms that are modeled as linear functions of past data. The models were sometimes used to examine the effects of making large, permanent changes in policy rules. The policy equations were replaced by possible new rules, and the model was simulated with the remaining equations, including the expectational terms, left in unchanged form. Such exercises are potentially misleading, because they contradict the probability structure of the estimated model. The model was fit to historical data under the assumption that the historical variation in policy can be accounted for by the model's stochastic disturbances – the additive error terms in the policy reaction functions. In the simulation experiment quite a different form of variation in policy is examined. If variations in policy of this form are not historically unprecedented, there is a misspecification in the model: something the model's structure implies is impossible has actually occurred in the past.

Recognizing this contradiction should remind us of the need for caution in extrapolating model results to predictions about situations far from what has been observed historically. It is not uninteresting to try changing the policy rule equations in the model, holding the other equations fixed, so long as we recognize that the changed policy rule equations are just a convenient way of generating an interesting sequence of disturbances to the originally estimated policy rule. When the implied sequence of policy rule disturbances (i.e., policy shocks) is very different in size or serial correlation properties from what has been observed historically, the model may become unreliable.

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[7] A more common label for this approach is the "real business cycle" approach. But while this approach began with models that contained no nominal rigidities and no role for monetary policy, its methodology has now been extended to models that include nominal rigidities, for example J. Kim [1996]

The DSGE literature has, surprisingly in the light of its connection to the idea of rational expectations, largely ignored this cautionary conclusion. Actual changes in monetary policy are recognized in advance by the public as possible policy actions. Since they are recognized in advance as possibilities, yet are not known with certainty to be occurring, when they do (or don't) occur the result is that a random variable is realized. One would think it is then a central conclusion of a rational expectations approach to policy analysis that the stochastic nature of policy changes is always important to correct analysis of their effects. A starting point for rational expectations analysis of policy changes over time should be recognition that they should always be modeled as sequences of values for disturbance terms.

Yet instead, the DSGE approach has often embraced the idea that the only kinds of policy changes worth studying are changes that are historically unprecedented, occur as complete surprises to the agents populating the model, and are sure never to be reversed. If a change in the policy reaction function is of this type, DSGE models do give an internally consistent answer as to the effects of the policy change. But the need for caution is still as great as with traditional SE models. Any evidence in the data about the effects of such an unprecedented policy shift has to be entirely indirect, an extrapolation based on a priori assumptions to a range of experience outside the range to which the model has been fit. And the results, despite being internally consistent, are answers to an uninteresting question. DSGE models as they are usually used in policy analysis describe the effects of policy changes of a type that never in fact occurs. These days the models that have evolved from traditional SE models often trace out the effects of non-stochastic shifts in policy reaction functions using rational expectations, just as do most DSGE modelers. Though the two types of models make very different choices in the tradeoffs among model abstraction, internal consistency, and fit to the data, the inherent limitations of simulating non-stochastic shifts in policy rules are common to both DSGE and the newer SE-style models.[8]

Note that there is a common thread in criticism of the identified VAR approach from the SE modeling side and the DSGE modeling side: both sides show discomfort with the notion of treating policy as "random". Some people have the idea that we cannot contemplate improving policy as if we could choose it rationally and at the same time think of it as a random variable. This notion is simply incorrect. When we consider historical policy decisions, we have to recognize that policy pursues multiple objectives in an uncertain environment. Economists at the Board of Governors and Federal Reserve Banks collect and analyze a large set of economic information on which the Federal Open Market Committee bases its decisions. Committee members compare staff forecasts of a wide range of macro variables to the members' desired paths for these variables. Each member's policy choice minimizes a loss function subject to a set of ancillary constraints, such as a desire to smooth interest rates and avoid disrupting financial markets. Federal Reserve policy is an outgrowth of both the members' economic concerns and the dynamic interplay among members. The result of this process is surely as "random" as any other aspect of economic behavior that we might try to model.

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[8] Examples of newer SE style models are Bryant [1991], Bryant, Hooper and Mann [1993], Taylor [1993], and in principle the new model described in Federal Reserve Board [1996]. The new Federal Reserve Board model included as an important design goal the ability to simulate both deterministic rule shifts with rational expectations and policy changes modeled as shocks to the existing rule.

When we consider offering advice on current or future policy decisions, we of course would not ordinarily propose flipping a coin to choose policy, but this does not mean that it is a mistake to think of policy choice as the realization of a random variable. Choices that are made systematically by one person or group are likely still to be unpredictable from the perspective of others. If, in a break with the past, monetary policy were to begin being set by a single, internally consistent, rational policy maker, this would be surprising to the public, and they would most likely remain uncertain for some time that the new pattern would persist. Even if we think of our modeling efforts as addressed to such a hypothetical unified rational policy maker, then, we would want to model policy choices as realizations of random variables in tracing their impact on the economy.

People who use models for policy analysis have generally understood DSGE-style analysis of non-stochastic changes in policy rule as characterizing effects of policy changes in the long run and understood analysis of the effects of policy shocks, with the reaction function equation fixed, as characterizing short run effects.[9] This is a reasonable interpretation, by and large. It recognizes that, if we can realistically contemplate changing coefficients in policy reaction functions that are treated in the model as non-stochastic, this is a source of inaccuracy in the model, requiring caution in "long run" extrapolations. It also recognizes that DSGE-style analysis of policy rule shifts, because it models policy as non-stochastic, cannot be applied to projecting the effects of policy changes of the type, and over the time horizons, that are the main subject of policy discussion. Ideally, we would like a model without either sort of limitation, whose stochastic characterization of policy behavior encompassed shifts in policy of all the kinds we actually consider. In such a model every interesting and plausible policy change, including ones that seem naturally described as changes in policy "rule", would be expressible as a sequence of shocks to the model's driving random variables. There are a few models in the literature that go some way toward this goal, modeling policy as switching between linear rules with additive errors according to some well defined Markov process, for example. But the analytical difficulties raised by even simple models like this are substantial.

We should add that this sharp contrast between DSGE modelers' approach to analysis of policy changes and our own reflects only a difference between common practice of DSGE modelers and our own methods. There is nothing in principle that ties DSGE models to the approach that has commonly been taken by DSGE modelers to policy analysis. Indeed Leeper and Sims [1994] and J. Kim [1996] are examples of DSGE models in which careful attention is paid to modeling the stochastic structure of policy and in which therefore the effects both of stochastic disturbances to policy and of deterministic changes in policy rule can be examined.

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[9] Another way of characterizing the distinction that one sometimes hears from policy analysts labels the effects of policy shocks, with the policy equation coefficients fixed, as the effects of "unanticipated" policy changes, and the effects of non-stochastic changes in policy rule as the effects of "anticipated" or "credible" policy changes. We regard this distinction as much less helpful than the long and short run distinction. It may encourage the idea that there is in fact some choice as to whether policy changes are to be credible when first announced or not. In fact, credibility arises only out of a consistent pattern of action.

There is also no fundamental conflict between the mathematics of our modeling approach in this paper and that of DSGE models. Most DSGE models are of course nonlinear, whereas ours our linear, but nonlinearities in DSGE models are usually not strong. Indeed one common approach to solving and fitting DSGE models to data is to take a linear approximation to them around a steady state. A linearized DSGE model becomes a VAR model, with a particular pattern of identifying restrictions on its coefficients. Linearized DSGE models are generally much more strongly restricted than identified VAR models, so that they involve many fewer free parameters to estimate. However the kinds of restrictions that are used to identify VAR models are often imposed as a subset of the restrictions used in DSGE models, so that identified VAR models can be thought of simply as weakly restricted DSGE models.

This is what in fact distinguishes DSGE from identified VAR modeling approaches. The former begins with a complete interpretation of each source of stochastic disturbance in the model, invoking many conventional but arbitrary restrictions on functional forms of utility and production functions and on stochastic properties of disturbances. The fitted model then has a full story to tell about how each source of disturbance affects the economy and the routes by which it does so. The identified VAR modeling approach instead begins with an unidentified time series model of the economy and introduces identifying information cautiously. The fitted model then fits the data well, usually much better than DSGE models of the same data, but has only an incomplete story to tell about how each source of disturbance affects the economy and the routes by which it does so. In an identified VAR typically many sources of disturbance are not completely interpreted, identified only as part of a vector of "private sector shocks", for example, that may mix technology shocks and taste shocks. The effects of monetary policy disturbances on the economy may be traced out, but complete stories as to how the effects work their way through the behavior of investors and consumers may not be available.

Each approach has its advantages and disadvantages. The identified VAR approach may give a more accurate impression of the true degree of uncertainty about results that emerge from the model. It also reduces the chance that we will be misled into thinking the data imply a result that actually flows almost entirely from initial ad hoc modeling assumptions. On the other hand, the identified VAR approach does not provide as convenient a framework for bringing to bear a priori knowledge or hypotheses about the structure of the economy.

Our conclusion after considering alternatives to and criticisms of the identified VAR approach is that such strictly linear, weakly identified models do have limitations. We would be uncomfortable extrapolating our estimates of policy effects to regimes of hyperinflation or to very different fiscal policy environments, for example.[10] But we regard it as an advantage, not a defect, of our approach that it recognizes the stochastic nature of variation in policy.

2.4 Inference

We take the perspective of the likelihood principle in measuring model fit and assessing how well various hypotheses accord with the data. That is, we take the task of reporting efforts at statistical model-fitting to be the task of characterizing the shape of the likelihood function. Most

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[10] Actually, we would be equally uncomfortable extrapolating policy effects implied by DSGE models fitted or calibrated to US data to such situations. But for somewhat different reasons.

existing econometric procedures can be interpreted as reasonable from this perspective. However it is a different perspective than what is usually taught in econometrics courses, and it does have implications that should affect practice in some areas, particularly when, as in this paper, near-non-stationary models or models with large numbers of parameters are being considered. We do not have space here to elaborate on it, but interested readers can consult Berger and Wolpert [1988] for a general discussion of the principle and Gelman, Carlin, Stern and Rubin [1995] for an approach to applied statistical work that takes a likelihood-principle perspective.

As we discuss results below, we will not be presenting measures of model fit and testing the restrictions in the models. Such tests can be useful as part of describing the likelihood function, but the models we are dealing with are for the most part only weakly overidentified. That is, they are almost as unrestricted as an unidentified reduced form model. Accordingly, they tend to fit very well in comparison to such models, and this is neither surprising nor very powerful evidence in favor of the interpretations of the data that they embody. We do present error bands about the impulse responses we trace out for our models.[11] These are important, because often differences among models in the form of their implied responses to monetary policy shocks influence our conclusions about how reliable the models are. We would not want to be choosing among models on the basis of differences in their implied impulse responses if estimates of those responses were in fact not sharply determined.

In models as large as some of those we consider here, the likelihood function itself can be ill-behaved. This is related to the well-known tendency of estimates to become unreasonable when degrees of freedom are low. We therefore multiply all the likelihood functions we discuss by a probability density function that downweights models with large coefficients on distant lags or with explosive dynamics. This p.d.f. plays the formal role of a Bayesian prior distribution, but it is not meant to represent a summary of all prior information we might have about model parameters. It is meant only to reflect, in a transparent way, beliefs that are likely to be uncontroversial across a wide range of users of the analysis.[12] This makes it possible to discuss larger models than have been feasible with previous approaches. The details of our reference prior are described in the Appendix, and the methods we use are put in a more general context in Sims and Zha [1996].

3. Identifying Monetary Policy

The history of empirical work in this area is largely one of expanding model scale, with progress in understanding of models at one scale providing the basis for expansion to more complex models. Most of this history can be described in the identified VAR framework, though much of it pre-existed the codification of this framework. We also recognize that to some extent

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[11] These error bands have the interpretation that people usually give to error bands intuitively: They correspond to regions within which the impulse responses lie with some stated probability, given what we have discovered about the model from the data. This means they are not classical confidence bands or regions, which are very difficult to construct, and of dubious usefulness, for models like these. See Sims and Zha [1995] for further discussion.

[12] Such a p.d.f. is sometimes called a "reference prior". The details of our reference prior are laid out in the Appendix.
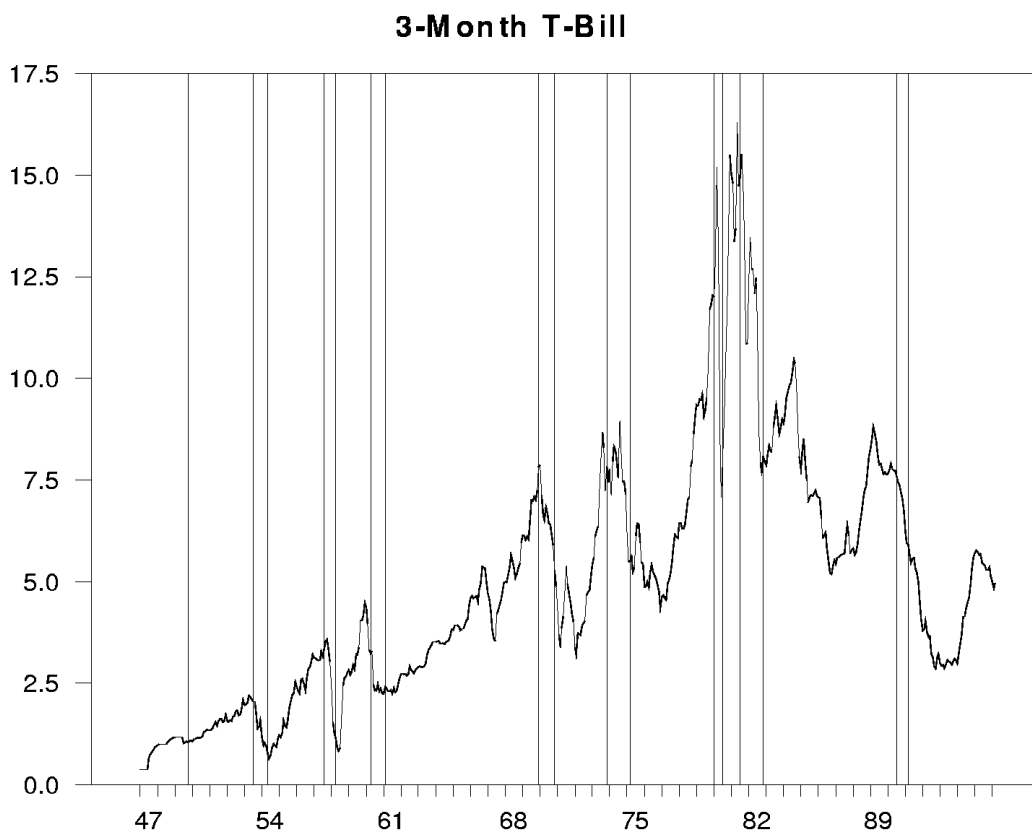
what we are describing is not an evolution over time, but a layering of evidence, using models of different levels of complexity, all of which are influencing economists beliefs even now.

