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Monetary Policy in Real Time

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Abstract

We analyse the panel of the Greenbook forecasts (sample 1970-1996) and a large panel of monthly variables for the US (sample 1970-2003) and show that the bulk of dynamics of both the variables and their forecasts is explained by two shocks. Moreover, a two factor model which exploits, in real time, information on many time series to extract a two dimensional signal, produces a degree of forecasting accuracy of the federal funds rate similar to that of the markets, and, for output and inflation, similar to that of the Greenbook forecasts. This leads us to conclude that the stochastic dimension of the US economy is two. We also show that dimension two is generated by a real and nominal shock, with output mainly driven by the real shock and inflation by the nominal shock. The implication is that, by tracking any forecastable measure of real activity and price dynamics, the Central Bank can track all fundamental dynamics in the economy.

JEL subject classification : E52, E58, C33, C53

Key words and phrases : Taylor rules, real time analysis, monetary policy, forecasting, large datasets

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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 interaction 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, 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 systematically responds 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 US 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 Committe (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 4 draw implications on the form of the policy function. Section 5 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; and 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 the 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
IP	21	Wages	10
Capacity ut.	8	Import & Export	3
Labor mkts.	32	Surveys	12
Cons. Spending	13	Money & Loans	16
Inventories & Orders	15	Prices	28
Financial mkts.	16	Misc.	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 now-cast 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 $t = v-2, v-1, v, v+1, \cdots, v+4$. 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 dimensional linear combination of present, past, and future observations $k_q(L)x_{t|v}$ such that the following mean squared error is minimized:

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

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, $1/n \sum_i \mathrm{MSE}_i(q)$, 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 components[2], 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.

[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.

Table 2 Percentage of variance explained by the first five dynamic principal components on $x_{t|2003Q4}$ - 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
Pers. Cons. Exp.	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
Ind. Prod. Index	0.88	0.93	0.94	0.95	0.96
Cap. Util. Rate	0.89	0.93	0.94	0.95	0.96
GDP Implicit Defl	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

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.

Table 3 Percentage of variance explained by the first five dynamic principal components on $z_{t|v}$

	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

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

These results tell us that, in order 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. (2001) 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].

Table 4 Percentage of variance explained by the first two dynamic principal components on $z_{t|v}$- 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
Pers cons exp	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
Bus fixed inv	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
Gov cons and inv	0.28	0.34	0.36	0.42	0.50	0.41	0.32
Unemp rate	0.74	0.74	0.76	0.77	0.78	0.87	0.87
Ind prod index	0.76	0.71	0.72	0.80	0.85	0.86	0.84
Cap util rate	0.74	0.75	0.83	0.85	0.79	0.85	0.83
GDP implicit defl	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
Compens 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

In their seminal paper, Sargent and Sims (1977) used a panel of eleven monthly time series from 1950 to 1970 for the US economy. They obtained a result similar to what we found in this paper and in Giannone, Reichlin and Sala (2003) for a large panel of US quarterly data from 1970 to 2003. The two-shocks finding appears to be a robust result, at least for the U.S. economy.

2.1 Forecasting output, inflation, and 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

[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.

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 becasue each vintage has missing data informations 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:

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

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, $\Lambda = [\Lambda'_1, ..., \Lambda'_n]'$ 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 $\mathrm{E}(\xi_{t|v}\xi'_{t|v}) = \Psi$. 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),

[5] Real time data, organized in vintages, have been obtained from the Philadelphia Fed Web site: *www.phil.frb.org/econ/forecast/reaindex.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, 2001 and Stock and Watson, 2002.

[8] We apply the criterion of Bai and Ng (2002) 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).

