FRED-QD: A Quarterly Database for Macroeconomic Research

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In this article, we present and describe FRED-QD, a large, quarterly frequency macroeconomic database that is currently available and regularly updated at https://research.stlouisfed.org/econ/mccracken/fred-databases/. The data provided are closely modeled to that used in Stock and Watson (2012a). As in our previous work on FRED-MD (McCracken and Ng, 2016), which is at a monthly frequency, our goal is simply to provide a publicly available source of macroeconomic "big data" that is updated in real time using the FRED® data service. We show that factors extracted from the FRED-QD dataset exhibit similar behavior to those extracted from the original Stock and Watson dataset. The dominant factors are shown to be insensitive to outliers, but outliers do affect the relative influence of the series, as indicated by leverage scores. We then investigate the role unit root tests play in the choice of transformation codes, with an emphasis on identifying instances in which the unit root-based codes differ from those already used in the literature. Finally, we show that factors extracted from our dataset are useful for forecasting a range of macroeconomic series and that the choice of transformation codes can contribute substantially to the accuracy of these forecasts. (JEL C30, C33, C82)

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1 INTRODUCTION

In our previous work, McCracken and Ng (2016), we describe and investigate a monthly frequency database of macroeconomic variables called FRED-MD. At some level, FRED-MD is not particularly innovative. It is, after all, just a collection of $N = 128$ standard U.S. macroeconomic time series that date back to January 1959 and have primarily been taken from FRED®, the data service maintained by the Federal Reserve Bank of St. Louis, and organized into a .csv file. That description, however, misses the point. Our main goal was to facilitate easy access to a standardized example of a data-rich environment that can be used for academic

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research. By automating this dataset, and maintaining a website that provides monthly frequency vintages, those who are interested in conducting research on big data can focus on the statistical problems associated with big data rather than having to put the dataset together themselves. This dataset frees the practitioner from dealing with issues related to, for example, updating the dataset when new data is released, managing series that become discontinued, and splicing series from different sources. More prosaically, FRED-MD facilitates comparison of methodologies developed for a common purpose.

FRED-MD has been successful. It has been used as a foil for applying big data methods including random subspace methods (Boot and Nibbering, 2019), sufficient dimension reduction (Barbarino and Bura, 2017), dynamic factor models (Stock and Watson, 2016), large Bayesian VARs (Giannone, Lenza, and Primiceri, 2018), various lasso-type regressions (Smeekes and Wijler, 2018), functional principal components, (Hu and Park, 2017), complete subset regression (Kotchoni, Leroux, and Stevanovich, 2019), and random forests (Medeiros et al., 2019). In addition, these various methods have been used to study a wide variety of economic and financial topics including bond risk premia (Bauer and Hamilton, 2017), the presence of real and financial tail risk (Nicolò and Lucchetta, 2016), liquidity shocks (Ellington, Florackis, and Milas, 2017), recession forecasting (Davig and Hall, 2019), identification of uncertainty shocks (Angelini et al., 2019), and identification of monetary policy shocks (Miranda-Agrippino and Ricco, 2017). Finally, and perhaps most rewarding, is that it is described as the inspiration to the development of a Canadian version of FRED-MD (Fortin-Gagnon et al., 2018).

While useful, FRED-MD has a glaring weakness. It does not include quarterly frequency data and thus does not provide information on gross domestic product (GDP), consumption, investment, government spending, or other macroeconomic series that come from the National Income and Product Accounts (NIPA). This is unfortunate because there are plenty of examples in the literature in which a quarterly frequency, data-rich environment is used for economic analysis. Examples include Stock and Watson (2012a,b), Schumacher and Breitung (2008), Gefang, Koop, and Poon (2019), Rossi and Sekhposyan (2015), Gonçalves, Perron, and Djogbenou (2017), Carrasco and Rossi (2016), Koopman and Mesters (2017), and Koop (2013).

In this article, we extend our previous work to a quarterly frequency dataset we call FRED-QD. The dataset is currently available at https://research.stlouisfed.org/econ/mccracken/fred-databases/. Like FRED-MD, FRED-QD is benchmarked to previous work by Stock and Watson (2012a, hereafter S&W). There, the authors organized a collection of $N = 200$ quarterly frequency macroeconomic series dating back to 1959:Q1 that they then used to analyze the dynamics of the Great Recession. Our quarterly frequency version of their dataset contains nearly all the series they used but, in addition, includes 48 more series, with an emphasis on including series related to non-household balance sheets. In total, the dataset consists of $N = 248$ quarterly frequency series dating back to 1959:Q1.[1] While many of the series are actually quarterly series, some are higher-frequency series that have been aggregated up to the quarterly frequency—typically as quarterly averages of monthly series.

It's worth noting that we provide the data in levels—without transforming them in any way. As such, some are stationary in levels, while others likely need to be transformed by taking logs, differencing, or both to reasonably be considered stationary. For each series we provide benchmark transformation codes. If the series was in the S&W dataset, we provide the transformation codes. For the additional series, many are taken from FRED-MD and we therefore provide those benchmark transformation codes. One reason to do this is to facilitate replication of the factor analysis provided in S&W as well as other results that may have used a similar dataset. Even so, given the well-documented changes in volatility and persistence of macroeconomic series described in Campbell (2007) and Stock and Watson (2007), it may be a good idea to reconsider the default transformation codes. After providing more details on the data, we investigate this possibility through the lens of unit root tests. While it is often the case that the unit root tests align with the original transformation codes, the tests are not uniformly supportive.

We then investigate whether factors extracted from FRED-QD are useful for forecasting macroeconomic aggregates. In particular, we focus on whether the unit root-implied transformation codes matter for factor-based forecasting.[2] Among the series that we forecast, we find that for real and financial series, factors estimated using the unit root-based transformation codes can provide additional predictive content but are more often dominated by those using the original transformation codes. In contrast, we find that when forecasting nominal price series, forecast accuracy is typically better when using factors estimated using the unit root-based codes. This result coincides with evidence provided by Medeiros et al. (2019) and Goulet Coulombe et al. (2019), who find that treating price inflation as I(0) leads to better forecasts of inflation than treating it as I(1)—which is precisely what the benchmark transformation codes recommend.

The remainder of the article proceeds as follows. Section 2 provides a more detailed description of the series in FRED-QD as well as choices that were made when putting them together. Section 3 presents a brief analysis of the behavior of factors extracted from our dataset, with an emphasis on their relationship with factors extracted from the original S&W dataset. Section 4 constructs statistical leverage scores as a means of identifying which series and data points have the greatest influence on the factors. Section 5 provides a detailed investigation of the degree to which unit root tests agree with the benchmark transformation codes. Section 6 investigates the degree to which factors are useful for forecasting, with particular attention to whether the unit root determined transformation codes improve the accuracy of the forecasts relative to the original codes. Section 7 concludes. A detailed list of the series is provided in the appendix.

2 FRED-QD

As with FRED-MD, the goal of FRED-QD is to provide a readily accessible, easy-to-use macroeconomic database that can form the basis of research on big data. To do so, we make the dataset publicly available at the same website as FRED-MD so that anyone can have access. Importantly, a new vintage of the dataset is created on the last business day of each month. This means that at the end of each month, (i) the most recent data releases have been added, (ii) revisions to the series in previous quarters have been taken on board, and (iii) institutional changes to existing series, periodically made by the statistical agencies, have been appropriately accounted for (e.g., a substitute series is found for a discontinued series).

Based on feedback we received for the FRED-MD project, the most recent vintage is always given a hotlink denoted "current." This allows the user to include that link within their code and thus always have access to the most recent vintage without having to go to the website manually and download the file. Previous vintages of the dataset are retained on the website. By retaining the older vintages, we facilitate replication of other research that has used FRED-QD. For example, if a researcher develops a new statistical method for working with big data and wants to compare their results with that from an existing paper, one can go back and find the exact vintage of FRED-QD used in that paper so that differences in results can be attributed to the method rather than the dataset.

On the website, we also provide a "Changes to FRED-QD" file that keeps a running tally of modifications that have occurred across the history of FRED-QD. For example, when creating the September 2018 vintage of FRED-QD, three non-household balance sheet series were discontinued and replaced with comparable series. This event, and the subsequent changes in mnemonics, was documented in the changes file. It's worth noting that changes can also arise due to issues not associated with statistical agencies. For example, legal issues regarding FRED®'s ability to post a given series, or to do so only with a substantial delay, sometimes arise. Examples of such are provided in the "Changes to FRED-MD" file, and one can expect similar issues to ultimately arise in FRED-QD.

With these issues in mind, FRED-QD consists of 248 quarterly series. A full list of the data is given in the appendix. FRED-QD seeks to keep roughly the same coverage as the S&W dataset while allowing the experts at FRED® to handle data revisions and definitional changes. The series are classified into 14 groups: NIPA; Industrial Production; Employment and Unemployment; Housing; Inventories, Orders, and Sales; Prices; Earnings and Productivity; Interest Rates; Money and Credit; Household Balance Sheets; Exchange Rates; Other; Stock Markets; and Non-Household Balance Sheets. These groups are similar to, but not the same as, those used in S&W. The original groups included (i) Housing Starts, (ii) Housing Prices, and (iii) Stock Prices, Wealth, & Household Balance Sheets, which we have rearranged to form the Housing, Household Balance Sheets, and Stock Markets groups. In addition, Non-Household Balance Sheets is a completely new group. These series were added as a reaction to the Financial Crisis of 07-09, during which financial balance sheets played a large role in initiating the crisis and exacerbating the recovery. As such, they could be useful in applications in which FRED-QD is used for business cycle analysis.

Of the 248 series, 70 series were not trivially accessed from FRED® and needed some kind of massaging prior to being comparable to the corresponding series in S&W. A large portion of those that needed massaging were simply a matter of making nominal series real using a deflator. For each of these series, this procedure is explained in the appendix. For the remaining modified series, a summary of the changes is provided in Table 1. For clarity, all series that required some form of modification are tagged with an "x" to indicate that the variable has been adjusted and thus differs from the original series from the source.

Table 1

Series Adjusted by FRED-QD

Number	Variable	Adjustment
60	Unemployment rate (<27 weeks)	(UNEMPLOY - UEMP27OV)/CLF16OV
61	Unemployment rate (>27 weeks)	UEMP27OV/CLF16OV
80	Help-wanted index	Splice LMJVTTUVUSM647S with Barnichon (2010) series
88	Real manu. and trade	(i) Adjust M0602BUSM144NNBR for inflation using PCEPI (ii) Seasonal adjust with ARIMA X12 (iii) Splice with NAICS series CMRMTSPL
89	Retail/food sales	Splice SIC series RETAIL with NAICS series RSAFS
90	New orders (durables)	Splice SIC series AMDMNO and NAICS series DGORDER
92	Unfilled orders (durables)	Splice SIC series AMDMUO and NAICS series AMDMUO
93	New orders (nondefense)	Splice SIC series ANDENO and NAICS series ANDENO
130	Crude Oil	Splice OILPRICE with MCOILWTICO
153	30yr mortgage to 10yr Treasury	MRTG - GS10
154	6mth T-bill - 3mth T-bill	TB6M - TB3M
155	1yr Treasury - 3mth T-bill	GS1 - TB3M
156	10yr Treasury - 3mth T-bill	GS10 - TB3M
157	3mth Commercial - 3mth T-bill	CPF3M - TB3M
172	Household/Nonprof liab to income	TLBSHNO/PI
174	Household/Nonprof networth to income	TNWBSHNO/PI
178	S&P 100 Volatility: VXO	Splice Bloom (2009) series with VXOCLS
184	Switzerland/U.S. FX	Filled back to 1959 from Banking/Monetary statistics
185	Japan/U.S. FX	Filled back to 1959 from Banking/Monetary statistics
186	U.K./U.S. FX	Filled back to 1959 from Banking/Monetary statistics
187	Cdn/U.S. FX	Filled back to 1959 from Banking/Monetary statistics
188	Consumer sentiment	Splice UMSCENT1 with UMSCENT
220	Help wanted to unemployed	HWI/UNEMPLOY
221	Initial claims	Splice monthly series M08297USM548NNBR with weekly ICSA
222	Business inventories	Splice SIC series and NAICS series BUSINV
223	Inventory to sales	Splice SIC series and NAICS series ISRATIO
224	Consumer credit to P.I.	NONREVSL/PI
235	Business liabilities to income	TLBSNNCB/BDI
238	Business net worth to income	TNWMVBSNNCB/BDI
240	NonCorp busi. liabilities to income	TLBSNNB/BDI
243	NonCorp busi. net worth to income	TNWBSNNB/BDI
244	Business income	(CNCF - FCTAX)/IPDPS

When producing each vintage of the dataset, an additional quarterly observation is added only after the first calendar month of the current quarter, which typically means once the first NIPA data, associated with the previous calendar quarter, are released. For example, the January, February, and March 2019 vintages of FRED-QD report quarterly data associated with 2018:Q4 but no data associated with 2019:Q1. The first vintage that contains any 2019:Q1 data is the April 2019 vintage. Within a calendar quarter, the existing quarterly values can be revised due to monthly frequency revisions of quarterly series such as GDP or monthly frequency series such as retail sales.

Due to data availability and the timing of data releases, FRED-QD is not a balanced panel. As we noted above, we introduce a new calendar quarter to the panel one month into the following quarter. In this vintage, any series that is released with more than a one-month lag is treated as missing (e.g., series associated with the Productivity and Costs release by the Bureau of Labor Statistics). In the following vintage, any series that is released with more than a two-month lag is treated as missing (e.g., series associated with the Financial Accounts of the United States [Z.1] data release by the Board of Governors of the Federal Reserve System). In the final vintage for that calendar quarter, all series have typically been released and there are no missing values.[3] As an example, the vintages for July, August, and September 2019 were missing 41, 18, and 0 observations associated with 2019:Q2, respectively. Another, less-regular reason for missing observations arises during government shutdowns. For example, U.S. statistical agencies were closed from December 22, 2018, through January 25, 2019. Because this led to delays in the release of many series, the January 2019 vintage of FRED-QD, which typically would be missing 40 or so observations associated with 2018:Q4 data, is instead missing 87 observations.

All but 38 series are available starting in 1959:Q1. There are a variety of reasons for series to have missing observations at the beginning of the sample: (i) Some series, such as Housing Permits, simply didn't exist in 1959:Q1 and only became available in 1960:Q1. (ii) Similarly, the Michigan Survey of Consumer Sentiment is missing two observation at the beginning of the sample because the survey was not conducted on a regular basis until 1959:Q1. (iii) For other series such as the Trade-weighted Exchange Rate, the series is available in FRED® only through 1973:Q1 and we have not found other documented sources with which to splice the series. (iv) Finally, FRED® primarily holds North American Industry Classification System (NAICS) data (though some older Standard Industrial Classification [SIC] data exist and are used whenever possible) from the Census Manufacturers Survey, and hence a few Value of Manufacturers' Orders components like Nondefense Capital Goods and especially Consumer Goods have a limited history.

