(Un)Predictability and Macroeconomic Stability*

Antonello D'Agostino
(ECARES, Université Libre de Bruxelles)

Domenico Giannone
(ECARES, Université Libre de Bruxelles)

Paolo Surico
(University of Bari)

October 2005

Abstract

This paper documents a new stylized fact of the U.S. greater macroeconomic stability of the last two decades or so. Using 131 monthly time series, three popular statistical methods and the forecasts of the Federal Reserve's Green book and the Survey of Professional Forecasters, we show that the ability of predicting several measures of inflation and real activity, *relative* to naive forecasts, declined remarkably across most models and horizons since the mid-1980s. This fact appears to reflect a prominent feature of the recent observations and thus represents a new challenge for competing explanations of the 'Great Moderation'.

JEL Classification: E37, E47, C22, C53.

Keywords: predictive accuracy, macroeconomic stability, forecasting models, sub-sample analysis, Fed Green book.

*We are grateful to Jan Groen and Christoph Schleicher for helpful suggestions. The views expressed in this paper are those of the authors, and do not necessarily reflect those of the Bank of England or the Monetary Policy Committee. Address for correspondence - Antonello D'Agostino: ECARES, Université Libre de Bruxelles - CP 114 - av. Jeanne, 44, B-1050, Brussels, Belgium. E-mail: adagosti@ulb.ac.be; Domenico Giannone: ECARES, Université Libre de Bruxelles - CP 114 - av. Jeanne, 44, B-1050, Brussels, Belgium. E-mail: dgiannon@ulb.ac.be; Paolo Surico: Monetary Assessment and Strategy, Bank of England, Threadneedle street - EC2R 8AH - London, United Kingdom. E-mail: paolo.surico@bankofengland.co.uk

1 Introduction

The behaviors of inflation and output in the United States were characterized by two major episodes over the postwar history. The first episode is a period of large volatility and high persistence that extends from the early 1970s to the mid-1980s. The second episode is associated with far more stable and erratic paths of inflation and output protracting from the second half of the 1980s to the present day. This stylized fact, documented by Kim and Nelson (1999), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001) and Cogley and Sargent (2002), is often referred to as the 'Great Moderation' and appears a robust feature of the macroeconomic landscape manifesting itself across a wide number of sectors and countries (see Stock and Watson, 2003).

The U.S. Great Moderation is one of the most investigated and debated topic in macroeconomics. Its popularity derives from the fact that alternative interpretations of that event bring about fairly different policy implications (see Bernanke, 2004 for a critical overview of this literature). If the decline in the volatility and persistence of inflation and output was simply the result of a more benign macroeconomic environment in the form of smaller shocks, then there is nothing which can prevent the 1970s to happen again, and we can only hope that the good luck will persist in the future. In contrast, if monetary policy can be held responsible for the large volatility of the 1970s and the beginning of the 1980s, then inspecting the policy decision process could disclose important insights for avoiding to repeat the mistakes of the past.

Despite a voluminous empirical literature, a consensus on the most likely cause of the Great Moderation has not emerged yet in the profession as several candidates, as opposed to just one, are often consistent with the historical features of such episode. This paper presents a new stylized fact which can prove helpful for discriminating among alternative explanations of the U.S. macroeconomic stability. Our main finding is that the fall in time series volatility is associated with a sizable decline, of the order of 30% on average, in the predictive accuracy of several widely used forecasting models *relative* to the accuracy of naive random walk forecasts. And, this pattern is not limited to the measures of inflation but also extends to several indicators of real economic activity and interest rates.

The generalized fall in predictive ability after the mid-1980s is particularly pronounced for forecasts horizons beyond one quarter. Furthermore, this empirical regularity is not simply specific to a single method, rather it is a common feature of all models including those used by public and private institutions. In particular, the forecasts for output and inflation of the Fed's Green book and the Survey of Professional Forecasters (SPF) are significantly more accurate than a random walk *only* before 1985. After this date, in contrast, the hypothesis of equal predictive ability between naive random walk forecasts and the predictions of those institutions is not rejected at all horizons but the current quarter.

The results of this paper may also be of interest for the empirical literature on asymmetric information. Romer and Romer (2000), for instance, consider a sample ending in the early 1990s and find that the Fed produced more accurate forecasts over inflation and output relative to several commercial providers. Our results imply that the informational advantage of the Fed and those private forecasters is in fact limited to the 1970s and the beginning of the 1980s. In contrast, during the last two decades no forecast model is better than *tossing a coin* beyond the first quarter horizon, thereby implying that *on average* uninformed economic agents can effectively anticipate future macroeconomics developments. On the other hand, econometric models and economists' judgement are quite helpful for the forecasts of the very short horizon that is relevant for conjunctural analysis.

Lastly, the literature on forecasting methods, recently surveyed by Stock and Watson (2005), has devoted a great deal of attention towards identifying the best model for predicting inflation and output. The majority of studies however are based on full-sample periods. Our findings reveal that most of the full sample predictability of U.S. macroeconomic series comes indeed from the years before 1985. Long time series appear to attach a far larger weight on the earlier subsample, which is characterized by a larger volatility of inflation and output. The results presented here suggests that some caution should be used in evaluating the performance of alternative forecasting models on the basis of a pool of different sub-periods as full sample analysis are likely to miss parameter instability.

The paper is organized as follows. The forecasting models are presented in Section 2 while the following part introduces the data and the definitions of predictability. The results on the full postwar period and the two sub-samples are reported in Sections 4 and 5. The latter in particular shows a robust correlation between the greater macroeconomic stability began in the mid-1980s and the decline in the predictability of most models over inflation and real activity. Section 6 shows that the Fed's and other Commercial Organizations' models are also associated with a remarkable fall in forecasting accuracy. Conclusions are drawn in the last section while the Appendix reports further sub-sample evidence.

2 The Forecasting Models

This section defines the concept of predictability and describes the data set. The goal of our investigation is to explore the nexus between the greater macroeconomic stability of the last two decades and the ability of several models in forecasting inflation, real activity and interest rates. We construct forecasts for nine monthly key macroeconomic series: three price indices, four measures of real activity and two interest rates. The data set consists of monthly observations from 1959:1 through 2003:12 on 131 U.S. macroeconomic time series including also the nine variables of interest.

Forecasts are based on traditional univariate time series models as well as on models exploiting larger information. Using all variables as predictors poses in fact a serious course of dimensionality problem for traditional models. In contrast, large cross-section forecasting methods can easily accommodate a large set of predictors. Among the latter, we consider two methods: Factor models forecasts (employed by Stock and Watson, 2002, and Giannone, Reichlin and Sala, 2005) and the Pooling of forecasts (introduced by Bates and Granger, 1969). The first method is based on the idea that a few common factors can capture and describe most information in the data. The second method combines forecasts from small scale traditional time series models.

The three nominal variable are the Producer Price Index (PPI), Consumer Price Index (CPI) and Personal Consumption Expenditure implicit Deflator ($PCED$). The four forecasted measures of real activity are Personal Income (PI), Industrial Production (IP) index, Unemployment Rate (UR), and Employees on non-farm Payrolls (EMP). Lastly we consider forecasts for the 3 months Treasury bills as a measure of short-term rate ($TBILL$) and the 10 year Treasury bonds as a measure of long-term rate ($TBOND$).