The simplest level of evidence involves bivariate modeling, with some single variable taken as a measure of the stance of monetary policy. Here the usual approach has been to argue that the monetary policy measure can be taken to be predetermined.

3.1 Timing Patterns

Part of the strength of the view that monetary policy has been an important generator of business cycle fluctuations comes from certain patterns in the data, apparent to the eye, that seem to support this view. For example, as we see in Figure 1, most postwar US recessions have been preceded by rising interest rates. If one concludes from this that most postwar US recessions have been preceded by periods of monetary tightening, the evidence for an important role of monetary policy in generating recessions seems strong. While it can be shown that one variable's "leading" another in timing is neither a necessary nor a sufficient condition for its being predetermined in a bivariate system of the form (1), people tend to assume, probably correctly, that the two conditions are at least likely to occur together, so a graph like this influences peoples' beliefs about the effects of monetary policy.
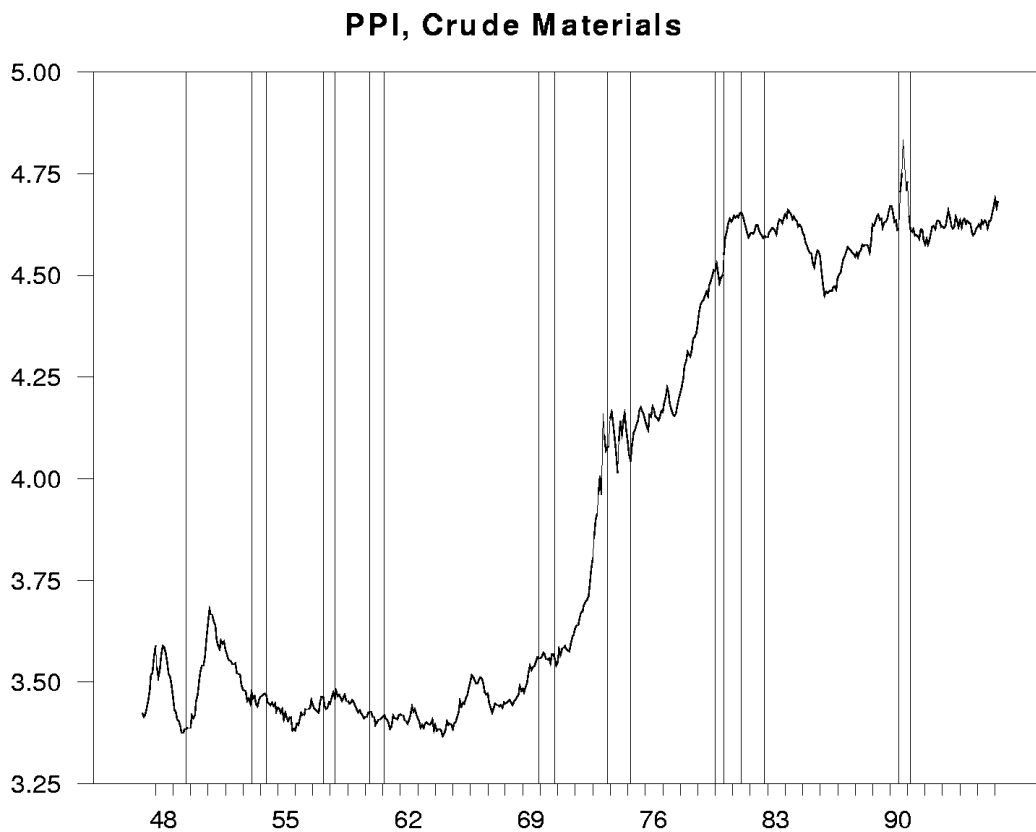
Figure 1

Notes to Figure 1: Data shown are 3-month US Treasury Bill rates. The vertical lines are at NBER peak and trough business cycle dates.

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But a little reflection turns up the problems of interpretation -- identification problems in other words -- that are pervasive in this area. Interest rates were generally rising from the 50's through the 70's. Interest rates fall sharply *after* business cycle peaks. How much of the pattern that strikes the eye comes simply from the rising trend interacting with the post-peak rate drops? The one cyclical peak that clearly does not show a preceding rate increase is also the only one since the early 80's, i.e. the only one during a period of generally declining interest rates. Interest rates are cyclical variables. A number of other variables show patterns like that in Figure 1. As shown in Figure 2, the Producers' Price Index for Crude Materials, for example, shows a pattern very similar to Figure 1 for the period since 1960, with if anything more clearly defined timing. Monetary policy, in order to control inflation, needs to set interest rates systematically, reacting to the state of the economy. If it does so, then whether or not it influences the state of real activity, a pattern like Figure1 could easily emerge.

Figure 2

PPI, Crude Materials

In what might be regarded as an early real business cycle model, Tobin [1970] showed that the timing patterns that monetarists had been documenting in order to support models with a causal role for monetary policy in generating cycles could emerge instead in a model with no such role for monetary policy. He answered the rich array of informally interpreted time series evidence presented by Milton Friedman and other monetarists with a simple dynamic general equilibrium model showing an alternative interpretation of essentially the same facts. Though both the analysis of the empirical evidence and the theoretical models have grown more complex,

the pattern of interplay between data and models today still echoes the Friedman-Tobin debate in many respects.

The recent literature has studied the joint behavior of larger sets of relevant time series. It has begun to explore the gap between text book macro models – with a single "M" and a single "R" – and the real world of monetary policy, with multiple definitions of M, reserves borrowed and unborrowed, and multiple interest rates. The counterarguments are now based on stochastic, rather than deterministic, dynamic general equilibrium models and are aimed at accounting for more than the simple timing relationships Tobin addressed.

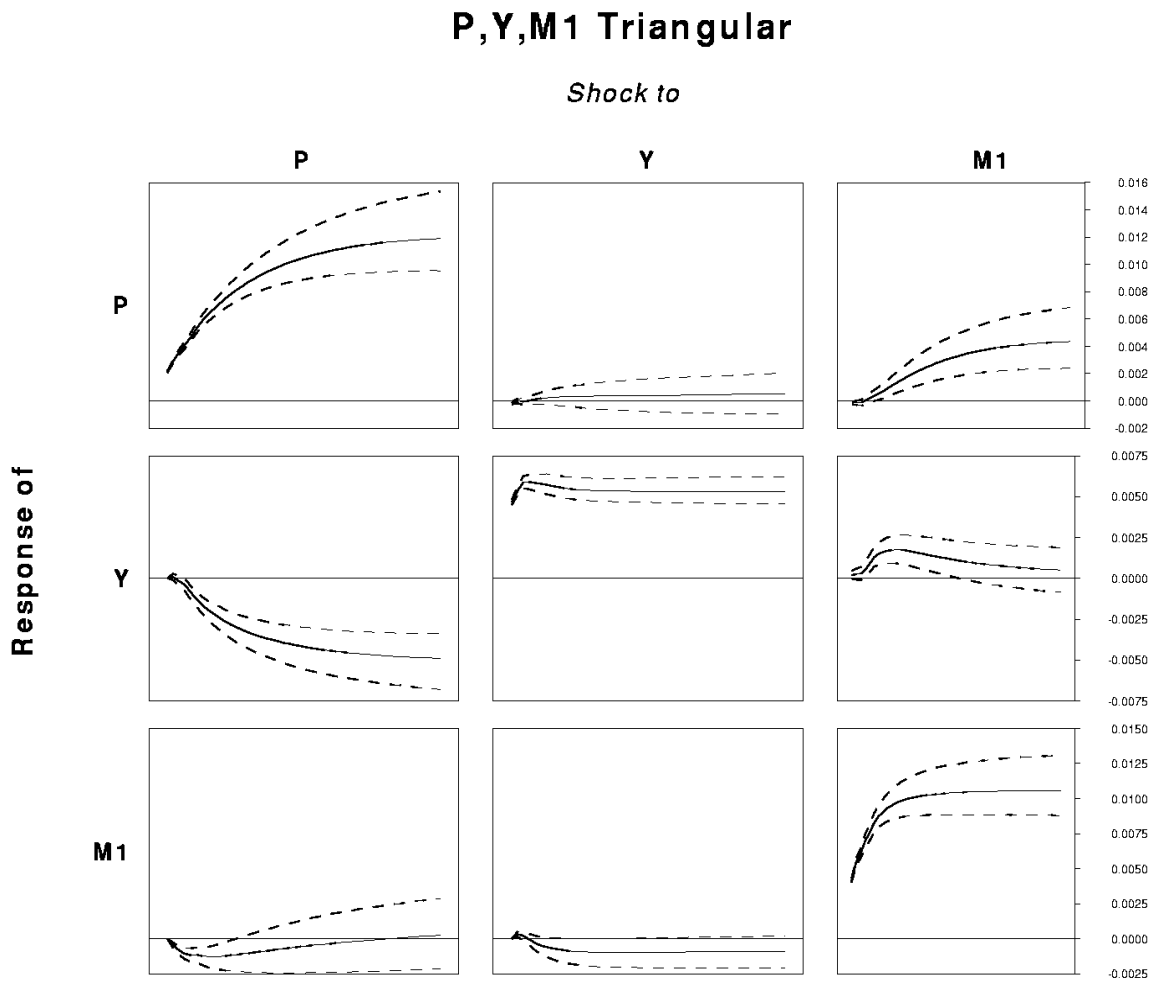### 3.2 *Money and Income,* Post Hoc Ergo Propter Hoc, Redux

Though the monetarist policy view is out of fashion, the statistical time series regularities that made it plausible are still there. The monetarist interpretation of them retains its surface appeal, and it remains an important test of other policy views that they be able to explain these regularities.[13]   Surprise changes in the stock of money ("innovations" in M) are persistent and predict subsequent movements in both prices and output in the same direction. As Milton Friedman argued, this relationship is more than a correlation and a timing pattern.[14] The timing of cyclical peaks is notoriously sensitive to differencing or other filtering of the data. The fact that monetary aggregates contain substantial variation that past output data does not help predict, and that this variation in M does help predict future output, is invariant to data filtering. The response of the price level to an M innovation is smooth and slow; the response of output is quicker and less sustained. Innovations in prices and output have little predictive power for money. Figure 3 shows how the impulse responses of a monthly VAR in M1, CPI, and real GDP, fit over 1960:1 through 1996:3,[15] summarize these regularities. A model with M2 in place of M1 provides a similar picture, though it implies a more persistent response of output to an M2 surprise.

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[13] B. Friedman and Kuttner [1992] present evidence that the monetarist statistical regularities have weakened for the 1970-90 period, in comparison with the 1960-79 period. But while the relationships are weaker statistically in the latter period, it does not seem that smaller effects are precisely estimated in the latter period, so as to strongly contradict results from the earlier period. There is some indication that the relationships have strengthened again in the most recent data.

[14] Friedman did not himself formulate this point quite this way. But in his writings, often in the context of qualitative discussion of historical episodes, he repeatedly emphasized that influences of current and past business activity on the money supply were weak, while the predictive value of changes in the money stock for future output was large. This amounts to a claim that monetary aggregates are close to predetermined in a bivariate system relating a monetary aggregate to a measure of real activity. The rational expectations version of monetarism formalized this in the same language now used by the identified VAR literature. It interpreted (e.g. in Barro, Robert J. [1977]) innovations in monetary aggregates as policy disturbances. This is equivalent to taking M to be predetermined.

[15] We use a number of series, like GDP here, that do not actually exist at the monthly level of time aggregation, and henceforth we will not in each instance point out in the text that the series is interpolated. In each case, we have used related series to interpolate the quarterly data. The methods we have used in doing so are described in the data appendix. Also, unless otherwise

Figure 3

P,Y,M1 Triangular

Shock to

Notes to Figure 3: The VAR system, like all those displayed in this paper, was estimated by finding the posterior mode using the reference prior described in the Appendix. Impulse responses in this reduced form were orthogonalized recursively in the order shown in the figure, with the last listed variable's innovation untransformed, the second to last taken as the part orthogonal to the last, etc. There were 6 lags and a constant term in the system. The responses are shown over 48 months. Data are measured in log units, except for interest rates, which are measured as annual rates (not per cent). Error bands represent 68% probability bands, point by point (approximately one-standard-error bands, if the posterior p.d.f. had a jointly Normal shape.)

stated we will be using the 1960:1 through 1996:3 time period as the estimation period, with six lags (so that the first data used are in 1959:7), and will be measuring all variables in log units except for interest rates and the unemployment rate.

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The smooth, slow response of prices does not easily fit a rational expectations monetarist view that treats money stock surprises as equivalent to price surprises. The money surprise leads to very predictable inflation, later. But a more eclectic monetarist view, that holds that money's effects arise through a variety of temporary frictions and money illusion, but that they dissipate over time, is quite consistent with the qualitative results in the last column of Figure 3. Note, though, that the each row of graphs is all on a common scale, so that the three responses displayed in the middle row "add up" (in a mean square sense) to an explanation for all the variation in output. The proportion accounted for by money surprises is small. Furthermore, the error bands show that versions of the model with no response at all of real output to money surprises are not strongly inconsistent with the data. (They seem to be within a "two-standard-error" band.) This model is therefore not consistent with the view that most business cycle fluctuations arise from random fluctuations in monetary policy. Though not often emphasized, the weakness of the statistical relation between monetary aggregates and real activity was noted even in early studies that used careful time series methods[16], and has been reconfirmed recently by B. Friedman and Kuttner [1992]
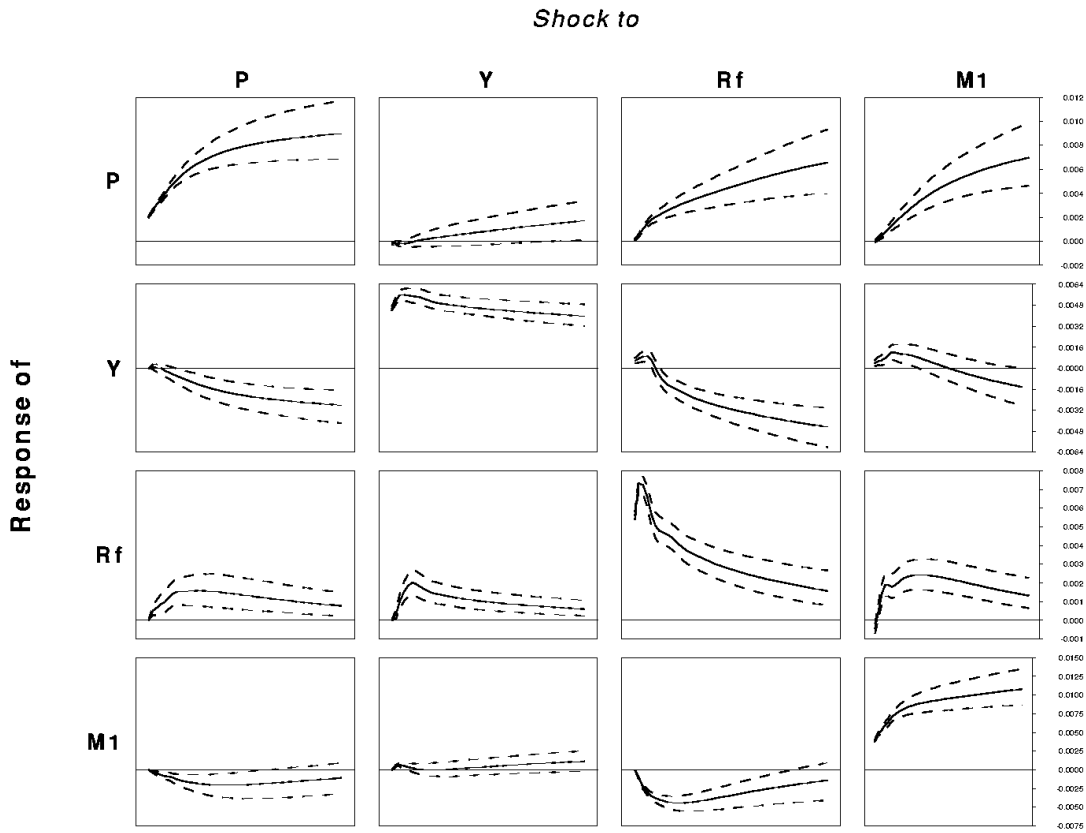
3.3 Interest Rates

In Sims [1980] one of us pointed out that though little of the variation in monetary aggregates is predictable from data on past prices and output, a considerable amount is predictable once information on past interest rates is taken into account. The component of money variation that is predictable from interest rates is more strongly related to output changes than other components. The proportion of output variation attributable to money stock surprises drops substantially in a system that includes a short interest rate. This pattern is confirmed in Figure 4, which shows that in a system including an interest rate on federal funds, money innovations have lost much of their predictive power for output.[17]

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[16] Sims [1972] for example.

