Across the pacific : The impact of American economic development on Chinese companies

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Abstract

Since the 1990s, multifactor models have been a hot topic in the field of empirical asset pricing. People usually mine factors based on company fundamental data. In recent years, alternative data such as text has gradually become a research hotspot. But there are fewer micro applications of macro data. Using the data of 120 US macroeconomic variables in the FRED-MD database, this paper first uses the partial least squares (PLS) method to model the volatility of the Chinese market. And the large explanatory power, we think it may be caused by factors such as trade wars. Then use traditional principal component analysis (PCA) and sparse principal component analysis (SPCA) to reduce the dimensionality of Chinese companies' systemic risk exposure to the US macro economy (calculated using macroeconomic indicators and individual stock returns), and compare the two According to the difference between the two methods, it is found that the sparse principal component analysis method can significantly improve the economic interpretation ability of the principal components. The results show that: Yields, Production, Market, and Housing have a significant impact (in the 10 sparse principal components). Our research helps to explore the impact of US macroeconomic development on Chinese companies, and can be used as effective information for investors to invest in the Chinese market.

Keywords: Factor Mimicking Portfolio , PCA , PLS , SparsePCA , Systemic risk exposure

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1. Intruduction

One of the main research topics in asset pricing in the 1990s has been the work initiated by Fama and French (1992)[1]. Fama and French show that the Capital Asset Pricing Model (CAPM) can no longer explain the cross-section of asset returns in the US. They propose an alternative model(Three-Factor Model) which includes, apart from the market factor, a factor related to book-to-market (B/M) which they call HML, and a factor related to size (MV) called SMB.

Since Fama and French proposed the three-factor model and knocked on the door of the multi-factor model, scholars have gone a long way to explore. In 2015, Fama and French[2] started from the dividend discount model and deduced that the value of the company is the net profit of each period The sum of the discounted value of the difference between the companys book value and the companys book changes, adding the profit factor and the investment factor on the basis of the Fama-French three-factor model, and proposed a new Fama-French five-factor model. Hou et al. (2015)[3] used entity investment Based on economic theory, the q-factor model was proposed. From the perspective of behavioral finance, Stambaugh et al. (2017) [4]explored the phenomenon of mispricing according to investors bounded rationality and cognitive biases, and proposed a new four-factor model. Liu - Stambaugh-Yuan (2019)[5] proposed a new three-factor model (CH-3) with Chinese market characteristics.

Hou et al. (2020)[6] summarized many factors currently being studied in academia and divided them into six categories according to the characteristics of the factors, namely, valuation and growth, investment, profitability, momentum, and trading. For friction and intangible assets, it can be found that most of the data required for the construction of factor indicators comes from financial markets and listed company data, but problems also arise as the times require. People are beginning to worry about the over-mining of factors, which leads to the independence of factors. Sexual issues, people are increasingly using unique data (alternative data) to carry out research, mainly text data.

Each of the studies mentioned above has explored the relationship between firm characteristics, etc., and cross-sectional differences in return on assets (Fama and French 1993, 2016, 2018; Hou, Xue, and Zhang 2015).Theoretical-based macroeconomics factors (e.g., consumption growth; see

Parker and Julliard, 2005[7]) and other nontradable factors (e.g., intermediary financial leverage; see Adrian, Etula, and Muir, 2014[8]) capture risks in the economy and thus should also explain cross-sectional expected returns.

Due to the low frequency of data, macroeconomic data are rarely used to construct factors and further construct investment portfolios. In addition, scholars have not yet paid attention to the impact of US macroeconomic development on Chinese companies. Therefore, this article first reduces macroeconomic data. Dimensional processing: (1) use 126 US macroeconomic indicators to model the volatility of the Chinese market, using the PLS method; (2) According to Engle (2020) [9], we use the monthly return data of listed companies in the Chinese market for 20 years from 2000 to 2020 to perform linear regression on 126 US macro data to obtain the panel data of regression coefficients, and perform traditional PCA and Sparse-PCA(Huang, Jiang, Li and Zhou, 2022[10]) , compare the dimension reduction results of the two, and compare them with the results of the aforementioned PLS, to observe the characteristics of the two processing methods, and further analyze the main US macroeconomic indicators that affect the Chinese market.Among them, the US macro variable data set comes from the FRED-MD database.

The remainder of this paper is organized as follows. Section 2 shows the part of Data descriptive and preprocessing. Section 3 modeles Chinese market volatility with US macro data using PLS.Section 4 uses the monthly returns of Chinese listed companies to model the US macroeconomic indicators to obtain systemic risk exposures,and performs PCA and SPCAon systematic risk exposures.Section 5 compare and analyzes the results of sparse principal components with the results of PLS .

2. Data descriptive and preprocessing

In this section, we describe our data sources and data construction.First,the database we use:

FRED-MD [11] database is a large, monthly frequency, macroeconomic database with the goal of establishing a convenient starting point for empirical analysis that requires big data.It is designed to be updated monthly using the FRED database and factors extracted from the dataset share the same predictive content as those based on various vintages of the so-called Stock-Watson dataset.Next, we first conduct a descriptive statistical analysis of macroeconomic data for 129 US monthly indicators.

2.1. Data Descriptive Statistics

First, we visually observe the volatility data of the Chinese market.

Table 1: Descriptive Statistics of Vol

	Count	Mean	Sd	Min	25%	50%	75%	Max
Vol	120	0.1183	0.0063	0	0.0080	0.0103	0.1334	0.3968

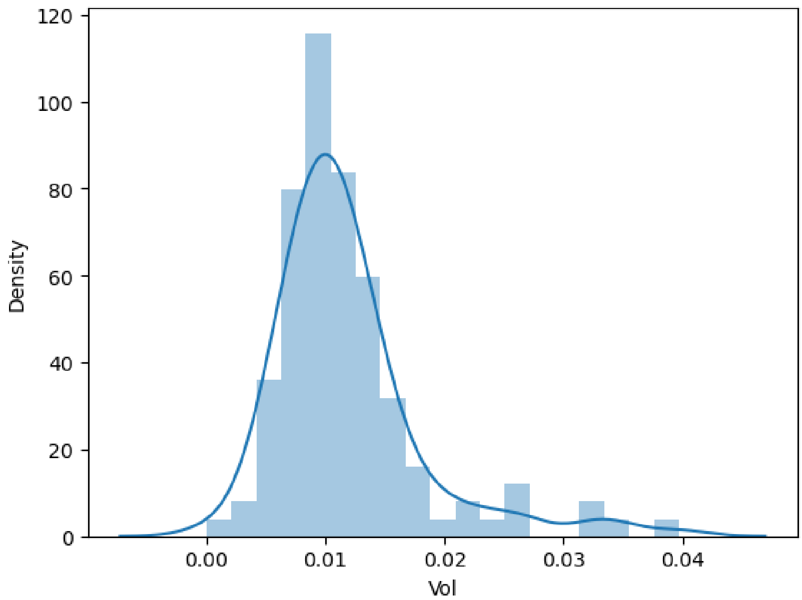


Figure 1: Distribution of Dissolved Variable ”Chinese Market Volatility”

It can be seen from the descriptive statistics and distribution chart of the explained variable ”China’s market volatility” that the Vol series presents a slight right-skewed shape, and its mean is slightly larger than the median. Next we show the descriptive statistics table of 126 macroeconomic variable data.

[Tab 1 about here][A.5]

Next, descriptive statistics are carried out on the monthly return data of Chinese listed companies. We download the monthly return data of Chinese listed companies from the stock market series in the CSMAR database - stock market trading section, and use the data that does not consider the reinvestment of cash dividends For the monthly stock return rate, for the original data, we fill the empty values in the data table with 0, delete companies that have been retained for less than 10 years (including 10 years), and retain listed companies in the following markets: Shanghai Stock Exchange A-share market, The Shenzhen A-share market, the Growth Enterprise Market, and the Science and Technology Innovation Board, a total of 584243 valid data.The calculation method of the monthly return on individual stocks without considering the reinvestment of cash dividends is as follows:

$$r_{n,t} = \frac{P_{n,t} * \prod_{i=1}^{m} \left[(1 + F_{n,i} + S_{n,i}) * C_{n,i}\right] + \sum_{i=1}^{m} \left\{\prod_{j=1}^{i} \left[\left(1 + F_{n,j-1} + S_{n,j-1}\right)^{*} C_{n,j-1}\right]^{*} D_{n,i}\right\}}{P_{n,t-1} + \sum_{i=1}^{m} \left\{\prod_{j=1}^{i} \left[\left(1 + F_{n,j-1} + S_{n,j-1}\right) * C_{n,j-1}\right] * C_{n,i} * S_{n,i} * K_{n,i}\right\}} - 1 \tag{1}$$

Among them, m represents the number of ex-rights and ex-dividend events of stock n durng the calculation period. $P_{n,t}$ represents the closing price of stock n on the last trading day in the t-th calculation period. $P_{n,t-1}$ represents the closing price of stock n on the last trading day of the t1 calculation period. $D_{n,i}$ represents the cash dividend per share of stock n on the i-th ex-right day. $F_{n,i}$ represents the number of bonus shares per share of stock n on the i-th ex-right day, and $S_{n,i}$ represents the per share of stock n on the i-th ex-right day The number of allotment shares. $K_{n,i}$ represents the allotment price per share of stock n on the ex-right day of i. $C_{n,i}$ represents the split number per share of stock n on the i-th ex-right day.

Descriptive statistics are made on the monthly return data of Chinese listed companies as follow.

2.2. Data preprocessing

For the original data, there are problems such as missing data, data noise, data redundancy, data duplication, and outliers. The missing values have been processed (filled with 0) before descriptive

Table 2: Descriptive statistics

Var	count	mean	std	min	25%	50%	75%	max
Mretnd	454978	0.0129	0.157	-0.85	-0.068468	0	0.0774	22.053

statistics. Next, the data is min-max The value is standardized, and the formula is as follows:

$$x = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Next, use the standardized data to calculate the correlation matrix. Since there are too many variables, it is inconvenient to display specific values. Therefore, the heat map [2] is drawn as follows. It can be clearly found that the correlation between the data is high, indicating that multicollinearity is relatively high serious.So ordinary least squares cannot be used, using PLS is the correct choice.

