

This PDF is a selection from a published volume from
the National Bureau of Economic Research

Volume Title: NBER Macroeconomics Annual 2004,
Volume 19

Volume Author/Editor: Mark Gertler and Kenneth
Rogoff, editors

Volume Publisher: MIT Press

Volume ISBN: 0-262-07263-7

Volume URL: <http://www.nber.org/books/gert05-1>

Publication Date: April 2005

Title: Monetary Policy in Real Time

Author: Domenico Giannone, Lucrezia Reichlin, Luca
Sala

URL: <http://www.nber.org/chapters/c6670>

Monetary Policy in Real Time

Domenico Giannone, Lucrezia Reichlin, and Luca Sala
ECARES, Université Libre de Bruxelles; ECARES, Université Libre de Bruxelles, and CEPR;
and IGIER and Università Bocconi

1. Introduction

It is widely recognized that the job of a central banker is a hard one because of the uncertainty under which policy decisions have to be made. There is uncertainty about the current state of the economy due to delays with which statistics are released and to the preliminary nature of the first releases, uncertainty about the nature of exogenous shocks, and uncertainty about the model (i.e., about the mechanisms that govern the interactions among policy, private-sector expectations, and economic performance).

Facing the complex problem of conducting policy under uncertainty, however, the central banker seems to respond systematically to (possibly filtered) output and inflation (Taylor, 1993, 1999; Clarida, Gali, and Gertler, 2000). Although the exact form of this rule has been the subject of debate, and although real-time estimates differ from the simple ex-post Taylor fit (e.g., Orphanides et al., 2000; Orphanides, 2001, 2003; Rudebusch, 2002), Taylor rules, defined in the broad sense, have been found to be a good characterization of monetary policy in the medium run.

This paper asks whether this finding reflects the conduct of monetary policy or the structure of the U.S. economy. We argue that the simplicity of the empirical monetary policy rule is a consequence of the simplicity of the U.S. economy and that a simple rule would have emerged, in ex-post analysis, even if policy had responded to variables other than output and inflation. From a real-time perspective, on the other hand, a rule in terms of forecastable contemporaneous and future output and inflation is observationally equivalent to a rule that responds to large movements in all real and nominal variables.

Simplicity, we find, takes three forms. First, only two shocks drive the U.S. macroeconomy. These shocks explain the fundamental business-cycle behavior of all key variables and, in particular, of the federal funds rate, inflation, and output.

Second, the two orthogonal shocks can be robustly identified as generating, respectively, medium- and long-run output dynamics and medium- and long-run inflation dynamics. Medium- and long-term inflation and output, therefore, capture well the two-dimensional space generated by the two shocks.

Third, once we extract from our series the medium- and long-run signal, we find that the leading-lagging structure linking gross domestic product (GDP) to other real variables is very simple and there is a lot of synchronization within the real bloc. The same is true for inflation and the nominal bloc.

Because two shocks explain the fundamental movements of the macroeconomy, and as long as the Fed responds systematically to these fundamental movements, the estimated rule would result in some version of the Taylor rule, i.e., as a function linking the federal funds rate to some transformation of output and inflation. Since the two large shocks are nominal and real and they generate a simple dynamics in the responses of, respectively, nominal and real variables, the transformation (the filters on output and inflation) has to be simple.

Simplicity is a consequence of the nature of the U.S. economy and does not necessarily reflect simple policy. Our claims about simplicity are based on the analysis of two panels of time series starting in 1970: the panel of the Greenbooks forecasts, i.e., the forecasts prepared by the Fed's staff to inform the Federal Open Market Committee (FOMC) meetings (available up to 1996), and a panel of 200 time series that roughly corresponds to what is used by the Fed in its short-term forecasting exercise (up to 2003).

We bring several pieces of evidence.

For both panels, two principal components explain more than 60% of the total variance and over 70% of the variance of key variables, such as the federal funds rate, output, industrial production, inflation measures (these percentages are even higher at medium- and long-run frequencies). This is not a surprising result, given strong comovements between economic variables (see, for example, Sargent and Sims, 1977; Stock and Watson, 2002; Giannone, Reichlin, and Sala, 2002; and Uhlig, 2003). It suggests that the stochastic dimension of the U.S. economy is two.

This finding is confirmed by a real-time forecasting exercise. The projection on two factors extracted from our large panel produces forecasts of the GDP growth rate and inflation comparable with the Greenbook forecasts and a forecast of the federal funds rate up to two quarters ahead, which is in line with that of the future market. Our analysis extends the forecasting exercise conducted in Bernanke and Boivin (2003) and Stock and Watson (1999) and brings new interpretation. Our forecast exercise mimics the real-time analysis conducted by the Fed in the sense that we use (as much as possible) sequential information sets that were available historically. (On the concept of real-time analysis, see Diebold and Rudebusch, 1991; Croushore and Stark, 1999; and Orphanides, 2001.) Since it is widely recognized that the Greenbook forecasts and future market forecasts are hard to beat, this is a remarkable result.

The good forecasting performance of the two-shocks model suggests that the role for judgmental action is small and that the Fed, on average, disregards movements that are idiosyncratic and not too correlated with the fundamental changes in the economy. Of course, the Fed may have reasons to respond, at particular times, to idiosyncratic events. However, if the Fed responded often to particular episodes generating idiosyncratic dynamics on exchange rate or financial markets, for example, our forecast based on two factors would be much poorer.

Finally, the *ex-ante* and *ex-post* structural analysis of shocks and propagation mechanisms, based on a novel identification procedure that exploits the cross-sectional information in our large panel, unravels common characteristics of the nominal and real side of the economy and indicates that the bulk of the dynamics of real variables is explained by the same shock, while nominal variables, at medium-long-run frequencies, are mainly explained by a shock orthogonal to it. The *ex-ante* analysis focuses on particular historical events of large inflation and output movements (recessions), which are the episodes in which the Fed moves aggressively and are therefore the more informative.

Our results suggest that a rule in terms of two variables is not identified uniquely. This might be bad news for econometricians, but it is good news for real-time monetary policy because, by tracking any forecastable measure of real activity and price dynamics, it does not leave out any other dimension of the fundamentals.

Finally, an implication of our result of near-orthogonality of output and inflation is that, while the dimension of the economy is two, the

dimension of the policy problem is one. Although we cannot rule out that this dichotomy may itself be the result of monetary policy, it is quite striking that real-nominal orthogonality is also a feature of the Fed's model that produces the Greenbooks forecasts. If this were really an exogenous feature of the economy, we would conclude not only that the U.S. economy is simple, but also that the job of the central banker is easier than one may think!

The paper is organized as follows. Section 2 investigates the question on the number of shocks in the U.S. economy analyzing both the panel of the Greenbook forecasts and a large panel of monthly time series on about 200 monthly variables since 1970. Section 3 studies the response of the federal funds rate to the exogenous shocks while Section 5 draw implications on the form of the policy function. Section 6 concludes.

2. The Dimension of the Greenbook Model and of the U.S. Economy

Macroeconomic variables comove, especially at business-cycle frequencies and in the long run. This implies that the multivariate dynamics of a large set of macroeconomic variables is driven by few large shocks. This feature might be obscured by short-run dynamics, typically reflecting measurement errors, poorly correlated across variables, and by the fact that the dynamics are not perfectly synchronized across time series, but they can be recovered by simple statistical methods. The degree of comovement can be measured by the percentage of the variance captured by the first few dynamic principal components or by checking the goodness of fit of the projection of the variables of interest onto principal components. Since macroeconomic series are autocorrelated, what we are interested in is the approximate *dynamic rank*, i.e., the approximate rank of the spectral density of the panel. Principal components computed from the latter are linear combinations of present, past, and future observations rather than contemporaneous standard principal components (see Brillinger, 1981; Forni et al., 2000).

Here we are dealing with two panels. First, a panel of about 200 series of monthly variables (only GDP and GDP deflator are quarterly), whose structure is illustrated by Table 1. (The appendixes provide a more detailed description of the data and of data transformations.)

Table 1
Structure of the panel

Category	# series	Category	# series
Industrial production	21	Wages	10
Capacity utilization	8	Import and export	3
Labor markets	32	Surveys	12
Consumption spending	13	Money and loans	16
Inventories and orders	15	Prices	28
Financial markets	16	Miscellaneous	6
Interest rates	10		

Surveys, industrial production series, labor market variables, and a number of other series labeled as miscellaneous are typically the variables used by the Fed to nowcast and forecast GDP. We have added prices and monetary and financial data (including exchange rates) to cover the nominal side of the economy.

Our second panel is that of fifteen selected variables from the Greenbook forecasts.¹ This is a subsample of the forecasts prepared by the board of governors at the Federal Reserve for the meetings of the FOMC. They are published in correspondence with the dates of the meetings (roughly every six weeks) and refer to quarterly data. Because Greenbook's forecasts are made publicly available with a five-year delay, our data set ends in 1996. We consider meetings closer to the middle of each quarter (four releases out of eight) and have selected the fifteen variables for which forecasts are available since 1978 and are reported up to four quarters ahead. This panel mainly contains forecasts of real variables, with less than a third representing nominal variables. To understand the structure of our data sets, let us define $z_{t|v}$ as the vector of the Greenbook forecasts computed at time v for observations at time $t = v - 2, v - 1, v, v + 1, \dots, v + 4$. If $t > v$, we have the forecasts; for $t = v$, we have the nowcasts; for $t < v$, the backcasts. For example, at $t = v - 1$, we have the first release of GDP and the final estimate of employment.

The same indexes can be used for the vintages of the panel of the 200 time series; let us define it as $x_{t|v}$.

Let us first consider the panel $x_{t|v}$, with $v = 2003Q4$. This is the last available vintage on the 200 time series.

To study the degree of collinearity in the panel, we compute, for each element $x_{it|v}$, $i = 1, \dots, n$, and for each $q = 1, 2, \dots, n$, the q

Table 2

Percentage of variance explained by the first five dynamic principal components on $x_{it|2003Q4}$, selected variables

	$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$
Average	0.49	0.63	0.71	0.77	0.82
Real GDP	0.63	0.74	0.77	0.83	0.86
Sales	0.71	0.77	0.83	0.86	0.88
Personal consumption expenditures	0.47	0.63	0.71	0.76	0.82
Services	0.41	0.55	0.61	0.66	0.74
Construction	0.48	0.61	0.70	0.76	0.82
Employment	0.85	0.91	0.93	0.95	0.95
Industrial production index	0.88	0.93	0.94	0.95	0.96
Capacity utilization rate	0.89	0.93	0.94	0.95	0.96
GDP implicit deflator	0.44	0.71	0.79	0.83	0.87
CPI	0.55	0.76	0.85	0.89	0.92
Wages	0.21	0.45	0.57	0.68	0.73
FFR	0.57	0.72	0.78	0.82	0.87

dimensional linear combination of present, past, and future observations $k_q(L)x_{it|v}$ such that the following mean squared error is minimized:

$$\text{MSE}_i(q) = \text{E}\{x_{it|v} - \text{Proj}[x_{it|v} | k_q(L)x_{it|v}]\}^2$$

This quantity will give us, for each variable, the variance explained by the q dynamic principal components (DPC). The average of these quantities over i , $1/n \sum_i \text{MSE}_i(q)$, gives us the variance explained for the whole panel (see Brillinger, 1981).

We are interested in how close the dynamic covariance of the panel (spectral density) is to rank two. If it were reasonably close, this would imply that the projection of the variables onto the first two dynamic principal components will give a good fit and that two macroeconomic shocks generate most of the dynamics of the variables.

Table 2 reports the results for some selected variables (for $t = v$) and the results for the sum of the mean squared errors over all variables and for principal components² (with $q = 1, 2, \dots, 5$). Two principal components explain more than 60% of the variance of each selected variable and of the whole panel. Key macroeconomic variables such as GDP, industrial production, employment, price indexes, and the federal funds rate show percentages way above the average, implying that they strongly comove with the rest of the economy.

Table 3
 Percentage of variance explained by the first five dynamic principal components on z_{it}

	Number of DPC				
	$q = 1$	$q = 2$	$q = 3$	$q = 4$	$q = 5$
$t = v - 2$	0.49	0.69	0.80	0.86	0.91
$t = v - 1$	0.53	0.72	0.82	0.87	0.91
$t = v$	0.53	0.74	0.84	0.89	0.93
$t = v + 1$	0.54	0.77	0.86	0.92	0.95
$t = v + 2$	0.54	0.77	0.87	0.92	0.95
$t = v + 3$	0.57	0.79	0.88	0.92	0.95
$t = v + 4$	0.53	0.77	0.87	0.92	0.95

If variables comove, the same must be true, in general, for the forecasts, even if model misspecification could induce decorrelation in some cases. Tables 3 and 4 report results describing the degree of comovements in the panel of the Greenbook forecasts for different horizons.

The principal component analysis of the Greenbook forecasts shows that the percentage of the variance explained by two principal components is larger than for the panel of the observations. This is not surprising because forecasting implies smoothing idiosyncratic dynamics that are typically highly volatile and unforecastable.

These results tell us that, to understand macroeconomic dynamics, we need to study the effect of few shocks only. Few shocks also explain the dynamics of the Greenbook forecasts.

More formal statistical analysis, along the lines of Forni et al. (2000) could be used to select the number of pervasive shocks for these panels. In this paper, however, since our goal is to understand the empirical success of the Taylor rule, which is expressed in term of two variables, we will follow a different route: fix the dimension of the economy at $q = 2$ and, having made this choice, study the forecasting performance and structural impulse responses with a two-shocks model.³

In their seminal paper, Sargent and Sims (1977) used a panel of eleven monthly time series from 1950 to 1970 for the U.S. economy. They obtained a result similar to what we found in this paper and in Giannone, Reichlin, and Sala (2002) for a large panel of U.S. quarterly data from 1982 to 2001. The two-shocks finding appears to be a robust result, at least for the U.S. economy.

Table 4
 Percentage of variance explained by the first two dynamic principal components on $z_{1,t}$, selected variables

	$t = v - 2$	$t = v - 1$	$t = v$	$t = v + 1$	$t = v + 2$	$t = v + 3$	$t = v + 4$
Real GDP	0.84	0.85	0.85	0.88	0.88	0.86	0.84
Final sales	0.72	0.75	0.84	0.83	0.78	0.83	0.81
Personal consumption expenditures	0.75	0.76	0.63	0.75	0.82	0.84	0.85
Services	0.38	0.70	0.59	0.58	0.64	0.67	0.68
Business fixed inventory	0.57	0.72	0.70	0.69	0.58	0.68	0.71
Residential structures	0.73	0.72	0.74	0.74	0.66	0.64	0.64
Government consumption and investment	0.28	0.34	0.36	0.42	0.50	0.41	0.32
Unemployment rate	0.74	0.74	0.76	0.77	0.78	0.87	0.87
Industrial production index	0.76	0.71	0.72	0.80	0.85	0.86	0.84
Capacity utilization rate	0.74	0.75	0.83	0.85	0.79	0.85	0.83
GDP implicit deflator	0.82	0.81	0.85	0.87	0.92	0.92	0.93
CPI	0.74	0.74	0.81	0.90	0.90	0.85	0.92
Output per hour	0.68	0.75	0.68	0.77	0.76	0.79	0.61
Compensation per hour	0.73	0.72	0.81	0.78	0.82	0.86	0.85
Unit labor cost	0.85	0.78	0.88	0.88	0.88	0.89	0.92

2.1 Forecasting Output, Inflation, and the Federal Funds Rate with Two Factors Extracted from Many Time Series

The descriptive analysis above suggests that output variables, aggregate price indexes, and the federal funds rate exhibit a higher than average degree of commonality: more than 70% of the variance of these variables can be explained by a projection on two aggregates.⁴ This in turn suggests that a models with two shocks should be empirically successful in explaining the federal funds rate.

In this section, we will produce forecasts of the federal funds rate using two orthogonal aggregate shocks extracted from our panel. We take the results of this forecast as a benchmark, i.e., the best we can obtain from a projection on a two-dimensional span. We expect to obtain results reasonably close to those of the private-market forecasts (the futures).

The same strategy will be used to forecast output and inflation. Given our results on the dimension of the Greenbook forecasts, we expect to obtain results similar to those reported in the Greenbook.

The forecasting exercise is a pseudo real-time experiment in which we try to mimic as closely as possible the real-time analysis performed by the Fed when forecasting, at each period of time, on the basis of different vintages of data sets.⁵ The experiment is real time because we consider the releases on GDP and GDP deflator specific to each vintage and because each vintage has missing data information at the end of the sample reflecting the calendar of data releases. This allows us to reproduce, each month within the quarter, the typical end of the sample unbalance faced by the Fed; due to the lack of synchronization of these releases, missing data are more or less numerous depending on the series considered. The experiment is pseudo because we do not have real-time information for variables other than GDP and GDP deflator.⁶

For each variable of interest, we write the forecast (or the nowcast) as:

$$x_{it|v}^* = \text{Proj}[x_{it|v} | \overline{\text{span}}(u_{t-k}, k \geq 0)]$$

where $u_t = [u_{1t} \ u_{2t}]'$ is the two-dimensional vector of the common shocks (normalized to be orthogonal white noise) estimated from the following model on the vector $x_{t|v}$ of the variables of the panel:

$$x_{t|v} = \Lambda F_t + \xi_{t|v}$$

$$F_t = AF_{t-1} + Bu_t$$

where F_t is the $r \times 1$ ($r \geq 2$) vector of the static factors, $\Lambda = [\Lambda'_1, \dots, \Lambda'_n]'$ is the $n \times r$ matrix of the loadings, B is a $r \times q$ matrix, and $\xi_{t|v}$ is the n -dimensional stationary vector process of the idiosyncratic component with covariance matrix $E(\xi_{t|v}\xi'_{t|v}) = \Psi$. We assume that the idiosyncratic components are weakly cross-correlated.⁷

Having set the dimension of u_t to be two, we identify the dimension of F_t , r , by statistical criteria.⁸ Notice that, while the dimension of u_t identifies the stochastic dimension of the economy (the number of common shocks), the dimension of $F_t(r)$, depends on the heterogeneity of the lag structure of the propagation mechanisms of those shocks. Typically, in a dynamic economy, $r > q$.