The series of interest are non stationary and depending on their nature some transformation are adopted prior to forecasting. In particular, we distinguish amon three categories:

- Prices: we forecast the h-months changes of yearly inflation. For instance, we forecast $(\pi_{t+h}^{CPI} - \pi_t^{CPI})$ for the Consumer Price Index where $\pi_t^{CPI} = (\log(CPI_t) - \log(CPI_{t-12})) \times 100$.
- Industrial Production, Employees on non-farm payrolls and Personal Income: we forecast the h-months ahead annualized growth rate. For example we forecast $(1200/h) \times (\log(IP_{t+h}) - \log(IP_t))$ for the Industrial production.
- Unemployment and interest rates: we forecast the h-months ahead changes. For instance we forecast $(UR_{t+h} - UR_t)$ for the Unemployment rate.

Turning to the forecasting models, we consider the following specifications:

1. A *Naive* forecast model in which forecasts of each (transformed) variable are simply a constant. This corresponds to a Random Walk (RW) model with drift for (i) the (log of) Industrial Production, Personal Income and Employment and (ii) the rates of annual prices inflation, unemployment and interest rates. We will use interchangeably *Naive* and RW.

2. Univariate forecasts (AR), where the forecasts are based exclusively on the own past values of the variable of interest.

3. Factor augmented AR forecast ($FAAR$), in which the univariate models are augmented with common factors extracted from the whole panel of series.

4. Pooling of bivariate forecasts ($POOL$): for each variable the forecast is defined as the average of 130 forecasts obtained by augmenting the AR model with each of the remaining 130 variables in the data set.

Pseudo out-of-sample forecasts are calculated for each variable and method over the horizons $h = 1, 3, 6$, and 12 months. The pseudo out-of-sample forecasting period begins in January 1970 and ends in December 2003. Forecasts constructed at date T are based on models that are estimated using observations dated T and earlier. We focus on rolling samples using, at each point in time, observations over the most recent 10 years.[1]

The choice of rolling samples is twofold. First, the goal of this paper is to investigate any possible time variation in predictability and rolling window estimators are appealing because no break date need to be imposed a priori. Second, large and persistent changes in the parameters of the models, like those associated with the Great Moderation, may result in less accurate estimates for the recursive samples.[2] The Mean Square Forecast Error (MSFE) is used as metric for evaluating the forecasts, while predictability is defined as the ratio between the MSFE of

[1]Results are robust to alternative window width selections. For the sake of completeness, we also report in Appendix C the results for the recursive forecasts, which confirm qualitatively the findings in the main text. In the latter case, the estimation period begins always in 1959:1.

[2]Rolling window estimators have the further advantage that they preserve the effect of estimation uncertainty on forecast performance. In contrast, estimation uncertainty vanishes

a given model and the Naive Random Walk model. A detailed description of the forecasting methods and the data set is reported in Appendix A and Appendix B.

It should be noted that the emphasis of our paper is on the predictability of a given model *relative* to that of a naive model. Another reading of our results is, in fact, that the relative performance of naive forecasts improved during the last two decades. In other words, the rise in predictive accuracy of a random walk is simply the flip side of the fall in predictive accuracy of all other models. We use the expression 'predictability of a given model' in *relative* sense throughout the paper, unless otherwise specified.

3 Full-sample Results

Our analysis begins with the full-sample evidence in Table 1. We report the relative predictability of four forecasting models, namely an AutoRegressive (AR) process, a Factor Augmented AutoRegressive (FAAR) forecast and a POOL of bivariate specifications. The Naive, Random Walk, model is chosen as benchmark. The methods are displayed in blocks of rows. The first three columns refer to inflation, the central panel reports results for four measures of real activity while the last two columns are about the interest rates. Asterisks indicate a rejection of the test of equal predictive accuracy between each model and the Naive.[3]

For all prices and real activity indicators and over all four horizons, the forecasts based on large information are significantly more accurate than the Naive

asymptotically for expanding window methods such as recursive estimation schemes (see Giacomini and White, 2005).

[3]Following Romer and Romer (2000), our inference is based on the regression: $(z_{ht} - \hat{z}_{ht}^{m})^2 - \left(z_{ht} - \hat{z}_{ht}^{Naive}\right)^2 = c + u_{ht}$ where z is the variable to be forecasted at horizon h using *model-m*. The estimate of c is simply the difference between *model-m* and a $Naive$ model MSFEs, and the standard error is corrected for heteroskedasticity and serial correlation over $h-1$ months. This testing procedure falls in the Diebold-Mariano-West framework, and Giacomini and White (2005, Section 3.2, see in particular Comment 4) show that by using rolling window estimators, as we do here, the limiting behavior of this type of tests is standard, and therefore standard asymptotic theory can be used for inference on the difference in predictive accuracy.

Table 1: *Relative Mean Square Forecast Errors - Full Period*

Random Walk (absolute values)

hor(m)	PPI	CPI	PCED	PI	IP	UR	EMP	TBILL	TBOND
1	0.45	0.11	0.06	45.58	75.84	0.03	9.45	0.31	0.11
3	1.83	0.59	0.32	13.93	46.23	0.14	7.25	1.29	0.47
6	4.40	1.63	0.94	7.72	35.04	0.45	6.66	2.50	0.99
12	11.87	5.02	2.90	5.03	25.30	1.38	5.75	4.74	2.20

Method AR (relative to RW)

hor(m)	PPI	CPI	PCED	PI	IP	UR	EMP	TBILL	TBOND
1	0.96	0.83***	0.83***	1.22	0.86*	0.91	0.60***	0.98	0.92
3	1.03	0.88*	0.82**	1.09	0.86	0.81*	0.53***	1.10	1.10
6	1.00	0.84	0.82	1.08	0.94	0.88	0.61***	1.05	1.05
12	1.05	0.93	1.00	1.01	0.95	0.97	0.75***	1.20	1.03

Method FAAR (relative to RW)

hor(m)	PPI	CPI	PCED	PI	IP	UR	EMP	TBILL	TBOND
1	0.94	0.76***	0.78***	1.15	0.74***	0.72***	0.50***	0.93	0.95
3	0.91	0.71***	0.77**	0.93	0.64**	0.58***	0.39***	1.06	1.19
6	0.84	0.60***	0.75	0.90	0.63*	0.55***	0.43***	0.95	1.17
12	0.84	0.60*	0.83	0.94	0.63	0.64*	0.56***	1.05	1.26

Method POOL (relative to RW)

hor(m)	PPI	CPI	PCED	PI	IP	UR	EMP	TBILL	TBOND
1	0.94	0.80***	0.80***	1.18	0.80**	0.83***	0.56***	0.94	0.91
3	0.96	0.81***	0.78**	1.02	0.76**	0.73**	0.47***	1.08	1.12
6	0.92	0.72**	0.76*	1.00	0.80*	0.76*	0.54***	0.99	1.07
12	0.92	0.73*	0.85	0.93**	0.78**	0.84***	0.65	1.12	1.07

Notes: Asterisks denote model forecasts that are statistically more accurate than the Naive at 1% ($***$), 5% ($**$) and 10% ($*$) significance levels.

forecasts and the Factor Augmented model produces the most accurate predictions. Univariate Autoregressive forecasts improve significantly on the Naive models only for the Employment measure and, in the short run, for two out of three prices measure. As far as interest rates are concerned, both Autoregressive and the data-rich forecasts do not significantly improve on the Naive forecast.

The evidence in Table 1 is consistent with the results in Stock and Watson (2005) and strongly supports the view that, in most situations, the non-benchmark models have a significant forecasting advantage relative to the Naive models. This is the case for all predicted series with the exception of the short-term and long-term interest rates.

It is worth emphasizing that this kind of evaluations have been typically used in the literature as model selection device for identifying the best forecasting method(s) in a pool of alternative candidates. We show in the next section however that these findings are largely driven by the 1970s and the beginning of the 1980s when the majority of macroeconomic series were highly persistent and volatile. This observation appears to limit the benefit of relative performance evaluations over long sample periods.