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 A). 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:

$$x_{it|v} = C_i(L)u_t + \xi_{t|v} = c_{i1}(L)u_{1t} + c_{i2}(L)u_{2t} + \xi_{t|v} \tag{2.1}$$

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

Appendix A details 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 $(x_{1|v}, x_{2|v}, \ldots, x_{v|v})'$ to apply the Kalman filter on the state-space model to obtain:

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

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 missing values corresponding to data not yet released. We write the model as:

$$\tilde{x}_{t|v} = \Lambda F_t + \xi_{t|v}$$
$$F_t = AF_{t-1} + Bu_t$$

where

[9] The Kalman filter step improves on the principal component estimator proposed by Stock and Watson, 2002 by allowing 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.

$$
\begin{aligned}
\mathrm{E}(\xi^2_{i,t|v}) \quad = \tilde{\psi}_{it|v} \quad &= \quad \psi_i \qquad \text{if } x_{it|v} \text{ is available} \\
&= \quad \infty \qquad \text{if } x_{it|v} \text{ is not available}
\end{aligned}
$$

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

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 the last available number of the federal funds rate and inflation at the date in which the forcast 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 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,

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

the Greenbook has similar performance to the random walk, as noticed by Atkeson and Ohanian (2001). In general, the factor model outperforms the SPF 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 short horizons 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. Altough that model achieves a good in-sample fit, it does very poorly in forecasting (see, for example, Rudebusch, 2001; Soderlind, Soderstrom, and Vredin, 2003)

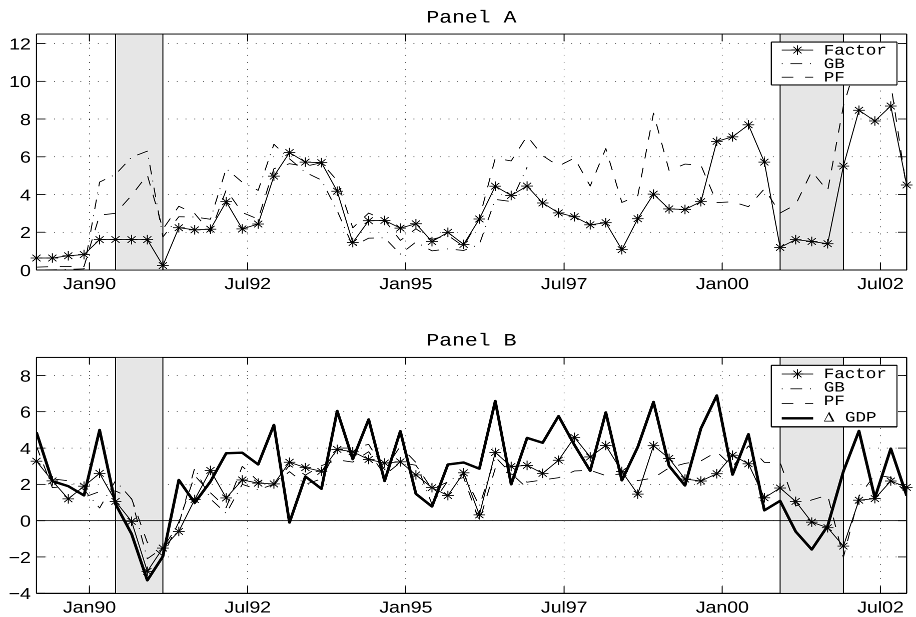
Table 5 Forecast Comparison: RMSE

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
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	-	-	-

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.