It is important to note that, to be able to express our forecasting equation in terms of a one-sided filter on the two-dimensional vector of the common shocks, we assume implicitly that they can be recovered from the past of F_t of $\dim r > q$ (see Remark 4 in Appendix 6.1). This assumption is reasonable, provided that there are enough leading variables in the panel and that r is sufficiently large (see Forni et al., 2003). Under this assumption, we can write the model for x_t as:

$$x_{it|v} = C_i(L)u_t + \xi_{t|v} = c_{i1}(L)u_{1t} + c_{i2}(L)u_{2t} + \xi_{t|v} \quad (1)$$

where $C_i(L) = \Lambda_i(I_r - AL)^{-1}B$ is the impulse response function of the i th variable to the common shocks.

The appendixes detail the estimation procedure. Let us outline it here. In the first step, we use principal components to estimate the parameters of the factor model $\hat{\Lambda}$, \hat{A} , \hat{B} , and $\hat{\Psi}$; in the second step, we use these estimates and the data $(x_{1|v}, x_{2|v}, \dots, x_{v|v})$ to apply the Kalman filter on the state-space model to obtain:

$$\hat{F}_t = \text{Proj}[F_t | x_{1|v}, \dots, x_{v|v}], \quad t = 0, 1, \dots, v + h$$

and \hat{u}_t . Notice that all these estimates depend on the vintage v , but we have dropped the subscript for notational simplicity.

Once we have the nowcast and the forecast of the factors, we can construct the nowcast and forecast of the variables.⁹ Notice that this forecasting method disregards the idiosyncratic component of each variable. The intuition is that the idiosyncratic element captures that part of the dynamics that is unforecastable because it is mostly explained by high-frequency variations that reflect measurement error or variable-specific dynamics.

Our objectives are the nowcasts and forecasts of the annualized quarterly growth rate of GDP, the annual rate of change of the GDP deflator, and the quarterly average of the federal funds rate.

We adapt this framework to estimate the factors on the basis of the incomplete data set, i.e., a data set that, as we have described, is some missing values corresponding to data not yet released. We write the model as:

$$\tilde{x}_{it|v} = \Lambda F_t + \xi_{it|v}$$

$$F_t = AF_{t-1} + Bu_t$$

where

$$\begin{aligned} E(\xi_{it|v}^2) &= \tilde{\psi}_{it|v} = \psi_i && \text{if } x_{it|v} \text{ is available} \\ &= \infty && \text{if } x_{it|v} \text{ is not available} \end{aligned}$$

$$\begin{aligned} \tilde{x}_{it|v} &= x_{it|v} && \text{if } x_{it|v} \text{ is available} \\ &= 0 && \text{if } x_{it|v} \text{ is not available} \end{aligned}$$

Notice that imposing $\psi_{it|v} = \infty$ when $x_{it|v}$ is missing implies that the filter will put no weight to the missing variable in the computation of the factors at time t .

The forecasts are computed each month, using the data available up to the first Friday. The parameters of the model are estimated using data up to the last date when the balanced panel is available.

In the estimation of the factor model, we use quarterly differences of the annual GDP deflator inflation and the quarterly differences of the federal funds rate, so we recover the levels of both variables by using the last available values. Our forecasts are compared with:

1. The Greenbook forecast for (quarterly) inflation and output (roughly corresponding to the second month of the quarter—four releases out of eight).
2. The survey of professional forecasts for quarterly output and inflation (released in the middle of the second month).
3. The futures on the federal funds rate (aggregate monthly forecast to obtain quarterly forecast—take the forecast first day of the first month).
4. The random walk forecast, only for inflation and the federal funds rate, where we assume that the forecast at all the horizons is given by

Table 5
Forecast comparison: root mean squared errors (RMSE)

	Quarters ahead ($h = t - v$)				
	0	1	2	3	4
GDP growth rate					
GB/2-shocks	1.09	1.03	1.00	0.88	0.86
Naive/2-shocks	1.23	1.02	0.98	0.94	0.93
SPF/2-shocks	1.14	1.00	0.99	0.99	1.01
2-shocks	1.83	2.21	2.30	2.39	2.43
Annual GDP deflator inflation					
GB/2-shocks	0.96	0.79	0.89	0.95	1.23
Random walk (RW)/2-shocks	1.05	1.10	1.15	1.20	1.22
SPF/2-shocks	0.99	0.92	0.98	1.17	1.27
2-shocks	0.30	0.40	0.48	0.55	0.60
Federal funds rate					
RW/2-shocks	1.23	1.17	—	—	—
Futures/2-shocks	0.47	0.76	—	—	—
2-shocks	0.41	0.79	—	—	—

the last available number of the federal funds rate and inflation at the date in which the forecast is taken.¹⁰ For the GDP growth rate, we construct a naive forecasts that predicts a constant growth rate equal to the average growth rate over the sample 1970:1–1988:12 to have a measure of overall forecastability.

Table 5 reports root mean squared errors (RMSE) of the three variables relative to our model (forecasts produced during the second month of the quarter) and the ratio of the RMSE by the survey of professional forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia, the Greenbook (GB), and the future markets with respect to our model. The forecasts are performed using the whole sample but are reported only since 1989, when we start having information on the future market forecasts. Notice that Greenbook forecasts are available to the public only up to 1996. The table shows the following features:

- Our forecasts on inflation and output are overall very close to the Greenbook forecasts, with our model doing better in the short-run for output and in the long-run for inflation. Notice also that the factor model does relatively well for the nowcast of output, where there is predictability, and for inflation at the longer horizons, which are those relevant for policy.

- For inflation, the factor model outperforms the random walk benchmark, suggesting that there is forecastability in inflation four quarters ahead. At that horizon, the Greenbook has similar performance to the random walk, as noticed by Atkeson and Ohanian (2001). In general, the factor model outperforms the SPF's, while it is close to the Greenbook forecasts.
- The random walk does poorly for the federal funds rate, and the market's forecast is best. The two-factors model does well, however, at horizon two. As many have observed (e.g., Evans, 1998), it is very hard for a statistical, automatic model to beat the markets at the short horizon since those forecasts incorporate information such as the dates of the meetings, the chair's last speech, and institutional events, to which models cannot adapt. As we will see below, however, our performance is close to the market's when the Fed moves its instrument a lot, especially during recessions. In general, the forecasting performance of the two-factor model is far superior to the one based on a Taylor rule using Greenbook's inflation forecasts and real-time output gap estimates. Although that model achieves a good in-sample fit, it does very poorly in forecasting (see, for example, Rudebusch, 2001; Soderlind, Soderstrom, and Vredin, 2003).

Overall, these results tell us that a simple linear two-factors model does well at mimicking the behavior of the Fed. Notice that this analysis qualifies results by Bernanke and Boivin (2003) and Stock and Watson (1999), which found that taking into account information on many variables helps forecasting. Our results confirm that finding and show that two shocks (dynamic factors) are sufficient to obtain it.

The analysis of forecasting performance over time sheds some further light on the federal funds rate behavior. Figures 1 to 3 illustrate forecast errors squared (panel A) and forecasts (panel B) for output at a zero-quarter horizon (nowcast), inflation at a one-year horizon, and the federal funds rate at a one-quarter horizon and for different forecasting models.

Let us make the following observations:

- The two-factors model does very well in forecasting output, especially during recessions, when all variables comove strongly. This is not surprising since it exploits optimally collinearity in the data. On average, we are close to the Greenbooks. Note that we identified the beginning of the last recession (first quarter of negative growth) one

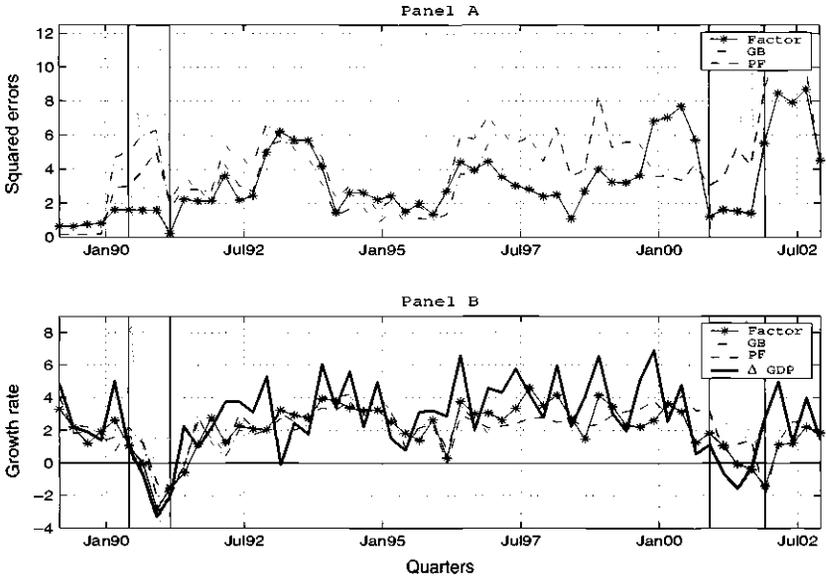


Figure 1
Forecasting GDP growth rate

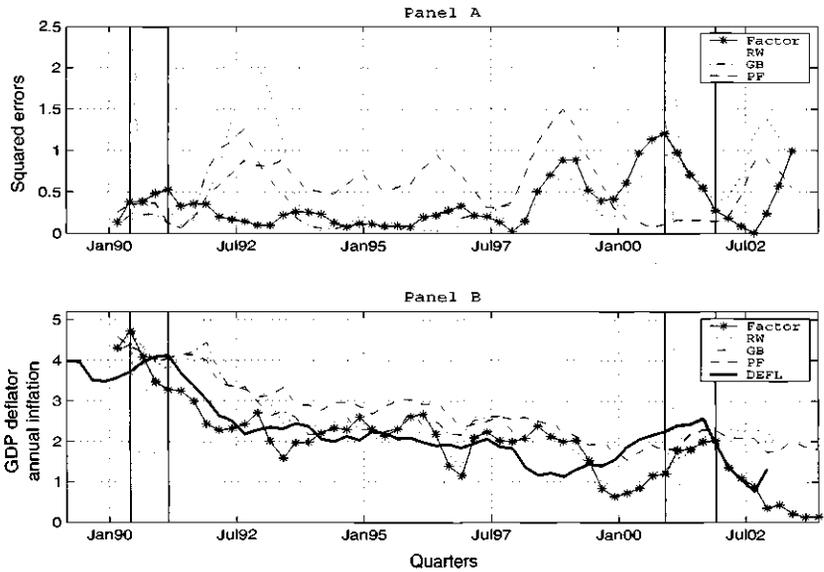


Figure 2
Forecasting inflation

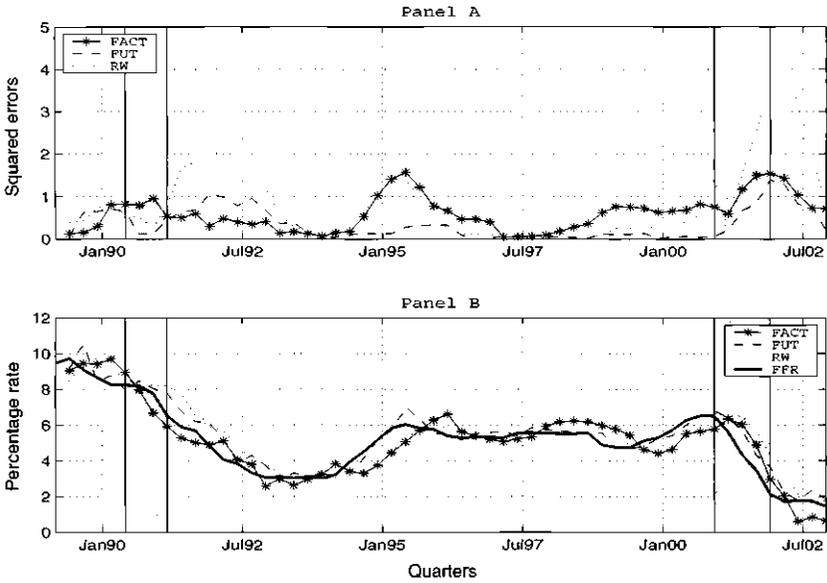


Figure 3
Tracking Greenspan

quarter after it occurred, while the SPF identified the peak when the recession had already ended.

- Concerning inflation, the two-factor model does well in detecting the decline that followed the 1990 recession. In addition, unlike the SPF, the model does not overestimate inflation in the 1990s (overprediction of inflation during this period has been noted by Brayton, Roberts, and Williams, 1999; Rudebusch, 2001), but it misses the upsurge of inflation in the late 1990s. Finally, it identifies well the last decline in inflation.
- For the federal funds rate, the factor model does well when it does well in predicting output and inflation and during recessions, when the Fed moves a lot. In particular, our model does well during the fall of the federal funds rate at the beginning of the 1990s because it can capture both the decline of output during the recession and the decline of inflation that occurred when the recession ended. The factor model can predict the monetary easing started in 2001, when it also predicts in a timely way the 2001 recession and the decline of inflation started in the second half of 2001. On the other hand, the two-factors forecast performs poorly during the preemptive strike against inflation in 1994,

when the Fed responded not only to its own predictions of inflation but also to market expectations (see Goodfriend, 2002) and during the monetary tightening that started in the late 1990s. That episode is associated with an increase in inflation that was not predicted by the two shocks. Finally, the two-shocks model does not predict the cut in the federal funds rate in the second half of 1998, which was not justified in terms of shocks on inflation and real activity but rather as a response to the financial market turbulence associated with the Russian crisis. This is an example of judgmental policy that cannot be incorporated in simple rules. (On this point, see Svensson (2003).)

What do the results of the forecasting exercise tell us about monetary policy in real time? The key message is that a two-shocks model does well in forecasting output and inflation even when compared with tough benchmarks such as the SPF and the Greenbook. This brings additional support to our claim that the relevant dimension of the U.S. economy is two. Second, the model produces a good forecast of the policy instrument, suggesting that it captures some essential elements of the forecasting model of the Fed and its reaction function. What are these elements? The first, as already observed, is the reduced dimension. The second is the particular version of output and inflation to which policy responds. We turn to this analysis in the next section.

3. The Dimension of the Policy Problem

3.1 *What are the Two Large Shocks?*

This section moves to the structural interpretation. If the stochastic dimension is two, two large shocks must drive the economy. Can we identify them?

Let us define the forecast errors from the Greenbook model as:

$$z_{it+h|t+1} - z_{it+h|t} = e_{it}^h$$

where $h = -1, 0, 1, \dots, 4$. For $h = -1$ and $h = 0$, we have errors on revisions, while for $h = 1, \dots, 4$ we have errors from the Fed's model.

Figure 4 plots errors for inflation against those for output at different values of h . Visual inspection of the figure suggests no clear pattern of correlation. Indeed, our calculations show that only a few of them are significantly different than zero, and very little survives once the recession of the mid-1970s is taken out of the sample. This suggests that the

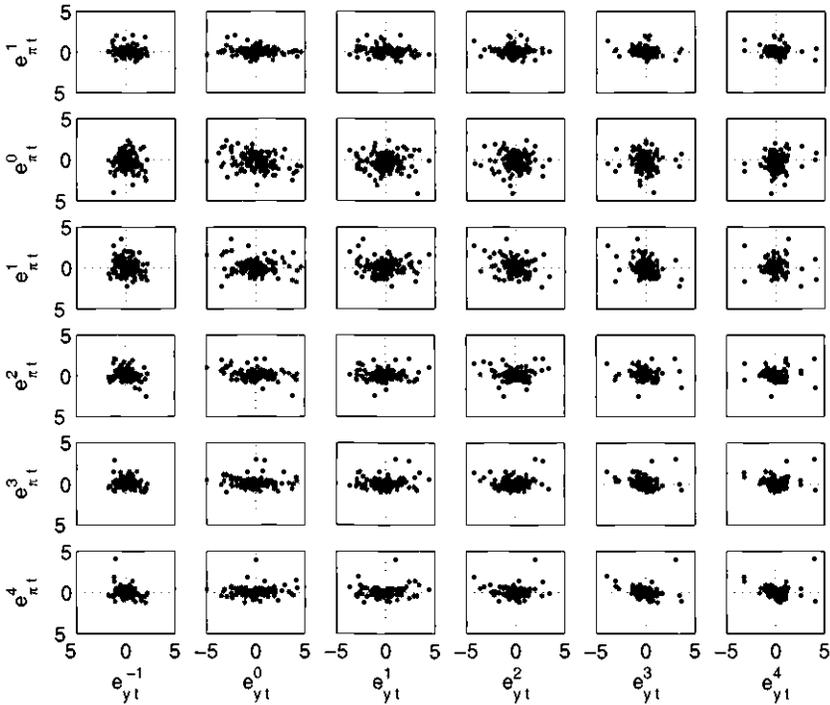


Figure 4
Correlation of inflation and output, Greenbook forecast errors

uncertainty about inflation originates from sources that are weakly correlated with the sources of uncertainty about real activity. In other words, the inflation and output shocks faced by the Fed are not much correlated. This is in line with the results reported by Romer and Romer (1994), who found that the ability of the Fed to predict output is not related to its ability to forecast inflation.

