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# FRED-MD: A Monthly Database for Macroeconomic Research


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This article describes a large, monthly frequency, macroeconomic database with the goal of establishing a convenient starting point for empirical analysis that requires "big data." The dataset mimics the coverage of those already used in the literature but has three appealing features. First, it is designed to be updated monthly using the Federal Reserve Economic Data (FRED) database. Second, it will be publicly accessible, facilitating comparison of related research and replication of empirical work. Third, it will relieve researchers from having to manage data changes and revisions. We show that factors extracted from our dataset share the same predictive content as those based on various vintages of the so-called Stock–Watson dataset. In addition, we suggest that diffusion indexes constructed as the partial sum of the factor estimates can potentially be useful for the study of business cycle chronology. Supplementary materials for this article are available online.



KEY WORDS: Big data; Diffusion index; Factors; Forecasting.


## 1. INTRODUCTION

A new trend in research is to make use of data that two decades ago were either not available or that previously were considered computationally prohibitive. This is true not just in medical science and engineering research, but also in many disciplines of social science. Economic research is no exception. Instead of working with $T$ time series observations of $N$ variables where $T$ is large and $N$ is quite small, we are now able to analyze a large number of variables without sacrificing information in the time series dimension. Bernanke and Boivin (2003) coined the term *data-rich environment* when $N$ and $T$ are both large. The breakthrough is the development of theory and methods to estimate large-dimensional factor models. Some use multivariate factor-augmented models for macroeconomic policy analysis while others use the factors in forecasting exercises. Factor-augmented regressions have been found to produce superior impulse responses and forecasts over competing methods, especially those that are based on a small set of predictors. A comprehensive survey of factor-based macroeconomic research is given in Stock and Watson (2015). Of course, for more data to be desirable, the data must be informative about the economic variables that we seek to explain. As such, assembling a good database is an important part of research. However, the data-collection process is time consuming, and it often involves judgment on details with which academic researchers have little expertise. The task can be overwhelming when $N$ is large.

Over the course of the past year, we have worked with the FRED (Federal Reserve Economic Data, *http://research.stlouisfed.org/fred2/*, is the St. Louis Fed's main, publicly available, economic database) data desk at the Federal Reserve Bank of St. Louis to develop FRED-MD, a macroeconomic database of 134 monthly U.S. indicators. The dataset will be updated in a timely manner and can be downloaded for free from the website *http://research.stlouisfed.org/econ/mccracken/sel/*. The goal is to reduce the overhead of macroeconometric analysis. Working with a more or less standard database should also facilitate replication and comparison of results. This article provides background information about FRED-MD.

To better understand the motivation of this project, it is useful to give some history of "big data" analysis in macroeconomic research. The first personalized U.S. macroeconomic database appears to be the one compiled by Stock and Watson (1996) for analyzing parameter instability over the sample 1959:1–1993:12. Their data collection was guided by four considerations:

> First, the sample should include the main monthly aggregates and coincident indicators. Second, the data should include important leading economic indicators. Third, the data should represent broad class of variables with differing time series properties. Fourth, the data should have consistent historical definitions or when the definitions are inconsistent, it should be possible to adjust the series with a simple additive or multiplicative splice. (Stock and Watson 1996, p. 12)

Using these criteria, Stock and Watson collected 76 series mostly drawn from CITIBASE. The data included industrial production, weekly hours, personal inventories, monetary aggregates, interest rates and interest-rate spreads, stock prices, and consumer expectations. The data were then classified into eight categories: (1) output and sales, (2) employment, (3) new orders, (4) inventories, (5) prices, (6) interest rates, (7) money and credit, and (8) other variables. This dataset was expanded in Stock and Watson (1998, 2002) to include 215 series that can be classified into 14 categories. In this iteration, the data were taken from the DRI/McGraw Hill database. Although over


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200 series were collected, the statistical analysis was based on a balanced panel of 149 series. The exercise consists of compressing information in the 149 series into a handful of factors and then using the factor estimates as predictors. This methodology has come to be known as "diffusion index forecasting." Marcellino, Stock, and Watson (2006) used 171 series for the sample 1959:1–2002:12 to assess this and alternative forecasting methodologies.

In an influential article, Bernanke and Boivin (2003) extended big data macroeconomic analysis from forecasting to semistructural macroeconomic modeling. They used three datasets to assess the robustness of their results. The first combined real-time data based on Stark and Croushore (2001). The second was a version of the first but with revised data. The third used the 215 variables in Stock and Watson (1999). Bernanke, Boivin, and Eliasz (2005) used 120 series from the DRI database to estimate a factor-augmented vector autoregression (FAVAR). This methodology uses a large number of economic indicators to estimate the common latent factors in the economy. As the estimated factors provide a parsimonious way to include information from many variables, a FAVAR is less vulnerable to subjective decisions about which variables to include. Factors are also useful when variables chosen for empirical analysis do not match up with concepts in theoretical models. Boivin and Giannoni (2006) considered estimation of dynamic stochastic general equilibrium (DSGE) models that explicitly treat measurement errors as the difference between the data and the model concepts. Boivin and Giannoni (2006) used 91 variables in their analysis that directly connects estimation of DSGE models with large-dimensional factor models because data with measurement errors can also be represented by factor models.

Until this point, more data were collected than were used in analysis because some of these series were available only as of 1967:01. The next phase of this literature focused primarily on balanced panels. Stock and Watson (2005, 2006) constructed data for 132 macroeconomic time series over the sample 1959:01–2003:12. The data, used to estimate structural FAVARs, were organized into 14 categories: (1) real output and income, (2) employment and hours, (3) real retail, manufacturing and trade sales, (4) consumption, (5) housing starts and sales, (6) real inventories, (7) orders, (8) stock prices, (9) exchange rates, (10) interest rates and spreads, (11) money and credit quantity aggregates, (12) price indexes, (13) average hourly earnings, and (14) miscellaneous. The data were drawn primarily from Global Insights Basic Economics Database (GSI), with a few series from the Conference Board and a few series based on the authors' calculations. This database of 132 series is sometimes referred to as the "Stock–Watson dataset." Bai and Ng (2008) used the data to compare diffusion index forecasting with predictors selected by hard thresholding.

Ludvigson and Ng (2011) updated the Stock–Watson data to 2007:12 and more broadly classified the data into eight groups: (1) output and income, (2) labor market, (3) housing, (4) consumption, orders and inventories, (5) money and credit, (6) bond and exchange rates, (7) prices, and (8) stock market. Factors estimated using the entire dataset were compared with an alternative estimator that takes advantage of the structure of the eight groups. The data were again updated in Jurado, Ludvigson, and Ng (2015) to 2011:12 and merged with 147 monthly financial time series to construct an index of macroeconomic uncertainty. The database has since been updated to 2013:05. Hereafter, we distinguish the vintages of GSI data by the end of sample. The 2003 vintage is the original data used in Stock and Watson (2005) and the 2011 vintage is the data used in Jurado, Ludvigson, and Ng (2015).

Many researchers have collected larger or smaller datasets but the coverage of the data is quite similar to the original Stock–Watson data. This is not surprising because most of the data come from the statistical agencies. Whether the database has more or fewer data series depends on the desired level of disaggregation. For example, Stock and Watson (2014) collected 270 disaggregated monthly series for the sample 1959:01–2010:08 to estimate turning points. For monthly macroeconomic forecasting and FAVARs, most analyses use between 100 and 150 series. One of our goals is to provide a core set of data that is readily available and updated regularly.

## 2. FRED-MD

If the same variables were reported year after year, the data-updating exercise would be straightforward. Assuming one has access to GSI, one would download the data and run a few programs. A dataset satisfying the first three criteria outlined in Stock and Watson (1996) should then be available. But the process is more involved in practice. The main difficulty is almost entirely due to changing definitions and data availability. Even with careful selection of variables that meet the fourth criterion of Stock and Watson (1996), researchers have often had to deal with data revisions that took place for one reason or another. As an example, an oil price variable is widely used in empirical work. Yet, the OILPRICE series in FRED that existed since 1946:1 has recently been discontinued. In its place is a WTI series that starts only from 1986:1. If one were to analyze 50 years of monthly data, one could not avoid having to melt or splice data from different sources, which is what makes the data-updating process difficult.

Consider updating from the vintage ending in 2011:12 through 2013:12. Even though the dataset was extended by merely 24 months, several issues had to be dealt with. The process is roughly as follows. Based on the mnemonics of the 2011 data, we started by retrieving from GSI the same data but for the extended sample. It was found that some series have changed names, so the first task was to locate the variables under their new names. Then quarterly implicit price deflators from the NIPA tables and monthly nominal consumption from the BLS were used to construct real monthly consumption. Next, we gathered data for business loans from FRED, the nominal effective exchange rates from the IMF, the Michigan index of consumer sentiment index from the Institute of Survey Research, and merged the GSI help-wanted index with the calculations from Barnichon (2010). This completed the data-collection exercise. The next step was to compare the new and old data over the overlapping sample to check for irregularities. It was found that the housing series in the 2014 dataset starts at a later date, orders and inventories have a new chain base, the exchange rate variables have been revised because of changes in trade weights, and several other series have gone through minor data revisions. It is difficult if not impossible to automate the process because judgment

Table 1. Series adjusted by FRED-MD

| Number | Variable | Adjustments |
|---|---|---|
| 4 | Real Manu. and Trade | (i) adjust M0602BUSM144NNBR for inflation using PCEPI<br>(ii) seasonal adjust with ARIMA X12<br>(iii) splice with NAICS series CMRMTSPL |
| 5 | Retail/Food Sales | splice SIC series RETAIL with NAICS series RSAFS |
| 21 | Help Wanted | from Barnichon (2010) |
| 22 | Help Wanted to unemployed | HWI/UNEMPLOY |
| 32 | Initial Claims | splice monthly series M08297USM548NNBR with weekly ICNSA |
| 65 | New orders (durables) | splice SIC series AMDMNO and NAICS series DGORDER |
| 66 | New orders (nondefense) | splice SIC series ANDENO and NAICS series ANDENO |
| 67 | Unfilled orders (durables) | splice SIC series AMDMUO and NAICS series AMDMUO |
| 68 | Business Inventories | splice SIC series and NAICS series BUSINV |
| 69 | Inventory to sales | splice SIC series and NAICS series ISRATIO |
| 79 | Consumer credit to P.I. | NONREVSL/PI |
| 85 | 3month Comm. Paper | splice M13002US35620M156NNBR, CP3M with CPF3M |
| 93 | 3month CP -FF | splice CP3M-FedFunds |
| 102 | Switzerland/U.S. FX | filled back to 1959 from Banking/Monetary statistics |
| 103 | Japan/U.S. FX | filled back to 1959 from Banking/Monetary statistics |
| 104 | U.K./U.S. FX | filled back to 1959 from Banking/Monetary statistics |
| 105 | Cdn/U.S. FX | filled back to 1959 from Banking/Monetary statistics |
| 110 | Crude Oil | splice OILPRICE with MCOILWTICO |
| 130 | Consumer sentiment | splice UMSCENT1 with UMSCENT |

is involved. Two researchers starting with the same raw data can end up using different data for analysis.

