FRED-MD: A Monthly Database for Macroeconomic Research

Michael W. McCracken* Serena Ng†

December 20, 2014

Abstract

This paper presents and 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 in real-time using the FRED database. Second, it will be publicly accessible, facilitating the replication of empirical work. Third, it will relieve researchers from the task of data changes and revisions. This will be handled by the data desk at the Federal Reserve Bank of St. Louis. We show that factors extracted from our dataset share the same predictive content as those based on the various vintages of the so-called Stock-Watson data. 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.

JEL Classification: C30, C33, G11, G12.
Keywords: diffusion index, forecasting, big data, factors.

*Research Division; Federal Reserve Bank of St. Louis; P.O. Box 442; St. Louis, MO 63166; michael.w.mccracken@stls.frb.org.

†Department of Economics, Columbia University, 420 W. 118 St. Room 1117, New York, NY 10025; Serena.Ng at Columbia.edu.

We thank Kenichi Shimizu and Joseph McGillicuddy for excellent research assistance. Financial support to the second author is provided by the National Science Foundation, SES-0962431. The views expressed here are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Board of Governors.

1 Introduction

A new trend in research is to make use of data that two decades ago were either not available, or that computational constraints prohibit their use. 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, macroeconomic policy and forecasting can now consider many more variables without compromising information in the time series dimension. When we work with datasets that have large N and large T, we are in what Bernanke and Boivin (2003) referred to as a *data rich environment*. Of course, more data is not always desirable unless the data are informative about the economic variables that we seek to explain. As such, assembling a good database is an important part of economic research. However, not only is the process time consuming, 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 year, we have worked with the FRED data desk at the Federal Reserve Bank of St. Louis to develop FRED-MD, a macroeconomic database of 135 monthly U.S. indicators. The data will be updated in a timely manner and can be downloaded for free from the website `http://research.stlouisfed.org/econ/mccracken/`. We hope that easy access to the data will stimulate more research that exploits the data rich environment. Working with a more or less standard database should also facilitate replication and comparison of results. This paper 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 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 8 categories: output and sales, employment, orders, inventories, prices, interest rates, exchange rates, government spending /taxes, and miscellaneous leading indicators. This dataset was expanded in Stock and Watson (1998, 2002) to include 215 series, subsequently classified into 14 categories. In this iteration, the data were taken from the DRI/McGraw Hill database. Although over 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 use the factor estimates as predictors. This methodology has come to be known as 'diffusion index forecasting'. Marcellino et al. (2006) analyzed 171 series for the sample 1959:1-2002:12 to assess different implementations of diffusion forecasting.

In an influential paper, Bernanke and Boivin (2003) considered the use of big data in monetary policy analysis.[1] This marked the beginning of using big data not just for forecasting, but also in structural macroeconomic modeling. Bernanke et al. (2005) used 120 series to estimate a factor augmented autoregression (FAVAR). Boivin and Giannoni (2006) considered estimation of DSGE models using 91 variables and interpreted measurement error as the difference between the data and model concepts. Data for these exercises were taken from the DRI database.

Up till this point, more data were collected than used in analysis because some of these series were available only from 1967:01. The next phase of this work 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: real output and income, employment and hours, real retail, manufacturing and trade sales, consumption, housing starts, sales, real inventories, orders, stock prices, exchange rates, interest rates and spreads, money and credit quantity aggregates, price indexes, average hourly earnings, and miscellaneous. The data were draw 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" in the research community. 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 8 groups: output and income, labor market, housing, consumption, orders and inventories, money and credit, interest rate, and exchange rates, prices and stock market. Factors estimated using the entire dataset were compared with an alternative estimator that takes advantage of the structure of the eight blocks. The data were again updated in Jurado et al. (2013) to

[1]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 used in Stock and Watson (1998).

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 et al. (2013).

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 desired level of disaggregation. For example, Stock and Watson (2014a) collected 270 disaggregated monthly series for the sample 1959:01-2010:08 to estimate turning points. For macroeconomic forecasting, most analyses use between 100 and 150 series.

2 FRED-MD

If the same variables were reported year after year, the data updating exercise is 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 often have 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 which existed since 1946:1 has recently been discontinued. In its place is a WTI series that only starts from 1986:1. If one was to analyze 50 years of monthly data, one cannot avoid having to melt or splice data from different sources, which is what makes the data updating process difficult.

To get a sense of the problems involved, consider the process of updating the data from the vintage which ended in 2011:12 to 2013:12. Based on the mnemonics of the 2011 data, used in Jurado et al. (2013), 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 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. To deal with such problems, replacing non-existing data by close substitutes or splicing seems routine. It is difficult if not impossible to automate the process as judgment 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, albeit with missing values for some variables. But the data are available only on a subscription basis; researchers without access will have to look to alternatives which inevitably involve multiple sources. There is also a catch to using the GSI data. The licensing agreement understandably prohibits redistribution of the data. Yet it is increasingly common to be required by journals to post the data used in empirical work. Authors are often at a loss what can and cannot be posted.

FRED-MD seeks to make available a database with three objectives in mind. First, it will be publicly available so that US and international researchers alike 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 the researchers from the burden of handling data changes and revisions. With these objectives in mind, we collect 135 monthly series with coverage that is similar to the original Stock-Waton data. A full list of the data is given in Appendix I, 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 paper, the latest vintage is 2014:10. While we provide a csv file with data for this sample, but FRED-MD is not a balanced panel for a number of reasons:

(1) The S&P PE ratio (series 84) 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 131) is available only quarterly prior to 1977:11 and recent data is available in FRED only with a 1-year lag,

(3) The trade-weighted exchange rate (series 102) 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) only exist through 1960:01,

(5) Currently, FRED primarily holds NAICS data (though some older SIC data exists and is used whenever possible) from the Census Manufacturers Survey and hence a few Value of Manufacturers' Orders components like Nondefense Capital Goods (series 66) and especially Consumer Goods (series 64) have a limited history.

Of course, the dataset can easily be turned into a balanced panel by removing these series involved. In MATLAB, these series can be identified by checking if the mean over the full sample is a NaN. We have not made outlier adjustments to the data. To be consistent with the previous GSI data used in empirical work, we start the data in 1959:01. In the first vintage of FRED-MD with the sample ending in 2014:08, the balanced panel has 122 series. A balanced panel consisting of 128 series can be constructed if the sample terminates in 2014:05.