How strong is the correlation between nominal and real variables induced by the two shocks? If it is weak, then there must be a real shock explaining the bulk of GDP dynamics, and a nominal shock explaining the bulk of inflation dynamics. To investigate this point, we compute ex-post and real-time impulse response functions to orthogonalized shocks extracted from our panel of observations. We will start by reporting ex-post estimates (i.e., estimates on revised data for the whole sample). We will move to the ex-ante real-time analysis in the next subsection.

For the ex-post exercise, we proceed as follows. We identify the real shock as the one that explains the maximum variance of the

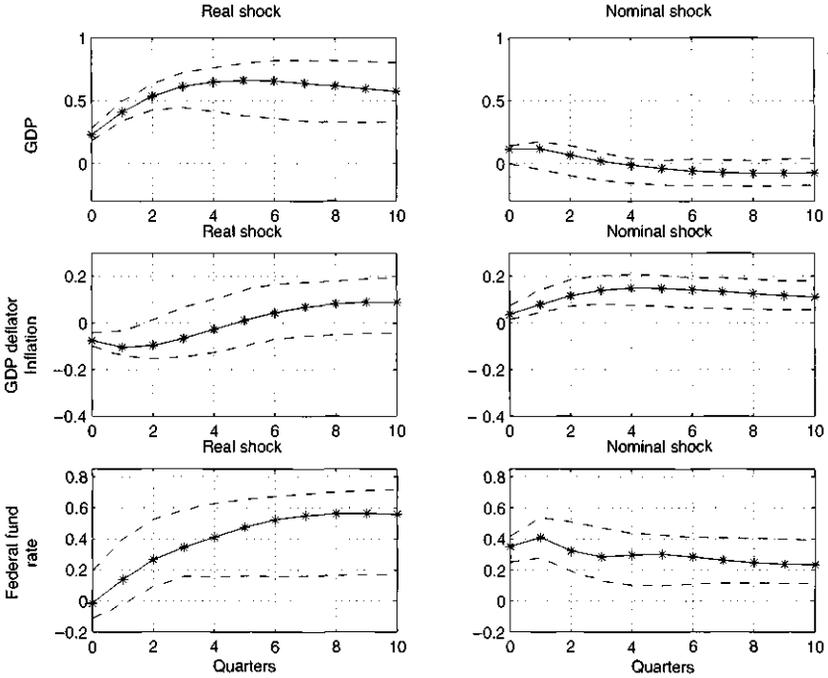


Figure 5
Impulse response functions

real variables in the panel. We propose that the following quantity is maximized:

$$\frac{\sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i1}^h)^2}{\sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i1}^h)^2 + \sum_{i \in J_R} \sum_{h=0}^{\infty} (c_{i2}^h)^2}$$

where J_R is the set containing the positions of the real variables in the panel. This identification procedure allows us to exploit information on the multivariate dynamics of the panel and to extract a shock that has its main effect on the real sector of the economy so that we can label it real. The other shock is labeled as nominal. Figure 5 illustrates impulse response functions for GDP, the federal funds rate, and inflation to the real and nominal shocks,¹¹ while Figure 6 reports ex-post conditional histories.¹²

A few comments are in order:

- The shape of the responses of the federal funds rate and output to the real shock are very similar, with the federal funds rate lagging GDP. In

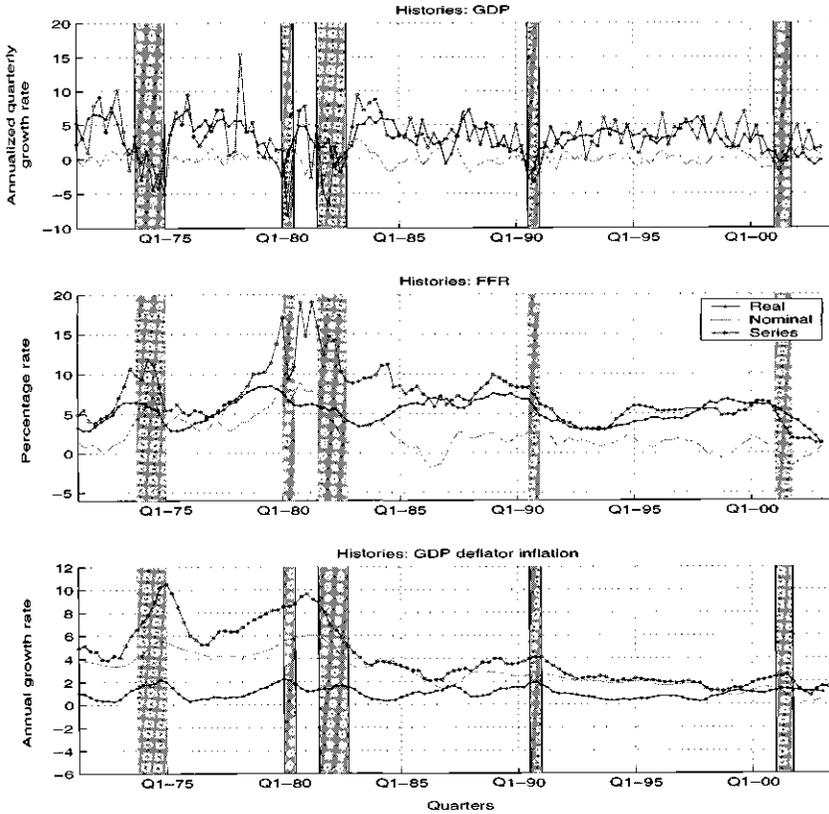


Figure 6
 Inflation, output, and the federal funds rate: realizations and conditional histories

response to the nominal shock, the federal funds rate leads inflation and it responds more than one to one.

- Even though this is not the focus of the paper, note that neither of the two shocks can be identified as a monetary policy shock. This is justified by two findings: one of the two shocks is permanent on output, the second moves inflation and the federal funds rate in the same direction. For further analysis on this point, see our earlier work in Giannone, Reichlin, and Sala (2002).
- GDP is driven mainly by the real shock, the deflator is driven mainly by the nominal shock, and the federal funds rate is driven by both.
- The real component explains a big part of recessions, in particular in the early 1990s. Since the dynamics of output associated to the nominal shock is small, the Phillips curve relation is weak.

• The sums of the conditional histories, for each variable, are their corresponding common component (the components driven by the two common shocks). We can infer from figure 6 that they represent a smoothed version of the variable, which tracks quite well medium-term dynamics.

Essentially, the federal funds rate responds vigorously to both shocks. At first sight, this is not surprising since they are the large shocks affecting output, and inflation and output and inflation are the variables usually considered as objectives of monetary policy. We will show in Section 4 that the previous statement can be generalized: to the extent that there are only two shocks in the economy, any couple of uncorrelated variables can be used to explain the movements in the federal funds rate.

As a robustness check, we also follow the more traditional strategy (see Blanchard and Quah, 1989) of assuming that there exists a transitory and a permanent shock on output. We impose the restriction that the long-run multiplier on the transitory shocks on output is equal to zero, i.e., that $c_{y,2}(1) = 0$ in equation (1).

Impulse response function and conditional histories from the two identification schemes give almost identical results. As expected, the permanent shock is almost identical to the real shock, while the transitory is identical to the nominal (we do not report results for this identification here; they are available on request).

3.2 *Real-Time Analysis of the Shocks*

Shocks in real time are conditional forecast errors derived from the real-time forecasting exercise. We can build on the forecasting exercise of the previous section to produce impulse response functions of the common shocks derived from the conditional real-time forecasts. Let us define:

$$w_{it}(T_1, T_2) = x_{it}^*|_{T_2} - x_{it}^*|_{T_1}, \quad T_2 > T_1$$

as the difference of the path for the common component of variable x_{it} , defined as x_{it}^* estimated at time T_2 , and the path that was expected at time T_1 . These quantities should be understood as weighted realizations of shocks that occurred between time T_1 and T_2 , where the weights depend on the propagation mechanism of the shocks.¹³ If a certain type of disturbance has been prevalent between T_1 and T_2 , then

$w_{it}(T_1, T_2)$ will reflect the series-specific propagation mechanism and the realizations of such disturbance.

More precisely, for $t > T_1$, $w_{it}(T_1, T_2)$ is an estimate of:

$$d_{i1}(L)u_{1,T_1+1} + d_{i2}(L)u_{2,T_1+1} + \cdots + d_{i1}(L)u_{1,T_2} + d_{i2}(L)u_{2,T_2}$$

A particular case is $t > T_1 + 1$, when $w_{it}(T_1, T_1 + 1)$ is an estimate of the impulse response function weighted by the realization of the shock at time $T_1 + 1$, i.e., $d_{i1}(L)u_{1,T_1+1} + d_{i2}(L)u_{2,T_1+1}$.

For example, suppose that T_1 is the first quarter of 2001, the last peak announced by the National Bureau of Economic Research (NBER), and that T_2 is the fourth quarter of 2001, the corresponding trough. Then $w_{it}(Q1.01, Q4.01)$ measures the convolution of the propagation mechanism for the variable x_{it} with the shocks that have generated the recession.

Forecast errors conditional on the permanent shocks can be obtained by shutting down the transitory shocks. The same can be done for the transitory shocks.

We report selected episodes: the two recessions in our sample and two episodes of inflation scares. From left to right, the plots in Figures 7 and 8 must be read as unconditional impulses on output, the federal funds rate, and inflation, and impulses conditional on the permanent shock for the same variables and impulses conditional on the transitory shock, respectively.

Here is what emerges from the analysis:

- *Recessions*

1. 1990Q3–1991Q1. The interest rate reacts to the decline in output with a lag, but very aggressively. Very little happens to inflation because the recession is almost entirely driven by the real shock. The interest rate therefore reacts to the real shock and not to the nominal.

2. 2001Q1–2001Q4. The real shock is also the driving force for this recession. Inflation dynamics is driven by the nominal shock. Inflation continues to decline conditionally on that shock, even after the recovery has started. The federal funds rate moves aggressively with output during the recession, moving before inflation declines.

- *Inflation scares*

1. 1993Q4–1995Q2. The upsurge of inflation is driven entirely by the nominal component, which also drives output upward. This is a case in which there is a Phillips relation. As we have seen from the ex-post conditional histories, a Phillips relation emerges conditionally only to

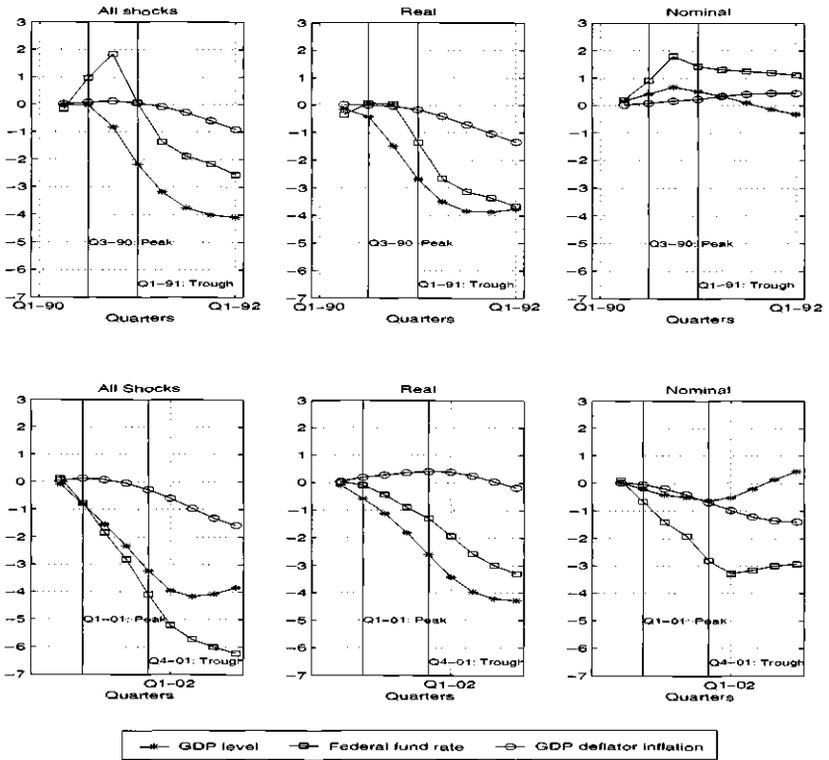


Figure 7
Recessions

the nominal shock, i.e., conditionally on the small shock on output. In this episode, the federal funds rate moves with output and leads inflation.

2. 1999Q2–2000Q3. Inflation moves up with the nominal shock and so does output. The federal funds rate moves upward aggressively with inflation.

The picture emerging from the ex-ante, real-time analysis is similar to what emerged from the ex-post analysis: the real shock affects output but not inflation, the nominal shock affects inflation but not output.

Notice that inflation moves very little during recessions. Facing large movements, the Fed reacts aggressively either to inflation or to output. What is most important, as noticed by Romer and Romer (1994), is that large movements in inflation and large movements in output are largely independent from one another.

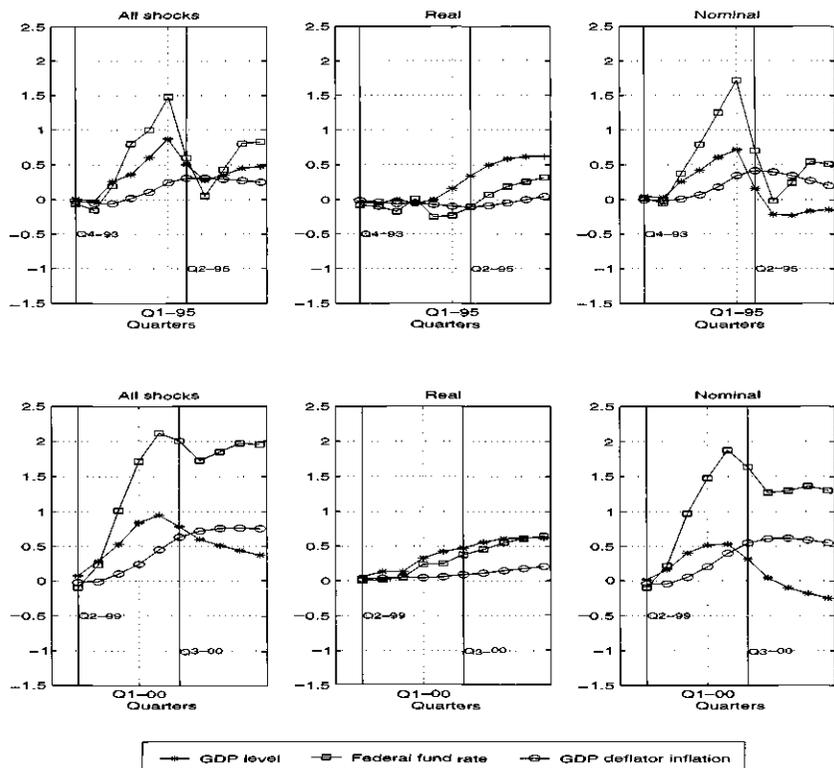


Figure 8
Inflation scores

4. Taylor Rules: Discussion

As we have seen, the fundamental business-cycle dynamics of the U.S. economy is driven by two shocks. We have seen from the historical account of the forecasting performance of the two-shocks model that the responses of the federal funds rate to nonfundamental fluctuations, i.e., to those fluctuations driven by shocks other than the two large common ones we have identified, are not systematic. In our framework, they are captured by the idiosyncratic component that is a white noise in first difference.¹⁴

It is then easy to see that, even if the Fed reacted, in addition to output and inflation, to other variables driven by the fundamentals, their inclusion in the federal funds rate equation would not improve the fit. This policy would be observationally equivalent to a systematic policy reacting to inflation and output only. Inflation and output, as we have

seen, are indeed highly correlated with, respectively, the nominal and real part of the economy and they are nearly orthogonal at business-cycle frequencies, so they capture well the two-dimensional space generated by the two fundamental shocks.

Ex-post estimates of the Taylor rule point at a simple function: the Taylor rule is a simple contemporaneous relation between the federal funds rate and the output gap and inflation. Does such simplicity reflect the simplicity of the Federal Reserve policy or the fact that real and nominal variables react similarly to, respectively, the real and nominal shocks?

To investigate this issue we have run two sets of regressions.

First, we have regressed the component of the federal funds rate generated by the real shock on the components of all real variables generated by the real shock (cumulated). Second, we have regressed the component of the federal funds rate generated by the nominal shock on the components of all nominal variables generated by the nominal shock (cumulated).

We have obtained two sets of fits—nominal and real—and constructed 10% lower and upper bands by excluding, at each t , the 20% of extreme points (10% lower and 10% upper). The upper quadrant of Figure 9 reports the bands as well as the projection of the federal funds rate on GDP and the federal funds rate conditional on the real shock that we have reported earlier (see Figure 6). The lower quadrant does the same for the nominal case.

Figure 9 shows a striking similarity of shapes within the real and nominal group. Not only do the lower and upper bounds move in the same direction, but both the projection of the federal funds rate on real GDP, conditional on the real shock, and the projection of the federal funds rate on the deflator, conditional on the nominal shock, are within the bands. Considering that the variables analyzed are quite different, this is indeed a strong result. The U.S. economy is simple not only because it is mainly driven by two shocks, but also because the responses of real variables to the real shock are similar and so are the responses of nominal variables to the nominal shock.