One advantage of taking the data from GSI is that it is "one-stop shopping," as over 100 series can be retrieved from one source. Because GSI does not directly collect data, they also deal with the problems of changing data availability and definitions, though researchers may not be aware of these changes. Furthermore, the GSI data are available only on a subscription basis; researchers without access will have to look to alternatives that inevitably involve multiple sources. There is also a catch to using the GSI data. The licensing agreement understandably prohibits redistribution of the data. Yet an increasingly common requirement among scholarly journals is to post the data used in empirical work. The data required for replication are often not available.

FRED-MD seeks to make available a database with three objectives in mind. First, it will be publicly available so that U.S. and international researchers alike will have access to the same data that satisfy the four criteria established in Stock and Watson (1996). Second, it will be updated on a timely basis. Third, it will relieve researchers from the burden of handling data changes and revisions. With these objectives in mind, we collect 134 monthly series with coverage that is similar to the original Stock–Watson data. A full list of the data is given in the Appendix, along with the comparable series in the GSI database. The suggested data transformation for each series is given in the column under TCODE. As of the writing of this article, the latest vintage is 2015:04.

In addition to data revisions and definitional changes, a one-time cost in moving from GSI to FRED is to find close substitutes to replace the proprietary variables constructed by GSI. A major appeal of FRED-MD is that this task is left to the data experts. In the first vintage of FRED-MD, 19 of the 134 series require some adjustments to the raw data available in FRED. We tag these variables with an asterisk to indicate that they have been adjusted and thus differ from the series from the source. A summary of the adjustments is shown in Table 1.

We highlight some of these adjustments. A major effort was undertaken to find replacements for the block of manufacturing and trade data in GSI because manufacturing orders, sales, and inventories data are crucial to analysis of business cycles. Finding long data series for these variables is complicated by the switch from the standard industrial classification (SIC) to the North American Industry Classification System (NAICS) in 1992. FRED primarily holds NAICS data from the Census Manufacturers Survey. Some older SIC data exist. The series in FRED-MD have been spliced with the SIC historical data available from the U.S. Census Bureau.

Other adjustments are necessary because old variables were phased out as the economy changed. Consumer credit outstanding in GSI is replaced by nonrevolving consumer credit. The exchange rate data in FRED start from 1971 because most countries were on a fixed exchange rate system. The 3-month commercial paper rate series has been discontinued since 1997:08, though a 3-month financial commercial paper rate series has existed since 1997:01. The FRED-MD data splice the current data with historical data from the Banking and Monetary Statistics series produced by the Federal Reserve Board of Governors and obtained from FRASER. (FRASER is a publicly accessible archive of historical documents maintained by the Federal Reserve Bank of St. Louis.) The West Texas oil price discontinued in 2013:07 is spliced with a West Texas-Oklahoma series available since 1986:01. We note that some these adjusted series are of independent interest even if the entire database is not.

While we provide a csv file with current and historical data, FRED-MD is not a balanced panel for a number of reasons:

1. The S&P PE ratio (series 83) is taken from Shiller's website and is released with roughly a 6-month lag. Hence, observations are missing at the end of the sample.
2. The Michigan Survey of Consumer Sentiment (series 130) is available only quarterly prior to 1977:11, and recent data are available in FRED with a 6-month lag.
3. The trade-weighted exchange rate (series 101) is available in FRED only through 1973:1, and we have not found other documented sources with which to splice the series.
4. Seasonally adjusted housing permits (series 55–59) exist only through 1960:01.
5. A few Value of Manufacturers' Orders components such as Nondefense Capital Goods (series 66) and especially Consumer Goods (series 64) have a limited history because of the new NAICS discussed above.

Of course, the dataset can easily be turned into a balanced panel by removing the relevant series. In MATLAB, these series can be identified by checking whether the mean over the full sample is a NAN. To be consistent with previous empirical work, we start the data in 1959:01. In the 2015:04 vintage of FRED-MD, 9 series have observations missing at the beginning of the sample, and 12 series have observations missing at the end of the sample. A balanced panel of 130 series dating from 1960:1 to 2014:12 can be formed by dropping series 64, 66, 101, and 130.

Going forward, vintages of FRED-MD data will come in (csv) files available for download from *http://research.stlouisfed.org/econ/mccracken/sel/*. The series listed in the Appendix is the core of FRED-MD, but it is likely that some series will eventually be retired and new ones will be gradually added. As an example, the help-wanted column of newspapers is no longer as good a measure of labor market slackness as it once was, as job-search websites such as MONSTER.COM have become more popular. At the moment, there is not enough data to build an HWI series based on internet data alone, but it should eventually be possible to splice the old help-wanted index with one that better reflects the modern economy. More financial variables will be added as there is increasing interest in understanding their role in business cycles. We are in the final stage of splicing the historical VXO data with the VIX to provide a measure of stock market volatility. This series will be included in FRED-MD in the near future.

## 3. FACTOR ESTIMATES

Primary uses of big macro datasets are diffusion index forecasting and estimation of factor augmented regressions. The factors serve the purpose of dimension reduction. In a large $N$ and large $T$ setting, the space spanned by the latent factors can be consistently estimated by static or dynamic principal components. (See Forni et al. 2000, 2005; Boivin and Ng 2005; Bai and Ng 2008; Stock and Watson 2006.) We therefore begin by examining the properties of the factors estimated using data from FRED-MD. The latest vintage is for the sample 1959:1–2015:04 with 675 observations. Following previous studies, we take 1960:1 as the start of the sample. After losing two observations to data transformation, the panel we use for analysis is for the sample 1960:3 to 2014:12 with 658 observations. Series 64, 66, 101, and 130 have missing observations in the beginning of the sample while series 130 also has missing values toward the end.

We estimate the static factors by principal component analysis (PCA) adapted to allow for missing values. This is essentially the expectation–maximization (EM) algorithm given in Stock and Watson (2002). In brief, observations that are missing are initialized to the unconditional mean based on the nonmissing values (which is zero since the data are demeaned and standardized) so that the panel is rebalanced. A $T \times r$ matrix of factors $F = (f_1, \dots, f_T)'$ and a $N \times r$ matrix of loadings $\lambda = (\lambda_1, \dots, \lambda_N)'$ are estimated from this panel using the normalization that $\lambda'\lambda/N = I_r$. The missing value for series $i$ at time $t$ is updated from zero to $\widehat{\lambda}_i' \widehat{f}_t$. This is multiplied by the standard deviation of the series and the mean is readded. The resulting value is treated as an observation for series $i$ at time $t$, and the mean and variance of the complete sample are recalculated. The data are demeaned and standardized again, and the factors and loadings are reestimated from the updated panel. The iteration stops when the factor estimates do not change.

We then select the number of significant factors. Many factor-selection procedures have been developed to determine the number of factors when $N$ and $T$ are large. They impose different assumptions on the factor model. Some test the largest eigenvalues directly, while others evaluate the fit of the model. We want to have a sense of whether the number of factors is sensitive to the vintage of data used. Hence, for our purpose, which criterion we use is not so important provided that the same criterion is used throughout. We use the $PC_p$ criteria developed in Bai and Ng (2002), which is a generalization of Mallow's $C_p$ criteria for large dimensional panels. The number of factors is chosen to minimize the sum of squared residuals while keeping the model parsimonious. The $PC_p$ penalty of $\frac{\log(\min(N,T))}{\min(N,T)}$ differs from the standard BIC penalty of $\log T$ because the factors are estimated from a two-dimensional panel. Using the fact that $\min(N, T)^{-1} \approx \frac{N+T}{NT}$ as $N, T \to \infty$, variations of the penalty can be obtained. For this analysis, we use the penalty $\frac{N+T}{NT} \log(\min(N, T))$, which has better finite sample properties. This criterion is referred to as $PC_{p2}$ in Bai and Ng (2002). The criterion finds eight factors in this sample (and nine if no outlier adjustment is performed). (We check for outliers in the transformed series prior to constructing the factors. An outlier is defined as an observation that deviates from the sample median by more than 10 interquartile ranges. The outliers are removed and treated as missing values.)

After the factors are estimated, we regress the $i$th series in the dataset on a set of $r$ (orthogonal) factors. For $k = 1, \dots, r$, this yields $R_i(k)^2$ for series $i$. The incremental explanatory power of factor $k$ is $mR_i^2(k) = R_i^2(k) - R_i^2(k-1), k = 2, \dots, r$ with $mR_i^2(1) = R_i^2(1)$. The average importance of factor-$k$ is $mR^2(k) = \frac{1}{N}\sum_{i=1}^N mR_i^2(k)$. The $PC_{p2}$ criterion finds $r = 8$ factors. Table 2 lists $R^2(j)$ and the 10 series with the highest $mR^2(j)$ for factor $j$. Factor 1 explains 0.159 of the variation in the data and can be interpreted as a real activity/employment factor since the $mR_i(1)$ associated with the industrial production and employment series are close to 0.7. Factor 2 contributes to 0.069 of the variation in the data and is dominated by forward-looking variables such as term interest rate spreads and

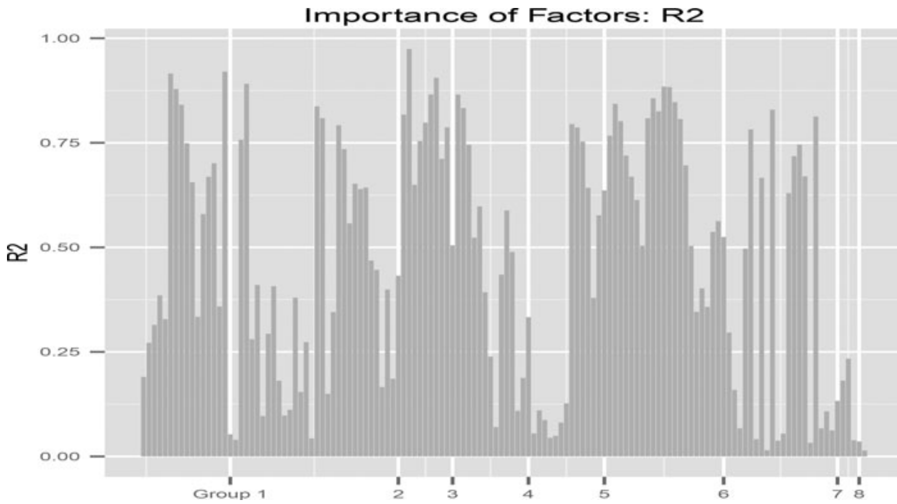


Figure 1. The figure shows the explanatory power of the first eight factors in the 134 series organized into eight groups as given in the Appendix. Group 1 is Output and income, Group 2 is Labor market, Group 3 is Housing, Group 4 is Consumption, orders, and inventories, Group 5 is Money and credit, Group 6 is Interest and exchange rates, Group 7 is Prices, and Group 8 is Stock market.

inventories. Factor 3 has an $mR^2(3)$ of 0.066 and its explanatory power is concentrated on price variables and hence can be interpreted as an inflation factor. Factors 4 and 5 are a mix of housing and interest rate variables. Like Factor 1, Factor 6 concentrates on real/employment variables. Factor 7 has explanatory power for stock market variables while factor 8 has explanatory power for exchange rates.