4 Forecast Performance over Sub-samples

This section presents evidence of a generalized historical decline in the predictability of several measures of inflation and real activity. Results for the short-term and the long-term interest rates are also presented.

To assist the reader in evaluating the importance of the historical decline in predictability, we compute the percentage change in the relative MSFEs moving from the period 1970-1985 to the period 1985-2005. Tables 2 to 4 summarize this information in the last column, displaying for each series and horizon the average percentage change across models. This statistics is reported in Appendix A.

4.1 Inflation

Table 2 reports the results for all models including the RW. Moving from Period I to Period II, the latter is associated with a sizable and robust moderation in the *absolute* values of the MSFEs. The percentage declines of the *relative* MSFEs reported in the last column are sizable, of 40% magnitude on average, and the largest drops during the post-1985 sample are associated with six and twelve month horizons, especially for *CPI*.

In order to gauge the statistical significance of the changes in predictive accuracy using *rolling samples*, Table 2 reports asterisks whenever the forecast of a model is more accurate than the Naive. At glance, the asterisks dominate the left part of Table 2, and as long as *CPI* and *PCE* are concerned the AR, $FAAR$ and $POOL$ methods outperform significantly the RW before 1985 *only*.

Table 2: *Relative MSFEs across Sub-Periods - Inflation*

	PERIOD I: sub-sample 1971:1 - 1984:12				PERIOD II: sub-sample 1985:1 - 2002:12					CHANGE
Series: Producer Price Index										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.55	1.03	1.01	0.99	1	0.37	0.89*	0.87*	0.88***	7%
3	2.23	1.05	0.85	0.94	3	1.51	1.01	0.98	0.99**	20%
6	5.79	0.95	0.67	0.82**	6	3.31	1.08	1.08	1.07	34%
12	17.95	1.02	0.65	0.84	12	7.12	1.13	1.20	1.09	33%
Series: Consumer Price Index										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.17	0.83***	0.75***	0.78***	1	0.07	0.85*	0.77**	0.83***	5%
3	0.94	0.84*	0.61***	0.74***	3	0.31	0.99	0.93	0.96**	38%
6	2.85	0.78*	0.46***	0.65***	6	0.68	1.04	1.05	0.98*	83%
12	9.43	0.87	0.44***	0.64**	12	1.57	1.22	1.32	1.16	118%
Series: Personal Consumption Expenditure Deflator										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.08	0.73***	0.71***	0.71***	1	0.05	0.96	0.88**	0.93***	9%
3	0.50	0.72***	0.67**	0.68***	3	0.18	1.04	0.98	1.01	29%
6	1.63	0.72**	0.66*	0.66**	6	0.40	1.13	1.05	1.08	48%
12	5.52	0.92	0.75	0.77	12	0.85	1.37	1.27	1.27	59%

Notes: The column 'change' reads the percentage historical decline in predictability averaged across methods (excluding Naive). Asterisks denote model forecasts that are statistically more accurate than the Naive at 1% ($***$), 5% ($**$) and 10% ($*$) significance levels.

The finding of equal predictive accuracy during the last two decades is not specific to the best forecasting model, rather it appears a common feature of all methods. This observation leads to a new interpretation of the results in Atkenson and Ohanian (2001) and D'Agostino and Giannone (2005) about the deterioration of the inflation forecasts on the basis of some Phillips curve models and $FAAR$ respectively.

Furthermore, the sizable fall in the persistence and volatility of different measures of inflation detected by Cogley and Sargent (2005) and Kim, Nelson and Piger (2004) around the mid-1980s suggests that such unpredictability could simply reflect a property of the most recent observations.

The macroeconomic fact identified in this section does not seem to be limited to the regime shift observed in the U.S. monetary policy history. While an international investigation is behind the scope of this paper, it is interesting to notice that using a time-varying Bayesian VAR Benati and Mumtaz (2005) find that inflation in the U.K. became far less predictable since 1992, which corresponds to the introduction of an explicit inflation target in the policy mandate of the Bank of England.

4.2 Real Activity

We now turn the attention to the real side of the economy and investigate the properties of the forecasts of Personal Income (*PI*), Industrial Production (*PI*), Unemployment Rate (*UR*) and EMPloyees nonfarm payrolls (*EMP*). Table 3 reports the results.

Table 3: *Relative MSFEs across Sub-Periods - Real Activity*

PERIOD I: sub-sample 1971:1 - 1984:12					PERIOD II: sub-sample 1985:1 - 2002:12					CHANGE
Series: Real Personal Income										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	38.54	1.02	0.95	0.98	1	51.09	1.33	1.27	1.30	21%
3	17.15	1.01	0.86	0.94	3	11.41	1.19	1.01	1.12	14%
6	10.41	1.05	0.83	0.96	6	5.62	1.12	1.01	1.05	2%
12	6.92	0.97	0.84	0.87*	12	3.55	1.07	1.09	1.02	3%
Series: Industrial Production										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	124.01	0.81*	0.65***	0.75**	1	38.14	0.97	0.95	0.92	14%
3	81.48	0.85	0.55**	0.73**	3	18.64	0.92	0.98	0.88	16%
6	61.42	0.94	0.49*	0.76*	6	14.41	0.97	1.11	0.95	34%
12	43.24	0.95	0.43**	0.72**	12	11.27	0.98	1.22	0.97	62%
Series: Unemployment Rate										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.05	0.86	0.63***	0.78**	1	0.02	0.99	0.88*	0.94***	21%
3	0.25	0.79	0.52***	0.69**	3	0.06	0.91	0.79*	0.84**	18%
6	0.80	0.88	0.49***	0.75	6	0.17	0.85	0.75	0.80*	22%
12	2.42	0.99	0.56**	0.82**	12	0.56	0.93	0.90	0.89	41%
Series: Employees on Nonfarm Payrolls										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	16.37	0.65***	0.51***	0.60***	1	4.04	0.42***	0.45***	0.40***	4%
3	12.39	0.60**	0.41***	0.53***	3	3.23	0.31***	0.34***	0.29***	-1%
6	11.16	0.70**	0.42***	0.60**	6	3.14	0.37**	0.44*	0.36*	-3%
12	9.21	0.82***	0.49***	0.69***	12	3.05	0.58**	0.72	0.56	8%

Notes: see Table 2.

The Great moderation is apparent in the decline of the absolute MSFEs of the *RW* for all variables and horizons but Real Personal Income one-month ahead. The $FAAR$ confirms itself as the best forecasting model. The significant advantage in predictive accuracy found in the earlier sample over most predicted series is however sizably reduced during Period II. Furthermore, the historical changes, averaged across models, in the last column are sizable, of order 20%, and the predictions of the $FAAR$ are always more accurate than the Naive model during the pre-1985 sample. A similar finding emerges for the $POOL$ forecasts and in fact the left panel of the Table, which refers to Period I, is clearly dominated by asterisks for output as well.

It is interesting to notice that the decline in predictability does not seem to extend to the labor market, especially at short horizons. The forecasts of *EMP* are associated with negative percentage changes at horizons 3 and 6, though the relative MSFEs are statistically different from one in both Periods. It remains to be assessed however whether such historical changes are statistically significant.

Bearing in mind the empirical evidence in McConnell and Perez-Quiros (2000), Kim, Nelson and Piger (2004) and Ahmed, Levin and Wilson (2004) about a sizable reduction in the volatility of real activity since the mid-1980s, the findings of Table 3 can be interpreted as another indication of a generalized phenomenon that appears intrinsic to the post-1985 data rather than specific to a particular forecasting model.