In many applications of big data, it is expected that the series are stationary. Since it is clear that not all of the series in FRED-QD are stationary in levels, we also provide benchmark transformation codes that are intended to transform the series so that they are stationary. In each instance, a decision is made to treat the series in levels or log levels, and then, based on whether that series is considered $I(0)$, $I(1)$, or $I(2)$, the variable is differenced to the appropriate degree. For a given series x, these codes take the following forms: (i) no transformation; (ii) Δx_t; (iii) $\Delta^2 x_t$; (iv) $\log(x_t)$; (v) $\Delta\log(x_t)$; (vi) $\Delta^2\log(x_t)$; and (vii) $\Delta(x_t/x_{t-1}-1.0)$. For most of the series, these codes are the original transformations used by S&W. For series that we've added, many are monthly series taken from FRED-MD that we have aggregated to a quarterly frequency. For these series, we use the benchmark transformation codes reported in FRED-MD. Finally, we also provide an indicator that identifies those series in FRED-QD that were used by S&W to estimate factors. This allows the user to focus on those series in the original S&W dataset if the additional series in FRED-QD are deemed extraneous for a particular application.

3 FACTOR ESTIMATES

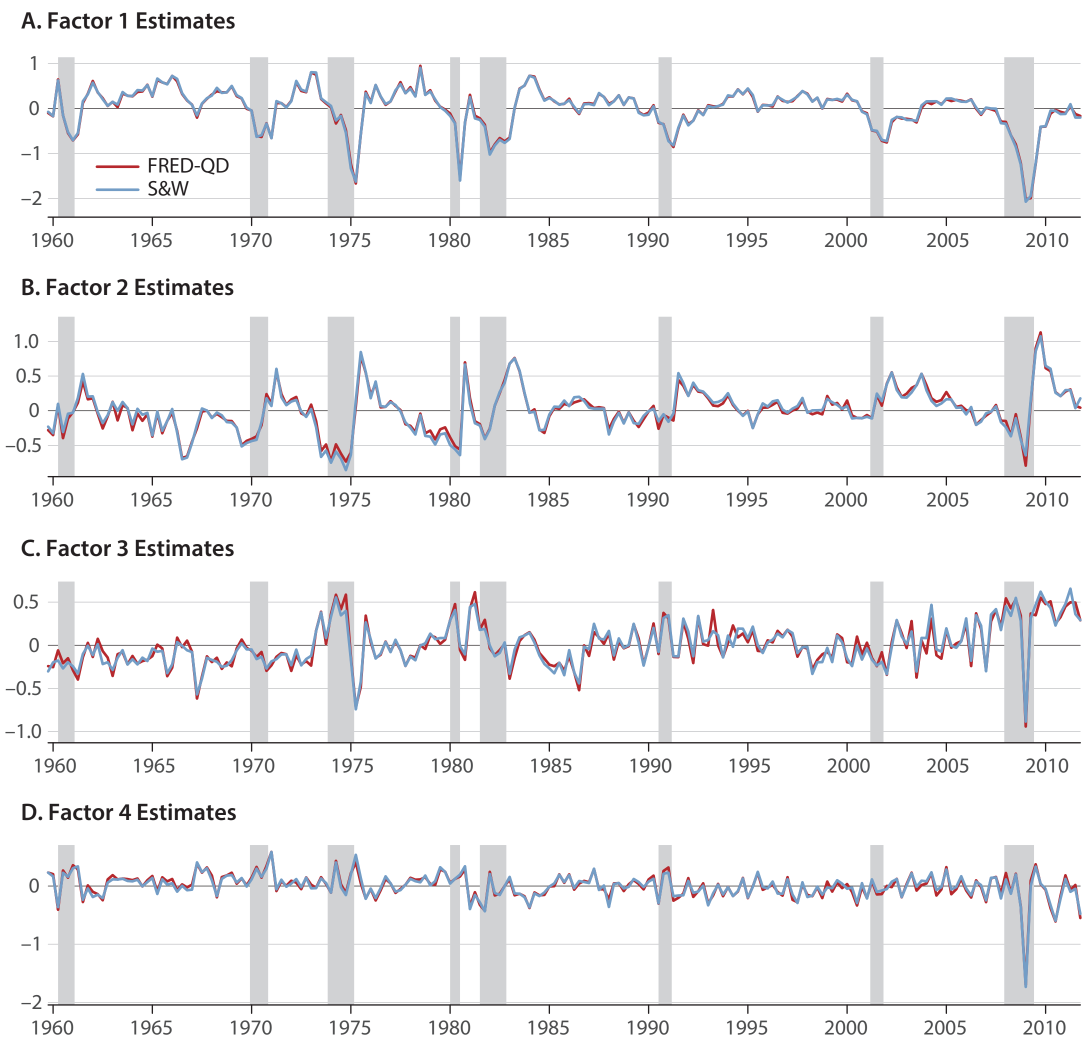
In this section, we provide an analysis of principal component analysis (PCA)-based factors extracted from FRED-QD. Principal components remain a simple way of transforming the information content in a large number of series into a smaller number of manageable series. Once the components have been extracted, they have been used for many purposes, including recession dating (Stock and Watson, 2016), forecasting (Boivin and Ng, 2005), measuring uncertainty (Jurado, Ludvigson, and Ng, 2015), and evaluating monetary policy (Bernanke and Boivin, 2003). Under certain assumptions, principal components provide consistent estimates of common factors and we will use the two terms interchangeably. We are mainly interested in differences in the data through the lens of PCA rather than the method itself.

Another motivation for analyzing the factors is that we have purposefully benchmarked FRED-QD to the large dataset of quarterly frequency series used by S&W. In that paper, the authors extract PCA-based factors and use them to disentangle the causes of the Great Recession. Hence, as a means of verifying that we have adequately captured the information in their dataset, we also provide a direct comparison of factors extracted from FRED-QD to those extracted from the original dataset used by S&W.[4] To do so, we use the September 2019 vintage of FRED-QD, but only those observations and series that were used to estimate factors in the original dataset. Keeping in mind that FRED-QD does not have 10 of the series in the original dataset, but provides a substitute for one of them, this ultimately gives us $T = 211$ observations ranging from 1959:Q1 to 2011:Q3 and $N = 125$ or 132 series when using FRED-QD or the original dataset, respectively.

Because FRED-QD has missing values and outliers that we treat as missing,[5] we estimate the factors by PCA adapted to allow for missing values. Our approach to doing so is closely related to the EM (expectation–maximization) algorithm given in Stock and Watson (2002). Each series is demeaned and normalized to unit variance using the sample means and standard deviations, respectively. If the time $t = 1,\ldots,T$ observation for series $i = 1,\ldots,N$ is missing, we initialize it to the unconditional sample mean based on the non-missing values (which is zero since the data are demeaned and standardized) so that the panel is rebalanced. Based on this panel, and for a given number of factors r, a $T \times r$ matrix of factors $F = (f_1,\ldots,f_T)'$ and a $N \times r$ matrix of loadings $\lambda = (\lambda_1,\ldots,\lambda_N)'$ are estimated using the normalization that $\lambda'\lambda/N = I_r$. We then update the missing values for each series from zero to $\hat{\lambda}_i'\hat{f}_t$. This is multiplied by the standard deviation of the series and the mean is re-added. 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 process of demeaning, standardizing, and estimating the factors and loadings is repeated using the updated panel. The iteration stops when the factor estimates do not change.[6]

Figure 1

FRED-QD and S&W Factor Estimates



NOTE: This figure shows the estimates of Factors 1-4 for both the S&W and FRED-QD datasets. For estimation of factors in the FRED-QD dataset, only series and observations that correspond to those in the S&W dataset are used. Gray bars indicate recessions as determined by the NBER.

We then select the number of significant factors r. We use the IC_p criteria developed in Bai and Ng (2002), which are generalizations 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. For this analysis, we use the penalty $\frac{N+T}{NT}\log\left(\min(N,T)\right)$ which is shown by Bai and Ng (2002) to have good finite sample properties. This criterion is referred to as IC_{p2}. For both the original dataset and the subset of FRED-QD used for this comparison, IC_{p2} selects $r = 4$ factors.

Table 2

Factor Estimates from FRED-QD and S&W

A. FRED-QD
Total variation explained by factors: 0.413

$mR^2(1)$	**0.211**	G#	$mR^2(2)$	**0.091**	G#	$mR^2(3)$	**0.063**	G#	$mR^2(4)$	**0.048**	G#
LNS14000025	0.784	3	OPHMFG	0.643	7	COMPRMS	0.608	7	EXUSEU	0.680	11
DMANEMP	0.760	3	TCU	0.496	2	USSTHPI	0.329	4	TWEXMMTH	0.412	11
LNS13023621	0.746	3	CUMFNS	0.427	2	COMPRNFB	0.319	7	PPIIDC	0.286	6
USTPU	0.726	3	PERMIT	0.414	4	WPSID61	0.311	6	WPSFD49502	0.284	6
IPBUSEQ	0.683	2	BUSLOANSx	0.368	9	ULCMFG	0.306	7	DGOERG3Q086SBEA	0.271	6
USPBS	0.662	3	GS10TB3Mx	0.356	8	RCPHBS	0.305	7	EXUSUKx	0.229	11
LNS14000026	0.649	3	HOUSTS	0.332	4	ACOGNOx	0.294	5	WPSID61	0.224	6
PNFIx	0.642	1	USEPUINDXM	0.309	12	SPCS20RSA	0.275	4	WPU0561	0.223	6
USTRADE	0.640	3	PRFIx	0.304	1	WPU0561	0.267	6	EXCAUSx	0.208	11
Y033RC1Q027SBEAx	0.609	1	CPF3MTB3Mx	0.301	8	PPIIDC	0.239	6	EXSZUSx	0.154	11

B. S&W
Total variation explained by factors: 0.417

$mR^2(1)$	**0.215**	G#	$mR^2(2)$	**0.097**	G#	$mR^2(3)$	**0.059**	G#	$mR^2(4)$	**0.046**	G#
LNS14000025	0.772	3	OPHMFG	0.526	7	COMPRMS	0.487	7	EXUSEU	0.561	11
DMANEMP	0.750	3	TCU	0.485	2	WPSID61	0.358	6	DGOERG3Q086SBEA	0.233	6
LNS13023621	0.741	3	PERMIT	0.417	4	COMPRNFB	0.322	7	PPIIDC	0.223	6
USTPU	0.714	3	CUMFNS	0.414	2	USSTHPI	0.312	4	WPSFD49502	0.216	6
IPBUSEQ	0.665	2	BUSLOANSx	0.365	9	WPU0561	0.309	6	TWEXMMTH	0.203	11
USPBS	0.644	3	GS10TB3Mx	0.363	8	RCPHBS	0.305	7	EXCAUSx	0.195	11
LNS14000026	0.638	3	USEPUINDXM	0.331	12	PPIIDC	0.284	6	EXUSUKx	0.193	11
PNFIx	0.630	1	HOUSTS	0.328	4	SPCS20RSA	0.247	4	WPU0561	0.181	6
USTRADE	0.628	3	NAPM	0.324		ULCMFG	0.218	7	TNWBSHNOx	0.165	10
Y033RC1Q027SBEAx	0.622	1	INVCQRMTSPL	0.321	5	WPSFD49502	0.210	6	WPSID61	0.154	6

NOTE: This table lists the 10 series that load most heavily on all four factors along with the R^2 in a regression of the series on the factor. For example, Factor 1 of FRED-QD explains 0.784 of the variation in LNS14000025. Factor 1 of FRED-QD has an mR^2 of 0.211. This is the fraction of the variation in 125 series explained by Factor 1. Results for the S&W dataset are also listed.

In Figure 1 we plot the four factors based on each dataset. The National Bureau of Economic Research (NBER) recession dates are shown by the gray bars. Visually, each of the four factors is very similar across the entire sample.[7] This is particularly true for Factor 1 for which the two estimates are nearly identical and have a correlation exceeding 0.99. The remaining three correlations are only marginally lower, with values of 0.988, 0.968, and 0.980 for Factors 2 through 4, respectively.

While the figure gives a visual characterization of the similarities of the factors, it is instructive to provide a more quantitative comparison. We do this by identifying which series are best explained by the factors. To do so, we regress the ith series in the dataset on a set of the r factors. For $k = 1,\ldots,r$, this yields coefficients of determination $R_i(k)^2$ for each series i. Because the factors are orthogonal and organized in decreasing order of their respective eigenvalues, the incremental explanatory power of factor k for series i 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 $mR^2(k) = \frac{1}{N}\sum_{i=1}^{N} mR_i^2(k)$. Table 2 lists $mR^2(k)$ and the 10 series with the highest $mR_i^2(k)$ for factor k. Panel A does so for the factors estimated using FRED-QD, while Panel B does the same but with the original S&W dataset. To simplify interpretation of the factors, we also include the group numbers for each of the 10 series.

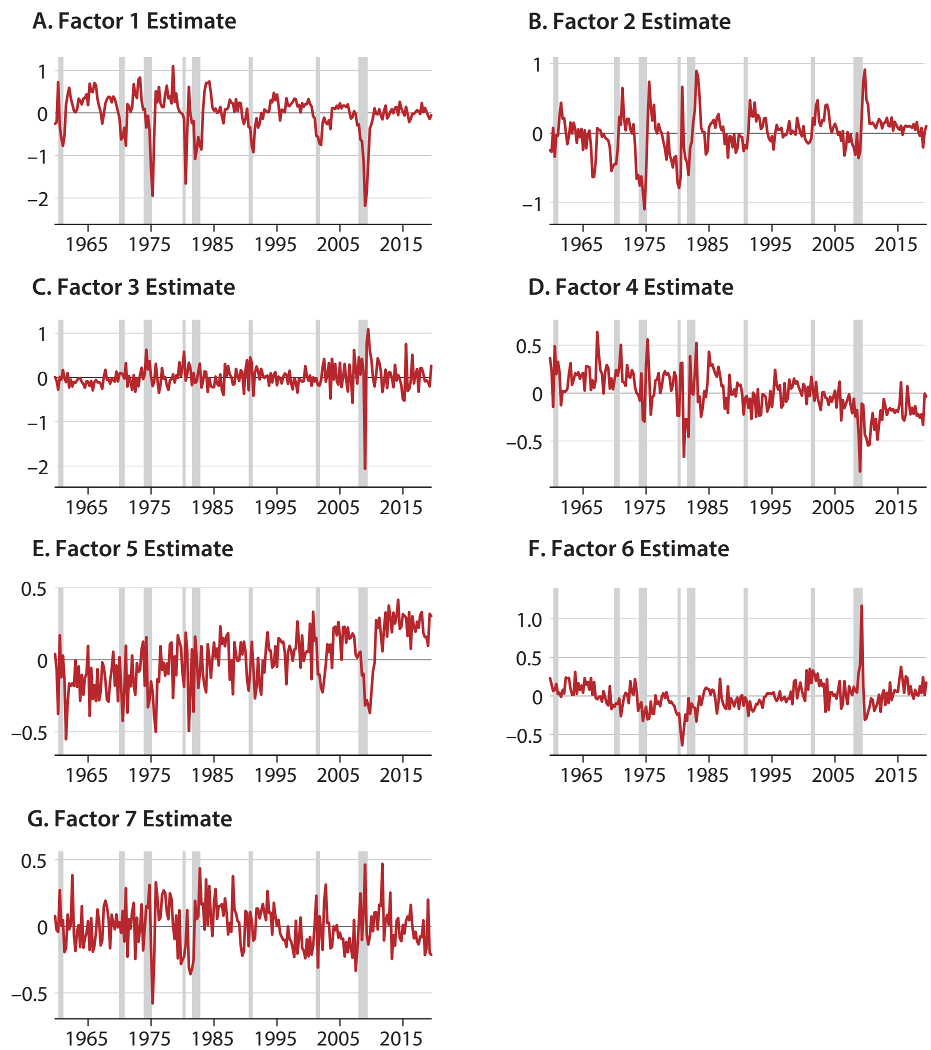
A quick look at Table 2 immediately reinforces the visual similarity from Figure 1. Regardless of which dataset is used to estimate the factors, the total variation explained by all four factors is nearly the same (i.e., 0.41), and the $mR^2(k)$ values are nearly the same as well (i.e., 0.21, 0.09, 0.06, and 0.05 for factors $k = 1,\ldots,4$). The similarity also carries over to the top 10 series with the highest $mR_i^2(k)$ values. While the rank ordering of the series varies a bit, 10, 8, 9, and 9 of the top 10 series coincide across the four factors, respectively. This is convenient because it implies that the interpretation of the factors remains unchanged when using FRED-QD rather than the original S&W dataset. Factor 1 is a real activity indicator that weighs heavily on series from the Employment, Industrial Production, and NIPA groups. Factor 2 is dominated by forward-looking series such as term interest rate spreads and inventories. Factor 3 has explanatory power concentrated in the Prices group as well as housing sector prices. Finally, Factor 4 is extensively weighted on both the Prices and Exchange Rates groups.