Figure 1 plots $R^2(8)$ ordered by groups. The horizontal axis in this figure is the series ID (i.e., variable number) as indicated in the Appendix and the $y$ axis is the fraction of variation in each series explained by eight factors. The eight factors explain 0.476 of the total variation in all series. (This is primarily due to the monetary base series, which took on extreme values during the financial crisis.) The relative importance of the common component varies across series. These eight factors explain over 0.5 of the variation in 68 series and between 0.25 and 0.5 of the variation in 27 series. The 10 series that are best explained by the factors are "houset," "ipmansics," "indpro," "permit," "cumfns," "t5yffm," "t10yffm," "ipfpnss," "housew," and "permitw." There are, however, 22 series that have the idiosyncratic component explaining 90% of the variation. The 10 series with the largest idiosyncratic component are "realln," "busloans," "claimsx," "cpiappsl," "ipfuels," "dtcolnvhfnm," "cuur0000sad," "dtcthfnm," "ddurrg3m086sbea," "cpimedsl," "invest." A case can be made to drop these series from the panel; as discussed in Boivin and Ng (2006), noisy data can worsen the quality of the factor estimates.

How does FRED-MD differ from the vintages of GSI data that have been used previously? We repeat the exercise in Table 2 for four vintages. Estimation always starts in 1960:3 but ends differently depending on the vintage. The 2003 vintage used in Stock and Watson (2005) ends in 2003:12. The 2007, 2011, and 2013 vintages of GSI data updated by Ludvigson and Ng end in 2007:12, 2011:12, and 2013:05, respectively. Table 3 reports the properties of the factor estimates. The $PCP_2$ criterion finds $r = 8$ factors in the 2003, 2007, and 2011 vintages and $r = 7$ factors in the 2013 vintage. Note that $N$ is roughly the same across vintages. Though $T$ is increased between 2003 and 2013, the number of factors has not changed much.

Table 3 shows that the explanatory power provided by the first four factors has been remarkably stable across databases. The first factor explains 0.156 of the total variation in the 2003 GSI data, 0.147 of the 2007 GSI data, 0.152 of the 2011 GSI data, and 0.157 of the 2013 GSI data, respectively. The first factor captures a significant fraction of the variation in industrial production and employment (ips43 is IP: mfg, ces003 is Emp: gds prod., and a0m082 is capacity utilization) explaining over 0.7 of variation in manufacturing output and employment in each vintage. The second factor explains between 0.071 and 0.076 of the total variation in the data and has good explanatory power for interest rate spreads. (sfybaac is the spread between the federal funds rate and Baa bonds.) The third factor explains between 0.054 and 0.065 of the variation in the data and is particularly successful in explaining variations in prices. (puc is cpi commodities, gmden is implicit price deflator of nondurables, punew is cpi all items, and puxm is cpi excluding medical care.) The fourth factor explains about 0.05 of total variation in the data and explains well the variations in interest rates.

Turning to factors five through eight, their $mR^2$ are noticeably lower than those for factors one through four, and the relative importance of the factors are also less stable. Factor five has good explanatory power for term spreads in all four older databases. In the 2003 and 2007 vintages, the monetary aggregates have $mR_i^2(6)$ of around 0.5; in the 2011 and 2014 vintages, the monetary aggregates are better explained by factor 8 with $mR_i^2(8)$ below 0.2. While the stock market variables are well explained by factor 8 in the 2003 and 2007 vintages, they are better explained by factors 6 and 7 in the 2011 and 2013 vintages. The $mR_i^2(6)$ and $mR_i^2(7)$ for SP500 is 0.4 in the 2011 vintage. This is unprecedentedly high, but perhaps not surprising in view of the volatility in the stock market around 2008.

We also recursively estimate the factors using the different data vintages. For $t$ starting in 1970:1, we record the number of factors $r_t$ selected by the $PC_{p2}$ criterion and the corresponding

Table 2. Factors estimated from FRED-MD: Total variation explained, 0.476

| $mR^2(1)$ | 0.159 | $mR^2(2)$ | 0.069 | $mR^2(3)$ | 0.066 | $mR^2(4)$ | 0.051 |
|---|---|---|---|---|---|---|---|
| usgood | 0.749 | t10yffm | 0.613 | cusr0000sac | 0.730 | aaa | 0.377 |
| payems | 0.731 | aaaffm | 0.611 | dndgrg3m086sbea | 0.717 | gs5 | 0.369 |
| manemp | 0.703 | baaffm | 0.586 | cpiaucsl | 0.675 | gs1 | 0.357 |
| napm | 0.658 | t5yffm | 0.562 | cusr0000sa0l5 | 0.644 | gs10 | 0.346 |
| ipmansics | 0.655 | tb3smffm | 0.466 | cuur0000sa0l2 | 0.621 | baa | 0.345 |
| dmanemp | 0.652 | tb6smffm | 0.460 | cpitrnsl | 0.603 | tb6ms | 0.326 |
| indpro | 0.632 | t1yffm | 0.412 | pcepi | 0.597 | houst | 0.268 |
| napmnoi | 0.608 | compapffx | 0.234 | cpiulfsl | 0.554 | houstw | 0.265 |
| napmpi | 0.606 | businvx | 0.231 | ppifcg | 0.496 | permitw | 0.262 |
| cumfns | 0.561 | houst | 0.192 | ppiitm | 0.489 | permit | 0.258 |
| $mR^2(5)$ | 0.041 | $mR^2(6)$ | 0.036 | $mR^2(7)$ | 0.029 | $mR^2(8)$ | 0.024 |
| gs5 | 0.275 | ipcongd | 0.225 | sp: indust | 0.504 | twexmmth | 0.403 |
| gs1 | 0.263 | isratiox | 0.173 | sp 500 | 0.502 | exszusx | 0.281 |
| gs10 | 0.255 | napmei | 0.168 | sp div yield | 0.388 | exusukx | 0.247 |
| t1yffm | 0.212 | ipfinal | 0.159 | sp pe ratio | 0.278 | exjpusx | 0.183 |
| tb6ms | 0.209 | ipdcongd | 0.155 | umcsentx | 0.138 | srvprd | 0.122 |
| permitw | 0.206 | tb6smffm | 0.148 | excausx | 0.128 | ces3000000008 | 0.109 |
| permit | 0.199 | napm | 0.140 | ipcongd | 0.097 | ces0600000008 | 0.102 |
| houstw | 0.191 | ipfpnss | 0.140 | tb3ms | 0.070 | usgovt | 0.091 |
| aaa | 0.190 | napmii | 0.136 | ipfinal | 0.067 | ustrade | 0.087 |
| tb3ms | 0.180 | awhman | 0.135 | m2sl | 0.065 | excausx | 0.080 |

NOTE: This table lists the 10 series that load most heavily on the first eight factors along with $R^2$ in a regression of the series on the factor. For example, factor 1 explains 0.749 of the variation in USGOOD. The first factor has an $mR^2$ of 0.159. This is the fraction of the variation in 134 series explained by the first factor.

$R^2(r_t)$. This is plotted in Figure 2. The NBER recession dates are shaded in gray. The top panel shows that the number of factors has crept up from a minimum of 2 in early 1970, to 6 in early 1980 where it stayed until the early 2000s until ultimately bouncing between 7 and 8 in the latter part of the sample. The bottom panel shows that the size of the common component has also increased from 0.25 in 1970 to about 0.45 in 1980 and has largely flatlined for the remainder of the sample. Interestingly, these increases in the number of factors and $R^2$ line up well with many of the NBER recession dates. Figure 2 shows that the number of factors and $R^2(r_t)$ also jumped when the GSI data were used.

Based on the properties of the factor estimates, we are encouraged that FRED-MD preserves the primary variations in

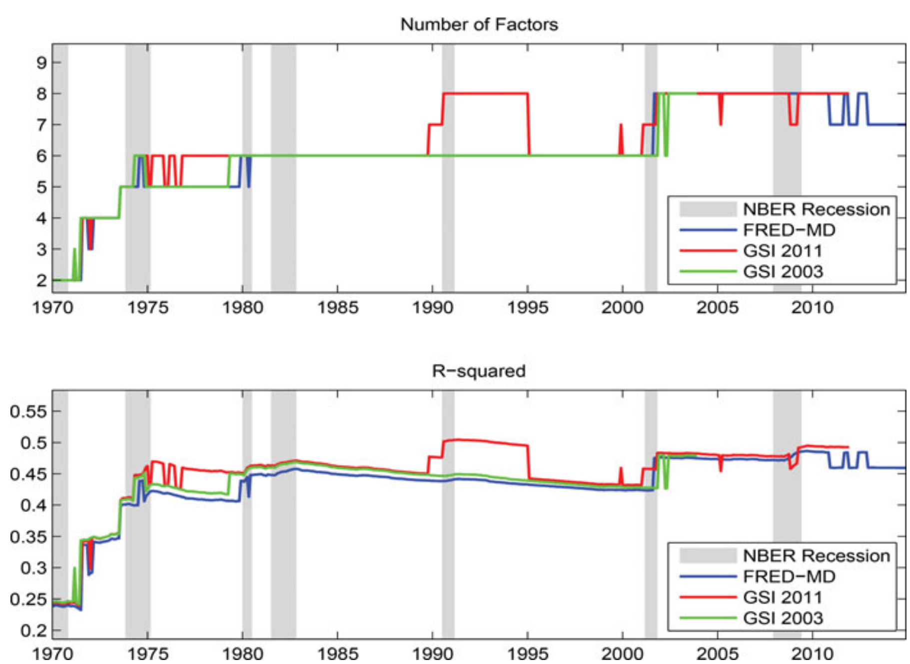


Figure 2. Number of factors and $R^2$: recursive estimation.

the GSI data used in previous work. While the variable names have changed over the years, there is little doubt that the first factor has strong association to real activity and that the second, third, and fourth factors have strong association with nominal variables not directly related to the stock market. These four factors explain about 0.3 of the variation of data. The remaining three or four factors explain another 0.12 to 0.15. The stock-market-related factors seemed to have gained importance over time, though it is necessary to monitor a few more vintages of FRED-MD to be sure this finding is robust.