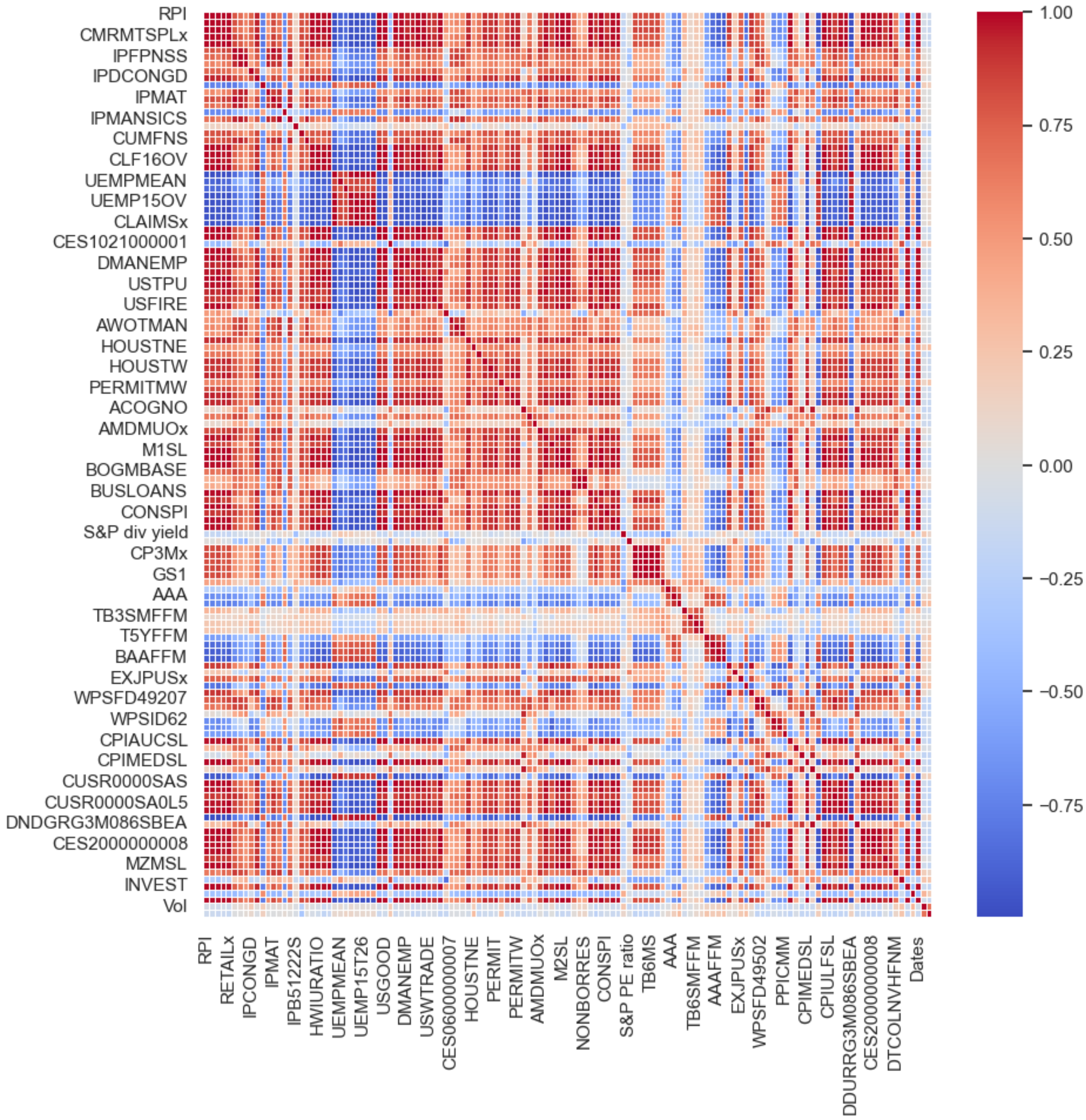


Figure 2: Correlation heatmap of normalized datasets

3. Modeling Chinese market volatility with US macro data using PLS

3.1. Partial Least Square

Partial Least Square (PLS) is similar to principal component analysis, and it is also a factor Subdata dimensionality reduction method. The objective formula of PLS when selecting the eigenvector matrix Ω_K is:

$$\begin{aligned} \mathrm{w_{j,t}} &= \mathrm{argmax\, Cov^2\left(R_{i,t}, Z_{i,t-1}R_{m,t}\right)} && (3)\\ \mathrm{s.t.\ w_t{}'w_t} &= \mathrm{1, Cov\left(Z_{i,t-1}R_{m,t}w_t, \left(Z_{i,t-1}R_{m,t}\right)w_{t,l}\right) = 0,} && (4)\\ \mathrm{l} &= \mathrm{1, 2, \ldots, j-1} && (5) \end{aligned}$$

Among them, Rm,t is the return of each stock. It can be seen from the formula that compared with PCA, which only considers the internal correlation (variance) of variables, PLS introduces the research target - stock returns, and examines the correlation between variables and returns (covariance). And carry out coordinate system reconstruction and dimensionality reduction according to the dimension most relevant to the income.

Specifically, the PLS component analysis process based on target information is as follows: First, we initialize the $t+h$ period return as $z_{t,0} = y_{t+h}$;secondly, for the k_{th} principal component, it is calculated in the order of k=1,,r as follows: For the characteristic variable X_{it} of asset i, do time series regression with $z_{t,k-1}$ to get the coefficient estimation $\hat{A}_i$:

$$X_{it} = \alpha_i + z'_{t,k-1}A_i + v^*_{i,t} \tag{6}$$

For the asset characteristics at time t and $\hat{A}_i$ do cross-sectional regression, the coefficient $\hat{B}_i$ is obtained:

$$X_{it} = \hat{A}'_l B_t + v^*_{i,t} \tag{7}$$

For the regression of income y_{t+h} and $\hat{B}_i$, the intercept and regression coefficient are obtained:

$$y_{t+h} = \alpha + \hat{B}'_l\beta + \epsilon_{t+h} \tag{8}$$

Next, we repeat iteratively so that k=k+1,$z_{t,k} = (z_{t,k-1}, \hat{\epsilon}^{(k)}_{t+h}$)until the rth principal component is found.

3.2. Parameter selection and model training

We firstly define the PLS function. The input values of the function are: input variable of training set (inXtrain), target value of training set (inytrain), input variable of test set (inXtest), target value of test set (inytest), input variable of out-of-sample data (inXoos), the test set (intest-data) and the out-of-sample test set (inoosdata). In this function, we select the top ten components with the largest variance contribution rate for training and prediction. The final output is the out-of-sample prediction result (datapls) under the best-performing parameter in the test set and the model weight value of each parameter (coefser)

The sample period is 120 months in total. We choose every 24 months as the training set, 12 months as the test set, and 1 month out of the sample to implement rolling window regression as shown below.

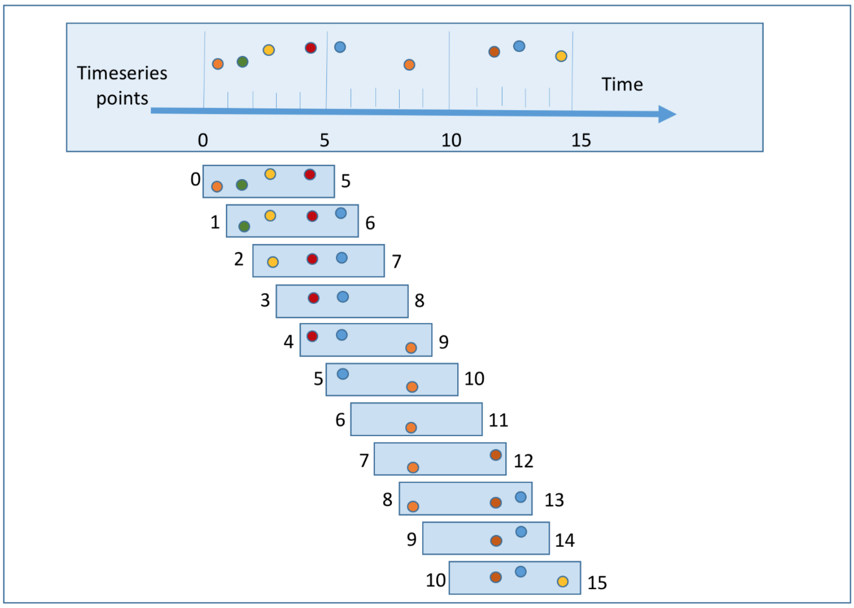


Figure 3: Schematic diagram of rolling window regression

3.2.1. Comparison of models under different parameters

Carry out rolling window partial least squares regression according to the above requirements, output the variable coefficients of each period, and draw them in a heat map[10], with 8 windows on the horizontal axis and 129 variables on the vertical axis. Looking vertically, the coefficients of each variable are Larger differences, viewed horizontally, the first six are relatively stable, while the latter two fluctuate greatly.