Figure 1 and Table 2 suggest that FRED-QD provides a reasonable replication of the original dataset—at least through the lens of PCA-based factor analysis. Even so, it also contains additional series not in the original S&W dataset, and thus it is reasonable to wonder if those series provide additional information. Using all of the series and observations in FRED-QD, IC_{p2} selects three additional factors, bringing the total up to $r = 7$. These are plotted in Figure 2. Factors 1 and 2 remain closely related to those constructed using the S&W dataset, with correlations of 0.99 and 0.96, respectively. Beyond that, the correlations drop off dramatically, with Factors 3 and 4 only exhibiting correlations of roughly 0.70.

The similarities and differences are more readily seen in Table 3. There we report the marginal R^2 values associated with the seven factors identified using the entirety of FRED-QD. As expected, Factors 1 and 2 retain the same interpretation as those reported in Figure 1 and Table 2. Factor 1 is a real activity factor that correlates strongly with series in the Employment

Figure 2

FRED-QD Factor Estimates



NOTE: This figure plots the PCA-based factors estimated using the full FRED-QD data set based on the benchmark transformation codes. Gray bars indicate recessions as determined by the NBER.

and Industrial Production groups, while Factor 2 remains a forward-looking factor that correlates heavily on interest rate term spreads as well as housing permits and starts. In contrast, while Factor 3 from the S&W dataset was a mixture of consumer prices and housing prices, when estimated using FRED-QD, Factor 3 is a pure consumer price index (CPI) with all of the top 10 $mR_i^2(3)$ values associated with the Prices group. In contrast, when using the full FRED-QD dataset, Factor 4 appears to be a second employment-oriented factor rather than a second prices-oriented factor, as we observed using the S&W dataset.

Table 3

Factors Estimated from FRED-QD: Total Variation Explained, 0.497

$mR^2(1)$	**0.199**	G#	$mR^2(2)$	**0.083**	G#	$mR^2(3)$	**0.073**	G#	$mR^2(4)$	**0.047**	G#
USPRIV	0.838	3	AAAFFM	0.506	8	CUSR0000SA0L2	0.753	6	IMFSLx	0.394	9
USGOOD	0.820	3	T5YFFM	0.475	8	CUSR0000SAC	0.737	6	CES9093000001	0.341	3
OUTMS	0.814	1	PERMIT	0.462	4	DGDSRG3Q086SBEA	0.734	6	CES9092000001	0.306	3
PAYEMS	0.811	3	BUSINVx	0.432	5	PCECTPI	0.718	6	USGOVT	0.237	3
IPMANSICS	0.797	2	HOUST	0.421	4	CPITRNSL	0.703	6	GFDEBTNx	0.237	14
INDPRO	0.784	2	PERMITS	0.407	4	DNDGRG3Q086SBEA	0.693	6	REVOLSLx	0.225	9
MANEMP	0.776	3	TCU	0.394	2	CUSR0000SA0L5	0.676	6	COMPRMS	0.211	7
HOANBS	0.774	3	S&P div yield	0.393	13	CPIAUCSL	0.669	6	USFIRE	0.203	3
UNRATE	0.768	3	GS10TB3Mx	0.380	8	WPSID61	0.642	6	USSERV	0.203	3
DMANEMP	0.765	3	CPF3MTB3Mx	0.360	8	CPIULFSL	0.635	6	EXUSEU	0.194	11

$mR^2(5)$	**0.037**	G#	$mR^2(6)$	**0.030**	G#	$mR^2(7)$	**0.027**	G#
OPHMFG	0.359	7	CONSPIx	0.274	10	USEPUINDXM	0.257	12
NWPIx	0.295	10	ULCNFB	0.228	7	TNWBSHNOx	0.208	10
AWHMAN	0.293	3	ULCBS	0.227	7	TABSHNOx	0.202	10
HWIx	0.290	3	CONSUMERx	0.220	9	TARESAx	0.192	10
OPHPBS	0.284	7	EXUSEU	0.208	11	TFAABSHNOx	0.192	10
OPHNFB	0.247	7	NONREVSLx	0.194	9	S&P 500	0.183	13
UNLPNBS	0.223	7	AHETPIx	0.187	7	S&P: indust	0.182	13
UNRATELTx	0.221	3	TOTALSLx	0.164	9	NASDAQCOM	0.171	13
ULCMFG	0.214	7	TB3SMFFM	0.149	8	GS10TB3Mx	0.155	8
TLBSNNCBBDIx	0.200	14	B020RE1Q156NBEA	0.143	1	TB6M3Mx	0.135	8

NOTE: See Table 2 note.

The interpretation of Factors 4 to 7 are less clear. While most of these factors exhibit considerable correlation with series in the Earnings and Productivity group (i.e., Group 7), a variety of other groups are represented. Factor 5 also correlates with Employment and both the Household and Non-Household Balance Sheet groups, while Factor 6 correlates with several series in the Money and Credit group. Finally, Factor 7 appears to be a weaker version of Factor 5 insofar as it too correlates heavily with several series in the Household Balance Sheet group. It is useful to note that these smaller factors are discarded using the criterion in Bai and Ng (2019b) that guards against outliers, an issue to which we now turn.

4 OUTLIERS AND HIGH LEVERAGE OBSERVATIONS

In this section, we provide a brief investigation into the importance of outliers and high leverage observations on the estimated factors. The statistics literature makes a distinction between these two concepts.[8] In a regression setting with predictors x and predictand y, an observation is an outlier if the residual is far from its mean. In contrast, the observation is said to have high leverage if x is far from the mean of its x_i values and yet the corresponding residual is not large. In the context of factor analysis, analogous definitions exist and we consider them below. Loosely speaking, the y variable is the factor and the x variable is the underlying data used to estimate the factor.

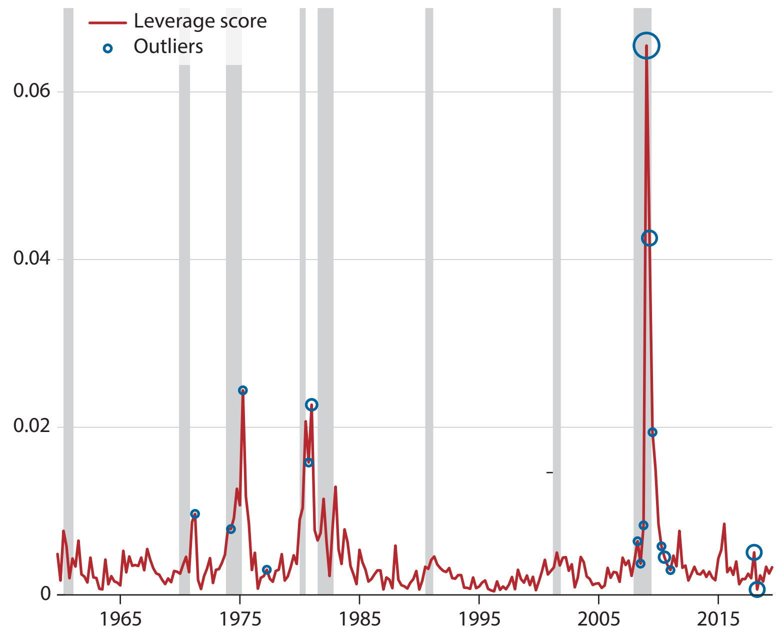
Following S&W, we define an outlier as an observation that deviates from the sample median by more than 10 interquartile ranges. By this definition, the S&W dataset and the corresponding subset of FRED-QD each have seven outliers. These are identified in 1971:Q1 and 1997:Q1 for a consumer credit series, in 2008:Q4 for three producer price series, and in 2010:Q2 for federal employment and consumer loans.[9] The full FRED-QD data has 30 outliers, 17 of which are found between 2008:Q1 and 2010:Q4 and are predominantly bank reserves variables. Two interest rate variables and a prices variable are also identified to be outliers in 1980:Q3 and Q4, as well as oil price in 1974:Q1 and six non-household balance sheet variables between 2017:Q4 and 2018:Q1.

Note, however, that this definition of an outlier does not depend on the value of the estimated factors. As such, it is not obvious that they should be removed prior to estimating the factors.[10] Without the outlier adjustment, the IC_{p2} criterion identifies eight factors in the data instead of seven. Nonetheless, the first six factors estimated with and without outlier adjustments are almost perfectly correlated, suggesting that the effect of these outliers on the largest factors is quite minimal.

In terms of high leverage observations, it seems likely that some of the 248 series, and (up to) 242 quarterly observations per series, are more important than others for estimating the factors. Using methods described in Mahoney (2011), we construct statistical leverage scores that inform us about the non-uniform structure of importance in the data. Consider a $T \times N$ data matrix X with singular value decomposition $X = U\Sigma V'$ and assumed to have a low-rank component of rank r. The factor estimates reported above can be expressed as $\left(\tilde{F}, \tilde{\Lambda}'\right) = \left(\sqrt{T}U_r, \sqrt{N}V_r D_r\right)$.

Figure 3

FRED-QD Leverage Scores



NOTE: This figure plots the statistical leverage score, p_t, of each quarter. Blue circles represent quarters where at least one value in a series is an outlier; circle size is relative to the number of outliers detected. Gray bars indicate recessions as determined by the NBER.

A different aspect of the eigenvectors will now be explored. Let $u_{(t)}$ be the tth row of the $T \times r$ matrix of left singular vectors U_r, and $v^{(i)}$ be the ith column of the $r \times N$ matrix of right singular vectors V_r'. Define the normalized row and column leverage scores as

$$p_t = \frac{\| u_{(t)} \|_2^2}{\sum_{t=1}^{T} \| u_{(t)} \|_2^2}, \qquad p^i = \frac{\| v^{(i)} \|_2^2}{\sum_{i=1}^{n} \| v^{(i)} \|_2^2}.$$

As $\sum_{t=1}^{T} p_t = \sum_{i=1}^{N} p^i = 1$, these probabilities also define an "importance sampling distribution" for the rows and the columns of X, respectively. The row scores are simply the diagonal entries of the "hat" matrix sometimes used to detect influential observations in regression settings. Here, it is used to evaluate the strength of each row of the top-r-left singular vectors, giving information about the relative importance of the time series data points. The column score evaluates the strength of each column of the top-r-right singular vectors and hence is informative about the relative importance of the data in the cross section.

We compute the row leverage scores for the full and balanced FRED-QD data with and without outlier adjustment. The results are similar, and hence to conserve space, in Figure 3 we plot the leverage scores for the full-sample of FRED-QD without outlier adjustment. If the information is uniformly dispersed over time, each of the T observations should have a score of $\frac{1}{T}$. In the FRED-QD data, six data points account for 20 percent of the mass in p_t: 2008:Q4, 2009:Q1, 1975:Q1, 1980:Q4, 1980:Q2, and 2009:Q2. These roughly coincide with the outliers detected by the interquartile-range method.

Turning to the column leverage scores, each p^i should be $\frac{1}{N}$ if information in the series is evenly dispersed. This is apparently not the case, as the (unreported) histogram of p^i is quite skewed. For the subpanel of FRED-QD data corresponding to the S&W dataset, the series with the top three scores are the U.S./euro exchange rate (EXUSEU), WPSID61, and PPIDC, regardless of whether an outlier adjustment is made. For the full FRED-QD panel, the series with the top scores are COMPRMS, EXUSEU, and GS5 without outlier adjustment, and NWPIx, S&P 500, and real household networth (TNWBSHNOx) with outlier adjustment. Apparently, the variables added to the full panel do change the information content of the panel. Nonetheless, these variables are already known to play an important role in business cycle modeling. This analysis simply reinforces their importance.

5 TRANSFORMATION CODES

As we noted earlier, the dataset provides benchmark transformation codes that are designed to make each series stationary. After having made the decision that the series should be managed in levels or log levels, the transformation codes are first and second differences based on whether the series is believed to be $I(0)$, $I(1)$, or $I(2)$. In this section, we revisit the benchmark transformation codes and do so through the lens of unit root tests. In particular, we apply unit root tests to each series in FRED-QD to see whether or not the unit root tests imply the benchmark transformation codes.