### 3.1 Predictability

In this subsection, we revisit the usefulness of factors for predicting macroeconomic aggregates—with an eye toward evaluating the usefulness of those factors extracted using FRED-MD. Specifically, we revisit a subset of the forecasting exercises conducted in Stock and Watson (2002). In particular we consider forecasts of U.S. industrial production, nonfarm employment, headline CPI inflation, and core CPI inflation at the 1, 6, and 12 month horizons. For each permutation of dependent variable and horizon, we have three goals: (1) document that the FRED-MD factors have predictive content above-and-beyond that contained in a baseline autoregressive model, (2) document that the FRED-MD factors compare favorably, in terms of predictive content, to factors extracted using the databases that have been previously used, and (3) document the predictive content of the FRED-MD factors during the most recent U.S. recovery.

In each case the models used for forecasting take the form

$$y_{t+h}^{h} = \alpha_h + \beta_h(L)\widehat{f}_t + \gamma_h(L)y_t + \varepsilon_{t+h}^{h},$$

for finite-order lag polynomials $\beta_h(L)$ and $\gamma_h(L)$. When predicting the real variables, we define the dependent variable as average annualized monthly growth. As an example, for IP we obtain

$$y_{t+h}^{h} = (1200/h)\ln(\mathrm{IP}_{t+h}/\mathrm{IP}_t).$$

When predicting the nominal variables we define the dependent variable similarly but treat inflation as $I(1)$. As an example, for CPI we obtain

$$y_{t+h}^{h} = (1200/h)\ln(\mathrm{CPI}_{t+h}/\mathrm{CPI}_t) - 1200\ln(\mathrm{CPI}_t/\mathrm{CPI}_{t-1})\,.$$

Regardless of whether the dependent variable is real or nominal, when $h = 1$ we drop the superscript and define $y_{t+1}^{1}$ as $y_{t+1}$.

All models are estimated recursively by ordinary least squares (OLS). We consider three out-of-sample periods. To get a clean comparison between FRED-MD and the older databases, the first two out-of-sample periods end with the last observation in the 2003 vintage of the GSI data. But to also get a feel for time variation in the predictive content of the factors, we initially allow the first forecast origin to occur in 1970:01 and then allow a second initial forecast origin to occur in 1990:01. The third out-of-sample period begins in 2008:01 and ends in 2014:12 and is intended only to evaluate the predictive content of the FRED-MD factors during the most recent recovery.

We compare the predictive content of $\widehat{f}_1$ constructed from FRED-MD with those constructed from the 2003 and 2011 vintages of the GSI data. To emphasize the predictive content of the factors, for a given horizon and dependent variable, we hold the model structure constant across time and across the datasets used to estimate the factors. To that end we used BIC to select the number of autoregressive lags ($0 \le p \le 6$ ) and lags of the first factor ($1 \le m \le 3$) over the 1960:03 to 2003:12 sample using FRED-MD. The models associated with factors from the other datasets then used the same model structure but with the FRED-MD factors replaced by their own. For each dependent variable (IP, Employment, headline CPI, core CPI), forecast horizon (1, 6, 12), and sample split (1970:01–2003:12, 1990:01–2003:12), we report the mean squared error (MSE) implied by the model using the FRED-MD factors and its ratio to the MSE associated with either the 2003 or 2011 vintage of GSI data. These ratios are denoted Ratio03 and Ratio11 in Table 4. Ratios greater than one favor the model using FRED-MD factors over those constructed from the GSI datasets. To determine whether any differences are statistically significant, we use the Diebold and Mariano (1995) and West (1996) $t$-type test statistic and N(0,1) critical values. Significance at the 5% level is denoted by an asterisk.

The results that assess the predictive power of $\widehat{f}_1$ are reported in the left panel of Table 4. A quick glance indicates that the MSE ratios all lie within a very tight range of 0.98 and 1.01. The right panel of Table 4 extends the analysis of Stock and Watson (2002) and add a single lag of $\widehat{f}_2$ to each model considered in the left panel. Using two factors instead of one changes the MSE only slightly. For one-period-ahead forecast of IP in the sample that starts in 1990, the MSE with two factors is 35.39, compared with 35.74 using one factor. But use of more factors does not always lower the MSE. As an example, the $h = 12$ month-ahead forecast for IP has an MSE of 11.20 when two factors are used, which is higher than the MSE of 9.22 when one factor is used.

Comparing across different datasets, there are a few instances in which we find statistically significant pairwise differences in the MSEs. For those models that include only lags of $\widehat{f}_1$, these largely occur when evaluated using the post-1970 sample. There is only one instance of significance using the post-1990 sample. For those models that contain lags of both $\widehat{f}_1$ and $\widehat{f}_2$, significance is largely relegated to the post-1990 sample. Regardless, of the 96 possible pairwise comparison considered in Table 4, only nine show any signs of significance and do so only when we ignore any issues associated with multiple testing.

To get a feel for the nominal predictive content of the FRED-MD factors themselves, in Table 5 we report (i) the improvement in MSE of those models that include the first factor relative to those that are purely autoregressive, and (ii) the improvement of those models that include the first and second factors relative to those that include only the first factor. For this exercise the FRED-MD factors are estimated using data that end in 2014:12. For ease of comparison with the previous tables, the models that include factors maintain the exact same autoregressive structure. As above, for each dependent variable (IP, Employment, headline CPI, core CPI), forecast horizon (1,6,12), and sample split (1970:01–2014:12, 1990:01–2014:12, 2008:01–2014:12), we report the mean squared error implied by the model using the FRED-MD factors and the ratio of MSEs from the two models. In the left panel, ratios less than one favor the model that includes the first factor. In the right panel, ratios less than one favor the model that includes both the first and second factors. To determine any sig-

Table 3. Estimates from earlier vintages of GSI data: Factors 1–4

| 2003 | | 2007 | | 2011 | | 2013 | |
|---|---|---|---|---|---|---|---|
| $mR^2(1)$ | 0.156 | | 0.147 | | 0.152 | | 0.157 |
| ips43 | 0.769 | ips43 | 0.787 | IP: mfg | 0.786 | IP: mfg | 0.766 |
| ips10 | 0.762 | ips10 | 0.765 | IP: total | 0.758 | Emp: gds prod | 0.751 |
| ces003 | 0.741 | utl11 | 0.735 | Emp: gds | 0.742 | IP: total | 0.736 |
| a0m082 | 0.721 | ces003 | 0.718 | Emp: total | 0.715 | Emp: total | 0.726 |
| ces015 | 0.713 | ces015 | 0.679 | Emp: mfg | 0.707 | Emp: mfg | 0.719 |
| $mR^2(2)$ | 0.076 | | 0.072 | | 0.072 | | 0.071 |
| sfybaac | 0.591 | sfybaac | 0.596 | Baa-FF | 0.580 | Baa-FF | 0.523 |
| sfyaaac | 0.568 | sfyaaac | 0.569 | Aaa-FF | 0.571 | Aaa-FF | 0.515 |
| sfygt10 | 0.537 | sfygt10 | 0.538 | 10 yr-FF | 0.559 | 10 yr-FF | 0.508 |
| sfygt5 | 0.514 | sfygt5 | 0.516 | 5 yr-FF | 0.537 | 5 yr-FF | 0.489 |
| pmcp | 0.337 | sfygt1 | 0.324 | 6 mo-FF | 0.352 | 6 mo-FF | 0.312 |
| $mR^2(3)$ | 0.054 | | 0.059 | | 0.065 | | 0.065 |
| puc | 0.759 | puc | 0.794 | cpi-U: comm. | 0.774 | cpi-U: comm. | 0.791 |
| gmdcn | 0.729 | gmdcn | 0.787 | pce nondble | 0.765 | pce: nondble | 0.768 |
| puxhs | 0.690 | puxhs | 0.749 | cpi-U: ex shelter | 0.740 | cpi-U: ex shelter | 0.755 |
| punew | 0.677 | punew | 0.731 | cpi-U: all | 0.725 | cpi-U: all | 0.741 |
| puxm | 0.637 | puxm | 0.692 | cpi-U: ex med | 0.689 | cpi-U: ex med | 0.706 |
| $mR^2(4)$ | 0.049 | | 0.048 | | 0.050 | | 0.049 |
| fygt1 | 0.450 | fygt5 | 0.456 | 1 yr T-bond | 0.555 | 1 yr T-bond | 0.504 |
| fygt5 | 0.450 | fygt1 | 0.449 | 5 yr T-bond | 0.543 | 5 yr T-bond | 0.490 |
| fygm6 | 0.410 | fygt10 | 0.425 | 6 mo T-bill | 0.509 | 6 mo T-bill | 0.460 |
| fygt10 | 0.409 | fygm6 | 0.403 | 10 yr T-bond | 0.502 | 10 yr T-bond | 0.448 |
| fyaaac | 0.373 | fyaaac | 0.377 | Aaa bond | 0.466 | Aaa bond | 0.405 |
| $mR^2(5)$ | 0.041 | | 0.039 | | 0.037 | | 0.040 |
| sfygm6 | 0.317 | sfygm6 | 0.255 | 6 mo-FF | 0.271 | 6 mo-FF | 0.254 |
| sfygt1 | 0.304 | sfygt1 | 0.239 | 1 yr-FF | 0.246 | 3 mo-FF | 0.218 |
| sfygm3 | 0.282 | sfygm3 | 0.220 | 3 mo-FF | 0.228 | 1 yr-FF | 0.214 |
| sfygt5 | 0.261 | sfygt5 | 0.203 | 5 yr-FF | 0.213 | Avg hrs | 0.207 |
| sfygt10 | 0.244 | ces151 | 0.202 | 10 yr-FF | 0.201 | 5 yr-FF | 0.206 |
| $mR^2(6)$ | 0.033 | | 0.030 | | 0.031 | | 0.030 |
| fmrra | 0.550 | fmrra | 0.411 | sp: indust | 0.437 | sp: indust | 0.232 |
| fmrnba | 0.461 | fmfba | 0.371 | sp 500 | 0.429 | sp 500 | 0.226 |
| gmdcs | 0.405 | fm1 | 0.335 | sp div yield | 0.339 | ip: cons gds | 0.213 |
| fm1 | 0.360 | fmrnba | 0.289 | sp PE | 0.281 | ip: final prod | 0.184 |
| fmfba | 0.349 | fm2 | 0.206 | ip: cons gds | 0.140 | sp div yield | 0.172 |
| $mR^2(7)$ | 0.030 | | 0.028 | | 0.028 | | 0.028 |
| hsfr | 0.249 | fspin | 0.241 | bp: total | 0.234 | sp 500 | 0.326 |
| hsmw | 0.172 | fspcom | 0.228 | bp: mw | 0.220 | sp: indust | 0.325 |
| hsbmw | 0.177 | fsdxp | 0.201 | emp: const | 0.201 | sp PE ratio | 0.267 |
| ces011 | 0.187 | ips12 | 0.138 | bp: south | 0.128 | sp div yield | 0.264 |
| ips12 | 0.199 | ips299 | 0.128 | starts: mw | 0.108 | starts: nonfarm | 0.163 |
| $mR^2(8)$ | 0.027 | | 0.029 | | 0.023 | | 0.024 |
| fspin | 0.535 | fspcom | 0.326 | Reserves total | 0.220 | Ex rate: avg | 0.198 |
| fspcom | 0.519 | fspin | 0.325 | M2 | 0.210 | Inst cred/PI | 0.196 |
| fsdxp | 0.423 | fsdxp | 0.236 | M1 | 0.196 | Ex rate: Switz | 0.183 |
| fspxe | 0.298 | fspxe | 0.164 | Ex rate: Switz: | 0.120 | Ex rate: UK | 0.175 |
| hhsntn | 0.121 | ces151 | 0.142 | Ex rate: UK | 0.115 | M1 | 0.137 |