Obviously variables are not completely synchronized, and some leading-lagging relations can be identified.¹⁵ The lower bound curve leads the upper bound curve. The projection on GDP leads the real component of the federal funds rate, which implies that the latter leads GDP (real variables). On the contrary, from the lower quadrant, we can see that the conditional federal funds rate leads inflation (nominal vari-

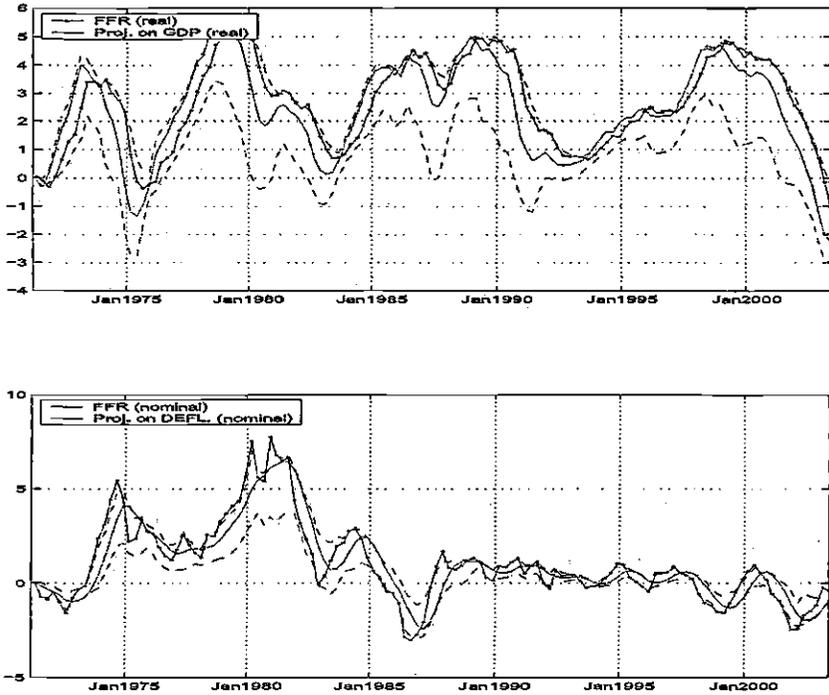


Figure 9
Taylor fits

ables) and crosses often the lower bound. The fact that the federal funds rate is lagging with respect to real variables might be a consequence of the fact that information about the real side of the economy is less timely than financial or price information.

From an ex-ante perspective, one possible interpretation of our results is that the Fed, instead of tracking two particular variables such as a version of measured output gap and inflation, follows a robust policy, moving when all real variables (and among them GDP) move and all nominal variables (and among them the inflation rate) move.

In real time, the exercise of nowcasting and forecasting by the Fed essentially amounts to smoothing out short-run dynamics and unforecassable idiosyncratic variance from output and inflation, making use of information contained in a large cossection of data and exploiting their comovements as well as their historical leading and lagging relations. This applies specific filters to output and inflation. Our analysis suggests also that the filters are two-sided and that this is a consequence of the fact that the variables, although rather synchronized, are

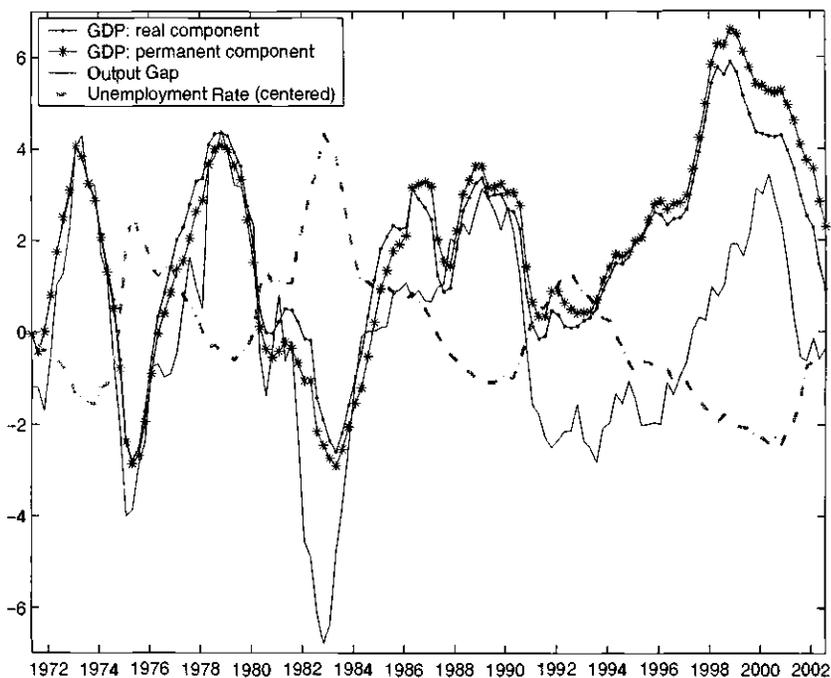


Figure 10

The output gap (centered), unemployment rate, the permanent component of output, output generated by the real shock

not perfectly aligned and that the leading ones are used to nowcast and forecast inflation and output.

We can also ask how the output variable we have used relates to current measures of the output gap. We have seen that we can interpret the large shock on output as either a real shock or as the shock generating long-run movements in output. However, Figure 10 shows that not only the output component generated by the real shock and the long-run component are empirically very close to one another, but (more disturbingly) that the output gap measured as the Hodrick-Prescott filter on output and the (centered) unemployment rate are both strongly correlated with those two components. The correlation, with the exception of the mid-1990s, is striking.

This suggests that a major aspect of uncertainty faced by the central bank is the lack of knowledge on whether shocks affecting the economy are of long or short duration. As we have seen, output growth at horizons longer than two quarters is unforecastable. This implies that it is hard to measure the long-run effect of the shocks and, as a conse-

quence, to distinguish between the output gap and long-run component of output. Although the permanent component contains, by construction, the zero frequency (long-run) component, its measure is strongly correlated with detrended output. The unemployment rate, on the other hand, is very persistent and its natural level is badly measured (see also Staiger, Stock, and Watson [1997] and Orphanides and Van Norden [2002] for the consequences of this observation on real-time monetary policy). This obviously leads to a problem of interpretation on what the Fed does. Does it follow the permanent component of output, the output gap, or simply the forecastable component of output growth?

Finally, let us notice that our model is estimated in difference form, which implies that the nonsystematic component of the policy equation has a unit root. This is a consequence of the fact that the real interest rate is very persistent (see, for example, Rudebusch, 2001). Since the federal funds rate, inflation, and output either have a unit root or are close to the unit root case, in real-time, their level is difficult to forecast. A rule in first differences is easier to implement (see also Orphanides, 2003). However, with a first difference specification, we cannot learn anything about important issues such as the level of the natural rate of interest or the natural rate of unemployment.

5. Conclusions and Some Caveats

The message of this paper can be summarized as follows. The complex dynamic interaction among many macroeconomic variables in the U.S. economy can be captured by two aggregates. The bulk of medium- and long-run dynamics of output is explained by one shock that has similar effects on all real variables and the bulk of medium- and long-run dynamics of inflation by a shock, orthogonal to it, that has a similar effect on all nominal variables. The federal funds rate, by responding to the two large shocks, can track the fundamental dynamics of both output and inflation, i.e., the dynamic correlated with the whole economy and that it is forecastable. Occasionally, the Fed may decide to monitor special events, such as exchange rate crises or surges in inflationary expectations from the private sector that are not correlated with its own forecasts of the fundamentals, but this judgmental part of policy seems to be small.

The consequence of these results is that the simple Taylor rule found to fit U.S. data so well may be interpreted as the ex-post result of a policy that ex-ante, responds vigorously when all real variables *or* all

nominal variables move together. The weak trade-off between output and inflation and between output and inflation in the Greenbook forecasts suggest that inflation scares and recession scares can be addressed as distinct stabilization problems.

The main purpose of our analysis has been to identify the history of U.S. monetary policy in the last twenty years and point out problems of interpretation of results from existing studies. From a real-time perspective, it is important to understand what the Fed has done, given uncertainty about the current and future state of the economy and the delays in data releases. We have seen that output growth is unforecastable at long horizons, which makes any rule based on the identification of the long run on output or its residual unreliable. Inflation, on the other hand, is more forecastable at longer horizons. In both cases, the forecastable component is one that correlates with the rest of the economy. A normative implication is that a robust rule should not depend on idiosyncratic movements of specific variables but rather move when all real or nominal variables move. One possible interpretation of this finding, is that the Fed, indeed, follows this type of rule. This conjecture is supported, in particular, by the fact that we replicate well the policy behavior during recessions. These situations are also those in which the Fed has been successful in reacting promptly to output decline.

There are other important aspects of the monetary policy debate where our analysis is not informative. Although we can say something about what the Fed has done, we cannot quantify the effect of monetary policy on the economy. For example, the finding on the weakness of the Phillips curve trade-off might be an effect of successful policy. Such analysis would require the specification of a structural model. At this stage, however, structural models have not produced forecasting results that even come close to those produced by the Greenbooks and by the markets.

6. Appendixes

6.1 *Econometrics*

Consider the model:

$$x_t = \Lambda F_t + \xi_t$$

$$F_t = AF_{t-1} + Bu_t$$

$$u_t \sim WN(0, I_q)$$

$$E(\xi_t \xi_t') = \Psi$$

where

F_t is the $r \times 1$ ($r \geq 2$) vector of the static factors

$\Lambda = [\Lambda'_1, \dots, \Lambda'_n]'$ is the $n \times r$ matrix of the loadings

B is a $r \times q$ matrix of full rank q

A is an $r \times r$ matrix and all roots of $\det(I_r - Az)$ lie outside the unit circle

ξ_t is the n -dimensional stationary linear process

We make two assumptions.

1. Common factors are pervasive:

$$\liminf_{n \rightarrow \infty} \left(\frac{1}{n} \Lambda' \Lambda \right) > 0$$

2. Idiosyncratic factors are nonpervasive:

$$\lim_{n \rightarrow \infty} \frac{1}{n} \left(\max_{v'v=1} v' \Psi v \right) = 0$$

Consider the following estimator of the common factors:

$$(\tilde{F}_t, \hat{\Lambda}) = \arg \min_{F_t, \Lambda} \sum_{t=1}^T \sum_{i=1}^n (x_{it} - \Lambda_i F_t)^2$$

Define the sample covariance matrix of the observable (x_t):

$$S = \frac{1}{T} \sum_{t=1}^T x_t x_t'$$

Denote by D the $r \times r$ diagonal matrix with diagonal elements given by the largest r eigenvalues of S and by V the $n \times r$ matrix of the corresponding eigenvectors subject to the normalization $V'V = I_r$. We estimate the factors as:

$$\tilde{F}_t = V' \tilde{x}_t$$

The factor loadings, $\hat{\Lambda}$, and the covariance matrix of the idiosyncratic components, $\hat{\Psi}$, are estimated by regressing the variables on the estimated factors:

$$\hat{\Lambda} = \sum_{t=1}^T x_t \tilde{F}_t' \left(\sum_{t=1}^T \tilde{F}_t \tilde{F}_t' \right)^{-1} = V$$

and:

$$\hat{\Psi} = S - VDV'$$

The other parameters are estimated by running a VAR on the estimated factors, specifically:

$$\hat{A} = \sum_{t=2}^T \tilde{F}_t \tilde{F}_{t-1}' \left(\sum_{t=2}^T \tilde{F}_{t-1} \tilde{F}_{t-1}' \right)^{-1}$$

$$\hat{\Sigma} = \frac{1}{T-1} \sum_{t=2}^T \tilde{F}_t \tilde{F}_t' - \hat{A} \left(\frac{1}{T-1} \sum_{t=2}^T \tilde{F}_{t-1} \tilde{F}_{t-1}' \right) \hat{A}'$$

Define P as the $q \times q$ diagonal matrix, with the entries given by the largest q eigenvalues of $\hat{\Sigma}$, and by M the $r \times q$ matrix of the corresponding eigenvectors:

$$\hat{B} = MP^{1/2}$$

The estimates $\hat{\Lambda}, \hat{\Psi}, \hat{A}, \hat{B}$ can be shown to be consistent as $n, T \rightarrow \infty$ (Forni et al., 2003).

Having obtained the estimates of the parameters of the factor model, the factors are reestimated as:

$$\hat{F}_t = \text{Proj}[F_t | x_1, \dots, x_T], \quad t = 0, 1, \dots, t+h$$

by applying the Kalman filter to the following state-space representation obtained by replacing estimated parameters in the factor representation:

$$x_t = \hat{\Lambda} F_t + \xi_t$$

$$F_t = \hat{A} F_{t-1} + \hat{B} u_t$$

$$u_t \sim WN(0, I_q)$$

$$E(\xi_t \xi_{t'}') = \text{diag } \hat{\Psi}$$

$$\text{and } \hat{u}_t = P^{-1/2} M' (\hat{F}_t - \hat{A} \hat{F}_{t-1}).$$

Remark 1 When applying the Kalman filter, we set to zero the off-diagonal elements of the estimated covariance matrix of the idiosyncratic since they are poorly estimated if n , the dimension of the panel, is large. However, assumptions A1 and A2 ensure that even under such restriction the factors can be consistently estimated.

Remark 2 The estimates of the factors in the second step are more efficient since the Kalman filter performs the best linear projection on the present and past observations.

Remark 3 In practice, the procedure outlined above is applied to standardized data, and then the sample mean and the sample standard deviation are reattributed accordingly.

Remark 4 Since the r -dimensional factors F_t are assumed to have a VAR representation, the q common shocks are fundamental; i.e., they can be recovered from the present and past of the r factors. Notice that, since $r \gg q$, our assumption is weaker than the assumption of the fundamental nature of the q -dimensional common shocks u_t with respect to any two of the factors, or any couple of common components. In particular, the common shocks u_t are in general a function not only of the present and past but also of the future of any couple of common components (see Forni et al., 2003).

6.2 The Dataset

Series:	Transformation	Variance explained by DPC		
		1	2	3
1 Index of IP: total	3	0.88	0.93	0.94
2 Index of IP: final products and non-industrial supplies	3	0.83	0.90	0.92
3 Index of IP: final products	3	0.78	0.86	0.89
4 Index of IP: consumer goods	3	0.70	0.79	0.83
5 Index of IP: durable consumer goods	3	0.73	0.80	0.83
6 Index of IP: nondurable consumer goods	3	0.33	0.47	0.59
7 Index of IP: business equipment	3	0.75	0.81	0.84
8 Index of IP: materials	3	0.84	0.89	0.93
9 Index of IP: materials, nonenergy, durables	3	0.79	0.85	0.90

(continued)

Series:	Transformation	Variance explained by DPC		
		1	2	3
10 Index of IP: materials, nonenergy, nondurables	3	0.78	0.82	0.85
11 Index of IP: mfg	3	0.87	0.92	0.94
12 Index of IP: mfg, durables	3	0.83	0.88	0.92
13 Index of IP: mfg, nondurables	3	0.67	0.73	0.80
14 Index of IP: mining	3	0.21	0.54	0.64
15 Index of IP: utilities	3	0.12	0.27	0.45
16 Index of IP: energy, total	3	0.24	0.45	0.57
17 Index of IP: nonenergy, total	3	0.89	0.93	0.95
18 Index of IP: motor vehicles and parts (MVP)	3	0.44	0.55	0.62
19 Index of IP: computers, comm. equip., and semiconductors (CCS)	3	0.35	0.47	0.58
20 Index of IP: nonenergy excl CCS	3	0.90	0.93	0.94
21 Index of IP: nonenergy excl CCS and MVP	3	0.89	0.92	0.93
22 Capacity utilization: total	2	0.89	0.93	0.94
23 Capacity utilization: mfg	2	0.90	0.93	0.94
24 Capacity utilization: mfg, durables	2	0.87	0.91	0.93
25 Capacity utilization: mfg, nondurables	2	0.78	0.83	0.86
26 Capacity utilization: mining	2	0.25	0.56	0.65
27 Capacity utilization: utilities	2	0.20	0.32	0.50
28 Capacity utilization: computers, comm. equip., and semiconductors	2	0.45	0.56	0.61
29 Capacity utilization: mfg excl CCS	2	0.90	0.93	0.94
30 Purchasing Managers Index (PMI)	0	0.86	0.88	0.90
31 ISM mfg index: production	0	0.83	0.87	0.89
32 Index of help-wanted advertising	3	0.77	0.83	0.87
33 No. of unemployed in the civ. labor force (CLF)	3	0.74	0.82	0.85
34 CLF employed: total	3	0.72	0.76	0.82
35 CLF employed: nonagricultural industries	3	0.70	0.74	0.80
36 Mean duration of unemployment	3	0.60	0.67	0.71
37 Persons unemployed less than 5 weeks	3	0.48	0.56	0.64
38 Persons unemployed 5 to 14 weeks	3	0.68	0.74	0.78
39 Persons unemployed 15 to 26 weeks	3	0.63	0.73	0.77
40 Persons unemployed 15+ weeks	3	0.70	0.77	0.80
41 Avg weekly initial claims	3	0.72	0.81	0.83

(continued)