[17]Todd [1991] showed that the finding implied by the point estimates in Sims [1980] and reproduced in Figure 4, that money innovations had essentially no predictive power for output once interest rates were introduced, was not robust. However the finding that interest rate innovations had more predictive power for output than did money innovations was robust across sample periods, time units, and variable definitions in Todd's study. A version of Figure 4 formed with M2 would show that M2 innovations have predictive power for output that is less diminished from that in a 3-variable model like that in Figure 3; but, in line with Todd's results, interest rate innovations have more predictive power for output than money innovations also in a model with M2 replacing M1.

Figure 4

P,Y,Rf,M1 Triangular

Shock to

Notes to Figure 4: See notes to Figure 3.

The responses to money innovations in this system show what is sometimes called the "liquidity puzzle": the interest rate declines only very slightly and temporarily as M jumps upward.[18] Central bankers usually think of themselves as controlling monetary aggregates via their control of interest rates, with lower interest rates inevitably accompanying a policy-generated expansion of M. The estimated pattern of response to a money innovation, with little or no reduction of interest rates as M rises, therefore seems to contradict common sense. The liquidity effect, which hypothesizes that the policy-induced increased liquidity of a monetary expansion should lower interest rates, seems not to be present.

This is not a problem for the interest rate innovation, corresponding to the third column of the figure. If this column is interpreted as representing a monetary contraction, it shows a strong liquidity effect, with money contracting quickly and staying persistently lower than average following an interest rate jump that is itself persistent. After an initial delay of six months or so, output declines persistently. But here we encounter what has been labeled the "price puzzle." In

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[18] For a discussion of the difficulties empirical researchers have had in finding a decline in interest rates following a monetary expansion, see Leeper and Gordon [1992]

the first row of the third column, we see that prices rise steadily following an interest rate innovation. Interpreting column 3 as a monetary contraction therefore requires accepting that monetary contraction produces inflation, which seems as unlikely an idea as the notion that monetary expansion fails to lower interest rates.

Notice that, though the fourth column displays a liquidity puzzle if it is the monetary policy shock, and the third column displays a price puzzle, it looks like the puzzles might be eliminated by taking something close to a difference of the two columns. The third column minus the fourth would show a positive movement in the Funds Rate, less persistent than that in column 3, a negative movement in *M1* more pronounced than in either column separately, a negative movement in *Y* without as much of an initial positive blip as in column 3 but with less persistence, and little movement in *P*. It turns out that a set of restrictions on A_0 that in itself has some appeal delivers approximately this result.   We present this very small model not as a preferred interpretation of the data, but as an illustration of types of reasoning and interpretation that we will apply again in more complicated settings below.

Suppose we postulate that, because data on the price level and output emerge only from complex data-gathering and processing that takes time, monetary policy makers do not respond within the month to changes in *P* and *Y*. Suppose further that we assume that *P* and *Y* are unresponsive within the month to changes in *R* and *M*. The justification for this assumption is that there are planning processes involved in changing output or in changing the prices of final goods. This is not to say that *P* and *Y* show no short-run changes. Crop failures, new inventions, consumers turning out to hate the new fall line of coats – can result in short-run variation in *P* and *Y*. But the financial signals embodied in monetary variables are postulated to influence *P* and *Y* only smoothly over time, very little within a month. This set of restrictions can be displayed in a matrix of X's and blanks as in Table.
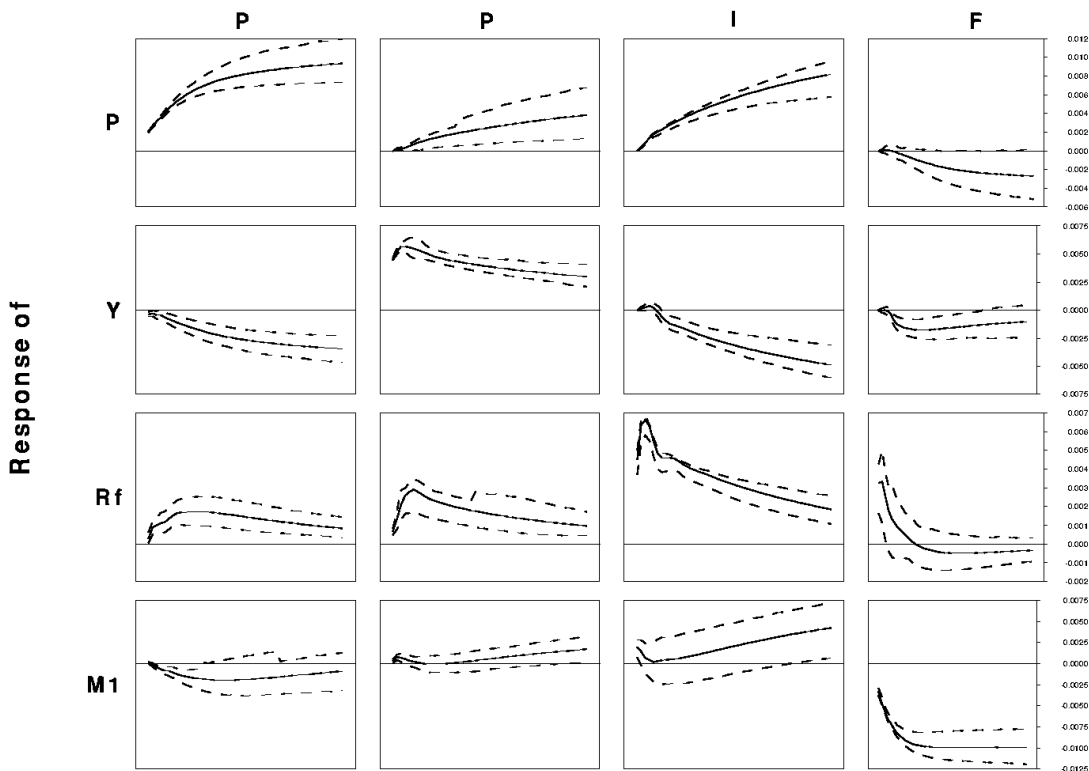
<div align="center">Table 1</div>

		P	Y	Rf	M1
P	*P*	X	X		
P	*Y*	X	X		
I	*Rf*	X	X	X	X
F	*M1*			X	X

The X's indicate coefficients in A_0 that are unrestricted, the blanks coefficients that are postulated to be zero. The labels in the first row are variable names. The bold labels in the first column are names of disturbances or shocks. The **F** shock is meant to represent random variation in Federal Reserve behavior, the **P** shocks private behavior of inertial variables that do not respond quickly to financial signals, and the **I** shock other disturbances to private sector behavior. (The **I** stands for "information", meaning that this component of non-policy behavior responds quickly to new information.)[19]   The two **P** equations have the same restrictions, and are therefore

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[19] We could have labeled this equation "**Md**", for money demand, as it contains contemporaneously all four of the traditional arguments of liquidity preference in an ISLM model. However over much of our sample period most of the deposits that make up *M1* paid interest, so a short interest rate like *Rf* did not represent the opportunity cost of holding *M1*. Probably more importantly, in this small model this sector has to be the locus of all non-policy effects on the

indistinguishable. They can be premultiplied by any orthonormal 2x2 matrix and still satisfy the same restrictions. Since we do not have separate interpretations for these two equations, we normalize them arbitrarily by changing the *Y* coefficient in the first row from an X to a blank. This results in a system that is overidentified by one restriction. The results of estimating this system are displayed in Figure 5.

Figure 5
Four Variable Restricted Model

Notes to Figure 5: See notes to Figure 3.

The fourth column of this Figure is a plausible candidate as a measure of the effect of a tightening of monetary policy. *Rf* rises initially, then returns to its original level over the course of a year or so. *M1* declines, and most of the variation in *M1* is accounted for by these policy disturbances. *Y* declines, persistently, but not much of the overall variance in output is attributed to the policy disturbance. *P* moves negligibly – very slightly downward. There are some problems with the interpretation. Since the output decline is so small (only about a tenth of a per cent), the price decline negligible, and the interest rate increase so temporary, it is hard to understand why *M1* responds so strongly and persistently (by almost a full percentage point).

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interest rate and *M1*. Thus we would not want to insist that this equation must be interpreted as money demand.

Note that the first three columns show that every private sector shock that implies inflation engenders a contractionary response in the interest rate. As we observed earlier, in discussing the robustness of conclusions from identified VAR's, this assures us that certain aspects of the results are not sensitive to the identifying assumptions. Most of observed variation in the interest rate is accounted for by these endogenous responses, not by what have been identified as policy shocks. Most variation in output and prices is accounted for by the first and third columns, which look like "supply shocks", in that they move prices and output in opposite directions, and the response of interest rates to the inflationary shock is at least as strong in these cases as when output moves in the same direction as prices, in column 2. From Figures 4 and 5 it appears that there is no possibility of transforming the system to produce a column in which interest rate rises are followed by substantial price declines. It might be possible, by approximately differencing columns 2 and 3, to produce another pattern similar to column 4, but with stronger output effects and weaker effects on *M1*.

Though this model is simple, the basic approach it takes, excluding certain variables from a contemporaneous impact on policy behavior while asserting that certain private sector variables respond only with a delay to financial variables, has been followed in one form or another in the identified VAR literature since at least Sims[1986]. Nonetheless this model cannot be a stopping place in our analysis. Forecasters find an array of additional variables – stock prices, long interest rates, exchange rates, commodity price indexes, for example – useful in forecasting prices and output. Federal Reserve behavior could certainly depend on such indicators of the state of the economy, and by omitting such variables we relegate their effects to the disturbance term. *M1* responds quickly to private sector behavior and is not directly controlled in the short run by the Federal Reserve. Bank reserves are subject to more direct control, and we have not modeled the link between them and *M*.
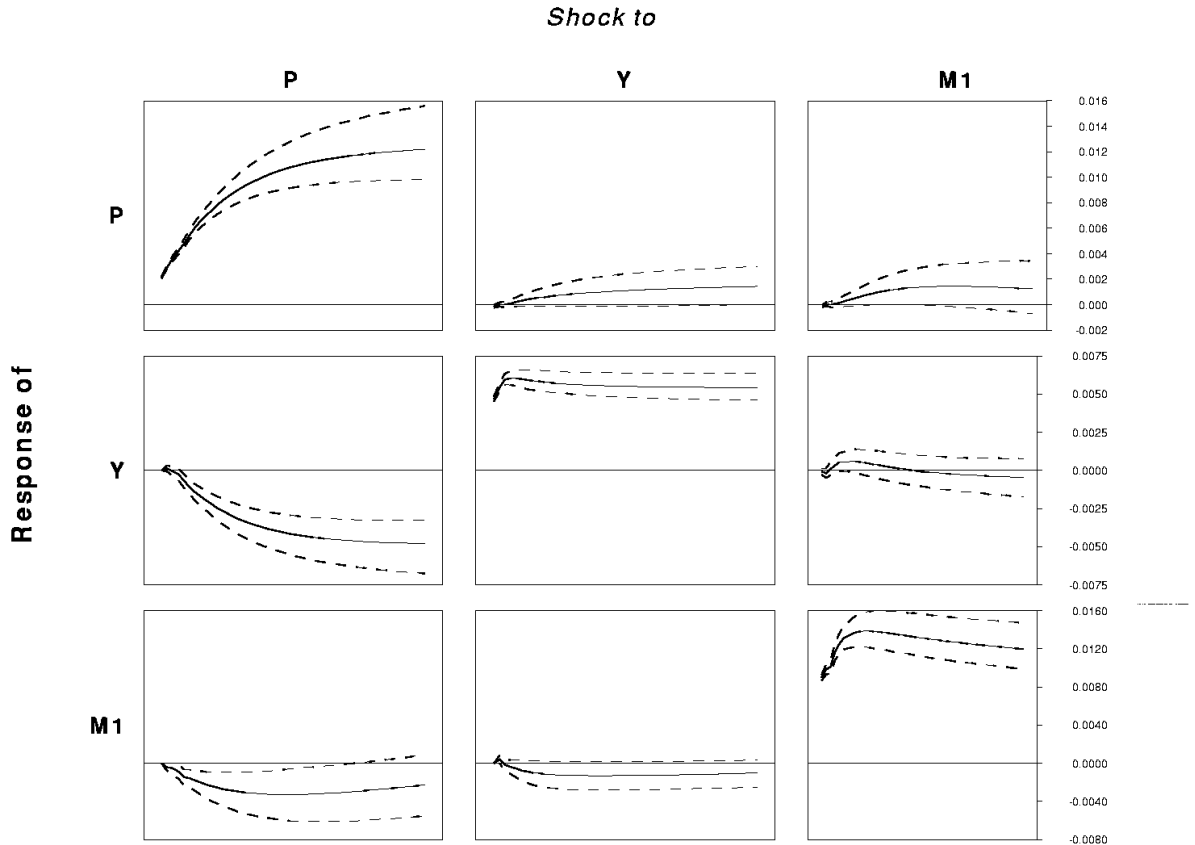
3.4 Reserves

One approach to circumventing the fact that much variation in *M1* is demand-determined is simply to replace *M* with a reserve aggregate that the Federal Reserve could be argued to control more directly. Familiarity with textbook discussions of the money multiplier might lead one to think that this will not qualitatively change results. But this is not the case. Consider Figure 6, which shows what happens when we replace *M1* by Total Reserves Adjusted for Reserve Requirements[20] in the model of Figure 3. The output response to an *M* shock, already modest in

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[20] We discovered in the course of our work that "adjustment for reserve requirements" has dubious effects on the reserve series. Because of the way the series is constructed, the ratio of adjusted to unadjusted reserves varies substantially from month to month even in periods when no changes in reserve requirements have occurred, because of fluctuations in the distribution of deposits across categories with different reserve requirements. This creates a component of demand-determined fluctuations in "reserves" that has nothing to do with Fed actions to change the volume of reserves. In our modeling, we sometimes found that even the signs of responses of adjusted and unadjusted reserves would differ, and that unadjusted reserves seemed to have a stronger relation to other nominal variables than adjusted reserves. Of course unadjusted reserves shows occasional large jumps, when requirements change and the change is accommodated by the Fed, that do not have the same effects as reserve changes not accompanied by requirements

Figure 3, has almost completely disappeared, and the price response is also much weaker. It is possible that this result is taking us closer to the truth: Use of *M1* or *M2* leads us to confuse endogenous components of the *M* aggregate with policy disturbances, exaggerating the effects of policy. However, we will see below that it is equally possible to maintain that reserves contain a substantial demand-determined component, so that neither surprise changes in reserves nor surprise changes in *M* are good measures of monetary policy.