NOTE: The numbers in the $mR_2(j)$ under 200x correspond to the fraction of variation explained by factor j using the vintage 200x. Variable names are given in the Appendix.

Table 4. Nonnested model comparisons

| | $h$ | | $\widehat{f}_1$ IP | $\widehat{f}_1$ Empl. | $\widehat{f}_1$ CPI | $\widehat{f}_1$ Core CPI | $\widehat{f}_1+\widehat{f}_2$ IP | $\widehat{f}_1+\widehat{f}_2$ Empl. | $\widehat{f}_1+\widehat{f}_2$ CPI | $\widehat{f}_1+\widehat{f}_2$ Core CPI |
|---|---|---|---|---|---|---|---|---|---|---|
| 1970 | 1 | MSE | 60.08 | 3.35 | 6.98 | 4.72 | 58.58 | 3.35 | 6.95 | 4.59 |
| | | Ratio03 | 0.98* | 0.99 | 1.00 | 1.00 | 0.98 | 0.99 | 1.00 | 1.00 |
| | | Ratio11 | 0.99* | 0.99 | 1.00 | 1.00 | 0.99 | 1.00 | 1.00 | 1.00 |
| | 6 | MSE | 27.73 | 2.27 | 2.59 | 2.23 | 20.11 | 1.95 | 2.64 | 2.20 |
| | | Ratio03 | 0.98 | 0.98 | 1.00 | 1.01 | 1.01 | 1.00 | 1.00 | 0.99 |
| | | Ratio11 | 0.98 | 0.99 | 1.00 | 1.01 | 1.01 | 1.00 | 1.00 | 1.00 |
| | 12 | MSE | 21.14 | 2.66 | 2.67 | 2.24 | 14.25 | 2.23 | 2.73 | 2.36 |
| | | Ratio03 | 0.99 | 0.98* | 1.00 | 1.01* | 1.03 | 1.00 | 1.01 | 1.00 |
| | | Ratio11 | 0.99 | 0.99 | 1.00 | 1.01* | 1.04 | 1.01 | 1.00 | 1.00 |
| 1990 | 1 | MSE | 35.74 | 1.51 | 4.79 | 1.47 | 35.39 | 1.59 | 4.82 | 1.52 |
| | | Ratio03 | 0.98 | 1.00 | 1.00 | 1.00 | 0.98 | 0.99 | 1.00 | 1.00 |
| | | Ratio11 | 1.00 | 1.01 | 1.00 | 1.00 | 0.99 | 0.99 | 1.00 | 1.00 |
| | 6 | MSE | 11.38 | 1.17 | 1.17 | 0.29 | 11.14 | 1.43 | 1.21 | 0.34 |
| | | Ratio03 | 0.98 | 0.99 | 1.00 | 0.98 | 1.00 | 0.96* | 1.01 | 1.01 |
| | | Ratio11 | 0.99 | 1.01 | 1.00 | 0.98 | 1.00 | 0.97* | 1.01 | 1.00 |
| | 12 | MSE | 9.22 | 1.86 | 1.11 | 0.28 | 11.20 | 2.52 | 1.08 | 0.29 |
| | | Ratio03 | 0.99* | 0.98 | 1.00 | 0.98 | 0.99 | 0.98 | 1.01 | 1.00 |
| | | Ratio11 | 0.99 | 0.99 | 1.00 | 0.99 | 0.99 | 0.98* | 1.00 | 1.00 |

nificant differences, we use the MSE-F statistic described in Clark and McCracken (2005) and obtain critical values using a fixed-regressor wild bootstrap as described in Clark and McCracken (2012).

The results are reported in Table 5. Significance at the 5% level is denoted by an asterisk. Consider the first four columns in which we compare a simple autoregressive model to one augmented by lags of the first factor. When evaluated over the entire post-1970 sample, the model that includes the first factor provides statistically significant MSE-based improvements across all horizons and for all dependent variables with the exception of CPI at the 6 month horizon. For IP and Employment, this improvement largely continues when we restrict ourselves to the post-1990 and post-2008 samples as well. In contrast, the first factor does not seem to provide any useful predictive content for either CPI or core CPI during the post-1990 or

Table 5. Nested model comparisons

| | $h$ | | $\widehat{f}_1$ vs. AR IP | $\widehat{f}_1$ vs. AR Empl. | $\widehat{f}_1$ vs. AR CPI | $\widehat{f}_1$ vs. AR Core CPI | $\widehat{f}_1+\widehat{f}_2$ vs. $\widehat{f}_1$ IP | $\widehat{f}_1+\widehat{f}_2$ vs. $\widehat{f}_1$ Empl. | $\widehat{f}_1+\widehat{f}_2$ vs. $\widehat{f}_1$ CPI | $\widehat{f}_1+\widehat{f}_2$ vs. $\widehat{f}_1$ Core CPI |
|---|---|---|---|---|---|---|---|---|---|---|
| 1970 | 1 | MSE | 71.55 | 3.29 | 9.68 | 3.94 | 63.08 | 2.90 | 9.61 | 3.80 |
| | | Ratio | 0.88* | 0.88* | 0.99* | 0.97* | 0.96* | 1.00* | 1.01 | 1.00 |
| | 6 | MSE | 30.35 | 2.27 | 5.02 | 2.10 | 28.70 | 2.13 | 5.00 | 1.85 |
| | | Ratio | 0.95* | 0.94* | 1.00 | 0.88* | 0.86* | 0.97* | 1.03 | 1.04 |
| | 12 | MSE | 24.83 | 4.34 | 4.63 | 2.39 | 22.99 | 2.75 | 4.26 | 1.93 |
| | | Ratio | 0.93* | 0.63* | 0.92* | 0.81* | 0.86* | 0.98 | 1.02 | 1.10 |
| 1990 | 1 | MSE | 58.76 | 1.41 | 10.18 | 1.16 | 51.03 | 1.43 | 10.51 | 1.28 |
| | | Ratio | 0.87* | 1.01 | 1.03 | 1.10 | 0.99 | 1.09 | 1.02 | 1.09 |
| | 6 | MSE | 21.16 | 1.33 | 5.16 | 0.31 | 19.54 | 1.29 | 6.18 | 0.53 |
| | | Ratio | 0.92* | 0.97* | 1.20 | 1.71 | 1.14 | 1.24 | 1.04 | 1.46 |
| | 12 | MSE | 19.49 | 4.22 | 3.82 | 0.35 | 17.46 | 2.24 | 4.67 | 0.63 |
| | | Ratio | 0.90* | 0.53* | 1.22 | 1.79 | 1.22 | 1.33 | 1.00 | 1.42 |
| 2008 | 1 | MSE | 95.81 | 1.85 | 17.09 | 0.67 | 80.76 | 1.53 | 18.69 | 1.04 |
| | | Ratio | 0.84* | 0.83* | 1.09 | 1.54 | 0.99 | 1.10 | 1.02 | 1.26 |
| | 6 | MSE | 47.25 | 2.57 | 14.26 | 0.31 | 45.18 | 2.14 | 18.65 | 1.07 |
| | | Ratio | 0.96 | 0.83* | 1.31 | 3.42 | 1.19 | 1.32 | 1.05 | 1.62 |
| | 12 | MSE | 46.27 | 8.61 | 9.99 | 0.41 | 41.42 | 3.69 | 13.68 | 1.50 |
| | | Ratio | 0.90 | 0.43* | 1.37 | 3.66 | 1.17 | 1.38 | 0.99 | 1.57 |

post-2008 samples. This is consistent with the finding in Bai and Ng (2008) that targeting individual predictors that underlie the factors may be more effective for forecasting inflation than using $\widehat{f}_1$.

In the second set of four columns, the baseline is the model that includes lags of the first factor and the competing model is the same but augmented with one lag of the second factor. As in the first four columns, there is considerable evidence of additional predictive content when evaluated over the entire post-1970 sample. This is particularly true for IP and Employment. But when we move to the later forecast periods, the second factor seems to lose much of its predictive content.

A primary use of large macroeconomic datasets is forecasting. Hence, it is important that the variables in FRED-MD have good predictive when used in diffusion index forecasting exercises. The results in this subsection suggest that there is little if any statistically significant difference in the predictive ability of the factors estimated from FRED-MD and the GSI data.

### 3.2 FDI: Factor-Based Diffusion Indexes

This subsection suggests a new use of the estimated factors in the study of business chronology. Our starting point is to reorganize the factor estimates into two groups: one for real activity, and one for nominal activity unrelated to the stock market. (The specific factors that enter the two groups will depend on the vintage of the data considered.) The task is to see if information about the state of the economy can be obtained by visualizing the factors as a group. We propose to consider factor-based diffusion indexes.