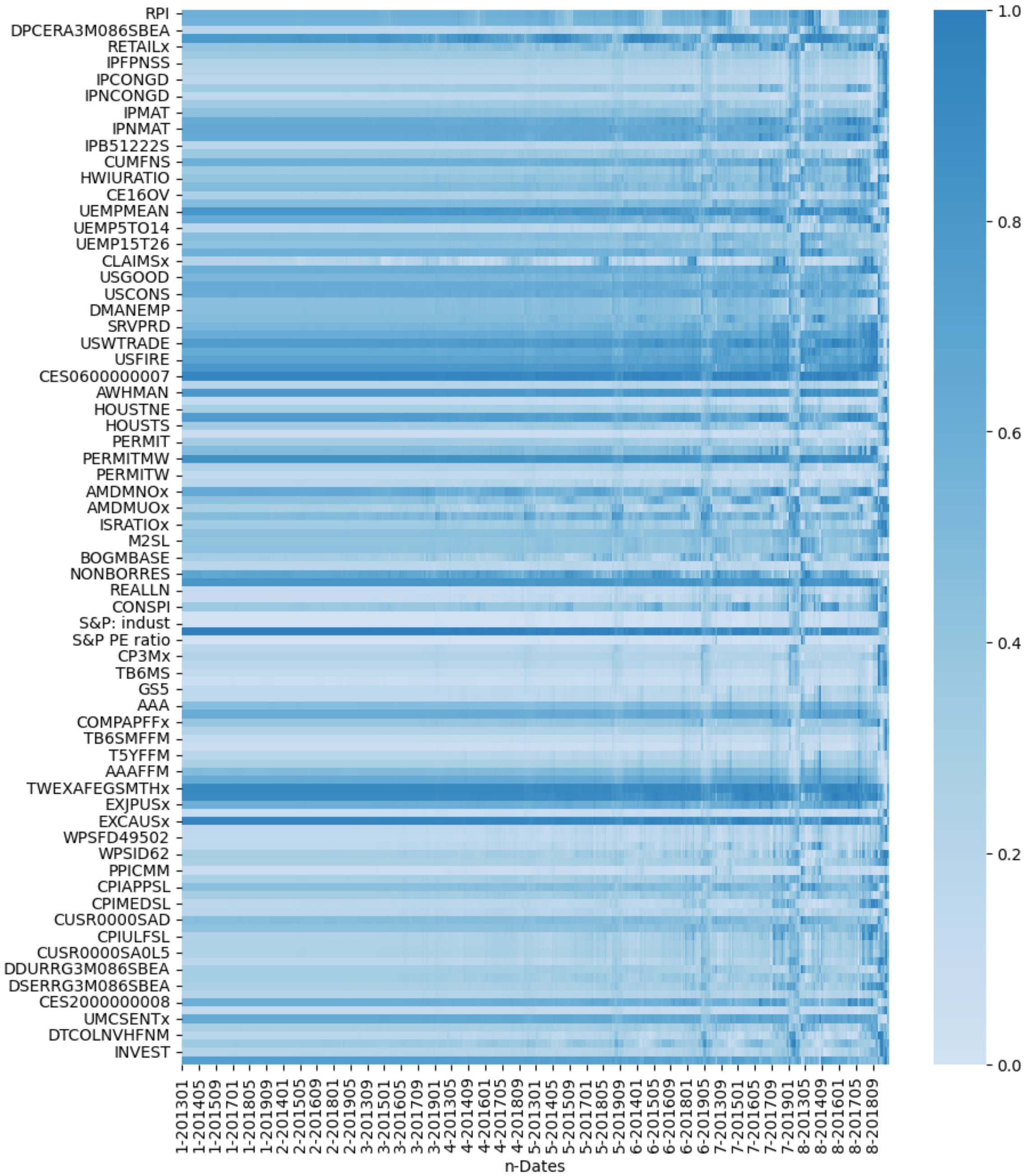


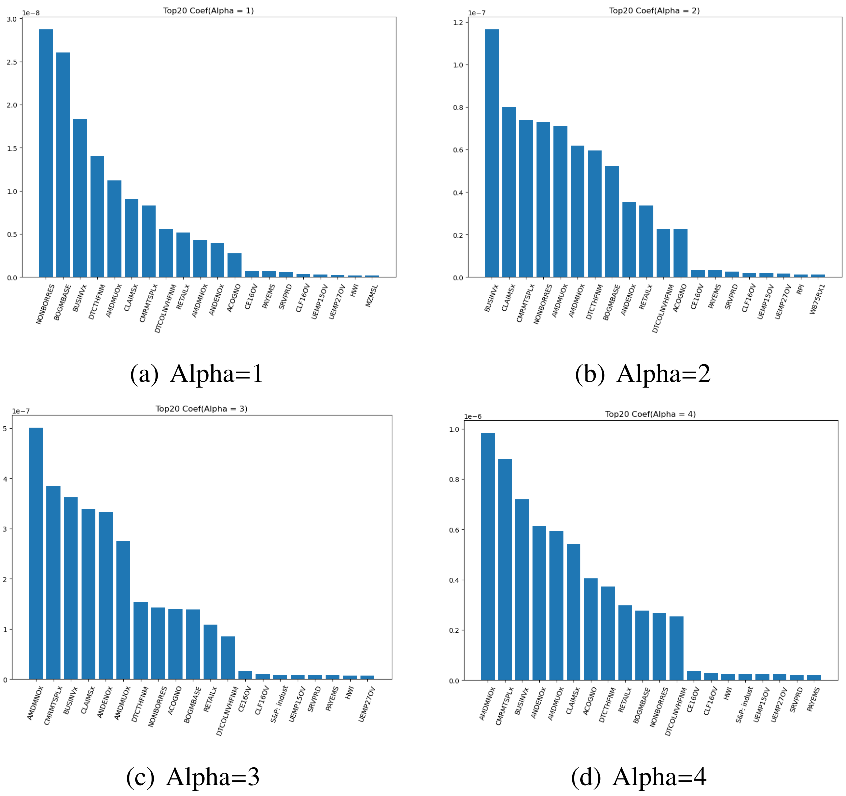
Figure 4: Partial Least Squares Regression Variable Coefficients

Next, based on the regression results, explore the weight of each macro variable index in each model, and output the top 20 variables with weight. The detailed information of the variables is as follows (taking Alpha=1 as an example):

Table 3: Top 20 coefs(taking Alpha=1 as an example)

Num	Fred	Description
1	NONBORRES	Reserves Of Depository Institutions
2	RPI	Real Personal Income
3	BUSINVx	Total Business Inventories
4	DTCTHFNM	Total Consumer Loans and Leases Outstanding
5	AMDMUOx	Unfilled Orders for Durable Goods
6	CLAIMSx	Initial Claims
7	CMRMTSPLx	Real Manu. and Trade Industries Sales
8	DTCOLNVHFNM	Consumer Motor Vehicle Loans Outstanding
9	RETAILx	Retail and Food Services Sales
10	AMDMNOx	New Orders for Durable Goods
11	ANDENOx	New Orders for Nondefense Capital Goods
12	ACOGNO	New Orders for Consumer Goods
13	CE16OV	Civilian Employment
14	PAYEMS	All Employees: Total nonfarm
15	SRVPRD	All Employees: Service-Providing Industries
16	CLF16OV	Civilian Labor Force
17	UEMP15OV	Civilians Unemployed - 15 Weeks Over
18	UEMP27OV	Civilians Unemployed for 27 Weeks and Over
19	HWI	Help-Wanted Index for United States
20	MZMSL	MZM Money Stock

Taking the results of the Alpha=1 model as an example, it can be seen from the table[3] that among the 20 variables that have strong explanatory power for the volatility of the Chinese market, 9 variables are related to commodities/consumption, 7 variables are related to employment, and the other 4 variables are related to Variables are related to the financial market and enterprise development. When Alpha is 2 to 8, the variables with strong explanatory power are also concentrated in the three main categories of commodities/consumption, employment, and financial market/enterprise development.



(a) Alpha=1

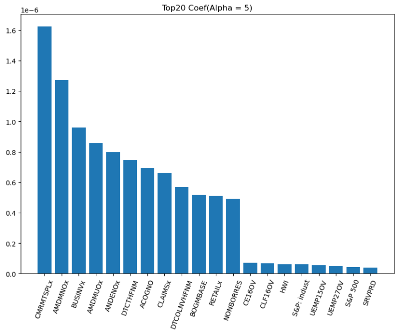
(b) Alpha=2

(c) Alpha=3

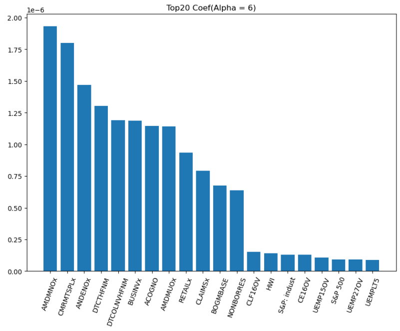
(d) Alpha=4

Figure 5: Top 20 coefs(.1)

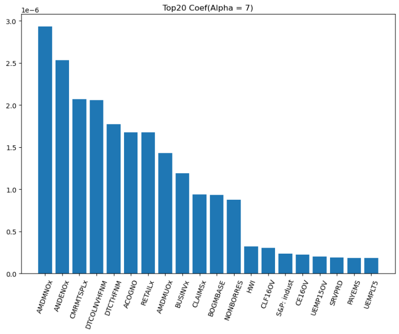
It can be seen from the above 8 histograms that the explanatory power of the first 1-2 variables is significantly higher than that of other variables, the explanatory power of the 3-12 variables is slightly weaker, and the explanatory power drops sharply from around the 13th. Looking at the detailed information of the variables in detail, it is found that AMDMNOx appears in the position with the highest explanatory power the most times, and when Alpha=3, the coefficient of AMDMNOx is close to 5.



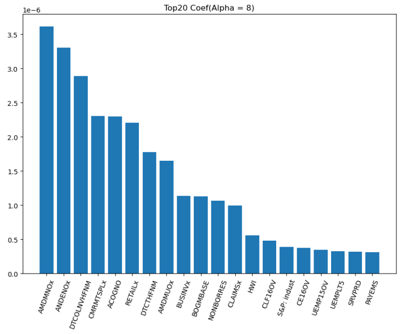
(a) Alpha=5



(b) Alpha=6



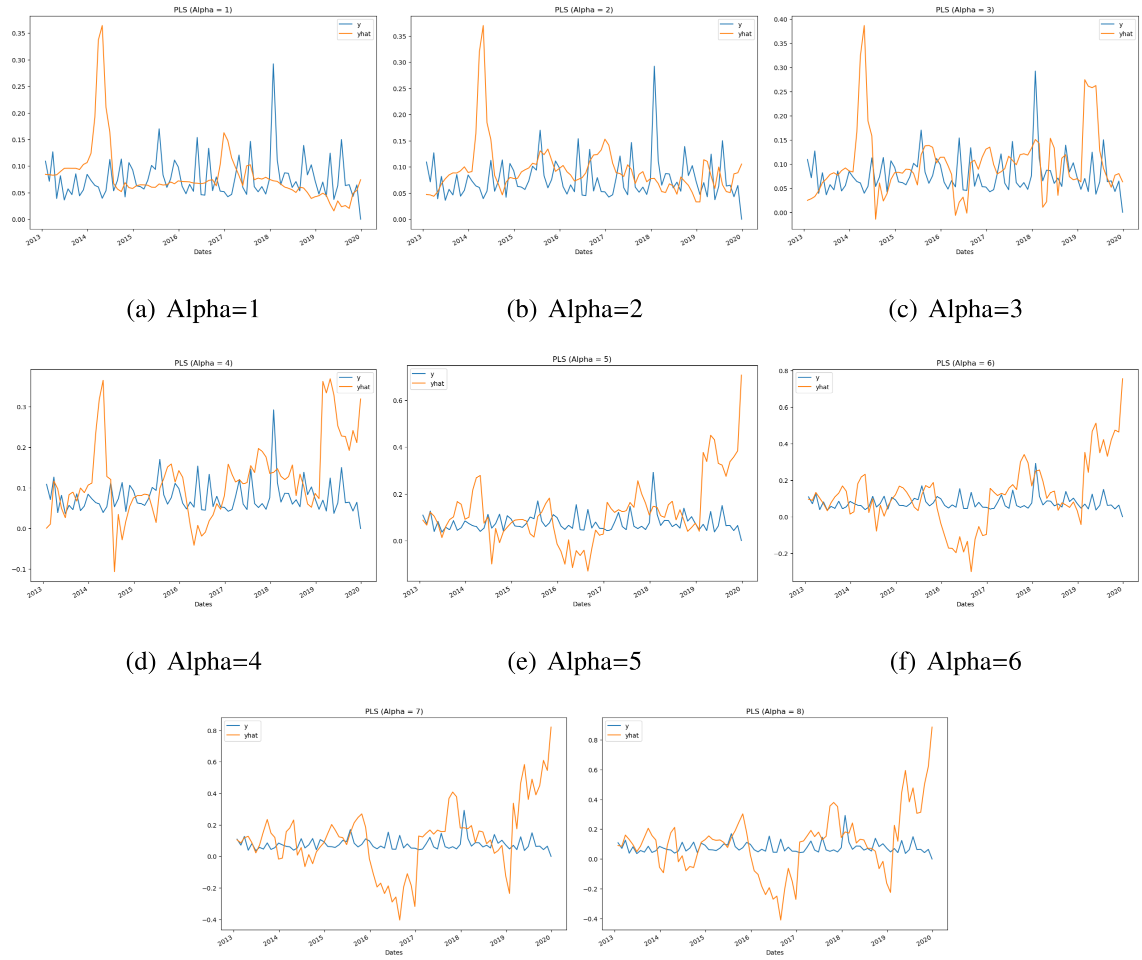
(c) Alpha=7



(d) Alpha=8

Figure 6: Top 20 coefs(.2)