Figure 6

Triangular System: *P*, *Y*, and *TR*

Shock to

Strongin [1995], Christiano, Eichenbaum and Evans [1996], and Bernanke and Mihov [1995] introduce some details of the banking system to analyze the consequences of the Fed's choice of the division of total reserves between borrowed and nonborrowed reserves. By concentrating exclusively on the reserves market, omitting consumer-level monetary aggregates from the model entirely, this line of work downplays the importance of private sector money demand behavior. These models have also tended to assume a recursive economic structure, with production sector variables appearing first in the recursive ordering. In addition, the authors have typically not discussed thoroughly the restrictions on nonpolicy equations that are necessary to justify their

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changes. This topic deserves exploration beyond what we have had time to give it in preparing this paper.

interpretations. Bernanke and Mihov address this shortcoming by providing economic interpretations for the banking sector equations in Strongin's and Christiano, Eichenbaum, and Evans's models.[21] These interpretations involve imposing restrictions not imposed by the original authors.

These reserves models can be understood in the context of a six-variable system including output, the price level , commodity prices (Pcm), the federal funds rate (Rf), nonborrowed reserves (NBR), and total reserves (TR).[22] The exclusion of the discount rate is justified by regarding it as an administered rate that is infrequently changed, does not play an important role in month-to-month policy decisions, and is changed mainly as a delayed response to already existing information. Table 2 describes the models in terms of their A_0 matrices. Equations are grouped into sectors, with a nonempty cell indicating that the variable labeled at the top of the matrix enters that equation. Empty cells correspond to zero restrictions. In the table, a "C" entry denotes a coefficient that is nonzero across models, while the "X" coefficients may or not be nonzero in different specifications. There are four behaviorally distinct sectors in the model: production (**P**), information (**I**), policy (**F**), and the banking system (**B**). Behavior in the production and information sectors is not specified, so shocks associated with those equations have no clear economic meaning other than that they are disturbances not associated with monetary policy or banking behavior.

Table 2

Recursive Models of the Reserves Market						
Sector	Vbl	Y	P	Pcm	Rf	NBR	TR
P	Y	C					
P	P	C	C				
I	Pc	C	C	C			
F	Rf	C	C	C	X	X	X
B	NBR	C	C	C	X	X	X
B	TR	C	C	C	X	X	X

The six-variable system allows at most 21 coefficients to be freely estimated. With the first three columns taking up 15 coefficients, no more than six unrestricted coefficients in the (3 x 3) "X" matrix may be estimated. Production and information sector variables enter policy and banking sector equations, implying those sectors observe and respond to output, overall prices, and commodity prices contemporaneously. Variables like commodity prices, which are determined in auction markets, are observable continuously, so it may be reasonable to assume the

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[21] Bernanke and Mihov [1995] also present a simultaneous model in which policy and banking behavior interact to determine equilibrium prices and quantities.

[22] All the models use monthly data from 1959:7 to 1996:3. See the Data Appendix for variable definitions. The VARs are estimated with 6 monthly lags and a constant term. All variables except interest rates are logged.

Fed responds to information gleaned from such series. The assumption that the Fed knows current values of real GDP and consumer prices is at best an approximation to the Fed's actual information set.

Bernanke and Mihov reinterpret Strongin's and Christiano, Eichenbaum, and Evans's work by attaching behavioral meaning to each equation in the **F** and **B** sectors. They impose the restriction that the coefficients on *TR* and *NBR* in the fifth equation are equal but have opposite signs, reflecting a view that the demand for borrowed reserves, *BWR*, should be homogeneous in the overall level of reserves. (Particularly in the short run, as here, there is certainly no reason this has to be true, though it may be a reasonable working hypothesis.) The inclusion of *Y* and *P* in the relation follows from the fact that the demand for reserves is derived from the need to satisfy reserve requirements and the desire to manage reserve positions closely. The presence of *Pc* is more difficult to justify, particularly since there are many other variables that could more appropriately be included in the derived demand function.

Strongin imposes three additional restrictions. He assumes the demand for TR is interest inelastic and that the Fed sets the supply of NBR without regard to the current funds rate. Since he does not impose the equal-and-opposite-signed restriction on the *NBR* and *TR* coefficients in the second equation, his system has one overidentifying restriction. The monetary policy shock, then, is a change in the composition between borrowed and nonborrowed reserves of a given quantity of total reserves. His model of reserves market behavior, normalized to have 1's on the diagonal, appears in Table 3. Note that Strongin's work did not use the *Pc* variable.

Table 3

Strongin's Identification

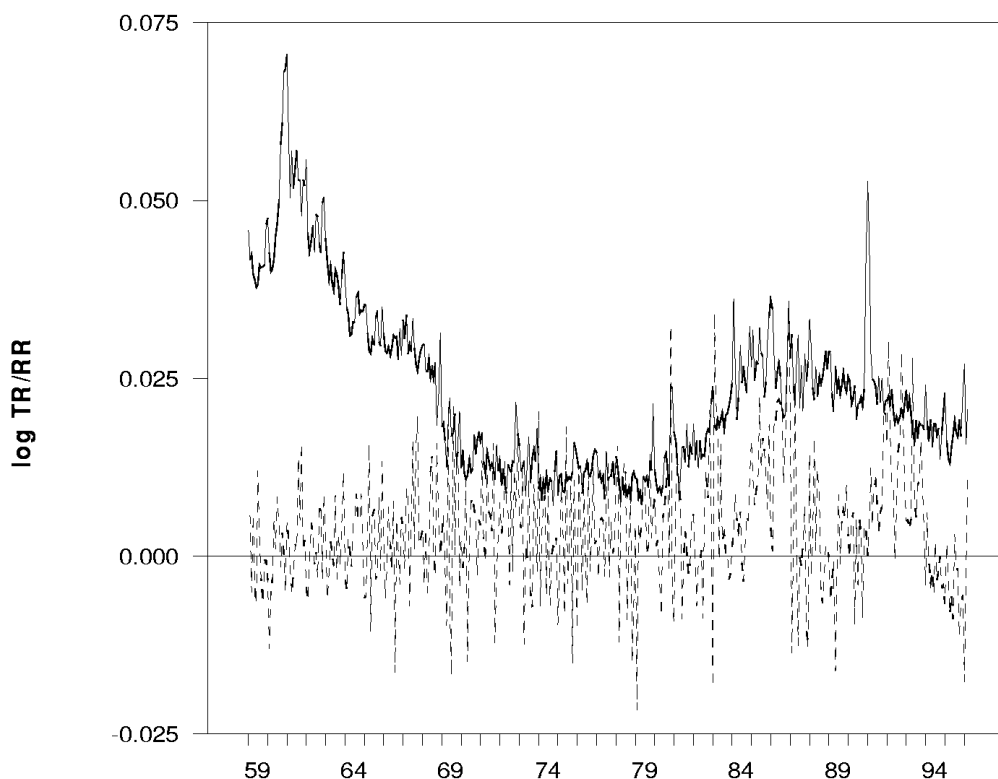| Sector	Vbl	Rf	NBR	TR	
F	*Rf*	0	1	X	
B	*NBR*	X	1	X	
B	*TR*	0	0	1	

Strongin justifies the assumption that demand is interest inelastic by appealing to institutional rigidities. He argues that within a reserve maintenance period the banking system as a whole must borrow at the discount window to meet a reserve shortfall. With the demand for required reserves largely determined by current and past deposits, if the demand for excess reserves is unresponsive to policy, the quantity of total reserves will be determined in the short run entirely by demand.[23] Though persuasive at the high frequencies associated with reserve settlement period, the argument carries less force at the monthly frequency of the data Strongin employs. Figure 7 shows the relation of excess reserves to monthly changes in required reserves over our

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[23] In terms of the estimated VAR, the entire monthly innovation in total reserves is attributed to shifts in the demand function. A necessary condition for the elasticity restriction to hold is that the demand for excess reserves be completely unresponsive to any variables policy may affect immediately. See Strongin (1995, pp. 467-472) for further details.

sample period. Though there are more reserves relative to the monthly changes in the early and late parts of the sample, through the whole period the changes and the excess reserves are of the same order of magnitude. Banks therefore have substantial room to trade tighter management of reserves against the interest costs of carrying excess reserves. In fact simple regressions of excess reserves on interest rates suggest a substantial interest-elasticity of excess reserves.

Figure 7

Excess Reserves and Change in Log Required Reserves

Notes to Figure 7: The solid line is excess reserves, measured as the logarithm of total reserves, base-adjusted and seasonally adjusted, divided by required reserves, also base-adjusted and seasonally adjusted. The dotted line is the change in the logarithm of required reserves.

The restriction in Strongin's identification that is most important in making his conclusions differ from those of other researchers is the claim that Federal Reserve behavior pays no attention within the month to the current Federal Funds rate. Most observers think that instead the Fed has target values of the funds rate and undertakes open market operations to stay close to those targets on a time scale considerably shorter than one month. Furthermore, Strongin assumes that the Federal Reserve manipulates the Federal Funds rate via manipulation of borrowings. In fact, most banks in most reserve accounting periods are not borrowing from the discount window at all. This is not just because the Federal Reserve "frowns" on excessive borrowing, but also because discount-window borrowing may be regarded as a signal of possible distress or mismanagement. The Federal Funds market is a private market in which credit-worthiness of borrowers is an important concern. An individual bank that needs to borrow an unusually large amount relative to its assets or to its history of borrowings is likely to raise questions and thus in

effect to face an individual upward-sloping supply of funds, just as is usually posited for individual business borrowers from banks. The Federal Reserve discount window, on the other hand, is meant to provide a safety valve for banks that are in temporary difficulties. But just because it does have this function, the fact that a bank is borrowing at the discount window may convey information, and banks may therefore be reluctant to use the discount window, despite the apparent profitability of doing so at a quoted discount rate.[24] Thus, though borrowing may indeed vary systematically with the structure of rates, we believe it is a mistake to think of the Fed as setting the Funds Rate by manipulating the level of borrowing. The Fed more likely sets the Funds Rate at a level it determines by assessing the overall state of the economy, undertaking open market operations to achieve its Funds Rate targets. Unusually high need for discount-window borrowing by banks is not likely simply to be choked off by a rise in the Funds Rate, as Strongin's specification would imply. Instead the Fed is likely to maintain its Funds Rate target while accommodating a temporary rise in demand for borrowing.

Christiano, Eichenbaum and Evans [1996] assume the Fed sets the supply of *NBR* without regard to either TR or Rf, but relax Strongin's assumption that borrowed and non-borrowed reserves are unresponsive to the funds rate. Their model of the reserves market is recorded in Table 4.

Table 4

Christiano, Eichenbaum and Evans's Model

Sector	Vbl	*Rf*	*NBR*	*TR*		
F	*Rf*	0	1	0		
B	*NBR*	1	X	X		
B	*TR*	0	X	1		

The rationale that Christiano, Eichenbaum, and Evans offer for their identification of policy is that open market operations directly affect non-borrowed reserves, making NBR a control variable for the monetary authority. Of course, as we have already discussed, the fact that the policy authority is choosing a variable does not imply that they do not choose to make it respond to other variables. Because this specification, like Strongin's, assumes the Fed pays no attention within the month to the Funds Rate, our arguments against Strongin's specification apply here as well.

In previous work, one of us (Sims [1992]) noted that a price puzzle, in which interest rate rises are followed by inflation, might arise in a model that did not include a rich enough specification of the information available to policy makers. If they can observe variables that forecast inflation, and if those variables are not included in the model, then there will be

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[24] Meulendyke [1992] and Clouse [1994] discuss the development of banks' reluctance to borrow at the discount window. Clouse emphasizes that the greater reluctance to borrow has weakened the relationship between borrowing and the Rf-Rd spread, and has impaired the effectiveness of the discount window in tempering unexpected pressure in the reserves market. He argues that this, in turn, has reduced the Fed's emphasis on borrowed reserves in the day-to-day management of the reserve market.

apparently unpredictable changes in interest rates that are actually systematic responses to information that implies inflation is on the way. This could make it appear that tightening of monetary policy generates inflation. Christiano, Eichenbaum, and Evans introduce commodity prices to reduce this source of bias. Policy authorities are assumed to observe and react to current values of commodity prices. However, CEE merge commodity prices with other variables in the **P** sector, having it share with other variables in that sector the property that it has no within-month response to monetary policy variables. Since commodity prices are determined in thick auction markets and change daily, the restriction that *Pcm* not respond within the month to monetary policy seems strained.