The use of diffusion indexes in the study of business cycle chronology has a long history. Burns and Mitchell (1946) pioneered the study of business cycle turning points using a variety of methods—one of which is to analyze the direction of change in the components of aggregate data. Series that increase, decrease, and stay unchanged over a given span are assigned values of 100, 0, and 50, respectively. A diffusion index is an index that aggregates components in a group (such as industrial production) and provides a summary of the direction of change for the group. (Historical data for these indexes are still available. See *http://www.nber.org/databases/macrohistory/contents/chapter16.html* and *http://research.stlouisfed.org/fred2/series/M1642AUSM461SNBR*.) Subsequent work by Broida (1955), among others, finds that the diffusion indexes have a high rate of falsely signaling turning points. This work was more or less discarded with occasional studies, such as by Kennedy (1994), who found that the diffusion indexes for industrial production and employment have predictive power in a 25-year sample beginning in 1967.

There is a renewed interest in using diffusion indexes to analyze business cycle turning points. Stock and Watson (2010, 2014) considered two approaches. The first is a "date and average" method that first identifies turning points in the individual series and looks for a common turning point. The second is an "average and date" method that looks for turning points in the three aggregate indicators, namely, (i) the Conference Board index, (ii) a weighted average of industrial production, employment, manufacturing trade, and personal income using the standard deviation of the series as weights, and (iii) a (dynamic) factor estimated from the same four series. They found the Burns–Mitchell idea of "date and average" to be more promising in detecting business cycle turning points.

Our approach is in the spirit of average and date, but differs from the Stock and Watson (2014) methodology in two ways. The first is that we estimate static instead of dynamic factors. This difference is not substantive because static and dynamic factors usually have similar properties. The specific property that is relevant here is variability of the factor estimates. Since the data are differenced to achieve stationarity, the factor estimates $\widehat{f}_t$ are too volatile for turning point analysis. If we apply the algorithm of Bry and Boschan (1971), $\widehat{f}_{1t}$ is in agreement with the NBER recessions dates only 65% of the time, and with the expansions dates 57% of the time.

To mitigate this problem, we form diffusion indexes from the partial sum of the common factors rather than the factors themselves, which is substantively different from the analysis in Stock and Watson (2014). To be precise, our real activity diffusion index is constructed as $\widehat{F}_{1t} = \sum_{j=1}^{t} \widehat{f}_{1j}$. While $\widehat{f}_{1t}$ isolates the common variations at higher frequencies, $\widehat{F}_{1t}$ zooms in on common variations at low frequencies. It may seem counterintuitive to learn about the state of a business cycle from the trend component. Informally, Moore (1961, p. 286) also plotted the diffusion indexes in cumulative form and found them useful. As well, the Bry and Boschan (1971) algorithm also looks for directional change in the smoothed series, which is an estimate of the trend.

The top panel of Figure 3 plots the real activity diffusion index $\widehat{F}_{1t}$ constructed from FRED-MD data. In the base case (blue line), the factors $\widehat{f}_t$ are estimated using all 134 series over the 1960:03–2014:12. To see whether the factor estimates are robust to the treatment of missing values, $\widehat{F}_{1t}$ is also plotted (in red) with $\widehat{f}_t$ estimated from a balanced panel of 130 series. (Note that $\widehat{F}_{2t}$-balanced was multiplied by $-1$ in order to keep the same sign as $\widehat{F}_{2t}$). The NBER recession dates are shaded in gray. We see that the $\widehat{F}_{1t}$ series always reaches a trough before the beginning of NBER recession dates and reaches a peak just after the recession is over. This is true even for the 1990 and 2001 recessions, which have been difficult to forecast. The real activity diffusion index estimated using the balanced panel is almost identical to the one estimated from the larger but unbalanced panel. Applying the algorithm of Bry and Boschan (1971) to $\widehat{F}_{1t}$, we find that the series perfectly classifies the NBER recession dates. It is less successful in classifying expansions, with a correct classification rate of 67%.

The bottom panel of Figure 3 shows the second diffusion index, constructed as $\widehat{F}_{2t} = \sum_{j=1}^{t} \widehat{f}_{2j}$. From Table 2, we can think of $\widehat{f}_{2t}$ as a nominal factor since it has good explanatory power for term spreads. This diffusion index peaks in the early 1980s when inflation was high and has been declining since the early 1990s. The diffusion indexes $\widehat{F}_{3t}$ and $\widehat{F}_{4t}$ exhibit the same secular movements as $\widehat{F}_{2t}$ and are not displayed. But since $\widehat{f}_{3t}$ and $\widehat{f}_{4t}$ have higher $mR^2$ for price and interest rate variables, whether we combine the three diffusion indexes $\widehat{F}_{2t}$, $\widehat{F}_{3t}$, and $\widehat{F}_{4t}$ or look at them individually, they seem to line up with price pressure inflation expectations in the past five decades. This is interesting even if these indexes seem unrelated to recessions.

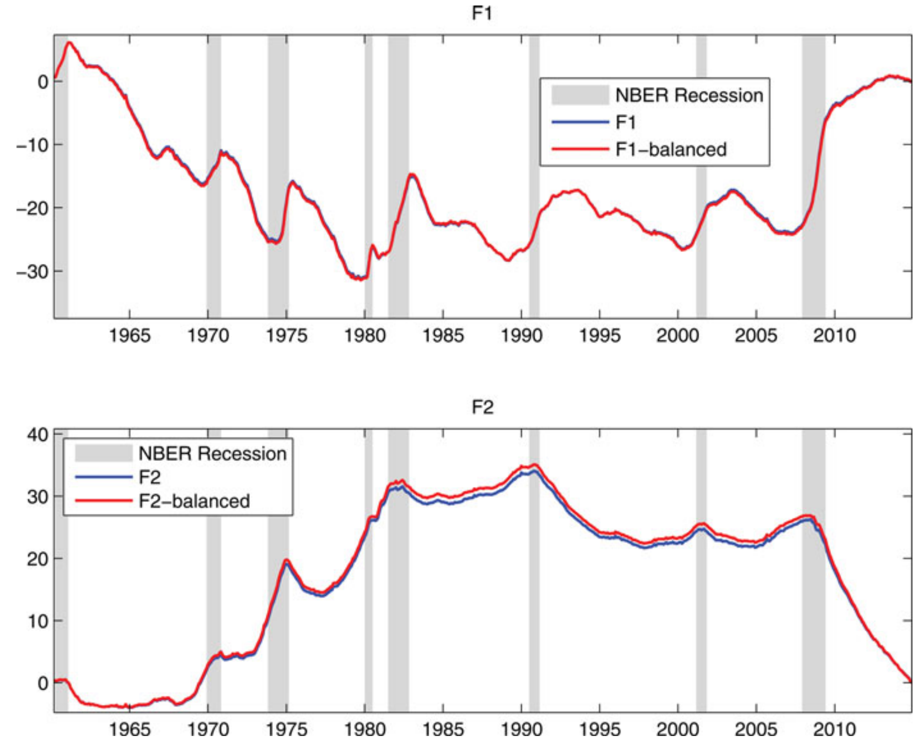


Figure 3. Diffusion indexes: $\widehat{F}_1$ and $\widehat{F}_2$.

Unfortunately, by construction, $\widehat{F}_{1t}$ has the drawback that it must take the value of zero at the end of the sample. (This is not numerically the case when missing data are allowed and the factors are estimated using the EM algorithm. Nevertheless, the $\widehat{F}_{1t}$ remains very close to zero at the end of the sample with any deviation arising from approximation error.) This problem arises because the factors are constructed as linear combinations of series that have been demeaned using the full sample. Hence, while $\widehat{F}_{1t}$ gives a good historical classification of recessions, it is ill-suited as a monitoring device for recent changes in

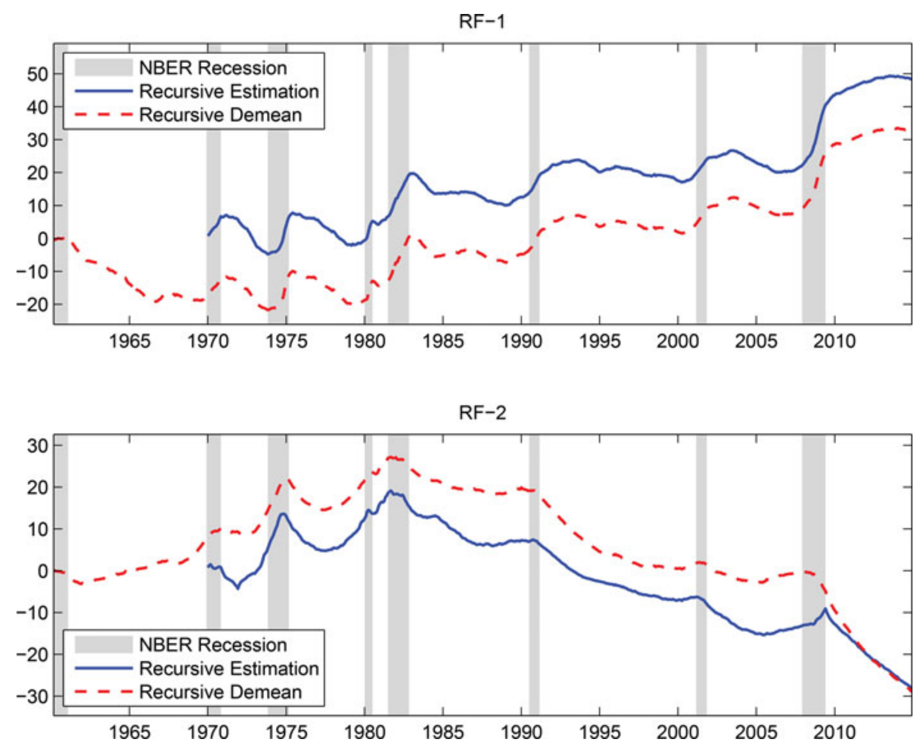


Figure 4. Recursively estimated diffusion indexes: $\mathrm{RFDI}_1$.

the business cycle. We attempt to handle this problem in two ways.

In the first, we demean the data recursively. For $i = 1, \dots, N$ and $t = 3, \dots, T$, let $\widetilde{x}_{it} = \frac{(x_{it} - \overline{x}_{it})}{\sigma_i}$, where $\overline{x}_{it} = \frac{1}{t}\sum_{s=1}^{t} x_{is}$ and $\sigma_i = \frac{1}{T}\sum_{s=1}^{T}(x_{it} - \frac{1}{T}\sum_{t=1}^{T} x_{it})^2$. We set $\overline{x}_{i1}$ and $\overline{x}_{i2}$ to the unconditional mean of series $i$. This recursive demeaning needs to be done only once. Now, each $\widetilde{x}_{it}$ is not necessarily mean zero over the whole sample, and neither are the means of the estimated factors, say $\widetilde{f}_{kt}, k = 1, \dots, r$. Hence, the corresponding real activity diffusion index $\widetilde{F}_{1t} = \sum_{j=1}^{t} \widetilde{f}_{1j}$ is no longer a Brownian bridge. Recursive demeaning requires a more delicate treatment of missing values, so we use only the balanced panel of 130 series to estimate the factors over the full sample. The recursively demeaned diffusion index $\widetilde{F}_{1t}$ is plotted in Figure 4. As with $\widehat{F}_{1t}$, the beginning of recessions are preceded by an upward turn in the index, and the end of recessions are preceded by downward turns. Based on the Bry–Boschan algorithm, $\widetilde{F}_{1t}$ has a correct classification rate for recessions of 0.98, missing only the recession in 1961:02 at the very beginning of the sample. The rate for correctly classifying expansions is 58%.