Next, we calculate the predicted value sequence from 2013 to 2020, and draw it to observe the difference between it and the real value sequence. The yellow sequence in the figure is the predicted value sequence, and the blue sequence is the real value sequence. On the whole, there is a certain prediction error between the out-of-sample fitting value and the real value of PLS, which varies with different parameters. Comparing the real value with the predicted value, it can be found that the predicted value fluctuates greatly. In particular, when Alpha is 4 to 8, the sequence shows an upward trend in recent years, but the real value does not have such a shape.



(a) Alpha=1 (b) Alpha=2 (c) Alpha=3

(d) Alpha=4 (e) Alpha=5 (f) Alpha=6

(g) Alpha=7 (h) Alpha=8

Figure 7: Comparison of the difference between each model predicted sequence and the real sequence

3.2.2. Model Evaluation and Selection:base on MSFE

Common evaluation indicators of forecasting models are mainly based on the measurement of forecasting error. In this paper, Mean Squared Forecasting Error (MSFE) is selected to compare the forecasting results of different parameters.

$$MSFE = \frac{1}{t_{period}} \sum_{t=1}^{t} (\hat{y} - y_{true})^2 \tag{9}$$

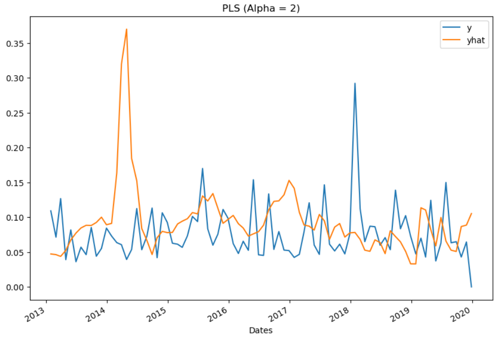
The figure below shows the MSFE value of the model when Alpha is 1 to 8. It can be seen from the table that when Alpha is 2, MSFE=0.0047, which is the smallest, so the model with Alpha=2

Table 4: MSFE of different Model

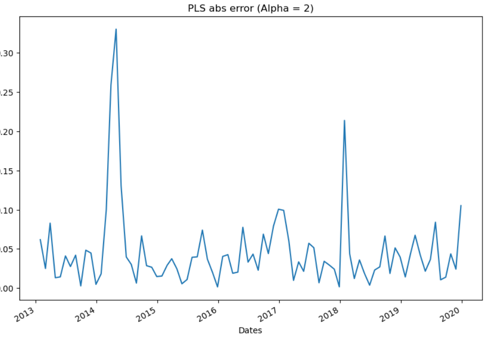
Parameter	1	2	3	4	5	6	7	8
MSFE	0.0050	0.0047	0.0068	0.0129	0.0238	0.0349	0.0504	0.0479

can be selected as our final model.

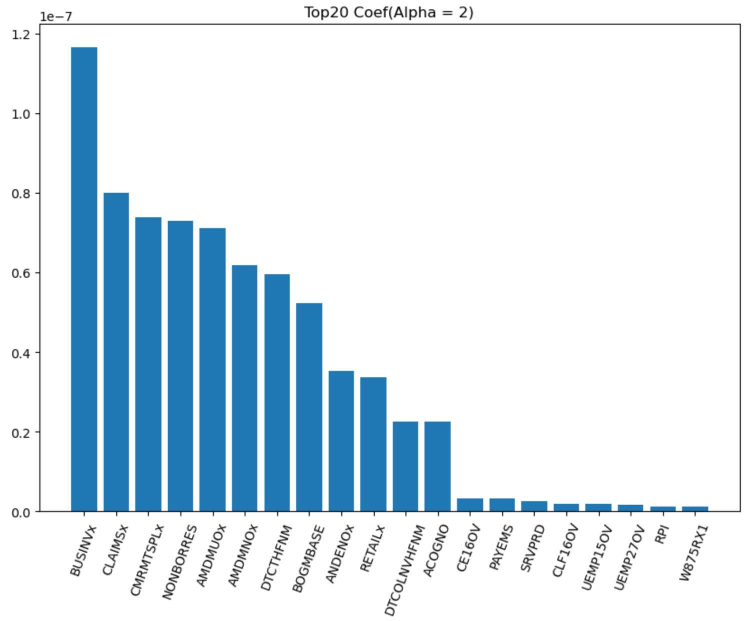
Next, plot the difference between the true and predicted values of our chosen model.



(a) Difference between true & prediction



(b) PLS Error



(c) Top 20 coef

Figure 8: The true and predicted values of our chosen model

As can be seen from the figure above, we selected the model with the smallest MSFE, and its predicted value series only had large anomalies around 2014 and 2018. In other cases, the differences were small, and the error series was relatively flat compared to other models. Looking at the top 20 variables by weight, BUSINVx has the highest weight. It may be due to the factors of the Sino-US trade war that the total inventory of enterprises has a certain explanatory power for the volatility of the Chinese market. Several variables with larger weights are also concentrated in commodities/consumption Within the scope, it can be proved to a certain extent that the U.S. consumer economy has a certain impact on China. Follow-up work can be carried out around this discovery, further constructing consumption factors, constructing a market-neutral portfolio, and exploring whether it will help investors invest in the Chinese market.

4. Performing PCA and SPCA on systematic risk exposures

4.1. Calculating Risk Exposure Using OLS Regression

We start by assuming that the underlying universal risk factors are known, and the basic multi-factor paradigm dictates that the return on any asset, say stock j, observed over an interval ending at time t, can be written as a linear function,

$$R_{j,t} = \alpha_j + \beta_{j,1} f_{1,t} + \beta_{j,2} f_{2,t} + \cdots + \beta_{j,K} f_{K,t} + \epsilon_{j,t} \tag{10}$$

where f denotes the general factor and β is the factor sensitivity; α_j is an intercept constant ,$\epsilon_{j,t}$ representing residual or "diversifiable" risk that is independent of the factor and uncorrelated across assets.

We refer to the practice of Richard Roll and Akshay Srivastava[2018], and use the monthly rate of return to regress 126 macroeconomic indicators.

$$R_{j,t} = \alpha_j + \beta_{j,i} f_{i,t} \tag{11}$$

Among them, $R_{j,t}$ is the return rate of individual stocks of the j-th company in the t-th month, and $f_{i,t}$ is the i-th macroeconomic variable in the t-th month,and $\beta j, i$ is the systematic risk exposure of the j-th company to the i-th macroeconomic indicator.

We performed regression on 2,248 valid companies in the sample, and obtained 285,496 regression coefficients for descriptive statistics as shown in the table below.

[Tab 2 about here][B.6]

4.2. *Intro of Perfoming PCA and SPCA*

In this section, we leverage advances in machine learning to compute sparse macrofactors from large macroeconomic databases (”big data”). Each existing macro factor in the literature is usually constructed using only one or two macro variables. However, many more variables may be relevant to measures such as labor force or housing market conditions, so relying on one or two separate variables may miss relevant information. To integrate information on numerous macrovariables from different categories, we use monthly data on 120 macrovariables from the extensive FRED-MD database (McCracken and Ng 2016). The categories of 120 macro variables include output and income; labor market; housing; consumption, orders and inventories; money and credit; yields and exchange rates; and inflation. These 120 variables represent diverse measures of a broad range of potentially relevant risks in the macroeconomy. We computed sparse principal components using machine learning tools (Jolliffe et al. 2003; Zou et al. 2006; d'Aspremont et al. 2008; Shen and Huang 2008; Sigg and Buhmann 2008; Johnstone and Lu 2009; Witten et al. 2009; Journe et al. 2010; Berthet and Rigollet 2013) to capture systemic risk represented by the full set of macro variables.

Principal Component Analysis (PCA) is a statistical method that can help us understand and analyze data by reducing its dimensionality. It does this by transforming the original data into a new coordinate system (also known as the principal component coordinate system). In this new coordinate system, each dimension of the original data is replaced by a new dimension (called a principal component). These principal components are linear combinations of the original data and are arranged in order from largest to smallest.

The popularity of traditional PCA is due to its ability to succinctly capture most of the information from a large number of variables. However, this comes at the cost of interpretability, since traditional principal components (PCs) are usually a linear combination of all underlying variables. Sparse PCA limits the cardinality of the PC's weight vector so that the PC is a sparse linear combination of the underlying variables. Sparse PCA helps explain PCs by setting many weights to zero. The purpose of sparse PCA is to improve interpretability through sparsity without unduly sacrificing interpretability.

For comparison, we calculate the top ten conventional PCs of 120 systematic risk exposures based on the panel data of 285,496 regression coefficients [2248x127] calculated in the previous section. Each regular PC is a linear combination of all 120 systematic exposures, making individual PCs difficult to interpret. We then extract the top ten sparse PCs for systematic exposures using the method of Sigg and Buhmann (2008). A high degree of sparsity facilitates an economic interpretation of sparse PCs.

