

Shocks*

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Abstract

What are the shocks that drive economic fluctuations? I examine technology and money shocks in some detail, and briefly review the evidence on oil price and credit shocks. I conclude that none of these popular candidates accounts for the bulk of economic fluctuations. I then examine whether “consumption shocks,” reflecting news that agents see but we do not, can account for fluctuations. I find that it may be possible to construct models with this feature, though it is more difficult than is commonly realized. If this view is correct, we will forever remain ignorant of the fundamental causes of economic fluctuations.

1 Introduction

What shocks are responsible for economic fluctuations? Despite at least two hundred years in which economists have observed fluctuations in economic activity, we still are not sure.

For example, a session of prominent macroeconomists at the 1993 AEA meetings addressed the question “What caused the 1990 recession?” (Blanchard (1993), Hall (1993), and Hansen and Prescott (1993)). They examined a long list of candidates—factor prices, especially oil, monetary policy, government purchases, tax increases, technology shocks, bank regulation, international factors, and sectoral shifts. They came up empty-handed. Prescott and Hansen claimed technology shocks, but interpreted these broadly enough to encompass any of the above and more (see below). Blanchard and Hall

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favored “consumption shocks.” Since consumption is an endogenous variable, the ultimate source of variability must be news about future values of any of the above. But *what* news and about *what* future event is not identified.

It is tempting to offer up a mixture of shocks in a spirit of compromise, so that recessions are sums of many small negative impulses, or to speculate that different shocks caused different historical episodes. However, there are good reasons to try to limit ourselves to a small number of recurring shocks. Business cycles are “all alike” in many ways. Investment and durables fall by more than output, hours fall by about as much as output, nondurable consumption by much less than output. Different shocks are unlikely to produce such similar responses. For example, if a shock (say a credit crunch) is temporary, it should cause a small reduction in consumption and a big decline in investment. If it is permanent (say a tax increase), it should cause a much larger decline in consumption and may not change investment at all. The need to produce roughly similar dynamics severely constrains the dynamic structure of the shocks and hence argues for a common source. Similarly, shocks in different places—preferences, technology, money, government spending, etc.—yield different correlations between series. In explicitly dynamic models, it is no longer true that any source of aggregate-demand decline is as good as another and kicks off the same dynamic pattern.

After an extensive review of technology and money shocks, and a brief review of oil and credit shocks, I conclude that *we have not found* large, identifiable, exogenous shocks to account for the bulk of output fluctuations. Monetary policy shocks account for at most 20% of the variation in output. Statistics that focus on predictability find almost no contribution of technology shocks to business-cycle output variation. Shocks to consumption and output—endogenous variables—always explain a robust 50–70% of output variation. Furthermore, specification uncertainty, choice of statistic, and sampling variation are as much of the story as point estimates. Plausible variations can generate numbers from 0 to 100% for both money and technology shocks.

I then ask whether we can account for fluctuations by “consumption shocks,” news consumers see but we do not see. This is an attractive view, and at least explains our persistent ignorance of the underlying shocks. But it is not as easy as it seems to specify a consistent dynamic model in which consumption shocks generate business-cycle fluctuations.

My review of the evidence for various shocks stresses four themes:

Theme 1: Despite the fact that empirical work assessing the contribution of shocks is often conducted in an atheoretical context, one’s view of the propagation mechanism, or economic theory, is crucially important for identifying shocks and evaluating their effect on output. The results can change drastically as one views the data from the perspective of different theoretical

frameworks, or as one imposes more theory on the estimation.

Theme 2: The *statistic* one chooses is crucially important as well. Variance decompositions, variance of Hodrick-Prescott filtered output, variance of Beveridge-Nelson filtered output, etc. all can give drastically different results.

Theme 3: Economic agents have a lot more information than we do. What is a shock to us may be known by them.

Theme 4: There are “level” variables, including the consumption/output ratio, M2 velocity, term spreads, and hours, that indicate the state of the economy, and hence can forecast long-horizon output with huge (60% or more) R^2 .

1.1 Some warnings

(1) *Exogeneity.* We traditionally search for *exogenous* shocks. Any VAR mechanically accounts for 100% of the variance of output by unforecastable movements in endogenous variables. To say that such a shock causes fluctuations just leads to the question, “Why did the endogenous variable move?” and a search for a deeper, exogenous shock. There is also an econometric reason to search for exogenous shocks: only responses to an exogenous variable can measure the effects of policy-induced changes in that variable.

Exogenous shocks are rare, however, and the imperialistic march of economics makes events truly outside the economic system rarer every day. We are used to thinking of government policy as exogenous, but a glance at the newspaper shows that policymakers watch the economy and economic forecasts obsessively. Monetary VARs recognize that policy responds to the economy and try to isolate the exogenous shocks as residuals to a policy rule. But why should a policymaker deliberately introduce a random component to his decisions? Any maximization objective in a nonstrategic environment leads to *deterministic* rules for setting controls as a function of state. The Fed always describes its actions as *responses* to events, not randomized experiments.¹

Technology shocks sound nicely exogenous. However, the growth literature is working hard to make technology endogenous, and the real business-cycle literature seems to have abandoned the technology interpretation of the residual, anyway. Prices are of course endogenous economic variables. Only

¹Of course, neither we nor economic agents have enough information to forecast policy perfectly. Residuals to an agent’s forecasting model can count as exogenous shocks, if only unanticipated money matters. Unfortunately, we have even less information than agents, so the innovation measured by our forecasting model is not likely to be the same as the innovation measured by agents’ models. Furthermore, if anticipated money matters, or in investigating other shocks, then responses to shocks that really reflect superior information may not be meaningful.

the weather remains exogenous,² but business cycles seem to have nothing to do with the weather.

It would be nice to point to recognizable *events*, of the type that are reported in newspapers, as the source of economic fluctuations, rather than to residuals from some equation. This search has been even more fruitless. Of course, Monday-morning quarterbacks always attribute fluctuations to a long list of events, typically an undigested summary of business-section headlines. But the fingers pointed at these events are seldom attached to a serious explanation of how the headline events are quantitatively capable of producing a large and protracted decline in output, or why similar headlines often *do not* have any effects. Finally, in expectational models, times when the Fed does nothing but was expected to do something are just as much a shock as times in which it did something unexpected; but these events rarely wind up in the newspaper. In the context of expectational models, it is not embarrassing that residuals to a forecasting equation are the underlying shocks.

(2) *Propagation*. Many papers try to study “shocks” without specifying much about the “propagation mechanism.” The study of shocks and propagation mechanisms are of course not separate enterprises. Shocks are only visible if we specify *something* about how they propagate to observable variables. More importantly, we can not really believe that a shock affects the economy unless we understand *how* it does so.

Real business-cycle models produce artificial time series, so we can use a lot of information about the propagation mechanism to identify and quantify the importance of its shocks. Dynamic monetary economics is at a much more primitive stage. The response patterns of cash-in-advance models are so far from the data that they are not much used in the empirical analysis of monetary shocks. Many other monetary models do not give any explicit dynamic predictions. Therefore, empirical researchers typically fish for VAR specifications to produce impulse-responses that capture qualitative monetary dynamics, for example as described in Friedman (1968). Other shocks, such as oil price, credit, etc., are not associated with well-spelled-out dynamic theories of their effects on the economy, so identification and evaluation is even more tenuous. For this reason, shock identification is often based on simplified stylized features rather than the predictions of explicit models — “demand” shocks have no long-run effect on output, “monetary” shocks are represented by unforecastable movements in the federal funds rate, and so forth.³

(3) *Who cares?* The answer to the question, “What exogenous shocks ac-

²For the moment. Advocates of economic policy to affect global warming and chaos theorists are trying hard to make the weather endogenous as well!

³I do not mean to sound critical. These identifying procedures *are* the state of the art.

count for output fluctuations?” has more limited implications than is usually recognized.

First, it may not have immediate policy implications. For example, suppose that oil prices have small direct effects on the economy, but they induce monetary policymakers to cause recessions. (Darby 1982 argues for this view.) In this case, oil prices are the exogenous shock, and the Federal Reserve is just part of the propagation mechanism. However, to say “oil shocks account for fluctuations” is a misleading description; *monetary policy* caused the recessions. We do not have to worry about Middle East politics to insulate the economy from fluctuations, we have to worry about the Fed.

Second, the point of most shock accounting papers is really a comparison of broad classes of as-yet-incomplete models of the *propagation mechanism*. They want to answer questions such as “Can *any* competitive equilibrium model account for fluctuations in output, or will we need monetary, sticky price, or noncompetitive models?” But it’s hard to come up with some behavior that a whole *class* of models, as yet not investigated, is incapable of producing. Furthermore, most classes of model are not, in fact, tied to specific shocks. Technology shocks could account for all of the fluctuations in output, yet do so through channels specified by imperfectly competitive models. Monetary shocks could account for fluctuations, through an intertemporal market-clearing mechanism (say a real business-cycle model with a cash-in-advance constraint) as well as through a sticky price mechanism.

Thus shock accounting does not really say that much about the plausibility of broad classes of economic model. They say even less about modeling *methodologies*, which is really at stake. I do not think Prescott would feel vindicated if the profession converged on the view that technology shocks account for 80% (or all) of output fluctuations, yet do so through fluctuations in the aggregate supply curve of an IS-LM model!

(4) *Information advantages*. Shock identification procedures are sensitive to the fact that economic agents and policymakers base *their* forecasts on more variables than we include in our VARs. The weather forecast Granger-causes the weather, but shooting the weatherman will not produce a sunny weekend.

(5) *Linearity*. The central question in this paper is whether each candidate shock can explain a large fraction of output variance (either variance of growth rates or forecast error variance). A lot of assumptions go even into this statement of the question.

First, are *recessions* different from other times? In virtually all economic models and in VAR representations, booms and busts are just different draws from the same distribution. Recessions may represent an interesting combination of large negative shocks, but they are not draws from a different process. In thinking qualitatively about the economy, however, we often study recessions

sions as if they were a distinct phenomenon. The above cited AEA session was not organized around “What accounts for the forecast error variance of output?” but “What caused the last *recession*?”

Second, does the economy respond to shocks in an importantly nonlinear way? Most qualitative discussions reflect such a belief, for example, the need for a “booster shot” to keep the economy from “sliding into a recession.” But real business cycle models and VAR techniques are decidedly linear, and there is little solid evidence for important nonlinear structure in the data.

With these warnings and the themes they motivate in mind, I turn to a quantitative examination of the evidence for some shocks.

2 Monetary shocks

Shocks to the quantity of money or other measures of Federal Reserve policy have long been suspected of influencing output. The central question for us is: How *much* output variation is due to monetary shocks? Even if the Fed *can* influence output, it does not follow that most fluctuations in output *are* in fact due to monetary policy shocks.

Ideally, we would address this question by using a well-specified model that identifies monetary shocks and predicts the economy’s response, as real business-cycle models do for technology shocks. However, we do not have empirically successful models of this sort, so most evidence for the effects of monetary shocks comes via vector autoregressions (VARs). Three issues guide our evaluation of these VARs.

(1) *Shape of impulse-responses.* In the absence of an empirically useful dynamic monetary theory, at least we can require the impulse-response functions to conform to qualitative theory such as Friedman (1968). Most VARs do not conform to this standard. Prices may go down, real interest rates go up, and output may be permanently affected by an expansionary shock. It is not very convincing to claim that money accounts for $x\%$ of the variance of output in such a VAR, since we have no idea *how* money produces its alleged effect.

(2) *Shock identification.* This is obviously a crucial decision, but theory offers little help. First, one has to pick *which variable* to use as an indicator of money-supply disturbances. I will examine the popular choices: M1, M2, the federal funds rate, and nonborrowed reserves.

Second, one must specify the *ordering*, or which variables are contemporaneously unaffected by shocks to other variables. The monetary variable often goes first—it is assumed not to be contemporaneously affected by any of the other variables. This is sometimes justified by the (false) assumption that the Fed and the money-supply process do not respond to within-period values of the other variables. Of course, the opposite assumption that mon-

etary aggregates do not contemporaneously affect economic variables is even worse! Nonrecursive identification schemes are also possible. The true shocks may be linear combinations of the innovations to several different variables. These schemes take linear combinations of the impulse-response functions, so they can have a major effect on the results, even when the error variance-covariance matrix is diagonal.

The results often depend on the identification scheme. In practice, researchers clearly experiment with orderings and present the scheme that gives the “best” results. If “best” means “responses that most closely correspond to the predictions of monetary theory” this is not so bad, and can almost be defended as a theory-based identification procedure.

(3) *Specification.* Much VAR evidence also turns out not to be robust to variable definitions, lags, unit root structure, trends, variables included in the VAR, at what horizon variance decompositions are calculated, and sampling error. (See Todd 1993.) My baseline VARs use log-levels, quarterly data and one year of lags. I have corroborated most results in monthly data and with two years of lags. Most but not all results are robust.

A preview of the results: I examine M2, M1, federal funds and nonborrowed reserve shocks in turn. A common pattern emerges. In simple VARs, each monetary shock seems to account for a large fraction of output variation. When more variables are introduced and as the specification is refined (fished) so that the responses are broadly consistent with monetary theory, we find that monetary shocks explain lower and lower fractions of output variance. In the end, I find evidence that monetary policy *can* affect the economy roughly the way Friedman said it would, though with suspiciously long lags, but I do not find evidence that monetary policy shocks *did* account for more than at most 20% of the variance of output, and likely much less.

2.1 M2

2.1.1 A simple M2, y, p VAR

I start with a simple VAR consisting of the logs of M2, output, and the price level, in the spirit of the first VARs run by Sims (1980). In the impulse-response functions, Figure 1, M2 shocks are persistent and lead to substantial rises in output and then prices. However, the output response is surprisingly drawn out. It peaks two to three *years* after the shock, and output seems to be *permanent*. The price response is also very sluggish.⁴

⁴Of course, one should be cautious in evaluating estimated long-horizon responses in this (any) VAR. Since the VAR is run in levels, and I happened not to estimate explosive roots in this VAR, the estimated responses to all shocks are transitory, but take 100-200 years to die out. Many of the VARs I estimate below have impulse responses that oscillate with periods of 20-40 years. For this reason, the graphs stop at a 5-year response.

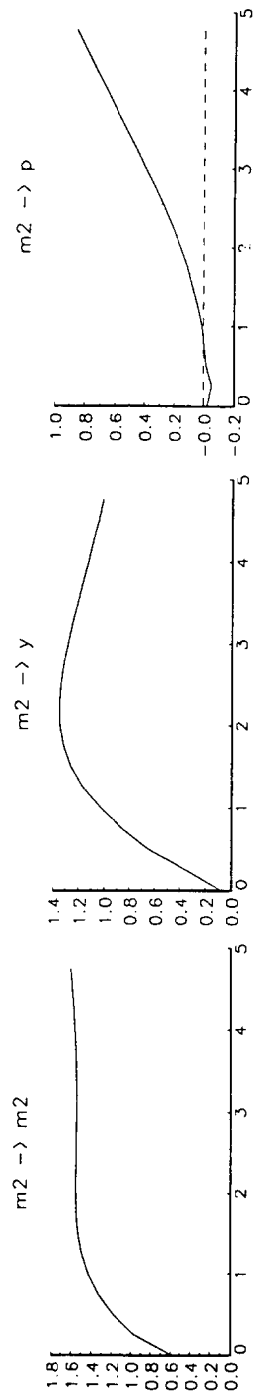


Figure 1: Response to 1σ m2 shocks, m2 y p VAR. Horizontal axis in years, vertical axis in %.

Table 1 shows variance decompositions for this VAR, and Table 2 summarizes output variance decompositions for all of the M2 VARs. The M2 shock accounts for dramatic fractions of the variance of output at long horizons, increasing from 32% at a one-year horizon to 82% (!) at a 3-year horizon. The M2 shock also accounts for 21% of quarterly output growth and 45% annually. Note how sensitive the results are to the horizon. This is far from an innocuous choice! This VAR is not sensitive to the order of orthogonalization (as long as one maintains some recursive scheme), or to the inclusion of trends.

Table 1:

Var. of	Shock and Horizon											
	1 Qtr.			1 Year			2 Year			3 Year		
	<i>M2</i>	<i>y</i>	<i>p</i>	<i>M2</i>	<i>y</i>	<i>p</i>	<i>M2</i>	<i>y</i>	<i>p</i>	<i>M2</i>	<i>y</i>	<i>p</i>
<i>M2</i>	100	0	0	99	1	0	98	0	2	94	1	5
<i>y</i>	1	99	0	32	68	0	70	30	0	82	17	1
<i>p</i>	1	3	96	0	7	92	1	17	83	3	24	73

Variance decomposition from $M2 - y - p$ VAR. Table entries are percent of horizon step ahead forecast error variance of the row variable explained by the column shock. VARs in log-levels with 4 lags, orthogonalized in the given order ($M2, y, p$). Quarterly data 1959:1–1992:4.

Table 2:

VAR	Forecast Error σ^2				VAR Δy	
	1Q	1Y	2Y	3Y	1Q	1Y
m2 y p	1	32	70	82	21	45
c y p	18	60	78	77	29	47
m2 ff c y p	1	20	39	41	11	21
m2 ff c y p; e. c. (s.e. of above)	0	16	28	25	11	21
ff c y p m2	0	5	12	14	4	6
m2 ff c h/pop y p, trend	0	8	11	7	7	5

Summary of output variance decompositions in M2 VARs. All VARs run in log-levels with 4 lags, unless otherwise indicated.

However, we obtain very small output effects if we view this VAR through the eyes of a simple rational expectations or cash-in-advance model in which

money can have only one-period effects,⁵ or if non-neutral effects of money must come through price shocks as in Lucas (1973). M2 shocks account for 1% of one-quarter ahead output variance and price shocks for less than 0.5%; price shocks account for less than 10% of output variance at any horizon, in any orthogonalization.

Also in line with a traditional monetarist view, virtually all M2 variance (94–99%) is due to M2 shocks. However, M2 shocks explain tiny fractions of price variance (0–3%); virtually all of the variance of prices is due to price shocks. Since price shocks do not have large effects on M2, we cannot understand this feature as Fed accommodation. Inflation is certainly not always and everywhere a monetary phenomenon in this VAR! These facts are common to most of the VARs that follow, so I concentrate on the central question of this paper, output variance decompositions.