In addition to data revisions and definitional changes, going from GSI to FRED necessitates finding 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 first vintage of FRED-MD, 21 out of 135 series require some adjustments to the raw data available in FRED. We tag these variables with an "x" to indicate that they been adjusted and thus differ from the series at source. A summary of the adjustments is as follows:

Number	Variable	Adjustments
4	Real Manu. and Trade	(i) adjust M0602BUSM144NNBR for inflation using PCEPI
		(ii) seasonal adjust with ARIMA X12
		(iii) splice with NAICS series CMRMTSPL
5	Retail/Food Sales	splice SIC series RETAIL with NAICS series RSAFS
17	IP: Resid. Utilities	FRB series IP.B51222.S
20	Capacity Utilization	FRB series CAPUTL.B00004.S
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 (non-defense)	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
80	Consumer credit to P.I.	NONREVSL to PI
81	3month Comm. Paper	splice M13002US35620M156NNBR, CP3M with CPF3M
90	3month CP -FF	splice CP3M-FedFunds
90	Switzerland/US FX	filled back to 1959 from Banking/Monetary statistics
91	Japan/US FX	filled back to 1959 from Banking/Monetary statistics
92	UK/US FX	filled back to 1959 from Banking/Monetary statistics
93	Cdn/US FX	filled back to 1959 from Banking/Monetary statistics
107	Crude Oil	splice OILPRICE with MCOILWTICO
127	Consumer sentiment	splice UMSCENT1 with UMSCENT

Some comments on these adjustments are in order. To replace the GSI data for manufacturing and trade series, we have to deal with the fact that data for orders, sales, and inventories are available from FRED starting in 1992 when the standard industrial classification (SIC) was changed to the

North American Industry Classification System (NAICS). These series in FRED-MD have been spliced with the SIC historical data when available from the CENSUS. Consumer credit outstanding in GSI is replaced by non-revolving consumer credit. The exchange rate data in FRED start from 1971, the three month commercial paper rate series has been discontinued since 1997:08 though a 3 month financial commercial paper rate series existed since 1997:01. The FRED-MD data splice the data with historical data from the Banking and Monetary Statistics series produced by the Federal Reserve Board of Governors and obtained from FRASER. The West Texas oil price which was 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.

Going forward, the FRED-MD data will come in one (csv) file available for download from `http://research.stlouisfed.org/econ/mccracken/`. 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. 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 like MONSTER.COM have become more popular. At the moment, there is not enough data to build a 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. This work will be handled by the experts at the data desk at FRED.

3 Factor Estimates

A primary use of big macro datasets is diffusion index forecasting and FAVAR which augments an otherwise standard vector autoregression with factors estimated from the big panel of data. This methodology has been found to produce superior forecasts over competing methods, especially those that are based on a small set of predictors. 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.[2]

We begin by examining the properties of the factors estimated from the vintage of FRED-MD that spans 1959:1 to -2014:08. After transforming the data, our estimation is based on the sample 1960:3-2014:08 for a total of T =655 observations. As mentioned earlier, a few series have missing observations in the beginning or the end of the sample. We estimate the static factors by PCA adapted to allow for missing values. It is essentially the EM algorithm given in Stock and Watson (2002). In brief, observations that are missing are initialized to the unconditional mean based on the non-missing values (which is zero since the data are demeaned and standardized) so that the

[2]See Forni et al. (2000, 2005), Boivin and Ng (2005), Bai and Ng (2008), Stock and Watson (2006).

panel is re-balanced. A $r \times 1$ vector f factors f_t and a $N \times r$ matrix of loadings λ 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 re-added back. Treating resulting value as an observation for series i and time t, the mean and variance of the complete sample are re-calculated. The data are demeaned and standardized again, and the factors and loadings are re-estimated from the updated panel. The iteration stops when the factor estimates do not change.[3] After the factors are estimated, we regress the i-th series in the dataset on a set of r (orthogonal) factors. For $k = 1, \ldots, r$, this yields $R_i(k)^2$ for series i. The incremental explanatory power of factor k is $mR_i^2(k) = R_i^2 k) - R_i^2(k-1)$, $k = 2, \ldots, r$ with $mR_i^2(1) = R_i^2(1)$. The average importance of factor-k is $mR^2(k) = \frac{1}{N}\sum_{i=1}^N mR_i^2(k)$.

We begin with an analysis of the number of factors. The PCP_2 criterion of Bai and Ng (2002) finds 8 factors explaining .445 of the total variation in the data (and seven if outlier adjustment is made).[4] Figure 1 plots $R^2(8)$) ordered by groups. The x axis in this figure is the id of the series as indicated in the Appendix and the y axis is the fraction of variation in each series explained by eight factors. These eight factors explain over .5 of the variation in 58 series and between .25 and .5 of the variation in 34 series. The ten series that are best explained by the factors are 'ipmansics', 'indpro', 't10yffm', 'caputlb00004s', 'gs1', 'ipfpnss', 't5yffm', 'aaaffm', 'ipfinal' , 'tb6ms', 'tb6smffm'. There are, however, 22 series that have the idiosyncratic component explaining 90% of the variation. The ten series with the largest idiosyncratic component are 'nonborres' 'cpimedsl' 'cuur0000sad' 'cpiappsl' 'ddurrg3m086sbea' 'invest' 'ces1021000001' 'ipfuels' 'claimsx' 'cusr0000sas'. 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.

Table 1 lists $R^2(j)$ and the ten series with the highest $mR^2(j)$ for factor j. Factor 1 explains .139 of the variation in the data and can be interpreted as a real activity/employment factor since the $mR(1)$ associated with industrial production and employment series are as high as .776. Factor 2 is dominated by forward looking variables like term interest rate spreads and inventories. Factor 3 has an $mR^2(3)$ of 0.065 and its explanatory power is concentrated on price variables, hence can be interpreted as an inflation factor. The explanatory power of Factor 4 concentrates on the interest rates. Factor 5 is a mix of labor market and term spread variables. Factor 6 and 7 both have explanatory power for stock market variables while factors 7 and 8 both have explanatory power for monetary aggregates.

How does FRED-MD differ from the vintages of GSI data that have been used previously?

[3] In this EM algorithm, the number of factors is determined by the space spanned by the data without missing values. The iteration does not change the number of factors.

[4] This is primarily due to the monetary base series which took on extreme values during the financial crisis.

We repeat the exercise in Table 1 for four vintages. Estimation always starts in 1960:3 but ends differently depending on the vintage. The first is the 2003 vintage used in Stock and Watson (2005). The sample ends in 2003:12. The 2007, 2011, and 2013 vintages updated by Ludvigson and Ng end in 2007:12, 2011:12, and 2013:05, respectively. Table 2 reports the properties of the factor estimates. The PCP_2 criterion of Bai and Ng (2002) finds $r = 8$ factors in the 2003 and 2007 vintages, and $r = 7$ factors in the 2013 vintage.

Table 2 shows that explanatory power provided by the first four factors have been remarkably stable across databases. The first factor explains 0.156 of the total variations of 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 variations in industrial production and employment,[5] explaining over .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.[6] 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.[7] Factor four explains about 0.05 of total variation in the data and explains well the variations in interest rates.