The endpoint problem associated with $\widehat{F}_{1t}$ is also a feature of the CUSUM of regression residuals. By construction, these residuals sum to zero when an intercept is included in the OLS regression. It is known that the residual-based CUSUM test for structural breaks lacks power at the end of the sample. However, recursive residuals were developed precisely to improve power against breaks at the end of the sample. Building on this analogy, our second approach to the endpoint problem is to construct the diffusion indexes from recursively estimated factors. For each $k = 1, \dots, r$, we recursively estimate the $f_{k,t}$ starting in 1970:01. In each month $t$, a historical sequence of factors $\widehat{f}_{k,s,t}$ is constructed for each $s = 1, \dots, t$. From each of these sequences, we save the most recent value of $f_{k,t,t}$. The partial sum of this series is used to construct a recursive diffusion index, denoted by $\widehat{\mathrm{RF}}_{1t}$.

There are two technical details with this exercise. The first issue arises from the fact that the factors are identified only up to an orthogonal rotation and, in particular, are not sign-identified. Hence, as we move from month to month, the "correct" sign of the estimated first factor has the potential to change. To avoid this issue, in each month $t$ we assume that the sign of the first factor in 1961:01 is positive (i.e., $\widehat{f}_{1,1961:01,t} > 0$). If the estimate is negative, we simply flip the sign of the entire series. Somewhat surprisingly, this happens very rarely and in fact never occurs at any point over the entire sample when using FRED-MD.

The second problem is due to missing values or the lack of variation in some series during the early part of the sample. In the first recursion, which starts 1970:01, four of the series are missing a large number of observations: ACOGNO (64), TWEXMMTH (101), oilprice (110), and UMCSENTx (130). For the first two we simply have no data. For the latter two, the transformed data are highly irregular after transformation. The oilprice series is essentially zero in the early sample (since the data are differenced) with a few large jumps followed by a similar decline. The Michigan sentiment series is only quarterly prior to 1970 and hence the transformation is not really operational. We therefore drop these four series from this exercise.

The recursively estimated diffusion index $\widehat{\mathrm{RF}}_{1t}$ is plotted in Figure 4, side by side with $\widetilde{F}_{1t}$. These series also tend to change direction at the beginning and the end of recessions. Evidently, it no longer ends the sample at zero; the most recent values of $\widetilde{F}_{1t}$ and $\widehat{\mathrm{RF}}_{1t}$ show no clear direction of change, which suggests that the economy is staying on its course. The bottom panel shows $\widehat{\mathrm{RF}}_{2t}$. As with $\widetilde{F}_{2t}$, the series peaked around 1981 when inflationary pressure was high. Obviously, more work is needed to study the statistical properties of both formulations of the diffusion indexes. But the results so far are encouraging. Since FRED-MD will be updated on a timely basis, these factor-based diffusion indexes can be useful tools in documenting the state of the economy.

## 4. CONCLUSION

This article introduces researchers to a set of 134 monthly macroeconomic variables based on the FRED database. The dataset starts in 1959:01 and will be updated on a timely basis hereafter. Changes to the dataset will be documented in a log file, also available at *http://research.stlouisfed.org/econ/mccracken/sel/*. In addition to open public access, the main appeal of the dataset is that revisions and data changes are taken care of by the data specialists at FRED. We sincerely thank them for their support in this work.

# APPENDIX: DATA APPENDIX

The column TCODE denotes the following data transformation for a series $x$: (1) no transformation; (2) $\Delta x_t$; (3) $\Delta^2 x_t$ ; (4) $\log(x_t)$; (5) $\Delta \log(x_t)$; (6) $\Delta^2 \log(x_t)$; (7) $\Delta(x_t/x_{t-1} - 1.0)$. The FRED column gives mnemonics in FRED followed by a short description. The comparable series in Global Insight is given in the column GSI.

Group 1. Output and income

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 1 | 5 | RPI | Real Personal Income | M_14386177 | PI |
| 2 | 2 | 5 | W875RX1 | Real personal income ex transfer receipts | M_145256755 | PI less transfers |
| 3 | 6 | 5 | INDPRO | IP Index | M_116460980 | IP: total |
| 4 | 7 | 5 | IPFPNSS | IP: Final Products and Nonindustrial Supplies | M_116460981 | IP: products |
| 5 | 8 | 5 | IPFINAL | IP: Final Products (Market Group) | M_116461268 | IP: final prod |
| 6 | 9 | 5 | IPCONGD | IP: Consumer Goods | M_116460982 | IP: cons gds |
| 7 | 10 | 5 | IPDCONGD | IP: Durable Consumer Goods | M_116460983 | IP: cons dble |
| 8 | 11 | 5 | IPNCONGD | IP: Nondurable Consumer Goods | M_116460988 | IP: cons nondble |
| 9 | 12 | 5 | IPBUSEQ | IP: Business Equipment | M_116460995 | IP: bus eqpt |
| 10 | 13 | 5 | IPMAT | IP: Materials | M_116461002 | IP: matls |
| 11 | 14 | 5 | IPDMAT | IP: Durable Materials | M_116461004 | IP: dble matls |
| 12 | 15 | 5 | IPNMAT | IP: Nondurable Materials | M_116461008 | IP: nondble matls |
| 13 | 16 | 5 | IPMANSICS | IP: Manufacturing (SIC) | M_116461013 | IP: mfg |
| 14 | 17 | 5 | IPB51222s | IP: Residential Utilities | M_116461276 | IP: res util |
| 15 | 18 | 5 | IPFUELS | IP: Fuels | M_116461275 | IP: fuels |
| 16 | 19 | 1 | NAPMPI | ISM Manufacturing: Production Index | M_110157212 | NAPM prodn |
| 17 | 20 | 2 | CUMFNS | Capacity Utilization: Manufacturing | M_116461602 | Cap util |

Group 2. Labor market

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 21* | 2 | HWI | Help-Wanted Index for United States | | Help wanted indx |
| 2 | 22* | 2 | HWIURATIO | Ratio of Help Wanted/No. Unemployed | M_110156531 | Help wanted/unemp |
| 3 | 23 | 5 | CLF16OV | Civilian Labor Force | M_110156467 | Emp CPS total |
| 4 | 24 | 5 | CE16OV | Civilian Employment | M_110156498 | Emp CPS nonag |
| 5 | 25 | 2 | UNRATE | Civilian Unemployment Rate | M_110156541 | U: all |
| 6 | 26 | 2 | UEMPMEAN | Average Duration of Unemployment (Weeks) | M_110156528 | U: mean duration |
| 7 | 27 | 5 | UEMPLT5 | Civilians Unemployed - Less Than 5 Weeks | M_110156527 | U < 5 wks |
| 8 | 28 | 5 | UEMP5TO14 | Civilians Unemployed for 5–14 Weeks | M_110156523 | U 5-14 wks |
| 9 | 29 | 5 | UEMP15OV | Civilians Unemployed - 15 Weeks & Over | M_110156524 | U 15+ wks |
| 10 | 30 | 5 | UEMP15T26 | Civilians Unemployed for 15–26 Weeks | M_110156525 | U 15-26 wks |
| 11 | 31 | 5 | UEMP27OV | Civilians Unemployed for 27 Weeks and Over | M_110156526 | U 27+ wks |
| 12 | 32* | 5 | CLAIMSx | Initial Claims | M_15186204 | UI claims |
| 13 | 33 | 5 | PAYEMS | All Employees: Total nonfarm | M_123109146 | Emp: total |
| 14 | 34 | 5 | USGOOD | All Employees: Goods-Producing Industries | M_123109172 | Emp: gds prod |
| 15 | 35 | 5 | CES1021000001 | All Employees: Mining and Logging: Mining | M_123109244 | Emp: mining |
| 16 | 36 | 5 | USCONS | All Employees: Construction | M_123109331 | Emp: const |
| 17 | 37 | 5 | MANEMP | All Employees: Manufacturing | M_123109542 | Emp: mfg |
| 18 | 38 | 5 | DMANEMP | All Employees: Durable goods | M_123109573 | Emp: dble gds |
| 19 | 39 | 5 | NDMANEMP | All Employees: Nondurable goods | M_123110741 | Emp: nondbles |
| 20 | 40 | 5 | SRVPRD | All Employees: Service-Providing Industries | M_123109193 | Emp: services |
| 21 | 41 | 5 | USTPU | All Employees: Trade, Transportation & Utilities | M_123111543 | Emp: TTU |
| 22 | 42 | 5 | USWTRADE | All Employees: Wholesale Trade | M_123111563 | Emp: wholesale |
| 23 | 43 | 5 | USTRADE | All Employees: Retail Trade | M_123111867 | Emp: retail |
| 24 | 44 | 5 | USFIRE | All Employees: Financial Activities | M_123112777 | Emp: FIRE |
| 25 | 45 | 5 | USGOVT | All Employees: Government | M_123114411 | Emp: Govt |
| 26 | 46 | 1 | CES0600000007 | Avg Weekly Hours: Goods-Producing | M_140687274 | Avg hrs |
| 27 | 47 | 2 | AWOTMAN | Avg Weekly Overtime Hours: Manufacturing | M_123109554 | Overtime: mfg |
| 28 | 48 | 1 | AWHMAN | Avg Weekly Hours: Manufacturing | M_14386098 | Avg hrs: mfg |
| 29 | 49 | 1 | NAPMEI | ISM Manufacturing: Employment Index | M_110157206 | NAPM empl |
| 30 | 127 | 6 | CES0600000008 | Avg Hourly Earnings: Goods-Producing | M_123109182 | AHE: goods |
| 31 | 128 | 6 | CES2000000008 | Avg Hourly Earnings: Construction | M_123109341 | AHE: const |
| 32 | 129 | 6 | CES3000000008 | Avg Hourly Earnings: Manufacturing | M_123109552 | AHE: mfg |

