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Forecasting Inflation and Output:
Comparing Data-Rich Models with Simple Rules

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Abstract

There has been a resurgence of interest in dynamic factor models for use by policy advisors. Dynamic factor methods can be used to incorporate a wide range of economic information when forecasting or measuring economic shocks. This article introduces dynamic factor models that underlie the data-rich methods and tests whether the data-rich models can help a benchmark autoregressive model forecast alternative measures of inflation and real economic activity at horizons of 3, 12 and 24 months ahead. We find that, over the last decade, the data rich models significantly improve the forecasts for a variety of real output and inflation indicators. For all the series that we examine, we find that the data-rich models become more useful when forecasting over longer horizons. The exception is the unemployment rate where the principal components provide significant forecasting information at all horizons.

Keywords: Dynamic Factor Model, Forecast Evaluation

JEL Classification: C32, C53, E31, E37

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Monetary policymakers focus on economic forecasts of a few key variables such as inflation, GDP and the unemployment rate, but they look at many other variables when making these forecasts. In principle, information about other economic indicators should be useful in forecasting economic variables. A key problem is deciding which, if any, other series to include. Recent studies have shown that dynamic factor models may provide a parsimonious way to include incoming information about a wide variety of economic activity. These models use a large data set to extract a few common factors.

Many researchers, including Stock and Watson (1999, 2002), Bernanke and Boivin (2003), Bernanke, Boivin, and Eliasz (2005), Giannone, Reichlin and Sala (2005) have promoted the idea that dynamic factor models can be used to improve empirical macroeconomic analysis. Stock and Watson have instead focused on forecasting. Bernanke and coauthors introduced the term 'data-rich environment' and have focused on applied policy models (structural VARs). The dynamic factor model has gained popularity for two important reasons.

First, augmenting VARs with dynamic factors is a way to mitigate omitted variable bias in structural vector autoregression models (SVARs). When Bernanke (1986) presented his first SVAR model at a Carnegie-Rochester Public Policy Conference, King (1986) commented on the paper, noting that omitting any important macro variable from the policymaker's information set would result in incorrect inference about the effects of monetary policy. In small dimension VARs, important variables are likely to be omitted. Giannone and Reichlin (2006) discuss the conditions under which using large data sets can help to identify economic structure

The second reason for the dynamic factor model's popularity is that it provides a framework for doing empirical analysis that is consistent with the stochastic structure of dynamic general equilibrium models. That is, these models determine a large number of variables with just a small number of structural shocks. A few shocks to preferences, technology and policy drive all the macro variables. The empirical framework fits nicely with the theoretical framework. Evans and Marshall (2006) and Boivin and Giannoni (2006) use dynamic factor techniques to estimate the parameters and shocks of general equilibrium models.

The first part of the paper introduces the dynamic factor model framework. The second part of the paper uses a Granger causality framework to test whether the data-rich models make a statistically significant improvement in the benchmark autoregressive forecasts.[1] To preview the results, we find that, for the past decade anyway, the data-rich framework provides additional information to significantly improve forecasts of inflation and real activity.

Introduction to Dynamic Factor Models

To get a sense of how dynamic factor models incorporate large amounts of information, consider the makeup of the U.S. economy. As of March 2006, the U.S. economy included about 110 million households with an average annual income of over $60,000. There were almost 9 million establishments (firm locations) as derived from quarterly tax filings and reports to various state Unemployment Insurance programs. Government statistical agencies collect data about prices and spending by consumers and

[1] See Eickmeier and Ziegler (2006) for a survey of the large and growing literature on forecasting with dynamic factor models.

firms in order to create the various price indices and spending categories that are used in compiling the National Income and Product Accounts.

Every day the decisions of these millions of households and firms are affected by common macroeconomic factors such as technology, tax rates, interest rates, and government spending. Shocks to these common factors both good and bad, affect spending, productivity, and work effort. The common factors and shocks to them are pervasive, affecting every economic indicator. The decisions of households and firms are also affected by idiosyncratic shocks that are particular to individual firms and households. There are good idiosyncratic shocks like births, strokes of genius, and opportunities taken. There are also bad idiosyncratic shocks like death, sickness, accidents and ideas that do not work out. In contrast to shocks to the common factors that affect everyone, like unexpected monetary policy actions or oil price increases, idiosyncratic shocks affect individuals or a particular market or economic sector.

Figure 1 illustrates the nature of the problem for the macroeconomists. In the center is the economy made up of households, firms, and government embedded in physical and institutional structures. To 'map' the economy, private firms and public agencies collect an enormous amount of information that is organized and reported by various public and private sources. The most important of these economic indicators are the gross domestic product (over $13.5 trillion in 2007), inflation (the CPI inflation trend has been rather steady around 2-1/2 percent over the last decade), and the number of jobs (payroll employment was about 138 million at the end of 2007). These data are aggregated using thousands of bits of information coming from a sample of the households, firms and government. In this paper we are going to use a much smaller, yet very rich data set including 157 time series describing the evolution of production, employment, spending, inflation, interest rates, exchange rates and asset prices. Incoming news about these time series informs us about the short-term stage of the business cycle and expected long-run trends for the major macroeconomic indicators.

On the left side of Figure 1 we sort the factors into those that are common to all the economic indicators—and those that are idiosyncratic. The level of technology in science and industry including management science is a common factor. Recent innovations in computer technology have changed the way everyone keeps track of information and communicates with others. Other common factors include monetary and fiscal policy. Although more difficult to measure, shocks to household preferences for consumption and leisure may also appear to be economy wide. Researchers want to measure these common factors and shocks to them both because they help forecast inflation and output, but also because they are needed to understand how the economy works in order to evaluate the effects of past and proposed policies.

The key assumption underlying the dynamic factor model is that each of the economic indicators is assumed to be driven by a common component made up of a small number of common factors and an idiosyncratic component. Because each of the economic indicators represents the activities of many households and firms, the idiosyncratic shocks estimated in our model may share some common elements. We assume, however, that, unlike the shocks to the common factors, the idiosyncratic shocks do not have economy-wide effects.

On the top right side of Figure 1 we see that a dynamic factor model can be used to estimate a set of common factors that affect all economic time series. The dynamic factor model is designed to extract the small number of common factors from a large set of economic indicators. Stock and Watson (1989) developed coincident and leading indicators of the business cycle using dynamic factor methods.[2] Stock and Watson (2002) also use this statistical model to make economic forecasts. Giannone, Reichlin and Small (2005) have developed a dynamic factor model that is used by at the Federal Reserve Board to make short-term forecasts for a large cross-section of data. The estimated common factors are reduced-form constructs—linear combinations of the structural factors that we would like to observe. On the bottom right side, we see that an economic model must be specified in order to identify the structural factors and the structural shocks that are of most interest to policymakers and policy advisors. Here we focus on using the information in the common factors to forecast indicators of inflation and output.

The basic statistical tools used are principal component and factor analysis.[3] We observe a large number of time series, $x_{i,t}$, i = 1, 2, ... , n; each observed over T periods. The key assumption in the factor model is that each of the individual x_i's can be decomposed into a small number of primitive factors which are common to all the x's and an idiosyncratic component $e_{i,t}$, that is uncorrelated with the primitive factors.

$$x_{it} = \lambda_i' F_t + e_{it}, \tag{1}$$

$$F_t = A(L) F_{t-1} + \varepsilon_t, \tag{2}$$

$$e_{it} = \rho_i(L) e_{it-1} + \upsilon_t, \tag{3}$$

[2] The Federal Reserve Bank of Chicago maintains this leading indicator index. See Evans, Liu, and Pham-Kantor (2002).

[3] For detailed development of these tools, see Forni et al. (2000) and Forni and Lippi (2001).

where $F_t = (F_{1t}, ..., F_{rt})'$ is a vector containing the q common factors and $A(L) = \sum_{j=0}^{p} A_j L^j$ is a polynomial in the lag operator, L. The time series x_{it} is related to the common factors by a vector of factor loadings, $\lambda_i = (\lambda_{i1}, ..., \lambda_{ir})'$. The disturbance term in (1), e_{it}, is the idiosyncratic component of x_{it}, while $\lambda_i^{'} F_t$ is the common component. If the model is static then it is represented by equation (1). Dynamics may be introduced through the common factor component as in equation (2) and/or through the idiosyncratic component as in equation (3). Boivin and Ng (2005) discuss alternative methods that have been developed to estimate the factors and the factor loadings.[4] Then they evaluate the forecasting performance of alternative methods of estimating the dynamic factors. For realistic assumptions about the data, they find that the best forecasting is a simple one that uses the large information set, but does not actually estimate the dynamic factors. We use this method, which involves two steps. The first step is to approximate the factors using the q largest principal components.[5] The second step is to use these principal components in the forecasting model.

