Toulouse School of Economics

M2 EEE Machine Learning

Final Project

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1 Introduction

Four dimension reduction devices: (1) Principal Component Analysis, (2) Ridge Regression, (3) Landweber Fridman (LF) regularization, (4) Partial least squares. Each involves a regularization or tuning parameter that is selected through genearlized cross validation (GCV).

Take two different data generating processes, (1) The eigenvalues of $\frac{X'X}{T}$ are bounded and decline to zero gradually. (2) Popular factor model with a finite number, r, of factors. Here, the r largest eigenvalues grow with N, while the remaining are bounded. In both cases, $\frac{X'X}{T}$ is ill-conditioned, which means the ratio of the largest to smallest eigenvalue diverges, and a regularization terms is needed to invert the matrix.

2 Data Generating Process

Large Sample Case: $N = 200$ and $T = 500$ Small Sample Case: $N = 100$ and $T = 50$

$$\underbrace{x_t}_{(N\times 1)} = \underbrace{\Lambda}_{(N\times r)} \underbrace{F_t}_{(r\times 1)} + \underbrace{\xi_t}_{(N\times 1)}$$

$$\underbrace{y_t}_{(1\times 1)} = \underbrace{\theta'}_{(1\times r)} \underbrace{F_t}_{(r\times 1)} + \underbrace{\nu_t}_{(1\times 1)}$$

$$\underbrace{y}_{(T\times 1)} = \underbrace{F}_{(T\times r)} \underbrace{\theta}_{(r\times 1)} + \underbrace{\nu}_{(T\times 1)}$$

$$\underbrace{X}_{(T\times N)} = \underbrace{F}_{(T\times r)} \underbrace{\Lambda'}_{(r\times N)} + \underbrace{\xi}_{(T\times N)}$$

DGP 1 (Few Factors Structure): θ is the $(r \times 1)$ vector of ones, $r = 4$ and $r_{max} = r+10$

DGP 2 (Many Factors Structure): θ is the $(r \times 1)$ vector of ones, $r = 50$ and $r_{max} = min(N, \frac{T}{2})$

DGP 3 (Five Factors but only One Relevant): $\theta = (1, 0_{1\times 4})$, $r = 5$ and $r_{max} = min(r + 10, min(N, \frac{T}{2}))$

$$F = [F_1, F_2']' \text{ and } F \times F' = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 3 & 0 \\ 0 & 0 & 0 & 0 & 4 \end{bmatrix}$$

$y = \hat{F}\theta + \nu$ where $\hat{F}$ is generated from X equation in DGP 3, and $\sigma_\nu = 0.1$

DGP 4 (x_t Has a Factor Structure but Unrelated to y_t):

θ is a vector of zeros with dimension $(r \times 1)$. $r = 5$, $r_{max} = r + 10$. $F \times F'$ is defined as in DGP 3.

DGP 5 (Eigenvalues Declining Slowly):

θ is an $(N \times 1)$ vector of ones. $r = N$, $r_{max} = min(N, \frac{T}{2}$.

$\Lambda = M \odot \xi$, with $\xi \sim (N \times N)$ matrix of $iidN(0, 1)$

$$M \sim (N \times N) = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \frac{1}{2} & \frac{1}{2} & \cdots & \frac{1}{2} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \end{bmatrix}$$

DGP 6 (Near Factor Model):

$\theta = 1$, $r = 1$, $r_{max} = r + 10$, $\Lambda' = \frac{1}{\sqrt{N}} 1_{r \times N}$

Estimation:

Set 1: Bai-Ng, PCA, PLS, Ridge, LF, LASSO Set 2: GCV, Mallows, AIC, BIC Set 3: Small Sample, Large Sample

Parameter Iteration (For Later) Simulation (Andy) Model Estimation (Jacob) Evaluation (Jacob) Output (Andy)