Series:	Transform- ation	Variance explained by DPC		
		1	2	3
42 Employment on nonag payrolls: total	3	0.85	0.91	0.93
43 Employment on nonag payrolls: total private	3	0.85	0.92	0.93
44 Employment on nonag payrolls: goods- producing	3	0.87	0.93	0.94
45 Employment on nonag payrolls: mining	3	0.21	0.46	0.54
46 Employment on nonag payrolls: construction	3	0.61	0.72	0.78
47 Employment on nonag payrolls: manufacturing	3	0.85	0.92	0.93
48 Employment on nonag payrolls: manufacturing, durables	3	0.86	0.92	0.93
49 Employment on nonag payrolls: manufacturing, nondurables	3	0.68	0.78	0.83
50 Employment on nonag payrolls: service-producing	3	0.70	0.76	0.84
51 Employment on nonag payrolls: utilities	3	0.08	0.21	0.59
52 Employment on nonag payrolls: retail trade	3	0.59	0.67	0.78
53 Employment on nonag payrolls: wholesale trade	3	0.66	0.78	0.83
54 Employment on nonag payrolls: financial activities	3	0.31	0.32	0.52
55 Employment on nonag payrolls: professional and business services	3	0.51	0.65	0.71
56 Employment on nonag payrolls: education and health services	3	0.19	0.26	0.42
57 Employment on nonag payrolls: leisure and hospitality	3	0.39	0.48	0.57
58 Employment on nonag payrolls: other services	3	0.32	0.39	0.59
59 Employment on nonag payrolls: government	3	0.25	0.36	0.45
60 Avg weekly hrs. of production or nonsupervisory workers ("PNW"): total private	3	0.49	0.61	0.65
61 Avg weekly hrs of PNW: mfg	3	0.57	0.65	0.70
62 Avg weekly overtime hrs of PNW: mfg	3	0.65	0.70	0.74
63 ISM mfg index: employment	3	0.70	0.77	0.80

(continued)

Series:	Transform- ation	Variance explained by DPC		
		1	2	3
64 Sales: mfg and trade—total (mil of chained 96\$)	3	0.71	0.77	0.83
65 Sales: mfg and trade—mfg, total (mil of chained 96\$)	3	0.76	0.82	0.87
66 Sales: mfg and trade—merchant wholesale (mil of chained 96\$)	3	0.53	0.60	0.70
67 Sales: mfg and trade—retail trade (mil of chained 96\$)	3	0.33	0.47	0.58
68 Personal cons. expenditure: total (bil of chained 96\$)	3	0.47	0.63	0.71
69 Personal cons. expenditure: durables (bil of chained 96\$)	3	0.36	0.53	0.62
70 Personal cons. expenditure: nondurables (bil of chained 96\$)	3	0.30	0.48	0.56
71 Personal cons. expenditure: services (bil of chained 96\$)	3	0.41	0.55	0.61
72 Personal cons. expenditure: durables—MVP—new autos (bil of chained 96\$)	3	0.19	0.42	0.57
73 Privately-owned housing, started: total (thous)	3	0.53	0.62	0.71
74 New privately-owned housing authorized: total (thous)	3	0.55	0.65	0.73
75 New 1-family houses sold: total (thous)	3	0.42	0.52	0.62
76 New 1-family houses—months supply at current rate	3	0.34	0.43	0.55
77 New 1-family houses for sale at end of period (thous)	3	0.46	0.51	0.57
78 Mobile homes—mfg shipments (thous)	3	0.45	0.55	0.61
79 Construction put in place: total (in mil of 96\$) (1)	3	0.48	0.61	0.71
80 Construction put in place: private (in mil of 96\$)	3	0.56	0.65	0.74
81 Inventories: mfg and trade: total (mil of chained 96\$)	3	0.65	0.70	0.76
82 Inventories: mfg and trade: mfg (mil of chained 96\$)	3	0.59	0.68	0.72
83 Inventories: mfg and trade: mfg, durables (mil of chained 96\$)	3	0.59	0.67	0.71
84 Inventories: mfg and trade: mfg, nondurables (mil of chained 96\$)	3	0.36	0.47	0.55
85 Inventories: mfg and trade: merchant wholesale (mil of chained 96\$)	3	0.30	0.39	0.49

(continued)

Series:	Transform- ation	Variance explained by DPC		
		1	2	3
86 Inventories: mfg and trade: retail trade (mil of chained 96\$)	3	0.48	0.61	0.67
87 ISM mfg index: inventories	0	0.74	0.79	0.86
88 ISM mfg index: new orders	0	0.84	0.86	0.87
89 ISM mfg index: suppliers deliveries	0	0.64	0.72	0.78
90 Mfg new orders: all mfg industries (in mil of current \$)	3	0.67	0.76	0.84
91 Mfg new orders: mfg industries with unfilled orders (in mil of current \$)	3	0.45	0.54	0.63
92 Mfg new orders: durables (in mil of current \$)	3	0.65	0.74	0.79
93 Mfg new orders: nondurables (in mil of current \$)	3	0.43	0.61	0.73
94 Mfg new orders: nondefense capital goods (in mil of current \$)	3	0.36	0.48	0.57
95 Mfg unfilled orders: all mfg industries (in mil of current \$)	3	0.55	0.62	0.72
96 NYSE composite index	3	0.27	0.41	0.51
97 S&P composite	3	0.26	0.41	0.50
98 S&P P/E ratio	3	0.44	0.56	0.63
99 Nominal effective exchange rate	3	0.15	0.37	0.46
100 Spot Euro/US (2)	3	0.15	0.39	0.48
101 Spot SZ/US	3	0.15	0.36	0.47
102 Spot Japan/US	3	0.17	0.32	0.43
103 Spot UK/US	3	0.11	0.28	0.40
104 Commercial paper outstanding (in mil of current \$)	3	0.41	0.49	0.56
105 Interest rate: federal funds rate	2	0.57	0.72	0.78
106 Interest rate: U.S. 3-mo Treasury (sec. market)	2	0.53	0.73	0.79
107 Interest rate: U.S. 6-mo Treasury (sec. market)	2	0.51	0.73	0.79
108 Interest rate: 1-year Treasury (constant maturity)	2	0.48	0.72	0.78
109 Interest rate: 5-year Treasury (constant maturity)	2	0.39	0.65	0.75
110 Interest rate: 7-year Treasury (constant maturity)	2	0.37	0.63	0.75
111 Interest rate: 10-year Treasury (constant maturity)	2	0.33	0.61	0.74
112 Bond yield: Moodys AAA corporate	2	0.36	0.59	0.71

(continued)

Series:	Transformation	Variance explained by DPC		
		1	2	3
113 Bond yield: Moodys BAA corporate	2	0.30	0.54	0.69
114 M1 (in bil of current \$)	3	0.15	0.30	0.51
115 M2 (in bil of current \$)	3	0.17	0.26	0.59
116 M3 (in bil of current \$)	3	0.07	0.19	0.52
117 Monetary base, adjusted for reserve requirement (rr) changes (bil of \$)	3	0.09	0.24	0.36
118 Depository institutions reserves: total (adj for rr changes)	3	0.09	0.24	0.43
119 Depository institutions: nonborrowed (adj for rr changes)	3	0.17	0.30	0.47
120 Loans and securities at all commercial banks: total (in mil of current \$)	3	0.30	0.38	0.58
121 Loans and securities at all comm banks: securities, total (in mil of \$)	3	0.31	0.39	0.47
122 Loans and securities at all comm banks: securities, U.S. govt (in mil of \$)	3	0.46	0.53	0.61
123 Loans and securities at all comm banks: real estate loans (in mil of \$)	3	0.41	0.51	0.60
124 Loans and securities at all comm banks: comm and Indus loans (in mil of \$)	3	0.39	0.47	0.59
125 Loans and securities at all comm banks: consumer loans (in mil of \$)	3	0.44	0.49	0.62
126 Delinquency rate on bank-held consumer installment loans (3)	3	0.18	0.28	0.39
127 PPI: finished goods (1982 = 100 for all PPI data)	4	0.34	0.67	0.75
128 PPI: finished consumer goods	4	0.29	0.62	0.71
129 PPI: intermediate materials	4	0.50	0.72	0.80
130 PPI: crude materials	4	0.15	0.33	0.43
131 PPI: finished goods excl food	4	0.40	0.66	0.78
132 Index of sensitive materials prices	4	0.53	0.60	0.67
133 CPI: all items (urban)	4	0.55	0.76	0.85
134 CPI: food and beverages	4	0.31	0.52	0.61
135 CPI: housing	4	0.55	0.69	0.78
136 CPI: apparel	4	0.20	0.43	0.52
137 CPI: transportation	4	0.30	0.49	0.68
138 CPI: medical care	4	0.51	0.66	0.70
139 CPI: commodities	4	0.33	0.63	0.76
140 CPI: commodities, durables	4	0.25	0.54	0.63
141 CPI: services	4	0.51	0.67	0.75

(continued)

Series:	Transformation	Variance explained by DPC		
		1	2	3
142 CPI: all items less food	4	0.51	0.70	0.82
143 CPI: all items less shelter	4	0.43	0.72	0.82
144 CPI: all items less medical care	4	0.53	0.75	0.84
145 CPI: all items less food and energy	4	0.57	0.74	0.81
146 Price of gold (\$/oz) on the London market (recorded in the p.m.)	4	0.14	0.54	0.64
147 PCE chain weight price index: total	4	0.45	0.77	0.85
148 PCE prices: total excl food and energy	4	0.37	0.66	0.72
149 PCE prices: durables	4	0.28	0.54	0.65
150 PCE prices: nondurables	4	0.37	0.65	0.78
151 PCE prices: services	4	0.28	0.52	0.60
152 Avg hourly earnings: total nonagricultural (in current \$)	4	0.21	0.45	0.57
153 Avg hourly earnings: construction (in current \$)	4	0.22	0.45	0.55
154 Avg hourly earnings: mfg (in current \$)	4	0.16	0.42	0.58
155 Avg hourly earnings: finance, insurance, and real estate (in current \$)	4	0.16	0.40	0.55
156 Avg hourly earnings: professional and business services (in current \$)	4	0.23	0.35	0.51
157 Avg hourly earnings: education and health services (in current \$)	4	0.25	0.38	0.49
158 Avg hourly earnings: other services (in current \$)	4	0.22	0.36	0.50
159 Total merchandise exports (FAS value) (in mil of \$)	3	0.34	0.50	0.60
160 Total merchandise imports (CIF value) (in mil of \$) (NSA)	3	0.43	0.57	0.66
161 Total merchandise imports (customs value) (in mil of \$)	3	0.35	0.46	0.54
162 Philadelphia Fed business outlook: general activity (5)	0	0.76	0.83	0.86
163 Outlook: new orders	0	0.70	0.77	0.81
164 Outlook: shipments	0	0.68	0.73	0.78
165 Outlook: inventories	0	0.50	0.59	0.64
166 Outlook: unfilled orders	0	0.73	0.76	0.79
167 Outlook: prices paid	0	0.40	0.65	0.82
168 Outlook: prices received	0	0.40	0.62	0.82
169 Outlook employment	0	0.77	0.81	0.84
170 Outlook: work hours	0	0.72	0.76	0.81

(continued)

Series:	Transform- ation	Variance explained by DPC		
		1	2	3
171 Federal govt deficit or surplus (in mil of current \$)	0	0.08	0.17	0.27
172 Real GDP	3	0.63	0.74	0.77
173 GDP deflator	4	0.44	0.71	0.79

0: no transformation. X_t

1: logarithm. $\log(X_t)$

2: quarterly differences. $(1 - L^3)X_t$

3: quarterly growth rates. $400(1 - L^3) \log(X_t)$

4: quarterly difference of yearly growth rates. $(1 - L^3)(1 - L^{12}) \log(X_t)$

Notes

We thank the Division of Monetary Affairs of the Federal Reserve Board for hosting this project and providing partial funding. In particular, we are indebted to David Small for helpful suggestions and Ryan Michaels for helping in the construction of the data set. Thanks are also due to Athanasios Orphanides, Barbara Rossi, Philippe Weil, and Mike Woodford as well as our discussants, Harald Uhlig and Mark Watson, and to participants at the NBER Macroeconomic Annual 2004 conference.

1. Greenbook data can be obtained from the Web site of the Philadelphia Fed: www.phil.frb.org/econ/forecast/greenbookdatasets.html.

2. These estimates are computed on data aggregated at the quarterly level.

3. For the project at the Board of Governors of the Federal Reserve, on which the present paper is based, we have used a formal analysis to select q and found it to be 2.

4. This percentage is above 80% if we concentrate on business-cycle frequencies.

5. Real-time data, organized in vintages, have been obtained from the Philadelphia Fed Web site: www.phil.frb.org/econ/forecast/reindex.html.

6. The fact that we use revised data should not affect our results because revision errors are typically series specific and hence have negligible effects when we extract the two common factors. The robustness of the pseudo real-time exercise has been demonstrated by Bernanke and Boivin (2003).

7. For a definition of identification conditions and other technical aspects of the model, see Forni, Hallin, Lippi, and Reichlin (2002); Stock and Watson (2002).

8. We apply the criterion of Bai and Ng (2000) for the sample 1970:1–1988:12. This criterion is very sensible to different specifications of the penalty term but suggests a quite large value of r . We select $r = 10$ and find that results are robust over larger values. This is explained by the fact that the methodology is robust if we select a static rank higher than the true one, provided that the dynamic rank, q , is well specified. On this point, see Forni, Giannone, Lippi, and Reichlin (2004).

9. The Kalman filter step improves on the principal component estimator proposed by Stock and Watson (2002) by allowing us to take into explicit account the dynamics of the

panel. An alternative strategy, in the frequency domain, is that followed by Forni, Hallin, Lippi, and Reichlin (2002).

10. As for the factor model, we use the real-time series of the GDP deflator.

11. Confidence intervals have been computed by bootstrap methods, as we did in Giannone, Reichlin, and Sala (2002) and as in Forni et al. (2003).

12. The mean has been attributed to the two conditional histories according to the long-run variance decomposition. For GDP, this corresponds to 1 to the real shock and 0 to the nominal; for the federal funds rate, .67 and .33, respectively; for the deflator, .8 and .2, respectively.

13. To isolate the effects of the shocks from the difference arising from the estimation of the parameters, we estimate the model at time T_1 and keep the same parameters to compute the signal at time T_2 .

14. The Ljung-Box Q-statistic at lag 1 on the idiosyncratic components of the federal funds rate is 1.2, with a p-value of 0.27. The statistic is also not significant for a higher lag.

15. This is not a surprising result since, if all real variables had contemporaneous conditional dynamics and so did nominal variables, we would have found the dynamic rank to be equal to the static rank, i.e., $r = q$.

References

- Atekeson, A., and L. E. Ohanian. (2001). Are Phillips curves useful for forecasting inflation? *Federal Reserve Bank of Minneapolis Quarterly Review* 25:2–11.
- Bai, J., and S. Ng. (2000). Determining the number of factors in approximate factor models. *Econometrica* 70:191–221.
- Bernanke, B. S., and J. Boivin. (2003). Monetary policy in a data rich environment. *Journal of Monetary Economics* 50:525–546.
- Blanchard, O. J., and D. Quah. (1989). The dynamic effects of aggregate demand and supply disturbances. *American Economic Review* 79:654–673.
- Brayton, F., J. M. Roberts, and J. C. Williams. (1999). What's happened to the Phillips curve? *Board of Governors of the Federal Reserve, Finance and Economics Discussion Series* 1999/49.
- Brillinger, D. R. (1981). *Time Series: Data Analysis and Theory*. San Francisco: Holden-Day.
- Clarida, R., J. Galí, and M. Gertler. (2000). Monetary policy rules and macroeconomic stability: Evidence and some theory. *Quarterly Journal of Economics* 115:147–180.
- Croushore, D., and T. Stark. (1999). A real-time data set for macroeconomists: Does the data vintage matter? *Review of Economics and Statistics*, forthcoming.
- Diebold, F. X., and G. Rudebusch. (1991). Forecasting output with the composite leading index: A real-time analysis. *Journal of the American Statistical Association* 86:603–610.
- Evans, C. L. (1998). Real-time Taylor rules and the federal funds futures market. *Chicago Fed Economic Perspectives* 2.
- Forni, M., D. Giannone, M. Lippi, and L. Reichlin. (2004). Opening the black box: Identifying shocks and propagation mechanisms in VAR and factor models. www.dynfactors.org.

- Forni, M., M. Hallin, M. Lippi, and L. Reichlin. (2000). The generalized factor model: Identification and estimation. *The Review of Economics and Statistics* 82:540–554.
- Forni, M., M. Hallin, M. Lippi, and L. Reichlin. (2002). The generalized dynamic factor model: One-sided estimation and forecasting. CEPR Working Paper No. 3432.
- Giannone, D., L. Reichlin, and L. Sala. (2002). Tracking Greenspan: Systematic and unsystematic monetary policy revisited. CEPR Working Paper No. 3550.
- Goodfriend, M. (2002). The phases of U.S. monetary policy: 1987 to 2001. *Economic Quarterly*. Federal Reserve Bank of Richmond.
- Orphanides, A. (2001). Monetary policy rules based on real-time data. *American Economic Review* 91:964–985.
- Orphanides, A. (2003). Historical monetary policy analysis and the Taylor rule. *Journal of Monetary Economics* 50:983–1022.
- Orphanides, A., R. D. Porter, D. L. Reifschneider, R. J. Tetlow, and F. Finan. (2000). Errors in the measurement of the output gap and the design of monetary policy. *Journal of Economics and Business* 52:117–141.
- Orphanides, A., and S. Van Norden. (2002). The unreliability of output gap estimates in real time. *The Review of Economics and Statistics* 84:569–583.
- Romer, C., and David H. Romer. (1994). What ends recessions? *NBER Macroeconomics Annual* 9:13–57.
- Rudebusch, G. D. (2001). Term structure evidence on interest rate smoothing and monetary policy inertia. *Journal of Monetary Economics* 49:1161–1187.
- Rudebusch, G. (2002). Assessing nominal income rules for monetary policy with model and data uncertainty. *Economic Journal* 112:402–432.
- Sargent, T. J., and C. A. Sims. (1977). Business cycle modelling without pretending to have much *a priori* economic theory. In *New Methods in Business Research*, C. Sims (ed.). Minneapolis: Federal Reserve Bank of Minneapolis.
- Soderlind, P., U. Soderstrom, and A. Vredin. (2003). Taylor rules and the predictability of interest rates. Sveriges Riksbank Working Paper Series No. 247.
- Staiger, D., J. H. Stock, and M. W. Watson. (1997). The NAIRU, unemployment, and monetary policy. *Journal of Economic Perspectives* 11:33–49.
- Stock, J. H., and M. W. Watson. (1999). Forecasting inflation. *Journal of Monetary Economics* 44:293–335.
- Stock, J. H., and M. W. Watson. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics* 40:147–162.
- Svensson, L. E. O. (2003). What is wrong with Taylor rules? Using judgment in monetary policy through targeting rules. *Journal of Economic Literature* 41:426–477.
- Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy* 39:195–214.
- Taylor, J. B. (1999). *Monetary policy rules*. Chicago, IL: University of Chicago Press.
- Uhlig, H. (2003). What moves real GDP? Humboldt University. Unpublished Manuscript.