Figure 1: **Forecasting GDP growth rate**



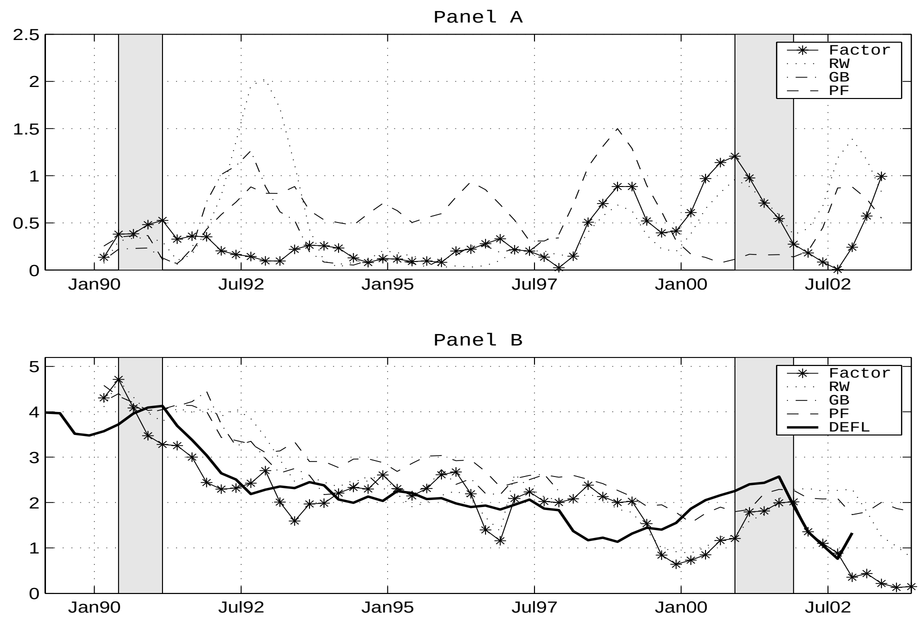
Let us make the following observations:

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

- Concerning inflation, the two-factors model does well in detecting the decline that followed the 1990 recession. In addition, unlike the SPF, the model does not over-estimate inflation in the 1990s (overprediction of inflation during this period has been noted by Brayton, Robertsa 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

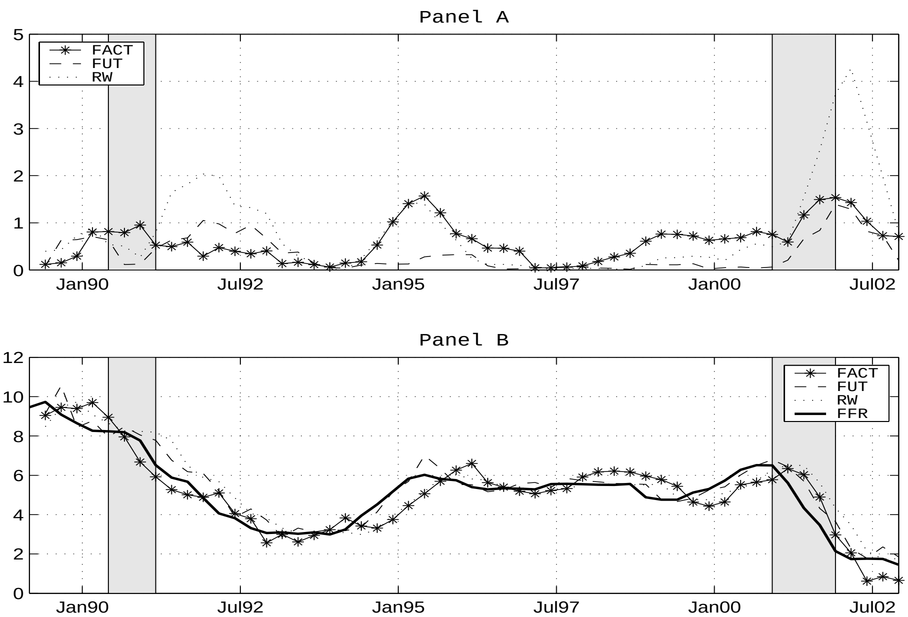
Figure 2: **Forecasting inflation**



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.

Figure 3: **Tracking Greenspan**



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:

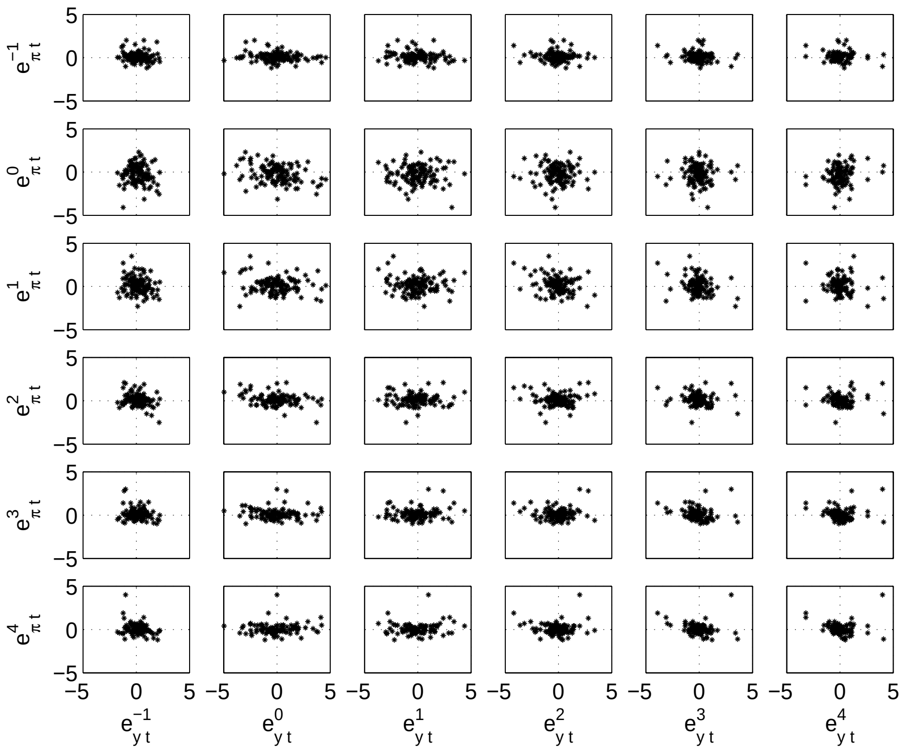
$$z_{it+h|t+1} - z_{it+h|t} = e_{it}^h$$

where $h = -1, 0, 1, \cdots, 4$. For $h = -1$ and $h = 0$, we have errors on revisions, while for $h = 1, \cdots, 4$ 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 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 in Romer and Romer (2000) 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

Figure 4: **Correlation of inflation and output Greenbook forecast errors**



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

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

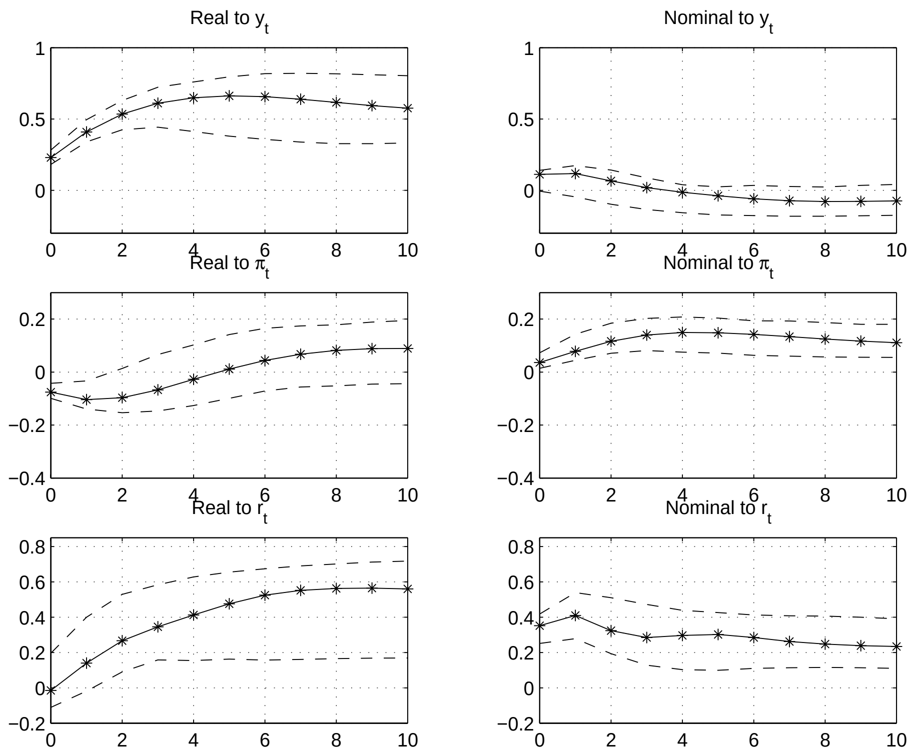
where J_R is the set containing the positions of the real variables in the panel.