4.3 Interest Rates

The behaviors of the interest rate forecasts in Table 4 contrast with the tendency across sub-samples of all other variables, especially at the very short horizon. In particular, the average *increase* in the relative predictive ability of the short-term rate is 10% and 5% for $h = 1$ and 3, being among the very few changes with a negative sign in our results. The $POOL$ forecasts are characterized by the most pronounced historical improvement and become more accurate than the RW in the most recent period. At the longer horizons of six and twelve months however the relative MSFEs either deteriorate or remain stable around values above one.

Table 4: *Relative MSFEs across Sub-Periods - Interest Rates*

PERIOD I: sub-sample 1971:1 - 1984:12					PERIOD II: sub-sample 1985:1 - 2002:12					CHANGE
Series: 3 Months Treasury Bills										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.64	1.00	0.94	0.95	1	0.05	0.84	0.87	0.81***	-10%
3	2.59	1.12	1.05	1.10	3	0.27	0.98	1.16	0.94**	-5%
6	4.63	1.06	0.88	0.98	6	0.83	1.03	1.25	1.01	11%
12	7.63	1.27	0.93	1.14	12	2.47	1.04	1.34	1.06	8%
Series: 10 Years Treasury Bonds										
hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL	Average
1	0.17	0.95	0.96	0.94	1	0.07	0.88**	0.92	0.87***	-9%
3	0.68	1.17	1.21	1.18	3	0.31	1.00	1.15	1.02	-11%
6	1.28	1.07	1.12	1.09	6	0.77	1.02	1.23	1.05	3%
12	2.57	1.04	1.12	1.06	12	1.91	1.01	1.42	1.09	7%

Notes: see Table 2.

The absolute MSFEs of the *RW* fall also for the long-term interest rate, though the historical decline is less pronounced than for the short-term rate. The other methods produce significantly more accurate one-month ahead forecasts in Period II, consistently with the results on the 3 Months Treasury Bills. At longer horizons, the performance of all forecasting models is however very close to the performance of RW. The latter finding holds true over both sub-samples and thus extends the results of interest rate unpredictability during Greenspan's tenure reported by Rudebusch (2002).

In summary, the *AR*, *FAAR* and *POOL* methods produce more accurate forecasts than the *RW* only at the very short horizon of one month and only during Period II. An interesting interpretation of this result is that a stronger policy activism and a better communication strategy have enriched the information content of the systematic component of monetary policy during the last two decades. Indeed, the St. Louis Fed President William Poole (2005) mentions the increase in transparency, and the consequent increase in predictability of monetary policy among the four identifying characteristics of the Greenspan era and argues convincingly that "*[..] improved predictability of policy has had much to do with improved effectiveness of policy*".

5 Evidence from Institutional Forecasters

Taking the results of the previous section at face value, we might conclude that inflation ad real activity became relatively less predictable since 1985. While this claim is valid across some popular statistical methods, it is less clear the extent to which it can also apply to larger, and possibly nonlinear, models of the size typically employed by Central Banks and private forecasters. Indeed, the forecasts produced by policy institutions are likely to involve some important elements of judgement, which can improve their predictive accuracy relative to more mechanical linear methods.

5.1 The Federal Reserve and the Professional Forecasters

We consider the predictions for output and its deflator from two large forecasters representing the private sector and the policy institutions. The source for the commercial providers is the Survey of Professional Forecasts (SPF). The survey was introduced by the American Statistical Association and the National Bureau of Economic Research and is currently maintained by the Philadelphia Fed. The SPF refers to quarterly measures and is conducted in the middle of the second month of each quarter. We consider the median of the individual forecasts.[4]

As far as institutional forecasts are concerned, we consider the forecasts of the Green book. These forecasts are prepared by the Board of Governors at the Federal Reserve for the meetings of the Federal Open Market Committee (FOCM), which takes place roughly every six weeks. The predicted series are quarterly inflation and output. The Green book forecast are made publicly available with a five-year delay, thereby implying that our sample ends in 1999. For compatibility with the timing of the SPF forecasts, we select meetings that are closer to the

[4]The data used in this section are available on the Web site of the Federal Reserve of Philadelphia. In particular, SPF: http://www.phil.frb.org/econ/spf/spfmed.html; Green book: http://www.phil.frb.org/econ/forecast/croushoresdatasets.html; Real-Time: http://www.phil.frb.org/econ/forecast/reaindex.html.

middle of each quarter (four meeting out of eight).

We consider four forecast horizons h_q ranging from 1 to 4 *quarters*. The one step ahead figures correspond to the predictions for the quarter in which the forecasts are made. For each h_q-steps ahead we consider the h_q-quarter growth rate of output and the h_q-quarter change in annual inflation based on the output implicit price deflator. The measure of output is Gross National Product (GNP) until 1991 and Gross Domestic Product (GDP) from 1992 onwards. The evaluation sample begins in 1975, as prior to this date the Greenbook forecasts were not always available up to the fourth quarter horizon. For the sake of comparability, we select 1975 as starting point also for the SPF forecasts, although the latter are available for a longer time period.

Data are continuously revised and thus an important issue we must confront with is the selection of appropriate measures of inflation and output to be predicted. Following Romer and Romer (2000), we consider the figures published after the next two subsequent quarters.

Finally, the Naive forecasts are computed as the sample average of the h_q-quarter growth rate of output and the h_q-quarters change of annual inflation based on the output implicit price deflator. In line with the forecasts from the statistical methods, the parameters for the Naive forecasts are computed using observations over the most recent 10 years, and real-time data as available at the time in which the GB and SPF forecasts were made.

5.2 The Decline of Predictive Accuracy

We turn now to the evaluation of the forecasts produced by the Federal Reserve and the SPF over inflation and real activity relative to a naive random walk model. Our goal is to assess the robustness of the historical decline in macroeconomic predictability by showing that this finding is independent from the model at hand. Results for inflation and output are presented in Table 5 and Table 6. The statistics refer to three periods: full sample, pre-1985 and post-1985 sub-samples.

Table 5: *Relative MSFEs of Institutional Forecasters - Inflation*

FULL SAMPLE: 1975:1 1999:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	0.26	0.35***	0.37***
2	0.79	0.30**	0.36**
3	1.57	0.29*	0.37
4	2.51	0.32	0.46

PERIOD I: sub-sample 1975:1 - 1984:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	0.54	0.30***	0.27***
2	1.72	0.21**	0.24**
3	3.51	0.21**	0.25*
4	5.69	0.23*	0.32*

PERIOD II: sub-sample 1985:1 - 1999:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	0.08	0.58**	0.82
2	0.17	0.93	1.15
3	0.28	0.97	1.39
4	0.39	1.18	1.82

Notes: Asterisks denote rejection of the null hypothesis of equal predictive accuracy between each model and the RW at 1% ($***$), 5% ($**$) and 10% ($*$) significance levels.

The top panel of Table 5 presents the finding for the full postwar period. The Green book and the SPF forecasts are far more accurate than a Naive model for inflation, being associated with significantly lower MSFEs over all horizons. The results of Period I in the middle panel are virtually identical to the full-sample results whereas the statistics in the bottom panel for the post-1985 period paint a quite different picture. In particular, the relative MSFEs of Period II are very close to *one* at most horizons, and the null hypothesis of equal predictive accuracy between the Naive forecast and the other forecasts is not rejected in all cases but $h_q = 1$ for the Green book.