Turning to factors five to eight, their $mR^2$are noticeably lower than those for factors one to 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 .5; in the 2011 and 2014 vintages, the monetary aggregates are better explained by factor 8 with $mR_i^2(8)$ below .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 PCP_2 criterion and the corresponding $R^2(r_t)$. This is plotted in Figure 2. The NBER recession dates are shaded in grey. The top panel shows that the number of factors has crept up from a minimum of 2 in early 1970, to 4 in early 1980, 6 in early 1990, to 7 in early 2000, and stands at 8 in 2014:08. The bottom panel shows that the size of the common component has also increased from .2 in 1970 ot .35 in 1980, .4 in 1990, .43

[5] ips43 is IP: mfg, ces003 is Emp: gds prod., and a0m082 is capacity utilization.

[6] sfybaac is the spread between the federal funds rate and Baa bonds.

[7] puc is cpi commodities, gmden is implicit price deflator of non- durables. punew is cpi all items, and puxm is cpi excluding medical care.

in 2000. Interestingly, these increases in the number of factors and R^2 line up well with 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 the GSI data used in previous work. While the variable names have changed over the years, it is a solid fact that the first factor has strong association to real activity, and the second, third and fourth factors have strong association with nominal variables not directly related to the stock market. These four factors explain over .3 of the variation of data. The remaining three or four factors explain another .12 to .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 if this finding is robust.

3.1 Predictability

In this subsection we revisit the usefulness of factors for predicting macroeconomic aggregates – with an eye towards 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 US recovery.

In each case the models used for forecasting take the form

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

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

$$y^h_{t+h} = (1200/h)\ln(IP_{t+h}/IP_t).$$

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

$$y^h_{t+h} = (1200/h)\ln(CPI_{t+h}/CPI_t) - 1200\ln(CPI_t/CPI_{t-1}).$$

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

All models are estimated recursively by OLS. We consider three out-of-sample periods. In order 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 2003 vintage of the GSI data. But in order to 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 2014:08 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. In order 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 as the representative factor. 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 implied by the corresponding model using the FRED-MD factors and the ratio of MSEs from the competing two models. To determine whether any differences are statistically significant, we use the Diebold-Mariano/West 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 3. A quick glance indicates that the MSE ratios all lie within a very tight range of 0.98 and 1.03. There is no significant difference between the MSEs for any combination of dependent variable, horizon, dataset, or sample split. The right panel of Table 3 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 only changes the MSE slightly. For one period ahead forecast of IP in the sample that starts in 1990, the MSE with two factors is 35.59, compared to 36.14 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 a MSE of 10.88 when two factors are used, which is higher than the MSE of 8.84 when one factor is used. But as far as comparison across data vintages is concerned, in large part the story remains the same.

Comparing across different datasets, there are no statistically significant differences in the MSEs for IP, CPI, and Core CPI across models. For Employment, there are no significant differences when evaluated across the entire post-1970 sample but a few differences appear in the post-1990 sample at the longer horizons. In sum, of the 96 possible pairwise comparison considered in Table 3, only 5 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 4 we report (i) the relative improvement in MSE of those models that include the first factor to those that are purely autoregressive, and (ii) the relative improvement of those models that include the first and second factors with those that only include the first factor. For this exercise the FRED-MD factors are estimated using data that ends in 2014:08. 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 - 2014:08, 1990:01 - 2014:08, 2008:01 - 2014:08) we report the mean squared error implied by the model using the FRED-MD factors and the ratio of MSEs from the two models. To determine any significant 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 4. Significant differences are marked with asteriks. 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-6. 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 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 $\widehat{f}_t$.

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 it's predictive content with only a few idiosyncratic instances in which there are statistically significant improvements - the largest of which is only 3%.

A primary use of large macroeconomic datasets is forecast. 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 no 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 re-organize the factors estimates into two groups: one for real activity, and one for nominal activity unrelated to the stock market.[8] The task is 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. A series that increases, decreases, and stays unchanged over a given span are assigned values of 100, 0, and 50 respectively. A diffusion index is an index that aggregates over components in a group (such as industrial production) and provides a summary of the direction of change for the group.[9] Subsequent work by Broida (1955), among others, find 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 Kenndey (1994) who found that the diffusion indexes for industrial production and employment have predictive power in a twenty-five year sample beginning in 1967.

There is a renewed interest in using diffusion indexes to analyze busiess cycle turning points. Stock and Watson (2010, 2014b) consider 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 find 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 (2014b) methodology in two ways. The first is that we estimate static instead of dynamic factors. This difference is not substantive because that static and dynamic factors usually have similar properties.

[8] The specific factors that enter the two groups will depend on the vintage of the data considered.

[9] 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`.

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 60% of the time, and with the expansions dates 53% 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 (2014b). To be precise, our real activity diffusion index is constructed as $\widehat{F}_{1t} = \sum_{j=1}^{t} \widehat{f}_{1t}$. 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 counter-intuitive 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 135 series over the 1960:03-2014:08. To use this opportunity to see that 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 122 series. The NBER recession dates are shaded in gray. We see that the $\widehat{F}_{1t}$ series always peaks before the beginning of NBER recession dates and reaches a trough 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 non-balanced 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 correct classification rate of 0.65.

The bottom panel of Figure 3 shows the second diffusion index, constructed as $\widehat{F}_{2t} = \sum_{j=1}^{t} \widehat{f}_{2t}$. From Table 1, 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 recall from Table 2 that $\widehat{f}_{3t}$ 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 last five decades. This is interesting even if these indexes seem unrelated to recessions.

Unfortunately, the $\widehat{F}_{1t}$ has the drawback that it must take the value of zero at the end of the sample.[10] This problem arises because the factors are constructed as linear combinations of series

[10] 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

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 the business cycle.

We attempt to handle this problem in two ways. The first is to demean the data differently before estimating the factors. We use backward recursive demeaning, For $i = 1, \ldots N$ and $t = 3, \ldots T$, 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 $\overline{x}_{i2}$ set to the unconditional mean of series i. This recursive demeaning only needs to be done 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 $\widetilde{f}_{kt}$, $k = 1, \ldots r$. 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 vales, so we only use the balanced panel of 122 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 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 correct classification rate for expansions is 0.55.

The end point problem associated with $\widehat{F}_{1t}$ is also a feature of the CUSUM of regression residuals. By construction, these residuals sums to zero when an intercept is included in the OLS regression. It is known that residual-based CUSUM tests 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 end point problem is to construct the diffusion indexes from recursively estimated factors. For each $k = 1, \ldots r$, 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 $s = 1, \ldots, t$. 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 $\widehat{RF}_{1t}$.

There are two technical details with this exercise. The first problem arises from the fact that the factors are only identified 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 =$1970:01, we assume that the sign of the first factor in 1961:01 is positive ($\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 no variation in some series during the early part

approximation error.