3 Estimation Methods

Ridge Estimator:

$$\widehat{y} = M_T^{\alpha} y = X(S_{xx} + \alpha I)^{-1} S_{xy}$$

LF Estimator:

$$\widehat{y} = M_T^{\alpha} y = X \sum_{j=1}^{\min(N,T)} \frac{\left(1 - \left(1 - d\widehat{\lambda}_j^2\right)^{1/\alpha}\right)}{\widehat{\lambda}_j^2} \left\langle y, \hat{\psi}_j \right\rangle_T \frac{X' \hat{\psi}_j}{T}$$

Spectral Cutoff/Principal Components Estimator:

$$\widehat{y} = M_T^{\alpha} y = \widehat{\Psi} \left(\widehat{\Psi}' \widehat{\Psi}\right)^{-1} \widehat{\Psi}' y$$

$$\text{Where } \widehat{\Psi} = \left[\widehat{\psi}_1 \left| \widehat{\psi}_2 \right| \dots \mid \widehat{\psi}_k\right]$$

Partial Least Squares Estimator:

$$\widehat{y} = M_T^{\alpha} y = X V_k \left(V_k' X' X V_k\right)^{-1} V_k' X' y$$

$$\text{Where } V_k = \left(X'y, \quad (X'X) X'y, \dots, (X'X)^{k-1} X'y\right)$$

3.1 Via SIMPLS Algorithm

$S = X^T y$

for $i \in 1 : k$

if $i = 1, [u, s, v] = svd(S)$

if $i > 1, [u, s, v] = svd(S - (P_k[:, i-1](P_k[:, i-1]^T P_k[:, i-1])^{-1} P_k[:, i-1]^T S))$

$T_k[:, i-1] = X R_k[:, i-1]$

$$P_k[:, i-1] = \frac{X^T T_k[:, i-1]}{T_k[:, i-1]^T T_k[:, i-1]}$$

$\widehat{y} = M_T^{\alpha} y = X R_k (T_k^T T_k)^{-1} T_k^T y$

4 Evaluation Methods

Generalized Cross Validation:

$$\hat{\alpha} = \arg\min_{\alpha \in A_T} \frac{T^{-1} \left\| y - M_T^{\alpha} y \right\|^2}{\left(1 - T^{-1} \operatorname{tr}\left(M_T^{\alpha}\right)\right)^2}$$

Mallows Criterion:

$$\hat{\alpha} = \arg\min_{\alpha \in A_T} T^{-1} \left\| y - M_T^{\alpha} y \right\|^2 + 2\widehat{\sigma}_{\varepsilon}^2 T^{-1} \operatorname{tr}\left(M_T^{\alpha}\right)$$

Where $\widehat{\sigma}_{\epsilon}^2$ is a consistent estimator of the variance of ϵ

So variance of ϵ is taken from the errors of the largest model, or from the model with all regressors for PC.

Leave-one-out Cross Validation:

$$\hat{\alpha} = \arg\min_{\alpha \in A_T} \frac{1}{T} \sum_{t=1}^{T} \left(\frac{y_i - \hat{y}_{i,\alpha}}{1 - M_T^{\alpha}[ii]} \right)^2$$

(GCV, $N = 100, T = 50$)

		PC	PLS	Ridge		LF	
	r	k	k	α	DOF	α	DOF
DGP 1	4.00	4.56	4.16	6.56	16.21	0.00	7.48
(s.e.)	–	(2.17)	(3.25)	(2.96)	(9.53)	(0.00)	(1.31)
DGP 2	50.00	20.24	4.76	0.56	47.49	0.00	31.85
(s.e.)	–	(5.55)	(6.32)	(0.46)	(2.00)	(0.00)	(2.20)
DGP 3	5.00	1.76	1.12	5.08	16.99	0.00	7.91
(s.e.)	–	(1.58)	(0.59)	(1.83)	(4.20)	(0.00)	(5.11)
DGP 4	5.00	1.76	1.84	8.48	14.52	0.03	3.52
(s.e.)	–	(3.18)	(2.88)	(3.01)	(7.83)	(0.01)	(6.64)
DGP 5	100.00	1.44	3.56	12.83	11.14	0.03	2.14
(s.e.)	–	(2.35)	(3.13)	(4.46)	(8.50)	(0.01)	(2.79)
DGP 6	1.00	2.44	1.16	4.85	16.69	0.28	2.58
(s.e.)	–	(2.55)	(0.78)	(3.27)	(7.89)	(0.45)	(1.00)