Comment

Harald Uhlig
Humboldt University, CentER,
Bundesbank, and CEPR

This paper holds an enticing promise. Start from the observation that Taylor rules work well to explain the observed paths for the federal funds rate. Add to that the insight of recent research on macroeconomic factors, that a large share of the movements in the main aggregates of the economy can be explained by only a few, perhaps two, fundamental forces or shocks; see, for example, Forni et al. (2000), Stock and Watson (2002), Uhlig (2003), and the paper at hand. Consider that it may be more appealing to state Taylor rules in terms of forecasts of the output gap and inflation rate, and note that macroeconomic factor models are good for providing forecasts. Then you get the promise that this paper holds: to understand monetary policy choices or to conduct monetary policy, pay attention to the macroeconomic factors and the two key shocks driving their movements.

This promise is enticing, because monetary policy needs to make its choices in a "data-rich environment" (Bernanke and Boivin, 2003). Ordinarily, one would need to pay attention to each bit of the plethora of information in the many time series observable by the policymaker and consider how to react to it. Similarly, analysts of monetary policy need to sift through the many influences on monetary policy to see why and when interest rates move. But equipped with the factor analysis in this paper, one can reduce and organize this wealth of information into a few key shocks only, which then warrant most of the attention. The rest is idiosyncratic noise, which one should not ignore entirely but which is of small residual importance. The techniques in the paper at hand show how to construct the relevant factors and to assess their impact on the key macroeconomic aggregate in real time, i.e., in terms of the data available to policymakers at decision time.

This discussion is organized around this promise. I agree that the factor model works remarkably well for forecasting inflation, output

growth, and the federal funds rate. I also agree that the main macroeconomic aggregates seem to be driven to a considerable degree by two shocks only: this indeed is an important insight. But I caution against the promise described above, which a reader of Giannone, Reichlin, and Sala's paper might take away all too easily as the implied conclusion. To show why I think this promise is problematic, I shall ask and answer three questions.

1. Do Taylor Rules Fit Because of Dimension Two?

Figure 1 shows a simple benchmark Taylor rule, estimated by regressing the federal funds rate on a constant, lagged inflation and the deviation of lagged log gross domestic product (GDP) from its five-year moving average (as a crude measure of the output gap), using quarterly data from 1971 to 2001. The R^2 is 0.60.

Giannone, Reichlin, and Sala (GRS) view these regressors as well as the federal funds rate as part of a panel x_t of macroeconomic time series, driven by ten macroeconomic factors F_t , which in turn are driven by two shocks u_t , plus noise ζ_t :

$$x_t = \Lambda F_t + \zeta_t$$

$$F_t = A F_{t-1} + B u_t$$

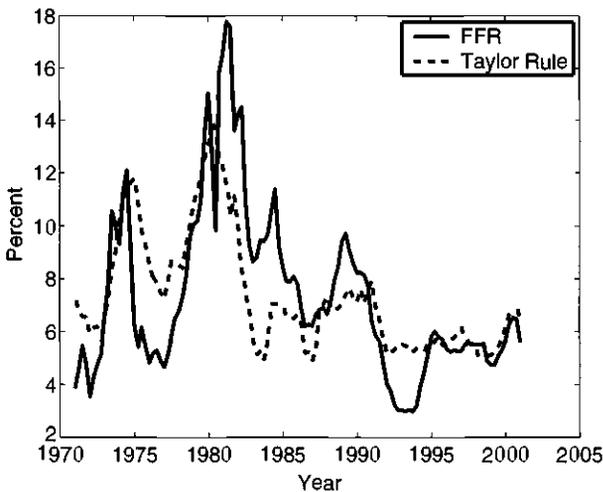


Figure 1

Taylor Rule, estimated with lagged CPI inflation and lagged log GDP minus its five-year moving average, quarterly data

Hence, the static dimension is ten, whereas the dynamic dimension is two. With this, instead of regressing the federal funds rate r_t on some measure of the output gap g_t and inflation π_t , it would seem to be more direct to regress the federal funds rate on the factors F_t , in particular as one can thereby avoid the noise component ξ_t in the regressors.

But in contrast to what one may be led to believe by GRS, this does not improve matters. First, while the original Taylor rule gets by with just two regressors, the first two factors alone provide a pretty bad fit (the R^2 is just 0.07), and even with all ten factors, the picture does not look great. See Figure 2: the R^2 increases to just 0.20.

Part of the reason for the bad fit seems to be that the factors are calculated with, for example, the first differences of interest rates, so they may be more informative about changes in the federal funds rate than its level. Thus, Figure 3 uses both the factors as well as their cumulative sums as regressors. This does not change the dynamic dimension since the two-dimensional shock vector u_t still suffices to explain also the evolution of the cumulative sums, but it does double the number of regressors. With two factors (and thus four regressors), one obtains an R^2 of 0.74, while with all ten factors (and thus twenty regressors), R^2 is 0.94, and one obtains nearly perfect fit. Of course, with twenty regressors, this may not be very surprising. Note that my results here are consistent with the results of Table 2 in their paper, where, for example, the first two dynamic principal components can explain 72% of the variance of the first difference of the federal funds rate, and additional regressors would presumably be needed also to get the level of the federal funds rate right. My results are also consistent with Section

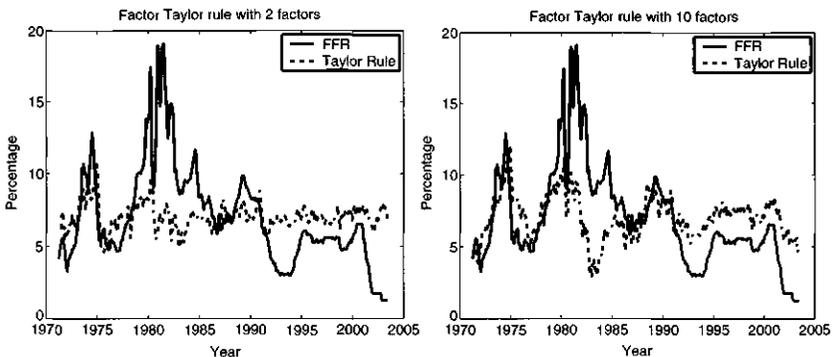


Figure 2
Taylor Rule, estimated with the first two respectively all ten factors

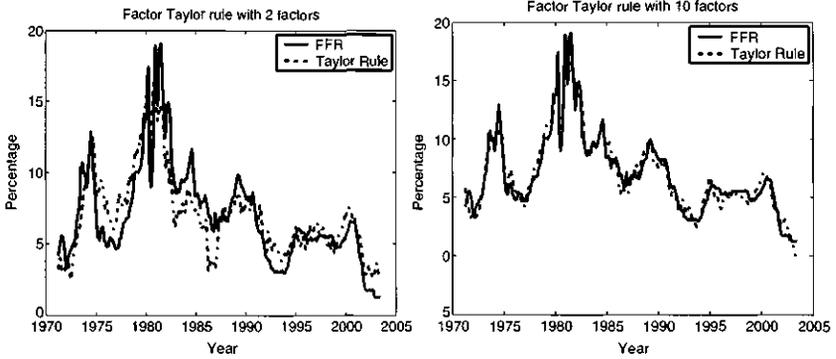


Figure 3

Taylor Rule, estimated with the first two respectively all ten factors plus their cumulative sums

4 of GRS, which concentrates not on the original federal funds rate series, but on that part of the federal funds rate series that can be explained with the real or the nominal factors, discarding the possibly more important noise of the federal funds rate factor regression.

What the exercise above shows is that a two-dimensional shock u_t does not imply at all that a Taylor rule with two regressors closely related to these u_t will fit well. Since F_t is ten-dimensional, and is thus recording lagged u_t 's as well, it would in fact be surprising if all this rather complicated dynamics of the two underlying shocks could be folded into just two macroeconomic time series, output and inflation. So the fact that the original Taylor rule fits so well may have little to do with the issue that the dynamic dimension of the economy is two. Instead, it is plausible that something else is going on: simple Taylor rules fit well because monetary policy cares about the output gap and inflation. Typical theoretical derivations of optimal monetary policy often have that feature; see, for example, Woodford, 2003 (And if not, one could try to identify those macroeconomic aggregates that the monetary policymaker cares about: it is these aggregates, not the factors, that should show up in Taylor rules of well-chosen monetary policy). Thus, there is a good chance that the noise component ζ_t in the output gap and inflation is of similar or even greater importance for monetary policy than the movements of the underlying factors. The two-factor model in turn also fits reasonably well because two factors suffice to fit the bulk of the cyclical dynamics in output and inflation. However, since the noise part ζ_t is missing in the factor model, the fit is worse.

To illuminate this, consider the original Taylor rule:

$$r_t = \alpha + \beta g_t + \gamma \pi_t + \varepsilon_t$$

and suppose that the output gap g_t and inflation π_t have a particularly simple dependence on two factors, which in turn have a particularly simple dynamic structure:

$$g_t = \lambda_g F_{1t} + \xi_{gt}$$

$$\pi_t = \lambda_\pi F_{2t} + \xi_{\pi t}$$

$$F_{1t} = u_{1t}$$

$$F_{2t} = u_{2t}$$

Assume that all innovations $\varepsilon_t, u_{1t}, u_{2t}, \xi_{gt}$, and $\xi_{\pi t}$ have zero mean and are mutually orthogonal. If the Taylor rule is recalculated using the factors, one obtains:

$$r_t = \alpha + (\beta \lambda_g) F_{1t} + (\gamma \lambda_\pi) F_{2t} + v_t$$

where

$$v_t = \beta \xi_{gt} + \gamma \xi_{\pi t} + \varepsilon_t$$

has a higher variance than ε_t , and the fit is therefore worse than the original Taylor rule. If the factors even have a dynamic structure, for example:

$$F_{1t} = a_1 F_{1,t-1} + u_{1t}$$

$$F_{2t} = a_2 F_{2,t-1} + u_{2t}$$

the best-fitting factor Taylor rule would now be:

$$r_t = \alpha + (\beta \lambda_g) F_{1t} - (a_1 \beta \lambda_g) F_{1,t-1} + (\gamma \lambda_\pi) F_{2t} - (a_2 \gamma \lambda_\pi) F_{2,t-1} + v_t$$

The fit is just as bad as for the factor Taylor rule in the simple specification above, but now four rather than two regressors are required in the factor Taylor rule, just to keep up with the original specification.

These arguments (plus the arguments in the third section below) provide good intuition for the findings above. In sum, a two-factor Taylor rule *does* work. But it is worse, not better, than the original output-gap-and-inflation Taylor rule. It is the original Taylor rule that captures the essence of the underlying economic logic, and the factor model just happens to provide a statistically good fit, not the other way around, as GRS may lead a reader to believe.

The key assumption in the arguments above is the orthogonality of ε_t to ξ_{gt}^z and $\xi_{\pi t}^z$. If it was the case, for example, that v_t is orthogonal to ξ_{gt}^z and $\xi_{\pi t}^z$ in the simple specification above, with:

$$\varepsilon_t = v_t - (\beta \xi_{gt}^z + \gamma \xi_{\pi t}^z)$$

then obviously the factor Taylor rule would fit better. One way to interpret GRS is that they take this perspective and not the perspective of the preceding argument. To check which perspective is appropriate, one needs to investigate why the Fed deviates from the Taylor rule, i.e., to explain the movements in ε_t . Let me turn to this issue now.

2. Why Does the Fed Deviate from the Taylor Rule?

There is another reason to be interested in explaining the movements in the residual of the original Taylor rule, even if one buys into the argument by GRS, that simple Taylor rules work because the economy is two-dimensional. If all we get out is another Taylor rule, have we really learned much? Central bankers often assert that their job is considerably more complicated than just running a Taylor rule. Whether this is just a self-serving claim (or worse the result of faulty monetary policy analysis) or whether their job is really considerably more complex shall not be the issue discussed here (although I do believe the latter to be the case). Rather, we do observe empirically that gaps remain between actual federal funds rate choices and those implied by Taylor rules (see, for example, Figure 1). So the interesting issue is, What explains these deviations from the Taylor rule, and can the macroeconomic factors help to resolve these issues?

To answer this question, I have done the following. I calculate the Taylor rule residual as in Figure 1 but based on data from 1955 to 2001. I fit a Bayesian vector autoregression (VAR) in this residual as well as PPI inflation, industrial production, hours worked, capacity utilization, private investment, and labor productivity in manufacturing, using quarterly data from 1973 to 2001 and two lags. The goal shall be to explain as much as possible of the movement in the Taylor rule residual with as few different types of shocks as possible. Thus, in the seven-dimensional space of the one-step-ahead prediction errors, I find those two dimensions that explain most of the sum of the k -step ahead prediction revision variances for the Taylor rule residual. I explain the details of this methodology in Uhlig (2003), and they are similar to the

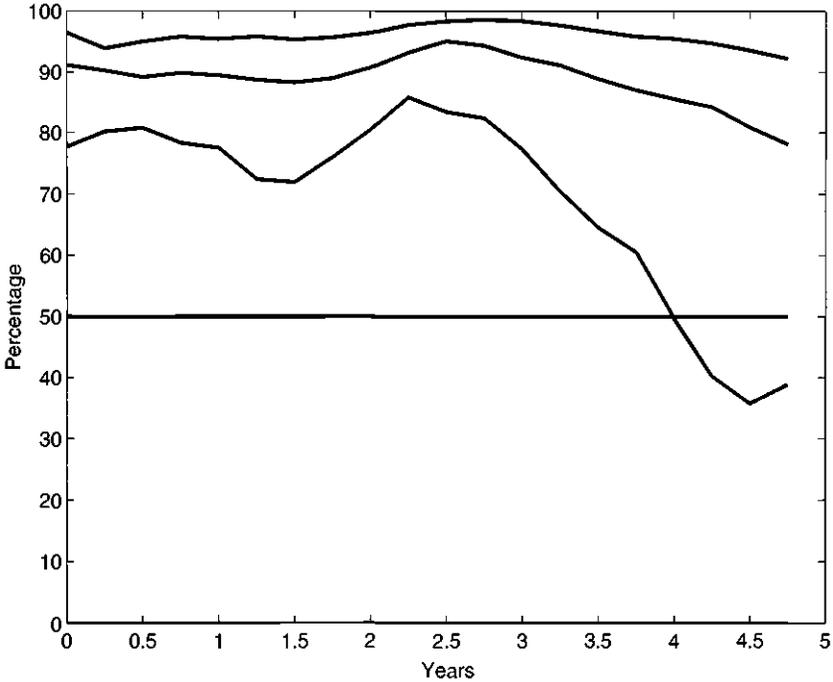


Figure 4
Fraction of the variance of the k -step ahead forecast revision for the Taylor rule residual, explained by two shocks in the seven-variable VAR with other economic variables

construction in GRS, Section 3.1, when they construct shocks to “explain the maximum of the variance of real variables in panel.”

I find the following. Two shocks can explain around 90% of the variance of the k -step-ahead prediction revision variance for all horizons k between 0 and five years (see Figure 4). The impulse response of the Taylor rule residual to the first shock is fairly persistent (see Figure 5) and coincides with movements of labor productivity in manufacturing in the opposite direction (see Figure 6). This suggests that the deviation here could be explained by a more subtle measurement of the output gap: the Fed sets interests rates higher than would be implied by the line calculated in Figure 1 because it sees output not supported by corresponding gains in productivity. And indeed, industrial production changes course from an initial expansion to a contraction within two years. The second shock looks like a quickly reverted error in interest rate policy (see Figure 7).