3.4.1 Results from Two Models Using Reserves

Under Strongin's behavioral assumptions, an expansionary policy shock increases *NBR* and decreases *BWR* by exactly the same amount. Inelastic demand for reserves forces the entire adjustment to a new mix of *NBR* and *BWR*, for a given quantity of *TR*, to fall on the funds rate. With only the funds rate free to equilibrate supply and demand for *NBR*, Strongin's policy effects resemble in exaggerated form the responses to an interest rate innovation reported in Sims[1986] and Bernanke and Blinder [1992]
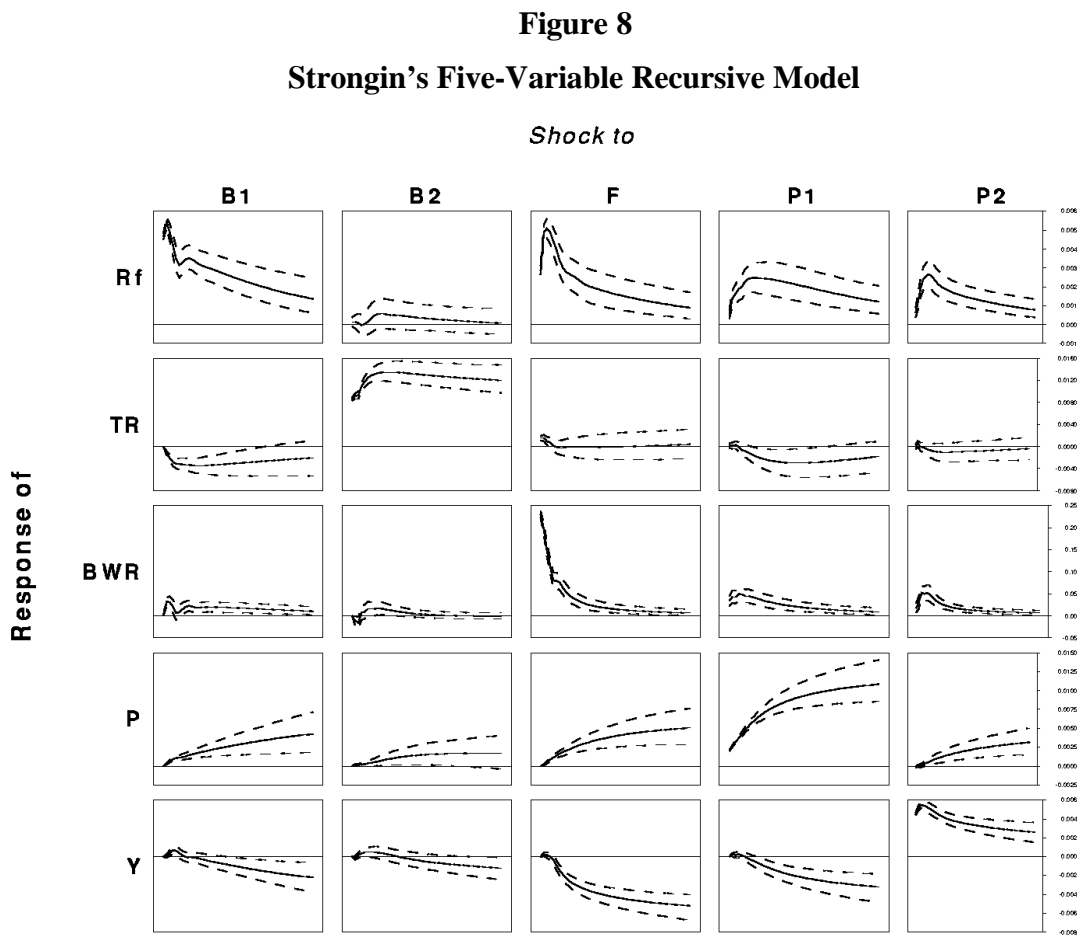
Figure 8

Strongin's Five-Variable Recursive Model

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Figure 8 reports the dynamic responses over four years to shocks identified by Strongin's model.[25] The first column reports responses to a contractionary monetary policy disturbance. *TR* and *Rf* move in opposite directions, with the liquidity effect very persistent. Borrowings rise temporarily after the shock. Real GDP decreases dramatically. Prices rise smoothly and steadily. The policy shock accounts for about half the variability of output over horizons of three or more years, the majority of the fluctuations in *BWR*, and a substantial proportion of funds rate movements in the short run. A shock to demand for reserves—shown in the second column—is accommodated almost dollar-for-dollar by open market purchases that raise *NBR* and alleviate the need for banks to borrow at the discount window. This highlights the strong implication of Strongin's model that the entire positive contemporaneous correlation between total reserves and nonborrowed reserves gets interpreted as an endogenous response of policy to a banking sector disturbance.

The figure again confirms a feature of policy behavior that we have already encountered: monetary policy responds to shocks that portend higher prices by contracting reserves and raising the funds rate. This pattern holds even for the first **P** shock, which lowers output while it raises prices.
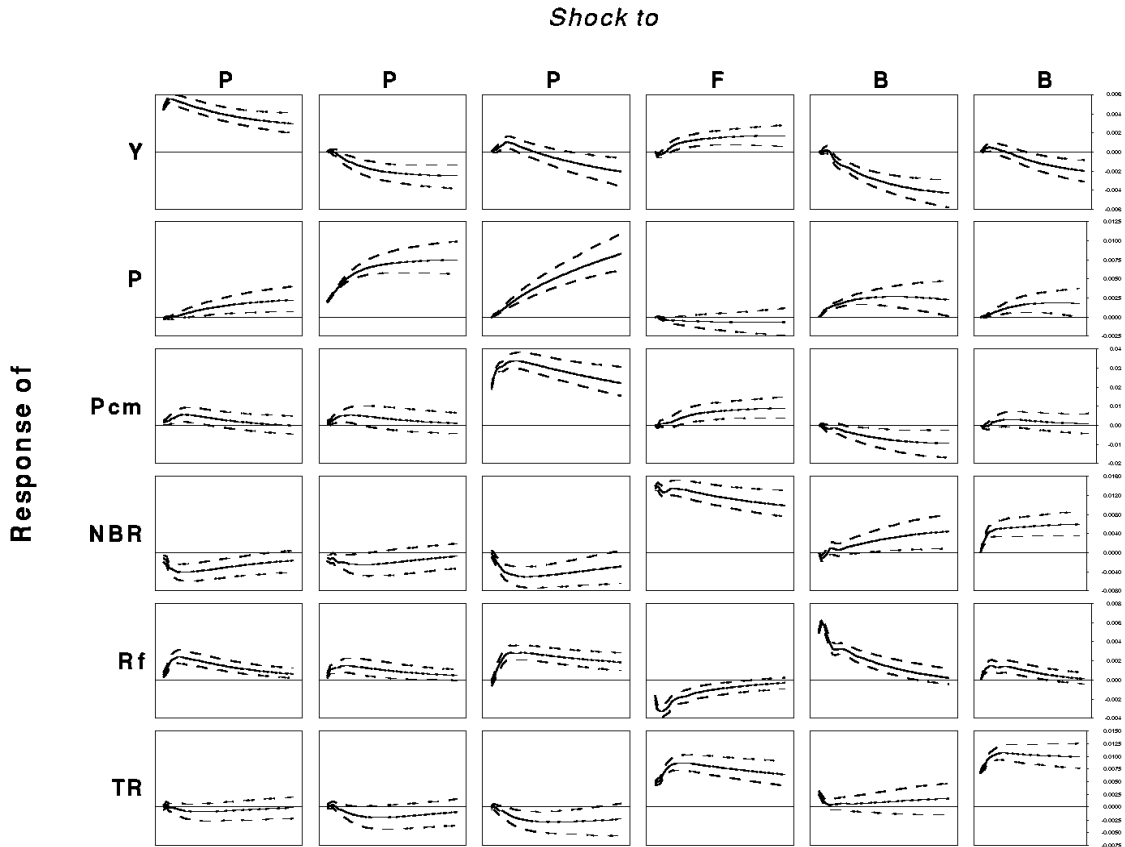
The substantial and sustained increase in prices following what is identified as a contractionary monetary policy shock in this specification confirms our view that it involves unreasonable characterizations of policy behavior that lead to confounding inflationary adverse supply disturbances originating in the private sector with what are supposed to be monetary policy disturbances.

Christiano, Eichenbaum, and Evans (CEE) add commodity prices to Strongin's five variables and relax Strongin's assumption that a monetary policy shock only changes the mix of a fixed quantity of total reserves. By allowing some of the effect of an increase in the supply of NBR to show up in an increase in the equilibrium quantity of TR, CEE's identification moderates the large policy effects that Strongin finds.

Figure 9

Christiano, Eichenbaum and Evans Recursive Identification

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[25] The sample period and modeling methods match those used in the rest of this paper, so the results do not matchStrongin's in detail, though they are quite similar to his.

The fourth column of Figure 9 attributes considerably less of observed variation in *Rf* to policy shocks than does the first column of Figure 8 (Strongin's model).[26] Total reserves rise with the expansion in nonborrowed reserves, allowing borrowed reserves to fall less than dollar-for-dollar with nonborrowed reserves. Output continues to rise persistently, but policy shocks account for only a small fraction of output's variability. The price level no longer falls following a monetary expansion; in fact monetary policy shocks have essentially no effect on finished goods prices. Commodity prices, on the other hand, respond to a policy shock as one would expect, with a contractionary shock decreasing commodity prices as it raises interest rates.

The response of policy to information about future inflation is as strong here as in the other specifications we have examined. The third column of Figure 9 shows that a jump in commodity prices signaling a gradual and smoothly increasing price level induces a smooth tightening of reserves and increase in the funds rate. The endogenous response of policy to production, information, and banking sector disturbances is the dominant source of funds rate variability; policy shocks account for only a small proportion of the error variance in the funds rate.[27]

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[26] Results in Figure 9 are from a VAR including *Y, P, Pcm, NBR, Rf*, and *TR*, in that order, with A_0 assumed lower triangular.

[27] Christiano, Eichenbaum, and Evans also consider results from identifying policy with funds rate innovations that are orthogonal to *Y, P,* and *Pc*. These effects are stronger than when *NBR* innovations are used, landing, as one would expect, midway between figures 1 and 2; this occurs

The CEE model has produced estimates of the effects of policy disturbances that are in themselves believable. However these estimates are built on assumptions about policy behavior and about the reaction of the economy to monetary policy that seem implausible.

4. An Integrated Approach

The existing research we have surveyed here has probably treated inclusion of reserves or *M* as mutually exclusive alternatives because of the technical and conceptual problems of working with models larger than the 6 or 7 variables included in most models in the literature. We consider in this section models that include both types of monetary aggregate, hoping to gain insight into how bank behavior and Federal Reserve policy interact.

4.1 Modeling Federal Reserve and Banking System Behavior

It is appealing to think that by using data on variables directly controlled by the Federal Reserve (like reserves, the Federal Funds Rate, and the Federal Reserve Discount Rate), together with others that are of more direct concern to banks (like Bank Loans, M2, M1, a bank loan rate index, a deposit rate index), we might come up with restrictions on which variables have an immediate impact on whose behavior, thereby separating banking system from Fed behavior. However this is not like separating component sectors of the private economy, or supply and demand in some market. Instead of two collections of individually negligible agents as in a competitive supply and demand model, we have one such collection (banks) and another single agent (the Federal Reserve) that is concerned with regulating the banks. Data on most aspects of bank behavior and balance sheet conditions is collected regularly and with little delay by the Federal Reserve as part of its regulatory function.

We therefore do not aim at separate blocks of equations to model Federal Reserve behavior and banking system behavior.   Instead we distinguish two aspects of Fed behavior: macroeconomic policy behavior and bank regulatory behavior.   The macroeconomic aspect represents the Fed's responsibility for controlling inflation and its concern for its effects on the overall level of economic activity. The bank regulatory aspect represents its concern that the banking system function smoothly and efficiently. In the day-to-day operation of the Federal Reserve open market desk keeping track of the level of reserves and of deposit flows that generate changes in reserve requirements is a central concern, as is of course also the Federal Funds rate. A candidate for a Federal Reserve behavior equation might seem then necessarily to include at a minimum a reserve variable and the Federal Funds rate. But in our view the Federal Reserve is concerned with reserve and deposit flows in the short run mainly because of their potential impact on the Funds rate, for which the Fed sets its objectives mainly in the light of broader macroeconomic conditions.   It tracks shifts in reserve requirements in order to accommodate them, so that they will not disturb credit markets and generate unwanted short-run macroeconomic impacts. We aim at defining one equation or block of equations that reflects how the Fed sets its desired level of interest rates in relation to the state of the economy as a whole,

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because a positive funds rate innovation lowers *NBR*, but raises *TR* slightly, implying that *BWR* do not increase dollar-for-dollar with the decline in *NBR*.

while another equation or block of equations represents the joint behavior of the banking sector and the Fed in relating reserves to deposit flows.

We model the Fed's behavior as not depending directly, within the month, on final goods prices, output, or GDP components, on the grounds that these variables can be measured only with substantial delay. In principle, we regard it as reasonable to allow Fed behavior to depend within the month on financial market variables that might serve as indicators of the state of the economy and that are observable on a daily basis – for example the value of the dollar, a stock price index, long interest rates, and a commodity price index. However, there is an argument for imposing a lag on the effects of even these variables on policy. Significant shifts in the Federal Reserve's macroeconomic policy stance require a process of consultation, analysis, and consensus-building that takes time. We have considered specifications with currently observable financial variables in the Federal Reserve's reaction function contemporaneously, and also specifications without inclusion of such variables.

Allowing for possible response of monetary policy to market interest rates raises some difficulties. To understand them it may help to consider a very simple model. Suppose policy sets a one-period interest rate $r(t)$, responding to an indicator $x(t)$ of the state of the economy, plus a random disturbance $e(t)$. There is a continuously observable two-period interest rate $R(t)$ which is related to $r(t)$ by term-structure considerations. There is also, however, a component $n(t)$ of the spread between the two rates that is a time-varying term premium, taken in this simple example to be independent of e.

Formally, we are supposing

policy:
$$r(t) = \boldsymbol{a}_0 x(t) + \boldsymbol{a}_1 x(t-1) + \boldsymbol{g} R(t) + \boldsymbol{e}(t) \tag{4}$$

arbitrage:
$$R(t) = \tfrac{1}{2}\left(r(t) + E_t\left[r(t+1)\right]\right) + \boldsymbol{n}(t) . \tag{5}$$

To complete the system we need to specify the time series properties of x and $\boldsymbol{n}$. We will assume $\boldsymbol{n}$ serially independent and x autoregressive according to

$$x(t) = \boldsymbol{q} x(t-1) + \boldsymbol{x}(t) . \tag{6}$$

Substituting (5) into (4) gives us

$$r(t) = \frac{2\boldsymbol{y}}{\boldsymbol{g}}\left\{\boldsymbol{a}_0 x(t) + \boldsymbol{a}_1 x(t-1) + \boldsymbol{e}(t) + \frac{\boldsymbol{g}}{2}\boldsymbol{n}(t)\right\} + \boldsymbol{y} E_t r(t+1) . \tag{7}$$

For the system to have a unique solution, we must have

$$\left|\frac{\boldsymbol{g}}{2-\boldsymbol{g}}\right| = \boldsymbol{y} < 1, \tag{8}$$

which is equivalent to $\boldsymbol{g} < 1$. This points to an inherent drawback of monetary policy that reacts systematically to market interest rates. Markets depend on policy to fix a path for nominal interest rates. A policy authority too sensitive to market rates can create indeterminacy by essentially abandoning its role in anchoring the term structure. In this model it seems easy to avoid such difficulties, since the $\boldsymbol{g} < 1$ condition is simple and understandable. But if the policy

authority were responding to several rates, and to other auction-market prices that are sensitive to interest rates, it might not be so clear when the boundary of indeterminacy was being crossed.