5 Empirical Application

5.1 Introduction and Data

Building on the long history of machine learning in forecasting macroeconomic variables[1] we use the Federal Reserve Bank's monthly database (FRED-MD) to apply the estimators discussed above on real data. This database was established for empirical analysis that requires 'big data' and hence constitutes an ideal environment to employ the methods discussed above. We took inspiration from the work of Coulombe et al. (2020) but limit ourselves to PC, Ridge, PLS and LF.[2] The dataset contains 134 monthly US macroeconomic and financial indicators observed from January 1959 to January 2021. An overview of all variables is given in the appendix. Following Coulombe et al. (2020) we predict three indicators which are of key economic interest, namely Industrial Production (INDPRO), Unemployment Rate (UNRATE), and housing starts (HOUST).[3] For each of these variables of interest Y_t we follow Coulombe et al (2020) in defining the forecast objective as

$$y_{t+h} = (1/h)ln(Y_{t+h}/Y_t) \tag{1}$$

where h denotes the number of periods ahead. This allows us to assess the performance of our predictive methods for further periods ahead. Given the nature of the data we expect the underlying factor structure to be similar to DGP XXXXXXXXX

5.2 Evaluation

We evaluate the performance of our methods on the out of sample MSE. To be able to compute the latter we split our data into a training and a test set where the former spans all observations from ... to ... amounting to 80% of the data. Denoting N the number of observations in the test set we calculate the MSE as

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \widehat{Y}_i)^2 \tag{2}$$

where $\widehat{Y}_i = \widehat{\Psi}\widehat{\delta}_{pc}$ for PCA and $\widehat{Y}_i = X\widehat{\delta}_m, m \in \{R, LF, PLS\}$ for all other models.

We conduct forecasts for $h = \{1, 3, 9\}$ periods ahead. In line with the findings of Coulombe et al (2020) we observe that the performance increases for further periods ahead. Given the simulation results we expect Ridge to deliver the best results, here defined as yielding the smallest out of sample MSE. Subsequently we report results similar to the simulation framework; we provide tables showing for each combination of estimator and parameter selection method the chosen penalty parameter/the number of factors as well as the degrees of freedom and the resulting out of sample MSE. Moreover, we visualize the out of sample MSE to ease comparison across methods and settings.

[1] See e.g. ...

[2] Unfortunately we were unable to use (1) Gu et al. (2020) as TSE does not have access to WDRS returns, (2) as only data on the resulting factors is available or (3) as they do not offer any replication data.

[3] Fortunately McCracken and Ng (2016), the accompanying paper of the dataset, outlines a transformation method for each variable to achieve stationarity. We apply those transformations in our data preparation.

5.3 Results and Discussion

From tables 1 to 3 we can immediately see that the estimated factor structure as well as the chosen penalty parameters are remarkably stable across both selection criteria and variables of interest. We were unable to discover evidence supporting nor disputing this finding in the literature related to the usage of FRED-MD.[4] In terms of forecasting power, we can see that LF yields the smallest out of sample MSE for $h = 1$ across all variables of interest. The difference to Ridge is, however, close to negligible.

Table 1: $Y_t = INDPRO$

Method	OOS MSE, $h = 1$	$alpha/k$	DOF
LF: GCV	0.000126	0.0001	14.532053
LF: Mallow	0.000126	0.0001	14.532053
PC: GCV	0.000162	13.0000	13.000000
PC: Mallow	0.000162	15.0000	15.000000
PLS: GCV	0.002139	15.0000	15.000000
PLS: Mallow	0.002139	15.0000	15.000000
Ridge: GCV	0.000130	0.1170	20.074885
Ridge: Mallow	0.000130	0.1170	20.074885