2.1.2 Level variables

VARs are all about forecasting. The best long-horizon output forecasting variables are ‘level’ variables: stationary variables that tell you if output is ‘below trend’ and hence must grow over several quarters. M2 velocity is such a level variable. It is stable over time (real M2 and output are *cointegrated*). Hence, if velocity is high, output must grow or M2 must decline to reestablish velocity. As it turns out, real output does the adjusting.

Figure 2 plots M2 velocity to make this point. In the left-hand panel, we see that M2 velocity is stable over time. Its fluctuations are surprisingly correlated with the level of the federal funds rate. Thus, M2 velocity will forecast output much as the funds rate does. However, variations in M2 velocity are tiny (note the vertical scale).⁶ The right-hand panel plots real M2 and output. As you can see, the level of real M2 does not stray far from that of output and M2 leads output, especially in the late 1970s and 1980s.

But there are many other level variables, including the consumption/output ratio, hours or unemployment rate, and term spreads. Figure 3 presents several of these level variables. As the Figure shows, they are all highly correlated, and any one seems to pick out NBER peaks and troughs as well as the others.

In particular, consumption and output are cointegrated, and consumption

⁵“Simple” here means that agents can find out the value of aggregates with a one-quarter lag.

⁶The interest elasticity of $M2/(py)$ is only about -0.02. Here is an OLS regression, 1959:1–1992:4:

$$\ln(M2) = -5.07 + 1.002\ln(py) - 0.025\ln(ff)$$

Since most of M2 pays interest, and since M2 velocity seems not to respond to the trend in interest rates, it is probably not wise to interpret the correlation between M2 velocity and interest rates in traditional money-demand terms.

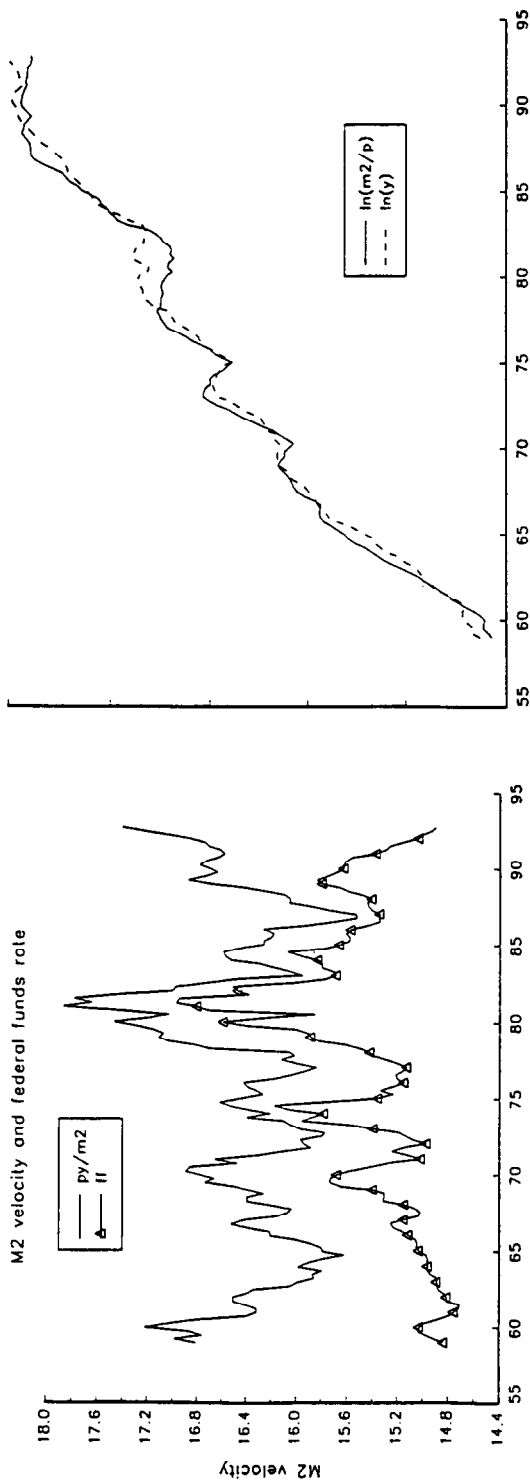


FIGURE 2

(Left) M2 velocity and federal funds rate
 (Right) M2 and output.

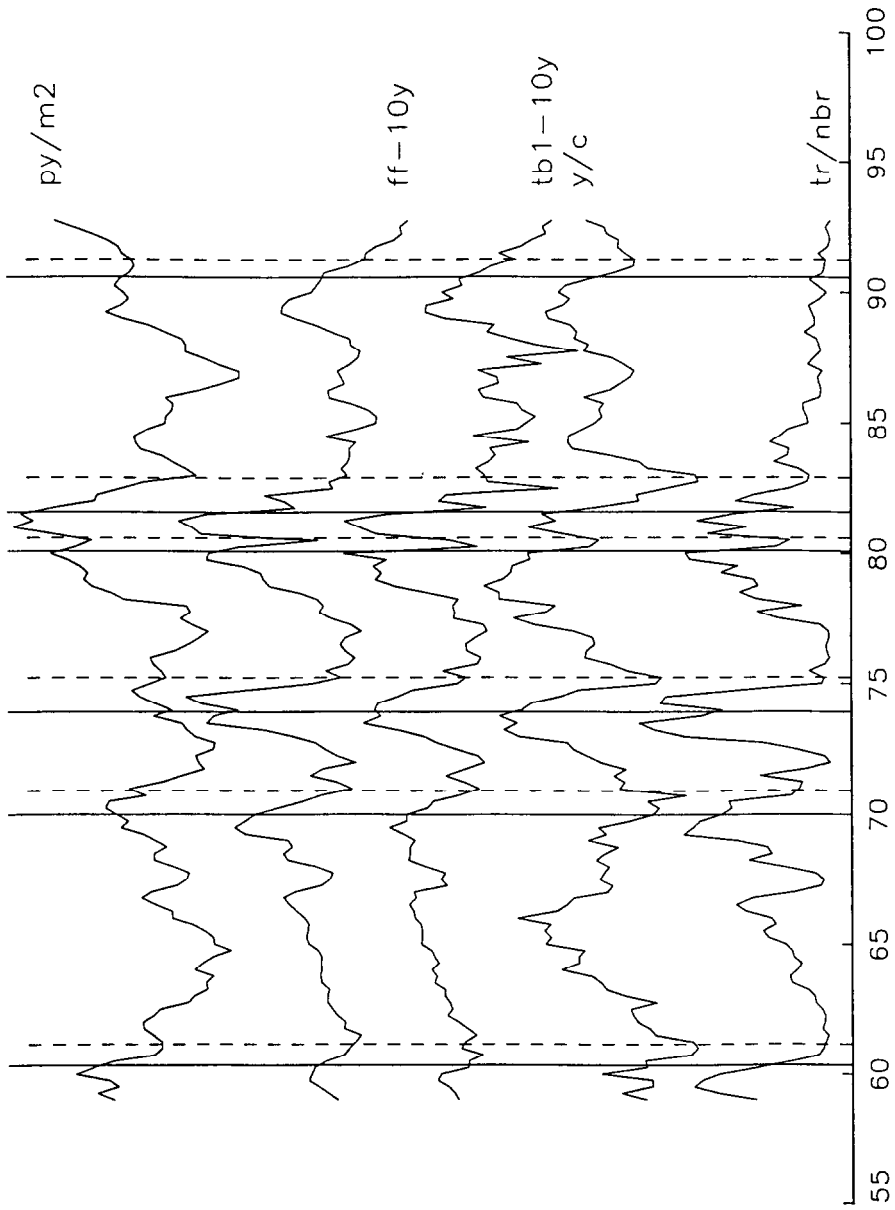


FIGURE 3
Several 'level' variables

tends to lead output over the cycle. Figure 4 presents the impulse-response function of a cyp VAR, and Table 2 includes the output variance decomposition. The response is almost identical to that of the M2 VAR; consumption also explains dramatic (60–78%) fractions of output forecast error variance, and essentially the same fractions of output growth!⁷ Thus, it seems that the level variable feature, rather than anything deep about money, explains the dramatic output forecast error variance decomposition.

The natural response is to include other variables, especially level variables, in the VAR, see whether money retains *marginal* forecast power.

2.1.3 A 5-variable VAR

I first run a 5-variable VAR with M2, federal funds, consumption, output, and prices. Figure 5 presents the impulse-response function, and Table 2 includes the output variance decomposition.

This impulse-response function starts to look more like a monetary VAR should. M2 shocks have an initial liquidity effect on nominal interest rates, and then an inflation effect. They have a hump-shaped effect on output and send prices upward. The implied real interest rate response is calculated as the nominal interest rate response less reinflation response, and is labeled “realr” in Figure 5 and subsequent Figures. It also shows a transitory liquidity effect. However, the responses are still surprisingly drawn out, and money still seems to have a permanent effect on output and certainly on consumption.

As the impulse-responses start to look more reasonable, the output variance decomposition starts to fall. At every horizon and in differences, M2 shocks account for about half of the variance of output than they did in the M2 y p VAR. This is still a sizable fraction, however, 20–40% rather than 40–80%.

2.1.4 Imposing velocity and c/y stability

Next, I impose the fact that M2 velocity and the consumption/output ratios are stable. To do this, I run the VAR in error-correction form, i.e., I run growth rates of all variables except federal funds on their lags and the lagged $\log c/y$ and $\log M2/(py)$ ratios.⁸ Figure 6 presents the impulse-response function and Table 2 includes the output variance decomposition. The responses

⁷The rest of the variance decomposition, not shown, is also similar. Consumption shocks account for 87–99% of consumption variance, and only prices account for prices.

⁸It is important that the imposed cointegrating vectors $m - y - p$ and $c - y$ really are stationary, or one estimates explosive roots. For this reason, the error-correction VAR uses total GDP for output, and consumption + 0.65 times government purchases for consumption.

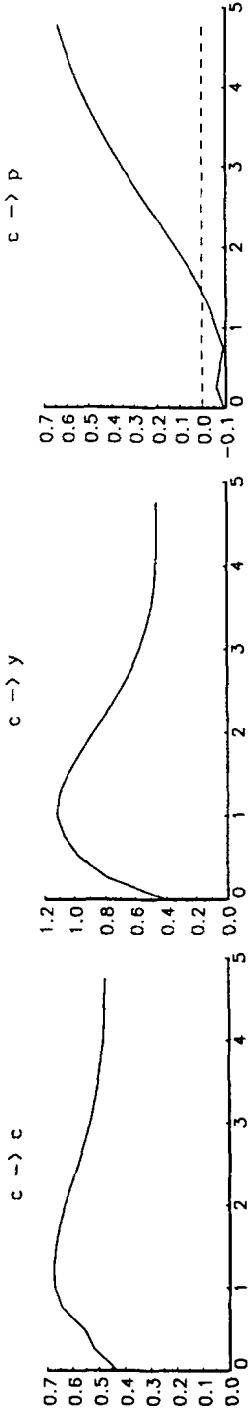


FIGURE 4
Responses to consumption shock, c y p VAR

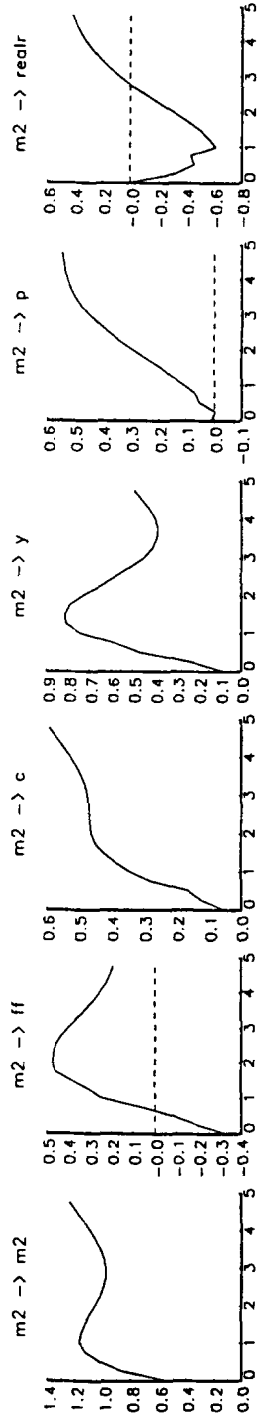


FIGURE 5
Responses to M2 shocks

look even more like monetary responses should. We now get transitory responses of consumption, output, and interest rates (the long-run output and consumption responses are less than one standard error from zero) along with the right signs of all the other variables.

The variance decompositions, reported in Table 2, show that the fractions of output variance explained have dropped by another half to a third. The forecast error variances due to M2 are 16%, 18%, and 25% at 1, 2, and 3-year horizons, and 11%, 21% of one-quarter and one-year output variance. Furthermore, standard errors are large; a 2σ confidence interval extends to nearly zero percent of output variance explained.

2.1.5 Using long-run restrictions to identify monetary policy shocks

A further refinement: perhaps one should identify a money-*supply* shock as a combination of federal funds and money innovations rather than one or the other alone. A money-supply shock should work up the money demand curve. To this end, and in order to impose the desirable feature that money-supply shocks should have transitory effects on real variables, I identify a money-supply shock as that combination of M2 and federal funds shocks that has exactly no *long-run* effect on output (and hence consumption, since they are assumed cointegrated). Since the long-run effect of an M2 shock on output is small and statistically insignificant in the previous VAR, this should be a small refinement to the results.⁹

It is. The money supply responses plotted in Figure 7 subtract some of the ff responses from the M2 responses. Hence the liquidity effect on interest rates is deeper and more prolonged and the output effects somewhat larger. By the orthogonalization assumption, money-supply (*ms*) shocks now have exactly zero long-run effect on output and hence consumption.

Table 3 presents the output variance decomposition, along with its mean and standard error in a 1000 replication bootstrap using the estimated VAR and reshuffling residuals. At a one-year horizon, the variance decomposition is essentially the same as before. 14% of output variance is explained by *ms* shocks rather than 16% by M2 shocks; the standard error is about the same (7%), and the mean of the variance decomposition in the bootstrap is about the same as the point estimate. However, at 2 and 3-year horizons, we obtain a very different result. In the point estimate, *ms* explains a whopping 42 and 46% of output variance, compared with 28 and 25% for M2. However, the large estimates are associated with large standard errors (17%). Worse, the mean (across replications) 2 and 3-year variance decomposition is only about 26%, about the same as M2. Similarly, the mean response of output to the

⁹Money *demand* shocks may reveal permanent changes in output and so induce output responses that do not die out.

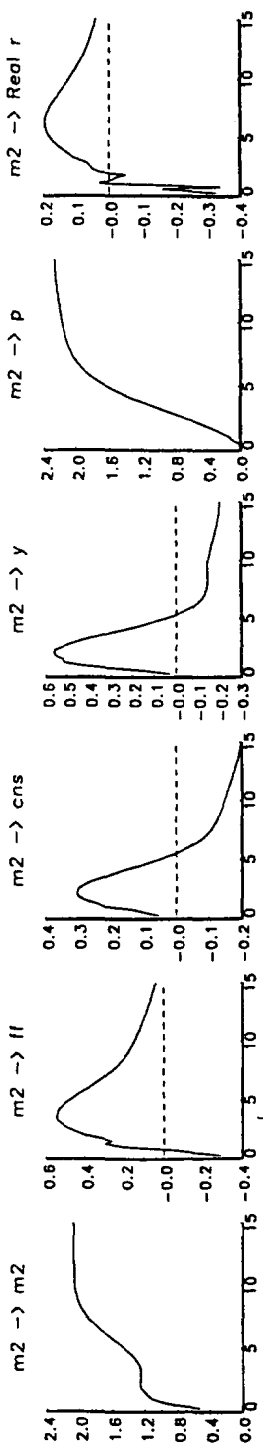


FIGURE 6
 Responses to M2 shocks, error-correction VAR
 using c/y and M2/py as forecasting variables

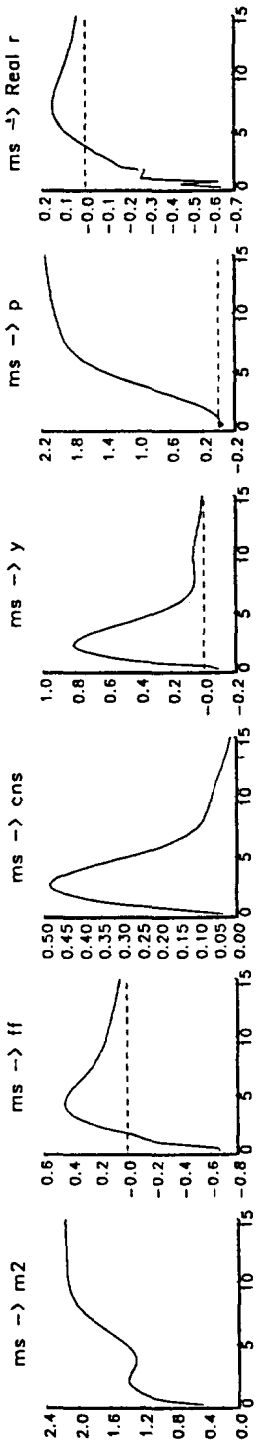


FIGURE 7
 Responses to money supply shocks. Ms shocks
 are the linear combination of M2 and ff shocks
 that have no long-run effect on output

money-supply shock peaks at 0.5, about the same value as the M2 shock, while the point estimate shown in Figure 7 peaks at 0.8. One can take the means as easily as the point estimates as consistent estimates of the true variance decomposition.

Table 3:

	1 Year		2 Years		3 Years	
	M2	M _s	M2	M _s	M2	M _s
point est.	16	14	28	46	25	46
mean	17	15	27	26	23	26
std. err.	8	7	10	17	11	17

Fraction of output forecast error variance due to M2 and money-supply shocks. “Mean” and “standard error” are calculated from a 1000 draw bootstrap.

There are two reasons for this strange sampling behavior. First, the ff responses are much less precisely estimated than the M2 responses. The ms responses are a linear combination of the M2 and ff responses and so inherit some of the larger sampling variation of the ff responses. Second, long-run responses are notoriously hard to estimate, since they involve sums of coefficients or an estimate of the spectral density at frequency zero. Even if the true long-run response is zero, the unconstrained estimate will not be zero in every sample. *Forcing* it to be equal to zero in each sample is the heart of the sampling problem. (Canova, Faust and Leeper (1993) discuss the difficulties of long-run VAR identification in detail.)