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].

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

[12] The sample mean has been attributed to the two conditional histories according to the long run

Figure 5: **Impulse Response Functions**



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

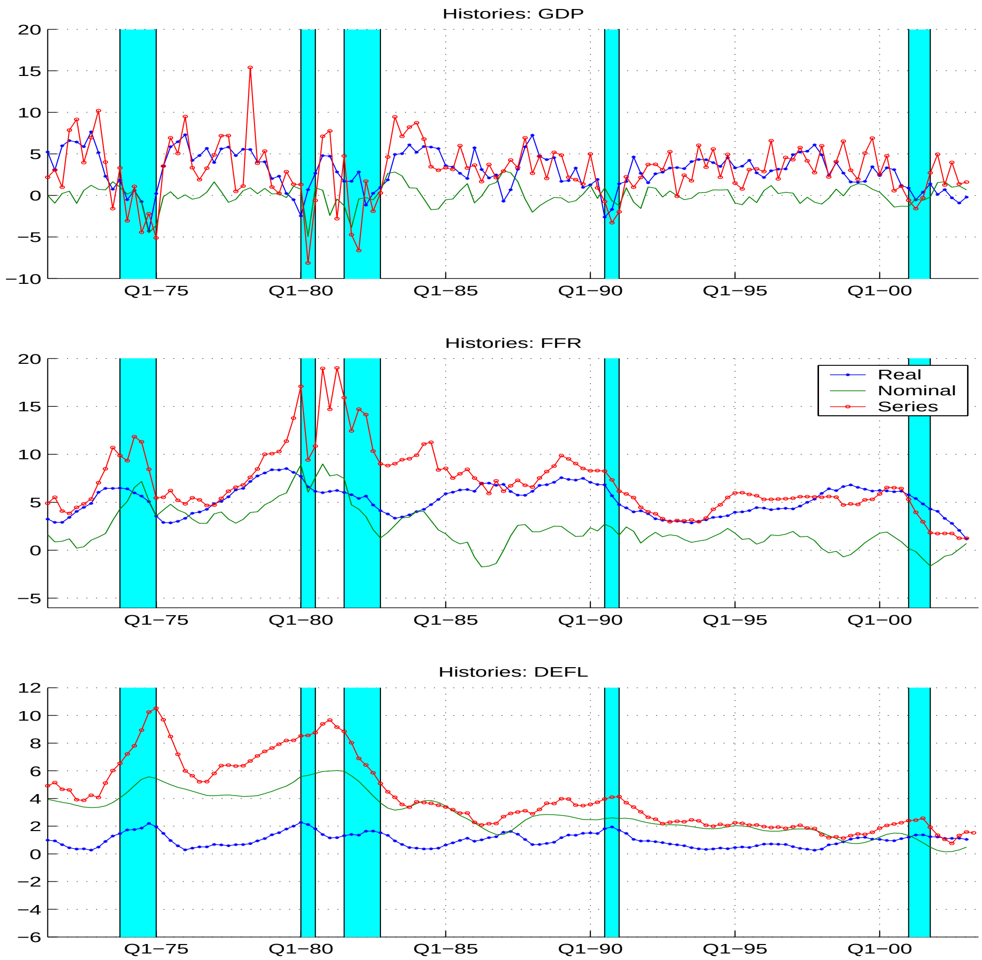
- Even though this is not the focus of the paper, note that neither of the two shocks can be identified as a monetary policy shock. This is justified by two findings: one of the two shocks is permanent on output, the second moves inflation and the federal funds rate in the same direction. For further analysis on this point, see 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.

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.

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



- 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 (2.1).

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:

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

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:

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

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., $d_1(L)u_{1,T_1+1} + d_2(L)u_{1,T_1+1}$.

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.