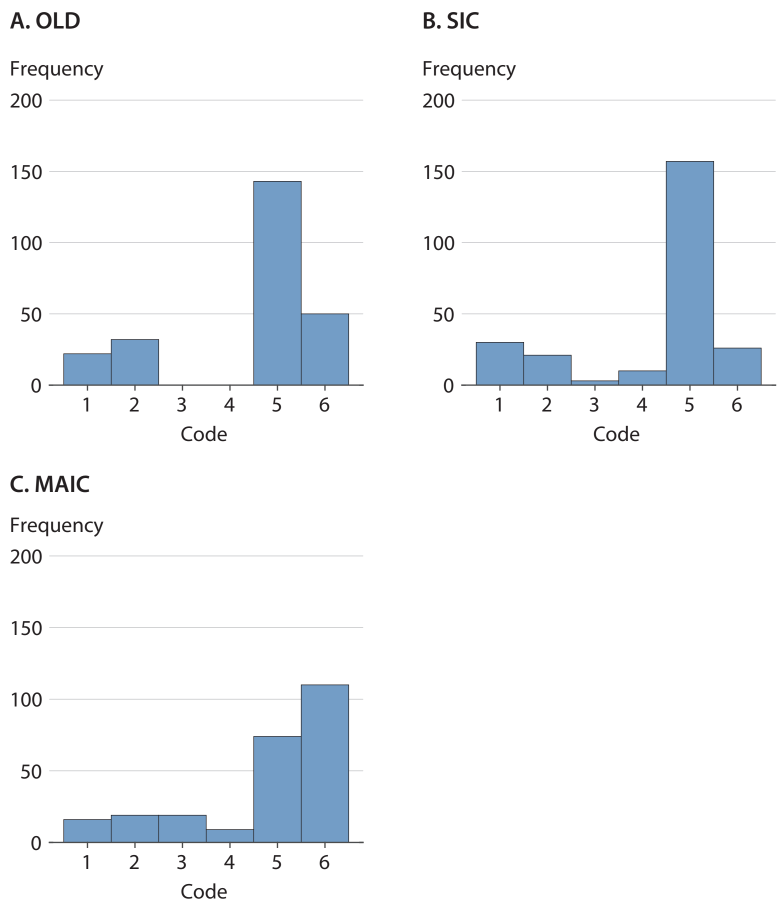
For each series, we apply two variants of the Dickey-Fuller generalized least-squares (DFGLS) tests as delineated in Elliott, Rothenberg, and Stock (1996). These two tests differ only in how the number of autoregressive lags are chosen. One uses the Schwarz's Information Criterion (SIC) to choose the appropriate number of lags, and the other uses a Modified Akaike Information Criteron (MAIC), developed in Ng and Perron (2001).[11] In each case the maximum number of lags is based on the recommendation in Schwert (1989), and hence for a given sample size T, $k_{\max} = \left\lfloor 12\left(T/100\right)^{1/4} \right\rfloor$.

We use the results of these tests to identify the appropriate transformation codes. For example, recall that for the DFGLS tests, the null hypothesis is that the series is $I(1)$. Hence, if we fail to reject, the series is differenced and the test is repeated until we reject the null. Depending on when this algorithm rejects the null determines the transformation code. For each test, and at each stage of the algorithm, we consider nominally 5 percent tests of the respective null.

For brevity we do not report the results of all the unit root tests. Instead, in Figure 4 we provide histograms of the implied transformation codes for all the series.[12] The first panel is the histogram of the codes reported in FRED-QD. All series have transformation codes of either 1, 2, 5, or 6, and hence no series are considered stationary in log levels (4) or second differences of levels (3). By far the bulk of the codes are 5s, and hence the series are considered

Figure 4

Factors Estimated from FRED-QD: Total Variation Explained, 0.497



NOTE: Each panel provides a histogram of frequencies of transformation codes. "OLD" refers to the benchmark codes provided in FRED-QD. "SIC" and "MAIC" refer to codes implied by the associated DFGLS unit root test.

stationary in log-first differences. These patterns change when we consider the unit root-based transformation codes. The largest changes occur when using the MAIC variant of the DFGLS test. Here we find that much of the mass associated with a code of 5 has shifted into a code of 6, leading to more than a doubling of the number of series that require double differencing in log levels. That said, some mass from the 5s has settled into the 4s, suggesting that some of the series may be $I(0)$ in log levels rather than log-first differences. There is also a modest shift in mass from the 1s and 2s into 3s, and hence the tests indicate some of the series are stationary in the second difference of the levels. In contrast, the SIC-based DFGLS test implies more modest deviations from the original transformation codes. There remains almost no mass on the 3s and 4s. The largest deviation from the benchmark codes comes from a shift of mass from the 6s into the 5s, and hence the SIC-based test indicates that some of the series have been overdifferenced.

Table 4

FRED-QD Median Transformation Codes by Group

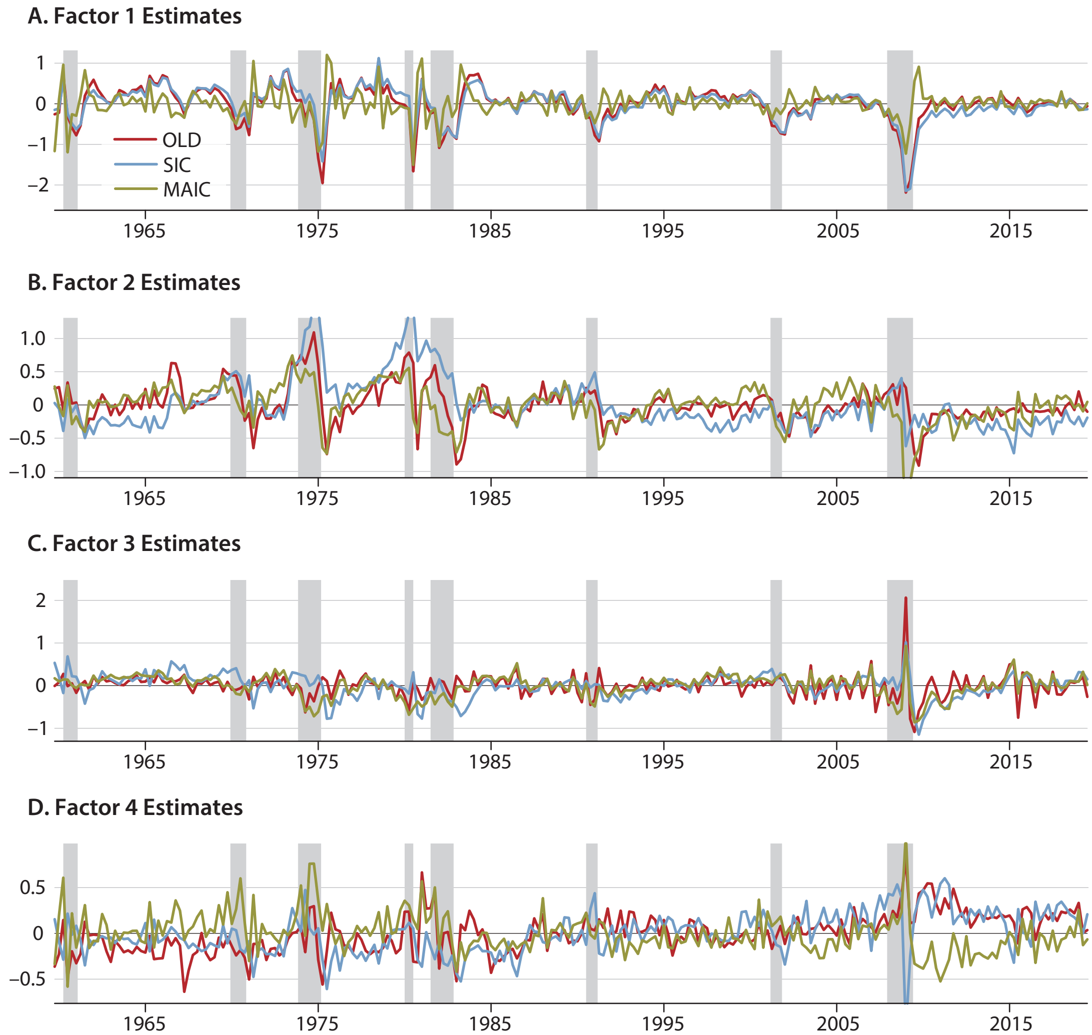
Group	Group name	OLD	SIC	MAIC
1	NIPA	5	5	6
2	Industrial Production	5	5	6
3	Employment and Unemployment	5	5	5
4	Housing	5	4.5	4.5
5	Inventories, Orders, and Sales	5	5	6
6	Prices	6	5	6
7	Earnings and Productivity	5	5	6
8	Interest Rates	1.5	1	2
9	Money and Credit	5	5	5
10	Household Balance Sheets	5	5	5
11	Exchange Rates	5	5	5
12	Other	1.5	1	1
13	Stock Markets	5	5	5
14	Non-Household Balance Sheets	5	5	5
	All	5	5	5

The histograms convey the fact that the unit root tests can imply transformation codes that don't align with the benchmark codes. Nevertheless, they do not convey where the changes are coming from. To address this issue, in Table 4 we report the median transformation codes by group. For the MAIC-based tests, much of the shift toward log second differences occurs in the NIPA, Industrial Production, and Earnings and Productivity groups. In contrast, for the SIC-based tests, the biggest change occurs for Prices, in which case the test recommends treating Prices as log first differences instead of log second differences. Both versions of the DFGLS tests disagree with the benchmark codes for Housing, of which several of the series are considered stationary in log levels and hence do not need to be differenced.

It's clear that the unit root tests recommend changes in some of the transformations. Even so, it's worth keeping in mind that many of the unit root-implied codes continue to coincide with the benchmark codes. It therefore need not be the case that factors based on the benchmark codes deviate significantly from factors based on the unit root codes. In Figure 5 we plot the first four factors based on the benchmark codes along with the corresponding factors constructed after using the unit root test determined codes. For the first factor, the SIC- and benchmark-implied factors largely coincide and exhibit a correlation of 0.95. In contrast, the MAIC-based variant deviates substantially from that constructed using the benchmark codes, with which they have a modest correlation of 0.56. For the remaining factors, substantial differences exist among the unit root-implied factors and those based on the benchmark codes.

Figure 5

FRED-QD Factor Estimates by Method of Series Transformation



NOTE: This figures plots the first four PCA-based factors corresponding to the benchmark (OLD) codes and those implied by the unit root tests (SIC and MAIC). Gray bars indicate recessions as determined by the NBER.

In Table 5, more detailed evidence on the differences in the factors can be gleaned from the marginal R^2 values for the factors plotted in Figure 5. Rather than go through these in detail we make only a few notable observations. One noticeable distinction among the factors is that while the MAIC-based factors remain heavily concentrated in the Employment and Industrial Production groups, the $mR^2(1)$ values are substantially lower than those associated with the benchmark and SIC-based codes. This likely follows from the propensity of the MAIC-based unit root tests to treat many NIPA and employment series as $I(2)$ rather than $I(1)$, which

Table 5

FRED-QD Factor Estimates by Method of Series Transformation

A. OLD
Total variation explained, 0.4025

$mR^2(1)$	0.199	G#	$mR^2(2)$	0.083	G#	$mR^2(3)$	0.073	G#	$mR^2(4)$	0.047	G#
USPRIV	0.838	3	AAAFFM	0.506	8	CUSR0000SA0L2	0.753	6	IMFSLx	0.394	9
USGOOD	0.820	3	T5YFFM	0.475	8	CUSR0000SAC	0.737	6	CES9093000001	0.341	3
OUTMS	0.814	1	PERMIT	0.462	4	DGDSRG3Q086SBEA	0.734	6	CES9092000001	0.306	3
PAYEMS	0.811	3	BUSINVx	0.432	5	PCECTPI	0.718	6	USGOVT	0.237	3
IPMANSICS	0.797	2	HOUST	0.421	4	CPITRNSL	0.703	6	GFDEBTNx	0.237	14
INDPRO	0.784	2	PERMITS	0.407	4	DNDGRG3Q086SBEA	0.693	6	REVOLSLx	0.225	9
MANEMP	0.776	3	TCU	0.394	2	CUSR0000SA0L5	0.676	6	COMPRMS	0.211	7
HOANBS	0.774	3	S&P div yield	0.393	13	CPIAUCSL	0.669	6	USFIRE	0.203	3
UNRATE	0.768	3	GS10TB3Mx	0.380	8	WPSID61	0.642	6	USSERV	0.203	3
DMANEMP	0.765	3	CPF3MTB3Mx	0.360	8	CPIULFSL	0.635	6	EXUSEU	0.194	11

B. SIC
Total variation explained, 0.4411

$mR^2(1)$	0.169	G#	$mR^2(2)$	0.147	G#	$mR^2(3)$	0.074	G#	$mR^2(4)$	0.051	G#
PAYEMS	0.844	3	PCECTPI	0.858	6	UNRATE	0.523	3	DGOERG3Q086SBEA	0.376	6
USPRIV	0.835	3	CPIAUCSL	0.846	6	LNS14000025	0.506	3	WPU0561	0.341	6
USGOOD	0.781	3	CUSR0000SA0L5	0.828	6	LNS14000026	0.466	3	OILPRICEx	0.324	6
USTPU	0.758	3	CPIULFSL	0.797	6	SPCS20RSA	0.462	4	ACOGNOx	0.281	5
SRVPRD	0.728	3	PCEPILFE	0.794	6	LNS14000012	0.462	3	WPSID62	0.264	6
MANEMP	0.723	3	IPDBS	0.790	6	ISRATIOx	0.383	5	PPIACO	0.258	6
DMANEMP	0.718	3	CPILFESL	0.787	6	UNRATELTx	0.350	3	B020RE1Q156NBEA	0.256	1
HOAMS	0.716	3	CUSR0000SAS	0.756	6	UNRATESTx	0.348	3	PPIIDC	0.255	6
HOANBS	0.704	3	DSERRG3Q086SBEA	0.746	6	HWIURATIOx	0.341	3	B021RE1Q156NBEA	0.244	1
USWTRADE	0.683	3	CUSR0000SA0L2	0.742	6	CLAIMSx	0.313	3	AWHMAN	0.243	3

C. MAIC
Total variation explained, 0.3327

$mR^2(1)$	0.127	G#	$mR^2(2)$	0.091	G#	$mR^2(3)$	0.066	G#	$mR^2(4)$	0.047	G#
OUTMS	0.854	1	SRVPRD	0.481	3	CUSR0000SAC	0.476	6	CPF3MTB3Mx	0.364	8
TCU	0.783	2	USPBS	0.412	3	CPITRNSL	0.468	6	S&P 500	0.275	13
USPRIV	0.781	3	PPIACO	0.399	6	UMCSENTx	0.446	12	DRIWCIL	0.273	9
USGOOD	0.774	3	WPSID61	0.396	6	WPSFD49207	0.435	6	TFAABSHNOx	0.269	10
IPMANSICS	0.751	2	INVCQRMTSPL	0.390	5	USSTHPI	0.423	4	AAAFFM	0.264	8
INDPRO	0.730	2	HOUST	0.368	4	WPSFD49502	0.421	6	TARESAx	0.262	10
PAYEMS	0.727	3	PPIIDC	0.366	6	CPIULFSL	0.408	6	S&P: indust	0.262	13
CUMFNS	0.723	2	USTRADE	0.361	3	PPIIDC	0.399	6	BAA	0.255	8
MANEMP	0.722	3	CUSR0000SAC	0.342	6	EXUSEU	0.388	11	NWPIx	0.242	10
DMANEMP	0.690	3	WPSFD49502	0.341	6	PPIACO	0.361	6	TNWBSHNOx	0.239	10

NOTE: See Table 2 note.

apparently leads to a loss of information due to overdifferencing. Another is the relatively clear interpretability of the SIC-based factors. Factor 1 is a clear employment factor, while Factor 2 is a pure consumer prices factor. Factor 3 is arguably an unemployment factor, and Factor 4 is heavily correlated with producer prices with an emphasis on energy and, specifically, oil prices.

