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Should Policy Makers Worry about Asymmetries in the Business Cycle?

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Abstract. *This paper reconsiders the conventional use of econometric models, especially identified vector autoregressive models, in guiding monetary policy. The main question I explore is whether these models are seriously flawed because they ignore asymmetries in the business cycles. Toward that end, models that allow for asymmetric business cycles—defined by the case where recessions and expansions are not mirror images of each other—are estimated. The results suggest that policy makers should worry about asymmetries in business cycles because most econometric models cannot capture empirically important asymmetries. In particular, estimated multiregime models show that the effects of monetary policy are stronger during turning points and outright recessions than in expansions. I conclude that the symmetry/asymmetry question has as much, and maybe even more, practical significance than debates over identification assumptions that have influenced much of the empirical macroeconomic literature over the past 20 years.*

Keywords. business cycles, asymmetries, vector autoregressions, switching models, monetary policy

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1 Introduction

Government policies that affect the macroeconomy—such as efforts to fight inflation or to end a recession—are clearly influenced by the opinion and advice of professional economists. A good example is the use of the staff of economists in the Federal Reserve System (both at the Board of Governors and the 12 regional Federal Reserve banks). Changes in tax laws are also heavily debated among economists before being voted upon by Congress. In the design of these policies, however, the role of formal empirical research has varied over time, and has never been well defined or easily characterized. There continues to be considerable debate about the appropriate role of econometric models in the policy-making process—especially attempts to determine the most likely effect of a change in policy.

There is extensive literature on using econometric models for policy-making, but a consensus on the “right” econometric model has never been reached. Three reasons have been given: (1) policy makers are given little guidance in choosing among competing econometric models; (2) there are serious questions about the models’ accuracy—as a general group—in forecasting; and (3) rational expectations theory and the “Lucas critique” cast serious doubt on whether most econometric models are appropriate for policy analysis.

In essence, serious disagreements remain between model builders and users over both the proper structure of a good model and the appropriate method for simulating the effect of a change in policy. Also, the most prominent large macroeconometric models have either performed poorly or have shown wide disagreements during some prominent episodes in the business cycle. A clear problem has been the inability to consistently

foresee recessions. Also, forecasts for general trends in inflation have often proven, in retrospect, to be dangerously misleading at times (e.g., the upward-trend inflation in the 1970s, and the downward trend in the mid-1980s and 1990s, were missed).

Recognizing the importance of the three problems noted above, this paper discusses a fourth problem: the most popular econometric models are incompatible with evidence of important asymmetric patterns in the business cycle *and* possibly also with the intuition of many of the final decision makers. Many studies have pointed out the statistical significance of various types of asymmetries in the business cycle. The goal of this paper is to concentrate on the economic significance of these asymmetries. In essence, I attempt to be constructive both by highlighting the neglected asymmetries problem, primarily in the context of monetary policy, and by pointing out ways that standard econometric models can be modified to handle business-cycle asymmetries.

The neglected asymmetries problem is most inherent in vector autoregressive models (called VARs), which are growing in popularity as an alternative to the large-scale econometric models that dominated empirical policy analysis throughout the 1960s, 1970s, and most of the 1980s. Almost invariably, VARs are assembled as a set of linear relationships among only four to nine of the most important macroeconomic variables—such as output, prices, money supply, and interest rates—with symmetrically distributed shocks driving business-cycle fluctuations. By definition, this type of structure intentionally rules out asymmetries. Ignoring the possibility of asymmetries and rarely testing for the adequacy of linear specifications, the literature on VARs has typically concentrated on identification schemes that break unexpected movements in variables such as GDP, an aggregate price index, interest rates, and the monetary base into different types of macroeconomic shocks such as output (quantity) versus price, and/or money supply versus money demand.

Estimating straightforward generalizations of the VAR framework that allow for asymmetries, I present results from monetary policy simulation that many econometric models would have great problems in replicating or even crudely capturing, simply because the models ignore asymmetries. In fact, the most interesting asymmetries are found at some of the most important times in the business cycle. Therefore, I conclude that policy makers should worry about asymmetries precisely because most econometric model builders do not seem to be concerned with them. Probably the most important point to make is that the symmetry/asymmetry question has as much, and maybe even more, practical significance than debates over the identification assumptions that have influenced much of the empirical macroeconomic literature over the past 20 years. In addition, I argue that a portion of the other three problems, and possibly a large portion, can be attributed to neglected asymmetries.

2 Business Cycle Asymmetries and Econometric Modeling

2.1 Defining asymmetries

The first steps in tackling the issues discussed in the introduction are to define asymmetries in the business cycle and build a framework for analyzing policy decisions when asymmetries are present.

The simplest definition of an asymmetric business cycle is one where recessions and expansions are not mirror images of each other: that is, downturns are not upturns multiplied by negative one. But because there are numerous types of asymmetric concepts or hypotheses that are plausible, it is easier to define what is meant by a symmetric business cycle, and point out the types of asymmetries that linear models cannot capture.

A symmetric business cycle is one where (1) all types of shocks are symmetrically distributed around zero, and (2) the dynamic propagation mechanisms that translate these shocks into output fluctuations do not depend on whether the shocks are positive or negative.

2.2 Conventional models

All linear models, with conventional VARs being the most prominent and clear example, satisfy the symmetry requirements. A simple two-variable example is:

$$y_t = a_0 + a_1 y_{t-1} + a_2 r_{t-1} + u_t \quad (1)$$

$$r_t = b_0 + b_1 y_{t-1} + b_2 r_{t-1} + z_t \quad (2)$$

where y represents output, and r is the interest rate.¹

¹In this paper, asymmetries in the error terms or shocks (e.g., u and z in Equations (1) and (2)), are ruled out as the source of business-cycle asymmetries. They are generally less interesting than other types of asymmetries, and can usually be captured by shifts in the intercept (a_0)

Much of the literature on VARs has been devoted to identifying and specifying a plausible causal ordering among endogenous variables such as y and r , which in this case boils down to determining which shock occurs first, u or z . When shocks to r occur first, possibly because of a change in monetary policy, Equation (1) can be replaced with

$$y_t = c_0 + c_1 y_{t-1} + c_2 r_{t-1} + c_3 z_t + e_t \quad (3)$$

Here, the c parameters are combinations of the a and b parameters in Equations (1) and (2). Most important, this equation highlights the case where z is the effective policy variable.

Using Equation (3) to map the effects of z_t on y_t is trivial, but the design of a realistic policy simulation is far from trivial. A typical VAR policy simulation would perturbate z at time t , and trace the effect of this policy exercise on both y and r for a number of periods forward by iterating on Equations (1) and (2) with e and z set at 0 in future time periods. In this case, the effects of policy (i.e., z) are linear and symmetric, because Equations (1) and (2) are linear and symmetric.

Note, however, that there is no requirement that z be set at 0 in future periods (as is typically done). In other words, a valid and plausible simulation can be created using a sequence of z terms. In addition, the b coefficients, which implicitly define the policy function, do not need to be interpreted as a representation of optimal decision making or even be consistent with rational expectations. (These points are discussed in greater detail below.)

Compared with Equations (1) and (2), state-of-the-art VARs have more variables and longer lag structures to capture dynamic relationships between the variables in a most flexible manner. And much of the VAR literature has been devoted to exploring more complicated identification schemes, with Gordon and Leeper (1994) and Bernanke and Mihov (1995) providing good examples of identification schemes that are based on theoretical considerations.² Despite technical sophistication in these dimensions, VAR model builders rarely test the underlying assumptions of linearity and symmetry across the business cycle. This paper shows that asymmetries should not be dismissed so readily, with economic significance being given greater emphasis than statistical significance. (Reasons for less emphasis on statistical tests of asymmetry than might be expected are discussed below.)