The results for real output are displayed in Table 6 and they bear out the evidence on inflation. In particular, the forecasts of the Green book and the SPF are significantly more accurate than the RW over the full-sample and the pre-1985 period. The statistics for the most recent years in the last row are associated however with relative MSFEs close to *one*, thereby revealing that more

Table 6: *Relative MSFEs of Institutional Forecasters - Output*

FULL SAMPLE: 1975:1 1999:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	12.59	0.44**	0.51**
2	9.11	0.49**	0.46**
3	7.45	0.48**	0.50***
4	6.49	0.51**	0.51***

PERIOD I: sub-sample 1975:1 - 1984:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	25.82	0.37**	0.45**
2	19.01	0.44**	0.41**
3	15.39	0.40***	0.45***
4	13.18	0.42***	0.46***

PERIOD II: sub-sample 1985:1 - 1999:4

hor(q)	RW	Fed's Green Book(GB)/RW	Survey of Professional Forecasters(SPF)/RW
1	3.77	0.73	0.77
2	2.51	0.77	0.70
3	2.15	0.85	0.73
4	2.03	0.89	0.74

Notes: see Table 5.

sophisticated forecasts for output are not immune to the generalized decline in predictability.[5]

These findings complement the statistics of the previous section and disclose two new results. First, in analogy to the statistical models, the performance of both the Green book and SPF predictions over the full-sample are driven mainly, if not completely, by the time period before 1985. Second, also the Green book and the SPF forecasts are characterized by a significant decline in the relative predictive accuracy such that the apparent advantage of the 1970s and the first half of the 1980s relative to a Naive model virtually vanished during the last two decades.

It is worth noticing however that, unlike the statistical models, the Green book forecasts retain some advantage over the Naive forecasts at the short horizon of one quarter during the latter sample. An explanation for this result is that

[5]As far as only the SPF predictions on real output growth are concerned, a similar result can be found in Campbell (2004). The focus of that paper however is on the contribution of reduced macroeconomic uncertainty, as measured by the size of the shocks, to the decline in output volatility rather than on documenting the generalized lack of predictability of a range of models in forecasting several measures of inflation and real activity.

the models employed by the Fed are flexible enough to use the information on higher frequency variables that is already available within a quarter for predicting the current values of other series. This feature makes those models particularly helpful for conjunctural analysis.[6]

6 Conclusions

This paper investigates the predictive accuracy of some widely used forecasting models, the forecasts of the Fed's Green Book and the Survey of Professional Forecasters on several U.S. macroeconomic time series. A main result is that, moving from the pre- to the post-1985 period, there exists a sizable and significant deterioration of the ability of these methods to forecast key macroeconomic indicators relative to a naive random walk model. This finding is very robust across forecast horizons and models, and extend also to the Fed's predictions of inflation and output. In particular, during the last two decades, the null hypothesis of equal predictive accuracy between naive forecasts and the predictions of a sophisticated method like the Green Book is not rejected for horizons beyond the first quarter.

It is worth emphasizing however that our findings should not be interpreted as suggesting that forecasting can be regarded as unimportant in modern policy making. In fact, the out of sample performance of a model *in real time* is a far more complex evaluation than our *ex-post* experiment could capture. As long as there exists some positive probability that the current macroeconomic stability may pause, large policy institutions like Central Banks will have a strong incentive to devote resources in forecasting inflation and output because it is in those times that their comparative advantage emerges. Furthermore, within the current quarter, which is arguably the relevant horizon for conjunctural analysis, the Fed's Green book continues to maintain a forecasting advantage relative to less

[6] A formalization of such procedures in a data-rich environment can be found in Giannone Reichlin and Sala (2005), and Giannone, Reichlin and Small (2005).

sophisticated models.

The generalized decline in the forecast ability of inflation and real activity documented in this paper appears to coincide with the historical decline in the volatility and persistence of inflation and real activity documented by McConnell and Perez-Quiros (2000), and Cogley and Sargent (2001) on U.S. data. While investigating any possible causality is beyond the scope of the paper, it is impressive to notice the timing of events as the break dates of these two stylized facts are concentrated in the first half of the 1980s. And, the short-term and the long-term interest rates one month ahead are the only series associated with more accurate forecasts over the most recent sample. This observation suggests that a more transparent communication strategy and a better monetary policy management could have contributed to such correlation.

At a more general level, this paper presents a new fact of the U.S. greater macroeconomic stability. The important implication that can be drawn from our analysis is that any theoretical model aimed at explaining the 'Great Moderation' must be also capable of accounting for the historical decline in the ability of predicting inflation and real activity indicators. An interesting avenue for future research is to investigate the correlation between forecast ability and policy regimes. It may well be the case that the fall in predictability is endogenous to the conduct of monetary policy.

References

[1] Ahmed Shaghil , Andrew T. Levin and Beth Anne Wilson (2004) "Recent U.S. Macroeconomic Stability: Good Policies, Good Practices, or Good Luck?", *The Review of Economics and Statistics*, 86(3), 824-832.

[2] Atkenson A. and Ohanian L. (2001), "Are Phillips Curves Useful for Forecasting Inflation?", *Federal Reserve Bank of Minneapolis Quarterly Review*, 25 (1).

[3] Bates, J.M., C.W.J. Granger (1969), "The combination of forecasts ", *Operations Research Quarterly*, 20, 451-68.

[4] Benati Luca, and Haroon Mumtaz (2005), "The 'Great Stability' in the U.K.: Good Policy or Good Luck?", mimeo, Bank of England.

[5] Bernanke, B.S., 2004, "The Great Moderation", Remarks at the meetings of the Eastern Economic Association, Washington, DC, February.

[6] Blanchard, Oliver J. and John A. Simon (2001), "The Long and Large Decline in U.S. Output Volatility", *Brookings Papers on Economic Activity,* 1, 135-164.

[7] Boivin, Jeanne and Serena Ng (2005), "Understanding and Comparing Factor-Based Forecasts", available at: http://www2.gsb.columbia.edu/faculty/JBoivin/Personal/

[8] Campbell, Sean, D., (2004), "Macroeconomic Volatility, Predictability and Uncertainty in the Great Moderation: Evidence from the Survey of Professional Forecasters", Federal Reserve Board Finance and Economics Discussion Series No. 2005-52.

[9] Cogley, Timothy W. and Thomas Sargent, (2002) "Evolving Post World War II U.S. Inflation Dynamics," *NBER Macroeconomics Annual* 16.

[10] D'Agostino, Antonello and Domenico Giannone, (2005), "Comparing Alternative Predictors Based on Large-Panel Factor Models, mimeo, ECARES, Universite Libre de Bruxelles.

[11] Diebold, Francis X., and R.S. Mariano, (1995), “Comparing Predictive Accuracy”, *Journal of Business and Economic Statistics*, 13, 253-265.

[12] Forni M., Hallin M., Lippi M. and L. Reichlin, (2002) “The Generalized Dynamic Factor Model: Identification and Estimation”, *The Review of Economics and Statistics*, November 2002

[13] Giacomini, Raffaella, and Halbert White, (2005), “Tests of Conditional Predictive Ability”, mimeo, UCLA.

[14] Giannone, Domenico, Lucrezia Reichlein and Luca Sala, (2005), “Monetary Policy in Real Time ”, *NBER Macroeconomics Annual*, Eds: Mark Gertler and Ken Rogoff, forthcoming.

[15] Giannone, Domenico, Lucrezia Reichlin and David Small, (2005), “Nowcasting GDP and Inflation: The Real Time Informational Content of Macroeconomic Data Releases”, Federal Reserve Board, Finance and Economics Discussion Series, 2005-42.