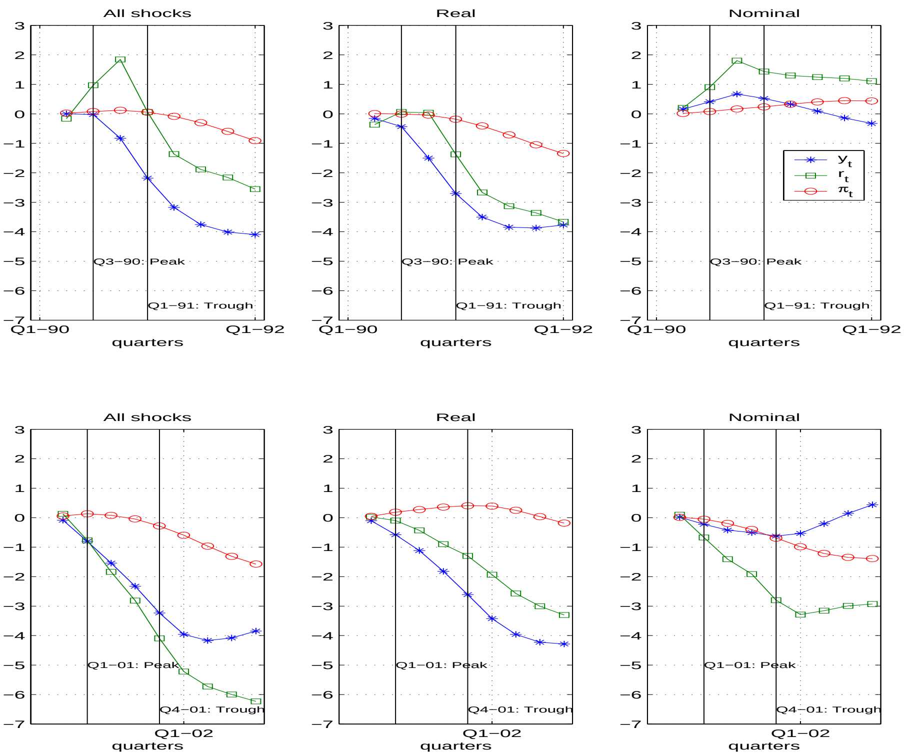
We report selected episodes: the two recessions in our sample and two episodes of "inflation scares". From left to right, the plots in Figures 7 and 8 must be read as: i) unconditional impulses on output, the federal funds rate and inflation; ii) impulses conditional on the permanent shock for the same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

Here is what emerges from the analysis:

- *Recessions.*

[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.

Figure 7: **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.

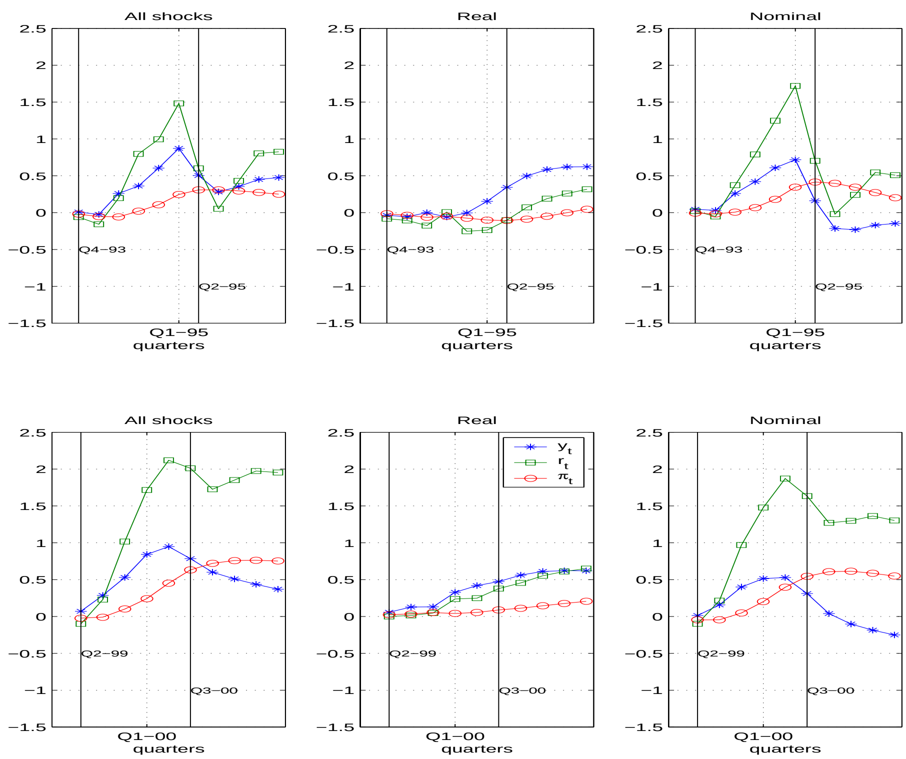
2. *2001Q1-2001Q4.* The real shock is also the driving force for this recession. Inflation dynamics is driven by the nominal shock. Inflation continues to decline, conditionally on that shock, even after the recovery has started. The federal funds rate moves aggressively with output during the recession,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