In summary, though the long-run restrictions are an attractive refinement, the sampling distribution is substantially worse when they are imposed. When we take this fact into account, the VAR with long-run restrictions does not provide solid evidence for an effect of monetary shocks larger than the 15–25%, with 7–12% standard errors, provided by the M2 VAR.

2.1.6 More variables and orthogonalization

Plausible variations can destroy the pretty pattern of the impulse-response functions and bring the variance decomposition down below 10%. This specification uncertainty is perhaps a reason even stronger than sampling uncertainty to doubt the 15–25% figure given above.

For example, I also include hours per capita and a trend in the VAR. Detrended hours are also a business-cycle ‘level’ variable: output is high when hours are high. (See Rotemberg and Woodford 1994.) Figure 8 shows the output response. M2 shocks now die out after 5 years, and have a transitory

and much shorter effect on output. But prices go off in the wrong direction. Table 2 includes the output variance decomposition. M2 shocks now account for less than 10% of the variance of output at any horizon.

The five-variable VAR is sensitive to the order of orthogonalization. Figure 9 presents the response of output when M2 is orthogonalized last (all shocks can affect M2 within a quarter), and Table 2 again presents the output variance decomposition. The liquidity/inflation effects disappear, M2 has permanent output effects, and no price effect. M2 shocks again account for less than 10% of the variance of output. My procedure of choosing the ordering to produce the “right” pattern of responses is not innocuous.

2.2 *M1*

M1 corresponds more closely to the idea of a non-interest-paying transactions balance. Figure 10 presents M1 velocity and the federal funds rate. In contrast to M2, M1 velocity responds sensibly to the rise in the federal funds rate. The interest elasticity is between¹⁰ -0.15 and -0.35 depending on specification, compared to -0.03 for M2. However, M1 velocity does not respond to cyclical variations in the federal funds rate, at least until the mid-1980s. M1 does not lead output, either directly or via an interest elasticity and the fact that interest rates lead output. As a result, it is less useful than M2 for forecasting output and contributes less to output variance, as we will see.

However, these facts do not mean we should throw M1 out. The theory of money demand refers to a transactions balance for which one pays at least an interest spread; if M1 shocks explain less output variance than M2 shocks, so much the worse for M2. One can simply read this fact as another case in which imposing theory sharpens (lowers) our estimates.

2.2.1 A simple M1 y p VAR

Figure 11 presents the responses to an M1 shock in a M1 y p VAR. The pattern looks broadly similar to M2. Money shocks are less persistent and may even have transitory, though still drawn out, effects on output. Prices are if anything even more sluggish. The responses are smaller. (For visual

¹⁰I estimated the following regressions from 1959:1 – 1992:4:

$$\ln(m1) = -3.71 + 0.81\ln(py) - 0.15\ln(ff)$$

and, imposing a unit income elasticity,

$$\ln(m1/py) = -5.69 - 0.34\ln(ff)$$

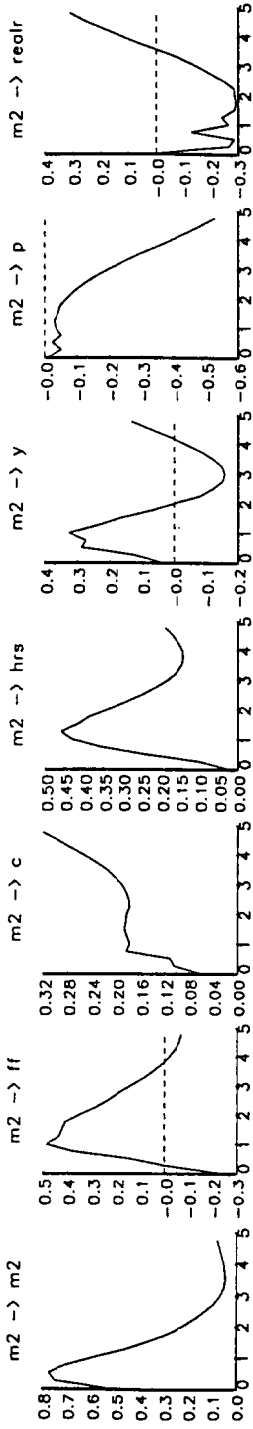


FIGURE 8
Responses to M2 shocks,
VAR with hours/per capita

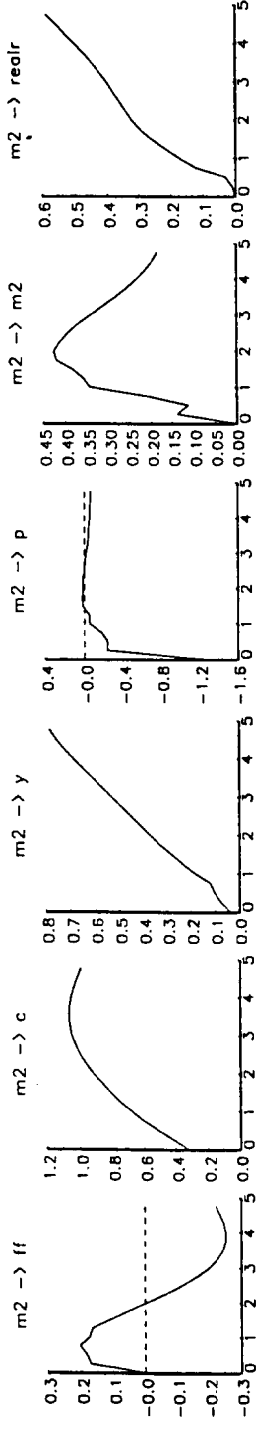


FIGURE 9
Responses to M2 shocks, when
M2 is orthogonalized last

M1 velocity and federal funds

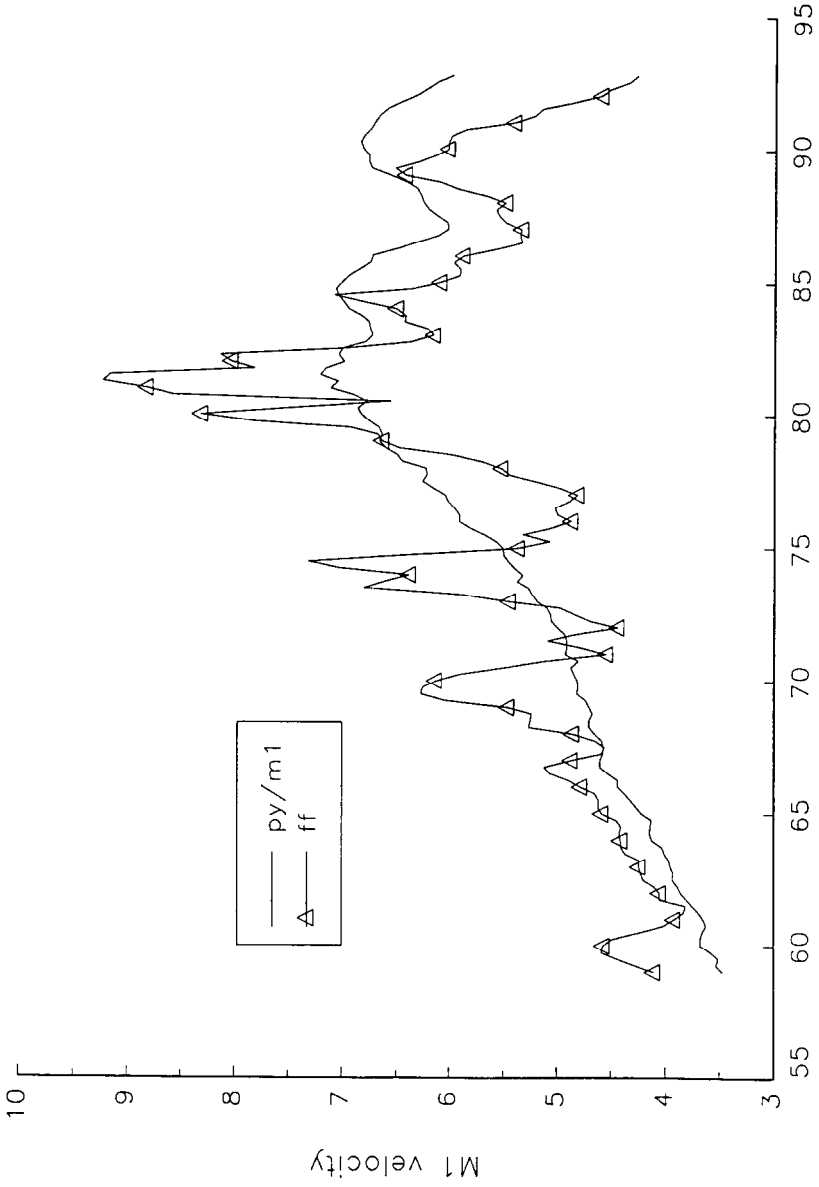


FIGURE 10
M1 velocity and federal funds rate

clarity, each graph has its own vertical scale.) Output rises to a peak of 0.7 after 1–2 years instead of 1.4 after 2–3 years.

Table 4 presents output variance decompositions for M1 VARs. Since the responses are smaller, the variance decompositions are smaller. M1 shocks explain less than 20% of output variance, compared to up to 80% for M2 in the same specification. In other respects, the decomposition is similar to M2: M1 shocks are still largely exogenous, price shocks account for essentially none of output variance and all of price variance.

Table 4:

VAR	Forecast error σ^2				Var Δy	
	1Q	1Y	2Y	3Y	1Q	1Y
M1 y p	3	16	20	20	11	19
y M1 p	3	1	1	1	9	9
M1 y p; trend	2	8	7	8	10	16
M1 ff c y p	3	2	3	8	8	10
M1 ff c y p, error corr.	2	6	5	4		
M1 ff c y p; e.c.; MS shocks	5	7	5	4		

Percent of output variance explained by M1 shocks.

Unlike the simple M2 y p VAR, this VAR is sensitive to ordering and trends. Table 4 presents variance decompositions with M1 ordered last and when a trend is included. Now less than 10% of output variance is explained by M1 shocks at any horizon. These changes destroy the pretty impulse-response pattern as well.

2.2.2 A five-variable VAR

Figure 12 presents the responses in a M1 c y p VAR, the same specification that provided such nicely shaped responses for M2. Here, the responses look nothing like what we expect of a monetary shock. As shown in Table 4, the fractions of output variance explained are tiny.

2.2.3 Imposing cointegrating vectors and long-run restrictions

As with M2, we may get better-looking response functions by imposing long-run restrictions. Though the level of interest rates is probably stable in the long-enough run, it has moved slowly in our sample. Thus, M1 velocity does not appear stationary. Rather, M1 - p - y - α ff, is a better candidate for a stationary variable. I also include c - y as a stationary variable. As a result of the slow movement of federal funds, the specification

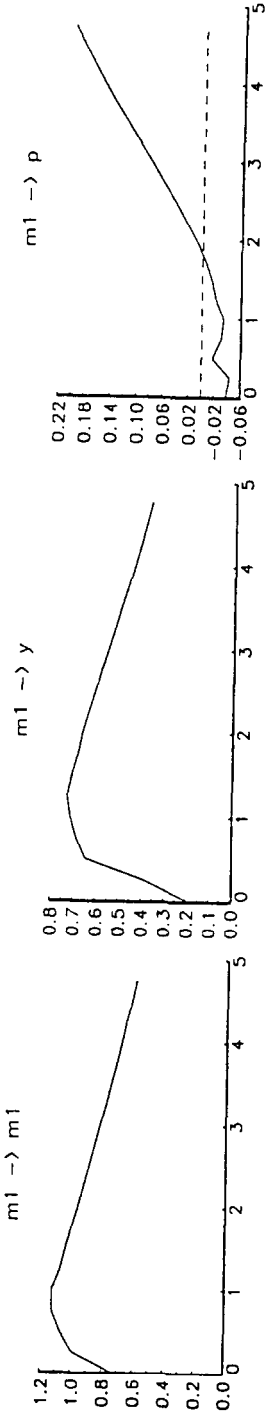


FIGURE 11
Response to M1 shocks in M1 y p VAR

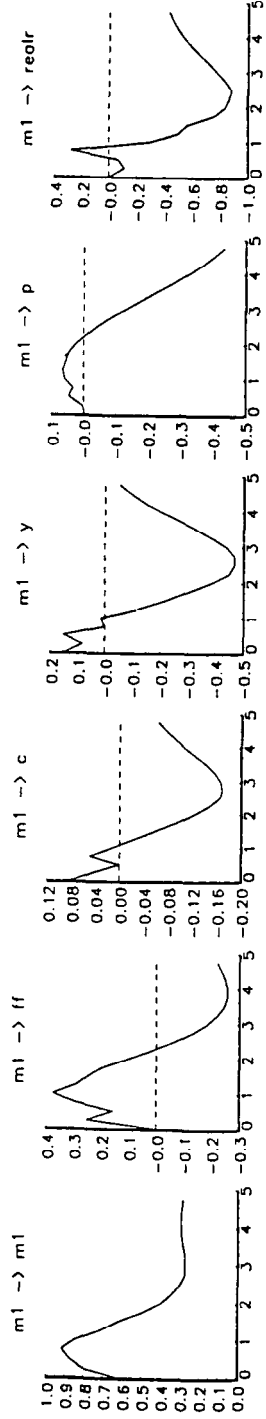


FIGURE 12
Responses to M1 shocks

with stationary levels of interest rates leads to explosive responses. Therefore, I run a VAR of differences of M1, ff, c, y, p on their lags and the lagged value of $c - y$ and $M1 - p - y - 0.75 \text{ ff}$. I use -0.75 for the interest elasticity of M1 demand, rather than -0.35 as suggested by the OLS regression presented above. -0.35 minimizes the sum of squared residuals, but the resulting $M1 - p - y - 0.35 \text{ ff}$ series still has a trend in our sample. The higher interest elasticity produces a series without a trend, and hence nonexplosive responses.¹¹

The top panel of Figure 13 presents responses to M1 shocks from this VAR. The bottom panel presents responses to money-supply shocks, identified above as the combination of M1 and ff shocks that leave output unchanged in the long run. These responses are consistent with what we expect for monetary shocks. M1 or MS shocks lead to a short liquidity effect, and then a permanent rise in federal funds. (The level of ff is not stationary in this specification, so there is no reason for this response to return to zero.) M1 or MS shocks lead to brief, transitory output and consumption responses and to increases in prices. The real rate shows a short liquidity effect as well. Since inflation eventually stops, the nonstationarity of ff is accounted for by a long-run increase in the real interest rate. The *brevity* of M1 shocks/ non-neutral effects is noteworthy, since it more closely corresponds with theory.

Table 4 includes the variance decomposition. Despite (or maybe because of) the attractive pattern of impulse responses, M1 or M1 money-supply shocks account for trivial fractions of output variance, around 5% at all horizons.

2.3 Federal funds

Bernanke and Blinder (1988) and Sims (1988), following a suggestion of McCallum (1983), argue that federal funds rate forecast errors measure monetary policy shocks better than monetary aggregates. Strongin (1992) and Christiano and Eichenbaum (1995) use nonborrowed reserves with much the same effect, which I examine in the next section.

The idea is that there are shocks to money demand, observed by the Fed but *not by us* (or we could produce a monetary aggregate-supply shock directly). The Fed accommodates such shocks by smoothing interest rates and allowing borrowed reserves to increase, as they do in accommodating seasonal demand shocks. The resulting demand-driven increases in monetary aggregates do not affect output or prices. Fed *policy* changes can be seen when there is a change in the Fed Funds rate, nonborrowed reserves (Christiano and Eichenbaum) or the nonborrowed reserve ratio (Strongin). Furthermore,

¹¹If all of this seems a little strained, it is. The point is to find a specification that produces the “right” pattern of impulse-responses, not to follow the dicta of atheoretical time-series specification.

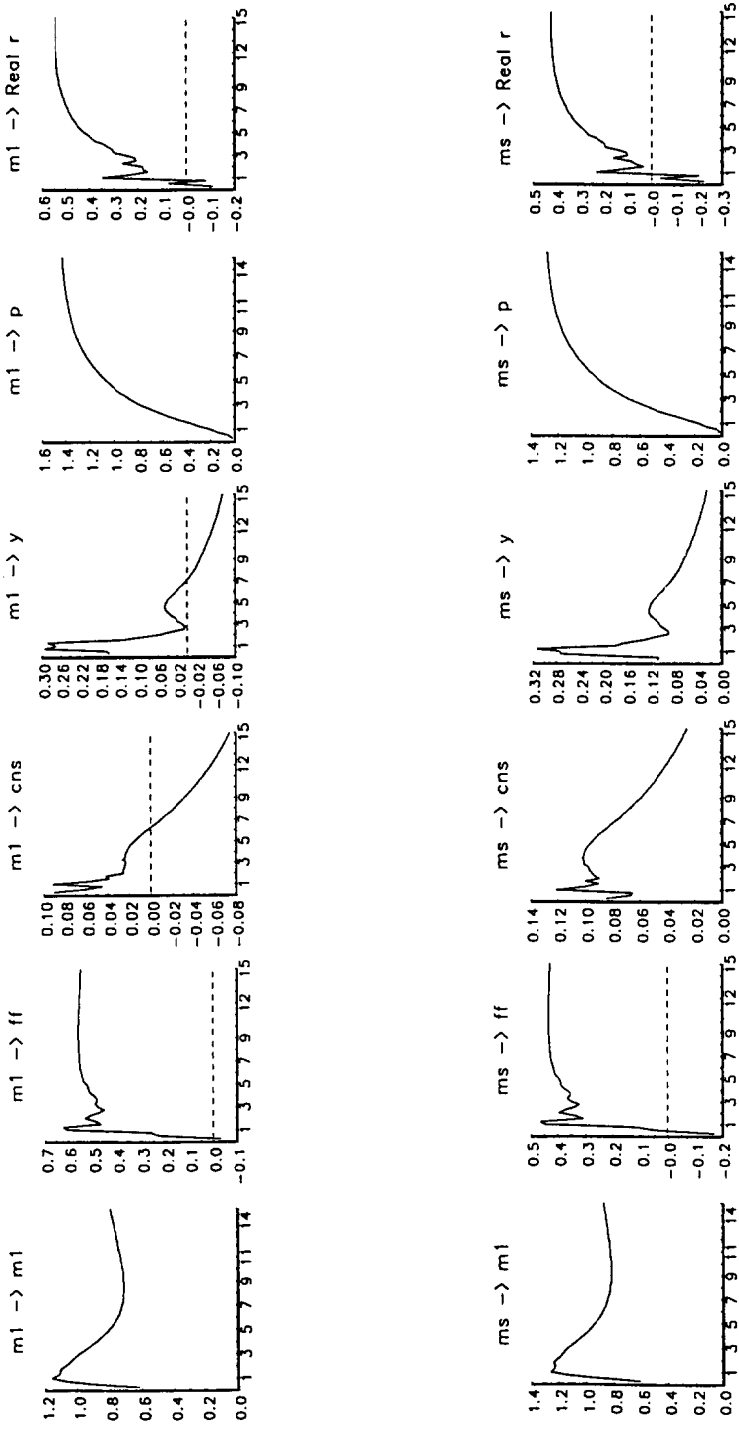


FIGURE 13

Responses to M1 (top) and money supply (bottom) shocks in a VAR that imposes stable c/y and money demand. Ms shocks are identified to produce no long-run output response.

the Fed has closer control of the federal funds rate and reserves, where M1 and M2 are controlled more indirectly.