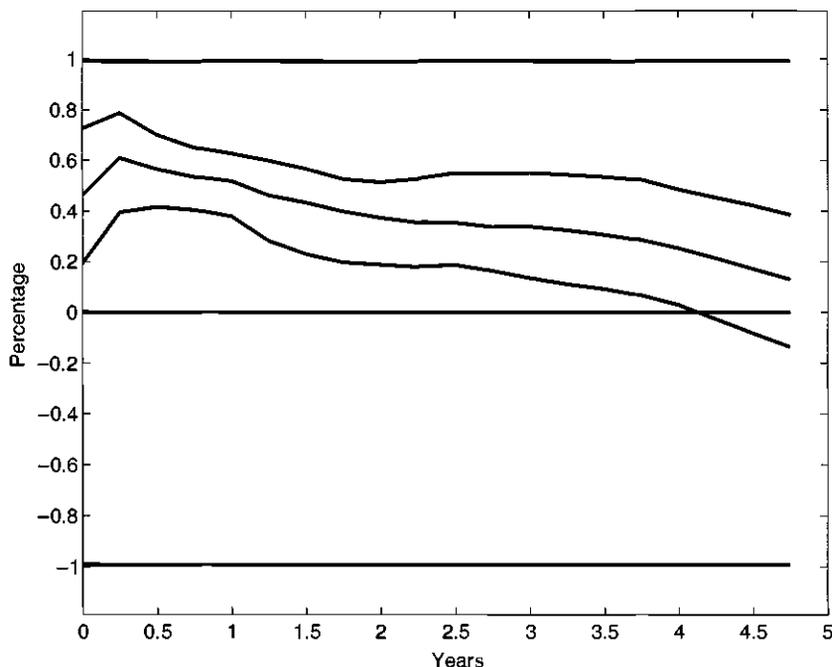


Figure 5
Impulse response of the Taylor rule residual to the first shock, $\theta = 0$

One can redo the same exercise using the ten factors in the VAR instead of the economic variables listed above. To obtain impulse responses for these variables, they can in turn be regressed on the VAR series and their innovations, plus their own lags. The results are now much less clear cut. First, the fraction of variance explained for the Taylor rule residual is not quite as high (see Figure 8). The impulse response of the Taylor rule residual to the first shock in Figure 9 seems to be in between the more persistent response of Figure 5 and the quick-error-reversal response in Figure 7. And the implied impulse responses of industrial production and productivity do not tell a clear-cut story (see Figure 10): industrial production has no clearly signed response, while productivity keeps expanding gradually.

This clinches the point made above: for monetary policy, the noise component of some key economic variables may be more important than the stochastic disturbances to the factors. The factors paint too coarse a picture to be a sufficiently precise guide to monetary policy or its analysis.

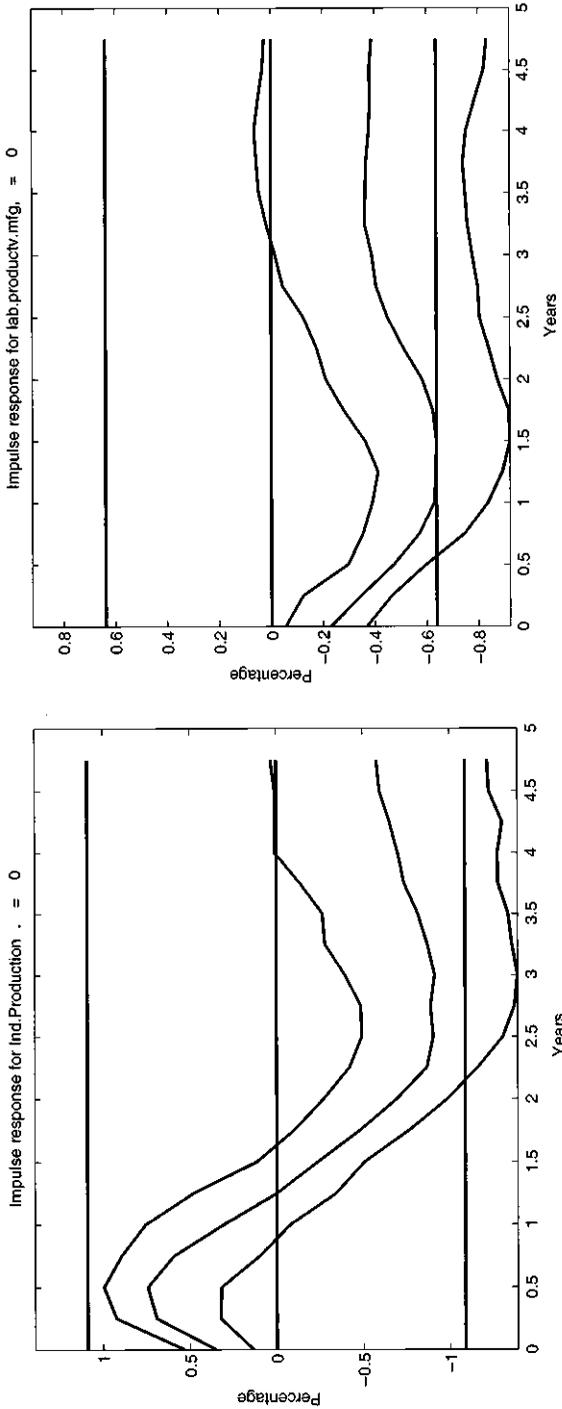


Figure 6
Impulse response of industrial production and labor productivity in manufacturing to the first shock, $\theta = 0$

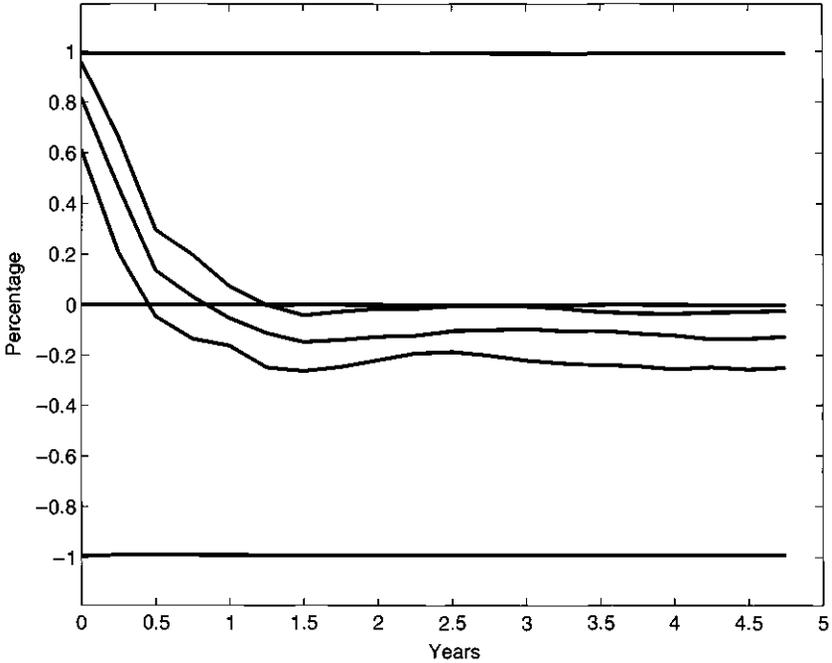


Figure 7
Impulse response of the Taylor rule residual to the second shock, $\theta = 90$

3. Do We Need to Worry About Causality?

At this point, a skeptical reader might point out that this discussion began with calculating factor Taylor rules with ten factors and their partial sums, and that they provided a nearly perfect fit. Shouldn't this be good news for an analysis of monetary policy, based on macroeconomic factors? But aside from factors capturing the economically relevant variables—the output gap and inflation—there is another reason that the Taylor rule estimated with all ten factors and their cumulative sums should fit well. The ten factors are the leading ten principal components of the variance-covariance matrix of a panel of macroeconomic time series. According to Table 1 in GRS, a substantial fraction of the variables included in the panel are closely related to monetary policy or are likely to react sensitively to changes in the federal funds rate. For example, the variables labeled as “financial markets,” “interest rates,” and “money and loans” count for 22% of the entire panel and probably an even higher fraction of the total variance. Since variance

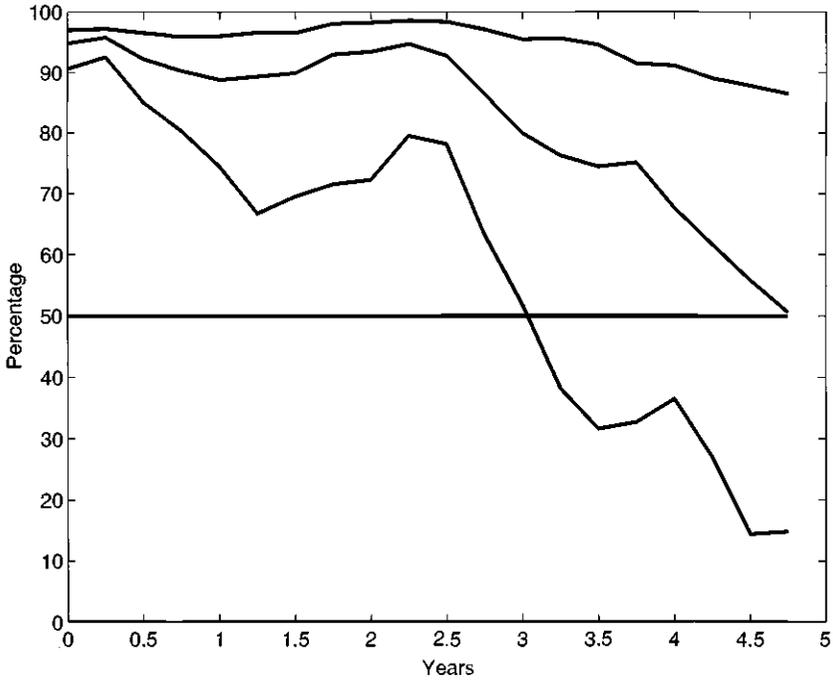


Figure 8
Fraction of the variance of the k -step ahead forecast revision for the Taylor rule residual, explained by two shocks in the eleven-variable VAR with ten factors

matters for the calculation of the principal components, the influence of these variables is likely to be even larger than 22%. So there is a sense in which the factor Taylor rules above or, likewise, the fraction of the variance in the federal funds rate explained by the factors as stated in the paper, are just regressions of the federal funds rate on itself.

Whether or not this is a problem hinges on whether or not one believes some monetary policy shocks are not explained by economic fundamentals. If there are none or if they are negligible, then the information contained in the movements of financial market variables just reflects the underlying economic fundamentals, and this appears to be the position the paper implicitly takes. Indeed, the paper gives an economic interpretation to the two shocks and views them as untainted by monetary policy shocks. A substantial fraction of the VAR literature on monetary policy can be read as supportive of this position.

On the other hand, if there are sizable monetary policy shocks, then the principal component shocks identified in the paper are likely to be

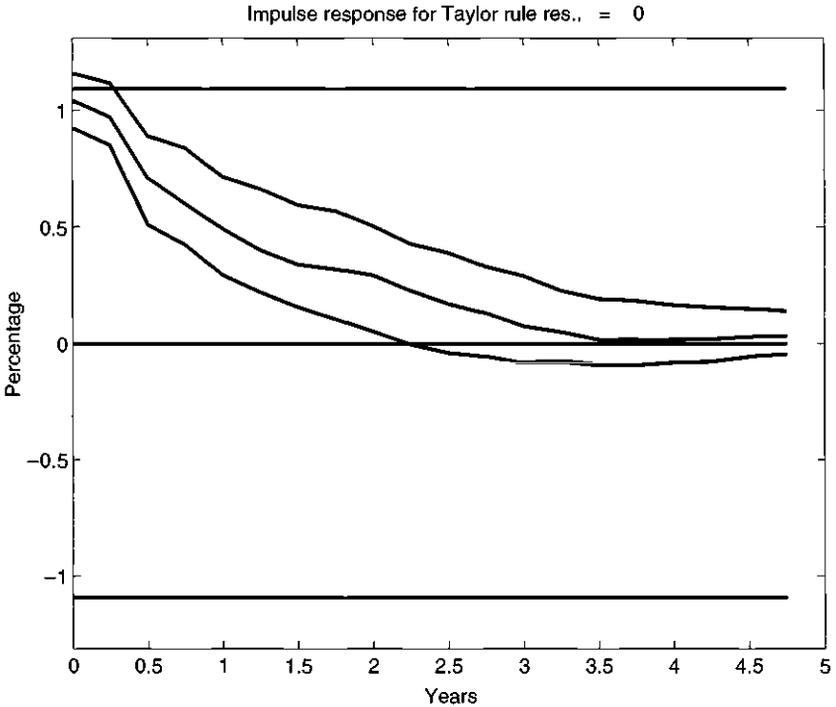


Figure 9

Impulse response of the Taylor rule residual to the first shock in the eleven-variable VAR with factors, $\theta = 0$

at least partly tainted by monetary policy shocks, or even to represent the monetary policy shocks themselves (when using some linear combination of the factor shocks). The 22% of the variables closely related or reacting sensitively to the federal funds rate then move in reaction to monetary policy choices, or even anticipate them, due to speeches, information released between federal open market committee (FOMC) meetings, etc., and so will the extracted factors. Even using factors extracted from data available before the FOMC meeting may just recover market expectations and echoes of previous Fed announcements. Analyzing the movements of the extracted factors thus will not be helpful for choosing interest rates or understanding these choices.

Another way to see this is to think about the information contained in futures. Table 5 in GRS shows that the root mean square error (RMSE) for futures/2-shocks is 0.47 for lead 0 and 0.76 for lead 1, so in terms of fitting monetary policy choices, one would do even better

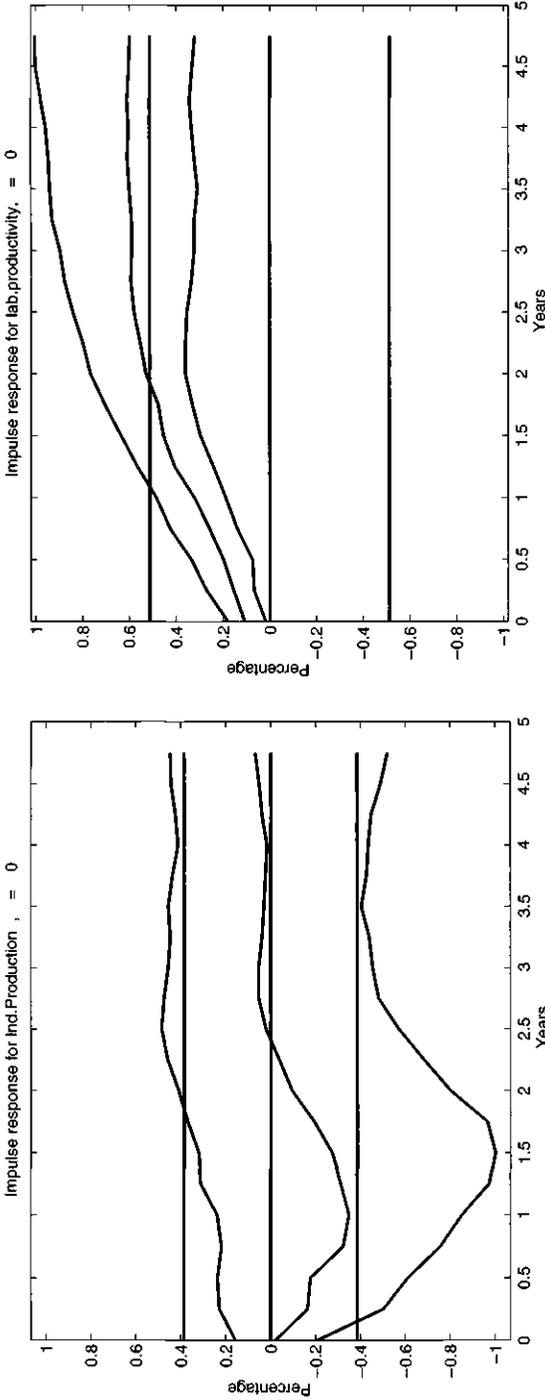


Figure 10 Implied impulse response of industrial production and labor productivity in manufacturing to the first shock in the eleven-variable VAR with factors, $\theta = 0$

with data on futures than with data on factors. But that does not imply that the Fed should follow what futures markets expect it to do nor is this of helpful guidance to the Fed; the futures presumably simply fit so well because they pay close attention to signals coming from the Fed about what it plans to do in the future, not the other way around. Thus, similarly, if the extracted factors contain market expectations about Fed policy, then the forecasts constructed with these factors for inflation and output growth rates are the resulting inflation rates and output growth rates, if the Fed fulfills these expectations. This is useful for monetary policy; for example, the Fed then can and should ask if it wants to deviate from these on-the-equilibrium-path expectations. But that does not answer the question about where these expectations came from in the first place.

So if there are monetary policy shocks, then one would ideally seek to find factors and factor innovations which are causal to Fed choices and Fed announcements, both for conducting policy as well as for understanding Fed choices. This gets us into the usual VAR identification debates. This debate is assumed away in this paper by implicitly assuming that monetary policy shocks are too small or matter too little to be of relevance to the extracted factors.

4. Conclusion

Current thinking about monetary policy (as in Woodford [2003], for example) focuses on the output gap, inflation rates, and their forecasts and relates them to choices of the interest rate. Perhaps it is sensible and possible to write down theories in which the relevant economic variables for conducting monetary policy are factors or in which the right measure of the output gap corresponds to what GRS have captured with their factors. But a priori, I remain skeptical. What matters to monetary policy are rather specific variables and their rather specific own dynamics: the macroeconomic factors can be somewhat but not sufficiently informative about them. The noise component does matter.

Thus, I view the methodology provided by GRS mainly as a method to provide the Fed with on-the-equilibrium-path forecasts of output, inflation, and interest rates, i.e., as a forecast of the economy, provided the Fed follow market expectations. Where these expectations come from or what the fundamental forces are to which the Fed reacts requires additional substantive identifying assumptions (like the absence of monetary policy shocks), which one ought to be careful in making.

Despite all these skeptical remarks and despite the obligation of the discussant to describe what he or she disagrees with, it is also important to emphasize where the agreements are and to point out the achievements of GRS. Their paper has convincingly demonstrated that two shocks capture the main dynamics of a large number of macroeconomic aggregates. This is interesting and it is an important base on which to build macroeconomic theories, which emphasize few, not many, driving forces. GRS have also shown that interesting things can be done with these factors. I share their view that there is much more of a dichotomy between the real and the nominal side of the economy than is often believed, and that it may be feasible for monetary policy to concentrate on fighting inflation without having to worry too much about the real side of the economy. Excessive worries about real effects were the original reason that the Volcker disinflation came so late. The real impact of the disinflation turned out to be smaller than many anticipated (see the discussion in Cogley and Sargent, 2004). Excessive worries sometimes dominate monetary policy discussions also, especially in policy circles outside central banks. It is remarkably hard to justify these worries with a proper analysis of the data, as I have found in my own work (see Uhlig, 2004), and as GRS have also shown in their paper. It is time to use data rather than just conventional wisdom as a guide to monetary policy analysis and to take these results seriously.