Our data matrix has 157 different monthly time series which begin in January 1983 and end 300 months later in December 2007.[6] In this particular case, the number of observations is larger than the number of cross-section units, although that need not be the case. One of the characteristics of this literature is that the number of primitive shocks is usually estimated to be small. Bai and Ng (2007) estimate that there are more than 2 and

[4] See also Schumacher (2007).
[5] Forni et al. (2000) derive conditions under which the largest principal components converge to the dynamic factors when there is weak correlation between e_{it} and e_{jt} for $i \neq j$.
[6] The set of information variables we use is similar to those used by Stock and Watson (2005a), and Bernanke, Boivin and Eliasz (2005). By contrast, the Chicago Fed National Activity Index, which is the first principle component of a data set that is comprised solely of real variables.

perhaps as many as 7 dynamic factors using the Stock and Watson (2005a) data set. Stock and Watson report a similar result using different methods. We start with a specification that encompass the range of estimates of the number of factors.

The Forecasting Models

We evaluate the potential of estimated factors to improve economic forecasts by nesting them within a baseline autoregressive model. We begin with two simple models: a random walk model that predicts future performance at each horizon to be equal to the average performance over the previous 12 months and a univariate regression based on the past 12 months of the relevant variable.

The first model is from Atkeson and Ohanian (2001), who show that a random walk model could predict the year-ahead inflation rate better than the standard Phillips Curve model. Stock and Watson (2005b) show that this better performance for the random walk model is particular to the most recent period of stable inflation and that their dynamic factor models (they used one with 157 variables and another with just 61 real variables) could do as well as the random walk model even in the most recent period. Note that we use the past 12-month average inflation rate as the forecast for the future—at all *h* horizons, 3, 12, and 24 months. Hence, if the inflation rate for the 12 months ending in December 2007 was 4 percent, the random walk forecast of inflation for the average inflation rate over the following 3, 12, and 24 months would be 4 percent. The Atkeson and Ohanian (AO) model for the *h*-month-ahead inflation rate is given as:

$$ {}_{AO}\pi_{\mathrm{t}}^{\mathrm{h}} = \frac{1}{12}\sum_{i=1}^{12}\pi_{t-i} + {}_{AO}u_t^h, \quad \text{where } \pi_{\mathrm{t}}^{\mathrm{h}} = \frac{1}{h}\sum_{i=0}^{h-1}\pi_{t+i}. \tag{4} $$

and π is the inflation rate as measured the change in the log of the price index and adjusted to be at an annual rate. The leading subscript AO indicates that this is the forecast and the forecast error for the AO model. The subscript t and superscript h indicate that this is the forecast for the average annual inflation rate for h months beginning in month t.

The autoregressive models (AR) have the same dependent variable as above, but the weights on the 12 lags are estimated.[7] For the h-month-ahead inflation forecast, the AR model is written as:

$$ {}_{AR}\pi_{\mathrm{t}}^{h} = \phi_0 + \sum_{i=1}^{12} \beta_i \pi_{t-i} + {}_{AR}u_t^h , \qquad (5) $$

We use the same 12 lags for the various horizons and we do not search across lag length for the best in-sample fit when estimating the parameters of the forecasting model.[8]

The third set of models includes the data-rich models (DRM). They use the largest principal components as estimates of the factors and adds them to the AR model in equation (5).[9]

$$ {}_{DRM}\pi_t^h = \phi_0 + \sum_{i=1}^{12} \beta_i \pi_{t-i} + \sum_{j=1}^{q} \sum_{k=1}^{m} PC_{j,t-k} + {}_{DRM}u_t^h \qquad (6) $$

The model adds m lags of the first q estimated factors to the AR model. Based on the findings of Bai and Ng (2007a), we expect to find a relatively small number of primitive factors that will be spanned by a combination of primitive factors and their lags. However, in preliminary work for this study, we found that the best models sometimes had more

[7] Technically, these are not purely autoregressive models. We could have used an AR model of the 1-month-ahead inflation rate and then iterate over h horizons. However, previous research suggests that forecasting the average over the forecast interval directly as we do here often works better than iterated forecasts in realistic (that is, relatively small) sample sizes.
[8] We used 12 lags to take account of seasonal regularities that remain in the data. Hansen (2008) provides theory and evidence to show that using information criteria to choose the best lag length in sample may result in choosing a model that does worst in out-of-sample prediction.
[9] See the Appendix for a listing of the entire data set and the transformation used to standardize each variable.

factors and lags than suggested by tests for the number of primitive factors. Therefore, we run models with q taking values from 1 to 7 and m taking values from 1 to 12. All the principal components enter the equation with the same lag length. Note that equation (6) is similar to the forecasting model used by Stock and Watson (2002).

Forecasting Inflation

In this section we report results from forecasting four measures of inflation: the Consumer Price Index (CPI), the chain price index for personal consumption expenditures (PCEPI), and the two versions of these indexes that exclude the prices of their food and energy components, the core CPI and the core PCEPI. The CPI is the most common measure of inflation and it is commonly used to escalate wages and government benefits. It is also the concept that has been most commonly used as the policy objective by central banks that target inflation. In November 2007 the Federal Reserve began releasing quarterly projections of both total and core measures of PCEPI inflation. The PCEPI is used to compute real personal consumption expenditures in the national income and product accounts.

For our empirical analysis, we chose to begin in January 1983. Our rationale follows the work of those who find a structural break in many macroeconomic variables beginning around that time period. The structural break has been attributed to improved monetary policy, changes in the way firms manufacture and distribute goods, and good luck.[10] The onset of this structural break is usually termed the Great Moderation. In this data set we are using data through December 2007. Pseudo out-of-sample forecasts are produced for January 1997 using models that are estimated using current vintage data. The

[10] See, for example, Ahmed, Levin, and Wilson (2004), McConnell and Quiros (2000), or Taylor (1998).

models (and the principal components) are updated each month, producing recursive inflation forecasts with the final forecast period ending in September 2007. The beginning of the estimation period is fixed, so the number of observations used to estimate the forecasting equations grows over time. The dependent variable in each of the regressions is an average over the relevant forecast interval. The regressors enter as monthly variables.

The Results. The inflation forecasting results are shown in Table 1 and Figures 2-4. The RMSEs for the 3-month forecast horizon are shown in the top panel of Table 1. The first row reports the results for the AO model. This random walk model does a bit better than the AR model only for Core CPI, but even here, the difference is small. The baseline AR model is shown in the second row. The RMSE for the AR is substantially lower than the AO model for the all-item indexes. The third row reports the RMSEs for the best DRMs. The inclusion of principal components significantly improve the forecasts for the CPI and its core measure, but they do not help forecast the PCEPI or the Core PCEPI.[11] Figure 2 shows the RMSEs from all the 3-month-ahead inflation forecasts. The best DRM for the CPI included 3 lags of 7 principal components, a surprising profligate model with 33 estimated parameters. In all the other cases, the best models were smaller, the Core CPI and the PCEPI included just 1 principal component and the best Core PCEPI model included just 1 lag of the first 3 principal components. Figure 2 clearly shows that the DRMs did not contribute much to the 3-month forecasts for the PCEPI or its core measure.

The second panel in Table 1 reports the results for the 12-month-ahead inflation forecasts. Once again the AO model does better than the AR model only in the case of the Core CPI. For all the other experiments reported in the paper, the AO model is worse than

[11] The asterisks in Tables 1 and 2 indicate that we can reject the hypothesis that the principal components do not help forecast at the 1 percent critical level using the McCracken (2007) out-of-sample test statistic.

the AR model which is usually worse than the model that is supplemented with the principal components. At the 12-month horizon, the information provided by the principal components is statistically significant at the 1-percent level for measures of inflation that we studied. Figure 3 shows that the DRMs do quite well when we extend the model to 12 months. For both measures of CPI inflation, the DRMs with 6 or 7 principal components did well, although the best model for the Core CPI included just 2 principal components with 3 lags of each. There was less improvement in the PCEPI and Core PCEPI, but the improvement was statistically significant.

The bottom panel of Table 1 reports the results for the 24-month-ahead inflation forecasts. The results are similar to those for the 12-month forecasts, but the improvement in the forecasts over the benchmark AR model is larger. The principal components displayed significant information for all measures of inflation.

Forecasting Real Activity

Next, we use these models to forecast four monthly indicators of real economic activity: (1) the index of coincident indicators; (2) the Purchasing Managers' Index (PMI), which is a diffusion index that measures activity in the manufacturing sector; (3) real personal consumption expenditures (PCE); and (4) the civilian unemployment rate.[12] The index of coincident indicators and real personal consumption expenditures are measured at an annual growth rates, the ISM index is measured in levels and the unemployment rate is measured as the first difference.

[12] The coincident index is published by the Conference Board, and it is comprised of (1) nonfarm payroll employment, (2) industrial production, (3) real manufacturing and trade sales, and (4) real personal income less transfer payments. The Purchasing Managers' Index is published by the Institute for Supply Management

The results of the out-of sample forecasts for the real variables are presented in table 2. The RMSEs of the random walk models are always the largest relative to the baseline AR and best DRM models. This result was not surprise macroeconomists and forecasters, but we report it to remind readers that the relative good performance of the random walk model in forecasting inflation and asset prices does not carry over into measures of real economic activity. The top panel displays results for the 3-month forecast horizon. The principal components are statistically significant predictors of the PMI and unemployment rate. Figure 4 displays the RMSEs for the specifications of the DRMs of real activity at the 3-month horizon. The best DRM forecast for the PMI included 1 lag of the first 7 principal components. The best DRM forecast of the unemployment rate included just 1 lag of the first principal component, but all of the DRMs with a few lags did well in predicting the unemployment rate. Including the principal components did not help to forecast the index of coincident indicators or real PCE at the 3-month horizon.