6 PREDICTABILITY OF FACTOR-BASED MODELS

In this section, we investigate the usefulness of factors for predicting macroeconomic aggregates. The structure of the forecasting exercise is motivated by a similar forecasting exercise conducted by Stock and Watson (2012b). Specifically, we construct one- and four-quarter-ahead forecasts of real GDP (log level), industrial production (log level), the unemployment rate (level), and the federal funds rate (level), as well as the CPI, personal consumption expenditures (PCE), GDP deflator, and PPI price indices (each in log level). These variables were chosen based on the results of the unit root tests in the previous section, with an eye toward emphasizing the role that transformation codes have on the predictive content of factors. For each permutation of the eight dependent variables Y and two horizons h, we have three goals: (i) document that the FRED-QD factors have predictive content above and beyond that contained in a baseline autoregressive model, (ii) document whether the choice of transformation codes can have a material effect on the predictive content of factors extracted from FRED-QD, and (iii) document those factors that exhibit the most predictive content for the target variables.

In each case, the models used for forecasting take the direct multistep form

$$y_t^{(h)} = \alpha_h + \sum_{j=0}^{p-1} \beta_j^{(h)} y_{t-h-j} + \delta^{(h)\prime} f_{t-h} + \varepsilon_t^{(h)}, \tag{1}$$

where

$$y_t^{(h)} = \left\{ \begin{array}{ll} Y_t & \text{if } Y_t \text{ is } I(0) \\ Y_t - Y_{t-h} & \text{if } Y_t \text{ is } I(1) \\ Y_t - Y_{t-h} - h\Delta Y_{t-h} & \text{if } Y_t \text{ is } I(2) \end{array} \right\}. \tag{2}$$

For brevity, when $h = 1$ we drop the superscript and define $y_t^{(1)}$ as y_t. At each forecast origin, the model is estimated by ordinary least squares and the h-step-ahead forecast of $y_{t+h}^{(h)}$ is then constructed as

$$\hat{y}_{t,h}^{(h)} = \hat{\alpha}_{h,t} + \sum_{j=0}^{p-1} \hat{\beta}_{j,t}^{(h)} y_{t-j} + \hat{\delta}_t^{(h)\prime} f_t. \tag{3}$$

Forecasts of Y_{t+h} are then computed in accordance with the order of integration of Y:

$$\hat{Y}_{t,h} = \left\{ \begin{array}{ll} \hat{y}_{t,h}^{(h)} & \text{if } Y_t \text{ is } I(0) \\ Y_t + \hat{y}_{t,h}^{(h)} & \text{if } Y_t \text{ is } I(1) \\ Y_t + h\Delta Y_t + \hat{y}_{t,h}^{(h)} & \text{if } Y_t \text{ is } I(2) \end{array} \right\}. \tag{4}$$

Following Stock and Watson (2012b), we fix the number of autoregressive lags p at four and only consider a single lag of the factor(s). Since it is not obvious which of the seven factors should be used to forecast any particular target variable, and since those factors could vary by horizon, we consider all $2^7 - 1 = 127$ possible choices of f_t as a potential predictor. Hence, in some cases, f is a scalar consisting of just one of the seven possible factors, while in other models f is a vector consisting of up to all seven factors.

All models are estimated using a rolling window of 106 (109) observations when $h = 1$ (4). The first forecast origin is R = 1985:Q1 + h, and the last forecast origin is T = 2018:Q4 – h, for a total of P = 134 (128) forecasts. At each forecast origin, we estimate the factors two different ways. For the first, we use the benchmark transformation codes provided in FRED-QD. For the second, at each forecast origin, we perform unit root tests on all series in FRED-QD using the past 106 (109) observations when $h = 1$ (4). Based on the outcome of these tests, we select transformation codes using the same algorithms described in the previous subsection. For brevity, we only consider the SIC-based DFGLS unit root test in this forecasting exercise. Using the MAIC-based unit root test leads to different results. Our goal is not to provide the "correct" set of results, but rather to demonstrate that sticking to previously established transformation codes may lead to inferior results.[13]

It's important to keep in mind that by taking a rolling-window approach to forecasting, we have potentially time-varying transformation codes and this has multiple effects on our forecasting exercise. Obviously, different transformation codes lead to distinct estimated factors as shown in Figure 5. In addition, given our direct multistep forecasting environment, different transformation codes also lead to time-varying definitions of $y^{(h)}$. For this reason, we measure accuracy of the forecasts relative to Y rather than $y^{(h)}$. In particular, we evaluate accuracy of the forecasts under quadratic loss using mean-squared errors $P^{-1}\sum_{t=R}^{T}\left(Y_{t+h}-\hat{Y}_{t,h}\right)^2$.

For each target variable Y and horizon h, there is a benchmark $AR(4)$ model that is estimated using the original (OLD) transformation codes. In addition, there are 127 models that augment the benchmark $AR(4)$, with at least one factor formed using the OLD transformation codes. The same is done using transformation codes based on the unit-root-testing algorithm (NEW). This leads to 128 more models, including an $AR(4)$ based on the NEW codes and 127 models that augment this $AR(4)$ with at least one of the seven factors.

For each of the 254 models that include at least one factor, we conduct a one-sided test of the null that the factors do not contribute finite-sample predictive content relative to the benchmark $AR(4)$. The null is stated in the context of the test of unconditional finite-sample predictive ability advocated by Giacomini and White (2006). However, in contrast to their recommended testing procedure, we follow Coroneo and Fabrizio (2020) and apply a fixed-b asymptotic approximation to the test statistic. Specifically, for each model $j = 1,\ldots,254$ that includes at least one factor, the test statistic takes the form $P^{-1/2}\sum_{t=R}^{T}\left(\hat{u}_{t+h,AR}^2-\hat{u}_{t+h,j}^2\right)\big/\hat{\omega}_j$, where $\hat{\omega}_j^2$ is an estimate of the long-run variance of $\hat{u}_{t+h,AR}^2 - \hat{u}_{t+h,j}^2$. This is estimated using the Bartlett kernel and bandwidth $\lfloor 1.3\sqrt{P}\rfloor+1$ as advocated in Lazarus et al. (2018). Critical values for the asymptotic distribution are approximated using the formula provided in Table 1 of Kiefer and Vogelsang (2005, p. 1146).

While this testing procedure allows us to ascertain whether the factors exhibit finite-sample predictive content beyond that in the benchmark $AR(4)$, there is an obvious multiple-testing problem. To mitigate the potential for multiple testing, we provide complementary evidence on accuracy using the model confidence set procedure advocated by Hansen, Lunde, and Nason (2011). This allows us to identify the subset of all 256 models that are statistically as accurate as the single most accurate model. Note that this information is related to, but not the same as, the previous test comparing each model to the benchmark. For example, it could be the case that the benchmark is the best model, and hence factors do not provide additional predictive content. Even so, many of the factor-based models may be contained in the model confidence set because they are approximately as accurate as the benchmark. With this difference of interpretation in mind, we use the $T_{R,\mathcal{M}} \equiv \max_{i,j\in\mathcal{M}}|t_{i,j}|$ statistic when implementing the model confidence set procedure. The distribution of this test statistic is approximated using a circular block bootstrap with block length $l = 12$ using software distributed by Sheppard (2018). To help identify the most-accurate models, we use a restrictive significance level of 25 percent—that is, the level associated with the model confidence set $\mathcal{M}_{75}$.[14]

Rather than report all of the testing results, we focus on a concise subset that provides evidence on our three forecasting goals. For each permutation of target variable Y and horizon h, we report the root-mean-squared error (RMSE) for the benchmark $AR(4)$, along with the relative RMSEs associated with the 10 most-accurate models. An asterisk denotes whether the models were more accurate than the $AR(4)$ at the 5 percent level using the fixed-b critical values. In addition, we report the number of OLD and NEW models that outperform the benchmark $AR(4)$. Finally, we report the number of models contained in the model confidence set. Since we want to identify the importance of the transformation codes, we also specify the number of models in the model confidence set that use the NEW factors based on the unit-root-driven transformation codes.

Tables 6 and 7 provide the results. In the first table we focus on the real and financial target variables, while in the second we focus on the price series. In Table 6 we find numerous evidence that the factors can provide additional predictive content beyond that of the benchmark $AR(4)$. For all four target variables and at both forecast horizons, the number of factor-based models that significantly outperform the benchmark range from a low of three models when forecasting the federal funds rate at the one-quarter horizon to a high of 142 models when forecasting the unemployment rate at the four-quarter horizon. To be fair, many of those that outperform the benchmark only do so to a modest degree. The largest gains occur for the unemployment rate at the four-quarter horizon, where accuracy is improved by a substantial 25 percent. For the other target variables and/or horizons, the largest gains range from 17 percent to as low as 3 percent.

One obvious feature of Table 6 is the dominance of the factors constructed using the OLD transformation codes. Across all target variables and horizons, exactly 16 out of a possible 80 top 10 most-accurate models are based on factors estimated using the NEW transformation codes. Seven of these instances occur when forecasting GDP growth, another seven occur when forecasting the federal funds rate, and the remaining two occur when forecasting the unemployment rate; in all cases these occur at the four-quarter horizon. In addition, for all

Table 6

FRED-QD Factor-Based Forecasts of Real and Financial Series

A. Horizon = 1

GDPC1 *AR*(4) RMSE = 0.0053804 Top 10 models			INDPRO *AR*(4) RMSE = 0.0088442 Top 10 models			UNRATE *AR*(4) RMSE = 0.19716 Top 10 models			FEDFUNDS *AR*(4) RMSE = 0.40622 Top 10 models		
Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio
1,2,5,7	OLD	0.94*	2,6,7	OLD	0.86*	1,2,3,5,6	OLD	0.83*	2,6	OLD	0.97*
1,2,5	OLD	0.94*	1,2,7	OLD	0.87*	1,2,5,6	OLD	0.83*	2	OLD	0.98*
1,2,3,4,5,6,7	OLD	0.94*	2,5,6,7	OLD	0.87*	1,2,3,6	OLD	0.83*	2,4	OLD	0.98*
1,2,3,4,5,7	OLD	0.95*	2,7	OLD	0.87*	1,2,5,6,7	OLD	0.83*	2,4,6	OLD	0.99
2,5,6	OLD	0.95*	2,6	OLD	0.87*	1,2,3,4,5,6	OLD	0.84*	6	OLD	1.00
1,2	OLD	0.95*	1,2	OLD	0.87*	1,2,6	OLD	0.84*	2,6,7	OLD	1.00
1,2,7	OLD	0.95*	1,2,6,7	OLD	0.88*	1,2,3,5,6,7	OLD	0.84*	2,5,6	OLD	1.00
1,2,5,6,7	OLD	0.95*	1,2,6	OLD	0.89*	1,2,3,6,7	OLD	0.84*		OLD	1.00
1,2,3,4,5,6	OLD	0.95*	2,5,6	OLD	0.89*	1,2,3,4,6	OLD	0.84*	2,3	OLD	1.00
1,2,3,4,5	OLD	0.95*	2	OLD	0.89*	1,2,4,5,6	OLD	0.84*	2,3,6	OLD	1.00
# in MCS = 256			# in MCS = 55			# in MCS = 66			# in MCS = 123		
# NEW in MCS = 128			# NEW in MCS = 9			# NEW in MCS = 13			# NEW in MCS = 45		
# OLD > *AR*(4) = 57			# OLD > *AR*(4) = 66			# OLD > *AR*(4) = 96			# OLD > *AR*(4) = 3		
# NEW > *AR*(4) = 3			# NEW > *AR*(4) = 29			# NEW > *AR*(4) = 42			# NEW > *AR*(4) = 0		

B. Horizon = 4

GDPC1 *AR*(4) RMSE = 0.016498 Top 10 models			INDPRO *AR*(4) RMSE = 0.037483 Top 10 models			UNRATE *AR*(4) RMSE = 0.85051 Top 10 models			FEDFUNDS *AR*(4) RMSE = 1.4129 Top 10 models		
Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio
1,2	NEW	0.86*	2,6,7	OLD	0.88*	2,3,4,6,7	OLD	0.75*	1,2	NEW	0.92*
1,2,6	NEW	0.87*	2,7	OLD	0.89*	1,2,3,4,5,7	NEW	0.75*	1,2,7	NEW	0.94*
1,2,5	NEW	0.88*	2,6	OLD	0.90*	2,3,4,6	OLD	0.75*	1,2,5	NEW	0.95*
2	NEW	0.88*	2	OLD	0.90*	2,3,6,7	OLD	0.75*	2	NEW	0.96
1,6	NEW	0.89*	2,4,7	OLD	0.90*	2,3,4,5,6,7	OLD	0.76*	1,2,5,7	NEW	0.97*
1,2,5,6	NEW	0.89*	2,5,7	OLD	0.91*	2,3,6	OLD	0.76*	2,7	NEW	0.99*
2,3,4,5,6	OLD	0.89*	2,4,6,7	OLD	0.91*	1,2,3,4,5,6,7	OLD	0.76*	6	OLD	0.99*
1,2,3,4,5	OLD	0.89*	2,5,6,7	OLD	0.91*	1,2,3,4,5,6	OLD	0.76*	2,5	NEW	1.00
2,3,4,6	OLD	0.90*	2,5	OLD	0.91*	1,2,3,4,6,7	NEW	0.76*	2,4,6	OLD	1.00
1,2,4	NEW	0.90*	2,4	OLD	0.92*	1,2,3,4,5	OLD	0.76*		OLD	1.00
# in MCS = 135			# in MCS = 98			# in MCS = 124			# in MCS = 17		
# NEW in MCS = 51			# NEW in MCS = 27			# NEW in MCS = 60			# NEW in MCS = 11		
# OLD > *AR*(4) = 62			# OLD > *AR*(4) = 64			# OLD > *AR*(4) = 78			# OLD > *AR*(4) = 1		
# NEW > *AR*(4) = 34			# NEW > *AR*(4) = 0			# NEW > *AR*(4) = 64			# NEW > *AR*(4) = 6		

NOTE: This table lists the 10 forecasting models with the lowest RMSE for four series at the one-quarter and four-quarter horizons. The combination of factors, use of OLD or NEW codes, and ratio of RMSE with the benchmark model (*AR*(4) with OLD codes) are given. Asterisks denote if the model is significantly better than the baseline at the 5 percent level using fixed-b critical values. The # of total/NEW models in the MCS and the # of OLD/NEW models significantly better than the baseline model are also listed for each dependent variable and horizon.