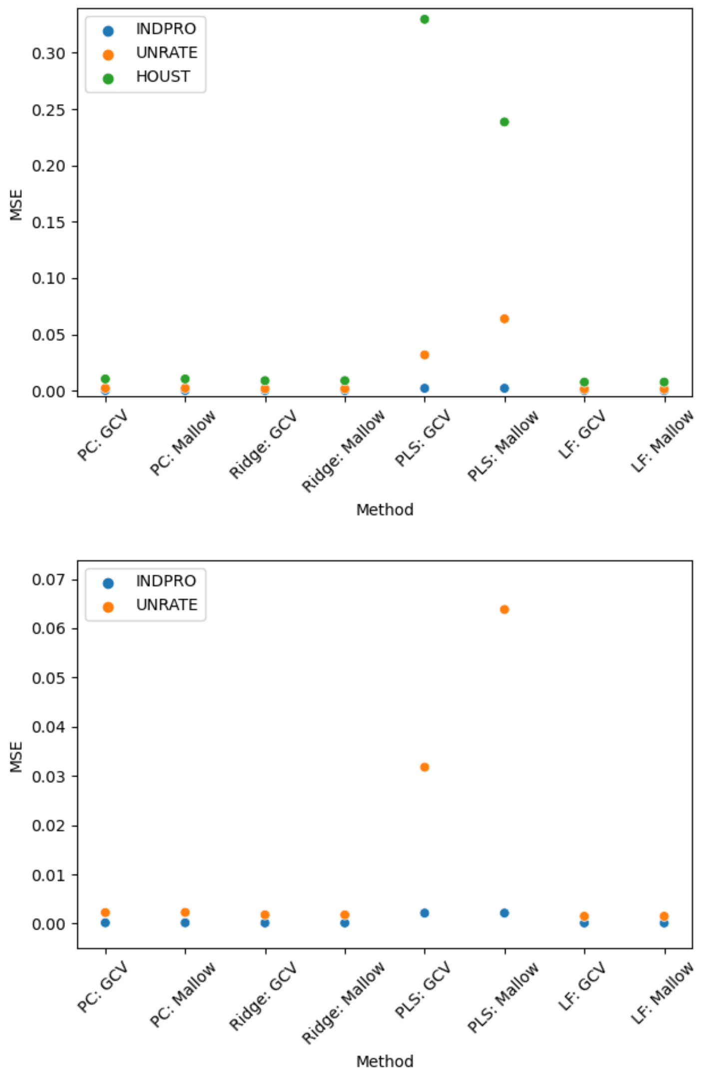
Table 2: $Y_t = UNRATE$

Method	OOS MSE, $h = 1$	$alpha/k$	DOF
LF: GCV	0.001488	0.0001	14.418940
LF: Mallow	0.001488	0.0001	14.418940
PC: GCV	0.002247	9.0000	9.000000
PC: Mallow	0.002276	15.0000	15.000000
PLS: GCV	0.031782	13.0000	13.000000
PLS: Mallow	0.063822	15.0000	15.000000
Ridge: GCV	0.001779	0.1170	20.008091
Ridge: Mallow	0.001779	0.1170	20.008091