4.3. Perfoming PCA and SPCA

Conventional PCA is a popular dimension-reduction technique.1 Suppose that we are interested in reducing the dimension of the T P data matrix $\mathcal{X}$, whose columns contain observations for P variables over T periods. We assume that the variables in $\mathcal{X}$ are standardized, so that each column of $\mathcal{X}$ has zero mean and unit variance. Consider the Tdimensional column vector Xw_1, where w_1 is a P-dimensional column vector of weights. The first PC can be computed in the context of the following optimization problem, which entails maximizing the variance of Xw_1 subject to a unit-norm constraint:

$$\arg\max_{\mathbf{w}_1} \mathbf{w}_1^\top \hat{\mathbf{C}} \mathbf{w}_1 \text{ subject to } \|\mathbf{w}_1\|_2 = 1, \tag{12}$$

where $\hat{\mathbf{C}} = \mathbf{X}^\top \mathbf{X}/T$ and $\|\cdot\|_2$ is the ℓ_2 norm. The first PC is given by $\hat{\mathbf{z}}_1 = \mathbf{X}_{\hat{\mathbf{w}}_1}$, where $\hat{\mathbf{w}}_1$ is the solution to Equation (2.1).

The weight vector $\hat{\mathbf{w}}_2$ for second PC is found by maximizing the variance of $\mathbf{X}^2_{\mathbf{w}}$ subject to $\|\mathbf{w}_2\|_2 = 1$ and $\mathbf{w}_2$ orthogonal to $\mathbf{w}_1$, while the second PC itself given by $\hat{\mathbf{z}}_2 = \mathbf{X}\hat{\mathbf{w}}_2$. Continuing in this manner, the first $\hat{p} \ll P$ PCs are given by $\hat{\mathbf{z}}_p = \mathbf{X}\hat{\mathbf{w}}_p$ for $p = 1, \ldots, \hat{p}$, where $\left\|\hat{\mathbf{w}}_p\right\|_2 = 1$ for $p = 1, \ldots, \hat{p}$ and $\hat{\mathbf{w}}_j^\top \hat{\mathbf{w}}_k = 0$ for $j \neq k$. The PCs themselves are also uncorrelated with each other. Intuitively, PCA uses the first $\hat{p}$ "dominant" PCs to reduce the dimension of the data from P to $\hat{p}$, while still capturing much of the variation in the data.

Because the elements of $\hat{\mathbf{w}}_p$ for $p = 1, \ldots, \hat{p}$ are all typically nonzero, the individual PCs can be difficult to interpret P Sparse PCA harnesses machine learning tools to induce sparsity in the weight vectors. The aim is to facilitate the interpretability of the PCs without unduly sacrificing the ability of the PCs to capture the variation in the data.

We implement sparse PCA via the approach of Sigg and Buhmann (2008), which induces sparsity by directly imposing the cardinality restriction $\left\|\mathbf{w}_p\right\|_0 \leq K$ on each weight vector. Sigg and Buhmann (2008) develop a version of the expectation-maximization (EM) algorithm (Dempster et al. 1977) based on a probabilistic expression of PCA to compute sparse weight vectors and corresponding sparse PCs, which we denote by $\hat{w}_p$ and $\hat{z}_p$, respectively, for $p = 1, ..., \hat{p}$.

I first conduct traditional principal component analysis, output 10 traditional principal components, and calculate the cumulative variance explanation rate of 93.61%. The weights in Table 2 illustrate the difficulty of explaining traditional PC. All weights in Table are nonzero, and the weights of individual PCs are generally quite large for variables of various categories; Likewise, the traditional PCs in Figure reflect the effects of multiple variables. In summary, the traditional PCs extracted from 126 systemic exposures are difficult to explain economically. Of course, traditional PCA maximizes the total variation in the underlying variables explained by the PC, so it is not designed to facilitate economic interpretation. Draw a heat map of the 10 principal components and the weight of the original risk exposure, as follows

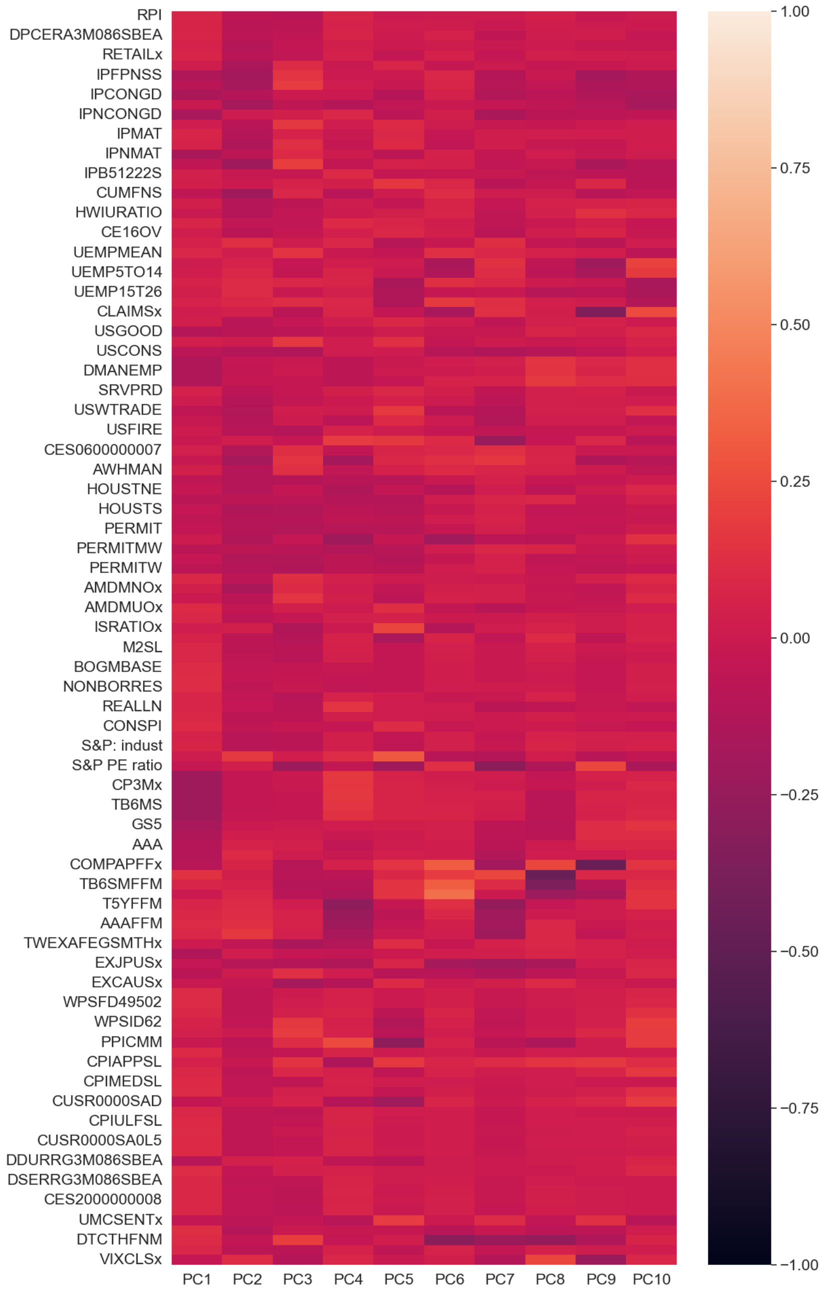


Figure 9: Coventional PCA components heatmap

Next, sparse principal component analysis is performed. We use the SparsePCAl class in Python's sklearn package to implement. The parameters are set to: n_components=10, alpha=0.1, and the output is 10 sparse principal components, which can jointly explain 90% of the original data.Firstly , we draw a heat map of the 10 principal components and the weight of the original risk exposure.The substantive sparsity in each weight vector enables us to intuitively interpret the ten sparse PCs as follows:

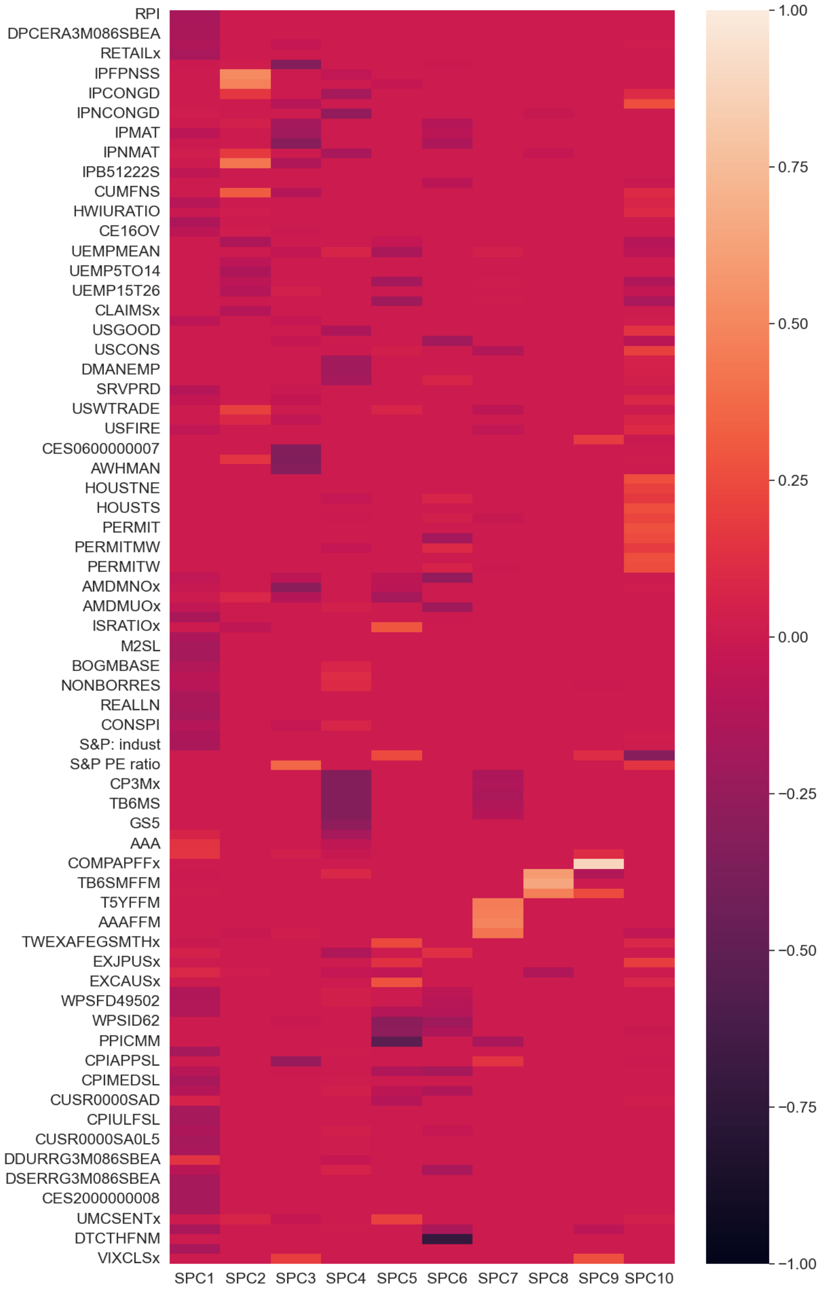


Figure 10: Sparse PCA components heatmap

1. ***Yields***. The second column of Table shows that the first sparse principal component, BAA (Moody's Seasoned Baa Corporate Bond Yield) is 0.16, AAA (Moody's Seasoned Aaa Cor-

porate Bond Yield) is 0.14, and DDURRG3M086SBEA (Personal consumption expenditures: Durable goods (chain- type price index)) is 0.14,GS10 (Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Quoted on an Investment Basis) is 0.07. It is predominantly a linear combination of the nominal interest rates included in FRED-MD, so that we interpret the first sparse PC as "yields."