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 (102), oilprice (111), and UMCSENTx (131). For the first two we simply have no data. For the latter two, the transformed data is 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 isn't really operational. We therefore drop these four series from the exercise. If we were to redo the recursive analysis starting in 1980 or later we would likely avoid having to drop any series. At the moment, we are only able to construct these recursive diffusion indexes for factors one and two, and these two series only available from 1970:01 onwards.

The recursively estimated diffusion index $\widehat{RF}_{1t}$ is plotted in Figure 4, side by side with $\widetilde{F}_{1t}$. The series also tends to change direction at the beginning and the end of recessions. Evidently, it no longer ends at zero; the most recent values of $\widetilde{F}_{1t}$ and $\widehat{RF}_{1t}$ show no clear direction of change, which suggests that the economy is staying in its course. The bottom panel shows $\widehat{RF}_{2t}$. 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 is encouraging. Since FRED-MD will be updated on a timely basis, these factor based diffusion indexes can be useful tools in the documenting the state of the economy.

4 Conclusion

This paper introduces researchers to a set of 135 monthly macroeconomic variables based on the database at FRED. The dataset starts in 1959:01 and will be updated on a timely basis hereafter. In addition to open public access, the main appeal of the data 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. We plan to put together a quarterly database in due course.

References

Bai, J. and Ng, S. 2002, Determining the Number of Factors in Approximate Factor Models, *Econometrica* **70:1**, 191–221.

Bai, J. and Ng, S. 2008, Forecasting Economic Time Series Using Targeted Predictors, *Journal of Econometrics* **146**, 304–317.

Barnichon, R. 2010, Building a Composite Help-Wanted Index, *Economics Letters* **109**(1), 175–178.

Bernanke, B. and Boivin, J. 2003, Monetary Policy in a Data Rich Environment, *Journal of Monetary Economics* **50:3**, 525–546.

Bernanke, B., Boivin, J. and Eliasz, P. 2005, Factor Augmented Vector Autoregressions (FVARs) and the Analysis of Monetary Policy, *Quarterly Journal of Economics* **120:1**, 387–422.

Boivin, J. and Giannoni, M. 2006, DSGE Models in a Data Rich Environment, NBER Working Paper 12272.

Boivin, J. and Ng, S. 2005, Undertanding and Comparing Factor Based Forecasts, *International Journal of Central Banking* **1:3**, 117–152.

Boivin, J. and Ng, S. 2006, Are More Data Always Better for Factor Analysis, *Journal of Econometrics* **132**, 169–194.

Broida, A. 1955, Diffusion Indexes, *American Statistician* **9**(3), 7–16.

Bry, G. and Boschan, C. 1971, *Cyclical Analysis of Time Series: Procedures and Computer Programs*, National Bureau of Economic Research, New York.

Burns, A. F. and Mitchell, W. C. 1946, *Measuring Business Cycle*, National Bureau of Economic Research, New York.

Clark, T. and McCracken, M. 2005, Evaluating Direct Multistep Forecasts, *Econometric Reviews* **24**, 369–404.

Clark, T. and McCracken, M. 2012, In-Sample Tetsts of Predictive Ability: A New Approach, *Journal of Econometrics* **170**(1), 1–14.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. 2000, The Generalized Dynamic Factor Model: Identification and Estimation, *Review of Economics and Statistics* **82:4**, 540–554.

Forni, M., Hallin, M., Lippi, M. and Reichlin, L. 2005, The Generalized Dynamic Factor Model, One Sided Estimation and Forecasting, *Journal of the American Statistical Association* **100**, 830–840.

Jurado, K., Ludvigson, S. and Ng, S. 2013, Measuring Macroeconomic Uncertainty, *American Economic Review*. mimeo, Columbia University.

Kenndey, J. E. 1994, The Information of Diffusion Indexes for Forecasting Related Economic Aggregates, *Economics Letters* **44**, 113–117.

Ludvigson, S. and Ng, S. 2009, Bond Risk Premia and Macro Factors, *Review of Fiancial Studies* **22**(12), 5027–5067.

Ludvigson, S. and Ng, S. 2011, A Factor Analysis of Bond Risk Premia, *in* D. Gilles and A. Ullah (eds), *Handbook of Empirical Economics and Finance*, Chapman and Hall, pp. 313–372.

Marcellino, M., Stock, J. and Watson, M. 2006, A Comparison of Direct and Iterated AR Methods for Forecasting Macroeconomic Time Series h-steps Ahead, *Journal of Econometrics* **135**, 499–526.

Moore, G. H. 1961, Diffusion Indexes, Rates of Change, and Forecasting, *in* G. H. Moore (ed.), *Business Cycle Indicators*, Vol. 1, pp. 282–293.

Stark, T. and Croushore, D. 2001, Forecasting with a Real Time Data Set for Macroeconomists, *Journal of Macroeconomics* **24**(4), 507–531.

Stock, J. and Watson, M. 2014a, Estimating Turning Points Using Large Data Sets, *Journal of Econometrics* **178**, 368–381.

Stock, J. and Watson, M. 2014b, Estimating Turning Points Using Large Data Sets, *Journal of Econometrics* **178**, 368–381.

Stock, J. and Watson, M. W. 2010, Modeling Inflation After the Crisis, NBER Working Paper 16488.

Stock, J. H. and Watson, M. W. 1996, Evidence on Structural Instability in Macroeconomic Time Series Relations, *Journal of Business and Economic Statistics* **14**, 11–30.

Stock, J. H. and Watson, M. W. 1998, Diffusion Indexes, NBER Working Paper 6702.

Stock, J. H. and Watson, M. W. 2002, Macroeconomic Forecasting Using Diffusion Indexes, *Journal of Business and Economic Statistics* **20:2**, 147–162.

Stock, J. H. and Watson, M. W. 2005, Implications of Dynamic Factor Models for VAR analysis, NBER WP 11467.

Stock, J. H. and Watson, M. W. 2006, Forecasting with Many Predictors, *Handbook of Forecasting*, North Holland.