Even with controversies over identification schemes and ignored asymmetries, VARs have clearly supplanted large econometric models in academic research. Nonetheless, large models, which cover many more variables and typically have hundreds of equations, still hold a place in economic forecasting and policy evaluation, even though academics tend to shy from the strong assumptions that motivate the “behavioral” equations or structural relationships in the large models (such as explicit consumption functions, somewhat inflexible money-demand equations, and equations describing capital equipment spending and other types of investment at very high levels of detail). In practice, large-model identification primarily takes the form of separating the endogenous variables into distinct blocks and allowing little or no contemporaneous correlation across the blocks. These identification assumptions are somewhat analogous to those in VARs, and differences have not been shown to be important in analyzing policy.³ While many large models typically have nonlinear equations that could allow for asymmetries, most can be closely approximated by smaller, linearized versions that only include the most important equations and variables. Most important, simulations of policy effects are typically dominated by relatively simple linear, and therefore symmetric, relationships. In essence, most large models are as ill-equipped as VARs to handle business-cycle asymmetries.

and b_0). It is also true that asymmetries can often be removed by recasting the units of time to be different than calendar time, or by creative transformations of the dependent and independent variables. However, these solutions make interpretations and simulations of the resulting models much more difficult.

²Also see the works of Leeper, Sims, and Zha (1996) for a VAR that is cast into a sophisticated Bayesian framework, and Pagan and Robertson (1995) for a review of the “price” and “liquidity” puzzle problems that tend to plague VARs with simple identification schemes.

³Two points are relevant here. (1) Identification schemes cannot solve the Lucas critique problems that attack the basic strategy used to construct these models: fitting equations to match past relationships among the important macro variables and the instruments of public policy. When policy affects the fundamental forward-looking decision process of both consumers and producers, a strong tie between the equations of an econometric model and previous patterns in the data may be a liability, not an asset. (2) Identification schemes tend to be more important in separating out historical policy shocks, while the lagged variables (or implied behavioral relationships) are more important in determining the effects of policy shocks.

2.3 Examples of asymmetric equations

It is not hard to allow for nonlinear and asymmetric effects.⁴ For example, a straightforward extension of Equation (1) can capture nonlinear policy effects:

$$y_t = a_0 + a_1 y_{t-1} + g(r_t; \phi) + u_t \quad (4)$$

Alternatively, a nonlinear and asymmetric relationship could be built directly around the policy variable, z :

$$y_t = a_0 + a_1 y_{t-1} + a_2 r_{t-1} + g(z_t; \phi) + e_t \quad (5)$$

In both cases, the contemporaneous effects of z are determined by the function $g(\cdot)$, which is parameterized by the vector ϕ . For example, the function could include a quadratic term (e.g., $g(z_t; \phi) = \phi_1 z_t + \phi_2 z_t^2$) or be noncontinuous and have different effects depending on whether z is positive or negative (e.g., $g(z_t; \phi) = \phi_1 z_t$ if $z_t < 0$; $= \phi_2 z_t$ if $z_t \geq 0$; and $\phi_1 \neq \phi_2$). Cover (1992) used the latter strategy to model a case where negative monetary policy shocks have a much greater impact than do positive monetary shocks (that are equal in magnitude).⁵

One problem with this type of modeling strategy is that there is no clear correspondence between nonlinear effects of policy and asymmetric business cycles. Also, because the policy variable is the only source of nonlinearity, there is great reliance on properly identifying and measuring this term.

Bilinear models, which can be considered a more direct generalization of VARs, use both quadratic and cross-product terms to allow for nonlinear relationships between the dependent and explanatory variables. An example that can provide asymmetric patterns that are related to the business cycle is:

$$y_t = a_0 + a_1 y_{t-1} + a_2 r_{t-1} + b_1 y_{t-1} r_t + e_t$$

Here, the effect of the policy variable enters through r and depends on the value of the lagged dependent variable.⁶ A positive value for b_1 and a sufficiently negative value for a_2 would make the effect of the policy variable remain negative, but fall in magnitude when output growth was high in the previous period.

Bilinear models are particularly interesting for empirical investigations, because they can capture fairly general nonlinear and asymmetric relationships by adding additional terms such as y_{t-1}^2 and $y_{t-1} r_{t-1}$ to an otherwise linear model. For this reason, results from a five-variable model that uses equations such as the one above are presented in the next section.

Threshold autoregressive (TAR) models share similarities with bilinear equations, but allow for greater degrees of nonlinearity and asymmetry. Therefore, TARs have received increasingly greater usage in business-cycle studies. Two good examples are Beaudry and Koop's (1993) study, where they added a depth-of-recession effect to show negative output shocks are much less persistent than positive shocks, and Pesaran and Potter's (1994) work that includes floor and ceiling effects in a model of GDP dynamics.

A simple but interesting TAR version for modeling the growth rate of output is

$$y_t = a_0 + a_1 y_{t-1} + a_2 z_t + b_0 s_t + b_1 s_t y_{t-1} + b_2 s_t z_t + b_3 s_t z_{t-1} + u_t$$

with

$$s_t = 0 \text{ if } y_{t-1} \geq 0, \text{ and } s_t = 1 \text{ if } y_{t-1} < 0$$

⁴This presentation covers nonlinear model building in very general terms. For a more comprehensive treatment of the various strategies, see the work of Granger and Terasvirta (1993).

⁵The asymmetric effects were initially reported as statistically significant, but unfortunately a computer-programming mistake caused Cover to overstate the test statistics value. Note that this approach also has similarities with TARs discussed below, and statistical tests need to consider generated regressor effects when z is created as a residual from another estimated equation.

⁶A related form that is often labeled as bilinear,

$$y_t = a_0 + a_1 y_{t-1} + a_2 z_t + e_t + b_2 e_{t-1} z_t + b_3 e_{t-1} z_{t-1}$$

can also be extended to the multivariate case, but is much more difficult to estimate because the nonlinear effect comes through the lagged-error term for the y equation and the policy variable, z , which also would need to be estimated as an error in the r equation. This would place greater reliance on properly identifying shocks to the system. For this reason, only the simpler bilinear form (which uses observed y and r instead of estimates of e and z to capture nonlinear effects), is computed for this study.

In this case, the effects of the right-hand side variables shift when output declines in the previous period, which is one possible definition for a recession.⁷ Although this type of model is plausible, in the next section, I only report results using a more flexible, alternative method for determining a shift in coefficients. This model, while not a true TAR, retains the general spirit of the asymmetric effects that these models often exhibit.

The second nonlinear model also shares features with switching models, and in particular Markov switching models (MSM), that are increasingly popular in empirical business-cycle analysis. The MSM that Hamilton (1989) estimated for output growth was based on an equation with two distinct regimes:

$$y_t = a_0 + a_1 s_t y + u_t$$

Here, s_t is considered an unobservable or latent variable that equals either 0 or 1. This yields a switching-in-the-mean effect.⁸ If $s = 1$ corresponds to recession periods, a negative value for the s coefficient, such that $a_0 + a_1 < 0$, is expected. It is not difficult to extend the model to add additional explanatory variables that have shifting coefficients and build an MSM that shares features with the TAR described above.

The most important difference between TARs and MSMs comes from the Markov feature that refers to the process that determines s . In an MSM, s is a completely exogenous, random variable that requires the estimation of additional terms:

$$p_{00} = \text{prob}(s_t = 0 \mid s_{t-1} = 0) \text{ and } p_{11} = \text{prob}(s_t = 1 \mid s_{t-1} = 1)$$

Note that $p_{00} > p_{11}$ means that expansions last longer on average than recessions.⁹

An MSM structure that is slightly easier to generalize to cases with more than two regimes and multivariate systems is

$$y_t = X_t \beta_{s(t)} + u_t$$

Here, X_t can be a vector that includes lagged y , r , and possibly z variables, with distinct sets of right-hand-side coefficients that are indexed by $s = 1, 2 \dots n$. Boldin (1995) followed this approach, using both nominal and real monetary aggregates, changes in short-term interest rates, and four different interest-rate spreads, as explanatory variables for industrial production (IP) growth, and found interesting and plausible asymmetric patterns.¹⁰

A large problem in estimating and interpreting MSMs is that the regimes are unobservable; therefore, their effects and incidence must be inferred from the data, which adds complications. The complications then grow in an exponential manner as these models become more flexible in capturing interrelationships among variables. More important, conventional testing strategies for determining the proper number of regimes, including the acceptance or rejection of a conventional one-regime model over a two-regime generalization, are not appropriate. The main problem is that a singularity condition in the likelihood function gives Lagrange Multiplier (LM, also known as score) tests no power to reject the single-regime hypothesis, and gives likelihood-ratio and Wald tests unconventional and unknown distributions.¹¹

Therefore, when estimating a two-regime model for the next section, I assumed $s = 1$ during the traditional, NBER-designated recession periods and turning points (including the quarters with the peaks and troughs). This is in keeping with Hamilton's general results, but admittedly may cause biases if an exogenous

⁷A more general parameterization would replace $y < 0$ with $y < c$, with c being estimated as well as the a and b terms. Granger and Terasvirta (1993) discussed many other generalizations that allow for smooth transitions (an example is $s_t = 1/(1 + \exp(-\gamma y_t))$).