[16] Kim, Chang-Jin, and Charles R. Nelson (1999) “Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle”, *The Review of Economics and Statistics*, 81, 608 – 616.

[17] Kim, Chang-Jin, Charles R. Nelson and Jeremy Piger (2004), “The Less-Volatile U.S. Economy: A Bayesian Investigation of Timing, Breadth, and Potential Explanations”, *Journal of Economic and Business Statistics*, 22, 80-93.

[18] McConnell, Margaret M, and Gabriel Perez-Quiros (2000) “Output Fluctuations in the United States: What has Changed Since the Early 1980’s”, *American Economic Review*, 90(5), 1464 – 1476.

[19] Poole, William (2005), Remarks: Panel on ”After Greenspan: Whither Fed Policy?” — Western Economic Association International Conference (WEAI), San Francisco, July 6, 2005.

[20] Romer, David, H. and Christina Romer (2000) "Federal Reserve Information and the Behavior of Interest Rates", *American Economic Review* 90, 429-457.

[21] Rudebusch, G., (2002) "Term Structure Evidence on Interest Rate Smoothing and Monetary Policy Inertia", *Journal of Monetary Economics* 49(6), September 2002, 1161-1187

[22] Stock, James and Mark Watson (2005), An Empirical Comparison of Methods for Forecasting Using Many Predictors, mimeo Harvard University.

[23] Stock, James and Mark Watson (2003) "Has the Business Cycle Changed? Evidence and Explanations" prepared for Federal Reserve Bank of Kansas City 2003 Jackson Hole Symposium.

[24] Stock, James and Mark Watson (2003) "Macroeconomic Forecasting Using Diffusion Indexes" *Journal of Business and Economics Statistics* 20, 147-42.

[25] West, Kenneth, D. (1996) "Asymptotic Inference about Predictive Ability" *Econometrica* 64, 1067-1084.

Appendix A: the Forecasting Models

We are interested in predicting some variable $Y^h_{i,t+h}$ using a potentially large number of predictors, $X_{i,t}, i = 1, ..., n$. To this end, we consider the following forecasting models:

Naive

$$Y^h_{i,t+h} = \alpha_i^{h,Naive} + e_{i,t+h}^{h,Naive}$$

Autoregressive

$$Y^h_{i,t+h} = \alpha_i^{h,AR} + \gamma_i^{h,AR}(L)X_{i,t} + e_{t+h}^{h,AR}$$

Augmented distributed lag

$$Y^h_{i,t+h} = \alpha_i^{h,ADL_j} + \gamma_i^{h,ADL_j}(L)X_{i,t} + \delta_j^{h,ADL_j}(L)X_{j,t} + e_{t+h}^{h,ADL_j}, j = 1, ..., n, j \neq i$$

r-factor model

$$Y^h_{i,t+h} = \alpha_i^{h,FAAR} + \gamma_i^{h,FAAR}(L)X_{i,t} + \lambda_i^{h,FAAR}\hat{F}_t + e_{t+h}^{h,FAAR}$$

The series are transformed by taking logarithms and/or differences. In general, growth rates are used for real quantity variables, first differences are used for nominal interest rates, and first differences for yearly growth rates for price series.

Table A shows the definition of $Y^h_{i,t+h}$ and $X_{i,t}$ in terms of the raw series Z_{it} for each of the nine variables that are forecasted. The transformations applied to all the predictors listed in Appendix B.

Table A: Forecasted Series

Series	*Acronyms*	Y_{t+h}^h	X_t
Real Personal Income	PI	$\left(\frac{1200}{h}\right)\ln\left(\frac{Z_{t+h}}{Z_t}\right)$	$\Delta\ln(Z_t)$
Industrial Production	IP	$\left(\frac{1200}{h}\right)\ln\left(\frac{Z_{t+h}}{Z_t}\right)$	$\Delta\ln(Z_t)$
Unemployment Rate	UR	$Z_{t+h}-Z_t$	ΔZ_t
Employment	EMP	$\left(\frac{1200}{h}\right)\ln\left(\frac{Z_{t+h}}{Z_t}\right)$	$\Delta\ln(Z_t)$
3-Mth Tbill Rate	TBILL	$Z_{t+h}-Z_t$	ΔZ_t
10-Yr Tbond Rate	TBOND	$Z_{t+h}-Z_t$	ΔZ_t
Producer Price Index	PPI	$100\times\ln\left(\frac{Z_{t+12+h}}{Z_{t+h}}\right)-100\times\ln\left(\frac{Z_{t+12}}{Z_{t-12}}\right)$	$\Delta\ln\left(\frac{Z_t}{Z_{t-12}}\right)$
Consumer Price Index	CPI	$100\times\ln\left(\frac{Z_{t+12+h}}{Z_{t+h}}\right)-100\times\ln\left(\frac{Z_{t+12}}{Z_{t-12}}\right)$	$\Delta\ln\left(\frac{Z_t}{Z_{t-12}}\right)$
PCE Deflator	PCED	$100\times\ln\left(\frac{Z_{t+12+h}}{Z_{t+h}}\right)-100\times\ln\left(\frac{Z_{t+12}}{Z_{t-12}}\right)$	$\Delta\ln\left(\frac{Z_t}{Z_{t-12}}\right)$

Notes: This table lists the nine forecasted series. The first column gives the description of the series, the second lists the abbreviation used in the results tables, the next two columns shows the transformations that define the variable forecast, Y_{t+h} and the predictors X.

Given a sample $t = T_{0T}, ..., T$, we estimate the common factors $\hat{F}_t$ by mean of the first r sample principal components of $W_t = (W_{1t}, ..., W_{nt})', t = T_{0,T}, ..., T$, where $W_{it} = \frac{X_{it}-\hat{\mu}_i}{\hat{\sigma}_i}$, and $\hat{\mu}_i$ and $\hat{\sigma}_i$ are the sample mean and standard deviation respectively. Specifically, $\hat{F}_t = \hat{\mathcal{V}}'W_t$, where $\hat{\mathcal{V}}$ is the $n \times r$ matrix of eigenvectors associated with the first r eigenvalues of $S = \frac{1}{T-T_{0T}+1}\sum_{t=T_{0T}}^{T} W_t W_t'$.

The parameters of the each model can be thus computed by Ordinary Least Square. We obtain the following forecasts:

$$\hat{Y}_{i,T+h|T}^h(Naive) = \hat{\alpha}_i^{h,Naive}$$

$$\hat{Y}_{i,t+h|T}^h(AR) = \hat{\alpha}_i^{h,AR} + \hat{\gamma}_i^{h,AR}(L)X_{i,T}$$

$$\hat{Y}_{i,T+h|T}^h(ADL_j) = \hat{\alpha}_i^{h,ADL_j}+\hat{\gamma}_i^{h,ADL_j}(L)X_{i,T}+\hat{\delta}_j^{h,ADL_j}(L)X_{j,T}, j = 1, ..., n, j \neq i$$

$$\hat{Y}_{i,t+h|T}^h(FAAR) = \hat{\alpha}_i^{h,FAAR} + \hat{\gamma}_i^{h,FAAR}(L)X_{i,T} + \hat{\lambda}_i^{h,FAAR}\hat{F}_T$$

Pooled forecasts from different ADL models are computed as:

$$\hat{Y}^h_{i,t+h|T}(POOL) = \sum_{j \neq i} \hat{Y}^h_{i,t+h|T}(ADL_j)$$

For rolling sample estimates we consider observations from a fixed window of ten years,. i.e. as data are monthly, $T_{0T} = T - 120$. For recursive samples, we always have T_{0T} =January 1959.