The middle panel of Table 2 reports the results for the 12-month forecast. Figure 6 shows the RMSEs for the specifications of the DRMs of real activity at the 12-month horizon. The best model for the index of coincident indicators has 4 principal components with 9 lags but is no better than the benchmark AR model. The best model for the PMI was the DRM with 4 principal components and 1 lag, but as with the coincident indicators, the principal components do not significantly improve the forecasts. The improvements in the forecasts of real PCE growth and the unemployment rate are statistically significant. Again, the best DRM of the unemployment rate includes just the first principal components, but now includes all 12 lags rather than just the first.

The bottom panel in Table 2 report results for the 24-month forecasts of real economic indicators. The best DRM for each of the variables is significantly better than the benchmark AR model. The pattern in the RMSEs for the index of coincident indicators is is similar to pattern in the 12-month results, but the forecasts are better relative to the benchmark AR model. There is a substantial improvement in the PMI and real PCE forecasts relative to the 12 month results. In both cases, the models with 4 lags and 8 to 10 lags do well. The 24-month unemployment rate models were a bit of an exception in that including more than one principal usually made the DRM model produce a RMSE that was larger than the benchmark AR model. The results for the best out-of-sample forecasting version of Equation (6) are summarized in Table 3.

Conclusion

In this paper we report the results of a simulated out-of-sample forecasting experiment in which we compared 85 models for each of 8 economic indicators over 3 forecasting horizons (for a total of 2040 models). The models were estimated over a period beginning in January 1983 and ending 2 months before the beginning of the forecast interval. We made 132 forecasts beginning in January 1997 and ending in December 2007. Generally, we find that the data-rich models can be used to improve forecasts of inflation and output. We found that using principal components to estimate the underlying common factors was useful in forecasting the CPI and its core measure at the 3-month horizon and all measures of inflation at the 12- and 24-month horizons. The factor methods were also helpful in predicting real variables. The data rich models were useful in predicting the unemployment rate over all horizons and all the real variables over 24-month horizons.

In this paper, we used a relatively unrestricted method that did not separately identify the common and idiosyncratic factors. In future research, we plan to identify the common factors and the factor loadings so that we can map source of the information that improves forecast accuracy. We also plan to investigate the benefits of using procedures recommended in Bai and Ng (2007b) for choosing fewer, but informative predictors. They find that one can improve forecast accuracy by using such procedures for each specific variables at each specific forecasting horizon. We are also interested in using dynamic factor methods in combination with economic theory to identify structural economic shocks. This is an emerging area of research that holds promise for doing policy analysis.

References

Atkeson Andrew, and Lee E. Ohanian, (2001), "Are Phillips Curves Useful for Forecasting Inflation?" FRBMN *Quarterly Review* 25(1):2-11.

Ahmed Shagil, Andrew 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):824-32.

Bai, Jushan, and Serena Ng. (2007a) "Determining the Number of Primitive Shocks in Factor Models," *Journal of Business and Economic Statistics* 25(1), 52-60.

Bai, Jushan, and Serena Ng. (2007b) "Forecasting Economic Time Series Using Targeted Predictors," Working paper University of Michigan, November 14. Forthcoming in *Journal of Econometrics*.

Bai, Jushan, and Serena Ng. (2005) "Understanding and Comparing Factor-Based Forecasts," *International Journal of Central Banking* 1(3), 117-151.

Bernanke Ben S., (1986), "Alternative Explanations of the Money-Income Correlation," *Carnegie-Rochester Conference Series on Public Policy* 25:49-100.

Bernanke Ben S., and Jean Boivin, (2003), "Monetary Policy in a Data-Rich Environment," *Journal of Monetary Economics*, 50(3):525-546.

Bernanke, Ben, Jean Boivin, and Piotr Eliasz (2005), "Measuring Monetary Policy: A Factor Augmented Vector Autoregressive (FAVAR) Approach," *Quarterly Journal of Economics* 120(1):387-422.

Boivin, Jean, and Marc P. Giannoni (2006), "DSGE Models in a Data-Rich Environment," Manuscript presented on July 6 in the Macro Seminar Series at the Federal Reserve Bank of St. Louis.

Boivin, Jean, and Serena Ng. (2005), "Understanding and Comparing Factor-Based Forecasts" *International Journal of Central Banking* 1 (December), 117-149.

Eickmeier, Sandra, and Christina Ziegler. (2006), "How Good Are Dynamic Factor Models at Forecasting Output and Inflation? A Meta-Analytic Approach," Deutsche Bundesbank Discussion Paper Sereies 2006-42.

Evans, Chales L., Chin Te Liu, and Genevieve Pham-Kanter, (2002), "The 2001 Recession and the Chicago Fed National Activity Index: Identifying Cycle Turning Points," Federal Reserve Bank of Chicago *Economic Perspectives* (Third Quarter), 26-43.

Evans, Charles L., and David A. Marshall (2006), “Fundamental Economic Shocks and the Macroeconomy,” manuscript October 15, 2006 version, Federal Reserve Bank of Chicago.

Forni, Mario, and Marco Lippi, (2001), “The Generalized Dynamic Factor Model: Representation Theory,” Econometric Theory, 17, 1113-1141.

Forni, Mario, Marc Hallin, Marco Lippi, and Lucrezia Reichlin, (2000), “The Generalized Dynamic-Factor Model: Identification and Estimation,” *Review of Economics and Statistics* 82(4), 540-554.

Giannone, Domenica, and Lucrezia Reichlin, (2006), “Does Information Help Recovering Sturctural Shocks From Past Observations?” European Central Bank Working Paper Series No. 632, May.

Giannone, Domenico, Lucrezia Reichlin, and Luca Sala, (2005), “Monetary Policy in real Time,” in Mark Gertler and Kenneth Rogoff, eds., NBER Macroeconomics Annual 2004, 161-200. MIT Press.

Giannone, Domenico, Lucrezia Reichlin, and David Small, (2005), “Nowcasting: The Real Time Informational Content of Macroeconomic Data Releases’’forthcoming in *Journal of Monetary Economics*, see http://homepages.ulb.ac.be/~dgiannon/Nowcasting.pdf

Hansen, Peter R. (2008), “In-Sample and Out-of-Sample Fit: Their Joint Distribution and its Implications for Model Selection and Model Averaging,” Working Paper, Stanford University, March 18.

King, Robert G., (1986), “Money and Business Cycles: Comments on Bernanke and Related Literature,” *Carnegie-Rochester Conference Series on Public Policy* 25, 101-116.

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), 1464-76.

McCracken, Michael W., (2007), "Asymptotics for Out-of-Sample Tests of Granger Causality," Journal of Econometrics, vol. 140 (October), 719-752.

Schumacher, Christian (2007), "Forecasting German GDP Using Alternative Factor Models Based on Large Datasets," Journal of Forecasting 26, 271-302.

Stock, James H., and Mark W. Watson, (2005a), "Implications of Dynamic Factor Models for VAR Analysis," NBER Working Paper 11467.

_______, (2005b), "Has Inflation Become Harder to Forecast?" Paper presented at the conference, "Quantitative Evidence on Price Determination," Board of Governors of the Federal Reserve System, September 29-30, Washington D.C.

_______, (2002), "Macroeconomic Forecasting Using Diffusion Indexes," *Journal of Business and Economic Statistics* 20: 147-162.

_______, (1999), "Forecasting Inflation," *Journal of Monetary Economics* 44:293-335.

_______, (1989), "New Indexes of Coincident and Leading Economic Indicators," *NBER Macroeconomics Annual, 351-393.*

Taylor, John, (1998), "Monetary Policy and the Long Boom," *Review*, Federal Reserve Bank of St. Louis, 80(6):3-11.

Table 1: Comparing Data-Rich Models of Inflation with Simple Rules
(RMSEs in percent at annual rates)

3 month	CPI	Core CPI	PCEPI	Core PCE
AO	2.03	0.61	1.54	0.69
AR(12)	1.76	0.62	1.44	0.67
DRM	1.67*	0.59*	1.42	0.67
12 month				
AO	1.15	0.48	0.84	0.40
AR(12)	0.99	0.49	0.77	0.38
DRM	0.90*	0.43*	0.71*	0.36*
24 month				
AO	1.00	0.51	0.78	0.39
AR(12)	0.80	0.50	0.69	0.36
DRM	0.63*	0.39*	0.59*	0.33*

* indicates that the DRM model is significantly more accurate than the AR(12) model at the 1-percent critical level.

Table 2: Comparing Data-Rich Models of Economic Activity with Simple Rules
(RMSEs in percent at annual rates for the Coincident Indicators and Real PCE)

3 month	Coincident Indicators	PMI	Real PCE	Unemployment Rate
AO	1.65	4.21	2.19	0.070
AR(12)	1.56	2.43	2.02	0.068
DRM	1.55	2.32*	2.03	0.062*
12 month				
AO	1.54	4.94	1.17	0.055
AR(12)	1.37	3.18	0.97	0.046
DRM	1.36	3.14	0.92*	0.040*
24 month				
AO	1.71	4.86	1.19	0.058
AR(12)	1.34	2.73	0.87	0.040
DRM	1.22*	2.43*	0.61*	0.038*

* reject the null hypothesis that the factors do not Granger cause the forecast variable at the 1-percent critical level.
Note: PMI is measured as the average level over the forecast horizon. The unemployment rate is measured as the average monthly change over the forecast horizon.