Figure 8: **Inflation scares**



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.

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 "non-fundamental" 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] .

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

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).

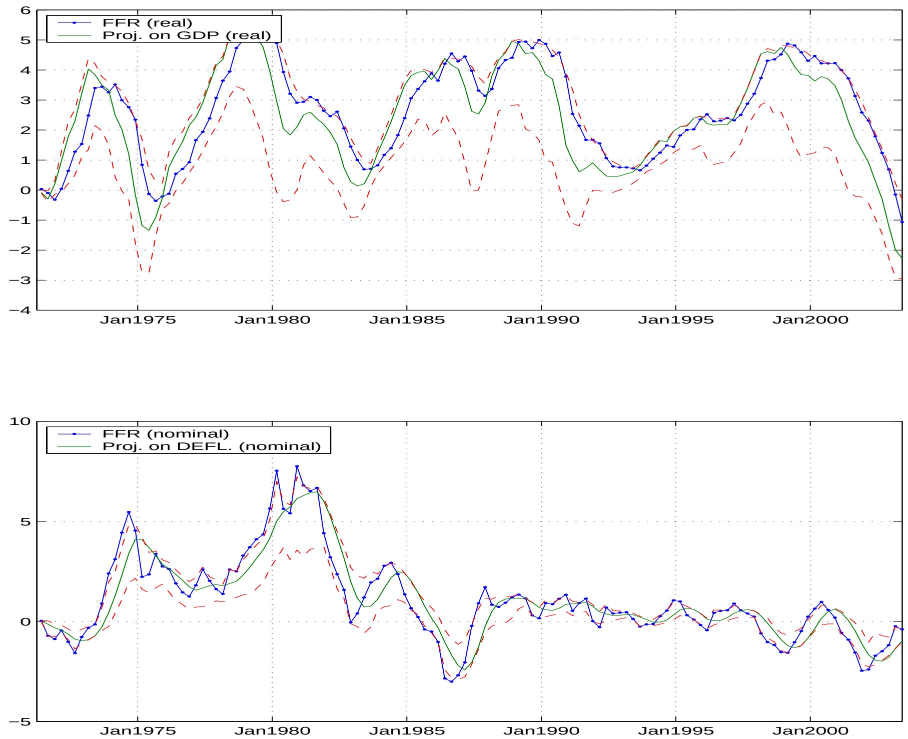
We have obtained two sets of fits – nominal and real – and constructed 10% lower and upper bands by excluding, at each t, the 20% of extreme points (10% lower and 10% upper). The upper quadrant of Figure 9 reports the bands as well as the projection of the federal funds rate on GDP and the federal funds 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 variables) 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.

[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., $r = q$.