2. ***Production***. From the third column of Table , we see that in the second sparse PC , IPFPNSS(Industrial Production: Final Products and Nonindustrial Supplies)is 0.51,IPFINAL(Industrial Production: Final Products) is 0.47,IPMANSICS(Industrial Production: Manufacturing (SIC)) is 0.43 ,CUMFNS(Capacity Utilization: Manufacturing (SIC)) is 0.32,USWTRADE(All Employees, Wholesale Trade) is 0.21. It is essentially a linear combination of various producer and consumer price indices and personal consumption expenditure deflators. We thus label the second sparse PC as Industrial Production.

3. ***Market*** . From the forth column of Table , we see that in the third sparse PC ,S&P PE ratio is 0.36 , VIXCLSx (CBOE Volatility Index: VIX) is 0.19,We label the thrid sparse PC as Market.

4. ***Bank*** . From the fifth column of Table , we see that in the forth sparse PC ,TOTRESNS (Reserves of Depository Institutions: Total) is 0.11 , NONBORRES (Reserves of Depository Institutions, Nonborrowed) is 0.1, TB3SMFFM (3-Month Treasury Bill Minus Federal Funds Rate) is 0.09 ,BOGMBASE (Monetary Base; Total) is 0.07,CONSPI is 0.07,UEMPMEAN (Average Weeks Unemployed) is 0.07 , so We label the thrid sparse PC as "Bank".

5. ***Currency*** . From the sixth column of Table , we see that in the fifth sparse PC ,ISRATIOx(Total Business: Inventories to Sales Ratio) is 0.29,EXCAUSx(Canadian Dollars to U.S. Dollar Spot Exchange Rate) is 0.28,S&P div yield(S&P 500 Dividend Yield) is 0.25,TWEXAFEGSMTHx(Nominal Broad U.S. Dollar Index) is 0.24,UMCSENTx(Consumer Sentiment Index)is 0.2,so We label the thrid sparse PC as Currency.

6. ***Housing*** . From the seventh column of Table , we see that in the sixth sparse PC , EXSZUSx(Switzerland / U.S. Foreign Exchange Rate) is 0.13, PERMITMW (New Pri-

vate Housing Permits, Midwest (SAAR) is 0.1,HOUSTMW(Housing Starts, Midwest) is 0.08,NDMANEMP (All Employees: Nondurable goods) is 0.07,PERMITW (New Private Housing Permits, West (SAAR)) is 0.06,HOUSTW (Housing Starts, West) is 0.04 . The sixth sparse PC is predominantly a linear combination of the risk exposure of housing start and new private housing permit variables in FRED-MD, as well as real estate loans.so We label the thrid sparse PC as ”Housing”.

7. ***Yield spreads*** . From the eighth column of Table , we see that in the seventh sparse PC , AAAFFM (Moodys Aaa Corporate Bond Minus FEDFUNDS) is 0.49 , T5YFFM (5-Year Treasury C Minus FEDFUNDS) is 0.46 , T10YFFM (10-Year Treasury C Minus FEDFUNDS) is 0.46 , BAAFFM (Moodys Baa Corporate Bond Minus FEDFUNDS) is 0.42 , CPIAPPSL (CPI : Apparel) is 0.14 , UEMPMEAN (Average Duration of Unemployment (Weeks)) is 0.05 , meaning that the sixth sparse PC is predominantly a linear combination of the risk exposure of interest rate spreads,so that we label this sparse PC as ”yield spreads”.

8. ***Treasury spreads*** . From the ninth column of Table , we see that in the eighth sparse PC , TB6SMFFM (6-Month Treasury C Minus FEDFUNDS) is 0.65, TB3SMFFM (3-Month Treasury C Minus FEDFUNDS) is 0.59 , T1YFFM (1-Year Treasury C Minus FEDFUNDS) is 0.47,so that we label this sparse PC as ”Treasury spread ”.

9. ***Treasury spreads 2*** . From the tenth column of Table , we see that in the ninth sparse PC , COMPAPFFx (3-Month Commercial Paper Minus FEDFUNDS) is 0.89,VIXCLSx is 0.27,T1YFFM (1-Year Treasury C Minus FEDFUNDS) is 0.25,USGOVT (All Employees: Government) is 0.18,so that we label this sparse PC as ”Treasury spread 2”.

10. ***Housing 2*** . From the 11th column of Table , we see that in the tenth sparse PC , PERMIT (New Private Housing Permits (SAAR)) is 0.27 ,PERMITS (New Private Housing Permits, South (SAAR)) is 0.26, IPDCONGD (Industrial Production: Durable Consumer Goods) is 0.26 ,HOUSTS(Housing Starts, South) is 0.26,HOUST (Housing Starts: Total New Privately Owned) is 0.26,PERMITNE (New Private Housing Permits, Northeast (SAAR) is 0.25 so that we label this sparse PC as ”Housing 2”.

Comparing the results in Tables 2 and 3 and Figures 1 and 2, the substantive sparsity imposed on the weight vectors greatly facilitates economic interpretation of the sparse vis--vis the conventional PCs. Fortunately, the increased interpretability of the sparse PCs comes at relatively little cost in terms of explanatory ability: despite the high degree of sparsity, the first ten sparse PCs still explain 93.31% of the total variation in the 120 macro variables (compared to 93.61% for the first ten conventional PCs).Next, draw the principal component line graph of traditional principal component analysis and sparse principal component analysis, as follows:

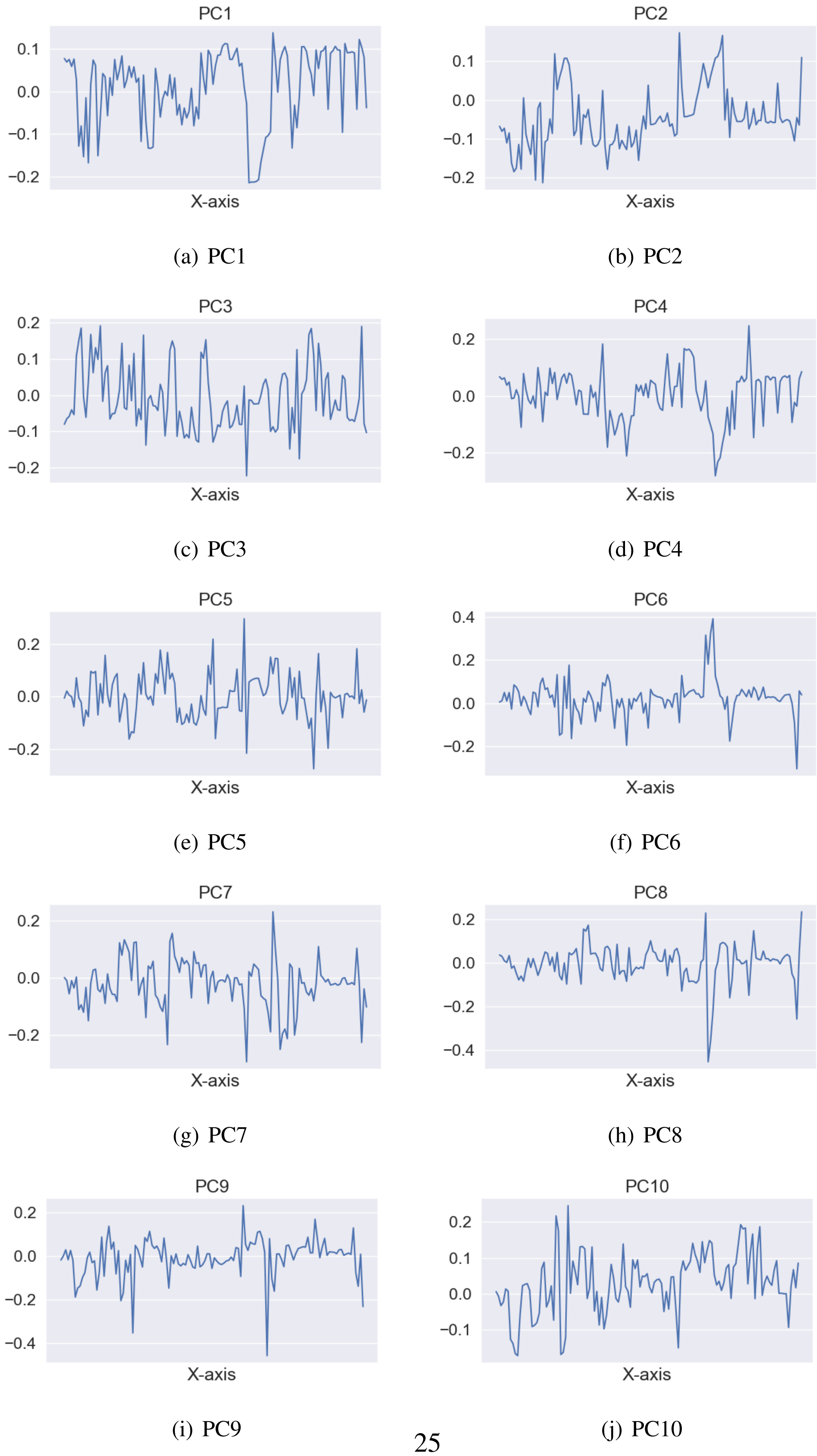
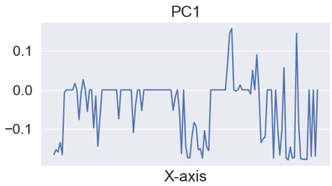
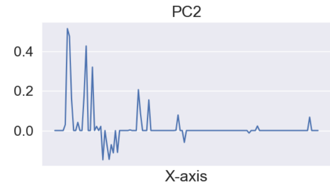


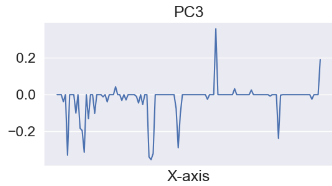
Figure 11: the principal component of traditional principal component analysis