Table 3
What's the Best Data-Rich Model?

Inflation			Real Activity		
3-month-ahead forecasts	*q**	*m*		*q*	*m*
CPI	7	3	Coincident Indicators	1	1
Core CPI	1	2	ISM PMI	7	1
PCEPI	1	9	Real PCE	1	1
Core PCEPI	3	1	Unemployment Rate	1	1
12-month-ahead forecasts					
CPI	6	1	Coincident Indicators	4	9
Core CPI	2	6	ISM PMI	4	1
PCEPI	2	9	Real PCE	4	6
Core PCEPI	6	1	Unemployment Rate	1	12
24-month-ahead forecasts					
CPI	7	3	Coincident Indicators	4	8
Core CPI	2	3	ISM PMI	1	12
PCEPI	7	5	Real PCE	4	10
Core PCEPI	6	1	Unemployment Rate	1	12

* q is the number of principal components and m is the number of lags in Equation (6).

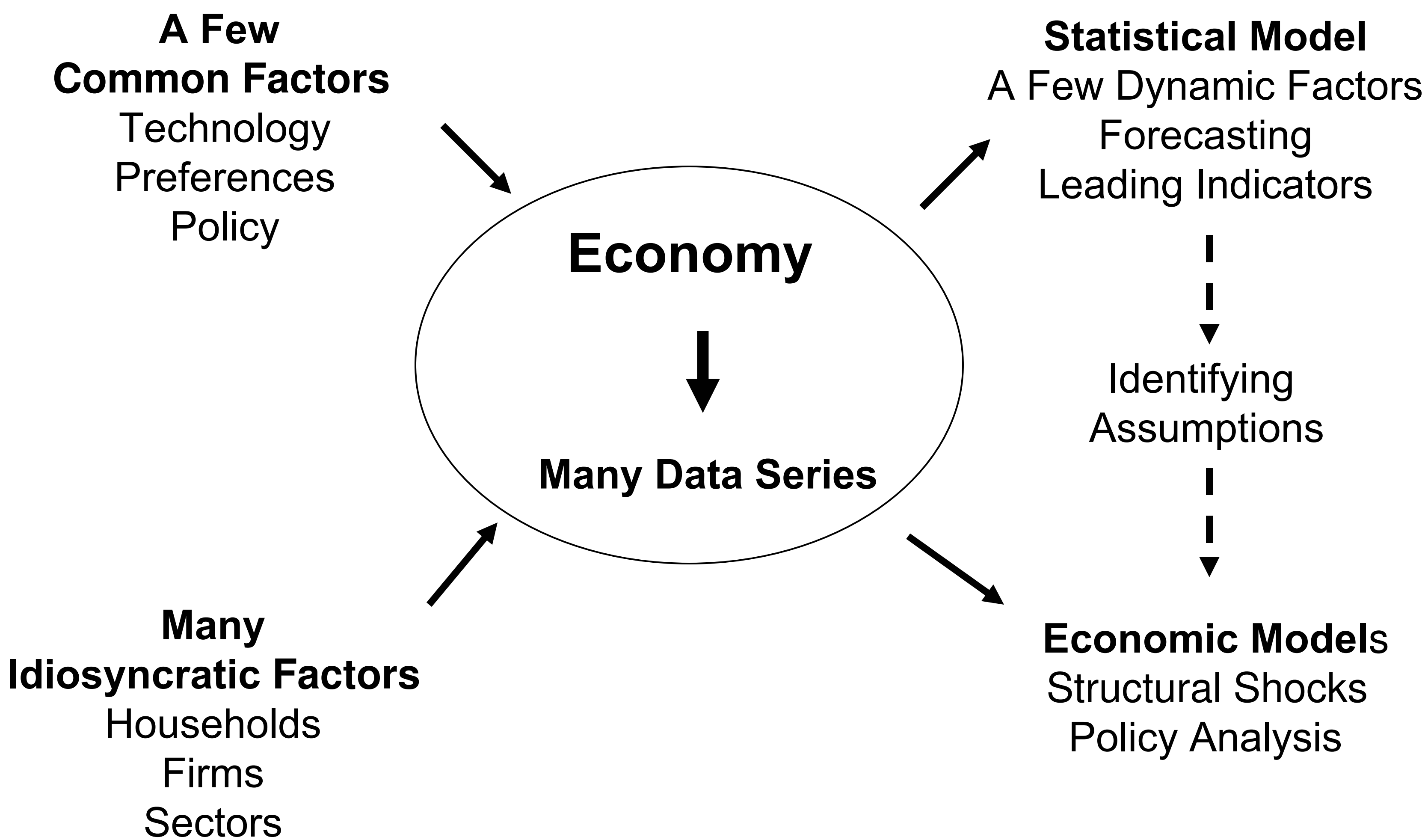
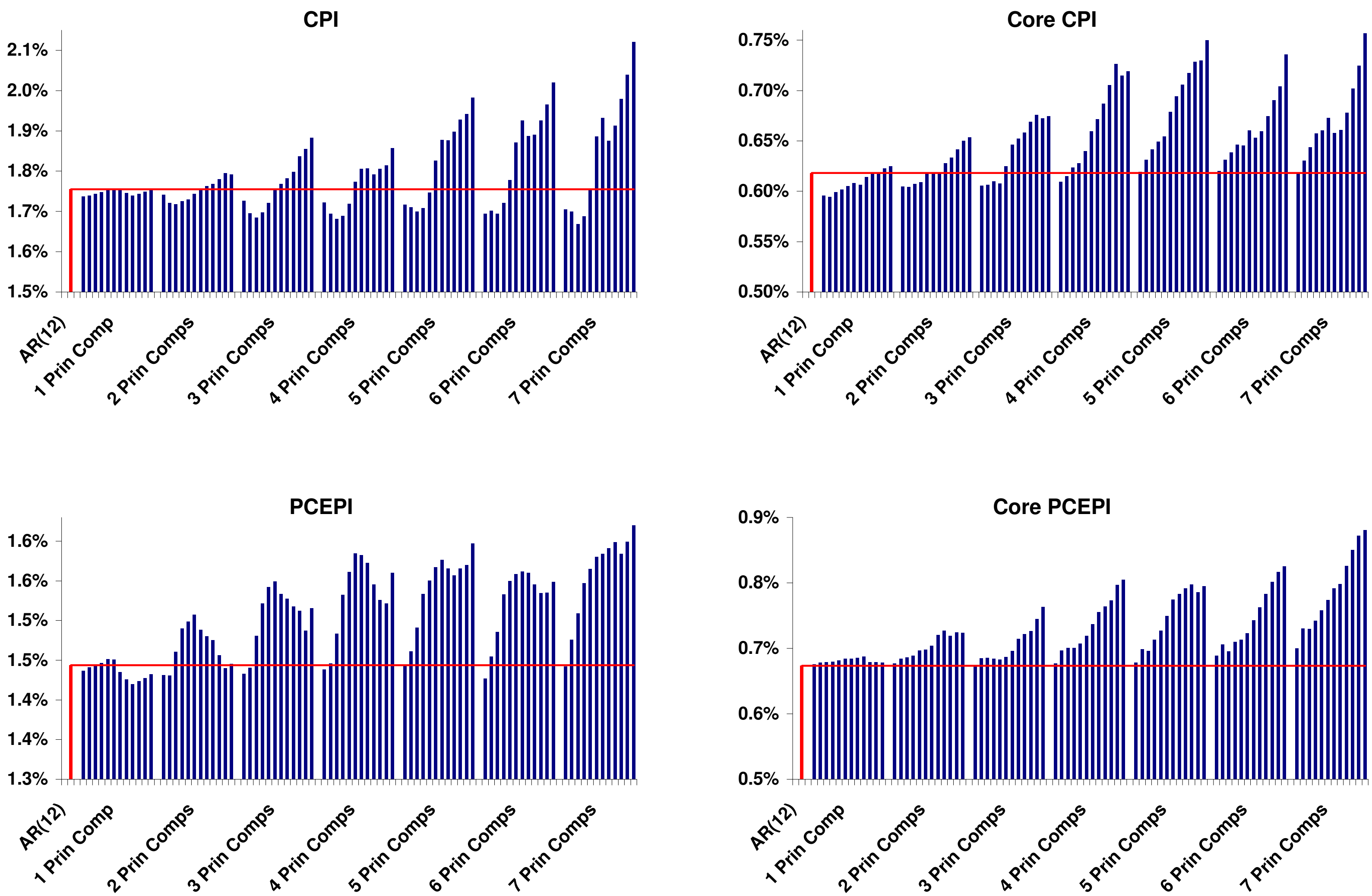