This search for policy shocks is not as innocuous as it may seem. To a monetarist, shocks to the right aggregate are all that matter, no matter how that shock is produced. Friedman and Schwartz (1963) do not blame the great depression on a *policy shock* that lowered monetary aggregates, but on the Fed's failure to *expand* the base as the money multiplier collapsed.

On a practical level, the federal funds rate is also a 'level' variable that is likely to forecast long-term output, as seen in Figure 3 above. We might expect it to do well in a VAR.

2.3.1 Simple ff y p VARs

The top panel of Figure 14 presents the responses to ff shocks in a simple ff y p VAR. Federal funds shocks are persistent. A rise in federal funds gives rise to an initial six-month rise in output and then a permanent decline. Last, there is a "price puzzle." In response to a contractionary federal funds shock, prices *increase* for 2 years, and only come back to where they started after 5 years.

Table 5 presents output variance decompositions. Federal funds shocks explain between 6 and 32% of output forecast error variance, as the horizon lengthens, and 24–28% of output growth variance at 1-quarter and 1-year horizons.

Table 5:

Forecast error σ^2				VAR Δy		VAR
1Q	1Y	2Y	3Y	1Q	1Y	
6	6	20	32	24	28	ff y p
0	15	37	50	21	31	y p ff
0	14	30	38	20	27	y p ff; trend
7	4	25	38	20	27	tb1s y p
0	11	41	54	20	39	y p tb1s; trend
0	13	26	20	12	16	c y p cp M1 ff
0	11	21	16	11	15	c y p cp M1 ff; trend
0	3	3	2	3	3	c h/pop y p cp M1 ff

Percentage of output variance explained by federal funds rate shocks. All VARs in log levels with 4 lags.

This VAR turns out to be somewhat sensitive to ordering and trends. The middle panel of Figure 14 presents the response to federal funds shocks when

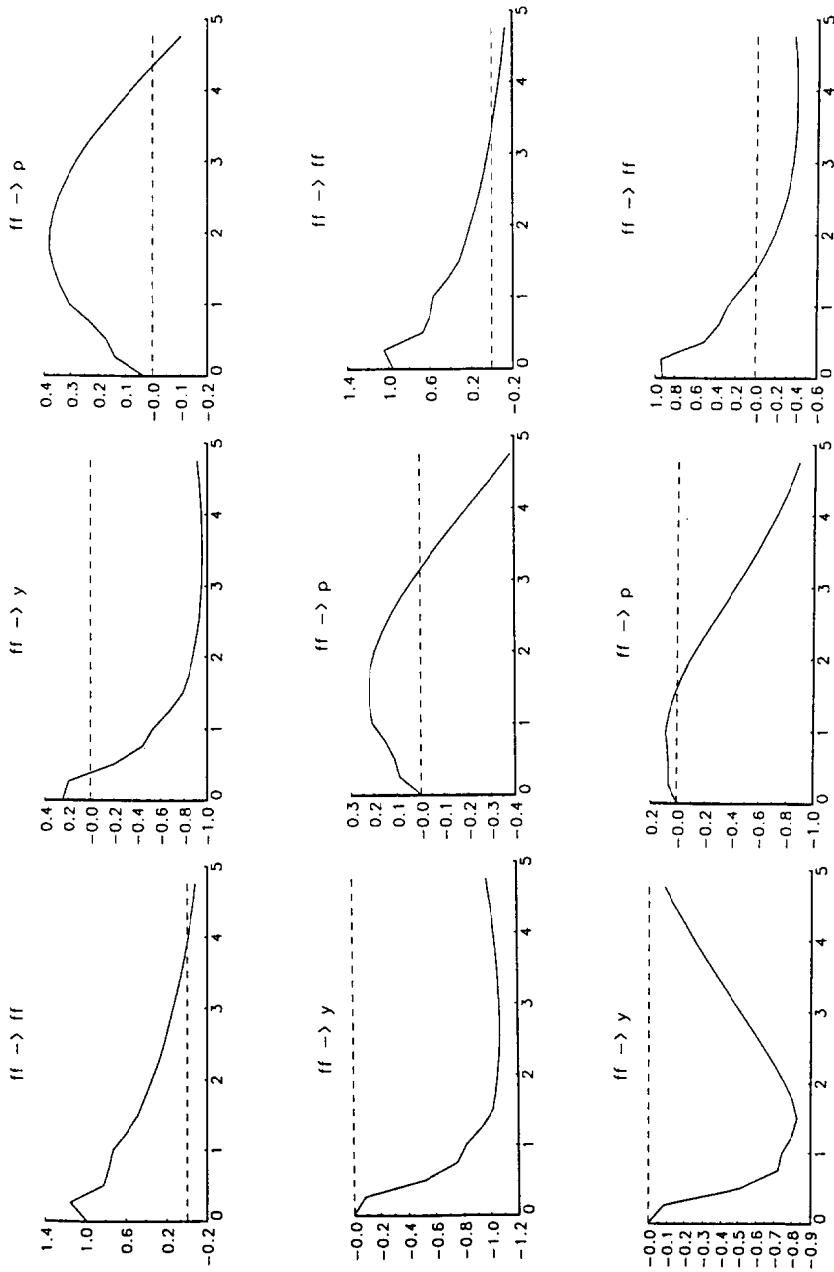


FIGURE 14
 Responses to federal funds rate shocks. Top panel: ff y p VAR.
 Middle panel: y p ff VAR (ff orthogonalized last). Bottom
 panel: y p ff VAR with trend.

they are orthogonalized last. This deepens the output response, removes the troublesome initial rise in output, and reduces the price puzzle somewhat. Summing and squaring the larger output response, we find a much larger output variance decomposition. 50% of the 3-year output forecast error is due to the ff shock, though somewhat more modest fractions at shorter horizons—14% and 30% at 1- and 2-year horizons, and 20–27% in growth rates.

The bottom panel of Figure 14 includes a trend in the VAR. Now the price puzzle is reduced even more, to a 2-year pause before prices start to decline. However, the output response is not as deep. This improvement in the *shape* of the VAR lowers the variance decomposition by about a third, as shown in Table 5.

Nothing is particularly special about the federal funds rate in this VAR. The second block of Table 5 includes results that use the one-month T-bill rate in place of the federal funds rate. The variance decomposition and response functions (not shown) are almost identical to those of federal funds.

2.3.2 Larger VARs

We need to put the federal funds shock in competition with other level variables as above. I follow Christiano and Eichenbaum, and Evans (1995) in adding an index of sensitive commodity prices to the VAR and orthogonalizing federal funds last. The price puzzle may be due to the fact that the Fed watches commodity prices and contracts on news of future inflation. As a result, part of the contractionary ff shock reflects news of rises in prices. By including commodity prices, we may control for an important part of the Fed's information set. (The warning about left-out variables and information sets is clearly at work here!) More practically, these modifications reduce the price puzzle and so produce better-looking pictures; this alone may be enough justification. I also include M1 to see how a monetary aggregate responds to the federal funds shock.

The top panel of Figure 15 presents the responses to federal funds shocks from this six-variable VAR. The responses are fairly sensible: there is a transitory output effect. Prices as measured by the GDP deflator still go slightly the wrong way for a year; however the commodity price index falls immediately and attains its permanent value after only two years. The funds shock produces a large, though transitory, decline in M1. The real rate response, implied by the H and price responses, has a single peak in the wrong direction, as a result of the small remaining price puzzle. A real rate calculated from the commodity price index shows a pure short-run liquidity effect.

The variance decomposition, Table 5, produces about the same numbers as the five-variable M2 VAR. 13–20% of output forecast error variance, and 12–16% of output growth is due to the federal funds shock. The figures are

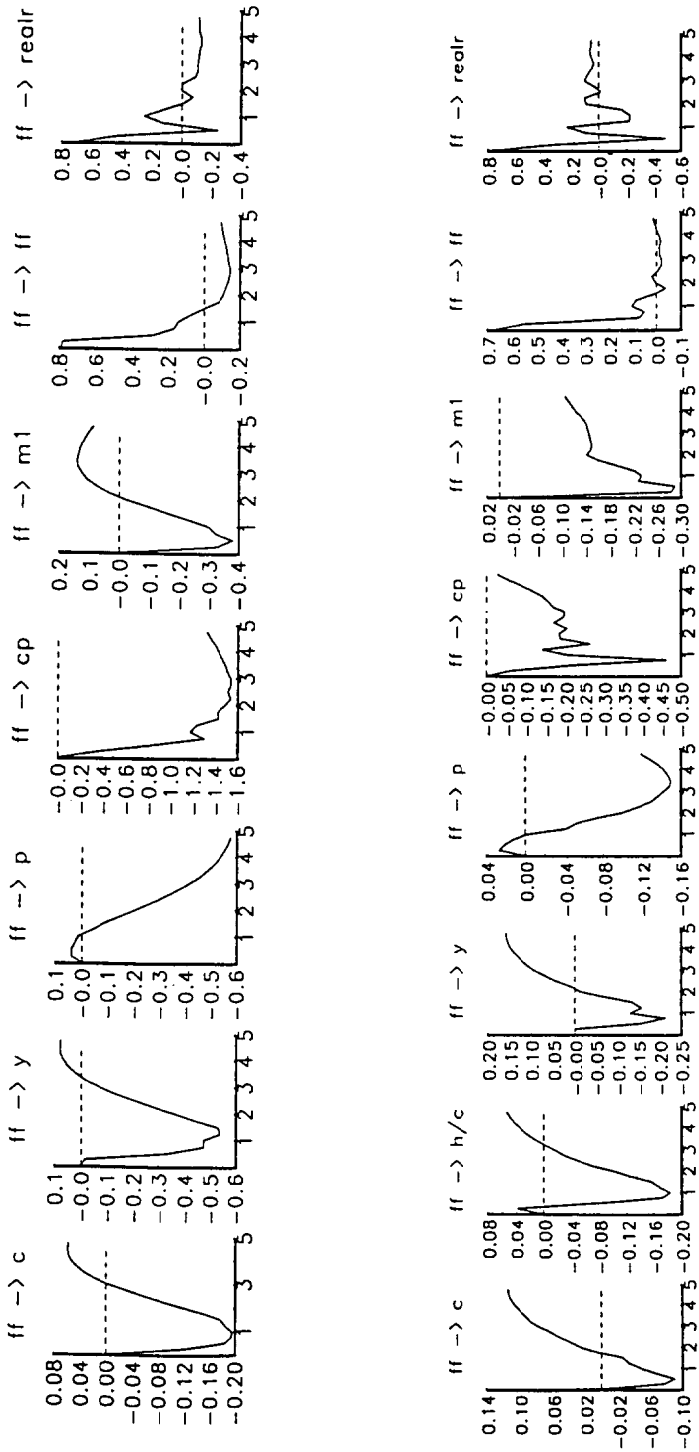


FIGURE 15

Responses to federal funds shocks, larger VARs. Real interest rate response is inferred from ff and p responses.

only slightly lower if a trend is included in the VAR.

This VAR is also sensitive to other variables. The bottom panel of Figure 15 shows what happens when log hours per capita are included. In this case, the shape of the response functions is still interpretable as monetary policy. In fact, as with the M1 VARs, the brevity of the output response is attractive. But the variance decompositions (Table 5) now drop precipitously to less than 5% at any horizon.

2.4 *Nonborrowed reserves*

Christiano and Eichenbaum (1995) use nonborrowed reserves to identify a monetary policy shock. Strongin (1992) uses the ratio of nonborrowed to total reserves. Strongin presents a detailed analysis of Fed operating procedures to suggest that this variable separates policy shocks from accommodated money-demand fluctuations. Since the nonborrowed reserve ratio is highly correlated with the federal funds rate (see Figure 3), we might expect similar results.

In fact, the results using the nonborrowed reserve ratio are almost identical to the federal funds results. Figure 16 presents responses to *nbr/tr* shocks in three-variable VARs. The pattern is almost identical to federal funds, Figure 16. With *nbr/tr* first, there is a small output movement in the wrong direction followed by a sustained decline and a big price puzzle. With *nbr/tr* last, the output decline is continuous, and the price puzzle is reduced.

The output variance decompositions summarized in Table 7 are also almost identical to their federal funds counterparts. With *nbr/tr* orthogonalized last, its shocks explain up to 52% of output variance at a three-year horizon and a substantial 32% of annual output growth.

Table 6:

VAR	Forecast error σ^2				VAR Δy	
	1Q	1Y	2Y	3Y	1Q	1Y
<i>nbr/tr</i> y p	7	4	20	34	23	34
y p <i>nbf/tr</i>	0	9	36	52	16	32
c y p cp M1 <i>nbf/tr</i>	0	10	28	28	11	18
c y p cp M1 <i>nbf/tr</i> ; trend	0	10	27	27	11	18
c h/ pop y p cp M1 <i>nbr/tr</i>	0	4	8	5	4	6

Percent of output variance explained by nonborrowed/total reserve shocks. All VARs in log levels with 4 lags.

Figure 17 presents responses from the usual five-variable VAR. The pattern is almost exactly the same as the federal funds pattern and conforms

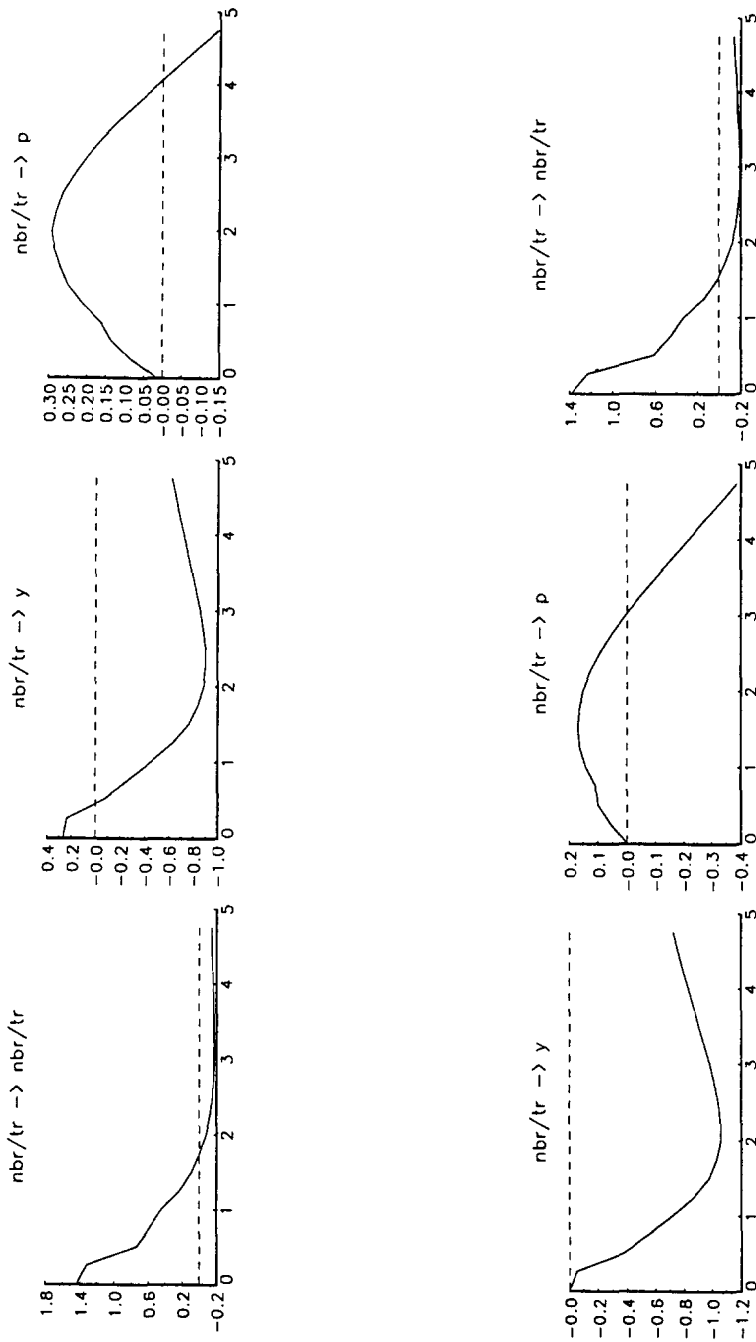


FIGURE 16

Responses to nonborrowed reserve/total reserve ratio shocks.
 Top panel: nbr/tr y p VAR, bottom panel: y p nbr/tr VAR. Both
 VARs in levels without trends.

roughly to the pattern we expect of a monetary shock. As before, the output variance decomposition declines, to a maximum of 28% at two- and three-year horizons, and 18% of annual output growth. Adding hours has the same effect as with federal funds. The impulse-response pattern is not that badly affected, but *nbr/tr* shocks now account for less than 8% of the variance of output.

2.5 *Long-horizon output forecasts*

In each of the above VARs, adding consumption substantially reduced the fraction of output variance explained by the monetary shocks. Here I look at the relative forecast power of consumption and monetary variables directly to see if consumption drives the monetary variables out.

Table 7 compares forecasts of 3-year output growth using federal funds, the real *M2/output* ratio, and the consumption/output ratio.¹² The top panel starts with single variable regressions. All variables significantly forecast output growth. The R^2 are high, as often happens in multiperiod forecasts with serially correlated right-hand variables. The consumption/output ratio has the highest t -statistic and, more importantly, $R^2 = 0.63$.

The second panel of Table 7 presents multiple regressions, which are the horse race. The first row compares federal funds and *M2*, out of curiosity over which is the “better” monetary variable. Recalling the correlation of federal funds and *M2* from Figure 2, the fact that both are individually significant in the multiple regression suggests that they capture the same information about output growth. The second row, though, which compares the fed funds *spread* and *M2*, suggests that the spread does have significant information beyond that contained in *M2*. (In a VAR, the spread gives very similar results as the level.)