⁸Hamilton also assumed that u_t follows an AR(4) process, which adds to the dynamic richness of the model, but does not affect the basic interpretation. Boldin (1996) explored the robustness of Hamilton's specification, and concluded that a three-regime MSM, but with a simpler autoregressive structure, better captures business-cycle dynamics.

⁹This setup assumes that recessions and expansions are not duration dependent (i.e., once a new regime begins, the odds of it ending do not vary over time). Also note that these two probabilities define the entire Markov switching process, since $p_{01} = \text{prob}(s_{t+1} = 1 \mid s_t = 0) = 1 - p_{00}$ and $p_{10} = \text{prob}(s_t = 0 \mid s_{t-1} = 1) = 1 - p_{11}$.

¹⁰Other examples of generalizations to Hamilton's framework that looked for related asymmetric patterns in monetary policy effects are the works of Rhee and Rich (1995), Ammer and Brunner (1995), and Garcia and Schaller (1995). These studies have limitations, because they make numerous auxiliary assumptions that mainly have to do with identifying the exact stance of monetary policy at any particular point in time, and are plagued by generated regressor problems.

¹¹See an earlier work (Boldin 1992) for more detail on the testing problem and a discussion of various algorithms for estimating these models.

and grossly incorrect regime-splitting procedure is used. Reasons why this is not considered a fatal problem are discussed below, after results from the model are presented.¹²

2.4 Economic versus statistical significance of asymmetries

Formal specification tests often suggest that linear structures do not adequately capture business-cycle dynamics. For example, Blanchard and Watson (1987) found unusual outliers in conventionally computed VAR residuals; Runkle (1987) and Spencer (1989) showed that VAR results are overly sensitive to reasonable changes in specifications and identification assumptions; and Abate and Boldin (1993) showed that linear output equations fail many diagnostic tests, even when a large set of explanatory variables is used. And as discussed above, two specific nonlinear modeling techniques, Hamilton's (1989) Markov-switching framework and Beaudry and Koop's (1993) depth-of-recession effect, have both received significant attention and been expanded upon by others to show interesting and plausible asymmetric patterns in business cycles.¹³

Nonetheless, it is still an open question as to whether asymmetries in output dynamics are significant enough to cause conventional models to give misleading results. The main problem is that statistical test results are either somewhat ambiguous or unconvincing to those who prefer linear models. But a conventional statistical test that uses a linear model as the null hypothesis that needs to be rejected with a high degree of confidence before added nonlinear terms are considered significant is not the best means for determining whether nonlinear models (and of course, consideration of their implied asymmetric effects) would be useful in policy making.

A simple framework for modeling the policy-making process can clarify the need to consider econometric models that allow for asymmetric business-cycle dynamics, irrespective of formal statistical tests. Assume a single control variable, z , and a single goal, maximizing $v(y)$. The variable y can be thought of as the growth rate of output, or the difference between actual output and potential, or even the inverse of the unemployment rate. The function $v(\cdot)$ is simply the policy maker's reward or objective function.

If there is no consensus on the right model to use, a rational policy maker would choose z to maximize

$$EV(z) = \sum_i \sum_j p_i d(e_j) v(f_i(y; z, x, e_j))$$

where $f_i(\cdot)$ specifies a particular model, including estimated parameters, that hypothesizes a direct relationship between the final target y , the policy variable z , additional exogenous variables x , and an error term e . For each model there is a corresponding total-probability measure, $p_i d(e_j)$ that relates to both the level of confidence that the particular model is correct and an error term of size e_j that is seen in the data.¹⁴

Policy makers that only consider one model, say a particular VAR labeled $i = 1$, are in essence assuming $p_i = 0$ for all other possibilities. Such strong belief in a single model is obviously unrealistic, but it may not be a major problem if all other plausible models give very similar results.

¹²A more general switching-model framework that does not rely on NBER business-cycle dates, but incorporates additional information to help identify the regime sequence, would use

$$\text{prob}(s_t = s_{t-1}; y_{t-1}, \gamma) = 1 - \gamma_1 / (1 + \exp(-\gamma_2(y_{t-1} - \gamma_3)))$$

If $\gamma_2 = 0$, the probability of switching is completely random and unrelated to the level of y in previous periods. Alternatively, if $\gamma_2 = 1$ and γ_2 is large, switches are determined almost entirely by unusually large negative shocks that affect the value of y in the previous period. This framework can nest both the simple Markov cases and TARs. For this paper, however, the complications and the loss in clarity that comes from making no assumptions about the actual regime dates, were seen as outweighing the benefits of being more general and limiting all potential biases.

¹³Some other noteworthy findings (but in no way an exhaustive list): Brunner (1992) used a semi-nonparametric approach to characterize significant asymmetries, and Ramsey and Rothman (1997) showed that asymmetries imply a time-irreversible property that is evident in most macroeconomic time series.

¹⁴For convenience, the error term is defined such that each model's error has the same probability distribution or data-generating process, and the possibilities are finite. This framework can be easily modified to allow for a continuous distribution with infinite possibilities and separate data-generating processes for each model's error term (but with all of the associated pdfs integrating to one, of course). And in a more general framework, y could be a vector of endogenous variables that include both output and price growth, and does not have to be limited to a single time period.

Another reason to use only one model would be the case were both $v(\cdot)$ and all $f_i(\cdot)$ are linear, so that $EV(z)$ can be recast as

$$E \left[\sum_i p_i (a_i + b_i z + c_i x + e) \right] = E [a' + b' z + c' x + u]$$

Here the parameters $a' = \sum_i p_i a_i$, $b' = \sum_i p_i b_i$, and $c' = \sum_i p_i c_i$ would be weighted averages of the parameters in the different models. Note that u , the resulting error term, can be safely ignored in this completely linear case if its expected value is zero. Therefore, point estimates from a single model that captures the general consensus of all plausible models may be good enough to use.

When $v(\cdot)$ is not linear, which is more realistic, point estimates from a model are not generally sufficient. In this case, policy makers would also need to know the distribution of the possible outcomes to make good decisions. But these are rarely given, because economists have not been very successful in communicating the relatively high level of uncertainty that surrounds all macroeconomic forecasts. Although it is tempting to place the problem entirely on the lap of those policy makers that only want to hear and consider a point estimate for next year's GDP and inflation rate, macroeconomics forecasters must shoulder part of the blame for exaggerating the precision in which they can model the economic forces that drive both output and inflation.

Note that the probabilities or weights attached to each model would consider the plausibility of each model relative to all other models being considered, with attention given to both their ability to explain past data patterns and an assessment of whether these models are relevant for future periods. These probabilities are not the type that come from conventional statistical tests that put one model on a pedestal, only to be knocked off when the evidence against that model is overwhelming.

Specifically, when $v(\cdot)$ is not even approximately linear and asymmetric effects are economically significant, there may be a great need to develop models where the relationships between y and z are far from linear, irrespective of test results from adding asymmetries to an otherwise linear model. Therefore, economic significance is stressed below. While economic significance is not easily defined (as it crosses many dimensions), findings that are attention-getting (in that they would likely change the design of policy if the nonlinear model were considered more plausible than linear models) are considered economically significant. In particular, interest is centered on cases where the effects of policy depend greatly on the stage of the business cycle.