Group 3. Housing

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 50 | 4 | HOUST | Housing Starts: Total New Privately Owned | M_110155536 | Starts: nonfarm |
| 2 | 51 | 4 | HOUSTNE | Housing Starts, Northeast | M_110155538 | Starts: NE |
| 3 | 52 | 4 | HOUSTMW | Housing Starts, Midwest | M_110155537 | Starts: MW |
| 4 | 53 | 4 | HOUSTS | Housing Starts, South | M_110155543 | Starts: South |
| 5 | 54 | 4 | HOUSTW | Housing Starts, West | M_110155544 | Starts: West |
| 6 | 55 | 4 | PERMIT | New Private Housing Permits (SAAR) | M_110155532 | BP: total |
| 7 | 56 | 4 | PERMITNE | New Private Housing Permits, Northeast (SAAR) | M_110155531 | BP: NE |
| 8 | 57 | 4 | PERMITMW | New Private Housing Permits, Midwest (SAAR) | M_110155530 | BP: MW |
| 9 | 58 | 4 | PERMITS | New Private Housing Permits, South (SAAR) | M_110155533 | BP: South |
| 10 | 59 | 4 | PERMITW | New Private Housing Permits, West (SAAR) | M_110155534 | BP: West |

Group 4. Consumption, orders, and inventories

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 3 | 5 | DPCERA3M086SBEA | Real personal consumption expenditures | M_123008274 | Real Consumption |
| 2 | 4* | 5 | CMRMTSPLx | Real Manu. and Trade Industries Sales | M_110156998 | M&T sales |
| 3 | 5* | 5 | RETAILx | Retail and Food Services Sales | M_130439509 | Retail sales |
| 4 | 60 | 1 | NAPM | ISM: PMI Composite Index | M_110157208 | PMI |
| 5 | 61 | 1 | NAPMNOI | ISM: New Orders Index | M_110157210 | NAPM new ordrs |
| 6 | 62 | 1 | NAPMSDI | ISM: Supplier Deliveries Index | M_110157205 | NAPM vendor del |
| 7 | 63 | 1 | NAPMII | ISM: Inventories Index | M_110157211 | NAPM Invent |
| 8 | 64 | 5 | ACOGNO | New Orders for Consumer Goods | M_14385863 | Orders: cons gds |
| 9 | 65* | 5 | AMDMNOx | New Orders for Durable Goods | M_14386110 | Orders: dble gds |
| 10 | 66* | 5 | ANDENOx | New Orders for Nondefense Capital Goods | M_178554409 | Orders: cap gds |
| 11 | 67* | 5 | AMDMUOx | Unfilled Orders for Durable Goods | M_14385946 | Unf orders: dble |
| 12 | 68* | 5 | BUSINVx | Total Business Inventories | M_15192014 | M&T invent |
| 13 | 69* | 2 | ISRATIOx | Total Business: Inventories to Sales Ratio | M_15191529 | M&T invent/sales |
| 14 | 130* | 2 | UMCSENTx | Consumer Sentiment Index | hhsntn | Consumer expect |

Group 5. Money and credit

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 70 | 6 | M1SL | M1 Money Stock | M_110154984 | M1 |
| 2 | 71 | 6 | M2SL | M2 Money Stock | M_110154985 | M2 |
| 3 | 72 | 5 | M2REAL | Real M2 Money Stock | M_110154985 | M2 (real) |
| 4 | 73 | 6 | AMBSL | St. Louis Adjusted Monetary Base | M_110154995 | MB |
| 5 | 74 | 6 | TOTRESNS | Total Reserves of Depository Institutions | M_110155011 | Reserves tot |
| 6 | 75 | 7 | NONBORRES | Reserves Of Depository Institutions | M_110155009 | Reserves nonbor |
| 7 | 76 | 6 | BUSLOANS | Commercial and Industrial Loans | BUSLOANS | C&I loan plus |
| 8 | 77 | 6 | REALLN | Real Estate Loans at All Commercial Banks | BUSLOANS | DC&I loans |
| 9 | 78 | 6 | NONREVSL | Total Nonrevolving Credit | M_110154564 | Cons credit |
| 10 | 79* | 2 | CONSPI | Nonrevolving consumer credit to Personal Income | M_110154569 | Inst cred/PI |
| 11 | 131 | 6 | MZMSL | MZM Money Stock | N.A. | N.A. |
| 12 | 132 | 6 | DTCOLNVHFNM | Consumer Motor Vehicle Loans Outstanding | N.A. | N.A. |
| 13 | 133 | 6 | DTCTHFNM | Total Consumer Loans and Leases Outstanding | N.A. | N.A. |
| 14 | 134 | 6 | INVEST | Securities in Bank Credit at All Commercial Banks | N.A. | N.A. |

Group 6. Interest and exchange rates

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 84 | 2 | FEDFUNDS | Effective Federal Funds Rate | M_110155157 | Fed Funds |
| 2 | 85* | 2 | CP3Mx | 3-Month AA Financial Commercial Paper Rate | CPF3M | Comm paper |
| 3 | 86 | 2 | TB3MS | 3-Month Treasury Bill | M_110155165 | 3 mo T-bill |
| 4 | 87 | 2 | TB6MS | 6-Month Treasury Bill | M_110155166 | 6 mo T-bill |
| 5 | 88 | 2 | GS1 | 1-Year Treasury Rate | M_110155168 | 1 yr T-bond |
| 6 | 89 | 2 | GS5 | 5-Year Treasury Rate | M_110155174 | 5 yr T-bond |
| 7 | 90 | 2 | GS10 | 10-Year Treasury Rate | M_110155169 | 10 yr T-bond |
| 8 | 91 | 2 | AAA | Moody's Seasoned Aaa Corporate Bond Yield | | Aaa bond |
| 9 | 92 | 2 | BAA | Moody's Seasoned Baa Corporate Bond Yield | | Baa bond |
| 10 | 93* | 1 | COMPAPFFx | 3-Month Commercial Paper Minus FEDFUNDS | | CP-FF spread |
| 11 | 94 | 1 | TB3SMFFM | 3-Month Treasury C Minus FEDFUNDS | | 3 mo-FF spread |
| 12 | 95 | 1 | TB6SMFFM | 6-Month Treasury C Minus FEDFUNDS | | 6 mo-FF spread |
| 13 | 96 | 1 | T1YFFM | 1-Year Treasury C Minus FEDFUNDS | | 1 yr-FF spread |
| 14 | 97 | 1 | T5YFFM | 5-Year Treasury C Minus FEDFUNDS | | 5 yr-FF spread |
| 15 | 98 | 1 | T10YFFM | 10-Year Treasury C Minus FEDFUNDS | | 10 yr-FF spread |
| 16 | 99 | 1 | AAAFFM | Moody's Aaa Corporate Bond Minus FEDFUNDS | | Aaa-FF spread |
| 17 | 100 | 1 | BAAFFM | Moody's Baa Corporate Bond Minus FEDFUNDS | | Baa-FF spread |
| 18 | 101 | 5 | TWEXMMTH | Trade Weighted U.S. Dollar Index: Major Currencies | | Ex rate: avg |
| 19 | 102* | 5 | EXSZUSx | Switzerland/U.S. Foreign Exchange Rate | M_110154768 | Ex rate: Switz |
| 20 | 103* | 5 | EXJPUSx | Japan/U.S. Foreign Exchange Rate | M_110154755 | Ex rate: Japan |
| 21 | 104* | 5 | EXUSUKx | U.S./U.K. Foreign Exchange Rate | M_110154772 | Ex rate: UK |
| 22 | 105* | 5 | EXCAUSx | Canada/U.S. Foreign Exchange Rate | M_110154744 | EX rate: Canada |

Group 7. Prices

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 106 | 6 | PPIFGS | PPI: Finished Goods | M110157517 | PPI: fin gds |
| 2 | 107 | 6 | PPIFCG | PPI: Finished Consumer Goods | M110157508 | PPI: cons gds |
| 3 | 108 | 6 | PPIITM | PPI: Intermediate Materials | M_110157527 | PPI: int matls |
| 4 | 109 | 6 | PPICRM | PPI: Crude Materials | M_110157500 | PPI: crude matls |
| 5 | 110* | 6 | OILPRICEx | Crude Oil, spliced WTI and Cushing | M_110157273 | Spot market price |
| 6 | 111 | 6 | PPICMM | PPI: Metals and metal products: | M_110157335 | PPI: nonferrous |
| 7 | 112 | 1 | NAPMPRI | ISM Manufacturing: Prices Index | M_110157204 | NAPM com price |
| 8 | 113 | 6 | CPIAUCSL | CPI: All Items | M_110157323 | CPI-U: all |
| 9 | 114 | 6 | CPIAPPSL | CPI: Apparel | M_110157299 | CPI-U: apparel |
| 10 | 115 | 6 | CPITRNSL | CPI: Transportation | M_110157302 | CPI-U: transp |
| 11 | 116 | 6 | CPIMEDSL | CPI: Medical Care | M_110157304 | CPI-U: medical |
| 12 | 117 | 6 | CUSR0000SAC | CPI: Commodities | M_110157314 | CPI-U: comm. |
| 13 | 118 | 6 | CUUR0000SAD | CPI: Durables | M_110157315 | CPI-U: dbles |
| 14 | 119 | 6 | CUSR0000SAS | CPI: Services | M_110157325 | CPI-U: services |
| 15 | 120 | 6 | CPIULFSL | CPI: All Items Less Food | M_110157328 | CPI-U: ex food |
| 16 | 121 | 6 | CUUR0000SA0L2 | CPI: All items less shelter | M_110157329 | CPI-U: ex shelter |
| 17 | 122 | 6 | CUSR0000SA0L5 | CPI: All items less medical care | M_110157330 | CPI-U: ex med |
| 18 | 123 | 6 | PCEPI | Personal Cons. Expend.: Chain Index | gmdc | PCE defl |
| 19 | 124 | 6 | DDURRG3M086SBEA | Personal Cons. Exp: Durable goods | gmdcd | PCE defl: dlbes |
| 20 | 125 | 6 | DNDGRG3M086SBEA | Personal Cons. Exp: Nondurable goods | gmdcn | PCE defl: nondble |
| 21 | 126 | 6 | DSERRG3M086SBEA | Personal Cons. Exp: Services | gmdcs | PCE defl: service |

Group 8. Stock market

| | id | tcode | fred | Description | gsi | gsi:description |
|---|---|---|---|---|---|---|
| 1 | 80* | 5 | S&P 500 | S&P's Common Stock Price Index: Composite | M_110155044 | S&P 500 |
| 2 | 81* | 5 | S&P: indust | S&P's Common Stock Price Index: Industrials | M_110155047 | S&P: indust |
| 3 | 82* | 2 | S&P div yield | S&P's Composite Common Stock: Dividend Yield | | S&P div yield |
| 4 | 83* | 5 | S&P PE ratio | S&P's Composite Common Stock: Price-Earnings Ratio | | S&P PE ratio |

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