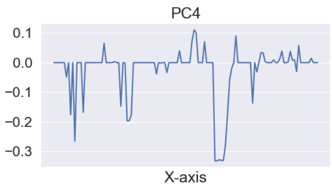
(a) SPC1



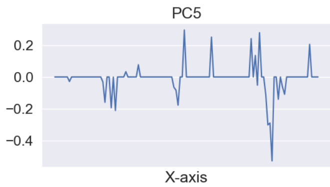
(b) SPC2



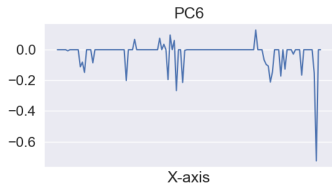
(c) SPC3



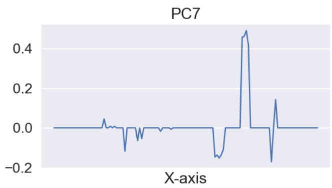
(d) SPC4



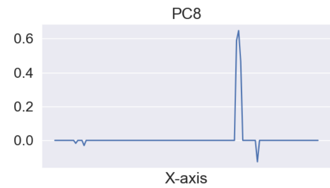
(e) SPC5



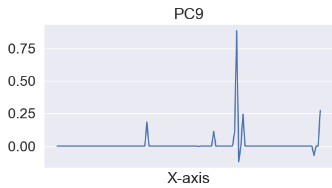
(f) SPC6



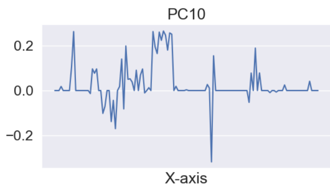
(g) SPC7



(h) SPC8



(i) SPC9



(j) SPC10

Figure 12: the principal component of Sparse principal component analysis

It can also be clearly found from the line chart that after using sparse principal component analysis, we can better understand which variables play an important role in each principal component, which helps us understand the meaning of the principal components more accurately . At the same time, it also helps us to better explain the economic significance of the principal components, because we can see which variables play an important role in each principal component. This is very helpful for our data analysis and decision making.

5. Compare and analyze the results of sparse principal components with the results of PLS

In the third section, we use the partial least squares method to model the volatility of the Chinese market with US macroeconomic data. It turns out that several variables with larger weights are also concentrated in the scope of commodities/consumption, which can prove to a certain extent that the US macroeconomic The consumption situation in the economy has a more significant impact on China's financial market. Because China is closely linked to the economic development of the United States, if the level of consumption in the United States is high, this may boost Chinese exports, which will have a positive impact on China's financial markets. Conversely, if U.S. consumption levels are low, this could dampen China's exports, which could have a negative impact on China's financial markets.

In the fourth section, we use the sparse principal component method to reduce the risk exposure of Chinese listed companies to the US macroeconomic indicators, and propose Yields, Production, Market, Bank, Currency, Housing, Yield spreads, and Treasury spreads. The main influencing factors are Yields, Production, Market and Housing.

1. **Yields**

   Yields refers to the return on investment, that is, the return investors get from their investment. In the United States, Yields usually refers to the yield on U.S. government bonds, that is, the yield on U.S. Treasury bonds. U.S. treasury bonds are one of the bonds most trusted by investors in the world, with a huge market size and extensive attention from global investors.

   Yields changes in U.S. Treasury bonds may affect global markets, including the Chinese market. When the Yields of U.S. Treasury bonds rise, investors may turn to bonds of other countries to obtain higher yields. This could lead to capital outflows from the United States and could cause volatility in global capital markets. Conversely, when the Yields of U.S. Treasury bonds decline, investors may flow into U.S. bonds, leading to capital inflows into the U.S., which may lead to the stability of the global capital market.

   In addition, the Yields of US Treasury bonds may also directly affect the Chinese market. Since China is one of the largest creditors to the United States, the value of China's holdings of U.S. bonds can be affected by changes in Yields for U.S. Treasuries. When the Yields of US treasury bonds rise, the value of US bonds held by China may decline, which may have an impact on China's fiscal balance. Conversely, when the yields of U.S. treasury bonds fall, the value of U.S. bonds held by China may rise, which may bring certain benefits to Chinas fiscal balance.

In addition, the Yields of US treasury bonds may also affect China's foreign exchange market. Since U.S. treasury bonds are one of the most trusted bonds by investors in the world, when the Yields of U.S. treasury bonds rise, it may cause global capital outflows, resulting in a depreciation of the dollar. This may have an impact on China's foreign exchange market, because China is one of the largest trading partners of the United States, and the trade between China and the United States is close, and China's foreign exchange receipts and payments may be affected by the depreciation of the US dollar.

In general, changes in the Yields of U.S. Treasury bonds may have multiple impacts on the Chinese market, including the capital market, fiscal revenue and expenditure, and the foreign exchange market. However, these effects are not absolute and depend on the influence of other factors.

2. **Production**

   Production refers to production, which refers to the total output produced in a country or region. In the United States, Production usually refers to the industrial production in the United States, that is, the total amount of products produced by industrial enterprises.

   Changes in U.S. industrial production may have multiple impacts on the Chinese market. First of all, the United States is one of China's largest trading partners, and the trade exchanges between China and the United States are close. Therefore, changes in US industrial production may directly affect China's trade volume. When U.S. industrial production declines, it may lead to a reduction in U.S. imports from China, thereby affecting Chinas exports. Conversely, when U.S. industrial production rises, it may lead to an increase in U.S. imports from China, thereby boosting Chinas exports.

In addition, changes in US industrial production may also affect China's trade balance. When U.S. industrial production declines, it may lead to a reduction in U.S. imports, thereby reducing the U.S. trade deficit. This may put some pressure on China's trade. Conversely, when U.S. industrial production rises, it may lead to an increase in U.S. imports, thereby increasing the U.S. trade deficit. This may bring some benefits to China's trade.

In addition, US industrial production may also affect China's exchange rate. Since the United States is one of China's largest trading partners and trade ties between China and the United States are close, China's exchange rate may be affected by changes in U.S. industrial production. When U.S. industrial production falls, it can cause the dollar to depreciate, which in turn makes the renminbi appreciate. Conversely, when U.S. industrial production rises, it may cause the U.S. dollar to appreciate, thereby devaluing the renminbi.

In general, changes in US industrial production may have multiple impacts on the Chinese market, including trade volume, trade balance, and exchange rates. However, these effects are not absolute and depend on the influence of other factors.

3. **Market**

The US financial market refers to the US stock market, bond market, foreign exchange market, futures market and other financial markets. Changes in the financial market in the United States may have various impacts on China's financial market.

First, changes in the US financial market may affect China's stock market. Because of the correlation between the stock markets in China and the United States, when the U.S. stock market is booming, it may drive the Chinese stock market up; when the U.S. stock market is down, it may drag the Chinese stock market down.

In addition, changes in the US financial market may also affect China's bond market. Since the bond markets in China and the US are also correlated, when the US bond market is booming, it may boost China's bond market; when the US bond market is down, it may drag China's bond market down.

In addition, changes in the US financial market may also affect China's foreign exchange market. Since the United States is one of China's largest trading partners and the trade between China and the United States is close, China's foreign exchange receipts and payments may be affected by changes in the US financial market. When U.S. financial markets are booming, it can cause the dollar to appreciate, thereby devaluing the renminbi. Conversely, when the U.S. financial market slumps, it may cause the dollar to depreciate, thereby making the renminbi appreciate.

In addition, changes in the US financial market may also affect China's futures market. Since the futures markets in China and the United States are also correlated, when the futures market in the United States is booming, it may promote the futures market in China; when the futures market in the United States is sluggish, it may drag down the futures market in China.

In general, changes in the US financial market may have various impacts on China's financial market, including the stock market, bond market, foreign exchange market and futures market. However, these effects are not absolute and depend on the influence of other factors.

4. **Housing**

   Housing refers to housing, which refers to the houses where people live. In the United States, Housing usually refers to the housing market in the United States, that is, the sales and rental market of houses.

   Changes in the US housing market may have multiple impacts on the Chinese market. First of all, the United States is one of China's largest trading partners, and the trade exchanges between China and the United States are close. Therefore, changes in the US housing market may directly affect China's trade volume. When the U.S. housing market booms, it may lead to an increase in U.S. imports from China, which in turn boosts Chinese exports. Conversely, when the U.S. housing market is down, it may lead to a reduction in U.S. imports from China, thereby affecting China's exports.

   In addition, changes in the US housing market may also affect China's foreign exchange market. Since the United States is one of China's largest trading partners and the trade between China and the United States is close, China's foreign exchange balance may be affected by changes in the US housing market. When the U.S. housing market booms, it can cause the dollar to appreciate, thereby devaluing the renminbi. Conversely, when the U.S. housing market slumps, it may lead to a depreciation of the dollar and thus an appreciation of the renminbi.

In addition, changes in the US housing market may also affect China's investment market. Since the housing market in the US is one of the markets most concerned by investors in the world, when the housing market in the US is booming, it may attract investors to flow into the US, resulting in capital inflows to the US. This may bring some pressure to China's investment market. Conversely, when the housing market in the United States is in a downturn, it may cause investors to flow out of the United States, thereby causing capital to flow out of the United States. This may bring certain benefits to China's investment market.

In general, changes in the housing market in the United States may have various impacts on the Chinese market, including trade volume, foreign exchange market and investment market. However, these effects are not absolute and depend on the influence of other factors.

In addition, it is also important to note that the US housing market is not independent of other markets, it is also affected by other markets. For example, the housing market in the United States is affected by the economic cycle and tends to slump during recessions and boom during recoveries. In addition, the housing market in the United States is also affected by factors such as monetary policy, interest rates, housing prices, and mortgage conditions. Therefore, to fully analyze the impact of the US housing market on the Chinese market, it is necessary to take these factors into account.

In general, using partial least squares and principal component analysis (traditional and sparse) to model the volatility and systemic macro risk exposure of the Chinese market, several categories of influence on the Chinese market were identified. Significant U.S. macroeconomic variables, and further, based on this conclusion in the future, these types of U.S. macroeconomic data can be used to assist investment in the Chinese market.