3 Results from Linear and Nonlinear VARs

3.1 Linear base case VAR

To set the base case, from which two nonlinear models were subsequently built, I estimated a five-variable, linear VAR of the macroeconomy using quarterly data. Aggregate activity was measured by both the (level of the) unemployment rate and the real GDP growth (annualized). Aggregate inflation was measured using the GDP price deflator. A PPI-based measure of relative inflation in industrial materials prices was also included, and the final variable, the Federal Funds less inflation over the past year, is considered the policy instrument.

The base-case VAR used four lags (a full year's worth) to estimate the dynamic interrelationships among the variables, and the setup was relatively uncontroversial. For example, the output growth and inflation variables—based on the chain-weight GDP concept—were standard, and the materials price variable was needed to prevent the “price puzzle” (restrictive monetary policy seems to be associated with *higher* future inflation) that commonly shows up in these types of VARs. The most unusual, but defensible choice was an inflation-adjusted interest rate as the policy variable.¹⁵

The inflation-adjusted Federal Funds rate variable is *not* meant to be a forward-looking real interest-rate series. Instead, it is used to simplify the analysis by assuming that the nominal Federal Funds rate and inflation are cointegrated, and the primary stance of monetary policy (i.e., determining whether monetary policy is being used to aggressively fight inflation or not) is captured by the level of short-term interest rates relative to the *current* trend in inflation.

Most important, the inflation-adjusted interest rate is the only variable that is not treated as endogenous in the simulations (i.e., impulse-response calculations). In most VAR studies, the policy variable is treated

¹⁵See the appendix for details on the data and the model, and a discussion of variations that were tried but did not greatly affect the results.

endogenously using an estimated explanatory equation that models the reaction function of the Federal Reserve as a dynamic response of policy to economic conditions. I run policy experiments that hold the inflation-adjusted interest rate constant, which implicitly assumes a simple reaction-function relationship between the Federal Funds rate (r) and inflation (π):

$$r_t = a + b(\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3}) + u_t$$

Here $b = 1$ is assumed. Another way to look at this choice for devising policy simulations is that a particular sequence of policy shocks (i.e., z terms in the equations in Section 2) have been chosen, and this always can be done for any desired path for the Federal Funds rate and any given Federal Reserve reaction function.

Note that this is not tantamount to assuming that the Federal Reserve does not have rational expectations. What is assumed is that the reduced form of this model does not necessarily capture the decision process of the Federal Reserve. In other words, it is not assumed that the Federal Reserve effectively uses this model to determine optimal monetary policy. The typical VAR simulation implies this assumption, which is incredulous to anyone that has studied monetary policy (from interest-rate to money-supply and back again to interest-rate targeting) and the fact that moves to become more expansionary or contractionary are typically both sustained and gradually implemented.¹⁶ But this is not generally a problem with interpreting VAR results. Their linear structures allow for the effect of the sequence of policy shocks to be calculated as the sum of the associated impulse responses for each shock. Unfortunately, this shortcut for considering a wide variety of policy exercises falls short when using nonlinear models. Therefore, when comparing results from linear and nonlinear models, it is most useful to devise a policy simulation that follows a more specific path. Using the inflation-adjusted Federal Funds rate is a reasonable way to accomplish this goal.¹⁷

The contemporaneous relationships among the variables, which provide the structural identification of the model and are often very important considerations in VARs, are shown in Table 1 in the Appendix. An almost triangular (recursive) relationship—going from material prices, to the unemployment rate, to real GDP growth, to inflation—is used with a few useful differences (from a simple triangular system). The main concepts used to identify the contemporaneous system was to make the two variables, material prices and the unemployment rate, contemporaneously independent of the policy instrument, and to rule out dubious contemporaneous feedback effects such as changes in the inflation-adjusted Federal Funds rate having an immediate impact on inflation. Contemporaneous, two-way feedback between inflation and real GDP growth (conditional on changes in unemployment) is allowed.

Showing that this VAR structure is reasonable, Figure 1 graphs the response of unemployment, output growth, and inflation to a 1% increase in the inflation-adjusted Federal Funds rate that is sustained for three years.¹⁸ The chart shows a clear negative effect on activity, as output falls immediately and unemployment rises with a one-quarter lag (because of the contemporaneous identification scheme), and the effects are fairly long lasting. Inflation, on the other hand, takes over one year to show a noticeable net negative response.

3.2 Bilinear VAR

The bilinear version of the same general VAR framework (using the same variables, lag, and contemporaneous structure) was estimated after adding four terms to the unemployment, output, and inflation equations. These additions are based on the multiplicative effects of the unemployment rate: a squared term for the lagged

¹⁶For the last point, see that Appendix that shows a typical VAR will follow an interest-rate increase with a gradual easing back down that starts in the next period. By instead holding the adjusted interest rate constant, a more realistic simulation can be studied.

¹⁷Also, this design does not assume that forces other than monetary policy cannot affect the spread between the Federal Funds rate and measures of inflation. Instead the implied assumption is that economic activity and aggregate prices respond in a similar manner to all of the forces or factors that are transmitted through the current Federal Funds rate less inflation over the past year. The effects are generally consistent with Bernanke and Blinder (1992) and the Appendix shows that there seem to be no serious biases from making this assumption (by comparing results from this model to more conventional VAR structures).

¹⁸In this case, the linear structure of the model makes the impulse responses of negative and positive shocks exact symmetric, mirror images of each other. This means that there is no need to show the effects of a decrease in the Federal Funds rate (i.e., expansionary monetary policy) for the base case, linear VAR in a separate chart. This symmetry cannot be guaranteed for nonlinear models, however. Fortunately, the comparisons of the linear and nonlinear VARs presented here are basically insensitive to using a decrease in the Federal Funds rate to trace impulse responses (see footnotes 22 and 25). The results are slightly more sensitive to changing the size of the increase, however, and this policy simulation was chosen as a reasonable option that policy makers might consider (but not the only reasonable option that could be chosen).

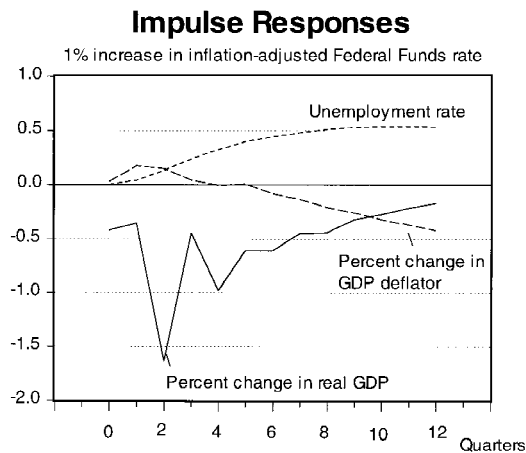


Figure 1
Simulation of a conventional (linear) VAR.

unemployment rate plus the cross-products of lagged unemployment times the lagged inflation-adjusted Federal Funds rate, lagged real GDP growth, and lagged inflation.¹⁹

The *F*-test values for the entire set of bilinear, squared, and cross-product terms were 1.42 (probability = .23), 1.49 (.21), and .69 (.60) for the unemployment, output-growth, and inflation equations, respectively.²⁰ While *F*-tests show this particular type of nonlinearity was less than convincing at conventional significance levels (i.e., the null hypothesis of no bilinear effects cannot be rejected with greater than 90% confidence), some of the bilinear terms were marginally significant. *T*-test statistics above 1.5 were found for the coefficient associated with the square of lagged unemployment in the unemployment equation and for the coefficients associated with the cross-product of lagged unemployment and lagged inflation in the unemployment, output-growth, and inflation equations.

The contemporaneous relationships for this bilinear VAR are shown in Table 2 in the Appendix. The differences from the linear case are minor; none of the estimated correlations changed from significantly positive to significantly negative or vice versa.