Using (6) to solve (7) forward, we arrive at

$$r(t) = \frac{2\mathbf{y}}{\mathbf{g}} \left\{ \frac{\mathbf{a}_0 + \mathbf{a}_1 \mathbf{q} \mathbf{y}}{1 - \mathbf{q} \mathbf{y}} x(t) + \mathbf{a}_1 x(t-1) \right\} + \frac{2\mathbf{y}}{\mathbf{g}} \mathbf{e}(t) + \mathbf{y} \mathbf{n}(t) \ . \tag{9}$$

We can also substitute (9) in (5) to produce

$$R(t) = \frac{\mathbf{y}}{\mathbf{g}} \left\{ \frac{\mathbf{a}_0 \cdot (1 + \mathbf{q}) + \mathbf{a}_1 \cdot (1 + \mathbf{q}^2 \mathbf{y})}{1 - \mathbf{q} \mathbf{y}} x(t) + \mathbf{a}_1 x(t-1) \right\} + \frac{\mathbf{y}}{\mathbf{g}} \mathbf{e}(t) + \left(1 + \frac{\mathbf{y}}{2} \right) \mathbf{n}(t) \tag{10}$$

If all we know about the policy reaction function is that it has the form (4), we have an identification problem. Any linear transformation of the pair of equations (9) and (10) that gives the disturbances in the two equations an identity covariance matrix will result in a system that satisfies the basic restrictions for an identified VAR, but in which *both* equations have the form (4) – a linear equation in $r(t)$, $R(t)$, $x(t)$, and $x(t-1)$. There will be versions of the system in which one equation has a scalar multiple of $\mathbf{e}$ as a disturbance, but also versions in which one equation has a scalar multiple of $\mathbf{n}$ as the disturbance. If these two equations were part of a larger model, we might have allowed for other variables to enter the equations, restricted the way they entered the two equations, and thought on this basis that we had identified the two equations. But if in fact the other variables were not important, we would have an unidentified, or weakly identified model. We would then run the risk of labeling an arbitrage condition as a policy rule and of confusing fluctuations in term risk premia with policy disturbances.

As we have set this model out, it is hard to see why the policy authority should want to react to R. We have assumed the authority can observe and react to the state of the economy, x, as rapidly as asset markets. All that the authority accomplishes by reacting to R is to make r depend on the term risk premium $\mathbf{n}$ in addition to $x(t)$ and $x(t-1)$. In these circumstances, with R containing no important information that the policy authority cannot access directly, it seems unlikely that the authority would react to R. Furthermore, even if it did react to R, we would not make a large error by estimating the model as if it did not. If we constrained the policy reaction function not to contain R, we would emerge with estimates of (9) instead of (4). The disturbance term in (9), though, is likely to be almost the same as that in (4). It is reasonable to think that policy-generated month-to-month variation in the short rate is substantially larger than month-to-month variation in the term risk premium.[28] Thus, since $\mathbf{y}$ and $\mathbf{g}$ are both less than one, the error term in (9) is dominated by variation in $\mathbf{e}$. Even if by constraining $\mathbf{g}$ to zero in (4) we mistakenly estimate (9) instead of (4), in other words, we will come pretty close to recovering the actual policy disturbance process, and thus also close to recovering the policy reaction function.

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[28] Though this is quite plausible when we are considering the "long" rate to be that on, say, a 3-month Treasury Bill and the short rate to be that on Federal Funds, it may become more dubious when we think of the long rate as that on a 10-year Treasury Bond.

The policy authority would have stronger reason to make g non-zero if it had an information disadvantage, i.e. if it was constrained to keep $a_0 = 0$ in (4). Then, by reacting to R the authority could in effect make $r(t)$ sensitive to $x(t)$ despite its inability to observe current x directly. However in these circumstances imposing the constraint that $g = 0$ will firmly identify the system.

This discussion suggests that we should be on the lookout for identification problems when trying to model several interest rates jointly. It makes sense to experiment with identification schemes that allow policy reactions to several longer interest rates and exclude current policy reactions to variables that are observed only with a delay. But it may turn out that such identification schemes fail, unable to distinguish between policy equations and arbitrage conditions. In that case, we may get good results by allowing only a single interest rate contemporaneously in the policy reaction function.

Notice that the criterion for whether we should include interest rates in the reaction function is definitely not the degree to which they improve the fit of a least squares regression. In this simple model, including current R on the right-hand side in a least squares estimate of a policy reaction function will generally improve the fit, and indeed will produce an estimate of that linear combination of (9) and (10) which has disturbance orthogonal to the disturbance in (10). If, as is to be expected, n is small, this will be approximately an estimate of the arbitrage relationship, almost unrelated to the policy reaction function. Clearly a multivariate approach, with careful thinking about simultaneity, is important in avoiding serious error in this context.

Through much of our sample period the behavior of one or more monetary aggregates was a focus of attention, and our models all include at least one monetary aggregate in the Fed macroeconomic policy equation. Of course an M will also appear in the equations describing the determination of reserves by joint bank and Fed behavior, representing the impact of deposit flows on required reserves.

As in our previous specifications of small models, there is a block we label **P** that sets "sluggish" private sector variables that do not respond immediately to financial signals. There is also a block labeled **I** of private sector variables that are set in auction markets and that we allow to depend contemporaneously on everything in the system. Before discussing further issues in model specification, we should look at the two sets of exclusion restrictions on A_0 for which we will present estimates.

Table 5

13- Variable Identification

	Vbl	R3	TR	M1	P	Y	U	INR	IR	C	R10	S	Pcm	Dol
FB	R3	1	1	1										
FB	TR		1	1										
P	M1			1	1	1	1	1	1	1			0.3	
P	P				1	1	1	1	1	1			0.3	
P	Y					1	1	1	1	1			0.3	
P	U						1	1	1	1			0.3	
P	INR							1	1	1			0.3	
P	IR								1	1			0.3	
P	C									1			0.3	
I	R10	1	1	1	1	1	1	1	1	1	1			
I	S	1	1	1	1	1	1	1	1	1	1	1		
I	Pcm	1	1	1	1	1	1	1	1	1	1	1	1	
I	Dol	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 5 displays the identification scheme for the smaller model. The list of variables in the model includes both a consumer-level monetary aggregate (*M1*) and total reserves (*TR*). It also contains the unemployment rate (*U*), consumption (*C*) and both residential and non-residential investment (*IR* and *INR*), allowing us to assess the plausibility of responses to monetary policy disturbances in some detail. It avoids the complications of allowing multiple short rates into the same model by including only one, the three-month Treasury Bill rate *R3*. It includes four "information variables" that are observed without delay and might influence Federal Reserve behavior: the S&P 500 stock price index (*S*), the 10-year Treasury Bond rate (*R10*), a commodity price index (*Pcm*) and an index of the value of the dollar (*Dol*). The rows and columns of the table correspond to rows and columns of A_0. The ones indicate coefficients that have been left free. The fractional entries (all .3 in this table) indicate coefficients that have been given smaller prior standard deviations than the coefficients corresponding to 1's. These entries can be thought of as "soft zero restrictions". The model was initially estimated with the prior covariance matrix determined (see the Appendix for just how) by the matrix in Table 5. However, in both this model and the larger one discussed below we found that the shape of the likelihood was highly non-Gaussian when the soft zero restrictions were used, and this created numerical difficulties in constructing confidence bands for the impulse responses.[29] When we replaced the soft zeros with hard zeros, the non-Gaussianity diminished greatly, without greatly changing the

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[29] We generated error bands by simulation methods, so it may not be clear why a non-Gaussian shape causes us difficulty. We used importance sampling methods (see Gelman, Carlin, Stern and Rubin [1995] for a discussion), which require that one be able efficiently to generate random draws from a reasonably good approximation to the actual p.d.f. one is studying. With the soft zeros, the likelihood has multiple peaks and non-linear ridges, very non-Gaussian characteristics. Gaussian approximations to this form were so bad that importance sampling was prohibitively inefficient, and we did not have time to program special methods for the particular shapes we were encountering. We should note that, though we found multiple peaks, these tended either to have qualitatively similar impulse responses or to have much lower likelihood than the ones we summarize here with impulse responses.

estimated impulse responses. So the results we present are those for a model with zeros in all positions where the entry in Table 5 is less than one.

Note that it labels its first two equations **FB**, combining banking and Fed behavior and normalizing them by setting the A_0 coefficient of *R3* in the second equation to zero. (It turns out that the estimated coefficient on *R3* in that equation is close to zero in any case, so that results are almost identical if instead the coefficient on *TR* in the first equation is set to zero, which might be more natural if the first equation is to be interpreted as reflecting macroeconomic policy concerns.) In this specification the Fed is modeled as not responding contemporaneously even to available information, like *Pcm* or *R10*. Results are almost unchanged in a version of the model where *Pcm* is allowed in to the first two equations contemporaneously. The **P** block is a standard list of non-financial private sector variables, except that it includes *M1*.

In this model, consumer-level demand for *M1* is taken to be interest-insensitive within the month; *M1* is a private-sector sluggish variable like *P* and *Y*. This specification is not one we want to defend as necessarily correct; we have experimented with it as a working hypothesis. Results are almost completely unchanged if, while excluding *Pcm,* we allow *R3* to enter all equations of the **P** block, as would be appropriate if there were a traditional money demand equation in the system, involving *R3*, *M1*, *P*, and *Y* contemporaneously, and if the disturbances in that equation were correlated with other shocks to the **P** sector. Then the triangularizing orthogonalization of the **P** block that we have imposed would spread *R3* coefficients over the whole block, even if only the money demand actually contained *R3*.

The **I** sector relates the four information variables to all the other variables, without delay. . The sluggish sector **P** is allowed to depend contemporaneously on *Pcm*, on the grounds that one aspect of sluggish behavior, price markup rules, might create such a direct dependence.

Besides the variations on this specification that we have already mentioned as leaving results unaffected (changing triangular ordering in the first two equations, allowing *Pcm* into the **FB** equations, replacing **P** block dependence on *Pcm* with dependence on *R3*), there are two others. We can allow *U* into the **FB** block equations, and we can exclude both *Pcm* and *R3* from the **P** block equations. The pattern of responses to the first two shocks is largely unchanged if we replace *TR*, which is total reserves adjusted for reserve requirements, by *TRU*, which is not adjusted for reserve requirement changes. The sixth column does show less tendency to oscillatory responses when *TRU* replaces *TR*, however. There are also variations that substantially change the pattern of results, and we will discuss these below, after we discuss the results themselves.
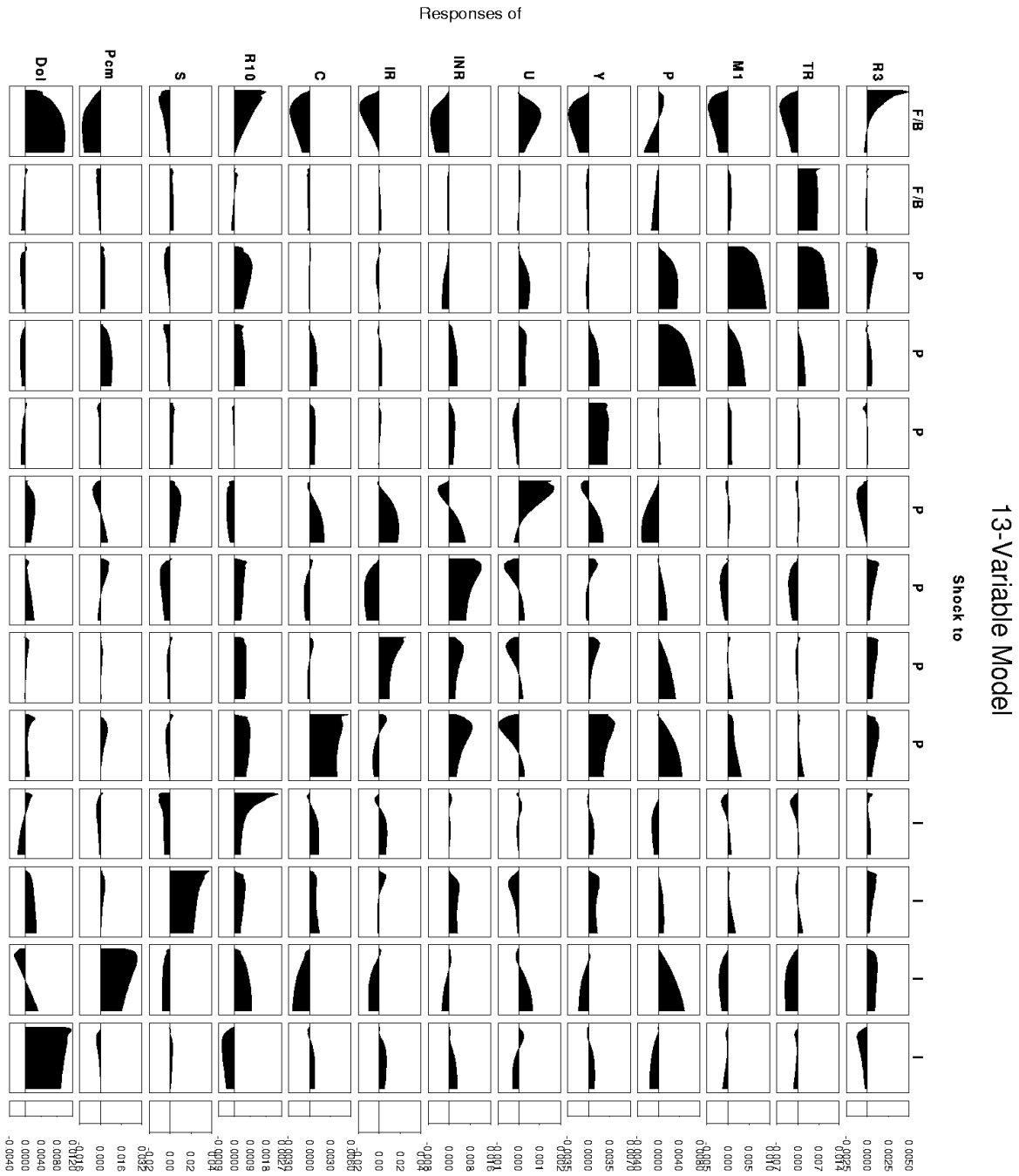
Figure 10