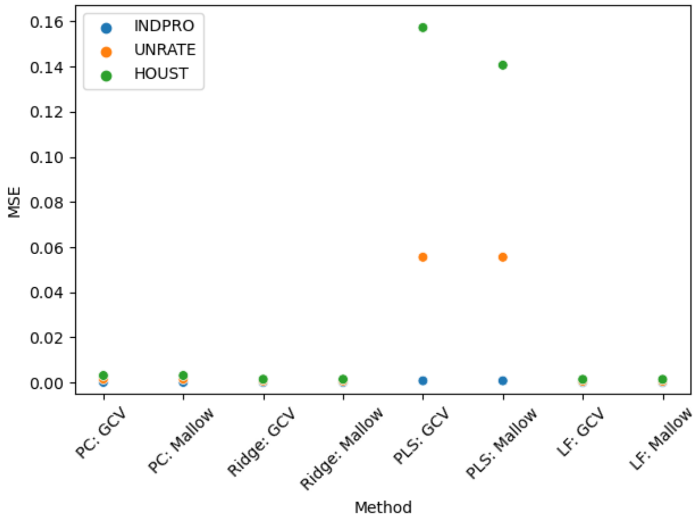
Table 3: $Y_t = HOUST$

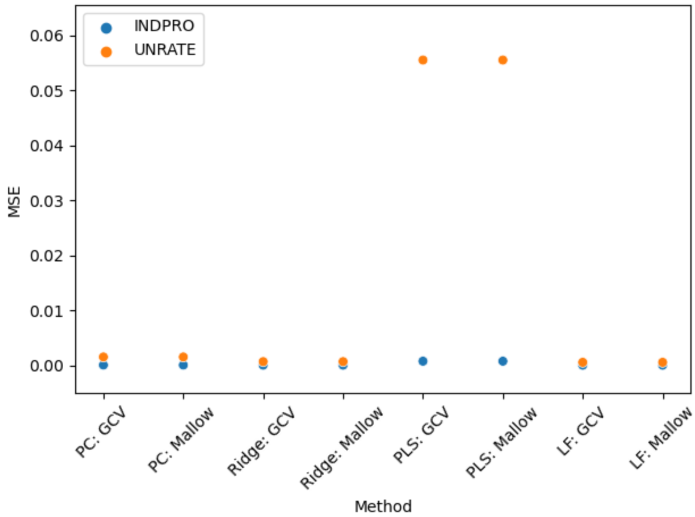
Method	OOS MSE, $h = 1$	$alpha/k$	DOF
LF: GCV	0.007627	0.0001	14.441119
LF: Mallow	0.007627	0.0001	14.441119
PC: GCV	0.010409	15.0000	15.000000
PC: Mallow	0.010409	15.0000	15.000000
PLS: GCV	0.329750	11.0000	11.000000
PLS: Mallow	0.238590	15.0000	15.000000
Ridge: GCV	0.008906	0.1170	20.052968
Ridge: Mallow	0.008906	0.1170	20.052968

[4]We apply the same exact estimators as in the simulations hence we see room for error only in our data preparation steps, which are, however, directly taken from the literature. Given the nature of the data we might take this finding as an indication for a stable factor structure. Future research could discover interesting patterns.