Table 7

FRED-QD Factor-Based Forecasts of Price Series

A. Horizon = 1

CPIAUCSL $AR(4)$ RMSE = 0.0051166 Top 10 models			PCECTPI $AR(4)$ RMSE = 0.0036182 Top 10 models			GDPCTPI $AR(4)$ RMSE = 0.0019032 Top 10 models			PPIACO $AR(4)$ RMSE = 0.020314 Top 10 models		
Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio
1,4,7	NEW	0.97*	1,7	NEW	0.97*	1	NEW	0.95*	4	NEW	0.91*
1,7	NEW	0.97*	1,2,7	NEW	0.97*	1,4	NEW	0.95*	4,5,6	NEW	0.91*
3,4,5,6,7	OLD	0.97*	2,5,6,7	OLD	0.98*	1,3	OLD	0.95*	1,4	NEW	0.91*
1,3,7	NEW	0.97*	2,6,7	OLD	0.98*	1,3,4	NEW	0.96*	4,5	NEW	0.91*
3,4,6,7	OLD	0.97*	1,2,6,7	NEW	0.98*	1,2	OLD	0.96*	4,5,7	NEW	0.91*
1,3,4,7	NEW	0.98*	2,4,6,7	OLD	0.98*	1,2,3	OLD	0.96*	4,6	NEW	0.91*
3,4,5,6	OLD	0.98*	2,4,6	OLD	0.98*	1,4,7	NEW	0.97*	1,4,5,6	NEW	0.91*
1,6,7	NEW	0.98*	2,6	OLD	0.98*	1,5	NEW	0.97*	1,4,6	NEW	0.91*
1,4,6,7	NEW	0.98*	1,2,3,7	NEW	0.98*	1,2,4	NEW	0.97*	4,5,6,7	NEW	0.91*
3,4,6	OLD	0.98*	2,5,6	OLD	0.98*	1,4,6	NEW	0.97*	1,4,5	NEW	0.91*
# in MCS = 214			# in MCS = 193			# in MCS = 64			# in MCS = 256		
# NEW in MCS = 105			# NEW in MCS = 88			# NEW in MCS = 33			# NEW in MCS = 128		
# OLD > $AR(4)$ = 34			# OLD > $AR(4)$ = 34			# OLD > $AR(4)$ = 38			# OLD > $AR(4)$ = 16		
# NEW > $AR(4)$ =23			# NEW > $AR(4)$ = 19			# NEW > $AR(4)$ = 35			# NEW > $AR(4)$ = 128		

B. Horizon = 4

CPIAUCSL $AR(4)$ RMSE = 0.015208 Top 10 models			PCECTPI $AR(4)$ RMSE = 0.011441 Top 10 models			GDPCTPI $AR(4)$ RMSE = 0.006606 Top 10 models			PPIACO $AR(4)$ RMSE = 0.068741 Top 10 models		
Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio	Factors	Codes	Ratio
1,2,3,4	NEW	0.90*	1,2,3,4,7	NEW	0.96*	1,2,7	OLD	0.94*	2,5,7	NEW	0.77*
1,2,3,5	NEW	0.91*	2,5	OLD	0.96*	1,2,3,7	OLD	0.95*	2,5	NEW	0.77*
1,2,3,4,5	NEW	0.91*	1,2,3,4	NEW	0.96*	1,5	NEW	0.95*	2,4,5,7	NEW	0.77*
1,2,3,5,7	NEW	0.91*	1,2,3,7	NEW	0.97*	1,5,6	NEW	0.95*	4,5,7	NEW	0.77*
1,2,3,4,7	NEW	0.92*	1,2,3	NEW	0.97*	1,5,7	NEW	0.96*	2,4,5	NEW	0.77*
1,2,3	NEW	0.92*	5	OLD	0.97*	1,5,6,7	NEW	0.96*	5,7	NEW	0.77*
1,2,3,4,5,7	NEW	0.92*	4,5	NEW	0.97*	1,2,5,7	OLD	0.96*	5	NEW	0.77*
2,3,4,5,7	NEW	0.92*	2,4,5	OLD	0.98*	1	NEW	0.96*	2,5,6	NEW	0.77*
1,2,3,7	NEW	0.93*	1,2,3,5,7	NEW	0.98*	1,6	NEW	0.96*	4,5	NEW	0.77*
2,3,5,7	NEW	0.93*	2,3,4	NEW	0.98*	1,6,7	NEW	0.96*	2,5,6,7	NEW	0.77*
# in MCS = 103			# in MCS = 72			# in MCS = 155			# in MCS = 256		
# NEW in MCS = 71			# NEW in MCS = 54			# NEW in MCS = 85			# NEW in MCS = 128		
# OLD > $AR(4)$ = 26			# OLD > $AR(4)$ = 11			# OLD > $AR(4)$ = 19			# OLD > $AR(4)$ = 63		
# NEW > $AR(4)$ = 84			# NEW > $AR(4)$ = 36			# NEW > $AR(4)$ = 23			# NEW > $AR(4)$ = 128		

NOTE: See Table 6 note.

but one permutation of target variable and horizon, there are more models based on the OLD transformation codes that outperform the $AR(4)$ benchmark.

Among those factor-based models that perform in the top 10, it isn't obvious that one particular factor is dominant and should always be used when forecasting. Even so, it is true that Factors 1 or 2 occur in all but two of the top 10 factor-based models. While that might suggest that those factors associated with the largest eigenvalues provide the most predictive content, one should not conclude the contributions are monotone. There are many instances, like that when forecasting industrial production at either horizon, where Factors 2, 6, and 7 are included, but Factors 1, 3, 4, and 5 are not. It's also worth noting that the number of factors necessary to improve accuracy relative to the benchmark $AR(4)$ varies across series and, to a lesser extent, horizon. When forecasting the federal funds rate, maximal gains are achieved when including only two factors, but when forecasting the unemployment rate, the best models include five factors. In fact, there are instances in which including all seven factors in the model lead to forecasts of the unemployment rate and GDP growth that outperform those based on the benchmark $AR(4)$ model.

Moving to Table 7, that associated with predicting the four price series, we again find substantial evidence that the factors can provide marginal predictive content beyond the benchmark $AR(4)$. In some cases, such as when forecasting the GDP deflator at the four-quarter horizon, the number of factor-based models that have marginal predictive content is as low as 42, but in other cases, such as when forecasting PPI at the same horizon, the number is as high as 191. Relative to the benefits of using factor-based models observed in Table 6, the top gains are typically smaller. When forecasting PPI at the four-quarter horizon, the gains are as large as 23 percent but are less than 10 percent for all other permutations of the target variable and horizon.

But in contrast to the results in Table 6, when forecasting prices, factor-based models using the NEW transformation codes generally dominate those that use the OLD codes. Among the 80 possible top 10 models, only 19 are based on models that use the OLD transformation codes. Interestingly, none of these instances occur when forecasting PPI, which is dominated by factors estimated using the NEW transformation codes. In addition, relative to Table 6, there tends to be more models in the confidence set that use the NEW transformation codes. Similarly, relative to Table 6, a larger number of factor models that use the NEW transformation codes outperform the benchmark $AR(4)$—and do so especially at the longer forecast horizon.

To understand why the NEW transformation codes work better for forecasting prices, recall that in Section 5 we found that the transformation codes implied by the SIC-based unit root tests treated many of the price series as $I(1)$ in logs, whereas the OLD codes treat them as $I(2)$ in logs. If the price series are $I(1)$, but are treated as $I(2)$, then they are being overdifferenced and information is lost. This has two effects: (i) It affects the information content in the factors, and (ii) it removes the predictable component of the price variable being forecasted. The former of these could, hypothetically, have affected forecasts of the real variables in Table 6 but was not sufficient to outperform factors constructed using the OLD transformation codes. In contrast, since prices are being forecasted in Table 7, the latter effect has a direct impact and thus seems likely to have played an important role.

In terms of which factors are most useful for forecasting, there is a bit more heterogeneity when forecasting prices. In Table 6, nearly every top 10 model had at least Factors 1 or 2 based on either the OLD or NEW transformation codes. While it is the case that a majority of the top 10 models in Table 7 contain Factors 1 or 2, some of the best models include neither Factors 1 or 2 and instead include Factors 4 or 5—this is particularly true when forecasting PPI for either forecasting horizon. Nevertheless, it remains true that many of the top 10 models contain more than just one or two factors and, in fact, several include as many as five or six factors.

7 CONCLUSION

As was the case for FRED-MD, the purpose of introducing FRED-QD is to provide easy access to a large set of macroeconomic data that can be used to conduct research using "big-data" methods. The primary difference between the two datasets is simply that FRED-QD provides quarterly frequency data and, as such, permits the inclusion of lower-frequency series such as those from the NIPA releases. Regardless of this difference, like FRED-MD, the dataset has been—and will continue to be—updated by the data specialists at FRED® on a regular basis to account for newly released data, data revisions, and other complicating issues that sporadically arise with data collection. We (again!) sincerely thank them for their support in this work. ■

APPENDIX

FRED-QD is a quarterly frequency companion to FRED-MD. It is designed to emulate the dataset used in Stock and Watson (2012a) but also contains several additional series. The columns in Table A1 denote the following: (i) "ID" denotes the series number; (ii) "S&W ID" denotes the series number in Stock and Watson (2012a); (iii) TCODE denotes one of the following data transformations 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) $\Delta^2\log(x_t)$, and (7) $\Delta(x_t/x_{t-1} - 1.0)$; (iv) "S&W factors" denotes whether a series was used in Stock and Watson (2012a) when constructing factors (i.e., 1 is yes and 0 is no); (v) "FRED® mnemonic" denotes the mnemonic we use for the dataset; (vi) "S&W mnemonic" denotes the mnemonic used in Stock and Watson (2012a); and (vii) "Description" gives a brief definition of the series. The series are loosely grouped based on Stock and Watson (2012a).

Details on construction of the data will be forthcoming, but a few general comments are in order. First, if the FRED® mnemonic does not end in "x," then the series comes directly from the FRED® data service (e.g., PCECC96 is real PCE). Otherwise, the series is a modified variant of a series from FRED® (e.g., PCDGx is nominal PCE durables, which is manually deflated using the PCE price index). The exception to this rule is the S&P data, which is taken from public sources. Lastly, monthly frequency series are aggregated to a quarterly frequency using averages.

Table A1A

Group 1: NIPA

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	1	1	5	0	GDPC1	GDP	Real GDP, 3 decimal (billions of chained 2012 dollars)
2	2	2	5	0	PCECC96	Consumption	Real PCE (billions of chained 2012 dollars)
3	3	3	5	1	PCDGx	Cons:Dur	Real PCE expenditures: durable goods (billions of chained 2012 dollars), deflated using PCE
4	4	4	5	1	PCESVx	Cons:Svc	Real PCE: services (billions of 2012 dollars), deflated using PCE
5	5	5	5	1	PCNDx	Cons:NonDur	Real PCE: nondurable goods (billions of 2012 dollars), deflated using PCE
6	6	6	5	0	GPDIC1	Investment	Real gross private domestic investment, 3 decimal (billions of chained 2012 dollars)
7	7	7	5	0	FPIx	FixedInv	Real private fixed investment (billions of chained 2012 dollars), deflated using PCE
8	8	8	5	1	Y033RC1Q027SBEAx	Inv:Equip&Software	Real gross private domestic investment: fixed investment: nonresidential: equipment (billions of chained 2012 dollars), deflated using PCE
9	9	9	5	1	PNFIx	FixInv:NonRes	Real private fixed investment: nonresidential (billions of chained 2012 dollars), deflated using PCE
10	10	10	5	1	PRFIx	FixedInv:Res	Real private fixed investment: residential (billions of chained 2012 dollars), deflated using PCE
11	11	11	1	1	A014RE1Q156NBEA	Inv:Inventories	Shares of GDP: gross private domestic invest-ment: change in private inventories (percent)
12	12	12	5	0	GCEC1	Gov.Spending	Real government consumption expenditures and gross investment (billions of chained 2012 dollars)
13	13	13	1	1	A823RL1Q225SBEA	Gov:Fed	Real government consumption expenditures and gross investment: federal (percent change from preceding period)
14	14	14	5	1	FGRECPTx	Real Gov Receipts	Real federal government current receipts (billions of chained 2012 dollars), deflated using PCE
15	15	15	5	1	SLCEx	Gov:State&Local	Real government state and local consumption expenditures (billions of chained 2012 dollars), deflated using PCE
16	16	16	5	1	EXPGSC1	Exports	Real exports of goods and services, 3 decimal (billions of chained 2012 dollars)
17	17	17	5	1	IMPGSC1	Imports	Real imports of goods and services, 3 decimal (billions of chained 2012 dollars)
18	18	18	5	0	DPIC96	Disp-Income	Real disposable personal income (billions of chained 2012 dollars)
19	19	19	5	0	OUTNFB	Ouput:NFB	Nonfarm business sector: real output (index: 2009 = 100)
20	20	20	5	0	OUTBS	Output:Bus	Business sector: real output (index: 2009 = 100)
21	21	21	5	0	OUTMS	Output:Manuf	Manufacturing sector: real output (index: 2009 = 100)
22	190	NA	2	0	B020RE1Q156NBEA		Shares of GDP: exports of goods and services (percent)
23	191	NA	2	0	B021RE1Q156NBEA		Shares of GDP: imports of goods and services (percent)

Table A1B

Group 2: Industrial Production (IP)

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	22	22	5	0	INDPRO	IP:Total index	IP index (index: 2012 = 100)
2	23	23	5	0	IPFINAL	IP:Final products	IP: final products (market group) (index: 2012 = 100)
3	24	24	5	0	IPCONGD	IP:Consumer goods	IP: consumer goods (index: 2012 = 100)
4	25	25	5	0	IPMAT	IP:Materials	IP: materials (index: 2012 = 100)
5	26	26	5	1	IPDMAT	IP:Dur gds materials	IP: durable materials (index: 2012 = 100)
6	27	27	5	1	IPNMAT	IP:Nondur gds materials	IP: nondurable goods materials (index: 2012 = 100)
7	28	28	5	1	IPDCONGD	IP:Dur Cons. Goods	IP: durable consumer goods (index: 2012 = 100)
8	29	29	5	1	IPB51110SQ	IP:Auto	IP: auto (index: 2012 = 100)
9	30	30	5	1	IPNCONGD	IP:NonDur Cons God	IP: nondurable consumer goods (index: 2012 = 100)
10	31	31	5	1	IPBUSEQ	IP:Bus Equip	IP: business equipment (index: 2012 = 100)
11	32	32	5	1	IPB51220SQ	IP:Energy Prds	IP: energy products (index: 2012 = 100)
12	33	33	1	1	TCU	Capu Tot	Capacity utilization: total industry (SIC) (percent of capacity)
13	34	34	1	1	CUMFNS	Capu Man.	Capacity utilization: manufacturing (SIC) (percent of capacity)
14	194	NA	5	0			IP: manufacturing (SIC) (index: 2012 = 100)
15	195	NA	5	0			IP: residential utilities (index: 2012 = 100)
16	196	NA	5	0			IP: fuels (index: 2012 = 100)