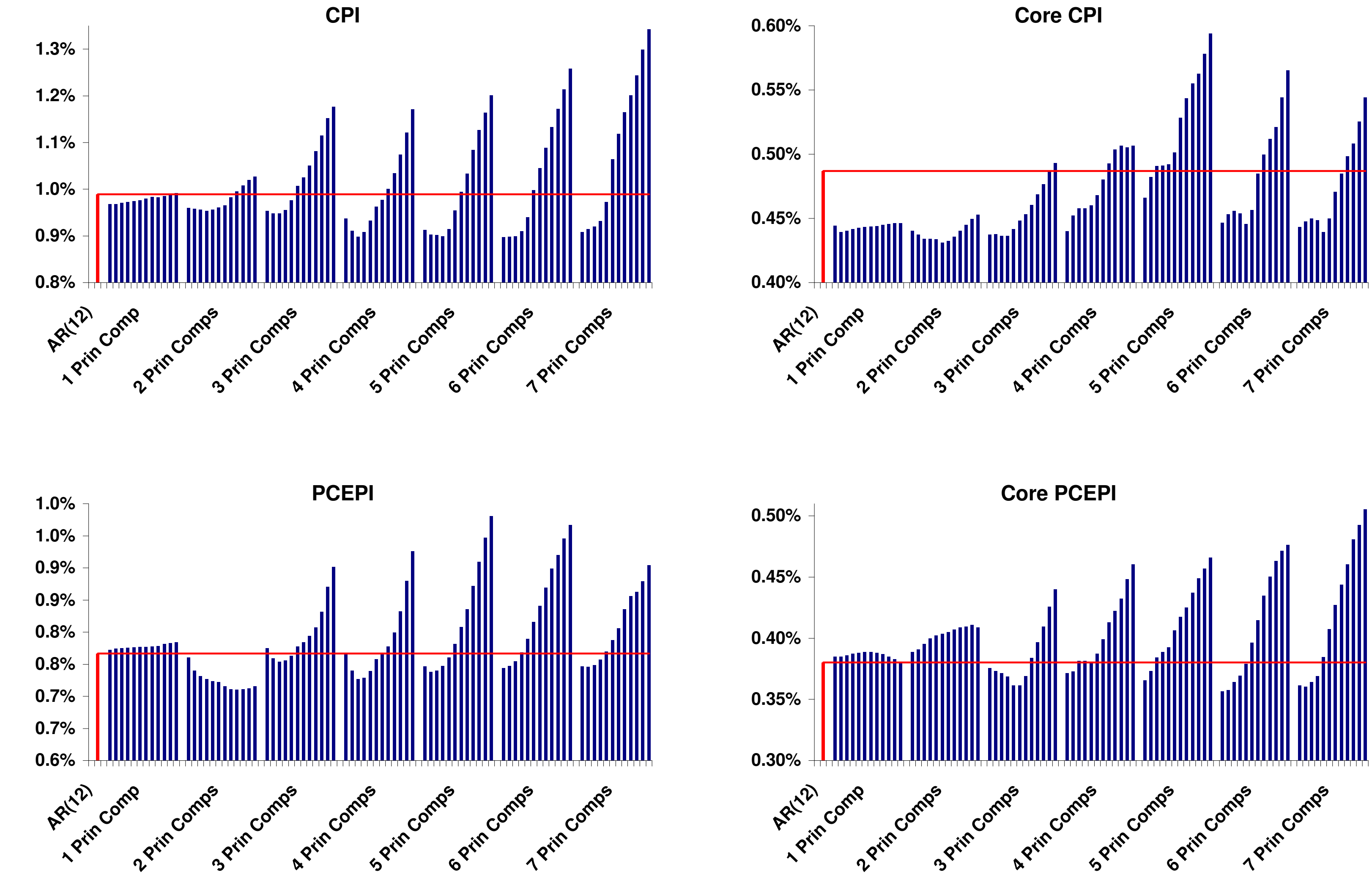
Figure 1. Schematic for data-rich models

Figure 2
Inflation Forecast Accuracy: RMSEs of 3-Month-Ahead Forecasts*



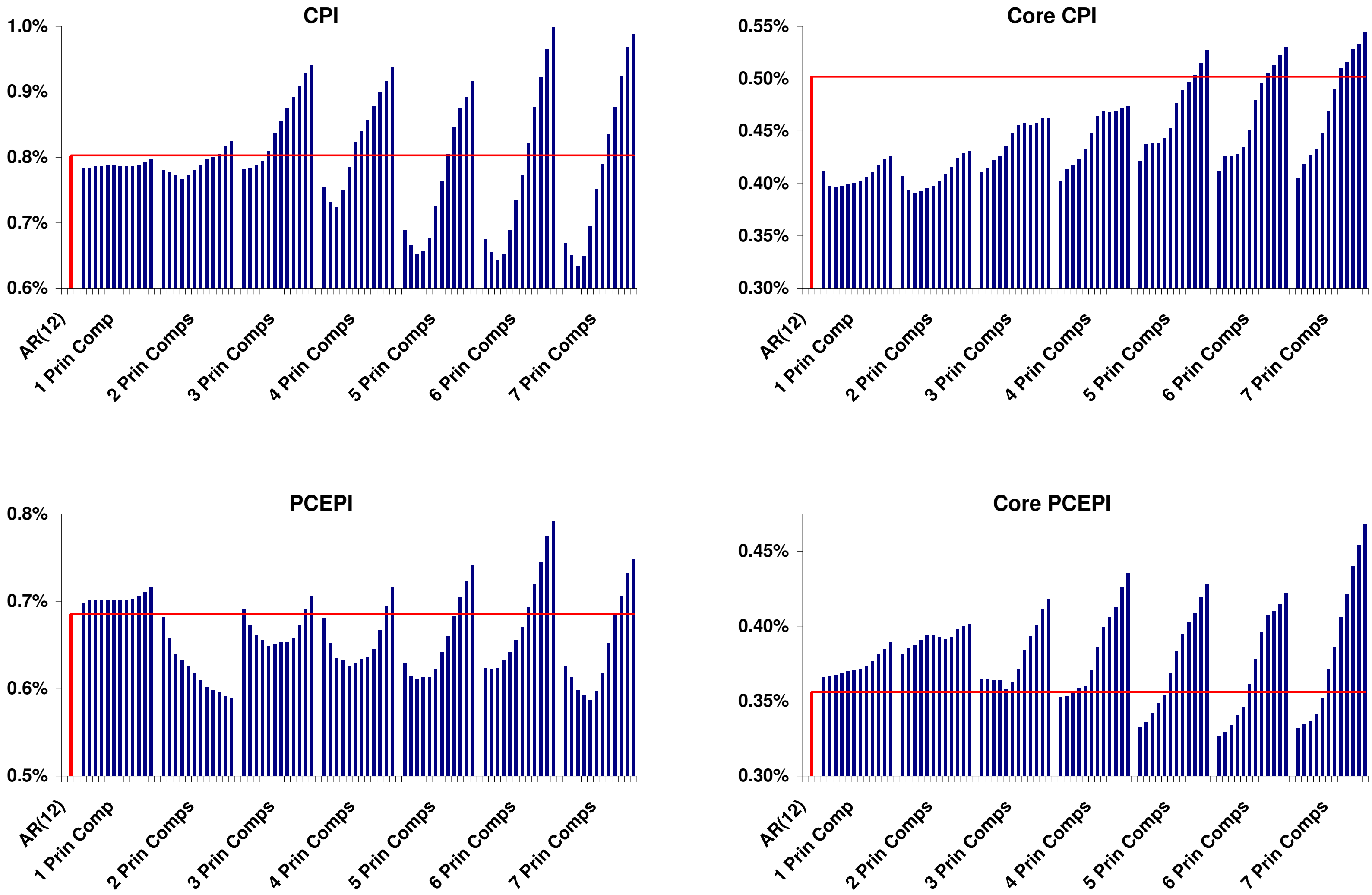
* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Figure 3
Inflation Forecast Accuracy: RMSEs of 12-Month-Ahead Forecasts*