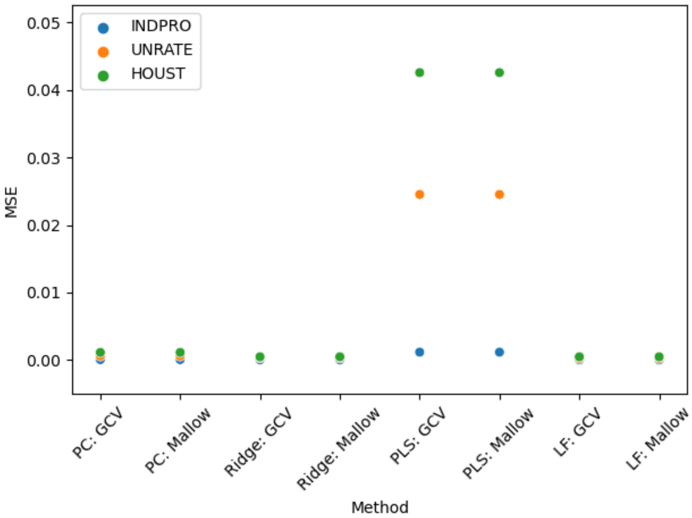


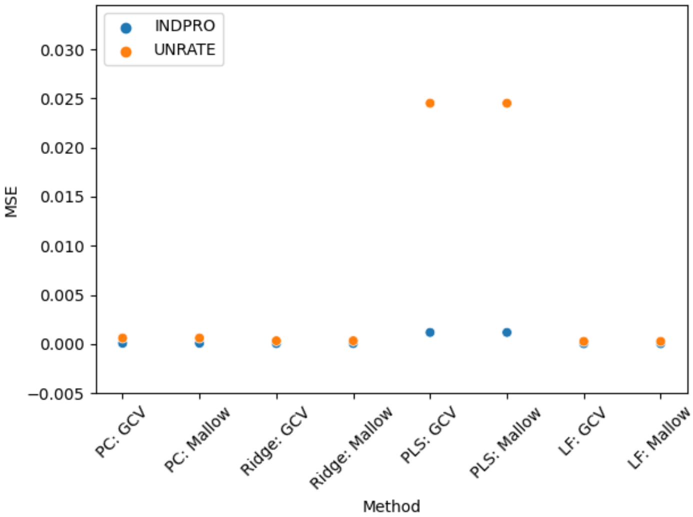
Out of sample MSE, $h = 1$





Out of sample MSE, $h = 3$





Out of sample MSE, $h = 9$

Appendix

Data Dictionary

Group 1: Output and income

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

Group 2: Labour market

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

Group 3: Housing

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

Group 4: Consumption, orders and inventories

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

Group 5: Money and credit

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

Group 6: Interest and exchange rates

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

Group 7: Prices

	id	tcode	fred	description	gsi	gsi:description
1	106	6	WPSFD49207	PPI: Finished Goods	M110157517	PPI: fin gds
2	107	6	WPSFD49502	PPI: Finished Consumer Goods	M110157508	PPI: cons gds
3	108	6	WPSID61	PPI: Intermediate Materials	M_110157527	PPI: int matls
4	109	6	WPSID62	PPI: Crude Materials	M_110157500	PPI: crude matls
5	110*	6	OILPRICEx	Crude Oil, spliced WTI and Cushing	M_110157273	Spot market price
6	111	6	PPICMM	PPI: Metals and metal products:	M_110157335	PPI: nonferrous
7	112	1	NAPMPRI	ISM Manufacturing: Prices Index	M_110157204	NAPM com price
8	113	6	CPIAUCSL	CPI : All Items	M_110157323	CPI-U: all
9	114	6	CPIAPPSL	CPI : Apparel	M_110157299	CPI-U: apparel
10	115	6	CPITRNSL	CPI : Transportation	M_110157302	CPI-U: transp
11	116	6	CPIMEDSL	CPI : Medical Care	M_110157304	CPI-U: medical
12	117	6	CUSR0000SAC	CPI : Commodities	M_110157314	CPI-U: comm.
13	118	6	CUUR0000SAD	CPI : Durables	M_110157315	CPI-U: dbles
14	119	6	CUSR0000SAS	CPI : Services	M_110157325	CPI-U: services
15	120	6	CPIULFSL	CPI : All Items Less Food	M_110157328	CPI-U: ex food
16	121	6	CUUR0000SA0L2	CPI : All items less shelter	M_110157329	CPI-U: ex shelter
17	122	6	CUSR0000SA0L5	CPI : All items less medical care	M_110157330	CPI-U: ex med
18	123	6	PCEPI	Personal Cons. Expend.: Chain Index	gmdc	PCE defl
19	124	6	DDURRG3M086SBEA	Personal Cons. Exp: Durable goods	gmdcd	PCE defl: dlbes
20	125	6	DNDGRG3M086SBEA	Personal Cons. Exp: Nondurable goods	gmdcn	PCE defl: nondble
21	126	6	DSERRG3M086SBEA	Personal Cons. Exp: Services	gmdcs	PCE defl: service

Group 8: Stock market

	id	tcode	fred	description	gsi	gsi:description
1	80*	5	S&P 500	S&P's Common Stock Price Index: Composite	M_110155044	S&P 500
2	81*	5	S&P: indust	S&P's Common Stock Price Index: Industrials	M_110155047	S&P: indust
3	82*	2	S&P div yield	S&P's Composite Common Stock: Dividend Yield		S&P div yield
4	83*	5	S&P PE ratio	S&P's Composite Common Stock: Price-Earnings Ratio		S&P PE ratio
5	135*	1	VXOCLSx	VXO		