Table 1: Factors Estimated from FRED-MD: Total Variation Explained, 0.446

$mR^2(1)$	0.139	$mR^2(2)$	0.069	$mR^2(3)$	0.065	$mR^2(4)$	0.050
IPMANSICS	0.776	BAAFFM	0.568	CUSR0000SAC	0.731	GS1	0.523
INDPRO	0.747	AAAFFM	0.568	DNDGRG3M086SBEA	0.717	GS5	0.506
USGOOD	0.730	T10YFFM	0.560	CPIAUCSL	0.689	TB6MS	0.485
MANEMP	0.702	T5YFFM	0.534	CUSR0000SA0L5	0.651	GS10	0.457
CAPUTLB00004S	0.698	TB3SMFFM	0.373	CUUR0000SA0L2	0.627	TB3MS	0.422
PAYEMS	0.684	TB6SMFFM	0.372	PCEPI	0.596	AAA	0.415
IPFPNSS	0.665	T1YFFM	0.344	CPITRNSL	0.594	CP3M	0.370
DMANEMP	0.649	BUSINVx	0.309	CPIULFSL	0.565	BAA	0.307
IPDMAT	0.600	NAPMPRI	0.260	PPIFCG	0.492	MZMSL	0.170
IPMAT	0.573	BAA	0.242	PPIFGS	0.472	FEDFUNDS	0.168
$mR^2(5)$	0036	$mR^2(6)$	0.030	$mR^2(7)$	0.027	$mR^2(8)$	0.026
CES0600000007	0.199	SP: indust	0.346	SP: indust	0.168	M2SL	0.275
TB6SMFFM	0.184	SP 500	0.344	SP 500	0.166	M3SL	0.275
AWHMAN	0.176	SP div yield	0.268	SP div yield	0.149	PERMIT	0.177
T1YFFM	0.157	SP PE ratio	0.203	SP PE ratio	0.144	MZMSL	0.135
TB3SMFFM	0.154	IPCONGD	0.169	M1SL	0.134	M1SL	0.134
NAPMPI	0.139	IPFINAL	0.146	NAPM	0.131	PERMITMW	0.129
ISRATIOx	0.139	IPDCONGD	0.118	M2SL	0.128	TOTRESNS	0.110
T5YFFM	0.138	UMCSENTx	0.112	M3SL	0.128	PERMITS	0.109
T10YFFM	0.138	M3SL	0.110	NAPMEI	0.127	USCONS	0.095
RETAILx	0.132	M2SL	0.110	CONSPI	0.115	HOUSTMW	0.094

This table lists the ten series that loads most heavily of the first eight factors along with R^2 in a regression of the series on the factor. For example, factor 1 explains 0.747 of the variation in indpro. The first factor has a marginal R^2 of .139. This is the fraction of the variation in 135 series explained by the first factor.

Table 2: 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

Table 3: Non-nested Model Comparisons

	h		$\widehat{f}_1$				$\widehat{f}_1 + \widehat{f}_2$			
			IP	Empl.	CPI	Core CPI	IP	Empl.	CPI	Core CPI
1970	1	MSE	57.58	3.34	7.05	4.75	56.84	3.36	6.99	4.55
		Ratio03	1.00	0.99	1.00	1.00	0.99	0.99	1.00	1.00
		Ratio11	0.98*	0.99	1.00	1.00	0.99	1.00	1.00	1.00
	6	MSE	26.61	2.26	2.75	2.37	19.88	1.95	2.81	2.31
		Ratio03	1.01	1.00	1.00	0.99	1.03	1.01	1.00	0.99
		Ratio11	0.97	0.99	1.00	1.01	1.02	0.99	1.00	1.00
	12	MSE	20.44	2.59	2.91	2.44	14.59	2.20	3.03	2.56
		Ratio03	1.01	1.00	1.00	0.99	1.04	0.99	1.00	0.99
		Ratio11	0.99	0.99	1.00	1.01	1.02	1.00	1.00	1.00
1990	1	MSE	36.14	1.41	4.44	1.49	35.59	1.45	4.46	1.54
		Ratio03	0.98	0.99	1.00	1.00	0.98	0.99	1.00	0.99
		Ratio11	0.99	1.01	1.00	0.99	0.99	1.00	1.00	1.00
	6	MSE	10.98	1.05	1.16	0.29	10.59	1.27	1.21	0.34
		Ratio03	1.00	0.98	1.02	1.01	1.00	0.94*	1.02	1.01
		Ratio11	0.98	1.01	0.99	0.97	0.99	0.96*	1.00	0.97
	12	MSE	8.84	1.72	1.08	0.29	10.88	2.35	1.06	0.29
		Ratio03	1.00	0.98	1.03	1.01	0.94	0.94*	1.03	1.02
		Ratio11	0.99	1.01	0.99	0.98	0.96	0.97*	1.00	0.97

Table 4: Nested Model Comparisons

	h		$\widehat{f}_1$ vs. AR				$\widehat{f}_1 + \widehat{f}_2$ vs. $\widehat{f}_1$			
			IP	Empl.	CPI	Core CPI	IP	Empl.	CPI	Core CPI
1970	1	MSE	70.52	3.29	9.68	3.98	60.16	2.91	9.57	3.84
		Ratio	0.85*	0.88*	0.99*	0.97*	0.98*	1.00	1.01	0.99*
	6	MSE	30.44	2.28	5.02	2.12	27.41	2.10	4.93	1.92
		Ratio	0.90*	0.92*	0.98	0.91*	0.82*	0.89*	1.02	1.02
	12	MSE	24.86	4.35	4.65	2.41	22.21	2.67	4.28	2.01
		Ratio	0.89*	0.61*	0.92*	0.83*	0.79*	0.92*	1.00	1.07
1990	1	MSE	58.39	1.40	9.98	1.19	48.98	1.39	10.17	1.29
		Ratio	0.84*	0.99	1.02	1.08	0.98*	1.03	1.01	1.10
	6	MSE	21.48	1.35	5.15	0.31	18.38	1.24	5.87	0.46
		Ratio	0.86*	0.92*	1.14	1.48	1.03	1.15	1.02	1.30
	12	MSE	19.71	4.27	3.84	0.35	16.83	2.16	4.42	0.52
		Ratio	0.85*	0.51*	1.15	1.46	1.12	1.29	0.97	1.18
2008	1	MSE	98.38	1.85	17.56	0.76	75.86	1.65	18.81	1.03
		Ratio	0.77*	0.89*	1.07	1.36	0.97*	1.01	1.01	1.28
	6	MSE	49.69	2.65	14.84	0.33	43.63	2.23	18.27	0.84
		Ratio	0.88*	0.84*	1.23	2.59	0.97	1.04	1.02	1.39
	12	MSE	46.17	8.91	10.37	0.42	38.95	3.81	13.35	1.10
		Ratio	0.84	0.43*	1.29	2.61	0.97	1.17	0.97	1.24