Because of nonlinear interrelationships between the variables, impulse responses from this model depend on the initial values of some variables. The simulation in Figure 2 sets the initial (past four quarters) values of all variables at their historical average. Most important is the level of the unemployment rate, which is set at 6% (recognizing that the level of this variable directly affects the additional squared and cross-product terms). The impulse responses are similar in shape to those in Figure 1. At the end of three years (of the policy experiment), the responses of real GDP growth and inflation were slightly higher in size than in the linear case, while the effect on the unemployment rate was almost exactly the same.

Exploring the nonlinear effects in greater detail, Figure 3 compares results from using different cases for the initial value of the unemployment rate. The dark lines are the same as in Figure 1, and provide the orienting values. In one of the other two simulations shown, the unemployment rate was increased 2%, from 6 to 8% for each of the four lagged quarters, and for the other simulation the unemployment rate was decreased to 4%.

These simulations show that the general shapes of the impulse-response functions are relatively insensitive to the initial level of unemployment. For unemployment, in particular, the three cases are almost indistinguishable. The effect of increasing the inflation-adjusted Federal Funds rate is found to be greatest on

¹⁹Versions with bilinear effects based on squares and cross-products of output growth were tried, but showed little differences in the impulse responses. Much more significant bilinear effects resulted from using the unemployment rate, which is highly correlated with Beaudry and Koop's (1994) cumulative depth-of-recession variable.

²⁰These *F*-tests were computed for separately estimated equations that ignored the contemporaneous relationships between the variables (i.e., each equation was expressed in its reduced form that only used lags as explanatory variables). These tests make use of the fact that bilinear effects should not be significant in the reduced-form equations when the linearity assumption is correct, irrespective of any assumptions about the contemporaneous relationships. Similar results were found when the assumed contemporaneous relationships were added (*F*-test values were 1.93, 1.21, and 0.84, respectively).

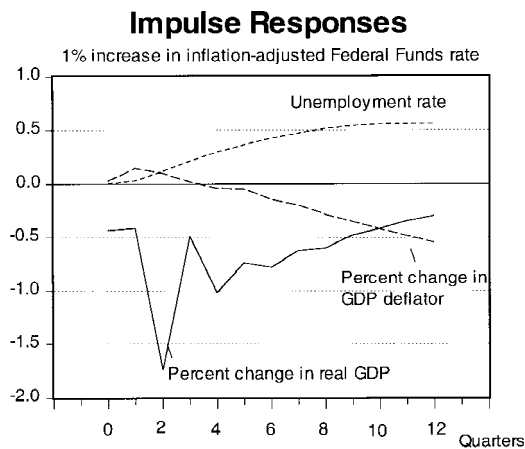


Figure 2
Simulation of bilinear VAR (initial values of variables at historical averages).

real GDP (both cumulatively and in the first eight quarters) and inflation (especially after six quarters), when the unemployment rate starts at a low level.²¹

An interesting but not completely explored property is seen with the impulse-response functions for inflation. Figure 3 shows a clear tendency for the wedge between the high- and low-unemployment cases to grow larger over time. This growing differential in impulse responses is somewhat surprising, because the differential in the unemployment rates of BL-2 and BL-3 at the end of the simulation is less than the 4% differential in the initial period (primarily because the unemployment equation shows mean reversion). This is most likely either a consequence of momentum effects on inflation that for some reason have little impact on unemployment and GDP growth, a sign of unstable and possibly untrustworthy dynamics, or an indication that the policy simulation is not appropriate for this model.

Nonetheless, the general results for this simple bilinear model are intuitively plausible. The impulse responses suggest that restrictive monetary policy is more effective in slowing activity at a business-cycle peak than at a trough. And further simulations (not shown) suggest that the stimulative effects of monetary policy are less at a trough than near a peak.²² The fundamental asymmetry, however, where longer-term effects on inflation are greatest when unemployment starts at a lower level, may not have important implications for the conduct of monetary policy. A Phillips-curve trade-off of lower inflation for increased unemployment was found irrespective of whether unemployment starts at 4% or 8%. It is an open question, however, as to whether differences between the bilinear and linear models would be considered economically significant by most policy makers.

3.3 Two-regime VARs

The second nonlinear model, a two-regime VAR, was built by splitting the 1961–1994 period into two sets of observations. The first set used all quarters that included months that the NBER had designated as a peak or a trough in the general business cycle and the quarters between these months. In other words, one regime included both recessions and turning points. The remaining quarters made up the second set of observations, which can be called the normal or expansion regime.

This split of the data into two regimes can be criticized on at least two fronts. First, the grouping of turning points (peak and troughs in the business cycle) with outright recessions (periods after a peak where activity is falling) might be considered an overly crude and potentially improper division of the business cycle. This choice was necessitated, however, by a need to have enough observations in each regime to produce reliable estimates of the dynamic equations. Even with the grouping of turning points and recessions, this set has only 36 quarters. An alternative interpretation of the result could be that only the results from the normal

²¹Technical difficulties in determining statistically significant differences in impulse responses are great, and are beyond the scope of this study.

²²Somewhat surprising (but as discussed in footnote 18), the effects of a 1% decrease in the inflation-adjusted funds rate is almost exactly symmetric to what is shown in Figures 2 and 3 (for all variables).

Impulse Responses

1% increase in inflation-adjusted Federal Funds rate

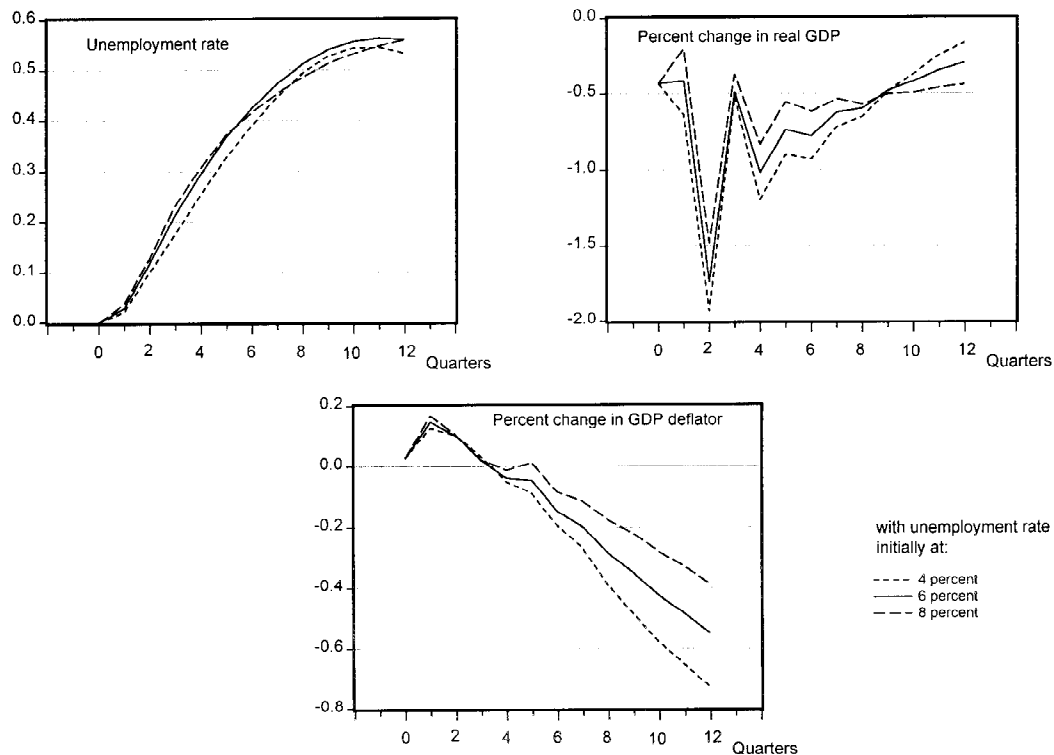


Figure 3
Bilinear VAR, changes in initial conditions.

expansion regime are useful (103 observations), and excluding potentially similar turning-point periods would not bias these results. Second, an endogenous sample-splitting procedure might be preferred. As discussed above, a Markov switching model framework that attempts to optimally divide the observations into recurring regimes based solely on the behavior of the data is one potential way to accomplish this task. However, these models are typically judged by how well they replicate NBER dates. Therefore, it is more direct to simply use the NBER dates. Another practical consideration is that even when a multiregime framework is correct, the estimation of multivariate switching models with complicated dynamics is fraught with numerous difficulties. Some are impossible to adequately overcome. The primary problem is that estimating the dates of the regime shifts adds greatly to the number of unknown terms or factors, decreasing the precision of the estimated dynamics within each regime.