Figure 9: **Taylor fits**

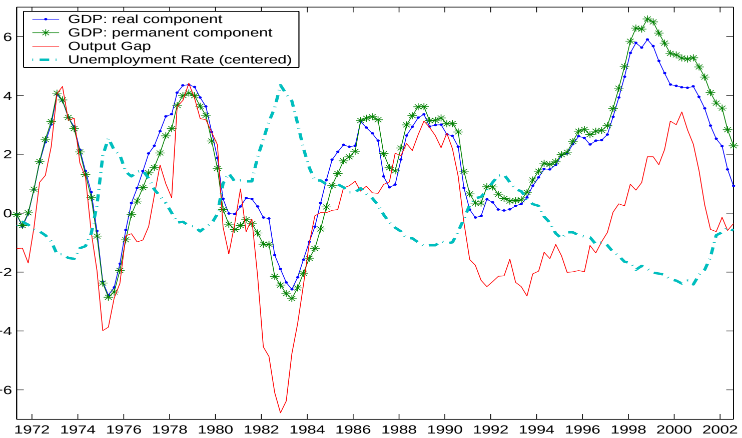


From an ex-ante perspective, one possible interpretation of our results is that the Fed, instead of tracking two particular variables such as a version of measured output gap and inflation, follows a "robust policy", moving when all real variables (and among them GDP) move and all nominal variables (and 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 unforecastable idiosyncratic variance from output and inflation, making use of information contained in a large coss-section 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 not perfectly aligned and 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.

Figure 10: **The output gap, (centered) unemployment rate, the permanent component of output, output generated by the real shock**



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 consequence, 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; 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 nonsystematc 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 at 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.

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Appendices

A Econometrics

Consider the model:

$$x_t = \Lambda F_t + \xi_t$$
$$F_t = AF_{t-1} + Bu_t$$
$$u_t \sim WN(0, I_q)$$
$$\mathrm{E}(\xi_t \xi_t') = \Psi$$

where

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

$\Lambda = [\Lambda_1', ..., \Lambda_n']'$ 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 $\det(\mathrm{I_r} - \mathrm{Az})$ lie outside the unit circle

ξ_t is the n-dimensional stationary linear process

We make two assumptions.

A1. Common factors are pervasive:

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

A2. Idiosyncratic factors are nonpervasive:

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

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:

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

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 $n, T \to \infty$ (Forni et al., 2003).

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

$$\hat{F}_t = \text{Proj}[F_t \mid x_1', \ldots, x_T'],\ t = 0, 1, \ldots, t+h$$

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

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

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

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

$$\text{E}(\xi_t \xi_{tv}') = \text{diag}\hat{\Psi}$$

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

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 $r >> q$, 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).

B The Dataset

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. $1200(1 - L^3)(1 - L^{12})\log(X_t)$

	Series	Transformations	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
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: Non-energy, 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: Non-energy excl CCS	3	0.90	0.93	0.94
21	Index of IP: Non-energy 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
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: lesiure 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

(Continued)

	Series	Transformations	Variance explained by DPC:		
			1	2	3
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
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: Durable - New autos (bil of chained 96$)	3	0.19	0.42	0.57
73	Privately-owned housing, started: Total (thous)	3	0.53	0.62	0.71
74	New privately-owned housing authorized: Total (thous)	3	0.55	0.65	0.73
75	New 1-family houses sold: Total (thous)	3	0.42	0.52	0.62
76	New 1-family houses – months supply @ current rate	3	0.34	0.43	0.55
77	New 1-family houses for sale at end of period (thous)	3	0.46	0.51	0.57
78	Mobile homes – mfg shipments (thous)	3	0.45	0.55	0.61
79	Construction put in place: Total (in mil of 96$) (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
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 indusries w/ 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
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 @ all commercial banks: Total (in mil of current $)	3	0.30	0.38	0.58
121	Loans and Securities @ all comm banks: Securities, total (in mil of $)	3	0.31	0.39	0.47
122	Loans and Securities @ all comm banks: Securities, U.S. govt (in mil of $)	3	0.46	0.53	0.61
123	Loans and Securities @ all comm banks: Real estate loans (in mil of $)	3	0.41	0.51	0.60
124	Loans and Securities @ all comm banks: Comm and Ind loans (in mil of $)	3	0.39	0.47	0.59
125	Loans and Securities @ 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

(Continued)

	Series	Transformations	Variance explained by DPC:		
			1	2	3
141	CPI: services	4	0.51	0.67	0.75
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
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