Figure 1: Importance of Component Component

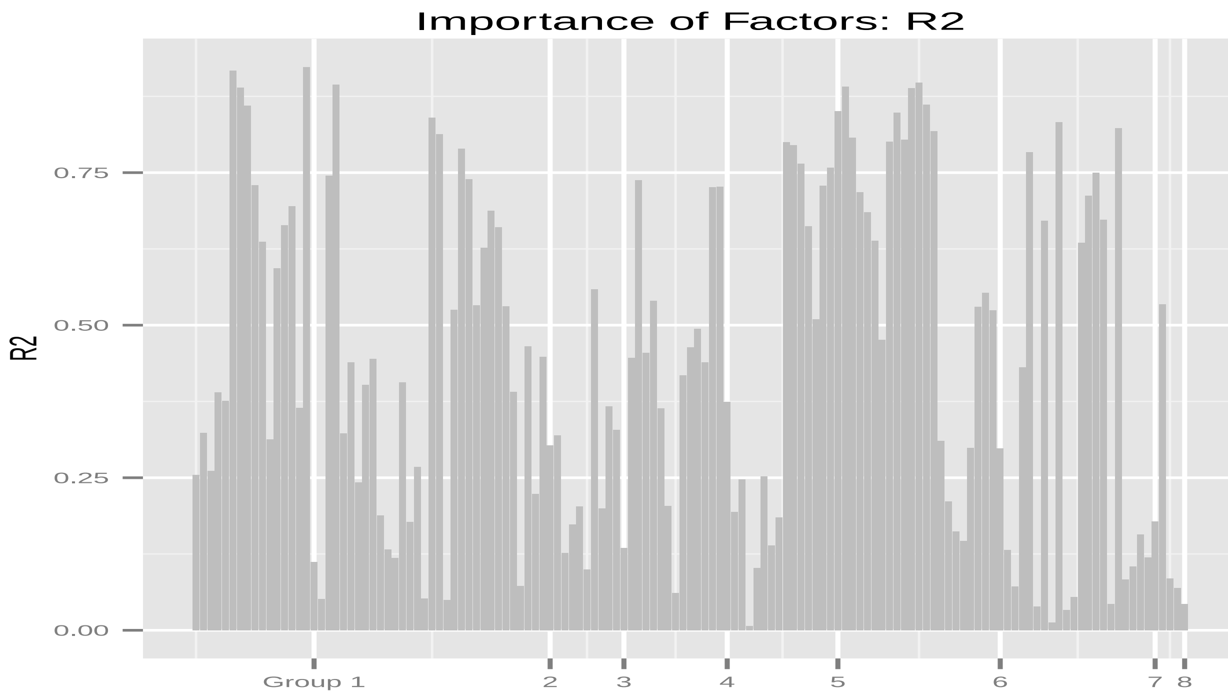


Figure 2: Number of factors and R^2: Recursive Estimation

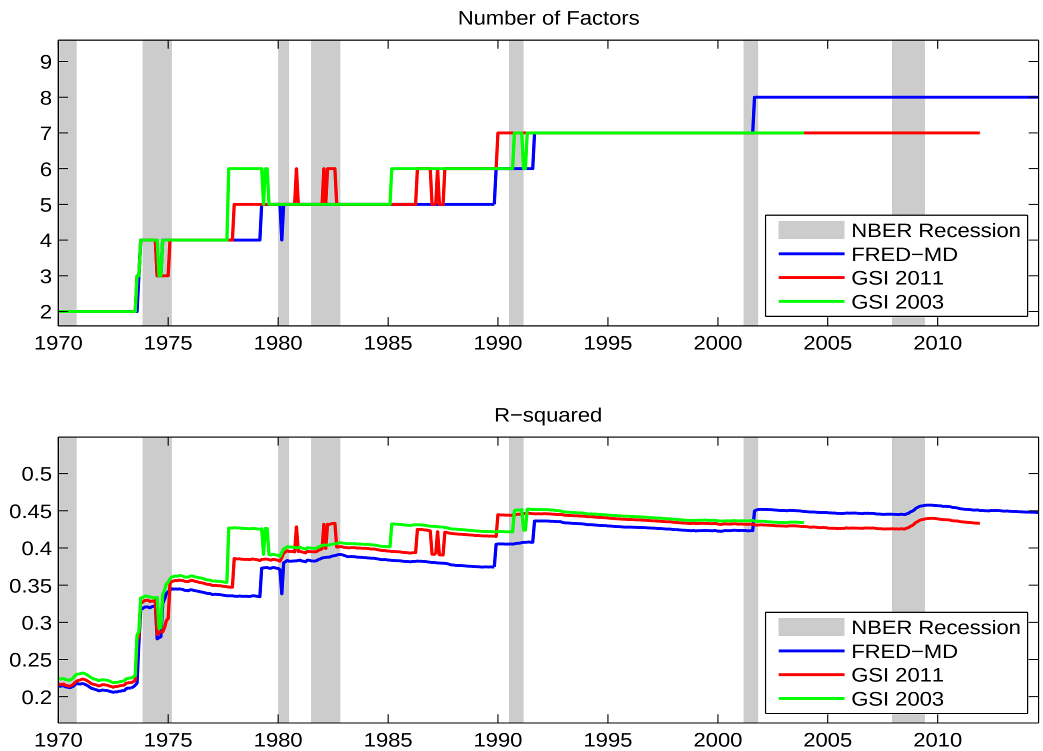


Figure 3: Diffusion Indexes: $\widehat{F}_1$ and $\widehat{F}_2$

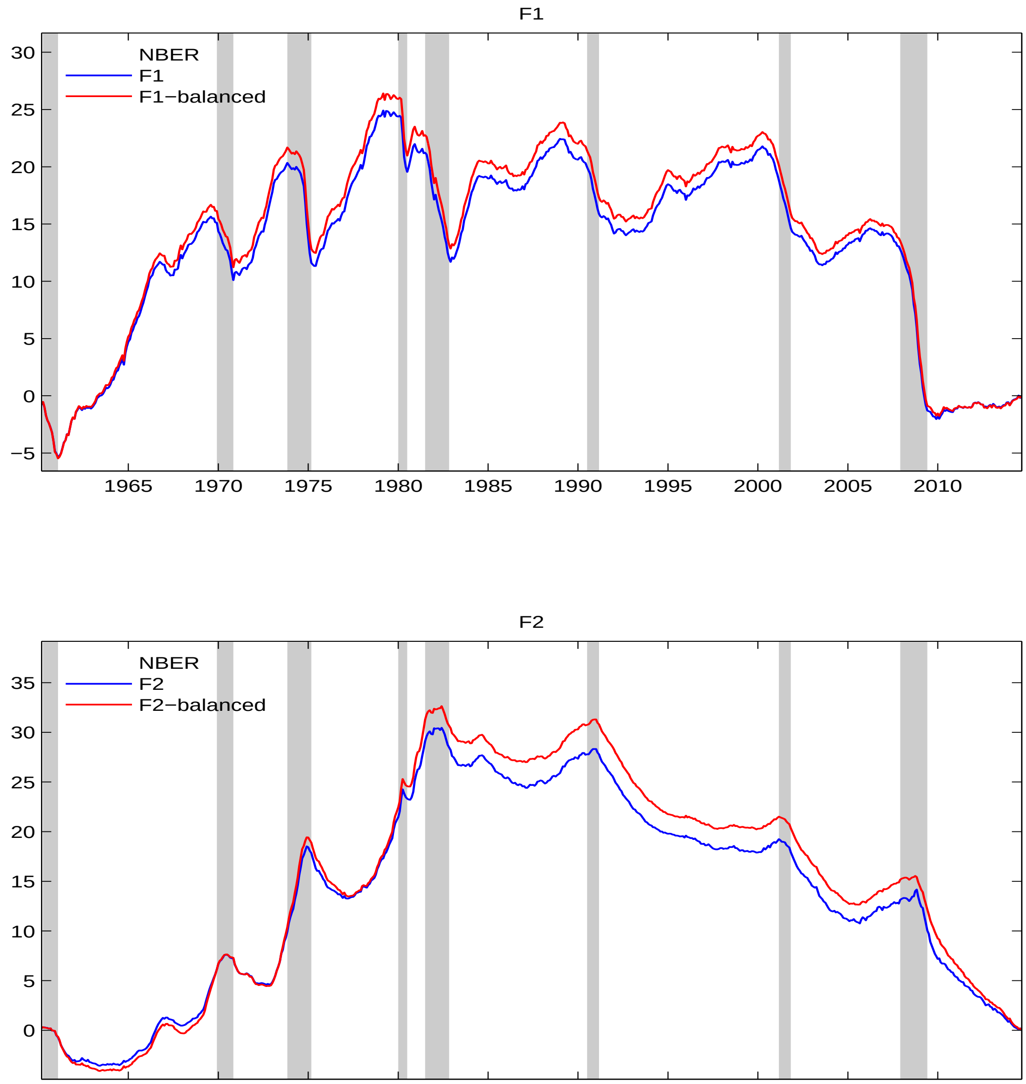
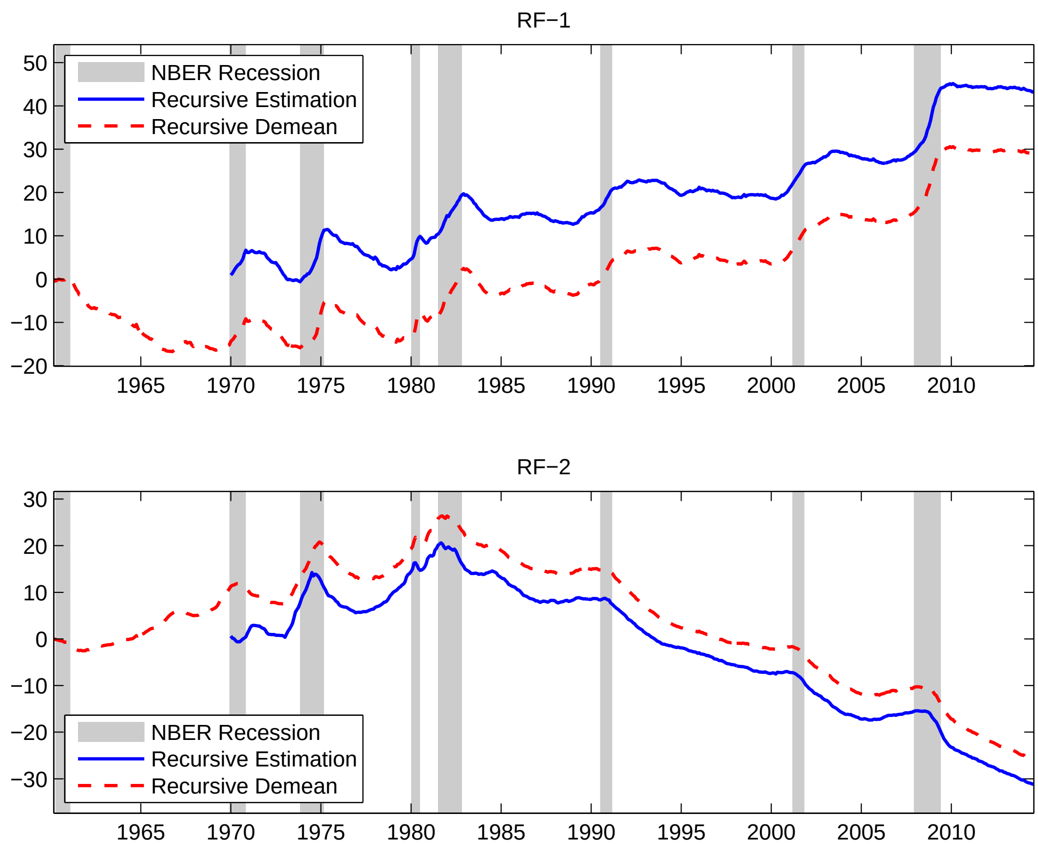


Figure 4: Recursively Estimated Diffusion Indexes: $RFDI_1$



Appendix

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

Group 1	id	tcode	fred	description	gsi	gsi:description
1	1	5	RPI	Real Personal Income	M_14386177	PI
2	2	5	W875RX1	RPI ex. Transfers	M_145256755	PI less transfers
3	6	5	INDPRO	IP Index	M_116460980	IP: total
4	7	5	IPFPNSS	IP: Final Products and Supplies	M_116460981	IP: products
5	8	5	IPFINAL	IP: Final Products	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	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	M_110157212	NAPM prodn
17	20*	2	CAPUTLB00004S	Capacity Utilization: Manufacturing	M_116461602	Cap util

Group 2	id	tcode	fred	description	gsi	gsi:description
1	21*	2	HWI	Help-Wanted Index for US		Help wanted indx
2	22*	2	HWIURATIO	Help Wanted to Unemployed ratio	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	M_110156528	U: mean duration