It is admitted that the results may be biased if either the sample-splitting procedure is a gross mischaracterization of business-cycle relationships or if the NBER dates are improperly influenced by ex-post knowledge of shifts in monetary policy.²³ While neither condition is seen as holding, the most defensible reason for the chosen sample-splitting procedure is that the splits have a significant enough probability of being correct that the results are worth studying.

²³The problem is that the NBER dates are determined by a committee that studies empirical patterns both before and after a potential turning point. Therefore, if a regression equation is estimated solely for recession periods, negative relationships between predetermined (lagged) exogenous and endogenous variables may become unrealistically accentuated. See my earlier work (Boldin 1994) for a discussion of the issues and controversies surrounding business-cycle dating methods.

Table 3 in the Appendix compares contemporaneous relationships in each regime, and in both cases the number of significant contemporaneous relationships is less than for the single-regime (linear and bilinear) VARs. Only one term shows a potentially important difference across the regimes: the contemporaneous correlation of the inflation-adjusted Federal Funds rate and real GDP growth is positive in expansions and negative at other times. However, the statistical significance of these correlations is low.

Chow-type *F*-tests were calculated to evaluate whether splitting each equation into two regimes is statistically significant (but of course, recognizing the serious biases from using the NBER peak and trough dates, these are only suggestive at best). For the output equation, the split was most significant, with an *F*-test value of 1.88 and an associated probability of less than .02 (for one regime being correct, assuming the conventional distribution). Unfortunately, this test is clearly biased toward rejecting one regime, because the sample split puts almost all quarters where output fell into one regime. For the unemployment equation, the *F*-test value is almost as high at 1.61, which is also not surprising, and the associated probability is .06. The effect of sample splitting is much less important in the inflation equation, with an *F*-test value of 1.15 and an associated probability of .31.²⁴

Because of biases from the sample-splitting procedure, it cannot be claimed that the *F*-test statistics reject the linear, one-regime base-case model with any degree of confidence. Nonetheless, the two-regime model shows a noticeable improvement in fitting the data. Therefore, the opposite—that there is no empirical support for important two-regime effects—cannot be claimed either. The best that can be said is that those predisposed to one view or the other would not change their minds based solely on these types of tests.

Figure 4 shows impulse-response functions that clearly exhibit significant business-cycle asymmetries.²⁵ The results for unemployment and real GDP growth are most dramatic: in expansions, the impact of an increase in the inflation-adjusted Federal Funds rate is almost insignificant in an economic sense, but in recessions (and turning points), the effect is most certainly attention-getting. Comparisons to the single-regime results, shown by the dark lines in Figure 4 (the same impulse responses as in Figure 1), show the single-regime impulse responses are at best only rough averages of the multiple-regime effects for inflation and real GDP growth. More important, an average across regimes is of little use when it fails to adequately capture the effects in any particular regime. For inflation, the results are more questionable than enlightening, as neither regime shows a clear negative net effect after three years (as with the single-regime VAR).

The impulse responses in Figure 4 do not fully represent the effects of restrictive monetary policy, however, even if the switching-VAR structure and NBER dating scheme is correct. For example, an engineered increase in interest rates may cause a recession, and this possibility was ruled out in the simulations. To consider the effect of causing a turning point in the business cycle, Figure 5 shows the impact of a switch from the normal or expansion regime to the recession-and-turning-points regime. It is not surprising that there is a large positive effect on unemployment, and at least initially, a large negative effect on real GDP growth. The positive effect on inflation is somewhat surprising and suggests that all else being equal (i.e., holding the stance of monetary policy constant), an intentionally created recession does not lower inflation. If policy makers considered this possibility in their design of monetary policy, it is likely that they would be more cautious in raising interest rates to fight inflation.

Robustness checks were made, using both longer lags in the VAR structure and alternative contemporaneous structures. For example, in one case the unemployment-rate equations were amended to allow increases in the inflation-adjusted Federal Funds rate to have an immediate impact on unemployment; and in another case, shocks to inflation were allowed to have separate immediate impacts on unemployment and output. The main goal was to determine whether both the regime-specific impulse responses and the effects of switching from expansion into recession that were presented and discussed above are robust to allowing for greater contemporaneous interactions. The results were most similar, showing general robustness on many fronts.²⁶

²⁴In the same manner as the bilinear tests, these *F*-tests were computed for separately estimated equations that ignored the contemporaneous relationships among the variables (see footnote 20). The two-regime effects were found to be weaker for output, much stronger for unemployment, and similar for inflation when the assumed contemporaneous relationships were added (*F*-test values were 1.24, 2.11, and 1.20, respectively).

²⁵Because the structure in each regime is linear, the effect of simulating a 1% decrease in the inflation-adjusted funds rate is symmetric (an exact mirror image) with what is shown in Figure 4.

²⁶The same change was also tried on the bilinear VAR, and the results were similar as well, save for a subdued response of real GDP growth. Initial versions of this paper reported some sensitivity to this change, suggesting that assumptions about the contemporaneous structure can

Impulse Responses

1% increase in inflation-adjusted Federal Funds rate

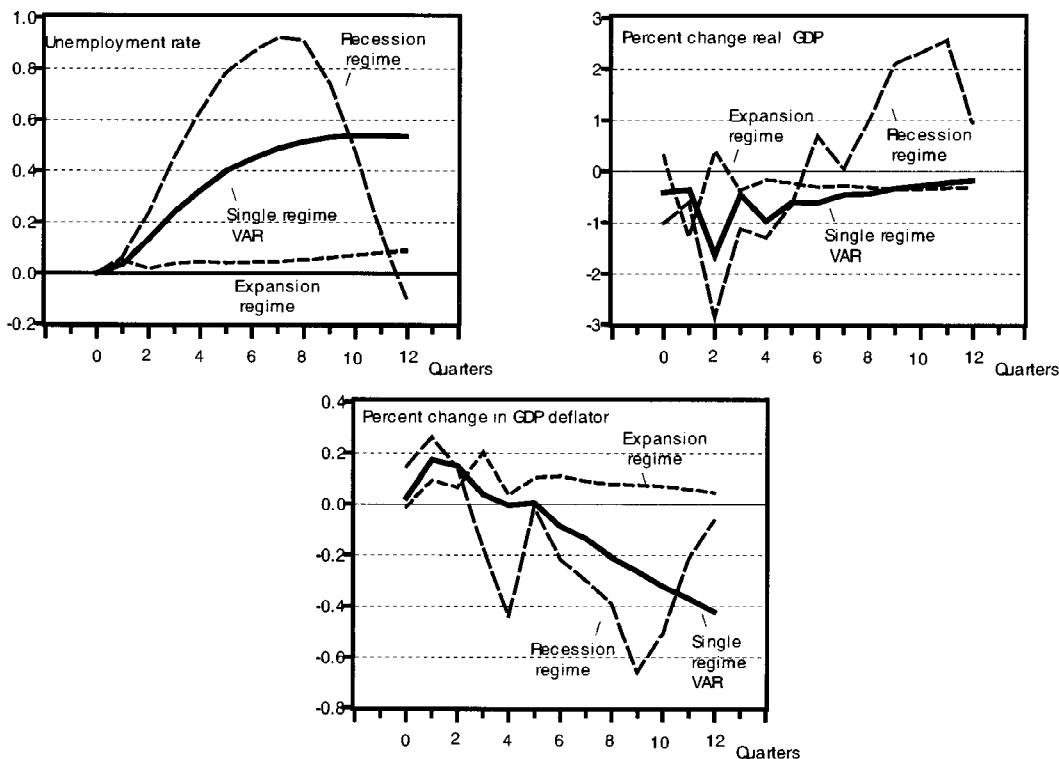


Figure 4
A two-regime VAR: impulse responses for unemployment rate (top left), real GDP (top right), and GDP deflator (bottom).