Figure 10's first column, which according to the motivation for our scheme of restrictions on A_0 ought to reflect disturbances to Fed macroeconomic policy concerns, shows effects on the economy that fit its interpretation as a monetary contraction. Short and long interest rates rise; reserves and M fall smoothly; output falls and unemployment rises; *GDP* components fall; commodity prices drop smoothly; the value of the dollar jumps upward and then rises further,

smoothly. Figure 11 shows an expanded view of this first column of Figure 10, with error bands.
The error bands are 68% probability bands, roughly one-standard-error on either side of the
impulse response. It can be seen that most of the responses are rather sharply estimated. The

Figure 11

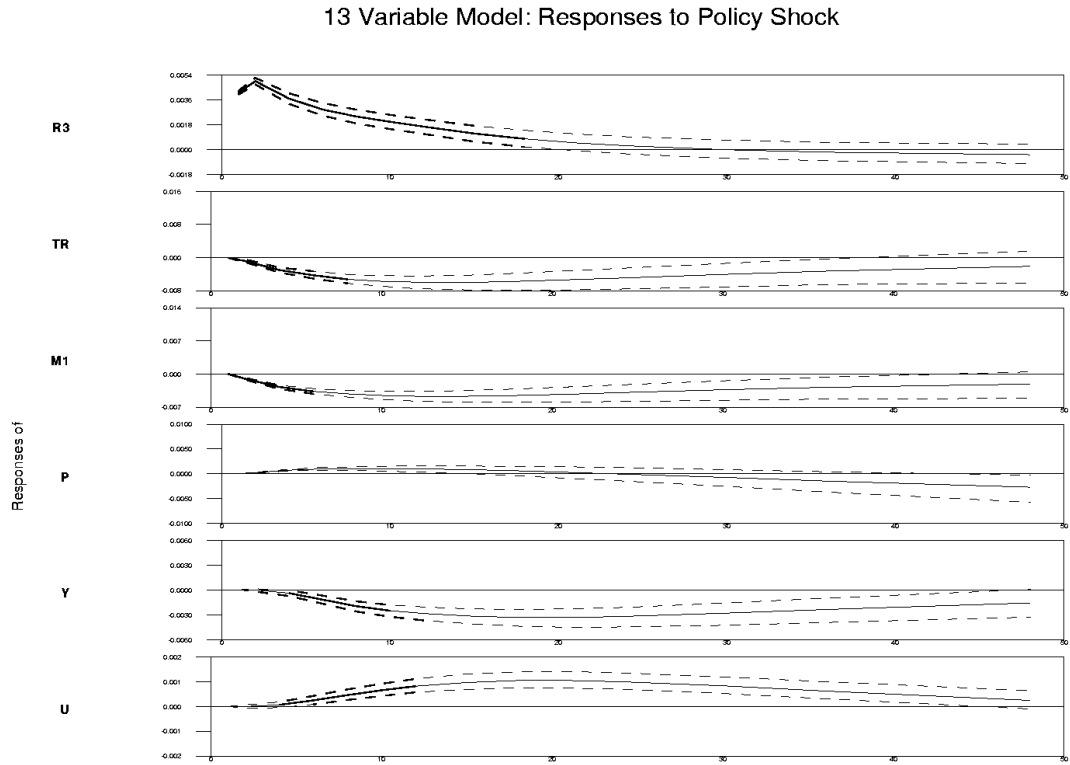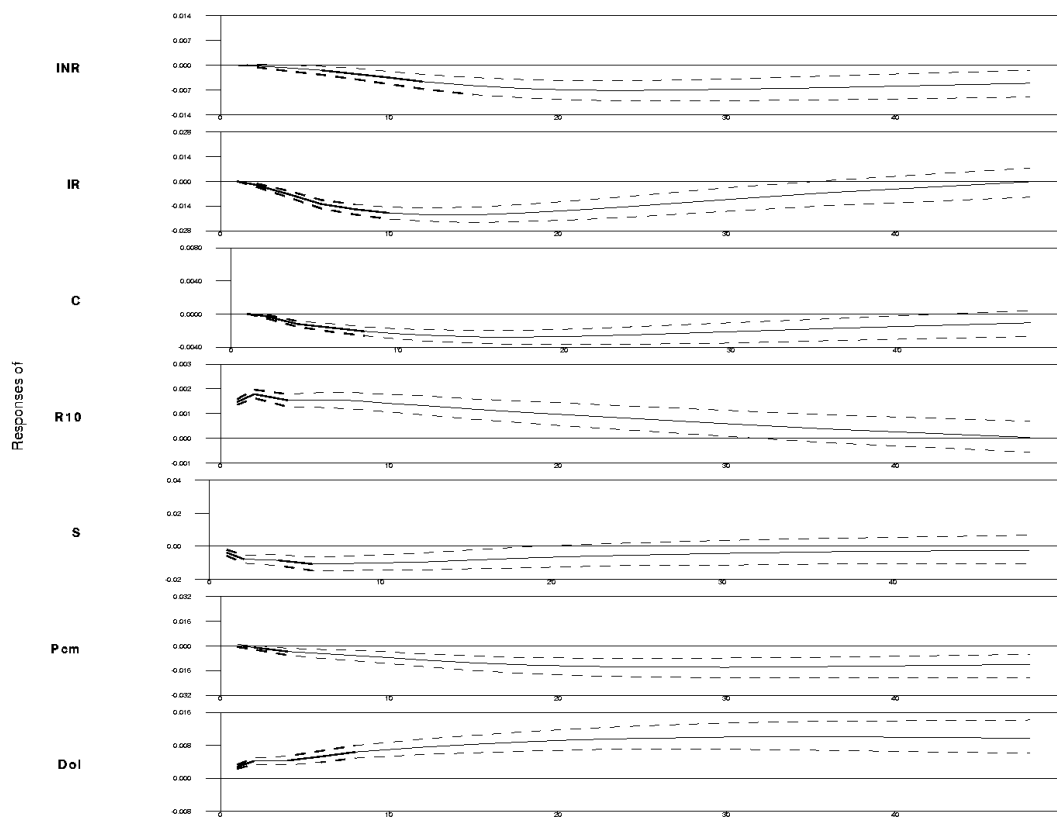13 Variable Model: Responses to Policy Shock

Figure 11 continued

response, though very small, appears to be more than two standard deviations away from zero in the positive direction for a few months. It does turn negative eventually, however, and the commodity price response is negative at all dates and roughly two standard deviations away from zero over much of the four-year span of the response.

The second column shows why a model using reserves as single monetary aggregate can be treacherous: it appears to reflect accommodation by the Fed of shifts in demand for reserves that are unrelated to movements in *M1*. (This result does not change notably when *TRU* replaces *TR*.) Such variation in reserves is, perhaps surprisingly, not primarily variation in excess reserves. Required reserves move quite closely in line with total reserves. The variation apparently arises from shifts in the composition of deposits among categories with different reserve requirements.

The third column of Figure 10 is identified as a private sector shock, and moves *M* and *TR* in the same direction. We have not tried in this model to separate money demand disturbances from other **P** sector disturbances, and this column, because it shows a rise in *P*, does not look like a pure money demand shock, even though the combination of rising monetary aggregates and rising interest rates with no accompanying rise in output could arise from a shift in money demand.

Regardless of exactly how it originates, it is clear that the column-3 disturbance is the most important single source of variation in both *M1* and *TR* and that there is nothing in its estimated form to indicate that the model's allocation of it to the **P** sector is an error. This is a disturbance that expands money supply and raises interest rates, without affecting output. It seems unlikely

that it mistakenly incorporates much of an expansionary monetary policy disturbance. The fact that the model is led by the data to allocate so much variation in monetary aggregates to non-policy disturbances shows why use of monetary aggregates as one-dimensional policy indicators is unsatisfactory.

If we examine the *P*, *Y*, and *U* rows of the Figure, we see that in each case the first two columns, corresponding to monetary policy and banking system disturbances, account for only a modest part of overall variation. For *P*, in fact, the first two columns make a negligible contribution. This model will not admit an interpretation of the sample period as one in which erratic shifts in monetary policy were the prime source of recessions and recoveries or of episodes of inflation and disinflation.

Scanning across the remaining columns of Figure 10, we can see that every column in which the Treasury Bill rate shows substantial movement shows movement in the same direction by *P* and *Pcm*. The first monetary policy column is the only one in which interest rates and either price variable show any substantial movement in opposite directions. This suggests both that none of the other columns are heavily contaminated with monetary policy shock components, and that a large fraction of the variance of interest rates must be attributed to systematic policy responses to the threat of inflation, not to erratic fluctuations in monetary policy. Here again, for the reasons discussed in the earlier section on method, this type of conclusion is robust to variations in the identification scheme.

Table 6

	Vbl	Rf	Rd	TR	RM2	Bs	Bl	RI	M1	Y	INR	IR	P	W	U	S	Pcm	R10	Dol
F	Rf	1		1															
F	Rd	1	1	1															
B	TR	1	1	1					1	1		0.3	0.3					0.1	
B	RM2	1	1	1	1				1	1		0.3	0.3					0.1	
B	Bs	1	1	1	1	1			1	1		0.3	0.3					0.1	
B	Bl	1	1	1	1	1	1		1	1		0.3	0.3					0.1	
B	RI	1	1	1	1	1	1	1	1	1		0.3	0.3					0.1	
Md	M1								1							0.3	0.3		
Md	Y								1	1						0.3	0.3		
P	INR								1	1	1					0.3	0.3		
P	IR								1	1	1	1				0.3	0.3		
P	P								1	1	1	1	1			0.3	0.3		
P	W								1	1	1	1	1	1		0.3	0.3		
P	U								1	1	1	1	1	1	1	0.3	0.3		
I	S	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			
I	Pcm	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
I	R10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
I	Dol	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 6 displays the identification scheme for a larger model that adds to the 13-variable model some variables related to the banking sector (an index of rates on *M2* deposits (*RM2*), bank holdings of securities (*Bs*), bank loans (*Bl*), and the prime interest rate (*Rl*)), the Federal Reserve discount rate, and the Funds rate. Here as with the previous model, we estimated initially with soft zero constraints as shown in the table, obtained reasonable point estimates, but then found numerical difficulties in producing error bands. As with the other model, we found that converting the soft zeros to hard zeros eliminated the numerical difficulties while leaving the

nature of the results largely unchanged. The results displayed are therefore all for the hard zero version of the model.

We display the impulse responses in Figure 12. Because there are two interest rates in this model that are naturally thought of as set by the Federal Reserve – the Federal Funds rate and the Discount rate – the first two columns of the figure are should be interpreted as responses to policy disturbances. They are similar to the first column of Figure 10 in the rows where the variables are comparable, but here the first column apparently represents a short-lived tightening of policy and the second a longer-lived one. Because the two policy disturbances are distinguished only by an arbitrary normalization, "policy shocks" could take the form of any linear combination of these two columns.
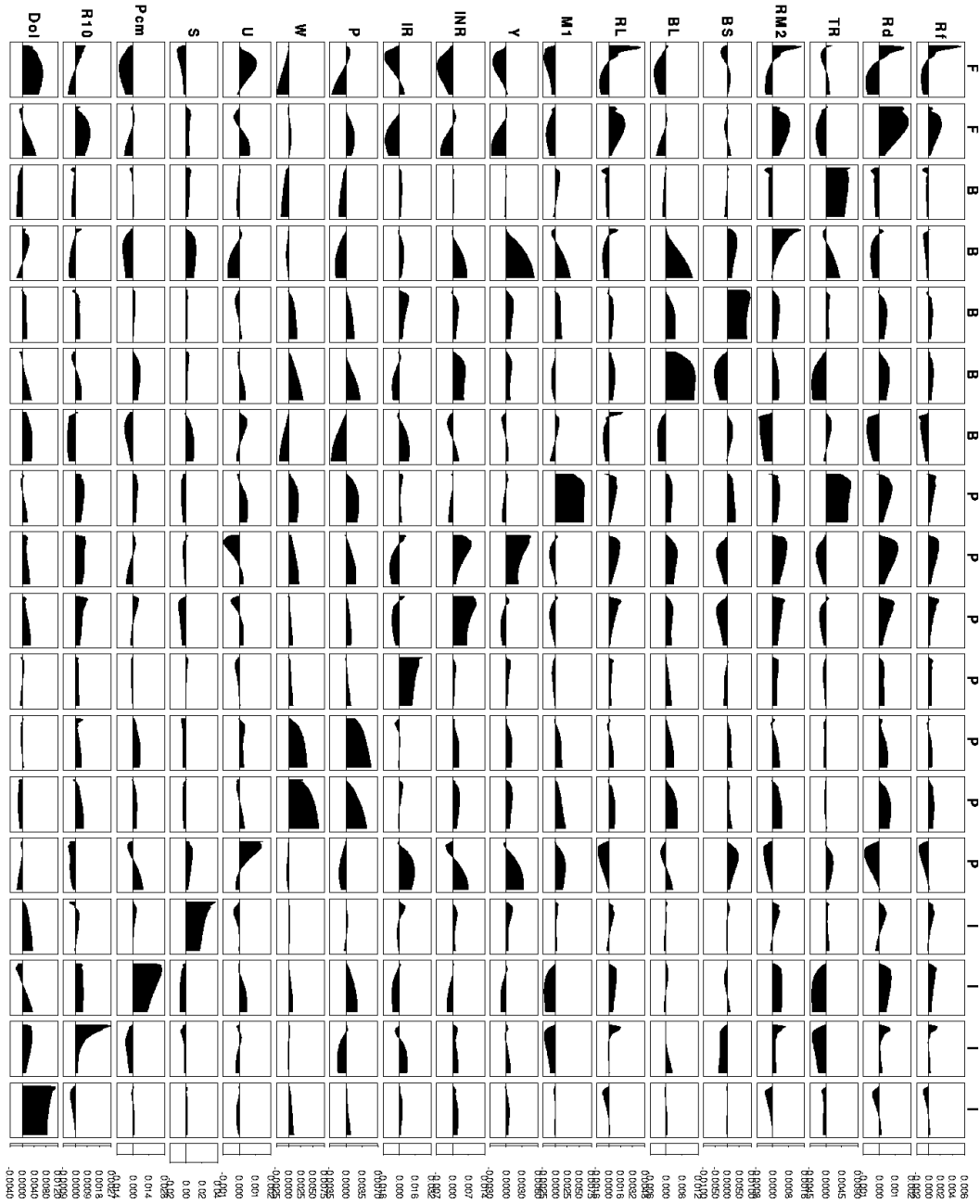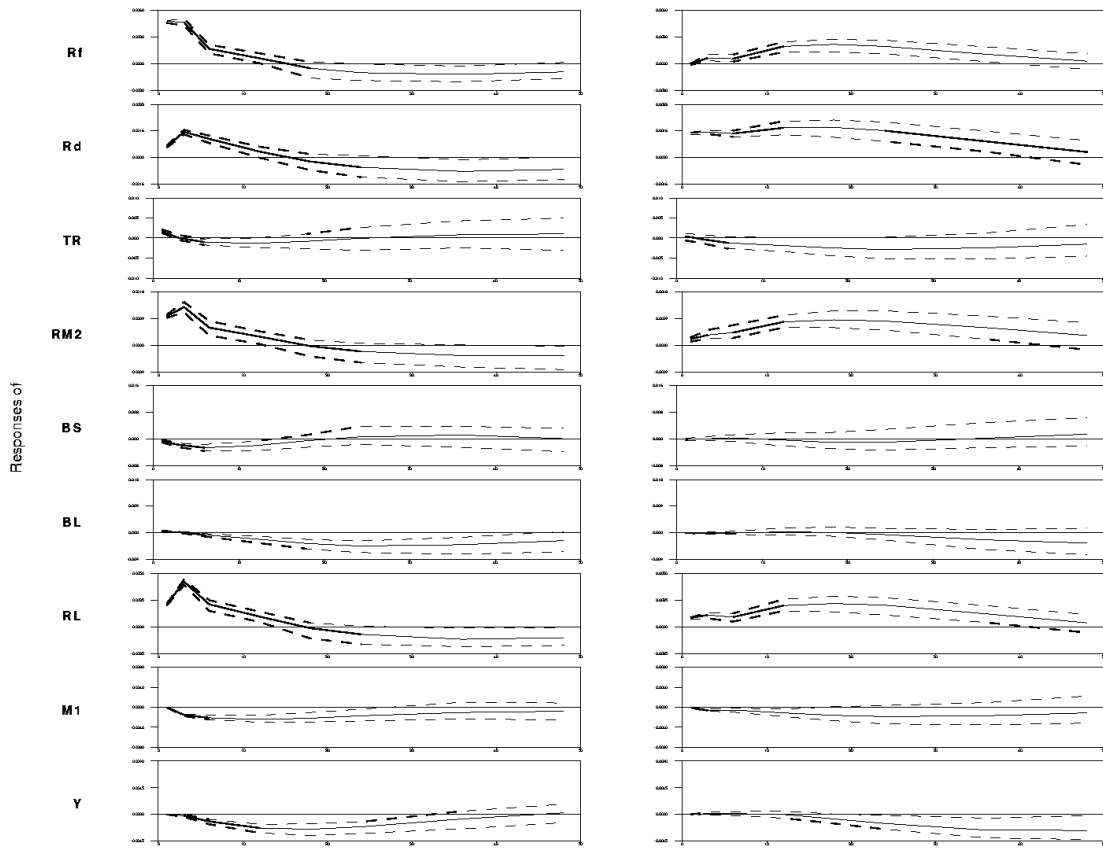
Figure 12