References

- Bernanke, B. S., and Boivin, J. (2003). Monetary policy in a data rich environment. *Journal of Monetary Economics* 50:525–546.
- Cogley, T., and Sargent, T. (2004). The conquest of U.S. inflation: Learning and robustness to model uncertainty. New York University. Unpublished Manuscript.
- Forni, M., M. Hallin, M. Lippi, and L. Reichlin. (2000). The generalized factor model: Identification and estimation. *The Review of Economics and Statistics* 82:540–554.
- Stock, J. H., and M. W. Watson. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics* 40:147–162.
- Uhlig, H. (2003). What moves real GDP? Humboldt University. Unpublished Manuscript.
- Uhlig, H. (2004). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, forthcoming.
- Woodford, M. (2003). *Interest and prices: Foundations of a theory of monetary policy*. Princeton, NJ: Princeton University Press.

Comment

Mark W. Watson
Princeton University and
NBER

1. Introduction

This paper considers three questions. How many shocks are needed to explain the comovement of variables in the macroeconomy? What are these common shocks? And what are the implications of these findings for empirical characterizations of monetary policy rules?

The paper argues that very few shocks—only two—are needed. The authors arrive at this conclusion using three complimentary exercises. First, they apply large- n dynamic factor analysis methods to a data set that includes 200 representative macroeconomic time series over the 1970–2003 time period. A distributed lag of two shocks (the equivalent of two dynamic factors) explains a large fraction of the common variance in these series. Second, they apply similar methods to a panel of forecasts of fifteen important variables from the Fed's Greenbook over the 1978–1996 period. Again, it seems that much of the variance in these forecasts is explained by two shocks. Finally, the 2-shock/200-variable model is used to construct pseudo-real-time forecasts of the growth rate of real gross domestic product (GDP), the growth rate of the GDP deflator, and the federal funds interest rate over the 1989–2003 time period. Short-run forecasts based on the two-factor model perform well.

The authors identify the shocks as real and nominal. Real variables are driven by the real shock, inflation is driven by the nominal shock, and both shocks are important for the federal funds rate. These results, the authors argue, provide a mechanical explanation for why the Taylor rule provides a good description of the federal funds rate. The federal funds rate depends on two shocks, output growth is related to one of the shocks, inflation is related to the other; thus, a regression of the federal funds on output growth and inflation fits the data well.

In my comments, I will address each of these points. First, I will review empirical results from the 1970s on the fit of the two-factor model to see how the results have changed over time. Remarkably, the empirical results from the 1970s are nearly identical to the results found in this paper. Second, in some parts of the paper, the authors argue that inflation is driven by the nominal shock, output is driven by the real shock, and the two shocks are uncorrelated. This implies that movements in output and inflation are uncorrelated, a result that appears at odds with a large literature that documents a positive correlation between movements in output and inflation (the Phillips correlation). I will present results that reconcile the paper's finding of a weak correlation between output and inflation, with a larger and stable Phillips correlation. Finally, I offer a few remarks about the paper's two-factor explanation for the fit of the Taylor rule.

2. Can the U.S. Macroeconomy Be Summarized by Two Factors? A View from the 1970s

Rigorous statistical analysis of multifactor models in macroeconomics started with the work of Sargent and Sims (1977) and Geweke (1977). Indeed, Sargent and Sims considered many of the same empirical questions addressed in this paper, albeit with somewhat different methods and data. They used small- n frequency domain factor analysis and U.S. macroeconomic data from 1950–1970, while this paper uses large- n factor methods and data from 1970–2003. A comparison of the results in the two papers provides an assessment of the robustness of the results to the sample period and statistical method.

Table 1 shows the results from both papers on the fit of the two-factor model. The results are strikingly similar. One factor explains much of the variance of the real variables. The second factor adds little additional explanatory power for the real series. In contrast, nominal prices require two factors. In both papers, retail sales have more idiosyncratic variability than the other real series and only a small fraction of the variability of M1 is explained by the two factors. The only major difference between the two sets of results is for sensitive materials prices, a result that is not surprising given the dramatic swings in this series that occurred in the sample period used by Giannone, Reichlin, and Sala. In summary, the good fit of the two-factor model seems a remarkably stable feature of the postwar U.S. data.

Table 1
 Fraction of variance explained by one- and two-factor models

Series	Sargent and Sims ¹		Giannone, Reichlin, and Sala ²	
	1 factor	2 factors	1 factor	2 factors
Average weekly hours	0.77	0.80	0.49	0.61
Layoffs	0.83	0.85	0.72	0.82
Employment	0.86	0.88	0.85	0.91
Unemployment	0.77	0.85	0.74	0.82
Industrial production	0.94	0.94	0.88	0.93
Retail sales	0.46	0.69	0.33	0.47
New orders durables	0.67	0.86	0.65	0.74
Sensitive material prices	0.19	0.74	0.53	0.60
Wholesale prices	0.20	0.69	0.34	0.67
M1	0.16	0.20	0.15	0.30

1. From Table 21 of Sargent and Sims (1977).

2. From Appendix 6.2.

3. What Happened to the Phillips Correlation?

The positive correlation between real activity and inflation is one of the most well-known stylized facts in macroeconomics. Yet this correlation is not apparent in the scatter plots in Figure 4 of the paper, and the paper argues that output and inflation are largely reflections of independent sources of variability. Has the Phillips correlation vanished, or is it somehow masked in the factor model? The answer to both questions is no. Rather, many of the results in this paper highlight correlation over high frequencies (where the correlation is weak) instead of business-cycle frequencies (where the correlation is stronger).

In the spirit of the paper's analysis, I have constructed an estimate of the real factor and an estimate of the inflation factor. For the real factor, I use the XCI described in Stock and Watson (1989), which is a weighted average of the logarithm of real personal income, industrial production, manufacturing and trade sales, and employment. For the inflation factor I use a simple average of the inflation rates of the consumer price index, the producer price index, and the price deflator for personal consumption expenditures.

Figure 1 shows an estimate of the coherence between the two factors estimated using monthly data from 1960–2003.¹ Recall that the coherence is a frequency domain of correlation (adjusted for phase shifts),

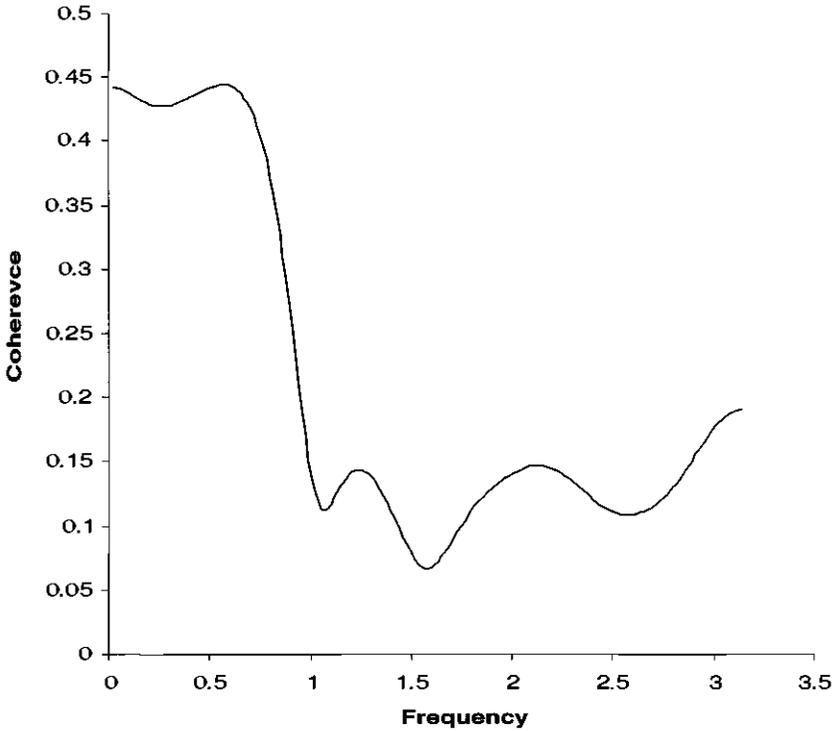


Figure 1
Coherence of output and inflation factors

so that, roughly speaking, the figure shows the correlation of the series over different frequencies. The coherence is approximately 0.45 for frequencies lower than 0.50 (periods longer than 12 months), but it is only 0.10 for frequencies higher than 1.0 (periods shorter than 6 months). Evidently, the series are very weakly correlated at high frequencies, but the correlation is substantially larger over business-cycle frequencies.

Figure 2 tells a similar story using the correlation of forecast errors constructed from a bivariate VAR of the two factors. Correlations are small for short horizons (less than 6 months), but they increase to values larger than 0.35 for horizons longer than 18 months.

Figures 1 and 2 show results for the 1960–2003 sample period, but similar results are obtained over the 1989–2003 period, the pseudo-out-of-sample period considered in this paper. Table 2 summarizes the results.

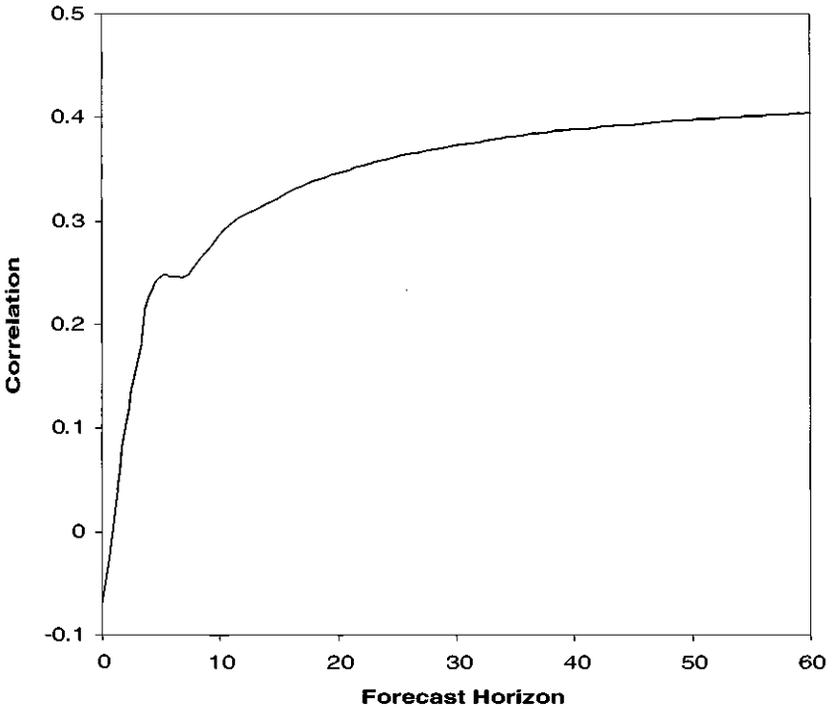


Figure 2
Correlation of output and inflation factor forecast errors

Table 2
Coherence and forecast error correlations

Sample period	Average coherence for periods		Correlation of forecast errors for forecast horizon			
	≤ 6	≥ 12	3	12	24	48
1960–2003	0.13	0.43	0.10	0.30	0.36	0.40
1989–2003	0.23	0.44	0.08	0.19	0.27	0.34

Note: These results are computed from estimated VAR(6) models using monthly data.

4. Using the Two-Factor Model to Rationalize the Fit of the Taylor Rule

If the two-factor model is correct, then the federal funds rate depends on two factors. The real factor is reflected in GDP, the nominal factor is reflected in inflation; thus, as the paper argues, it is reasonable that a Taylor rule specification should fit the data well. Yet the story is little more complicated. GDP growth and inflation are imperfect indicators of the underlying factors. The logic of the factor model then says that including (potentially many) other variables in the regression may significantly improve the fit of the Taylor rule because these additional variables help the regression estimate the factors. Indeed, this logic suggests that a better way to study the monetary policy rule is to use factor models like those developed in this paper and in the complementary analysis in Bernanke and Boivin (2003) and Giannone, Reichlin, and Sala (2002).

Note

1. The coherence was estimated from a VAR(6) model estimated from the first differences of the two factors. Similar results were found using different lag lengths in the VAR.

References

- Bernanke, B. S., and J. Boivin. (2003). Monetary policy in a data-rich environment. *Journal of Monetary Economics* 50:3.
- Geweke, J. (1977). The dynamic factor analysis of economic time series. In *Latent Variables in Socio-Economic Models*, D. J. Aigner and A. S. Goldberger (eds.). Amsterdam: North Holland, pp. 365–383.
- Giannone, D., L. Reichlin, and L. Sala. (2002). Tracking Greenspan: Systematic and unsystematic monetary policy revisited. ECARES, Universite Libre de Bruxelles, Manuscript.
- Sargent, T. J., and C. A. Sims. (1977). Business cycle modeling without pretending to have too much a-priori economic theory. In *New Methods in Business Cycle Research*, C. Sims et al. (eds.). Minneapolis: Federal Reserve Bank of Minneapolis.
- Stock, J. H., and M. W. Watson. (1989). New indexes of coincident and leading economic indicators. *NBER Macroeconomics Annual* 4:351–393.

Discussion

Lucrezia Reichlin commented on Harald Uhlig's discussion and pointed out that, as shown in his example, not any two aggregates were going to give as good a fit as output and inflation did in the Taylor rule. Inflation and output, she claimed, are very collinear with the rest of the economy and that was why one gets very good forecasting results by projecting on two shocks. She also believed that her forecasting results were very impressive since nobody in the vector autoregression (VAR) literature had gotten close to such results.

Reichlin also responded to Uhlig's concern about the fact that the authors mainly looked at the systematic part and not at the residuals. She said that their empirical work showed that the residual part, the nonsystematic part, was very small, which does not mean that the Federal Reserve always followed systematic output and inflation, as was seen in her example of the Russian crisis episode, but that on average one could explain the bulk of its actions by looking at the systematic part.

There was some discussion among the participants about Uhlig's reservations about the Phillips curve models. Michael Woodford stated that simple models of the Phillips curve relationship, even the ones that did not have any kind of important disturbances to them, were not going to imply that an increase in real activity should lead to the same increase in inflation. According to Woodford, the authors showed that there was a first type of shock that permanently increased real GDP and had little effect on inflation. If one interpreted that permanent increase in real GDP as also a productivity-driven increase in GDP, then one should not expect much effect on inflation. Then there was a second shock that had a big effect on inflation and could be interpreted as a disturbance orthogonal to a technology shock, which had a tempo-

rary effect both on the real activity and on inflation, which in turn was what a Phillips curve relationship implied.

Mark Gertler commented that in his opinion Uhlig's point was that even if one had a Phillips curve, the actual reduced-form correlation between output and inflation depended on how well the central bank was performing. He added that one might want to split the sample and look at pre- and post-1979, since in his view if the central bank was doing well, as was the case of the Federal Reserve from the mid-1990s, then the economy might not look very different from what a real business cycle model, with some qualifications, would predict. Reichlin remarked that although the lags in the Phillips curve might be coming from the effect of policy, and one way to tackle this problem was to look at subsamples, she believed that their forecasting results showed that if one ran the model through the whole period, on average, one tracked the federal funds rate well.

Several discussants expressed their view on the number of shocks needed to characterize the economy. Robert Gordon said that in his opinion the economy was characterized by three factors, although they could be reduced to two. The three original factors were the real factor, used also by the authors, that we observed in the form of the negative correlation between unemployment and output; nominal inflation, which was driven by the growth of money; and the supply shocks, which were used to solve the dilemma that sometimes output was negatively correlated with inflation, as in the case of an increase in oil prices, and other times this correlation was positive, as occurred when the economy was hit by a pure monetary shock as in the German hyperinflation. But if one used a simple model with a vertical long-run Phillips curve, a short-run positively sloped Phillips curve on the output-inflation space, a negatively sloped demand curve, and finally a policy response, then two shocks, demand and supply shocks, were enough to obtain the responses the authors were looking for. According to Matthew Shapiro, two real shocks were needed to fit most of the data. He argued that there were short-term productivity shocks and there were other shocks that moved the trend, either the growth rate of productivity or the NAIRU, and if one implemented a Taylor rule, one had to keep track of both the timeless and the time-variant parts of unemployment, so he wondered how the authors could get such good results with only one real shock. Reichlin answered these comments by saying that they had run different specifications of the

model, with two and three shocks, and found that the third shock was very small. She added that from the forecasting results they had shown, one did not seem to need a third shock to improve the forecasting of the model.

Jean Boivin stated that in one of his papers they found that to be able to track well the dynamic response of the economy, as the one obtained in a VAR setup, more than two factors were necessary. He then wondered about the size of the residuals in the policy rules of the authors and if the key for the difference in their results could be found there. Reichlin replied that she did not think that their results contradicted his since what she and her co-authors were saying was that, given that the dimension was roughly two, then the Taylor rule should be a good fit. This did not mean, she added, that one could not improve the Taylor rule, which could be done by writing the Taylor rule in terms of shocks, although in that case one might run into invertibility problems, as Mark Watson pointed out. Concerning the size of the residuals, she commented that when looking at the federal funds rate in first differences, medium-run frequencies, one could explain 80% of the variation, which meant that 20% of the variation was what they called unsystematic behavior and this led them to think that there was no other dimension.