The third and fourth rows run a horse race between federal funds and the consumption/output ratio. The fed funds variables are insignificant, and the coefficients are substantially lower than in the single-variable regressions. The consumption coefficient and significance are hardly affected by the inclusion of either fed funds variable. Thus, consumption drives out federal funds as a forecaster of output. The fifth row runs a similar race between the real *M2/output* and consumption/output ratios. Again, whether measured by the coefficient or the t -statistics, consumption drives out *M2*.

Figure 18 also suggests that consumption does a better job of forecasting output growth than the monetary variables. Not only is the R^2 higher, but

¹²All the regressions contain a trend. This significantly improves the forecast performance of the interest-rate variables. There is a secular decline in output growth, visible in Figure 18. The interest-rate spreads have no trend, so are not significant and have tiny R^2 in regressions with no trend, while the interest-rate levels do better simply because they have some trend.

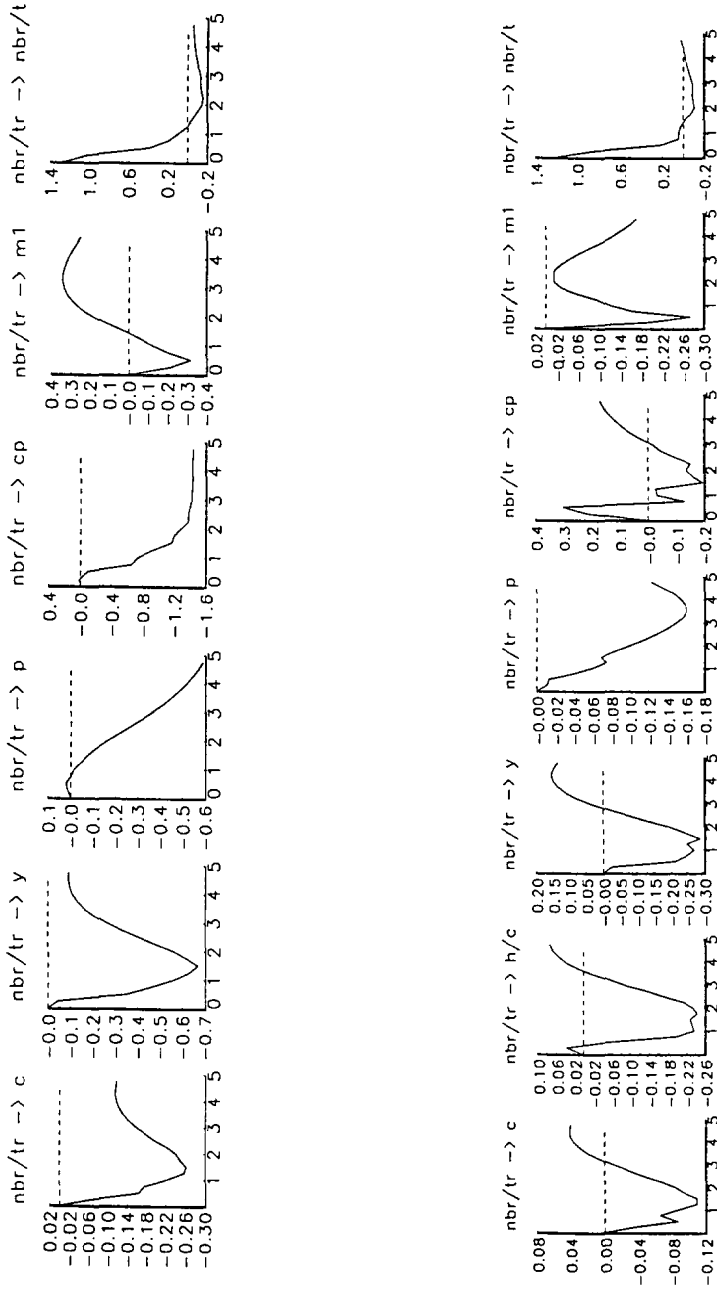


FIGURE 17

Responses to nonborrowed reserve/total reserve shocks.
 VARS in log levels without trends.

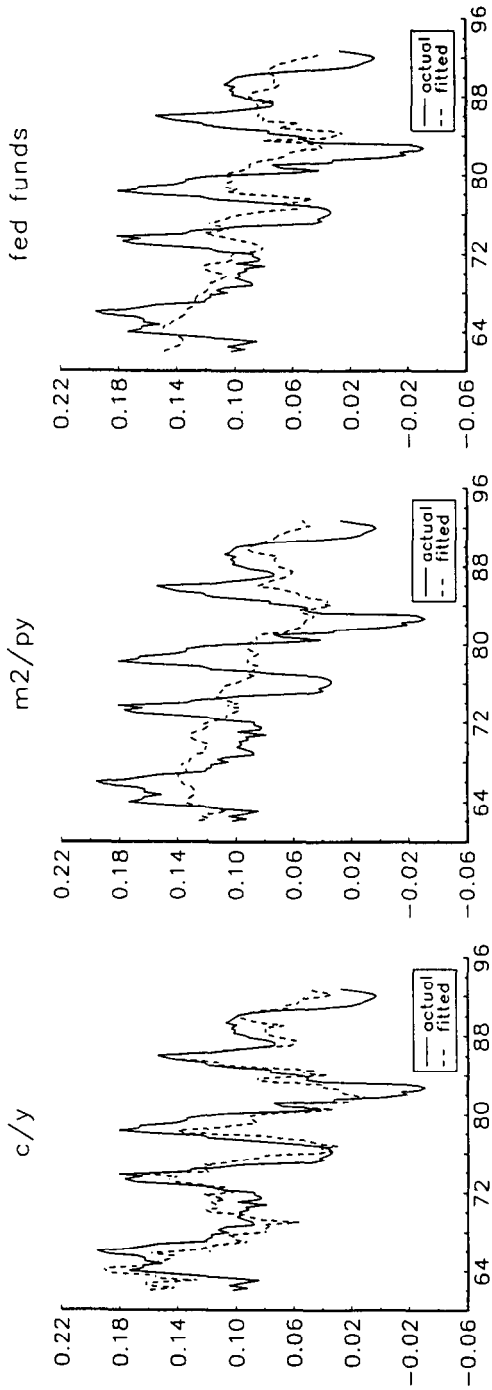


FIGURE 18

Actual 3-year output growth and fitted values from forecasting regressions. All regressions contain a trend.

Table 7:

I. Single Regressions					
	ff	ff-10y	M2/py	c/y	
coef.	-0.35	-0.95	0.43	1.70	
t.	-2.08	-4.76	2.38	8.40	
\bar{R}^2	0.26	0.34	0.31	0.63	
II. Multiple Regressions					
	ff	ff-10y	M2/py	c/y	\bar{R}^2
coef.	0.19		0.54		0.31
t.	0.43		1.42		
coef.		-0.73	0.20		0.35
t.		-5.40	1.04		
coef.	-0.01			1.70	0.63
t.	-0.06			7.32	
coef.		-0.14		1.64	0.63
t.		-0.45		6.23	
coef.			0.16	1.62	0.64
t.			0.87	6.45	

OLS forecasting regressions of three-year log output growth. All regressions include a time trend, $y_{t+3} - y_t = \alpha + \gamma t + \beta x_t + \epsilon_{t+3}$. Standard errors corrected for error overlap and heteroskedasticity.

the consumption forecasts also seem contemporaneous with output growth, where the fed funds rate forecast lags.

2.6 Summary of VAR results

In each case, I started with a simple system, and the monetary shock seemed to explain large fractions of output variation at long horizons, up to 82% for M2. However, the response functions of these simple VARs did not conform to even qualitative monetary theory.

By adding more variables, playing with orthogonalization and imposing cointegration structure, I was able to find specifications in which point estimates did capture reasonable monetary dynamics. In each case, the fractions of output variance declined as the responses started to look better. The *largest* credible point estimates were in the 20–25% range at two- to three-year horizons. Even this result is tenuous; adding hours to the VARs drove the explained fractions of output variance down to less than 10% by making the output responses briefer, consistent with monetary theory. Consumption seems to drive out all of the monetary variables in a long-horizon forecasting horse race.

Furthermore, all the VARs explained very little output variance at horizons less than a year, where a short-run non-neutrality is most likely to show up. Viewing the results through the majority of current explicit monetary models, which do not predict protracted non-neutralities, we again obtain less than 10% of output variance explained by monetary shocks.

Thus these VARs *do* provide evidence that monetary shocks *can* temporarily raise output, lower interest rates, and eventually raise prices. However, they do not reliably indicate that a large fraction of postwar U.S. output variance *is* in fact due to monetary policy shocks.

Even the largest figures are certainly an overstatement, for several reasons. (1) Other real variables can help forecast output and drive down the contribution of monetary variables. (2) The Fed and private agents are likely to have information advantages, so that M2 or federal funds move in anticipation of news about the economy that we do not include in a VAR.¹³ In addition, monetary aggregates and the economy undoubtedly react to each other within a period. For both reasons, the *identification* of a money-supply

¹³Sims (1992) puts it nicely: "...because interest rates and money are closely linked to investment portfolio decisions, they tend to react quickly to new information, as other asset market variables do. Money and interest rates have strong predictive value for aggregate activity for the same reason that stock prices do... One can imagine, in other words, that the historical pattern of monetary tightness preceding recessions is misleading. High interest rates might 'produce' contractions in activity the way the cock's crow produces the sunrise." This is at heart the same point made by King and Plosser (1984) as well as Tobin (1970): money that really responds to output can look like it causes output.

shock is tenuous. (3) Very little theory is used to restrict the *form* of the VAR. Believing that money even accounts for 15–25% of output variation at a 2–3-year horizon (and virtually zero at a 1-quarter horizon) requires us to understand *how* it produces such a response. (4) Once we recognize sampling uncertainty and (more importantly) specification uncertainty (the reader can easily see how much fishing went into producing good-looking impulse responses), the range of estimates consistent with the data is very large.

2.7 Systematic monetary policy

Variance decompositions can answer the question “How much output variance is due to monetary policy *shocks*?” This is a different question than “How much output variance is due to monetary *policy*?” unless one imposes the view that systematic policy has no effect whatsoever.

For example, many economists believe that postwar output is more stable than prewar output because the Fed learned to systematically offset real shocks. Similarly, output might be much more variable if the Fed stopped accommodating seasonal and other shifts in money demand (such as after the 1987 stock-market crash). If so, a *negative* fraction of output variance is due to monetary policy.

These examples presume that systematic or anticipated monetary policy can have real effects. But variance decompositions and impulse-responses are poorly suited to addressing these issues. Variance decompositions cannot be negative! When we read an impulse-response function as a measure of the effects of a monetary shock, we implicitly assume that anticipated money has no real effect.¹⁴ If anticipated money *has* real effects, then the response function measures the response of y to the current m shock *and* the path of future m 's that the shock sets in motion.¹⁵

Does anticipated money matter? It is hard to swallow the persistent

¹⁴And that the VAR has isolated shocks to agents' information sets.

¹⁵To make this point explicitly, suppose that the “structural” model is

$$\begin{aligned} a_{yy}(L)y_t &= a_{ymu}(L)(m_t - E_{t-1}(m_t)) + a_{yma}(L)m_t + \epsilon_{yt} \\ a_{mm}(L)m_t &= a_{my}(L)y_t + \epsilon_{mt} \end{aligned} \tag{1}$$

Inverting this model to find the moving average representation, the y response to the m shock is

$$y_t = (\cdot)\epsilon_{yt} + \frac{a_{ymu}(L)a_{mm}(L) + a_{yma}(L)}{a_{yy}(L)a_{mm}(L) - a_{yma}(L)a_{my}(L)}\epsilon_{mt}.$$

As you can see, the parameters $a_{mm}(L)$ and $a_{my}(L)$ affect this response. In the special case that y does not respond to anticipated m , $a_{yma}(L) = 0$, so the true response is the

responses of output to monetary shocks found above as delayed responses to unanticipated money. However, since the monetary variables also have protracted responses to the shocks, the output responses are consistent with a view that money has short-lived effects on output, if anticipated money does matter.

If we accept this view, then the study of systematic monetary policy (accommodation of seasonal and other shifts in money demand, systematic stabilization of other shocks), or monetary institutions (deposit insurance, lender of last resort) may be more important to macroeconomics than an assessment of how much output can be further stabilized by making monetary policy more predictable. It may not be the answers that are wrong; We may simply be asking the wrong *question*.

3 Technology shocks

The real business-cycle literature is dominated by the assumption that “technology shocks” drive economic fluctuations. A typical production function is

$$Y_t = (A_t N_t)^\alpha K_t^{1-\alpha},$$

and A_t is the shock.¹⁶ Of course, the models are capable of producing responses to many shocks, including government spending, financing, and monetary shocks (when appropriate frictions are introduced.) However, technology shocks—shocks to current period marginal productivity—are centrally important for obtaining realistic artificial time-series in current models. Other shocks have not been found to contribute much to output variation or cyclical comovement in the real business-cycle paradigm.

Obviously, technology contains *some* stochastic element, so the crucial question is “How *much* variation in output can technology shocks explain?” Prescott (1986) presents a famous calculation that 70% of the volatility of GNP is due to technology shocks. Thus calculation is made by calibrating a model economy, i.e., choosing values for preference and technology parameters *and* for the variance and autocorrelation of the technology shock. Then, “70%” refers to the variance of Hodrick-Prescott filtered model output divided by Hodrick-Prescott filtered actual output.

same as the impulse-response,

$$\frac{a_{ymu}(L)}{a_{yy}(L)}$$

which is independent of the money-supply rule.

¹⁶Up until now, we have been using the word “shock” for “innovation”; all “shocks” were unpredictable. The real business-cycle literature uses the word “shock” to describe the Solow residual A_t even if it is predictable. I will conform to this unfortunate terminology.

This calculation is obviously sensitive to the calibrated value of the variance of the technology shock and possibly other parameters as well. Double the standard deviation of the technology shock, and you double the predicted standard deviation of output. The fraction can come out over 100% if you are not careful! It is not a variance.

Eichenbaum (1991) uses GMM to quantify the sampling uncertainty of the calibration procedure and finds that the estimate of $\text{var}(y_{\text{model}}/\text{var}y_{\text{data}})$ is 0.78 *with a standard error of 0.64!* Sensibly enough, virtually all of this uncertainty comes from uncertainty in the calibrated variance and autocorrelation of the technology shock.

I will concentrate on a different source of “whimsy” (Eichenbaum’s terminology), how the point estimates are affected by the choice of *statistic*.

To start with, Eichenbaum only considers sampling variation *given* a set of moments that we pick model parameters to match. The fractionist output variance explained is also obviously sensitive to the calibration procedure: if one included only $\text{var}(y)$ in the list of moments to be matched, then the calibration procedure will “explain” 100% of the variance of output by picking a suitable variance of the technology shock.

Furthermore, consider the effect of correlation between output and productivity. Real business-cycle models have one shock and many series. They are stochastically singular, i.e., functions of each time series are *perfectly* correlated. In the data, they are not. Instead of counting model variance/data variance, we could insist that the model explain only the variance of a single dynamic factor of output, Solow residuals, labor, consumption, investment, etc., or the projection of output on Solow residuals. These calculations will yield smaller numbers.

As an extreme example, Gordon (1993) argues that when one accounts for measurement error in capital and hours, there is no correlation left between productivity and output. He exploits the model’s prediction of an almost perfect correlation (see below) to conclude that *productivity shocks explain 0% of the variance of output*. Gordon’s productivity series still have plenty of *variance* and so might still produce a high number using Prescott’s statistic.

The next section shows how statistics that focus on the *predictability* of output can give numbers much smaller than Prescott’s.

3.1 *Forecastability and calculations that technology shocks explain very little*

3.1.1 **A simple VAR**

I start with a simple characterization of the data. Blanchard and Quah (1989), Shapiro and Watson (1988) and Cochrane (1994) present VARs that decompose output into permanent and transitory shocks. Figure 19 presents

the impulse-response function of a consumption-output VAR in this spirit (it is closest, obviously, to Cochrane 1994, but the message of other specifications is similar). I regress log consumption and output growth on the log consumption/output ratio and two lagged growths.¹⁷ In the left-hand panel of Figure 19 the shocks are identified by forcing the long-run output response of the transitory shock to zero, following Blanchard and Quah. It happens that this orthogonalization is almost exactly the same as the conventional y -first orthogonalization. Orthogonalizing with consumption first, shown in the right-hand panel of Figure 19, produces a similar picture.

The impulse-response functions reveal a large transitory component to output. As shown in Table 8, the transitory shock accounts for 89% of the variance of output growth and 89%, 73%, and 63% of the 1, 2, and 3-year output forecast error variance, respectively.

Table 8:

Var of	Shock and Horizon							
	1 Year		2 Years		3 Years		Differences	
	perm	trans	perm	trans	perm	trans	perm	trans
consumption	78	22	86	15	90	10	77	23
output	12	89	27	73	37	63	11	89

Variance decomposition. Table entries give the percent of the forecast error variance of the row variable due to the column shock at the indicated horizon. The VAR consists of a regression of Δc and Δy on $c-y$ and two lags of Δc and Δy . The shocks are orthogonalized so that the transitory shock has no long-run effect on output.

We can compare the implied $c-y$ VAR representation predicted by models to Figure 19 and Table 9 to see how well the models reproduce the second moments of consumption and output. This use of the VAR does not require us to find structural interpretations of the shocks, which is a contentious issue. (See Hansen and Sargent 1991, Lippi and Reichlin 1993, Blanchard and Quah 1993, Cassou and Mittinik 1990, and Cochrane 1994 for some of the identification debate.)

¹⁷The VAR uses log nondurable plus services consumption and log private GDP - GDP less government purchases - for output. The use of private GDP is a minor refinement, suggested by King, Plosser, Stock, and Watson (1991). The consumption/private GDP ratio is more stable than the consumption/GDP ratio, and hence better forecasts business-cycle variation in output. Also, models are designed to explain private-sector GDP.