Effect of switch to recession regime

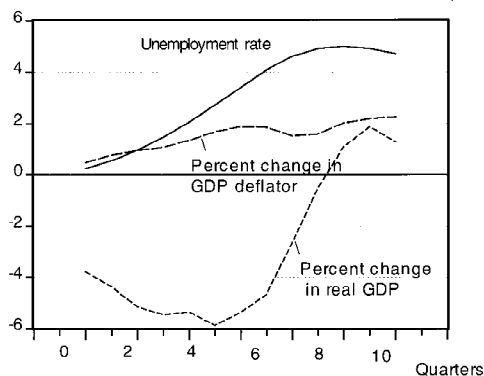


Figure 5
A two-regime VAR: the effects of switching to a recession regime.

matter greatly in a nonlinear model, but much less so in a linear model. A check of the computer program producing these results showed that the impulse responses were incorrectly computed, however, because they were calculated before full convergence of the model simulations. This suggests greater care is needed when nonlinear models are simulated. Further work is needed before concluding that linear and nonlinear models share similar sensitivities and insensitivities to assumptions about the contemporaneous structure.

4 Additional Remarks and Conclusion

4.1 Areas for extension and other considerations

The nonlinear models presented above certainly suggest that policy makers should more than just consider, but worry about business-cycle asymmetries. Further extensions of these models are probably needed, however, to make them convincing enough to become a major part of the policy debate. Four areas are likely to show the most promise:

1. Combining bilinear and multiple-regime effects.
2. Adding variables and equations for items such as monetary aggregates, investments, and leading indicators. Exploring the effects of multiple-regime Federal Reserve reaction functions also makes sense.
3. Estimating long-run relationships that are analogous to cointegration in linear models and possible cobreaking effects (where two or more variables have a common shift in trend).
4. Endogenous regime splitting.

The last area would be a potential step away from using NBER dating schemes, and is likely to require the most creative and potentially controversial specification decisions.

While this paper downplayed tests for statistical significance, arguing that it is best at this stage to consider business-cycle asymmetries as plausible, it should be recognized that proving the statistical significance of asymmetries is neither an easy nor a fruitless task. Further work is definitely called for in testing nonlinear and multiple-regime models. It is also important to build confidence intervals around the impulse responses from policy simulations. There are serious technical difficulties in these areas (and their discussion is beyond the scope of this paper), but the problems do not seem insurmountable using Monte Carlo or bootstrap computer-simulation techniques.

It is in the area of forecasting performance, however, that unconventional models are likely to be judged most closely and probably most harshly. Speaking directly to this point, Ramsey (1996) discussed the fact that despite “abundant evidence of nonlinearity in almost all economic and financial time series, . . . the record of improvements is meager” for nonlinear forecasting models. Instead of advocating the simpler, linear models, however, Ramsey pointed out that the “difficulties in forecasting are not only more serious and more prevalent, but are qualitatively different” (when nonlinearities are present). In fact, Ramsey argued that the general experience of most forecasters where “good fit does not give good forecasts” is suggestive of the nonlinearities.

Ramsey identified benefits of nonlinear models, of which the types of asymmetric business-cycle models presented here are a subclass. One benefit is to more closely capture plausible causal relationships, instead of simply providing representations of the data that are atheoretical in nature. Another benefit is to provide clearer evidence of the kinds of shifts and breakdowns in past relationships that might provide instructive guidance to policy makers.

In fact, because of general testing and forecasting problems and because there is no consensus on the proper asymmetric model, it does not seem possible to settle the debate about the significance of asymmetries with empirical evidence alone. Further research is needed to tie the empirical evidence for asymmetries to business-cycle theory.

In considering any theory as a guide to econometric model building, it should be recognized that linear models are often used in empirical applications for the sake of convenience. Even the real business-cycle view of the macroeconomy, which often assumes that monetary policy has no effect on the real side of the economy, cannot rule out the possibility that productivity shocks have asymmetric effects on output. From the Keynesian macroeconomic tradition, it is well-accepted that liquidity trap problems, in which nominal interest rates become so low that any attempt to conduct expansionary monetary policy is like pushing on a string, cannot be modeled by completely symmetric, linear econometric structures. Also, the traditional monetarist view allows for the effects of monetary policy to vary over time. In fact, many economists who believe in the importance of monetary policy consider negative money shocks to be more potent than positive ones, especially at the top of a business cycle.

Other sets of models to consider are those with kinked aggregate-supply schedules, such as that discussed by Ball and Mankiw (1994). They followed the new Keynesian school of macroeconomic theory, and showed a case in which negative monetary shocks not only had an effect on output that was much greater than that of positive monetary shocks (that are equal in magnitude), but one in which the differential increased with the

level of the inflation rate. Greenwald and Stiglitz (1992) also built on the Keynesian macroeconomic framework, but concentrated on investment behavior. They argued that monetary policy affects not only the LM curve, but the IS curve as well, with a credit-rationing channel that could easily produce asymmetric dynamics. In summary, a more convincing presentation of business-cycle asymmetries built using model structures that better correspond to the theoretical explanations and models of Ball and Mankiw (1994) and Greenwald and Stiglitz (1992) may be a good start.

4.2 Conclusion

For theoretical, practical, and empirical reasons, policy makers should seriously consider asymmetries in the business cycle. This investigation showed that the effects of monetary policy seem to depend on the stage of the business cycle in an economically significant way. Two distinct nonlinear macro-models were estimated and simulated, and both showed some interesting asymmetric effects that are related to the business cycle, with a nod toward the multiple-regime, switching-type model for finding stronger asymmetric effects. In fact, if switching VAR results were considered more realistic than conventional VAR results, they would significantly alter the design of monetary policy. Although this study cannot determine the weight that policy makers should place on models with asymmetric features, an objective reading of the results in this study shows that it is inappropriate to place zero weight on nonlinear, multiple-regime models.

Appendix A: Notes on VAR Model Structure and Policy Simulations

The data used to estimate the models was based on the versions available in December 1997. They are: dy = gross domestic product (GDP—chain-weight basis, annualized growth); dp = GDP price deflator (annualized growth); dmp = crude materials prices (BCI series number 99, annualized growth less GDP deflator inflation); un = unemployment rate (percent level, with .2 adjustment for 1994 change in BLS survey methods); and $fedfunds$ = Federal Reserve interbank overnight funds rate. Each series passes a stationarity (ADF unit-root) test.