Table A1C

Group 3: Employment and Unemployment

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	35	35	5	0	PAYEMS	Emp:Nonfarm	All employees: total nonfarm (thousands of persons)
2	36	36	5	0	USPRIV	Emp:Private	All employees: total private industries (thousands of persons)
3	37	37	5	0	MANEMP	Emp:mfg	All employees: manufacturing (thousands of persons)
4	38	38	5	0	SRVPRD	Emp:Services	All employees: service-providing industries (thousands of persons)
5	39	39	5	0	USGOOD	Emp:Goods	All employees: goods-producing industries (thousands of persons)
6	40	40	5	1	DMANEMP	Emp:DurGoods	All employees: durable goods (thousands of persons)
7	41	41	5	0	NDMANEMP	Emp:Nondur Goods	All employees: nondurable goods (thousands of persons)
8	42	42	5	1	USCONS	Emp:Const	All employees: construction (thousands of persons)
9	43	43	5	1	USEHS	Emp:Edu&Health	All employees: education and health services (thousands of persons)
10	44	44	5	1	USFIRE	Emp:Finance	All employees: financial activities (thousands of persons)
11	45	45	5	1	USINFO	Emp:Infor	All employees: information services (thousands of persons)
12	46	46	5	1	USPBS	Emp:Bus Serv	All employees: professional and business services (thousands of persons)
13	47	47	5	1	USLAH	Emp:Leisure	All employees: leisure and hospitality (thousands of persons)
14	48	48	5	1	USSERV	Emp:OtherSvcs	All employees: other services (thousands of persons)
15	49	49	5	1	USMINE	Emp:Mining/NatRes	All employees: mining and logging (thousands of persons)
16	50	50	5	1	USTPU	Emp:Trade&Trans	All employees: trade, transportation, and utilities (thousands of persons)
17	51	51	5	0	USGOVT	Emp:Gov	All employees: government (thousands of persons)
18	52	52	5	1	USTRADE	Emp:Retail	All employees: retail trade (thousands of persons)
19	53	53	5	1	USWTRADE	Emp:Wholesal	All employees: wholesale trade (thousands of persons)
20	54	54	5	1	CES9091000001	Emp:Gov(Fed)	All employees: government: federal (thousands of persons)
21	55	55	5	1	CES9092000001	Emp:Gov (State)	All employees: government: state government (thousands of persons)
22	56	56	5	1	CES9093000001	Emp:Gov (Local)	All employees: government: local government (thousands of persons)
23	57	57	5	0	CE16OV	Emp:Total (HHSurve)	Civilian employment (thousands of persons)
24	58	58	2	0	CIVPART	LF Part Rate	Civilian labor force participation rate (percent)
25	59	59	2	0	UNRATE	Unemp Rate	Civilian unemployment rate (percent)

Continued on next page

Table A1C, cont'd

Group 3: Employment and Unemployment

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
26	60	60	2	0	UNRATESTx	Urate_ST	Unemployment rate for less than 27 weeks of unemployment (percent)
27	61	61	2	0	UNRATELTx	Urate_LT	Unemployment rate for more than 27 weeks of unemployment (percent)
28	62	62	2	1	LNS14000012	Urate:Age16-19	Unemployment rate: ages 16 to 19 (percent)
29	63	63	2	1	LNS14000025	Urate:Age>20 Men	Unemployment rate: age 20 and over, men (percent)
30	64	64	2	1	LNS14000026	Urate:Age>20 Women	Unemployment rate: age 20 and over, women (percent)
31	65	65	5	1	UEMPLT5	U:Dur<5wks	Number of civilians unemployed less than 5 weeks (thousands of persons)
32	66	66	5	1	UEMP5TO14	U:Dur5-14wks	Number of civilians unemployed 5 to 14 weeks (thousands of persons)
33	67	67	5	1	UEMP15T26	U:dur>15-26wks	Number of civilians unemployed 15 to 26 weeks (thousands of persons)
34	68	68	5	1	UEMP27OV	U:Dur>27wks	Number of civilians unemployed 27 weeks or over (thousands of persons)
35	69	69	5	1	LNS13023621	U:Job losers	Unemployment level: job losers (thousands of persons)
36	70	70	5	1	LNS13023557	U:LF Reenty	Unemployment level: reentrants to labor force (thousands of persons)
37	71	71	5	1	LNS13023705	U:Job Leavers	Unemployment level: job leavers (thousands of persons)
38	72	72	5	1	LNS13023569	U:New Entrants	Unemployment level: new entrants (thousands of persons)
39	73	73	5	1	LNS12032194	Emp:SlackWk	Employment level: part-time for economic reasons, all industries (thousands of persons)
40	74	74	5	0	HOABS	EmpHrs:Bus Sec	Business sector: hours of all persons (index: 2009 = 100)
41	75	75	5	0	HOAMS	EmpHrs:mfg	Manufacturing sector: hours of all persons (index: 2009 = 100)
42	76	76	5	0	HOANBS	EmpHrs:nfb	Nonfarm business sector: hours of all persons (index: 2009 = 100)
43	77	77	1	1	AWHMAN	AWH Man	Average weekly hours of production and non-supervisory employees: manufacturing (hours)
44	78	78	2	1	AWHNONAG	AWH Privat	Average weekly hours of production and non-supervisory employees: total private (hours)
45	79	79	2	1	AWOTMAN	AWH Overtime	Average weekly overtime hours of production and nonsupervisory employees: manufacturing (hours)
46	80	80	1	0	HWIx	HelpWnted	Help-wanted index
47	197	NA	2	0	UEMPMEAN		Average (mean) duration of unemployment (weeks)
48	198	NA	2	0	CES0600000007		Average weekly hours of production and non-supervisory employees: goods producing
49	220	NA	2	0	HWIURATIOx		Ratio of help wanted to number unemployed
50	221	NA	5	0	CLAIMSx		Initial claims

Table A1D

Group 4: Housing

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	81	81	5	0	HOUST	Hstarts	Housing starts: total: new privately owned housing units started (thousands of units)
2	82	82	5	0	HOUST5F	Hstarts >5units	Privately owned housing starts: 5-unit structures or more (thousands of units)
3	83	83	5	1	PERMIT	Hpermits	New private housing units authorized by building permits (thousands of units)
4	84	84	5	1	HOUSTMW	Hstarts:MW	Housing starts in Midwest census region (thousands of units)
5	85	85	5	1	HOUSTNE	Hstarts:NE	Housing starts in Northeast census region (thousands of units)
6	86	86	5	1	HOUSTS	Hstarts:S	Housing starts in South census region (thousands of units)
7	87	87	5	1	HOUSTW	Hstarts:W	Housing starts in West census region (thousands of units)
8	179	190	5	1	USSTHPI	Real Hprice:OFHEO	All-transactions house price index for the United States (index: 1980:Q1 = 100)
9	180	191	5	1	SPCS10RSA	Real CS_10	S&P/Case-Shiller 10-City Composite Home Price Index (index: January 2000 = 100)
10	181	192	5	1	SPCS20RSA	Real CS_20	S&P/Case-Shiller 20-City Composite Home Price Index (index: January 2000 = 100)
11	227	NA	5	0	PERMITNE		New private housing units authorized by building permits in the Northeast census region (thousands, SAAR)
12	228	NA	5	0	PERMITMW		New private housing units authorized by building permits in the Midwest census region (thousands, SAAR)
13	229	NA	5	0	PERMITS		New private housing units authorized by building permits in the South census region (thousands, SAAR)
14	230	NA	5	0	PERMITW		New private housing units authorized by building permits in the West census region (thousands, SAAR)

NOTE: SAAR, seasonally adjusted annual rate.

Table A1E

Group 5: Inventories, Orders, and Sales

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	88	89	5	0	CMRMTSPLx	MT Sales	Real manufacturing and trade industries sales (millions of chained 2012 dollars)
2	89	90	5	1	RSAFSx	Ret. Sale	Real retail and food services sales (millions of chained 2012 dollars), deflated by core PCE
3	90	91	5	1	AMDMNOx	Orders(DurMfg)	Real manufacturers' new orders: durable goods (millions of 2012 dollars), deflated by core PCE
4	91	92	5	1	ACOGNOx	Orders(Cons Goods/Mat.)	Real value of manufacturers' new orders for consumer goods industries (millions of 2012 dollars), deflated by core PCE
5	92	93	5	1	AMDMUOx	UnfOrders(DurGds)	Real value of manufacturers' unfilled orders for durable goods industries (millions of 2012 dollars), deflated by core PCE
6	93	94	5	1	ANDENOx	Orders(NonDefCap)	Real value of manufacturers' new orders for capital goods: nondefense capital goods industries (millions of 2012 dollars), deflated by core PCE
7	94	96	5	1	INVCQRMTSPL	MT Invent	Real manufacturing and trade inventories (millions of 2012 dollars)
8	222	NA	5	0	BUSINVx		Total business inventories (millions of dollars)
9	223	NA	2	0	ISRATIOx		Total business: inventories-to-sales ratio

Table A1F

Group 6: Prices

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	95	97	6	0	PCECTPI	PCED	PCE: chain-type price index (index: 2009 = 100)
2	96	98	6	0	PCEPILFE	PCED_LFE	PCE excluding food and energy (chain-type price index) (index: 2009 = 100)
3	97	99	6	0	GDPCTPI	GDP Defl	GDP: chain-type price index (index: 2009 = 100)
4	98	100	6	1	GPDICTPI	GPDI Defl	Gross private domestic investment: chain-type price index (index: 2009 = 100)
5	99	101	6	1	IPDBS	BusSec Defl	Business sector: implicit price deflator (index: 2009 = 100)
6	100	102	6	0	DGDSRG3Q086SBEA	PCED_Goods	PCE: goods (chain-type price index)
7	101	103	6	0	DDURRG3Q086SBEA	PCED_DurGoods	PCE: durable goods (chain-type price index)
8	102	104	6	0	DSERRG3Q086SBEA	PCED_Serv	PCE: services (chain-type price index)
9	103	105	6	0	DNDGRG3Q086SBEA	PCED_NDurGoods	PCE: Nondurable goods (chain-type price index)
10	104	106	6	0	DHCERG3Q086SBEA	PCED_ HouseholdServ.	PCE: services: household consumption expenditures (chain-type price index)
11	105	107	6	1	DMOTRG3Q086SBEA	PCED_MotorVec	PCE: durable goods: motor vehicles and parts (chain-type price index)
12	106	108	6	1	DFDHRG3Q086SBEA	PCED_DurHousehold	PCE: durable goods: furnishings and durable household equipment (chain-type price index)
13	107	109	6	1	DREQRG3Q086SBEA	PCED_Recreation	PCE: durable goods: recreational goods and vehicles (chain-type price index)
14	108	110	6	1	DODGRG3Q086SBEA	PCED_OthDurGds	PCE: durable goods: other durable goods (chain-type price index)
15	109	111	6	1	DFXARG3Q086SBEA	PCED_Food_Bev	PCE: nondurable goods: food and beverages purchased for off-premises consumption (chain-type price index)
16	110	112	6	1	DCLORG3Q086SBEA	PCED_Clothing	PCE: nondurable goods: clothing and footwear (chain-type price index)
17	111	113	6	1	DGOERG3Q086SBEA	PCED_Gas_Enrgy	PCE: nondurable goods: gasoline and other energy goods (chain-type price index)
18	112	114	6	1	DONGRG3Q086SBEA	PCED_OthNDurGds	PCE: nondurable goods: other nondurable goods (chain-type price index)
19	113	115	6	1	DHUTRG3Q086SBEA	PCED_Housing-Utilities	PCE: services: housing and utilities (chain-type price index)
20	114	116	6	1	DHLCRG3Q086SBEA	PCED_HealthCare	PCE: services: health care (chain-type price index)
21	115	117	6	1	DTRSRG3Q086SBEA	PCED_TransSvg	PCE: transportation services (chain-type price index)
22	116	118	6	1	DRCARG3Q086SBEA	PCED_RecServices	PCE: recreation services (chain-type price index)
23	117	119	6	1	DFSARG3Q086SBEA	PCED_FoodServ_ Acc.	PCE: services: food services and accommoda-tions (chain-type price index)
24	118	120	6	1	DIFSRG3Q086SBEA	PCED_FIRE	PCE: financial services and insurance (chain-type price index)
25	119	121	6	1	DOTSRG3Q086SBEA	PCED_OtherServices	PCE: other services (chain-type price index)

Continued on next page

Table A1F, cont'd

Group 6: Prices

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
26	120	122	6	0	CPIAUCSL	CPI	CPI for all urban consumers: all items (index: 1982-84=100)
27	121	123	6	0	CPILFESL	CPI_LFE	CPI for all urban consumers: all items less food and energy (index: 1982-84 = 100)
28	122	124	6	0	WPSFD49207	PPI:FinGds	PPI by commodity for finished goods (index: 1982 = 100)
29	123	125	6	0	PPIACO	PPI	PPI for all commodities (index: 1982 = 100)
30	124	126	6	1	WPSFD49502	PPI:FinConsGds	PPI by commodity for finished consumer goods (index: 1982 = 100)
31	125	127	6	1	WPSFD4111	PPI:FinConsGds (Food)	PPI by commodity for finished consumer foods (index: 1982 = 100)
32	126	128	6	1	PPIIDC	PPI:IndCom	PPI by commodity industrial commodities (index: 1982 = 100)
33	127	129	6	1	WPSID61	PPI:IntMat	PPI by commodity intermediate materials: supplies and components (index: 1982 = 100)
34	128	133	5	1	WPU0531	Real Price:NatGas	PPI by commodity for fuels and related products and power: natural gas (Index: 1982 = 100)
35	129	134	5	1	WPU0561	Real Price:Oil	PPI by commodity for fuels and related products and power: crude petroleum (domestic production) (index: 1982 = 100)
36	130	135	5	0	OILPRICEx	Real Crudeoil Price	Real crude oil prices: West Texas Intermediate (WTI) Cushing, Oklahoma (2012 dollars per barrel), deflated by core PCE
37	205	NA	6	0	WPSID62		PPI: Crude materials for further processing (index: 1982 = 100)
38	206	NA	6	0	PPICMM		PPI: Commodities: metals and metal products: primary nonferrous metals (index: 1982 = 100)
39	207	NA	6	0	CPIAPPSL		CPI for all urban consumers: apparel (index: 1982-84 = 100)
40	208	NA	6	0	CPITRNSL		CPI for all urban consumers: transportation (index: 1982-84 = 100)
41	209	NA	6	0	CPIMEDSL		CPI for all urban consumers: medical care (index: 1982-84 = 100)
42	210	NA	6	0	CUSR0000SAC		CPI for all urban consumers: commodities (index: 1982-84 = 100)
43	211	NA	6	0	CUSR0000SAD		CPI for all urban consumers: durables (index: 1982-84=100)
44	212	NA	6	0	CUSR0000SAS		CPI for all urban consumers: services (index: 1982-84=100)
45	213	NA	6	0	CPIULFSL		CPI for all urban consumers: all items less food (index: 1982-84 = 100)
46	214	NA	6	0	CUSR0000SA0L2		CPI for all urban consumers: all items less shelter (index: 1982-84 = 100)
47	215	NA	6	0	CUSR0000SA0L5		CPI for all urban consumers: all items less medical care (index: 1982-84 = 100)
48	233	NA	6	0	CUSR0000SEHC		CPI for all urban consumers: owners' equivalent rent of residences (index: December 1982 = 100)