Our Mean Square Forecast error measure for forecast evaluation is equal to:

$$MSFE^{t_1}_{t_0}(i, h, m) = \frac{1}{t_1 - t_0 + 1} \sum_{t=t_0}^{t_1} \left(\hat{Y}^h_{i,t+h|T}(m) - Y^h_{t+h} \right)^2$$

where $1970 : 1 \leq t_0 \leq t_1 < 2003 : 12 - h$. This is the average squared error between time T_0 and T_1, for variable i, at horizon h, using model m. Predictability is defined as the ratio between the MSFE of a give model and the Naive one, and is measured as:

$$PRED^{t_1}_{t_0}(i, h, m) = \frac{MSFE^{t_1}_{t_0}(i, h, m)}{MSFE^{t_1}_{t_0}(i, h, Naive)}$$

The percentage decline in the relative MSFE of the *i-th* predicted series is averaged across models excluding the RW, and is computed as:

$$CHANGE\,(i, h) = 100 \left[\frac{\sum_{m=1}^{M} \left(\frac{PRED^{II}(i,h,m) - PRED^{I}(i,h,m)}{PRED^{I}(i,h,m)} \right)}{M} \right]$$

with $m = AR$, $FAAR$ and $POOL$, the number of models $M = 3$ and $h = 1$, 3, 6 and 12.

Appendix B: the Data Set

Table B: Data Transformation

	Definition	Transformation
1	$X_{it} = Z_{it}$	no transformation
2	$X_{it} = \Delta Z_{it}$	monthly difference
4	$X_{it} = \ln Z_{it}$	log
5	$X_{it} = \Delta \ln Z_{it} \times 100$	monthly growth rate
6	$X_{it} = \Delta \ln \frac{Z_{it}}{Z_{it-12}} \times 100$	monthly difference of yearly growth rate

Code	Description	Transf.
A0M051	Personal income less transfer payments (AR, bil. chain 2000 $)	5
A0M224R	Real Consumption (AC) A0m224/gmdc	5
A0M057	Manufacturing and trade sales (mil. Chain 1996 $)	5
A0M059	Sales of retail stores (mil. Chain 2000 $)	5
IPS10	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	5
IPS11	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL	5
IPS299	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS	5
IPS12	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS	5
IPS13	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	5
IPS18	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	5
IPS25	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	5
IPS32	INDUSTRIAL PRODUCTION INDEX - MATERIALS	5
IPS34	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	5
IPS38	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	5
IPS43	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	5
IPS307	INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES	5
IPS306	INDUSTRIAL PRODUCTION INDEX - FUELS	5
PMP	NAPM PRODUCTION INDEX (PERCENT)	1
A0m082	Capacity Utilization (Mfg)	2
LHEL	INDEX OF HELP-WANTED ADVERTISING IN NEWSPAPERS (1967=100;SA)	2
LHELX	EMPLOYMENT: RATIO; HELP-WANTED ADS:NO. UNEMPLOYED CLF	2
LHEM	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)	5
LHNAG	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	5
LHUR	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	2
LHU680	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	2
LHU5	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	5
LHU14	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	5
LHU15	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	5
LHU26	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	5
LHU27	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS,SA)	5
A0M005	Average weekly initial claims, unemploy. insurance (thous.)	5
CES002	EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE	5
CES003	EMPLOYEES ON NONFARM PAYROLLS - GOODS-PRODUCING	5
CES006	EMPLOYEES ON NONFARM PAYROLLS - MINING	5
CES011	EMPLOYEES ON NONFARM PAYROLLS - CONSTRUCTION	5
CES015	EMPLOYEES ON NONFARM PAYROLLS - MANUFACTURING	5
CES017	EMPLOYEES ON NONFARM PAYROLLS - DURABLE GOODS	5
CES033	EMPLOYEES ON NONFARM PAYROLLS - NONDURABLE GOODS	5
CES046	EMPLOYEES ON NONFARM PAYROLLS - SERVICE-PROVIDING	5
CES048	EMPLOYEES ON NONFARM PAYROLLS - TRADE, TRANSPORTATION, AND UTILITIES	5
CES049	EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE	5
CES053	EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE	5
CES088	EMPLOYEES ON NONFARM PAYROLLS - FINANCIAL ACTIVITIES	5
CES140	EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT	5
A0M048	Employee hours in nonag. establishments (AR, bil. hours)	5
CES151	AVG WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS	1
CES155	AVG WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS	2
aom001	Average weekly hours, mfg. (hours)	1
PMEMP	NAPM EMPLOYMENT INDEX (PERCENT)	1
HSFR	HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA	4
HSNE	HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	4
HSMW	HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	4
HSSOU	HOUSING STARTS:SOUTH (THOUS.U.)S.A.	4
HSWST	HOUSING STARTS:WEST (THOUS.U.)S.A.	4
HSBR	HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)	4
HSBNE	HOUSES AUTHORIZED BY BUILD. PERMITS:NORTHEAST(THOU.U.)S.A	4
HSBMW	HOUSES AUTHORIZED BY BUILD. PERMITS:MIDWEST(THOU.U.)S.A.	4
HSBSOU	HOUSES AUTHORIZED BY BUILD. PERMITS:SOUTH(THOU.U.)S.A.	4
HSBWST	HOUSES AUTHORIZED BY BUILD. PERMITS:WEST(THOU.U.)S.A.	4
PMI	PURCHASING MANAGERS' INDEX (SA)	1
PMNO	NAPM NEW ORDERS INDEX (PERCENT)	1
PMDEL	NAPM VENDOR DELIVERIES INDEX (PERCENT)	1
PMNV	NAPM INVENTORIES INDEX (PERCENT)	1

Data appendix (continue...)

Code	Description	Transf.
A0M008	Mfrs' new orders, consumer goods and materials (bil. chain 1982 $)	5
A0M007	Mfrs' new orders, durable goods industries (bil. chain 2000 $)	5
A0M027	Mfrs' new orders, nondefense capital goods (mil. chain 1982 $)	5
A1M092	Mfrs' unfilled orders, durable goods indus. (bil. chain 2000 $)	5
A0M070	Manufacturing and trade inventories (bil. chain 2000 $)	5
A0M077	Ratio, mfg. and trade inventories to sales (based on chain 2000 $)	2
FM1	MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	6
FM2	MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,	6
FM3	MONEY STOCK: M3(M2+LG TIME DEP,TERM RP'S&INST ONLY MMMFS)(BIL$,SA)	6
FM2DQ	MONEY SUPPLY - M2 IN 1996 DOLLARS (BCI)	5
FMFBA	MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	6
FMRRA	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	6
FMRNBA	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(MIL$,SA)	6
FCLNQ	COMMERCIAL & INDUSTRIAL LOANS OUSTANDING IN 1996 DOLLARS (BCI)	6
FCLBMC	WKLY RP LG COM'L BANKS:NET CHANGE COM'L & INDUS LOANS(BIL$,SAAR)	1
CCINRV	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	6
A0M095	Ratio, consumer installment credit to personal income (pct.)	2
FSPCOM	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	5
FSPIN	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS (1941-43=10)	5
FSDXP	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)	2
FSPXE	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)	5
FYFF	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	2
CP90	Cmmercial Paper Rate (AC)	2
FYGM3	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	2
FYGM6	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	2
FYGT1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	2
FYGT5	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	2
FYGT10	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	2
FYAAAC	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)	2
FYBAAC	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)	2
scp90	cp90-fyff	1
sfygm3	fygm3-fyff	1
sFYGM6	fygm6-fyff	1
sFYGT1	fygt1-fyff	1
sFYGT5	fygt5-fyff	1
sFYGT10	fygt10-fyff	1
sFYAAAC	fyaaac-fyff	1
sFYBAAC	fybaac-fyff	1
EXRUS	UNITED STATES;EFFECTIVE EXCHANGE RATE(MERM)(INDEX NO.)	5
EXRSW	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	5
EXRJAN	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	5
EXRUK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	5
EXRCAN	FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	5
PWFSA	PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)	6
PWFCSA	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)	6
PWIMSA	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)	6
PWCMSA	PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)	6
PSM99Q	INDEX OF SENSITIVE MATERIALS PRICES (1990=100)(BCI-99A)	6
PMCP	NAPM COMMODITY PRICES INDEX (PERCENT)	1
PUNEW	CPI-U: ALL ITEMS (82-84=100,SA)	6
PU83	CPI-U: APPAREL & UPKEEP (82-84=100,SA)	6
PU84	CPI-U: TRANSPORTATION (82-84=100,SA)	6
PU85	CPI-U: MEDICAL CARE (82-84=100,SA)	6
PUC	CPI-U: COMMODITIES (82-84=100,SA)	6
PUCD	CPI-U: DURABLES (82-84=100,SA)	6
PUS	CPI-U: SERVICES (82-84=100,SA)	6
PUXF	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)	6
PUXHS	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)	6
PUXM	CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)	6
GMDC	PCE,IMPL PR DEFL:PCE (1987=100)	6
GMDCD	PCE,IMPL PR DEFL:PCE; DURABLES (1987=100)	6
GMDCN	PCE,IMPL PR DEFL:PCE; NONDURABLES (1996=100)	6
GMDCS	PCE,IMPL PR DEFL:PCE; SERVICES (1987=100)	6
CES275	AVG HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS	6
CES277	AVG HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS	6
CES278	AVG HOURLY EARNINGS OF PRODUCTION OR NONSUPERVISORY WORKERS	6
HHSNTN	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)	2