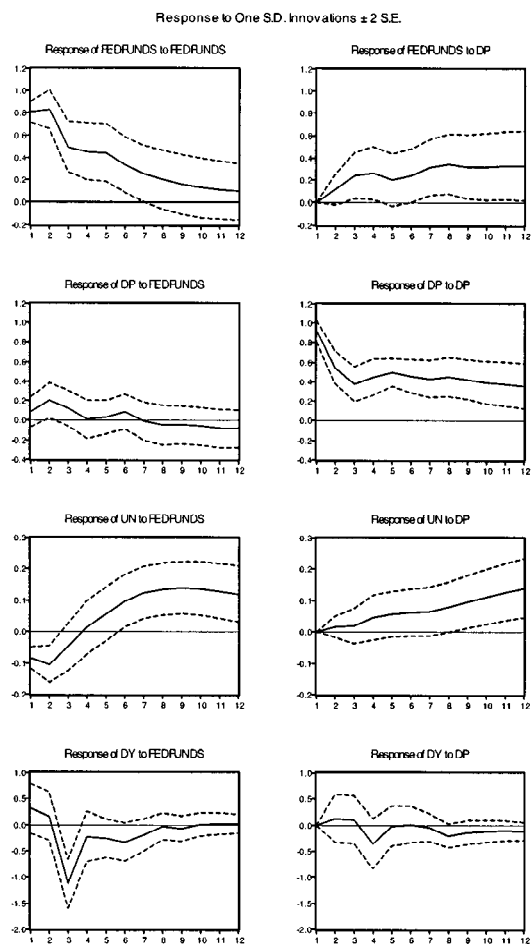
1. Most macroeconomic VARs do not include both the unemployment rate and GDP growth, as this has potential for double-counting some aggregate activity. Contemporaneous changes in unemployment can explain almost 50% of the variation in GDP growth, and even more when lags are included in the estimated equation for GDP growth. This is not necessarily a problem in a VAR, however, as residuals in the GDP equation primarily reflect unexplained changes in labor productivity (output per worker). Instead, using both series might be considered an unnecessary addition to the size of the empirical model and complexity of the estimated dynamics. In fact, in the first draft of this paper, results were reported for a four-variable VAR that excluded the unemployment rate. The five-variable version was added after receiving suggestions on improving the general properties of the base linear model; namely, the goal was to make the immediate response of output to increases in the Federal Funds rate negative. The four-variable VAR showed an initial positive response, although small. Also, the unemployment rate is a series that policy makers are most interested in monitoring, and it tends to accentuate nonlinear effects in the other models. Nonetheless, most of the comparisons of the four-variable VAR and nonlinear analogues are very similar, and results are available upon request.
2. At first glance, those familiar with conventional VAR results may find the impulse responses to be larger and more persistent than expected. However, this is primarily an artifact of the persistence of the policy simulation (where the 1% increase in the inflation-adjusted interest Federal Funds rate is held for three years). An estimated reaction function would cause this rate to fall (slowly) after the initial increase, and the resulting impulse responses would show about one-half the effect after three years. Taking the persistence of the policy simulation into account, the impulse-response functions are fairly consistent with most previously published VAR results. The persistence in the policy simulation primarily helps to highlight differences in linear and nonlinear models (and should not be considered the only and right way to simulate a policy action).
3. The general shapes of the impulse response functions are not very sensitive to plausible and statistically defensible changes in either the number of lags or many reasonable changes in the contemporaneous structure. I also estimated cases that used either the level or the first difference in the nominal Federal Funds rate as the policy variable. See Appendix B for two cases where interest rates are treated as fully

endogenous after the initial shock. Recognizing the lessened persistence in the implied policy shows very similar effects on output and unemployment (and arguably less plausible effects on inflation). The similarities are primarily the result of including a full year's worth of lags of inflation in each equation; policy experiments for the inflation-adjusted interest rate can be closely replicated with a VAR system that uses the level of the nominal Federal Funds rate.

4. The immediate increase in inflation when the Federal Funds rate is given a positive shock is a problem that is not as easily correctable as might be thought. It is difficult to empirically differentiate between increases in interest rates that anticipate rising inflation and those that result from monetary policy that attempts to slow a surprisingly persistent acceleration in inflation. The fact that the cumulative effect is negative is typically considered a solution to the "price puzzle" that plagues many VAR systems.
5. In considering the design contemporaneous scheme and the policy simulations, it is important to recognize that future changes in the nominal funds rate are correlated one-to-one with changes in the inflation rate (because the inflation-adjusted rate is held constant). Because four lags of inflation are in all equations, the system is overidentified when all five variables are considered endogenous. While it is feasible to allow one of the shocks in the other four variables to affect the inflation-adjusted Federal Funds rate, the design of the policy simulation would make these types of effects irrelevant. (However, the system is fully identified when the Federal Funds rate is excluded from the list of endogenous variables.)

B. Appendix Charts: Alternative VAR Simulations (all variables treated as endogenous)

Set A Using Levels for Federal Funds and Inflation Rate
Appendix Chart A Impulse Responses



Set B Using Differences
Appendix Chart B Impulse Responses

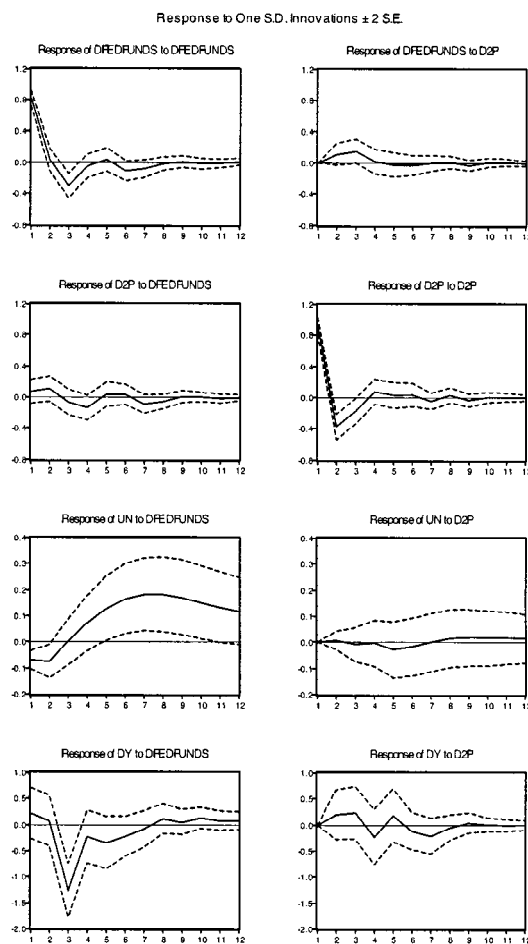


Table 1

Linear (Base Case) VAR—Contemporaneous Correlations

| Dependent Variable | Independent Variable Shocks ^a | | | | |
|------------------------|--|--------------|---------------|----------|-------------------|
| | Materials Prices | Unemployment | Federal Funds | Real GDP | Price Deflator |
| Crude materials prices | 1 | 0 | 0 | 0 | 0 |
| Unemployment rate | – | 1 | 0 | 0 | 0 |
| Federal Funds | 0 | 0 | 1 | 0 | 0 |
| Real GDP | (–) | – | (–) | 1 | – |
| GDP price deflator | + | (–) | 0 | – | 1 |

Table 2

Bilinear VAR—Contemporaneous Correlations

| Dependent Variable | Independent Variable Shocks ^a | | | | |
|------------------------|--|--------------|---------------|----------|-------------------|
| | Materials Prices | Unemployment | Federal Funds | Real GDP | Price Deflator |
| Crude materials prices | 1 | 0 | 0 | 0 | 0 |
| Unemployment rate | – | 1 | 0 | 0 | 0 |
| Federal Funds | 0 | 0 | 1 | 0 | 0 |
| Real GDP | (+) | – | (–) | 1 | – |
| GDP price deflator | + | (–) | 0 | (–) | 1 |

Table 3

Two-Regime VAR—Contemporaneous Correlations

| Dependent Variable | Independent Variable Shocks ^a | | | | |
|------------------------|--|--------------|---------------|----------|-------------------|
| | Materials Prices | Unemployment | Federal Funds | Real GDP | Price Deflator |
| Crude materials prices | 1 | 0 | 0 | 0 | 0 |
| Unemployment rate | –/– | 1 | 0 | 0 | 0 |
| Federal Funds | 0 | 0 | 1 | 0 | 0 |
| Real GDP | (+)/(+) | –/– | (+)/(–) | 1 | (–)/(–) |
| GDP price deflator | (+)/(+) | (–)/(–) | 0 | (–)/(–) | 1 |

^a 1 = identified variable; 0 = zero correlation assumed. Estimated correlation: + = positive; – = negative; () not significant at the 10% level. When two symbols are given, the first symbol represents expansion periods; the second symbol shows recessions and turning points.

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Stanley E. Zin, Carnegie-Mellon University

Editorial Policy

The *SNDE* is formed in recognition that advances in statistics and dynamical systems theory may increase our understanding of economic and financial markets. The journal will seek both theoretical and applied papers that characterize and motivate nonlinear phenomena. Researchers will be encouraged to assist replication of empirical results by providing copies of data and programs online. Algorithms and rapid communications will also be published.