7	27	5	UEMPLT5	Civilians Unemployed <5 Weeks	M_110156527	U < 5 wks
8	28	5	UEMP5TO14	Civilians Unemployed 5-14 Weeks	M_110156523	U 5-14 wks
9	29	5	UEMP15OV	Civilians Unemployed >15 Weeks	M_110156524	U 15+ wks
10	30	5	UEMP15T26	Civilians Unemployed 15-26 Weeks	M_110156525	U 15-26 wks
11	31	5	UEMP27OV	Civilians Unemployed >27 Weeks	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	M_123109172	Emp: gds prod
15	35	5	CES1021000001	All Employees: Mining and Logging	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 Industries	M_123109193	Emp: services
21	41	5	USTPU	All Employees: TT&U	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	Hours: Goods-Producing	M_140687274	Avg hrs
27	47	2	AWOTMAN	Overtime Hours: Manufacturing	M_123109554	Overtime: mfg
28	48	1	AWHMAN	Hours: Manufacturing	M_14386098	Avg hrs: mfg
29	49	1	NAPMEI	ISM Manufacturing: Employment	M_110157206	NAPM empl
30	128	6	CES0600000008	Ave. Hourly Earnings: Goods	M_123109182	AHE: goods
31	129	6	CES2000000008	Ave. Hourly Earnings: Construction	M_123109341	AHE: const
32	130	6	CES3000000008	Ave. Hourly Earnings: Manufacturing	M_123109552	AHE: mfg