Appendix C: Recursive Sub-samples

Table C1: Relative MSFEs - Full Period using Recursive Samples

hor	PPI	CPI	PCED	PI	IP	UR	EMP	TBILL	TBOND
Random Walk (absolute values)									
1	0.45	0.11	0.06	45.42	75.00	0.03	9.28	0.31	0.11
3	1.79	0.57	0.31	13.80	44.88	0.14	6.96	1.27	0.47
6	4.24	1.54	0.89	7.56	33.35	0.42	6.23	2.43	0.97
12	11.15	4.58	2.71	4.88	23.63	1.24	5.20	4.46	2.10
Method AR (relative to RW)									
1	1.00	0.89	0.86	1.03	0.83	0.91	0.57	0.96	0.90
3	1.02	0.92	0.86	1.03	0.82	0.80	0.50	1.10	1.06
6	1.00	0.88	0.85	1.00	0.89	0.83	0.59	1.06	1.02
12	1.06	0.96	1.01	0.98	0.94	0.93	0.75	1.16	1.00
Method FAAR (relative to RW)									
1	0.94	0.80	0.80	0.96	0.71	0.73	0.48	0.89	0.89
3	0.85	0.71	0.78	0.92	0.60	0.57	0.39	0.98	1.07
6	0.76	0.62	0.77	0.89	0.59	0.52	0.43	0.86	1.03
12	0.71	0.62	0.83	0.90	0.59	0.55	0.53	0.90	1.03
Method POOL (relative to RW)									
1	0.97	0.86	0.85	1.01	0.78	0.85	0.53	0.93	0.89
3	0.95	0.85	0.82	0.99	0.74	0.72	0.45	1.07	1.06
6	0.90	0.79	0.80	0.94	0.77	0.72	0.52	0.99	1.02
12	0.92	0.80	0.90	0.92	0.77	0.78	0.66	1.08	1.01

Table C2: Relative MSFEs - Sub-Periods using Recursive Samples

PERIOD I: sub-sample 1971:1-1984:12 PERIOD II: sub-sample 1985:1-2002:12

Series: Producer Price Index

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	0.55	1.01	0.94	0.97	1	0.37	0.98	0.95	0.97
3	2.20	1.04	0.78	0.93	3	1.47	1	0.92	0.97
6	5.63	0.97	0.63	0.84	6	3.15	1.04	0.94	0.99
12	16.98	1.06	0.60	0.88	12	6.59	1.08	0.94	1

Series: Consumer Price Index

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	0.17	0.83	0.74	0.79	1	0.07	0.99	0.91	0.98
3	0.91	0.86	0.62	0.78	3	0.30	1.06	0.91	1.02
6	2.68	0.81	0.51	0.71	6	0.65	1.12	0.97	1.04
12	8.58	0.89	0.49	0.72	12	1.45	1.29	1.22	1.2

Series: Personal Consumption Expenditure Deflator

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	0.08	0.73	0.69	0.71	1	0.05	1.05	0.96	1.03
3	0.49	0.74	0.67	0.70	3	0.17	1.13	1.01	1.09
6	1.56	0.74	0.67	0.69	6	0.37	1.22	1.1	1.17
12	5.16	0.94	0.73	0.82	12	0.78	1.36	1.35	1.28

Series: Real Personal Income

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	38.35	1.04	0.95	1	1	50.94	1.03	0.97	1.01
3	16.89	1.04	0.89	0.98	3	11.39	1.02	0.95	1.00
6	10.15	1.02	0.8	0.94	6	5.53	0.97	1.02	0.94
12	6.80	0.99	0.8	0.89	12	3.38	0.97	1.06	0.96

Series: Industrial Production

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	123.40	0.80	0.64	0.74	1	37.12	0.93	0.91	0.89
3	79.90	0.83	0.53	0.74	3	17.48	0.79	0.82	0.75
6	59.27	0.91	0.46	0.77	6	13.07	0.82	1.03	0.79
12	41.45	0.95	0.41	0.75	12	9.69	0.89	1.23	0.85

Series: Unemployment Rate

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	0.05	0.87	0.64	0.80	1	0.02	0.98	0.91	0.93
3	0.24	0.78	0.52	0.69	3	0.06	0.86	0.70	0.80
6	0.74	0.83	0.48	0.72	6	0.16	0.80	0.69	0.74
12	2.19	0.95	0.49	0.79	12	0.49	0.85	0.75	0.78

Series: Employees on Nonfarm Payrolls

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	15.88	0.62	0.49	0.58	1	4.11	0.40	0.46	0.38
3	11.72	0.57	0.40	0.51	3	3.24	0.29	0.35	0.27
6	10.30	0.67	0.41	0.59	6	3.05	0.37	0.48	0.35
12	8.24	0.82	0.46	0.70	12	2.81	0.60	0.7	0.58

Series: 3 Months Treasury Bills

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
5 1	0.63	0.97	0.9	0.94	1	0.0	0.86	0.71	0.81
3	2.54	1.10	0.98	1.07	3	0.28	1.11	0.98	1.03
6	4.48	1.02	0.81	0.96	6	0.83	1.20	1.08	1.12
12	7.01	1.21	0.85	1.12	12	2.46	1.04	1.01	0.99

Series: 10 Years Treasury Bonds

hor	RW	AR	FAAR	POOL	hor	RW	AR	FAAR	POOL
1	0.16	0.91	0.91	0.91	1	0.07	0.87	0.86	0.86
3	0.67	1.10	1.11	1.10	3	0.32	1	1.02	1.00
6	1.23	1.02	1.03	1.02	6	0.76	1.02	1.04	1.02
12	2.37	0.99	1.03	1	12	1.89	1.01	1.04	1.01