Responses of

18 Variable Model

Shock to

40

Figure 13

18 Variable Model Policy Responses, with Error Bands

Responses of

INR

IR
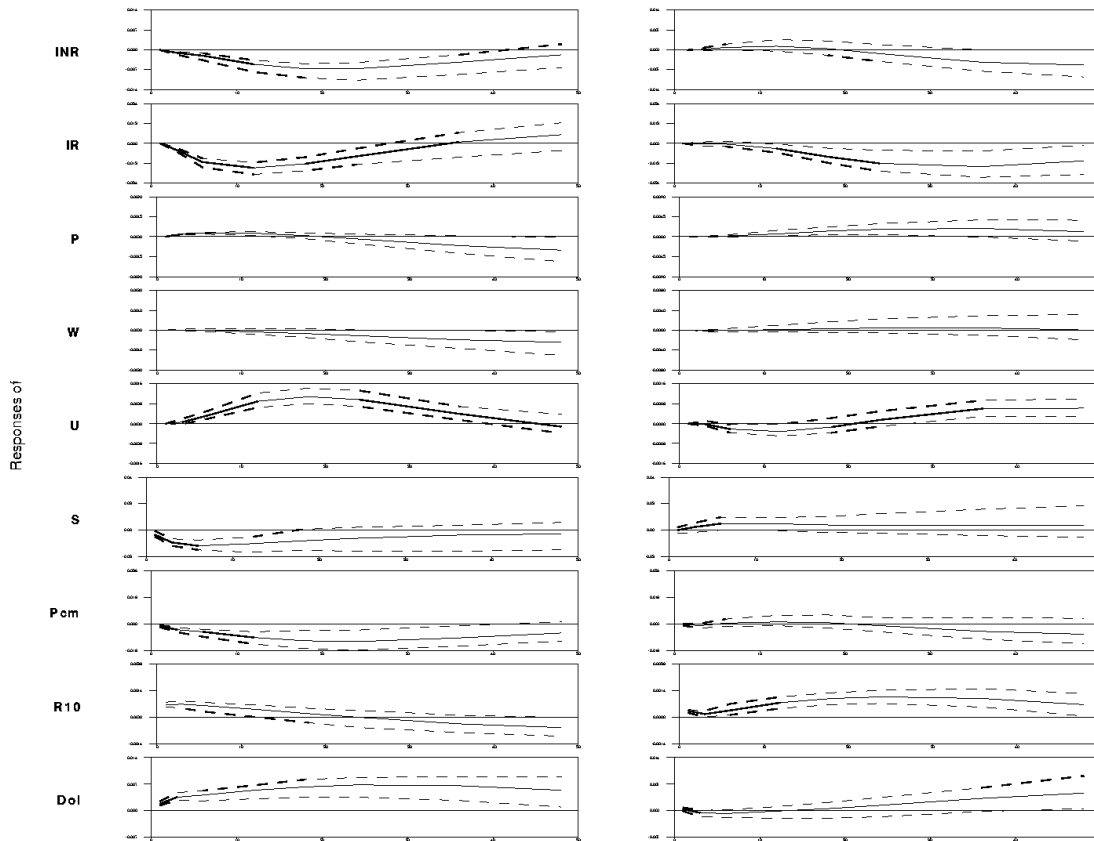
P

W

U

S

Pcm

R10

Dol

Figure 13 shows the responses to the two columns of policy shocks on a larger scale, and with 68% error bands. The first column's responses are fairly sharply determined, though slightly less sharply than the responses in the 13-variable model. The second column's responses mostly leave zero response within the range of high probability, except for responses of interest rates. We see that the first column's disturbance generates an outflow of *M1* deposits, offset initially by a decline in bank securities but then later by a decline in bank loans. This seems to be a reasonable pattern for the banking system's response to a monetary contraction, reinforcing the plausibility of our identification. The fact that *Rf* and *Rd* move in different patterns in the two columns shows that the two variables have considerable independent variation. But there seems to be only one column's worth of substantial non-interest-rate effects here. A policy action that moved *Rf* and *Rd* in the same direction by about the same amount would have effects that approximately sum across the two columns of Figure 13. These would be slightly stronger for the most part than what appears in column 1 of that figure, but not very different on the whole.

Note that in Figure 12 there is, as in Figure 10, a column that accounts for much of the variance of *M1* and reserves and has them moving in the same direction, and in the same direction as interest rates. This column is the 8th in the figure, but the first in the **P** sector.

Also as in the 13-variable model, here we find prices and interest rates moving in the same direction in response to nearly all disturbances. In this case, though, there is one disturbance in the **I** sector, in addition to the main policy disturbance, that moves interest rates up and prices down – the 17th column. This disturbance seems to have negligible real effects, and it involves a sharp, temporary movement in long rates that seems incommensurate with the small associated

movements in *Rf* and *Rd*. Nonetheless, from the form of responses to it, it appears possible that this disturbance could be contaminated with a monetary-policy-shock component.

These results are basically easy to defend, but let us add a note of caution here. We are not sure of the implications of our numerical difficulties in the less restricted models that we initially thought more plausible than these.   It could be that when we resolve them we will see that there is much more statistical uncertainty in these results than what is presented here would suggest. Also, we experimented with a version of the 18-variable model that included the three-month Treasury Bill rate in addition to the Funds rate. This version of the model proved quite capable of producing the kind of identification confusion we discussed in the context of the example model of equations (4)-(5) above.   A reasonable-looking fitted model, after some small change in specification or sample period, might show "impulse response rotation", with what looked like a monetary policy shock emerging as an **I** sector shock, while the shock formally identified as a monetary policy shock ceased to make sense. This is exactly the pattern that would be expected if the Treasury Bill rate were tightly linked to the Funds rate by term-structure arbitrage relationships and contained little information useful to policy authorities. As we pointed out in our discussion above, in such circumstances including the Bill rate in the model can weaken identification without improving the accuracy of the model.   We think therefore that we are justified in reacting to these difficulties by looking at a model without the Treasury Bill rate, but it would of course be more satisfactory to find a way to model the two short rates jointly while maintaining robust identification.

5. Conclusion

What we have presented here is clearly far from the last word on these issues, even in the context of identified VAR research.   It remains quite possible, for example, that we are still attributing to policy disturbances some variation that actually originates in adverse supply shocks. This would tend to attenuate the estimated price-reducing effects of monetary contraction and exaggerate the estimated output-reducing effects. With similar methods, using smaller models, Soyoung Kim [1995] finds very small real effects and larger price effects using data for other countries, and Cushman and Zha [1994], exploiting the identification possibilities that arise for a small open economy, also find small real effects.

Nonetheless we regard our estimates as having some chance of being about right. We think that using the larger modeling framework makes it possible to get a clearer understanding of what the identification problems are, and to become more confident in interpreting results as we trace effects across a wider variety of variables. We believe that we have rather firmly established the unreliability of identifications that treat a monetary aggregate, whether reserves or an *M* variable, as moving mainly in response to policy disturbances in the short run. The bulk of movements in both aggregates arise from policy accommodating private sector demand shifts. And we believe we have confirmed that most movements in monetary policy instruments are responses to the state of the economy, not random deviations by the monetary authorities from their usual patterns of behavior. To policy analysts, accustomed to basing policy recommendations on current and expected economic conditions, this finding is surely unsurprising, but it should nonetheless be disturbing. It implies that careful attention to modeling of the policy-setting process is essential to accurate statistical assessment of the effects of policy. Much existing empirical policy modeling

ignores or treats casually the implications of policy endogeneity. We hope to have demonstrated that careful treatment of policy endogeneity is feasible, as well as important.

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Data Appendix

All data are monthly from July 1959 to March 1996.

Rf = Federal funds rate, effective rate, percent per annum.

Rd = discount window borrowing rate at the Federal Reserve Bank of New York, percent per annum.

TR = total reserves, adjusted for breaks due to changes in reserve requirements, SA, Bil.$.

TRU = total reserves, not adjusted for breaks due to changes in reserve requirements, SA, Bil.$.

RM2 = M2 own rate of return: deposit-weighted averages of annual effective yields on deposits in M2.

BS = Securities at all commercial banks, SA, Bil.$: computed as total loans and securities at all commercial banks less total loans and leases at all commercial banks.

BL = Total loans and leases at all commercial banks, SA, Bil.$.

RL = Prime rate on short-term business loans, average of daily figures, percent per annum.

M1 = M1 money stock, SA, Bil.$.

M2* = M2 money stock less M1 money stock, SA, Bil.$.

Y = real gross domestic product, SA, Bil. Chain 1992$: monthly series interpolated from national income and product accounts quarterly series using Chow-Lin procedure with underlying monthly data on total industrial production, civilian employment 16 years or older, retail sales deflated by consumer prices, real personal consumption expenditures, and the National Association of Purchasing Managers' Composite Index.

INR = real private non-residential fixed investment, SA, Bil. Chain 1992$: monthly series interpolated from national income and product accounts quarterly private non-residential fixed investment series using Chow-Lin procedure with underlying monthly data on real value of new construction of privately owned nonresidential industrial structures, total equipment component of industrial production, industrial machinery and equipment component of industrial production, intermediate products and business supplies component of industrial production, manufacturers' shipments to capital goods industries, and manufacturers' shipments of construction materials, supplies, and intermediate products.

IR = real residential fixed investment, SA, Bil. Chain 1992$: monthly series interpolated from national income and product accounts quarterly private residential fixed investment series using Chow-Lin procedure with underlying monthly data on housing starts, construction supplies component of industrial production, manufacturers' shipments of construction materials, supplies, and intermediate products, and real value of new construction of privately owned residential buildings.

P = consumer price index for urban consumers, total, SA.

U = civilian unemployment rate, SA, percent.

R3 = 3-month Treasury bill rate, secondary market, percent per annum.

Pc = crude materials component of the producers' price index, SA.

Pcm = IMF index of world commodity prices.

R10 = 10-year Treasury bond yield, constant maturity, percent per annum.

E = trade-weighted value of the U.S. dollar, Atlanta Fed index, 1980=100.

Appendix: The Prior

For sufficient detail on the prior to actually use our methods, and for an appreciation of the numerical and mathematical considerations that led us to this particular form, refer to Sims and

Zha [1996]. Here we outline our approach. We postulate a joint normal prior, initially with diagonal covariance matrix, on the elements of A_0 that are not constrained to zero. In the case of reduced form models, we choose an ordering of the variables in which to constrain A_0 to be triangular, an exactly identified normalization. We then specify a joint normal prior on all the coefficients in A_s, $s > 0$ *conditional* on A_0. To make the prior center on specifications in which reduced form models for individual variables are random walks, we make the conditional mean of $A_1 | A_0$ be A_0 itself, while the conditional mean of $A_s | A_0$, $s > 1$ is zero. The prior standard deviations of the elements of the A_s matrices shrink with increasing s, and these elements are initially taken as uncorrelated. It may seem that this approach, constructing the prior from a marginal on A_0 and a conditional distribution for $A_s | A_0$, $s > 1$, is roundabout and complicated, but it turns out to be critical to making the method numerically feasible in large models.

On this base prior we then layer additional components, constructed as "dummy observations". The dummy observations induce correlations across elements of A in the prior. The dummy observations express beliefs that no-change forecasts of the model's variables are likely to be quite good. Of special note is that in large dynamic systems like this, the same phenomenon that leads to the well-known bias toward stationarity of least squares estimators leads to a bias toward explaining implausibly large fractions of the historically observed variation in the data with deterministic components of the model. We found that dummy observations of this "no-change-forecasts should be good" type also express the belief that models that explain too much with deterministic components are implausible. It appears that using such dummy observations is essential to getting sensible results in models of this scale, yet conventional time series diagnostic testing might not reveal situations where this bias is distorting results. This point is discussed further in Sims and Zha [1996].

Though these priors may seem complicated, they were not influential in determining the character of the results. In small models, where the bias toward excessively strong deterministic components is not great, results with a flat prior and with our prior look quite similar. The prior tends to make the estimated impulse responses smoother without changing their overall form. The prior was not manipulated to make results look more reasonable, except in the case of the "soft zero constraints" in the prior on A_0 that were discussed in the text.