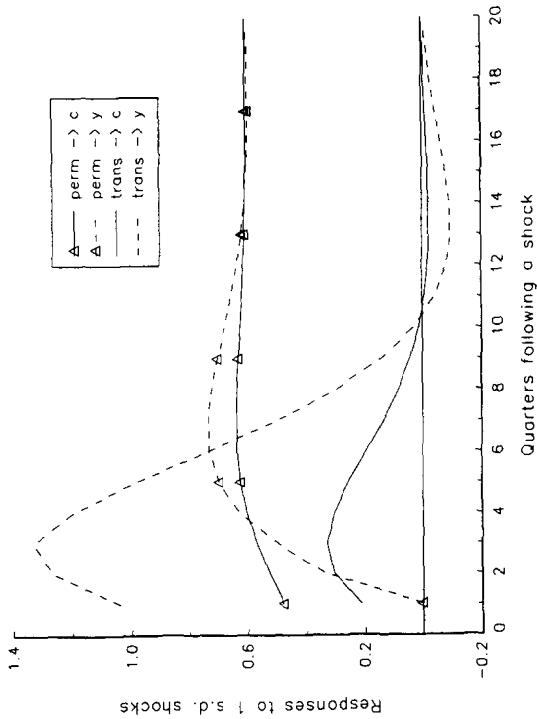
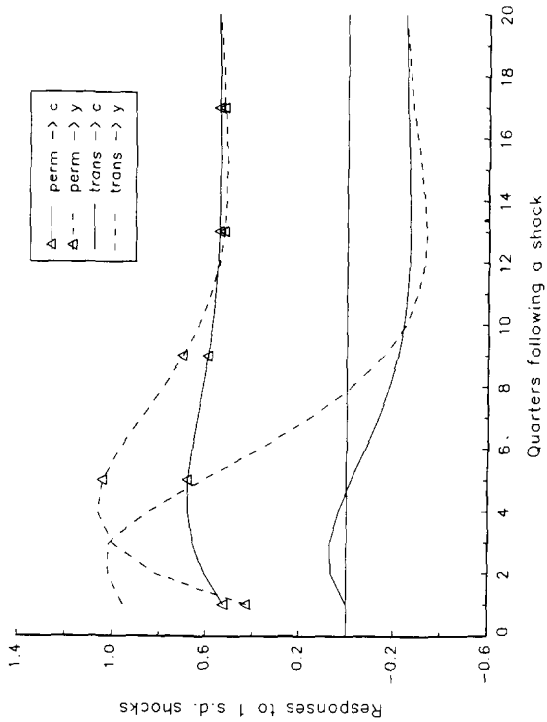


FIGURE 19

Impulse-response function from nondurable + services consumption-private output VAR. Right-hand panel is orthogonalized with consumption first (y shock does not affect c contemporaneously). Left-hand panel is orthogonalized so that the transitory shock has no long-run impact on output.

3.1.2 A model, and Blanchard and Quah's small number

Now, let us see what impulse-response function a standard model *does* predict. Figure 20 shows the response to a 1% technology shock of the King, Plosser, and Rebelo (1988) model with linear utility for leisure as in Hansen (1985) and Rogerson (1988). The model is

$$\max E \sum_{t=1}^{\infty} \beta^t (\ln(C_t) + \theta(1 - N_t)) \text{ s.t.}$$

$$Y_t(A_t N_t)^\alpha K_t^{1-\alpha} = C_t + I_t$$

$$K_{t+1} = (1 - \delta)K_t + I_t$$

$$\ln A_t = g + \ln A_{t-1} + \epsilon_t$$

Parameters are calibrated as in Campbell (1992) to produce a nonstochastic steady state with growth $g = 2\%$ and rate of return $= 6\%$. $\alpha = 2/3, \delta = 0.1, N = 1/3$.

It turns out that consumption and output are invertible functions of the technology shock, so a c-y VAR should recover the technology shock and should find no other shock. Thus, the responses to a technology shock are also the model's predictions for the VAR impulse-response function.

Comparing Figure 20 and Figure 19, this standard real business-cycle model produces time series that look something like the *permanent* shock in the data. The *transitory* shock and its response are absent from the model's impulse-response function. In this way, we reproduce Blanchard and Quah's result:

Small fractions of the variance of output are due to technology (permanent) shocks.

From the above variance decomposition, about 12%, 27%, and 37% at 1, 2, and 3-year horizons, and 11% in annual growth rates. (Mechanically, the number rises to 100% as the horizon increases.)

3.1.3 Predictability and a small number inspired by Rotemberg and Woodford

The essential message of the c-y VAR is that *output contains a large predictable component*. This is good news. If a recession is a period in which output is "below trend," we *must* expect output to grow more in the future, and vice-versa in a boom. The predictability of long-run output growth verifies that there are such periods. The left-hand panel of Table 9 makes this predictability point directly: regressions of output growth on the consumption/output ratio yield R^2 values up to 0.4 at a two-year horizon. R^2

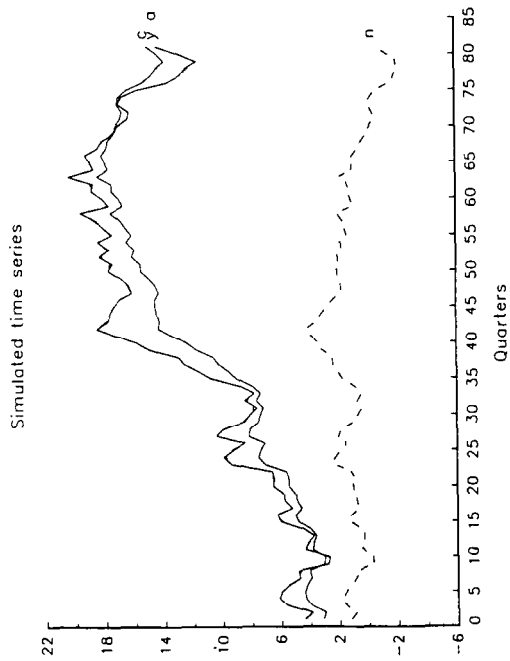
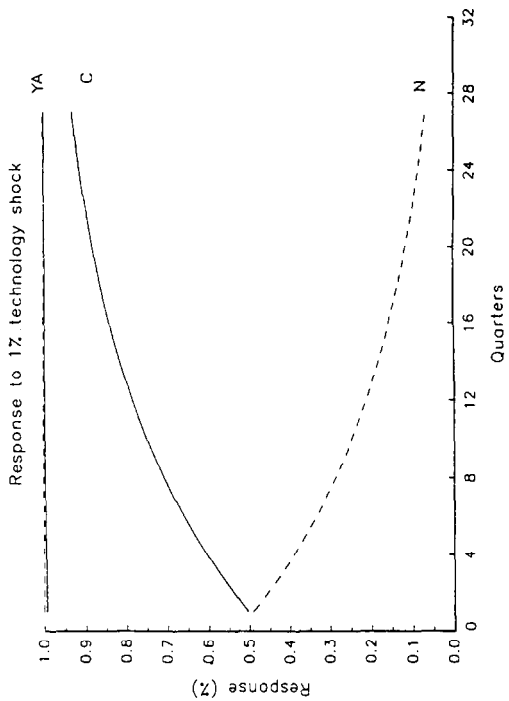


FIGURE 20
 Artificial time series and response to 1% technology
 shock in King/Plosser/Rebelo model.

Table 9:

Horizon	Output				Solow Residual			
	1Q	1Y	2Y	3Y	1Q	1Y	2Y	3Y
coefficient	0.15	0.85	1.37	1.53	0.23	0.83	1.07	1.07
<i>t</i> -statistic	3.76	6.64	6.71	5.62	7.93	9.95	8.55	6.61
R^2	0.06	0.31	0.45	0.48	0.27	0.60	0.53	0.45

Regressions of output growth and Solow residual on consumption/output ratio, $y_{t+h} - y_t = \beta(c_t - y_t) + \epsilon_{t+h}$. $c = \log$ nondurable plus services consumption. $y = \log$ (gdp-government purchases). Solow residual = $y - 1/3 \ln(k) - 2/3 \ln(\text{hours})$, k inferred from gross fixed investment with $\delta = 0.1$. Coefficients estimated by OLS; *t*-statistics corrected for serial correlation due to overlapping data and for conditional heteroskedsticity.

above 0.6 can be obtained by adding a trend, as in Figure 18, interest rates, unemployment, hours, or other variables.

This observation suggests another calculation: define the “business-cycle” component of output as the *forecastable* or *transitory* component of output. Since model output is basically unforecastable, we expect to find that the model explains small fractions of the variance of the business-cycle component of output. This point is emphasized by Rotemberg and Woodford (1994); it can also be seen in the flat model spectral densities reported by Watson (1993).

One such calculation is the ratio of k -period forecastable output growth to that predicted by the model

$$\frac{\text{var}(E_t y_{t+k} - y_t)_{\text{model}}}{\text{var}(E_t y_{t+k} - y_t)_{\text{data}}}$$

If we divide both numerator and denominator by $\text{var}(y_{t+k} - y_t)$ and calibrate the model (variance of technology shock) so that $\text{var}(y_{t+k} - y_t)_{\text{model}} = \text{var}(y_{t+k} - y_t)_{\text{data}}$, the above statistic is the same as the ratio of long-horizon R^2

$$R_k^2 = \frac{\text{var}(E_t y_{t+k} - y_t)}{\text{var}(y_{t+k} - y_t)}$$

in the data and in the model. Table 10 presents forecasting R^2 in the data (from Table 9) and in several models. The table just presents the R^2 ; the results of division are obvious.

For the standard model (identified by the technology process $a_t = a_{t-1} + \epsilon_t$ in the table), output forecasting R^2 is pitifully small. In the data, we see the substantial forecast R^2 . Dividing the two, we obtain:

Table 10:

Model	1Q	1Y	2Y	3Y	$VAR(BN)/$ $VAR(\Delta y)$
Data (c-y VAR)	0.06	0.31	0.45	0.48	17.0
std. model: $a_t = a_{t-1} + \epsilon_t$	3.5E-06	1.1E-05	1.7E-05	2.0E-05	0.0007
differenced estimate	0.997	0.45	0.14	0.09	2.6
trend estimate	0.74	0.42	0.39	0.44	19.2
random walk a + smooth news	0.12	0.36	0.51	0.58	20.6
news from a, y, c, hrs VAR	0.76	0.57	0.46	0.44	70.6

Long-horizon output growth forecast R^2 and ratio of Beveridge-Nelson detrended output variance to variance of output growth.

Technology shocks explain 0.002% or less of business-cycle variation in output!

3.1.4 Beveridge Nelson detrending in place of the Hodrick Prescott Filter

What if Prescott had detrended output using the Beveridge-Nelson detrending method in place of the Hodrick-Prescott filter? The Beveridge-Nelson (1981) trend is defined as the level output will reach when all dynamics have worked themselves out.¹⁸ It formalizes the idea that the cyclical component is the part that is forecast to die out. The Beveridge-Nelson trend is visually indistinguishable from the Hodrick-Prescott trend in the plots of data and trend used to justify Hodrick-Prescott detrending (see Cochrane 1994 for a plot of the B-N trend, and Prescott 1986 for the HP filtered trend).

The variance of Beveridge-Nelson detrended data is $var(y_t - \lim_{k \rightarrow \infty} E_t y_{t+k})$ and so is the limit of the numerator of the long-horizon R_k^2 . The denominator of long-horizon R_k^2 explodes as $k \rightarrow \infty$, however. For that reason, the last column of Table 10 presents the variance of Beveridge-Nelson detrended output divided by the variance of output growth. Dividing the “model” number by the “data” number, we obtain the fraction of *Beveridge-Nelson* detrended output due to technology shocks. (This calculation is still a little generous to technology shocks. I allow the calibrator to freely and counterfactually

¹⁸Formally, the Beveridge-Nelson trend is

$$y_t^{trend} = \lim_{k \rightarrow \infty} (E_t y_{t+k} - kE(\Delta y)) = y_t + \sum_{j=1}^{\infty} E_t(\Delta y_{t+j}) - E(\Delta y)$$

assume a large variation of Solow residuals in order to match output growth variance.

For the standard model, the Beveridge-Nelson detrended output has a variance 0.07% that of output growth. In the data, Beveridge-Nelson detrended output variance is 17 times the variance of output growth. Dividing the two, we find again that

Technology shocks explain 0.002% or less of Beveridge-Nelson detrended output variance!

A seemingly minor change in the detrending method produces a dramatic change in the result. The standard model, while a useful stochastic growth model, does not seem to produce any business cycles!

3.2 Endogenous dynamics; a small number inspired by Christiano

Output and technology are so close in Figure 20 that they are barely distinguishable. All the dynamics of output come from the assumed dynamics of the shock. (Christiano 1988 and Eichenbaum 1993 emphasize this point.) This observation suggests that we define the fraction of output variance explained by the model as the variation generated by the propagation mechanism, rather than simply assumed in the external shocks.

To quantify this point, Table 11 presents the correlation of long-run output growth with Solow residual growth and the ratio of the variance of output growth to the variance of the Solow residual in the data and several models. As the table shows, the correlation between output and Solow residual is nearly perfect in this standard model, and there is essentially no amplification of shocks.

The model explains essentially 0% of output fluctuations.

3.3 Forecastable technology shocks

Of course, all of the above calculations depend on the structure and parameterization of the real business-cycle model as well as the nature of its shocks. A first repair is obvious enough that it is worth pursuing here: since output dynamics look a lot like shock dynamics, put in some interesting technology shock dynamics.

This path is not as innocuous as it seems. Hall (1990) and Evans (1992) attack the idea that Solow residuals represent technology shocks by showing that they are forecastable by a number of variables, including military spending, government purchases, and monetary aggregates. Table 9 shows that Solow residuals are about as predictable as output from the c/y ratio,

Table 11:

Model	1Q	1Y	2Y	3Y
	Correlation: $\text{corr}(y_{t+k} - y_t, a_{t+k} - a_t)$			
Data	0.85	0.79	0.75	0.74
Std. model $a_t = a_{t-1} + \epsilon_t$	1-(2E-06)	1-(6E-06)	1-(9E-06)	1-(1E-05)
Differenced estimate	0.95	0.99	0.99	0.99
Trend estimate	0.69	0.93	0.97	0.98
Random walk a + smooth news	0.90	0.91	0.92	0.92
News from a, y, c, hrs VAR	0.97	0.96	0.97	0.98
	Amplification: $\text{VAR}(y_{t+k} - y_t)/\text{VAR}(a_{t+k} - a_t)$			
Data	1.68	2.01	1.96	1.91
Std. model $a_t = a_{t-1} + \epsilon_t$	0.98	0.98	0.99	0.99
Differenced estimate	1.30	1.27	1.13	1.07
Trend estimate	1.89	2.17	2.20	2.21
Random walk a + smooth news	1.40	1.44	1.40	1.33
News from a, y, c, hrs VAR	2.46	2.20	2.05	1.92

Correlation of long-run output growth with Solow residual, and ratio of output growth variance to Solow residual variance.

but Rotemberg and Woodford (1993) argue that changes in technology should not be forecastable. On *a priori* grounds, then, these authors argue that we should not try to repair the technology shock view by allowing forecastable technology shocks.

Of course, some components of government spending (infrastructure, military, R&D, NASA, etc.) may actually *cause* increases in technology. Proponents of such spending certainly advocate this view loudly enough! Also, government spending, even in wars, must respond to forecasted tax revenues, and monetary policy may accommodate predicted expansions in real activity. Since policymakers and private agents have more information than our VAR, spurious Granger-causality is likely. Finally, many real business-cycle advocates have abandoned the pure technology shock view of the Solow residual (see below), in which case forecastable movements are more plausible. I take a pragmatic view and investigate the consequences of forecastable technology shocks; purists are free to disregard the results.

What dynamic structure should we put in for the technology shock? A natural idea is to use the structure found in the data. To this end, I ran two autoregressions of Solow residuals on lagged Solow residuals:

$$\text{Differences : } \Delta a_t = \mu + \sum_{j=1}^4 \beta_j \Delta a_{t-j} + \epsilon_t$$

and

$$\text{Levels with trend : } a_t = a_0 + bt + \sum_{j=1}^4 \beta_j a_{t-j} + \epsilon_t.$$

(As one would expect, a specification in levels without a trend produced almost exactly the same result as with differences. Below, I consider multivariate Solow residual forecasts.)

Figure 21 presents the estimated impulse-responses for the Solow residuals, together with the responses of output, consumption, and labor when technology shocks with the estimated dynamics are fed through the RBC model. The differenced specification produces a very persistent shock, while the trend specification produces a transitory shock. You still get out what you put in: the shape of both output responses is essentially that of the shock response. The stationary shock is amplified somewhat as investment rises to smooth the transitory shock forward, and labor supply increases to take advantage of transitorily higher wages. The transitory shock produces a transitory output response, like the response to the transitory shock in the data; the permanent shock produces a permanent output response like that of the permanent shock in the data.

Tables 10 and 11 include forecastability and correlation/amplification statistics for these models, marked “Differenced estimate” and “Trend estimate.” As we might suspect from the graph, the permanent technology shock produces low output R^2 once the initial rise in output has passed, high correlation of output and technology shock, and small amplification. It only explains about $2.6/17 = 15\%$ of Beveridge-Nelson detrended output variance. The stationary shock does much better: the forecast R^2 are similar to those found in the data, and shocks are amplified. It explains a little more than all of Beveridge-Nelson detrended output variance. Thus, we *can* get transitory output variation and amplification out of a real business-cycle model by assuming a transitory technology shock.

The data will not be helpful in determining which shock process is correct, however. The stationary shock process has a very slowly declining response function, so no test could tell it from the unit root shock process. Conversely, the examples warn us to beware empiricists who make seemingly innocuous detrending assumptions; they have major effects on the properties of the real business-cycle model. We may not *know* much about unit roots, but in this case, we do *care*.