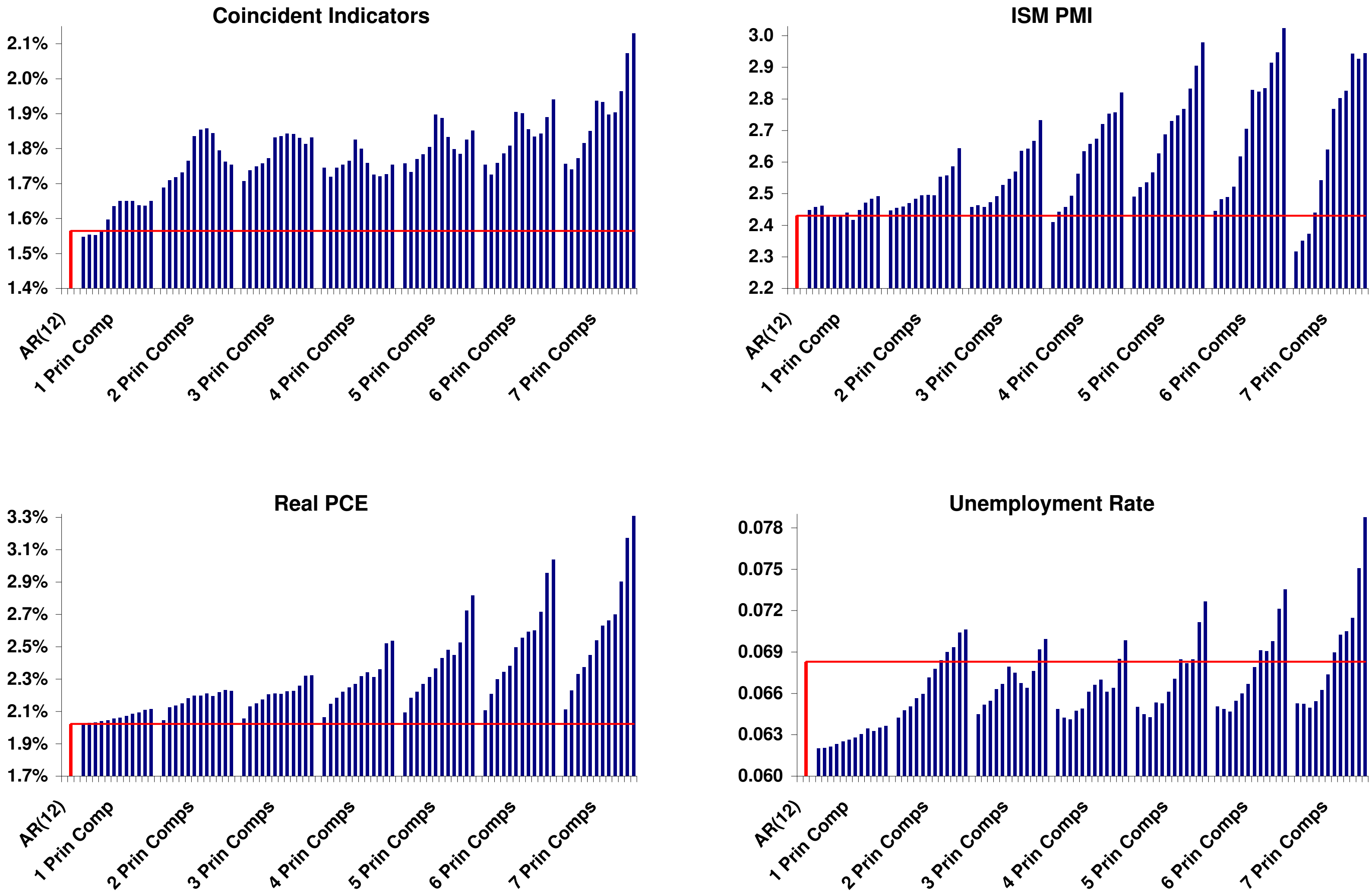
* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Figure 4
Inflation Forecast Accuracy: RMSEs of 24-Month-Ahead Forecasts*



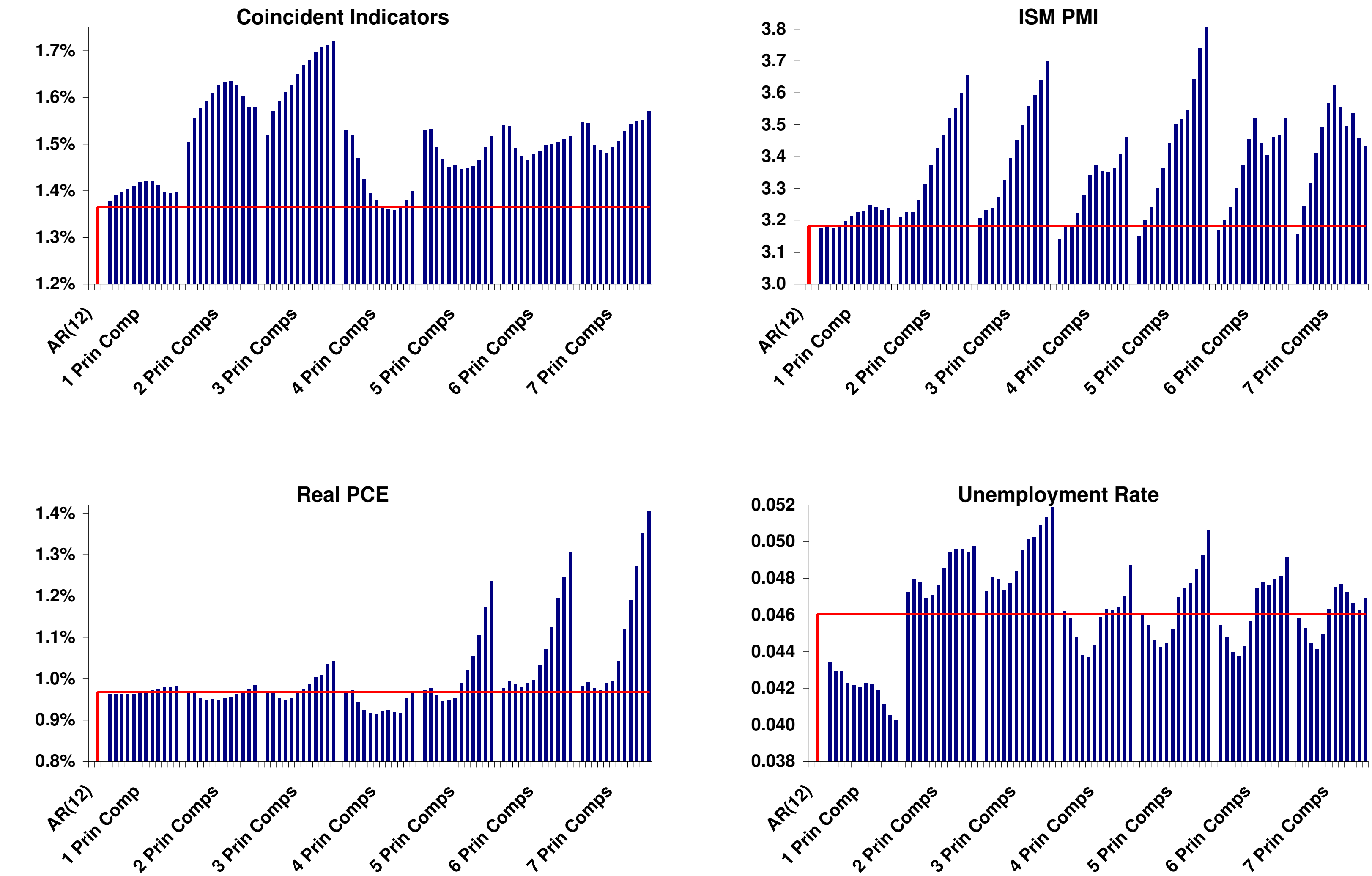
* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Figure 5
Economic Activity Forecast Accuracy: RMSEs of 3-Month-Ahead Forecasts*



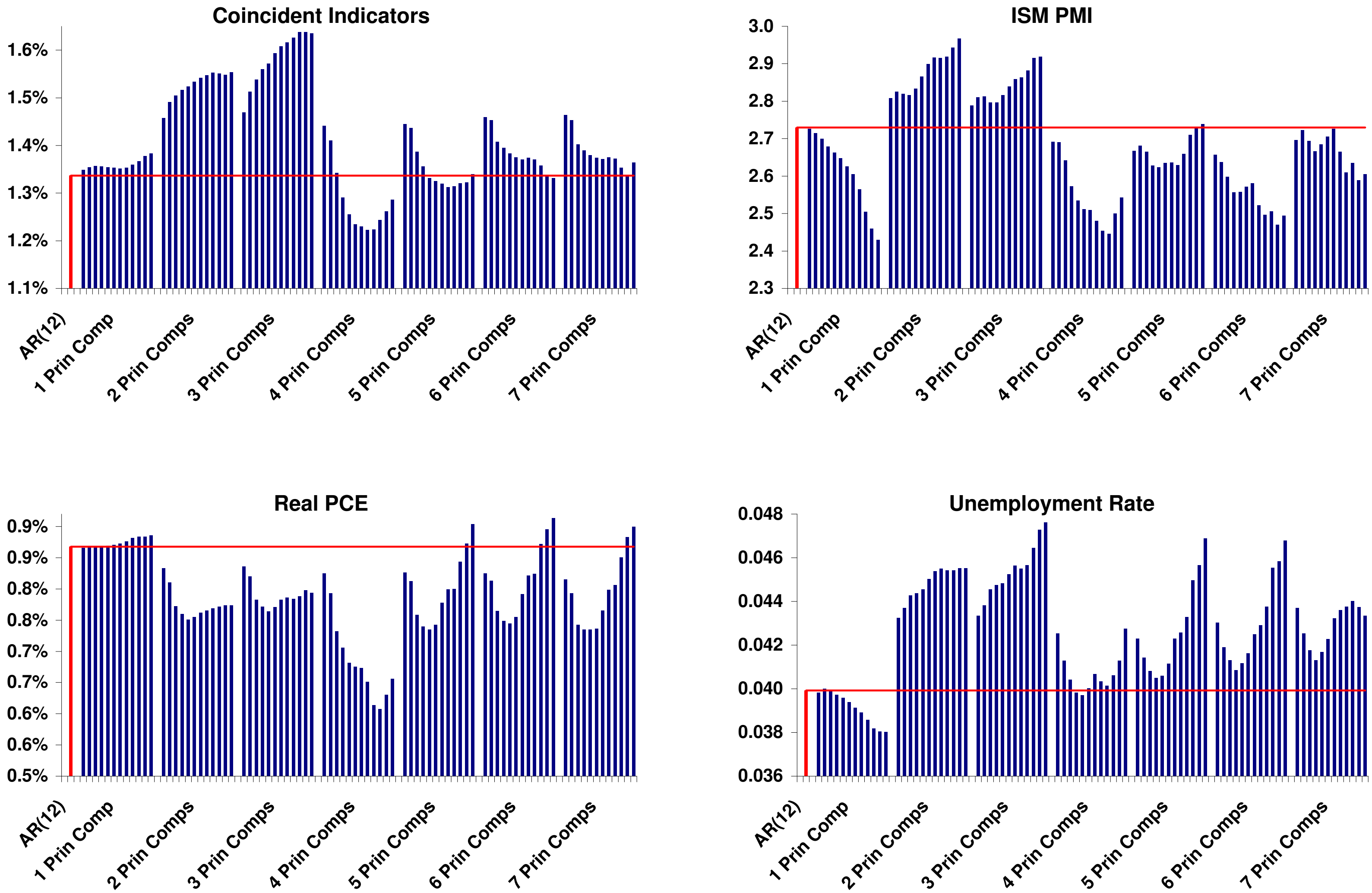
* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Figure 6
Economic Activity Forecast Accuracy: RMSEs of 12-Month-Ahead Forecasts*



* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Figure 7
Economic Activity Forecast Accuracy: RMSEs of 24-Month-Ahead Forecasts*



* Each group of principal components includes RMSEs from models with lags from 1 to 12.

Appendix			
Data Used in the DFM Analysis, Their Transformation and Their Source			
	Description		
	<u>Real Output and Income</u>	**Transformation**	**Source**
1	IP: Total Index (SA, 2002=100)	DLN	FRB
2	IP: Final Products and Nonindustrial Supplies (SA, 2002=100)	DLN	FRB
3	IP: Final Products {Mkt Group} (SA, 2002=100)	DLN	FRB
4	IP: Consumer Goods (SA, 2002=100)	DLN	FRB
5	IP: Durable Consumer Goods (SA, 2002=100)	DLN	FRB
6	IP: Nondurable Consumer Goods (SA, 2002=100)	DLN	FRB
7	IP: Business Equipment (SA, 2002=100)	DLN	FRB
8	IP: Materials (SA, 2002=100)	DLN	FRB
9	IP: Durable Materials (SA, 2002=100)	DLN	FRB
10	IP: Nondurable Materials (SA, 2002=100)	DLN	FRB
11	IP: Manufacturing (SIC) (SA, 2002=100)	DLN	FRB
12	IP: Durable Manufacturing [NAICS] (SA, 2002=100)	DLN	FRB
13	IP: Nonindustrial Supplies (SA, 2002=100)	DLN	FRB
14	IP: Nondurable Manufacturing [NAICS] (SA, 2002=100)	DLN	FRB
15	Industrial Production: Mining (SA, 2002=100)	DLN	FRB
16	IP: Consumer Energy Products: Residential Utilities (SA, 2002=100)	DLN	FRB
17	IP: Consumer Energy Products: Fuels (SA, 2002=100)	DLN	FRB
18	IP: Electric and Gas Utilities (SA, 2002=100)	DLN	FRB
19	IP: Motor Vehicle Assemblies (SAAR, Mil.Units)	DLN	FRB
20	ISM Mfg: Production Index (SA, 50+ = Econ Expand)	LV	ISM
21	Capacity Utilization: Manufacturing [SIC] (SA, % of Capacity)	DLV	FRB
22	Real Personal Income (SAAR, Bil.Chn.2000$)	DLN	BEA/H
23	Real Personal Income Less Transfer Payments (SAAR, Bil.Chn.2000$)	DLN	BEA/H
24	Real Disposable Personal Income (SAAR, Bil.Chn.2000$)	DLN	BEA
	<u>Employment and Hours</u>		
25	Index of Help-Wanted Advertising in Newspapers (SA,1987=100)	DLN	CNFBOARD
26	Ratio: Help-Wanted Advertising in Newspapers/Number Unemployed (SA)	DLN	CB/BLS/H
27	Civilian Employment: Sixteen Years & Over (SA, Thousands)	DLN	BLS
28	Civilian Employment: Nonagricultural Industries: 16 yr + (SA, Thous)	DLN	BLS
29	Civilian Unemployment Rate: 16 yr + (SA, %)	DLV	BLS
30	Civilian Unemployment Rate: Men, 25-54 Years (SA, %)	DLV	BLS
31	Average {Mean} Duration of Unemployment (SA, Weeks)	DLV	BLS
32	Civilians Unemployed for Less Than 5 Weeks (SA, Thous.)	DLN	BLS
33	Civilians Unemployed for 5-14 Weeks (SA, Thous.)	DLN	BLS
34	Civilians Unemployed for 15 Weeks and Over (SA, Thous.)	DLN	BLS
35	Civilians Unemployed for 15-26 Weeks (SA, Thous.)	DLN	BLS
36	Civilians Unemployed for 27 Weeks and Over (SA, Thous.)	DLN	BLS
37	Unemployment Insurance: Initial Claims, State Programs (SA, Thous)	DLV	DOL
38	All Employees: Total Nonfarm (SA, Thous)	DLN	BLS
39	All Employees: Total Private Industries (SA, Thous)	DLN	BLS
40	All Employees: Goods-producing Industries (SA, Thous)	DLN	BLS
41	All Employees: Mining (SA, Thous)	DLN	BLS
42	All Employees: Construction (SA, Thous)	DLN	BLS

43	All Employees: Manufacturing (SA, Thous)	DLN	BLS
44	All Employees: Durable Goods Manufacturing (SA, Thous)	DLN	BLS
45	All Employees: Nondurable Goods Manufacturing (SA, Thous)	DLN	BLS
46	All Employees: Service-providing Industries (SA, Thous)	DLN	BLS
47	All Employees: Trade, Transportation & Utilities (SA, Thous)	DLN	BLS
48	All Employees: Wholesale Trade (SA, Thous)	DLN	BLS
49	All Employees: Retail Trade (SA, Thous)	DLN	BLS
50	All Employees: Financial Activities (SA, Thous)	DLN	BLS
51	All Employees: Government (SA, Thous)	DLN	BLS
52	Aggregate Weekly Hours Index: Total Private Industries (SA, 2002=100)	DLN	BLS
53	Average Weekly Hours: Goods-producing Industries (SA, Hrs)	LV	BLS
54	Average Weekly Hours: Overtime: Manufacturing (SA, Hrs)	DLV	BLS
55	Average Weekly Hours: Manufacturing (SA, Hrs)	DLV	BLS
56	ISM Mfg: Employment Index (SA, 50+ = Econ Expand)	LV	ISM
	Real Retail, Manufacturing and Trade Sales		
57	Manufacturing & Trade Sales (SA, Mil.Chn.2000$)	DLN	CNFBOARD
58	Manufacturing & Trade Inventories (EOP, SA, Bil.Chn.2000$)	DLN	CNFBOARD
59	Mfg & Trade: Inventories/Sales Ratio (SA, Chn.2000$)	DLN	CNFBOARD
60	Manufacturers' Shipments of Mobile Homes (SAAR, Thous.Units)	LN	CENSUS
61	Real Retail Sales & Food Services	DLN	AUTHORS
	Inventories and Orders		
62	ISM Mfg: Inventories Index (SA, 50+ = Econ Expand)	LV	ISM
63	ISM Mfg: New Orders Index (SA, 50+ = Econ Expand)	LV	ISM
64	Mfrs New Orders: Durable Goods (SA, Mil.Chn.2000$)	DLN	CNFBOARD
65	Manufacturers New Orders: Nondefense Capital Goods (SA, Mil. 1982$)	DLN	CNFBOARD
66	Mfrs Unfilled Orders: Durable Goods (SA, EOP, Mil.Chn.2000$)	DLN	CNFBOARD
	Consumption		
67	Real Personal Consumption Expenditures: Durable Goods (SAAR, Bil.Chn.2000$)	DLN	BEA
68	Real Personal Consumption Expenditures: Nondurable Goods (SAAR, Bil.Chn.2000$)	DLN	BEA
69	Real Personal Consumption Expenditures: Services (SAAR, Bil.Chn.2000$)	DLN	BEA
70	Real Personal Consumption Expenditures (SAAR, Bil.Chn.2000$)	DLN	BEA
	Housing Starts and Sales		
71	Housing Starts (SAAR, Thous.Units)	LN	CENSUS
72	Housing Starts: Northeast (SAAR, Thous.Units)	LN	CENSUS
73	Housing Starts: Midwest (SAAR, Thous.Units)	LN	CENSUS
74	Housing Starts: South (SAAR, Thous.Units)	LN	CENSUS
75	Housing Starts: West (SAAR, Thous.Units)	LN	CENSUS
76	New Pvt Housing Units Authorized by Building Permit (SAAR, Thous.Units)	LN	CENSUS
77	Housing Units Authorized by Permit: Northeast (SAAR, Thous.Units)	LN	CENSUS
78	Housing Units Authorized by Permit: Midwest (SAAR, Thous.Units)	LN	CENSUS
79	Housing Units Authorized by Permit: South (SAAR, Thous.Units)	LN	CENSUS
80	Housing Units Authorized by Permit: West (SAAR, Thous.Units)	LN	CENSUS
81	Total Public Construction (SAAR, Mil. Chained 1996$)	DLN	AUTHORS
82	Private Construction: Nonresidential (SAAR, Mil. Chained 1996$	DLN	AUTHORS