Table A1G

Group 7: Earning and Productivity

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	131	136	5	0	AHETPIx	Real AHE:PrivInd	Real average hourly earnings of production and nonsupervisory employees: total private (2012 dollars per hour), deflated by core PCE
2	132	137	5	0	CES2000000008x	Real AHE:Const	Real average hourly earnings of production and nonsupervisory employees: construction (2012 dollars per hour), deflated by core PCE
3	133	138	5	0	CES3000000008x	Real AHE:MFG	Real average hourly earnings of production and nonsupervisory employees: manufacturing (2012 dollars per hour), deflated by core PCE
4	134	139	5	1	COMPRMS	CPH:Mfg	Manufacturing sector: real compensation per hour (index: 2012 = 100)
5	135	140	5	1	COMPRNFB	CPH:NFB	Nonfarm business sector: real compensation per hour (index: 2012 = 100)
6	136	141	5	1	RCPHBS	CPH:Bus	Business sector: real compensation per hour (index: 2012 = 100)
7	137	142	5	1	OPHMFG	OPH:mfg	Manufacturing sector: real output per hour of all persons (index: 2012 = 100)
8	138	143	5	1	OPHNFB	OPH:nfb	Nonfarm business sector: real output per hour of all persons (index: 2012 = 100)
9	139	144	5	0	OPHPBS	OPH:Bus	Business sector: real output per hour of all persons (index: 2012 = 100)
10	140	145	5	0	ULCBS	ULC:Bus	Business sector: unit labor cost (index: 2012 = 100)
11	141	146	5	1	ULCMFG	ULC:Mfg	Manufacturing sector: unit labor cost (index: 2012 = 100)
12	142	147	5	1	ULCNFB	ULC:NFB	Nonfarm business sector: unit labor cost (index: 2012=100)
13	143	148	5	1	UNLPNBS	UNLPay:nfb	Nonfarm business sector: unit nonlabor payments (index: 2012 = 100)
14	216	NA	6	0	CES0600000008		Average hourly earnings of production and nonsupervisory employees: goods producing (dollars per hour)

Table A1H

Group 8: Interest Rates

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	144	149	2	1	FEDFUNDS	FedFunds	Effective federal funds rate (percent)
2	145	150	2	1	TB3MS	TB-3Mth	3-Month Treasury bill (T-bill): secondary market rate (percent)
3	146	151	2	0	TB6MS	TM-6MTH	6-Month T-bill: secondary market rate (percent)
4	147	153	2	0	GS1	TB-1YR	1-Year Treasury constant maturity rate (percent)
5	148	154	2	0	GS10	TB-10YR	10-Year Treasury constant maturity rate (percent)
6	149	155	2	0	MORTGAGE30US	Mort-30Yr	30-Year conventional mortgage rate (percent)
7	150	156	2	0	AAA	AAA Bond	Moody's Seasoned Aaa Corporate Bond Yield© (percent)
8	151	157	2	0	BAA	BAA Bond	Moody's Seasoned Baa Corporate Bond Yield© (percent)
9	152	158	1	1	BAA10YM	BAA_GS10	Moody's Seasoned Baa Corporate Bond Yield relative to yield on 10-year Treasury constant maturity (percent)
10	153	159	1	1	MORTG10YRx	MRTG_GS10	30-Year conventional mortgage rate relative to 10-year Treasury constant maturity (percent)
11	154	160	1	1	TB6M3Mx	tb6m_tb3m	6-Month T-bill minus 3-month T-bill, secondary market (percent)
12	155	161	1	1	GS1TB3Mx	GS1_tb3m	1-Year Treasury constant maturity minus 3-month T-bill, secondary market (percent)
13	156	162	1	1	GS10TB3Mx	GS10_tb3m	10-Year Treasury constant maturity minus 3-month T-bill, secondary market (percent)
14	157	163	1	1	CPF3MTB3Mx	CP_Tbill Spread	3-Month commercial paper minus 3-month T-bill, secondary market (percent)
15	201	NA	2	0	GS5		5-Year Treasury constant maturity rate
16	202	NA	1	0	TB3SMFFM		3-Month Treasury constant maturity minus federal funds rate
17	203	NA	1	0	T5YFFM		5-Year Treasury constant maturity minus federal funds rate
18	204	NA	1	0	AAAFFM		Moody's Seasoned Aaa Corporate Bond minus federal funds rate
19	225	NA	2	0	CP3M		3-Month AA financial commercial paper rate
20	226	NA	1	0	COMPAPFF		3-Month commercial paper minus federal funds rate

Table A1I

Group 9: Money and Credit

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	158	167	5	0	AMBSLREAL	Real Mbase	St. Louis adjusted monetary base (millions of 1982-84 dollars), deflated by CPI
2	159	168	5	0	IMFSLx	Real InsMMF	Real institutional money funds (billions of 2012 dollars), deflated by core PCE
3	160	169	5	0	M1REAL	Real m1	Real M1 money stock (billions of 1982-84 dollars), deflated by CPI
4	161	170	5	0	M2REAL	Real m2	Real M2 money stock (billions of 1982-84 dollars), deflated by CPI
5	162	171	5	0	MZMREAL	Real mzm	Real MZM money stock (billions of 1982-84 dollars), deflated by CPI
6	163	172	5	1	BUSLOANSx	Real C&Lloand	Real commercial and industrial loans, all commercial banks (billions of 2012 dollars), deflated by core PCE
7	164	173	5	1	CONSUMERx	Real ConsLoans	Real consumer loans at all commercial banks (billions of 2012 dollars), deflated by core PCE
8	165	174	5	1	NONREVSLx	Real NonRevCredit	Total real nonrevolving credit owned and securitized, outstanding (billions of 2012 dollars), deflated by core PCE
9	166	175	5	1	REALLNx	Real LoansRealEst	Real real estate loans, all commercial banks (billions of 2012 dollars), deflated by core PCE
10	167	176	5	1	REVOLSLx	Real RevolvCredit	Total real revolving credit owned and securitized, outstanding (billions of 2012 dollars), deflated by core PCE
11	168	177	5	0	TOTALSLx	Real ConsuCred	Total consumer credit outstanding (billions of 2012 dollars), deflated by core PCE
12	169	178	1	1	DRIWCIL	FRBSLO_Consumers	Federal Reserve Bank Senior Loans Officer Opinion Survey: net percentage of domestic respondents reporting increased willingness to make consumer installment loans
13	199	NA	6	0	TOTRESNS		Total reserves of depository institutions (billions of dollars)
14	200	NA	7	0	NONBORRES		Reserves of depository institutions, nonborrowed (millions of dollars)
15	217	NA	6	0	DTCOLNVHFNM		Consumer motor vehicle loans outstanding owned by finance companies (millions of dollars)
16	218	NA	6	0	DTCTHFNM		Total consumer loans and leases outstanding owned and securitized by finance companies (millions of dollars)
17	219	NA	6	0	INVEST		Securities in bank credit at all commercial banks (billions of dollars)

Table A1J

Group 10: Household Balance Sheets

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	170	179	5	0	TABSHNOx	Real HHW:TASA	Real total assets of households and nonprofit organizations (billions of 2012 dollars), deflated by core PCE
2	171	181	5	1	TLBSHNOx	Real HHW:LiabSA	Real total liabilities of households and non-profit organizations (billions of 2012 dollars), deflated by core PCE
3	172	182	5	0	LIABPIx	liab_PDISA	Liabilities of households and nonprofit organizations relative to personal disposable income (percent)
4	173	183	5	1	TNWBSHNOx	Real HHW:WSA	Real net worth of households and nonprofit organizations (billions of 2012 dollars), deflated by core PCE
5	174	184	1	0	NWPIx	W_PDISA	Net worth of households and nonprofit organizations relative to disposable personal income (percent)
6	175	185	5	1	TARESAx	Real HHW:TA_RESA	Real assets of households and nonprofit organizations excluding real estate assets (billions of 2012 dollars), deflated by core PCE
7	176	186	5	1	HNOREMQ027Sx	Real HHW:RESA	Real estate assets of households and nonprofit organizations (billions of 2012 dollars), deflated by core PCE
8	177	188	5	1	TFAABSHNOx	Real HHW:FinSA	Real total financial assets of households and nonprofit organizations (billions of 2012 dollars), deflated by core PCE
9	224	NA	2	0	CONSPIx		Nonrevolving consumer credit to personal income

Table A1K

Group 11: Exchange Rates

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	182	193	5	1	TWEXMMTH	Ex rate:major	Trade weighted U.S. dollar index: major currencies (index: March 1973 = 100)
2	183	194	5	1	EXUSEU	Ex rate:Euro	U.S./euro foreign exchange rate (U.S. dollars to one euro)
3	184	195	5	1	EXSZUSx	Ex rate:Switz	Switzerland/U.S. foreign exchange rate
4	185	196	5	1	EXJPUSx	Ex rate:Japan	Japan/U.S. foreign exchange rate
5	186	197	5	1	EXUSUKx	Ex rate:UK	U.S./U.K. foreign exchange rate
6	187	198	5	1	EXCAUSx	EX rate:Canada	Canada/U.S. foreign exchange rate

Table A1L

Group 12: Other

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	188	199	1	1	UMCSENTx	Cons. Expectations	University of Michigan: Consumer Sentiment (Index 1966:Q1 = 100)
2	189	200	2	1	USEPUINDXM	PolicyUncertainty	Economic Policy Uncertainty Index for United States

Table A1M

Group 13: Stock Markets

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	178	189	1	1	VXOCLSx	VXO	CBOE S&P 100 Volatility Index: VXO
2	231	NA	5	0	NIKKEI225		Nikkei stock average
3	232	NA	5	0	NASDAQCOM		NASDAQ composite (index: Feb. 5, 1971 = 100)
4	245	180	5	0	S&P 500		S&P's Common Stock Price Index: composite
5	246	NA	5	0	S&P: indust		S&P's Common Stock Price Index: industrials
6	247	NA	2	0	S&P div yield		S&P's composite common stock: dividend yield
7	248	NA	5	0	S&P PE ratio		S&P's composite common stock: price-earnings ratio

Table A1N

Group 14: Non-Household Balance Sheets

Number	ID #	S&W ID #	TCODE	S&W factors	FRED® mnemonic	S&W mnemonic	Description
1	192	NA	2	0	GFDEGDQ188S		Federal debt: total public debt as percent of GDP (percent)
2	193	NA	2	0	GFDEBTNx		Real federal debt: total public debt (millions of 2012 dollars), deflated by PCE
3	234	NA	5	0	TLBSNNCBx		Real nonfinancial corporate business sector liabilities (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
4	235	NA	1	0	TLBSNNCBBDIx		Nonfinancial corporate business sector liabilities to disposable business income (percent)
5	236	NA	5	0	TTAABSNNCBx		Real nonfinancial corporate business sector assets (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
6	237	NA	5	0	TNWMVBSNNCBx		Real nonfinancial corporate business sector net worth (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
7	238	NA	2	0	TNWMVBSNNCBBDIx		Nonfinancial corporate business sector net worth to disposable business income (percent)
8	239	NA	5	0	TLBSNNBx		Real nonfinancial noncorporate business sector liabilities (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
9	240	NA	1	0	TLBSNNBBDIx		Nonfinancial noncorporate business sector liabilities to disposable business income (percent)
10	241	NA	5	0	TABSNNBx		Real nonfinancial noncorporate business sector assets (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
11	242	NA	5	0	TNWBSNNBx		Real nonfinancial noncorporate business sector net worth (billions of 2012 dollars), deflated by implicit price deflator for business sector IPDBS
12	243	NA	2	0	TNWBSNNBBDIx		Nonfinancial noncorporate business sector net worth to disposable business income (percent)
13	244	NA	5	0	CNCFx		Real disposable business income, billions of 2012 dollars (corporate cash flow with IVA minus taxes on corporate income, deflated by implicit price deflator for business sector IPDBS)

NOTES

[1] FRED-QD does not contain 10 series that are in the original S&W dataset. Using the S&W numbering system, these are #88 (construction contracts), #130 (index of sensitive materials prices), #131 (spot market price index of commodities), #165 and #166 (measures of credit spreads and excess bond premia, respectively, developed in Gilchrist and Zakrajsek, 2012), #95 and #132 (ISM index of supplier deliveries and ISM commodity price index, respectively), #152 and #164 (3-month eurodollar deposit rate and its spread with a 3-month T-bill, respectively), and #187 (Dow Jones industrials index). In all but two cases, these are series not available in FRED®. Three-month eurodollar deposit rates are in FRED® but are not updated on a regular basis because the source (i.e., the Organisation for Economic Co-operation and Development) does not update them regularly. The last of these, #187, has been replaced with the S&P 500 Industrials Index.

[2] Throughout we focus on factors that are $I(0)$. In contrast, Choi and Jeong (2020) provide theoretical and empirical results comparing the forecast accuracy of factors when one has the opportunity to construct them so that they are either $I(0)$ or . $I(1)$ In the context of autoregressive models, Diebold and Kilian (2000) provide simulation evidence on a similar issue.

[3] The S&P price-to-earnings (PE) ratio and dividend yield are taken from Robert Shiller's website: http://www.econ.yale.edu/~shiller/data.htm. These series are updated less consistently than the other series in the dataset. In some idiosyncratic cases, these may be missing for a longer sequence of vintages.

[4] The data are currently posted on Mark Watson's website: https://www.princeton.edu/~mwatson/publi.html.

[5] See Section 4 for further discussion.

[6] The dominant factors are almost identical when the missing values are imputed using the method in Bai and Ng (2019a).

[7] The factors have been multiplied by –1 where necessary to make the two estimates positively correlated.

[8] These differ from the concept of an influential observation. An observation is influential if its inclusion substantially changes the parameter estimates. See Chatterjee and Hadi (1986) and Rousseeuw and Zomeren (1990).

[9] For the S&W data, these are REVOLSL, WPU0561, PPIDC, PPITM, CES9091000001, and CONSUMER. For the subset of FRED-QD data, PPITM is replaced by WPSID61.

[10] The dates associated with these outliers, many of which are recessions, also makes the exogeneity of these events questionable.

[11] In unreported results we chose lag lengths based on the sequential *t*-test (Seq.t), as described in Ng and Perron (1995). The results were very similar to those for the MAIC, and hence we do not report them, for brevity.

[12] We omit nonborrowed reserves from these figures because it is the only series with transformation code 7. This code exists because nonborrowed reserves, which should be positive, turned negative during the Financial Crisis. This precludes the use of transformation code 5.

[13] In part we focus on the SIC-based factors because of our intuition on what some transformations "should" be. For example, MAIC-based tests recommend treating real GDP as $I(2)$ in log levels. This does not strike us as reasonable.

[14] In unreported work, we also considered a weaker 10 percent level of significance. For several of the variables, nearly all of the models were included in the model confidence set despite, what appeared to be, substantial differences in mean-squared errors.

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