Table 10 and 11 show that the transitory shock model still predicts far too much correlation, so almost all output dynamics are due to the assumed shock dynamics. Most importantly, there is now no stochastic *growth*, no permanent shock as found in the data. Making the assumed shock process have a response that does not go to zero does not help much. The series are still correlated, output has the same response as the shock, and correspondingly

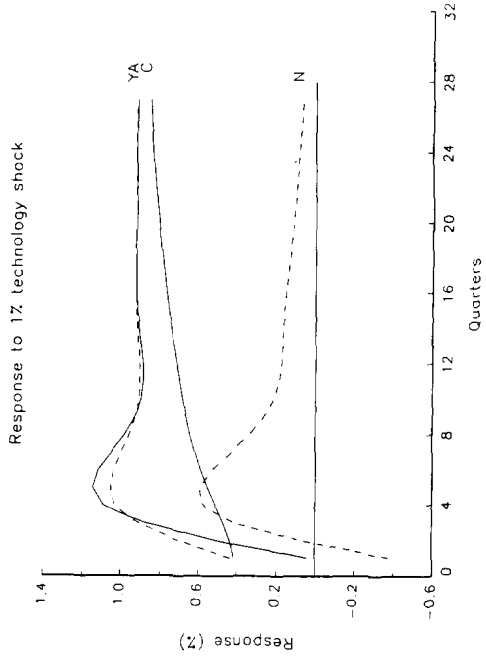
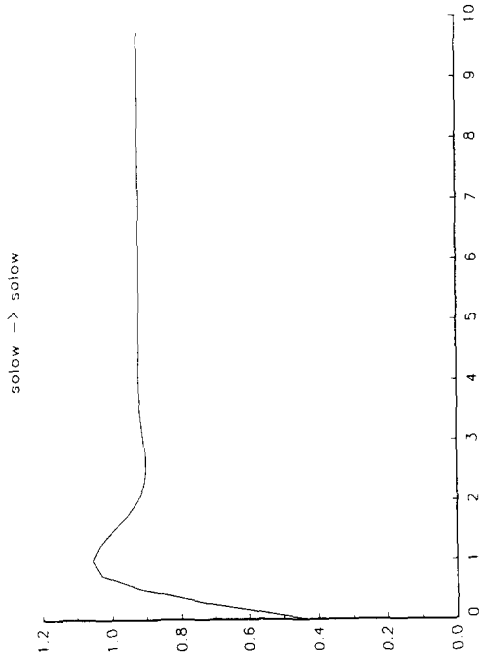
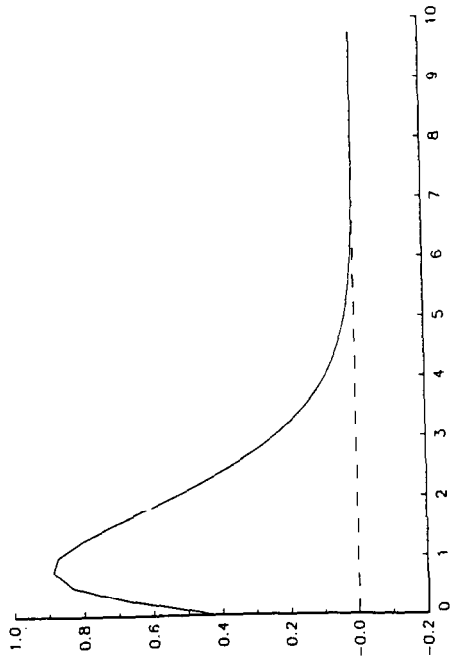


FIGURE 21

solow -> solow



Response to 1% technology shock

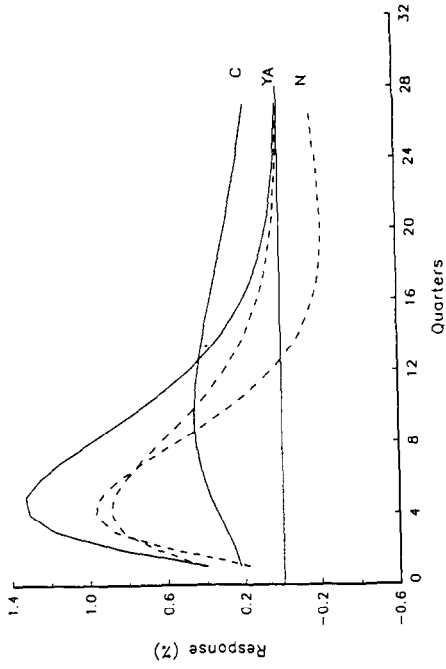


FIGURE 21

Estimated impulse-response function for Solow residuals and KPR model responses to technology shocks with the estimated structure.

less forecastability and amplification.

The real business-cycle model needs *more shocks*. The problem we are having is that it is hard to match a *single* shock model to a *multiple* shock world. To decide how much of the variance of output is due to technology shocks, it would help to have *some* model of the other shocks. Real business-cycle modelers have tended to ignore the stochastic singularity in their model's predictions, citing measurement error. However, it seems that one of the babies — either transitory, business-cycle dynamics or stochastic growth — gets thrown out with the bath water by doing so. Below, I examine whether news about future technology shocks can serve as an extra shock.

3.4 *Production function, labor-hoarding*

The estimated technology shock depends on the assumed form of the production function. Labor and capital hoarding have recently been examined, in part to explain the forecastability of Solow residuals. (Burnside, Eichenbaum, and Rebelo 1993, Eichenbaum 1993, Sbordone 1993.) For example, suppose the production function is

$$Y_t = (A_t N_t E_t)^\alpha (K_t U_t)^{1-\alpha}$$

where E represents effort and U represents capital utilization. The Solow residual is now $(A_t E_t)^\alpha U_t^{1-\alpha}$, so variables that Granger-cause endogenous effort and capital utilization will Granger-cause the residual, even maintaining the assumption that they do not Granger-cause the true technology shock A_t .

Indeed, Burnside, Eichenbaum, and Rebelo find that when variable effort is added, the model predicts forecastable Solow residuals. They also find that adding labor effort drops the Prescott-style calculation of the explained variance of output from 80% to 31%. Eichenbaum (1993) finds even stronger results when capital hoarding is introduced.

These calculations suggest that variations on the structure and parameterization of the RBC model have large effects on the estimated importance of technology shocks.

3.5 *Interpreting technology shocks*

Much of the controversy over real business cycles stems from common-sense resistance to the idea that variations in the state of knowledge drive fluctuations. In particular, ancient Rome aside, it is hard to interpret declines in technology and some authors argue against forecastability or dynamic structure in technology.

From the point of view of measurement, *anything* that causes output to vary given capital and labor will result in a Solow residual and hence will be

identified as a “technology shock.” Labor or capital hoarding, money, taxes, or any other friction that causes output to be less than $N^\alpha K^{1-\alpha}$ will have the same effect. Plosser (1989) argues for this interpretation of technology shocks. Recently, Hansen and Prescott (1993) seem to have adopted the latter interpretation.

Every nation has a set of rules and regulations that govern the conduct of business. These have consequences for the incentives to adopt more advanced technologies and for the resources required to operate existing ones. ...Systems that divert entrepreneurial talent from improving technologies to rent-seeking activities...[and] changes in the legal and regulatory system within a country often induce negative as well as positive changes in technology.

In a separate discussion, they liken technology shocks to small perturbations in all the factors that make the United States a better place in which to do business than India. In short, *technology shocks are changes in the inefficiencies induced by policy!*

In cataloguing views on the source of fluctuations, real business-cycle theorists are now fishing in the same pond as all other macroeconomists, though with a well-specified rod consisting of explicit dynamic models. Any of the items in the list on the first page of this paper would cause a measured “technology shock.” In fact, the thrust of much recent real business-cycle research has been to include explicitly tax and other stochastic, real distortions. This is good news for the real business-cycle *methodology*, since it now can produce explicit dynamic models with the kind of distortions economists have been interested in for generations. Eventually, we should be able to make calculations like the above to quantify the impact of government spending, taxation, monetary and credit shocks in the context of explicit dynamic models. However, it is obviously bad news for the view that *technology shocks*, narrowly defined, as the source of fluctuations: it says that the calculations we have made do not bear on the issue.

3.6 *Summary*

Table 12 summarizes a few calculations of the importance of technology shocks. We started with Prescott’s calculation that 70% of the variance of output is explained by technology shocks. However, this calculation turns out to be subject to enormous sampling error. Perhaps more importantly, the *statistic* one uses turns out to matter very much. The fact that standard stochastic growth models produce little output forecastability and output dynamics very close to shock dynamics suggests numbers as low as 0%. Modifications to the production function can have a similar effect. Mean-reverting

(i.e., forecastable) technology shocks can give rise to mean-reverting and hence forecastable output, but this fix is controversial and puts us in danger of losing stochastic growth. Finally, the concept of technology shocks seems to have melted away. It is now interpreted so broadly that it can stand for essentially any distortion that causes a measured Solow residual. With this interpretation, it is *vacuous* to say that technology shocks cause fluctuations.

Table 12:

Author	Statistic or Observation	Fraction
Prescott	$\frac{\sigma^2(HP\ filtered\ y_{model})}{\sigma^2(HP\ filtered\ y_{data})}$	70%
Eichenbaum	Sampling error	78% +/- 64%
Blanchard-Quah	$\sigma^2(y)$ from perm. shock	$\frac{1Y\ 2Y\ 3Y}{12\%27\%37\%}$
Rotemberg-Woodford	$\frac{\sigma^2(E_t(y_{t+k})-y_t)_{model}}{\sigma^2(E_t(y_{t+k})-y_t)_{data}}$	0.002%
Christiano	$\frac{\sigma^2(y-a)}{\sigma^2(y)}, 1 - corr(y, a)$	tiny
Beveridge-Nelson	B-N trend, not HP filter	0.003%
Gordon	corr(shock, output)	0
Burnside, Eichenbaum, Rebelo	Labor hoarding	31%

Summary of calculations of the contribution of technology shocks to output variability. Author gives the inspiration for the calculation: numbers are my calculations, not theirs.

4 Some new contenders

4.1 Oil prices and reallocation

Hamilton (1983) suggested that oil price shocks account for postwar recessions. Every postwar recession was preceded by an oil price increase. VARs suggest that oil prices are econometrically exogenous, and, since the big increases are due to OPEC or the Texas Railroad Commission, exogeneity rings true. However, big technology, monetary, and federal funds shocks also occur

around the beginning of every postwar recession and can appear exogenous in VARs.

I run two simple VARs using the producer price index for crude petroleum. The first VAR just includes output, the second includes both output and consumption, in the style of the monetary VARs examined above. Figure 22 presents the responses of output to the oil price shocks, and Table 13 presents the output variance decompositions. As the figure shows, innovations in oil prices do produce sustained output declines. However, the magnitude of the declines is much smaller than the declines produced by output or consumption shocks. Summing and squaring, less than 10% of the variance of output is explained by oil price shocks. (Oil prices account for 80% or more, and usually 99%, of oil price variance, confirming Hamilton's exogeneity tests.) The problem is simple. There are only a few large oil price changes. Yes, they were followed by recessions, but the rest of the fluctuations in output are not preceded by oil price changes, and the severity of the recessions does not occur in strict proportion to the oil price innovation. Given this evidence, it does not seem worth the space required to sort out whether this small contribution remains when put into competition with monetary variables or technology shocks.

Table 13:

VAR	Horizon				Differences
	1Q	1Y	2Y	3Y	
Oil, y	1	4	7	8	4
Oil, y, c	0	0	2	5	1

Output variance decomposition, oil price VARs. Table entries give the percentage of output variance accounted for by oil price shocks.

The biggest sticking point for oil price advocates is the propagation mechanism. Imported oil is a small fraction of GDP, so traditional production theory suggests that even large increases in its price should have small effects on output. A general equilibrium model might generate a larger response, for example if labor supply declines when there is an oil shock. But Kim and Loungani (1992) construct such a model and find that oil shocks only account for 18% of the variance of output with a CES production function. Finn (1993) constructs a real business-cycle model with varying capital utilization that explains the forecastability of Solow residuals from energy price increases. She also finds 7–19% of output variance explained. Furthermore, standard models predict symmetric effects, so that real oil price declines should cause booms.

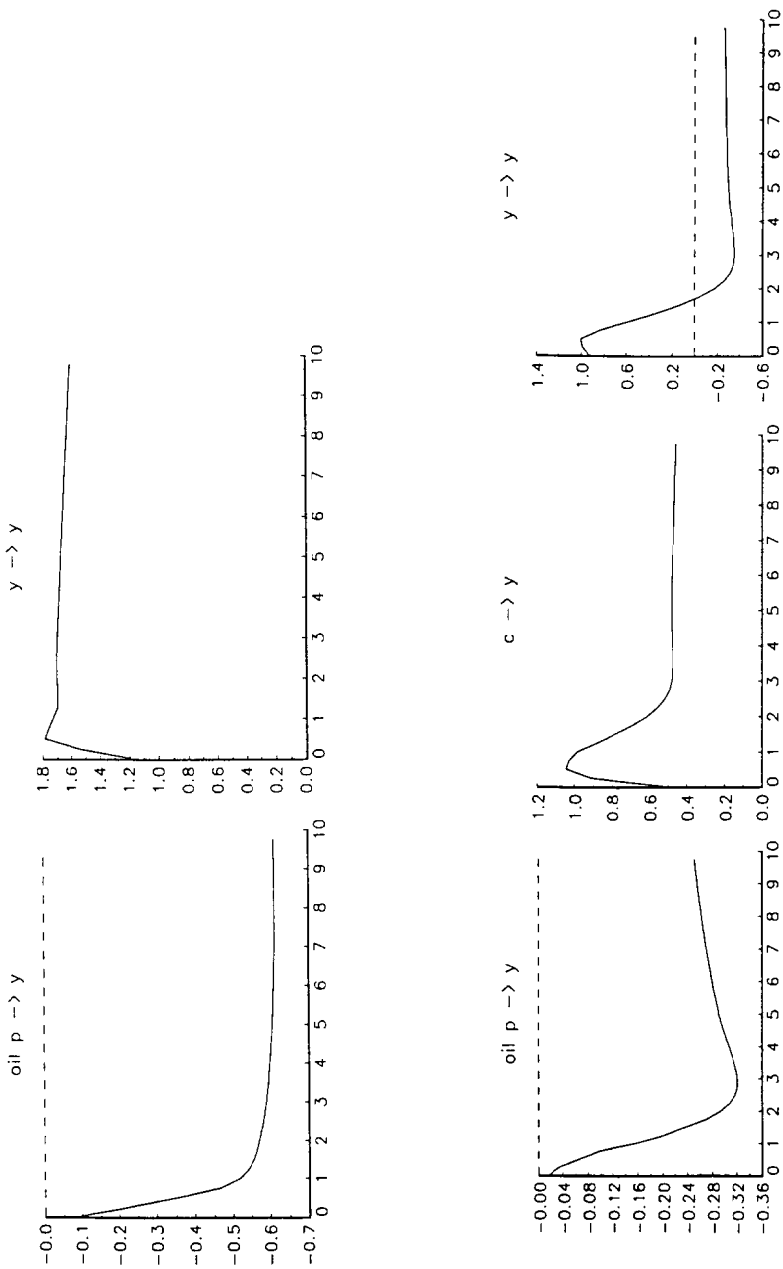


FIGURE 22

Output responses in oil price VARs. Top: Oil price output VAR. Bottom: oil price, consumption, output VAR. VARs in log levels, 4 lags.

Of course, the small input problem applies to money as well. The cost of holding reserves plus cash (the money “imported” into the economy) is the interest cost, on the order of 1/10% of GDP. Thus, viewing money services as an input to production, the same classical theory says that variations in the money stock should have tiny effects on output. In response to this problem, theorists are working hard on models with frictions in which variations in this small money stock *can* have large effects. Similarly, work is underway on models in which oil price changes can have large and possibly asymmetric effects on output. Hamilton (1988) examines a two-period multisector model with fixed costs to reallocating labor across sectors. Atkeson and Kehoe (1993) add putty-clay capital whose energy usage is built in forever once installed. Rotemberg and Woodford (1993) advocate imperfectly competitive models.

An emerging empirical literature supports some of these stories. Bresnahan and Ramey (1992) show that when oil prices rise, plants that produce small cars operate at capacity; plants that produce large cars are idle. Over the long run, more small car plants are created, but a short-run decline in output and employment results. Davis and Haltiwanger (1990) show that job churning is countercyclical.

4.2 *Credit shocks*

There is much descriptive evidence that problems in credit allocation are part of economic fluctuations. Bernanke (1983) argued that the disappearance of bank intermediaries, rather than a scarcity of the medium of exchange, accounted for falling output in the great depression. Wojnilower (1980) (1985) argues that the beginning of recessions, like prewar financial panics, were often accompanied by “credit crunches” in which there was much nonprice rationing of credit.

However, credit *shocks* do not seem to explain a large part of postwar U.S. output fluctuations. As Bernanke’s (1994) review makes clear, most credit research is aimed at demonstrating a credit *channel* or amplification mechanism for open market operations or other shocks. Credit *shocks* may have been important in prewar recessions accompanied by banking panics, and it is perhaps a success story of postwar macroeconomic policy that such shocks have been avoided or that the economy has been insulated from their effects.

Current empirical work on credit imperfections (for example, Fazzari, Hubbard, and Peterson 1988, Gertler and Gilchrist 1991, or Kashyap, Stein, and Wilcox 1993) essentially documents a small firm residual in investment. The smallest of firms either pay a few percent more for credit than estimated betas or q predict, or they face constraints whose shadow values are of the same magnitude. This evidence mirrors evidence in finance that small firm

stocks pay a few percentage points more risk premiums than the static CAPM and regression beta estimates predict. Since small firms are small, it is hard to imagine that these effects are central reasons why *large* firms or aggregate output goes down in recessions. In a nice survey, Ramey (1993) shows that monetary aggregates drive credit indicators out of VARs similar to those discussed above. (However, Bernanke 1994 responds by arguing that wide monetary aggregates may be good indicators of credit conditions.)

5 Consumption or news shocks

We have examined popular candidates for shocks, and found little solid evidence that they account for the bulk of business-cycle fluctuations. Shocks to consumption, output, or other endogenous variables dominate most calculations. Other contenders, such as government spending or financing shocks, are not quantitatively plausible.

One response to this observation is to advocate models with nonlinear dynamics, chaos, etc. Such models can enormously amplify small shocks or display dynamics with no external shocks at all. However, standard economic models seem very resistant to chaos. So far, either very stylized environments or extreme parameter values must be invoked (see Boldrin and Woodford 1990 for a survey).

Since we can not seem to find observable exogenous shocks, how about *unobservable* shocks? Surely agents have much more information than we do. Suppose they get bad news about the future. Then, consumption declines and sets off a recession. We economists, like Hall (1993) and Blanchard (1993), conclude that consumption shocks or declines in consumer confidence “caused” the recession.