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

Group 4	id	tcode	fred	description	gsi	gsi:description
1	3	5	DPCERA3M086SBEA	Real PCE	M_123008274	Real Consumption
2	4*	5	CMRMTSPLx	Real M&T 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	Orders: Consumer Goods	M_14385863	Orders: cons gds
9	65*	5	AMDMNOx	Orders: Durable Goods	M_14386110	Orders: dble gds
10	66*	5	ANDENOx	Orders: Nondefense Capital Goods	M_178554409	Orders: cap gds
11	67*	5	AMDMUOx	Unfilled Orders: Durable Goods	M_14385946	Unf orders: dble
12	68*	5	BUSINVx	Total Business Inventories	M_15192014	M&T invent
13	69*	2	ISRATIOx	Inventories to Sales Ratio	M_15191529	M&T invent/sales
14	131*	2	UMCSENTx	Consumer Sentiment Index	hhsntn	Consumer expect

Group 5	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	6	M3SL	MABMM301USM189S in FRED, M3 for the United States	M_110155013	Currency
4	73	5	M2REAL	Real M2 Money Stock	M_110154985	M2 (real)
5	74	6	AMBSL	St. Louis Adjusted Monetary Base	M_110154995	MB
6	75	6	TOTRESNS	Total Reserves	M_110155011	Reserves tot
7	76	6	NONBORRES	Nonborrowed Reserves	M_110155009	Reserves nonbor
8	77	6	BUSLOANS	Commercial and Industrial Loans	BUSLOANS	C&I loan plus
9	78	1	REALLN	Real Estate Loans	BUSLOANS	DC&I loans
10	79	6	NONREVSL	Total Nonrevolving Credit	M_110154564	Cons credit
11	80*	2	CONSPI	Credit to PI ratio	M_110154569	Inst cred/PI
12	132	6	MZMSL	MZM Money Stock	N.A.	N.A.
13	133	6	DTCOLNVHFNM	Consumer Motor Vehicle Loans	N.A.	N.A.
14	134	6	DTCTHFNM	Total Consumer Loans and Leases	N.A.	N.A.
15	135	6	INVEST	Securities in Bank Credit	N.A.	N.A.

Group 6	id	tcode	fred	description	gsi	gsi:description
1	85	2	FEDFUNDS	Effective Federal Funds Rate	M_110155157	Fed Funds
2	86*	2	CP3M	3-Month AA Comm. Paper Rate	CPF3M	Comm paper
3	87	2	TB3MS	3-Month T-bill	M_110155165	3 mo T-bill
4	88	2	TB6MS	6-Month T-bill	M_110155166	6 mo T-bill
5	89	2	GS1	1-Year T-bond	M_110155168	1 yr T-bond
6	90	2	GS5	5-Year T-bond	M_110155174	5 yr T-bond
7	91	2	GS10	10-Year T-bond	M_110155169	10 yr T-bond
8	92	2	AAA	Aaa Corporate Bond Yield		Aaa bond
9	93	2	BAA	Baa Corporate Bond Yield		Baa bond
10	94*	1	COMPAPFF	CP - FFR spread		CP-FF spread
11	95	1	TB3SMFFM	3 Mo. - FFR spread		3 mo-FF spread
12	96	1	TB6SMFFM	6 Mo. - FFR spread		6 mo-FF spread
13	97	1	T1YFFM	1 yr. - FFR spread		1 yr-FF spread
14	98	1	T5YFFM	5 yr. - FFR spread		5 yr-FF spread
15	99	1	T10YFFM	10 yr. - FFR spread		10 yr-FF spread
16	100	1	AAAFFM	Aaa - FFR spread		Aaa-FF spread
17	101	1	BAAFFM	Baa - FFR spread		Baa-FF spread
18	102	5	TWEXMMTH	Trade Weighted U.S. FX Rate		Ex rate: avg
19	103	5	EXSZUS	Switzerland / U.S. FX Rate	M_110154768	Ex rate: Switz
20	104	5	EXJPUS	Japan / U.S. FX Rate	M_110154755	Ex rate: Japan
21	105	5	EXUSUK	U.S. / U.K. FX Rate	M_110154772	Ex rate: UK
22	106	5	EXCAUS	Canada / U.S. FX Rate	M_110154744	EX rate: Canada

Group 7	id	tcode	fred	description	gsi	gsi:description
1	107	6	PPIFGS	PPI: Finished Goods	M_110157517	PPI: fin gds
2	108	6	PPIFCG	PPI: Finished Consumer Goods	M_110157508	PPI: cons gds
3	109	6	PPIITM	PPI: Intermediate Materials	M_110157527	PPI: int materials
4	110	6	PPICRM	PPI: Crude Materials	M_110157500	PPI: crude materials
5	111*	6	oilprice	Crude Oil Prices: WTI	M_110157273	Spot market price
6	112	6	PPICMM	PPI: Commodities	M_110157335	PPI: nonferrous
7	113	1	NAPMPRI	ISM Manufacturing: Prices	M_110157204	NAPM com price
8	114	6	CPIAUCSL	CPI: All Items	M_110157323	CPI-U: all
9	115	6	CPIAPPSL	CPI: Apparel	M_110157299	CPI-U: apparel
10	116	6	CPITRNSL	CPI: Transportation	M_110157302	CPI-U: transp
11	117	6	CPIMEDSL	CPI: Medical Care	M_110157304	CPI-U: medical
12	118	6	CUSR0000SAC	CPI: Commodities	M_110157314	CPI-U: comm.
13	119	6	CUUR0000SAD	CPI: Durables	M_110157315	CPI-U: dbles
14	120	6	CUSR0000SAS	CPI: Services	M_110157325	CPI-U: services
15	121	6	CPIULFSL	CPI: All Items Less Food	M_110157328	CPI-U: ex food
16	122	6	CUUR0000SA0L2	CPI: All items less shelter	M_110157329	CPI-U: ex shelter
17	123	6	CUSR0000SA0L5	CPI: All items less medical care	M_110157330	CPI-U: ex med
18	124	6	PCEPI	PCE: Chain-type Price Index	gmdc	PCE defl
19	125	6	DDURRG3M086SBEA	PCE: Durable goods	gmdcd	PCE defl: dlbes
20	126	6	DNDGRG3M086SBEA	PCE: Nondurable goods	gmdcn	PCE defl: nondble
21	127	6	DSERRG3M086SBEA	PCE: Services	gmdcs	PCE defl: service

Group 8	id	tcode	fred	description	gsi	gsi:description
1	81*	5	S&P 500	S&P: Composite	M_110155044	S&P 500
2	82*	5	S&P: indust	S&P: Industrials	M_110155047	S&P: indust
3	83*	2	S&P div yield	S&P: Dividend Yield		S&P div yield
4	84*	5	S&P PE ratio	S&P: Price-Earnings Ratio		S&P PE ratio