	<u>**Stock Prices**</u>		
83	Stock Price Index: Standard & Poor's 500 Composite (1941-43=10)	DLN	WSJ
84	Stock Price Index: Standard & Poor's 500 Industrials (1941-43=10)	DLN	FINTIMES
85	S&P: Composite 500, Dividend Yield (%)	DLV	S&P/H
86	S&P: 500 Composite, P/E Ratio, 4-Qtr Trailing Earnings (Ratio)	DLN	S&P/H
87	Stock Price Index: NASDAQ Composite (Feb-5-71=100)	DLN	WSJ
	<u>**Exchange Rates**</u>		
88	Nominal Broad Trade-Weighted Exchange Value of the US$ (Jan-97=100)	DLN	FRB
89	Real Broad Trade-Weighted Exchange Value of the US$ (Mar-73=100)	DLN	FRB
90	Foreign Exchange Rate: Switzerland (Franc/US$)	DLN	FRB
91	Foreign Exchange Rate: Japan (Yen/US$)	DLN	FRB
92	Foreign Exchange Rate: United Kingdom (US$/Pound)	DLN	FRB
93	Foreign Exchange Rate: Canada (C$/US$)	DLN	FRB
	<u>**Interest Rates**</u>		
94	Federal Funds [effective] Rate (% p.a.)	DLV	FRB
95	3-Month Nonfinancial Commercial Paper (% per annum)	DLV	FRB
96	3-Month Treasury Bills, Secondary Market (% p.a.)	DLV	FRB
97	6-Month Treasury Bills, Secondary Market (% p.a.)	DLV	FRB
98	1-Year Treasury Bill Yield at Constant Maturity (% p.a.)	DLV	FRB
99	5-Year Treasury Note Yield at Constant Maturity (% p.a.)	DLV	FRB
100	10-Year Treasury Note Yield at Constant Maturity (% p.a.)	DLV	FRB
101	Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)	DLV	FRB
102	Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	DLV	FRB
	<u>**Yield Spreads**</u>		
	Eight Series Listed Below Minus the Federal Funds Rate		
103	3-Month Nonfinancial Commercial Paper (% per annum)	LV	FRB
104	3-Month Treasury Bills, Secondary Market (% p.a.)	LV	FRB
105	6-Month Treasury Bills, Secondary Market (% p.a.)	LV	FRB
106	1-Year Treasury Bill Yield at Constant Maturity (% p.a.)	LV	FRB
107	5-Year Treasury Note Yield at Constant Maturity (% p.a.)	LV	FRB
108	10-Year Treasury Note Yield at Constant Maturity (% p.a.)	LV	FRB
109	Moody's Seasoned Aaa Corporate Bond Yield (% p.a.)	LV	FRB
110	Moody's Seasoned Baa Corporate Bond Yield (% p.a.)	LV	FRB
	<u>**Money and Credit Quantity Aggregates**</u>		
111	Money Stock: M1 (SA, Bil.$)	DLN	FRB
112	Money Stock: M2 (SA, Bil.$)	DLN	FRB
113	Money Stock: Institutional Money Funds (SA, Bil.$)	DLN	FRB
114	Real Money Stock: M2 (SA, Bil.Chn.2000$)	DLN	FRB/BEA/H
	St. Louis Adjusted Monetary Base		
115	Adj Monetary Base inc Deposits to Satisfy Clearing Bal Contracts (SA, Bil.$)	DLN	FRBSTL
116	Adjusted Reserves of Depository Institutions (SA, Mil.$)	DLN	FRB
117	Adjusted Nonborrowed Reserves of Depository Institutions (SA, Mil.$)	DLN	FRB
118	Real Commercial and Industrial Loans Outstanding (SA, Mil.Chn.2000$)	DLN	FRB/BEA/H

119	C & I Loans in Bank Credit: All Commercial Banks (SA, Bil.$)	DLN	FRB
120	Consumer Revolving Credit Outstanding (EOP, SA, Bil.$)	DLN	FRB
121	Nonrevolving Consumer Credit Outstanding (EOP, SA, Bil.$)	DLN	FRB
122	Ratio: Consumer Installment Credit to Personal Income (SA, %)	DLV	FRB/BEA/H
	Price Indexes and Wages		
123	PPI: Finished Goods (SA, 1982=100)	DLN	BLS
124	PPI: Finished Consumer Goods (SA, 1982=100)	DLN	BLS
125	PPI: Finished Goods: Capital Equipment (SA, 1982=100)	DLN	BLS
126	PPI: Intermediate Materials, Supplies and Components (SA, 1982=100)	DLN	BLS
127	PPI: Crude Materials for Further Processing (SA, 1982=100)	DLN	BLS
128	PPI: Fuels and Related Products and Power (NSA, 1982=100)	DLN	BLS
129	PPI: Industrial Commodities Less Fuels & Power (NSA, 1982=100)	DLN	BLS
130	Reuters/Jefferies CRB Futures Price Index: All Commodities (1967=100)	DLN	CRB
131	CPI-U: All Items (SA, 1982-84=100)	DLN	BLS
132	CPI-U: Apparel (SA, 1982-84=100)	DLN	BLS
133	CPI-U: Transportation (SA, 1982-84=100)	DLN	BLS
134	CPI-U: Medical Care (SA, 1982-84=100)	DLN	BLS
135	CPI-U: Housing (SA, 1982-84=100)	DLN	BLS
136	FRB Cleveland Median CPI (SAAR, %chg)	LV	FRBCLV
137	CPI-U: Commodities (SA, 1982-84=100)	DLN	BLS
138	CPI-U: Durables (SA, 1982-84=100)	DLN	BLS
139	CPI-U: Services (SA, 1982-84=100)	DLN	BLS
140	CPI-U: All Items Less Food and Energy (SA, 1982-84=100)	DLN	BLS
141	CPI-U: All Items Less Food (SA, 1982-84=100)	DLN	BLS
142	CPI-U: All Items Less Shelter (SA, 1982-84=100)	DLN	BLS
143	CPI-U: All Items Less Medical Care (SA, 1982-84=100)	DLN	BLS
144	PCE: Chain Price Index (SA, 2000=100)	DLN	BEA
145	PCE: Durable Goods: Chain Price Index (SA, 2000=100)	DLN	BEA
146	PCE: Nondurable Goods: Chain Price Index (SA, 2000=100)	DLN	BEA
147	PCE: Services: Chain Price Index (SA, 2000=100)	DLN	BEA
148	PCE less Food & Energy: Chain Price Index (SA, 2000=100)	DLN	BEA
149	Avg Hourly Earnings: Goods-producing Industries (SA, $/Hr)	DLN	BLS
150	Avg Hourly Earnings: Construction (SA, $/Hr)	DLN	BLS
151	Avg Hourly Earnings: Manufacturing (SA, $/Hr)	DLN	BLS
152	New 1-Family Houses: Median Sales Price (Dollars)	DLN	CENSUS
153	NAR Median Sales Price: Existing 1-Family Homes, United States ($)	DLN	REALTOR
	Miscellaneous		
154	ISM Mfg: Supplier Deliveries Index (SA, 50+ = Slower)	LV	ISM
155	University of Michigan: Inflation Expectations	LV	UMICH/FRED
156	University of Michigan: Consumer Expectations (NSA, Q1-66=100)	DLV	UMICH
157	ISM Mfg: PMI Composite Index (SA, 50+ = Econ Expand)	LV	ISM
	Addenda:		
	Nomenclature: By Transformation		
	DLN: Change in logs, annualized		
	DLV: Change in levels		
	LV: Levels		

	Nomenclature: By Data Source		
	AUTHORS: Calculation by authors		
	BEA: Bureau of Economic Analysis		
	BLS: Bureau of Labor Statistics		
	CENSUS: U.S. Department of the Census		
	CB/CNFBOARD: The Conference Board		
	CRB: Commodity Research Bureau		
	DOL: Department of Labor		
	FINTIMES: Financial Times		
	FRB: Board of Governors of the Federal Reserve System		
	FRBCLV: Federal Reserve Bank of Cleveland		
	FRBSTL: Federal Reserve Bank of St. Louis		
	FRED: Federal Reserve Economic Data, Federal Reserve Bank of St. Louis		
	H: Haver Analytics		
	IP: Industrial Production		
	ISM: Institute for Supply Management		
	REALTOR: National Association of Realtors		
	S&P: Standard & Poors		
	UMICH: University of Michigan Survey Research Center		
	WSJ: *The Wall Street Journal*		