One might doubt that agents in the economy can forecast so much better than economists. We too are consumers, and we spend more time reading the paper and poring over the data than most. But this argument forgets aggregation. Each person has information about his own prospects, most of which is idiosyncratic. Total consumption aggregates all this information about aggregate activity. Ask a consumer about next year’s GDP and he will answer “I don’t know.” But he may know that his factory is closing, and hence he is consuming less. This idiosyncratic shock is correlated with future GDP. Summing over consumers, aggregate consumption can reveal information about future aggregate activity, although neither consumers in the economy nor economists who study it can name what the crucial pieces of information are.

5.1 *Response to a simple news shock*

To make consumption shocks more than an exercise in residual-naming, we need to specify *what* news is about and verify that the series we see behave as they do. Unfortunately, standard intertemporal models do not produce consumption-led recessions. One might think that good news about the future would increase consumption through the wealth effect and set off a surge in investment to build up the capital stock to the new higher desired level. (See Fama 1992 for an articulation of this view.) But increasing both consumption and investment requires an increase in output. In standard equilibrium models, output does not respond to such shifts in “demand.” If consumption increases, investment must go down; if the rate of return rises enough to make investment increase, it must come at the expense of consumption.

To be specific, Figure 23 plots the response of the King, Plosser, Rebelo model to *news* that a 1% permanent technology shock will happen in one year. Consumption rises instantly, and then varies slowly due to intertemporal substitution effects. Labor *declines*. There is no current technology shock, and capital has not changed, so there is no wage-rate increase to induce more labor supply. At higher consumption levels, consumers choose to work less. Since labor diminishes, and technology and capital are unchanged, current output ($Y - (AN)^\alpha K^{1-\alpha}$) also goes down. Investment, the residual between declining output and rising consumption, declines so much I could not fit it on the graph. The boom only comes when the technology shock actually happens.

Thus, news of a future improvement in technology sets off a *recession* (or, perhaps more appropriately, a *binge* and a *vacation*) in the standard real business-cycle model. This behavior is robust to parameterization and to variations on the model, including adjustment costs to investment, varying labor effort, and varying capital utilization (I tried all three). In the remainder of this section, I explore several ways of getting around this problem and implementing the consumption shock view.

5.2 *Smooth news + technology shocks*

Recall that the data show more than one shock. Large fractions of the variance of output are attributed to shocks that are *orthogonal* to consumption. Perhaps we do not need “consumption-led” recessions after all. Perhaps a model with a news shock *and* a technology shock can mimic the consumption-output VAR of Figure 23.

To pursue this idea, I modify the standard real business-cycle model to include a random walk technology shock as well as a shock that carries news of a small but very persistent long-term rise in technology. Letting a_t denote

Response to news of 1% technology shock

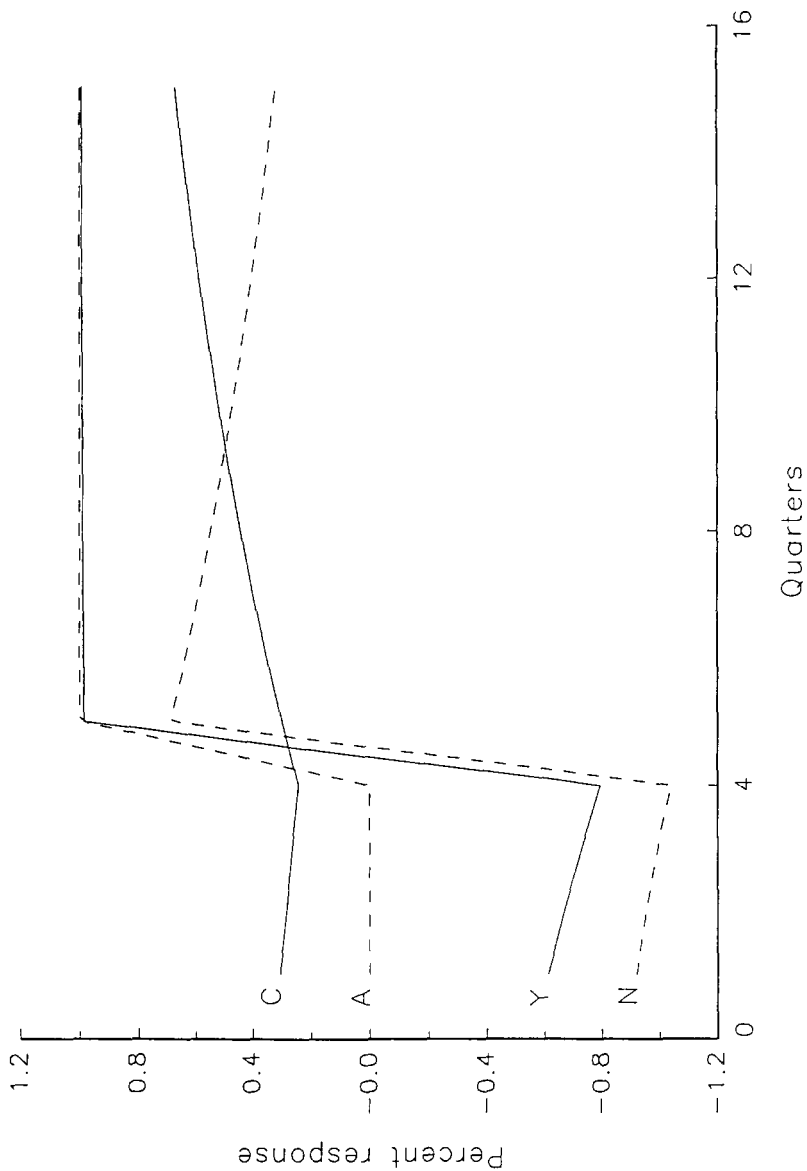


FIGURE 23
Response of King/Plosser/Rebelo model to news
of a 1 percent technology shock.

the log technology shock and z_t the news variable, the shock process is

$$\begin{bmatrix} a_t \\ z_t \end{bmatrix} = \begin{bmatrix} 1 & \theta(L) \\ 0 & \rho \end{bmatrix} \begin{bmatrix} a_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \delta_t \end{bmatrix}$$

with parameter values $\theta(L) = 1 + L + L^2 + \dots + L^{12}$, $\rho = 0.8$, $\sigma_\epsilon = 1$, $\sigma_\delta = 0.05$, $E(\epsilon_t \delta_t) = 0$.

The left panel of Figure 24 presents responses to the news shock δ_t . The shock is constructed to forecast a long slow increase in technology, which can be seen in the figure. Output, labor supply, and consumption behave as smoothed versions of the news shock discussed above.

The right-hand panel of Figure 24 presents the impulse-response function of the implied consumption/output VAR. The VAR shocks are orthogonalized so that a transitory shock has no permanent effect on output. As in the estimated c-y VAR, Figure 19, there is a strong transitory component to output. Consumption responds very little to this transitory shock. The permanent shock causes a delayed rise in output, as in the data, though the rise here is slower. Consumption rises more slowly in response to the permanent shock than in the data.

The VAR successfully hides the fact that consumption and output move in opposite directions in response to the news shock. Consumption and output both *rise* in response to both permanent and transitory VAR shocks. The VAR shocks do not recover the original news and technology innovations but linear combinations of them. In fact, model consumption and output innovations have a 0.61 correlation coefficient, which is higher than 0.41 found in the data.

Table 14 presents the variance decomposition of the implied c-y VAR. As in the data, transitory shocks account for the vast majority of output fluctuations at one to three year horizons, while the variance of consumption is mostly due to the permanent shock. Table 15 presents the implied coefficients and R^2 in long-horizon output forecasting regressions, based on the $c - y$ ratio. As in the data, Table 15, the coefficients are positive (low output relative to consumption means high future output growth). The coefficients rise with horizon, as does the R^2 , up to a maximum of about 0.4. The rise is a little slower in this example than in the data, but the pattern is the same. As shown in Table 3, the entire time- t information set (not just $c - y$) gives even higher long-horizon R^2 , up to 0.6, and a Beveridge-Nelson detrended output variance almost exactly that of the data. And this model *does* display stochastic growth.

5.3 News from a VAR

Instead of dreaming up joint processes for news and technology, an alternative procedure (suggested by King and Watson 1993) is to send the RBC model

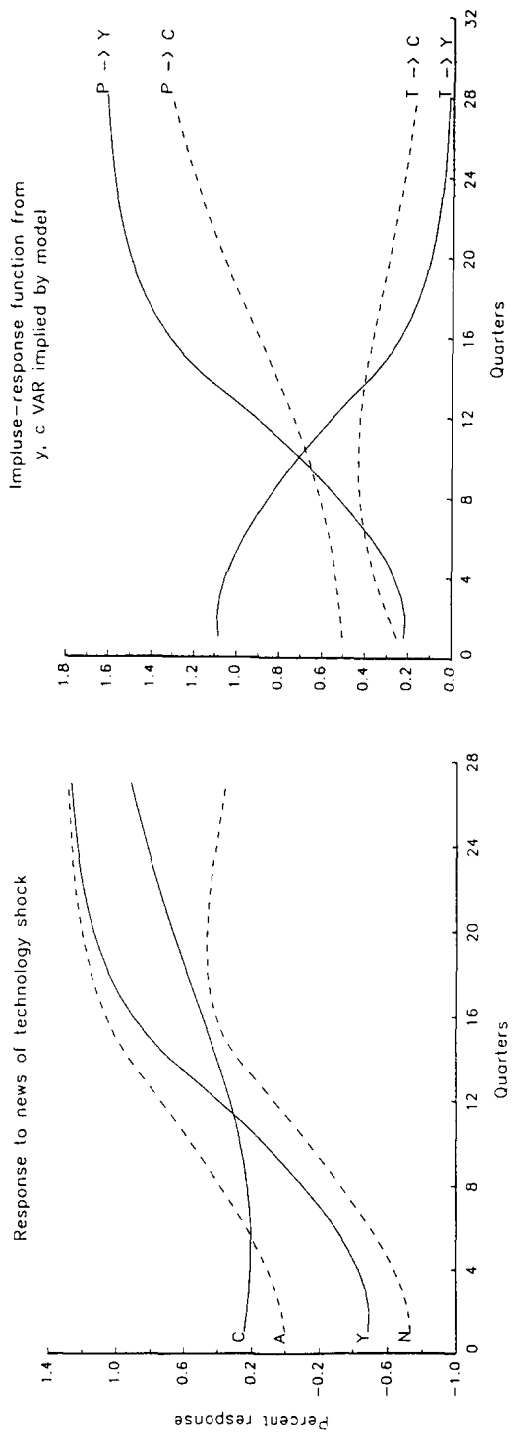


FIGURE 24

Left panel: Response of King/Plosser/Rebelo model to news shock.
 Right panel: Impulse-response of implied consumption output VAR, with transitory shock defined to have no permanent effect on output.

Table 14:

Variance of	Shocks and Horizon					
	1 Year		2 Years		3 Years	
	perm	trans	perm	trans	perm	trans
c	74	26	70	30	71	29
y	5	95	10	90	25	75

Decomposition of variance from c-y VAR implied by real business-cycle model with smooth news about future technology shocks. The VAR shocks are orthogonalized so that the transitory shock has no long-run effect on output.

Table 15:

Horizon	1/4	1	2	5	7
b	0.03	0.23	0.65	1.98	2.68
R^2	0.001	0.02	0.08	0.28	0.39

Coefficients and R^2 in regression of horizon output growth on consumption/output ratio, $y_{t+k} - y_t = \alpha + \beta(c_t - y_t) + \epsilon_{t+k}$ implied by King, Plosser, Rebelo model with smooth news and random walk technology shocks.

technology shock forecasts from a VAR. One VAR that gives plausible results (not all do) uses Solow residuals, output, consumption, and hours, estimated in log levels. The top panel of Figure 25 presents the response of Solow residuals to each shock in the VAR. As you can see, there are permanent and transitory components and an interesting dynamic structure.

Now, feed this shock structure through the real business-cycle model, and what comes out? The bottom panel of Figure 25 presents the response to the technology innovation (remember, there are four more shocks in this model!) and the response function of the consumption/output VAR implied by the model. That VAR has a pattern similar to that found in the data, Figure 19.

5.4 *Comments on the approach*

These models are obviously not the last word. Certainly, the number and dynamic specification of the news shocks and the parameterization and structure of the real business-cycle model can be varied to make the model's implied c-y VAR fit more closely to that seen in the data.

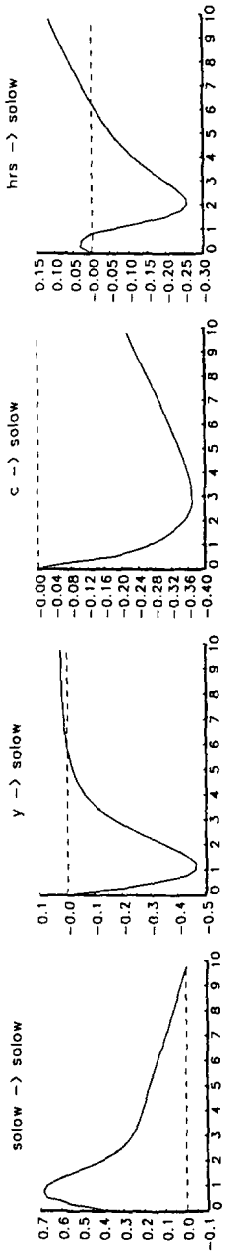
One hungers for a theorem, which I don't know how to prove or disprove: given a particular stochastic growth model, can one always dream up a model for information about technology shocks to generate an arbitrary c-y VAR? Or is there some discipline in the exercise?

One can also imagine changes to the structure of the model that would make it easier to generate business-cycle dynamics from consumption shocks. The proportional technology shock in the real business-cycle model is carefully crafted to give a wealth effect, raising consumption, and a transitorily higher wage, to induce higher labor supply. It is not necessary that news be of such a variable; in fact, as we have seen, it hurts the model to be so. Thus, news about, say government spending shocks, that have wealth effects but no intertemporal substitution effects, may much more easily generate business-cycle-type dynamics.

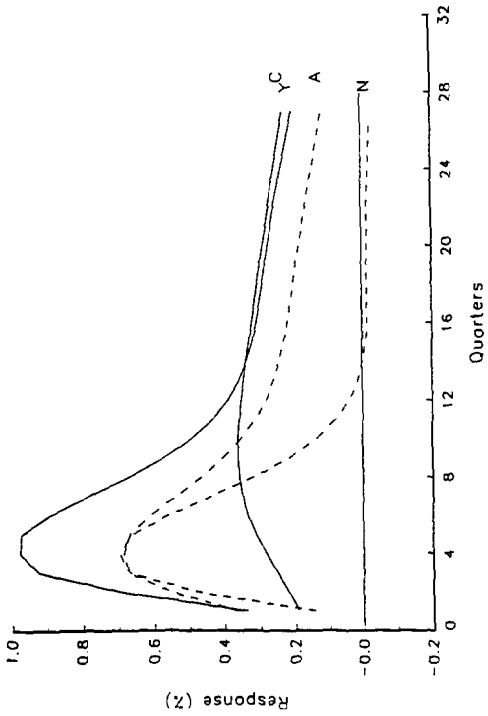
However, there are differences between model and data that news shocks cannot repair. News shocks cannot remove the stochastic singularity from every VAR. For example, with a production function $Y_t = (A_t N_t)^\alpha K_t^{1-\alpha}$ and utility $u(C_t) + v(1 - N_t)$, one first-order condition states that

$$v'(1 - N_t) = \frac{u'(C_t)N_t}{\alpha Y_t}.$$

Given two of output, labor, and consumption, this equation determines the third exactly. Hence, a VAR with consumption, output, and labor will have two shocks, not three.



Response to 1% technology shock



Impulse-response function from
y, c VAR implied by model

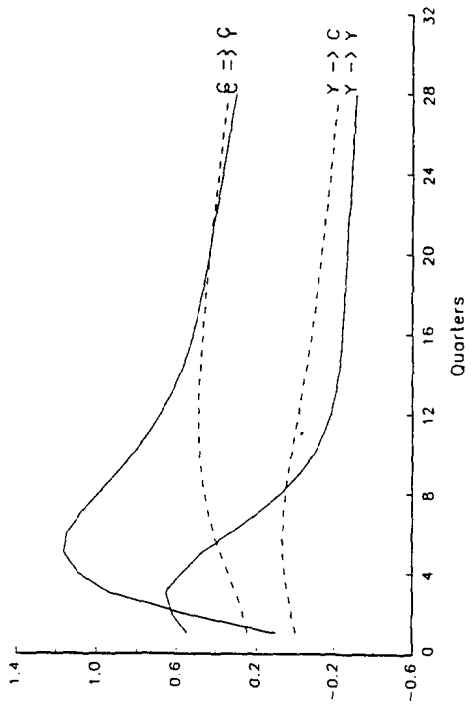


FIGURE 25

Top: response function from estimated VAR of solow residual, y, c, hours. Bottom: response to technology shock and implied c-y impulse response from RBC model.

5.5 Summary

News shocks can repair some of the defects of the technology shock view discussed above. The model with news shocks predicts a substantial transitory movement in output; it captures both growth and cycles, and it removes the stochastic singularity in the c-y VAR. Since output moves on news with no contemporaneous change in the technology shocks, output and technology are no longer perfectly correlated. An econometrician faced with data from this economy would conclude that “consumption shocks” are an important source of transitory variation in output.

Of course, “technology shocks” still are the driving variable in a fundamental sense. However, as before, one can interpret these shocks broadly. News that taxes are likely to be raised, or that some other long-lasting distortion is likely to come about, will function as well as news of true productivity.

6 Conclusions

I find that none of the popular candidates for observable shocks robustly accounts for the bulk of business-cycle fluctuations in output. What does this mean?

One of the new candidates, such as oil-reallocation, credit shocks, or nonlinear dynamics, may be flushed out and deliver an explanation for fluctuations. New propagation mechanisms, such as noncompetitive models or a lending channel, may help us to see that traditional technology money or other shocks do in fact have large and frequent effects. Since these models are in their infancy, it is hard to speculate what they will provide.

On the other hand, real business-cycle theorists may refine their models to produce more business-cycle-type (forecastable) dynamics and more amplification of technology shocks. Dynamic monetary theory and shock identification may improve so that monetary policy shocks can credibly account for a large fraction of output variation.

The other possibility is that consumption and output move on news that we do not see. This view at least explains our persistent ignorance, but it means that we may *forever* be ignorant of the true shocks that drive fluctuations. The surprise is that this view is not true by construction. Models that explain business-cycle dynamics with news shocks must be constructed and matched to data just like other models. Real business-cycle models do not easily generate business-cycle dynamics with shocks that do not affect current period marginal productivity.

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