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Appendix A. Table1

fred	Count	Mean	Sd	Min	Max
RPI	120	14942.66	1230.62	12852.3	17008.96
W875RX1	120	12381.46	1076.18	10437.5	14152.5
DPCERA3M086SBEA	120	107.31	7.98	95.29	121.39
CMRMTSPLx	120	1363939.6	100433.4	1159614	1525606
RETAILx	120	438902.72	48641.93	345959	523862
INDPRO	120	99.04	3.59	89.27	104.17
IPFPNSS	120	99.6	1.87	93.76	102.88
IPFINAL	120	100.01	1.8	94.32	103.34
IPCONGD	120	99.36	1.32	96.54	102.14
IPDCONGD	120	93.44	8.23	76.98	106.27
IPNCONGD	120	101.13	1.41	98.31	104.71
IPBUSEQ	120	98.46	5.4	82.59	105.2
IPMAT	120	98.62	5.49	84.29	106.14
IPDMAT	120	98	5.38	79.59	105.02
IPNMAT	120	100.06	1.64	95.34	102.92
IPMANSICS	120	98.92	2.33	90.8	101.98
IPB51222S	120	103.46	5.51	86.77	117.72
IPFUELS	120	94.65	4.33	83	101.78
CUMFNS	120	74.94	1.99	67.79	78.17
HWI	120	5088.96	1443.5	2666	7574
HWIURATIO	120	0.62	0.35	0.18	1.24
CLF16OV	120	157605.43	3350.48	153214	164579
CE16OV	120	147860.73	6277.04	138438	158735
UNRATE	120	6.22	2.06	3.5	9.9
UEMPMEAN	120	30.82	6.4	19.7	40.7

UEMPLT5	120	2442.33	247.17	1846	2933
UEMP5TO14	120	2449.73	485.77	1654	3534
UEMP15OV	120	4852.1	2370.69	1997	9130
UEMP15T26	120	1479.9	504.21	747	2793
UEMP27OV	120	3372.18	1878.77	1146	6800
CLAIMSx	120	311593.33	79577.76	211800	485750
PAYEMS	120	140421.76	6908.01	129698	151919
USGOOD	120	19335.34	1056.21	17627	21071
CES1021000001	120	719.75	79.43	593.3	851
USCONS	120	6363.44	703.54	5427	7557
MANEMP	120	12201.64	391.45	11453	12830
DMANEMP	120	7622.9	284.4	6985	8062
NDMANEMP	120	4578.74	121.15	4434	4795
SRVPRD	120	121086.42	5859.68	112071	130859
USTPU	120	26373.22	1089.61	24461	27828
USWTRADE	120	5696.56	158.13	5375	5899.1
USTRADE	120	15310.2	494.2	14397.1	15920
USFIRE	120	8123.86	365.03	7676	8832
USGOVT	120	22189.56	277.02	21814	22996
CES0600000007	120	41.12	0.36	39.6	41.7
AWOTMAN	120	4.26	0.22	3.4	4.8
AWHMAN	120	41.73	0.32	40.5	42.3
HOUST	120	993.79	257.57	517	1547
HOUSTNE	120	101.43	30.2	46	219
HOUSTMW	120	149.13	38.44	60	243
HOUSTS	120	502.7	134.04	265	781
HOUSTW	120	240.53	81.07	90	398
PERMIT	120	1047.77	275.14	542	1509

PERMITNE	120	111.3	35.88	58	287
PERMITMW	120	157.98	35.57	89	245
PERMITS	120	524.63	137.7	257	790
PERMITW	120	253.86	83.29	97	397
ACOGNO	120	194876.03	12003.64	165716	214158
AMDMNOx	120	224201.04	18327.02	180450	304221
ANDENOx	120	74640.78	10521.39	56916	144012
AMDMUOx	120	1103515.23	135888.37	827911	1285367
BUSINVx	120	1751268.62	194204.85	1333698	2054491
ISRATIOx	120	1.34	0.06	1.24	1.44
M1SL	120	2875.17	686.82	1674.7	4011.2
M2SL	120	11752.08	2017.56	8458.5	15329.1
M2REAL	120	4922.62	628.48	3883.3	5922.8
BOGMBASE	120	3283740	661996.23	1961200	4075000
TOTRESNS	120	2003.76	523.01	1038.6	2842
NONBORRES	120	1994218.33	537955.83	970200	2841800
BUSLOANS	120	1761.01	391.73	1184.91	2366.78
REALLN	120	3871.15	358.4	3489.04	4622.04
NONREVSL	120	2379.96	435.36	1627.69	3100.59
CONSPI	120	0.15	0.01	0.13	0.16
SP 500	120	1962.2	590.15	1079.8	3176.75
SP: indust	120	2619.04	802.89	1391.77	4294.39
SP div yield	120	1.99	0.11	1.76	2.3
SP PE ratio	120	21.92	6.98	14.42	67.79
FEDFUNDS	120	0.61	0.76	0.07	2.42
CP3Mx	120	0.74	0.8	0.11	2.69
TB3MS	120	0.57	0.78	0.01	2.4
TB6MS	120	0.64	0.79	0.04	2.48

GS1	120	0.74	0.81	0.1	2.7
GS5	120	1.65	0.59	0.62	3
GS10	120	2.41	0.55	1.5	3.85
AAA	120	4.03	0.54	2.98	5.35
BAA	120	4.99	0.58	3.87	6.34
COMPAPFFx	120	0.13	0.12	-0.18	0.57
TB3SMFFM	120	-0.05	0.07	-0.3	0.19
TB6SMFFM	120	0.03	0.11	-0.37	0.36
T1YFFM	120	0.13	0.18	-0.44	0.61
T5YFFM	120	1.04	0.61	-0.63	2.38
T10YFFM	120	1.79	0.91	-0.49	3.65
AAAFFM	120	3.41	1.1	0.86	5.22
BAAFFM	120	4.38	1.15	1.75	6.21
TWEXAFEGSMTHx	120	99.03	10.16	82.68	114.01
EXSZUSx	120	0.96	0.05	0.78	1.13
EXJPUSx	120	101.21	14.07	76.64	123.72
EXUSUKx	120	1.47	0.14	1.22	1.71
EXCAUSx	120	1.17	0.14	0.96	1.42
WPSFD49207	120	195.55	7.25	177.7	207.5
WPSFD49502	120	207.41	8.36	186.4	219.9
WPSID61	120	194.67	7.76	178.9	204.7
WPSID62	120	213.84	29.44	162.1	263.7
OILPRICEx	120	72.45	21.94	30.32	110.04
PPICMM	120	200.79	23.19	157.1	260.7
CPIAUCSL	120	237.11	11.07	217.2	258.2
CPIAPPSL	120	125.02	2.55	118.92	128.58
CPITRNSL	120	207.24	9.31	188.78	223.27
CPIMEDSL	120	443.29	35.41	382.74	510.61

CUSR0000SAC	120	183.36	4.25	172.93	189.88
CUSR0000SAD	120	108.98	3.19	103.89	113.31
CUSR0000SAS	120	290.29	20.92	259.83	329.1
CPIULFSL	120	236.39	11.03	216.89	257.84
CUSR0000SA0L2	120	223.75	7	207.48	236.15
CUSR0000SA0L5	120	227.14	10.01	208.82	246.1
PCEPI	120	102.92	4.21	95.35	110.75
DDURRG3M086SBEA	120	94.43	5.56	85.37	103.55
DNDGRG3M086SBEA	120	97.95	2.52	91.26	101.39
DSERRG3M086SBEA	120	106.13	7.01	95.29	119.07
CES0600000008	120	22.11	1.42	20.09	25.08
CES2000000008	120	25.38	1.73	23.03	28.9
CES3000000008	120	20.04	1.13	18.43	22.44
UMCSENTx	120	85.5	11.27	55.8	101.4
MZMSL	120	12980.53	2202.16	9422.6	17020.5
DTCOLNVHFNM	120	299701.22	24310.26	218553.65	343472.98
DTCTHFNM	120	781625.95	66062.61	642123.82	896866.51
INVEST	120	2972.59	426.98	2294.19	3824.32
VXOCLSx	120	16.29	5.5	8.02	37.3

Appendix B. Table2

Table B.6: Description of ols paras

Fred	count	mean	std	min	mid	max
RPI	2248	0.0030	0.0089	-0.0595	0.0022	0.0460
W875RX1	2248	0.0027	0.0084	-0.0578	0.0020	0.0481
DPCERA3M086SBEA	2248	0.0028	0.0086	-0.0614	0.0019	0.0556
CMRMTSPLx	2248	0.0025	0.0086	-0.1090	0.0017	0.0487
RETAILx	2248	0.0021	0.0089	-0.0666	0.0013	0.0644
INDPRO	2248	0.0035	0.0112	-0.2397	0.0029	0.0518
IPFPNSS	2248	-0.0013	0.0174	-0.3920	0.0016	0.1178
IPFINAL	2248	0.0019	0.0154	-0.3443	0.0039	0.1160
IPCONGD	2248	-0.0041	0.0156	-0.2387	-0.0010	0.0838
IPDCONGD	2248	-0.0021	0.0122	-0.3162	-0.0018	0.0397
IPNCONGD	2248	-0.0020	0.0153	-0.0762	0.0021	0.0990
IPBUSEQ	2248	0.0047	0.0095	-0.1249	0.0044	0.0895
IPMAT	2248	0.0032	0.0101	-0.1530	0.0017	0.0525
IPDMAT	2248	0.0029	0.0118	-0.2059	0.0011	0.0622
IPNMAT	2248	-0.0063	0.0145	-0.1819	-0.0038	0.0879
IPMANSICS	2248	0.0007	0.0160	-0.3992	0.0020	0.1034
IPB51222S	2248	0.0008	0.0082	-0.0573	0.0004	0.0480
IPFUELS	2248	0.0034	0.0070	-0.0244	0.0028	0.0456
CUMFNS	2248	-0.0033	0.0148	-0.3963	-0.0019	0.0457
HWI	2248	0.0009	0.0082	-0.1110	0.0006	0.0614
HWIURATIO	2248	-0.0012	0.0076	-0.1130	-0.0010	0.0547
CLF16OV	2248	0.0041	0.0084	-0.0534	0.0032	0.0489
CE16OV	2248	0.0009	0.0067	-0.0646	0.0007	0.0350
UNRATE	2248	0.0031	0.0096	-0.0312	0.0020	0.1653

UEMPMEAN	2248	0.0015	0.0104	-0.0314	0.0005	0.2032
UEMPLT5	2248	0.0013	0.0085	-0.0601	0.0007	0.1062
UEMP5TO14	2248	0.0044	0.0091	-0.0506	0.0033	0.1157
UEMP15OV	2248	0.0024	0.0111	-0.0294	0.0012	0.2160
UEMP15T26	2248	0.0061	0.0107	-0.0262	0.0049	0.2523
UEMP27OV	2248	0.0001	0.0113	-0.0350	-0.0009	0.2592
CLAIMSx	2248	0.0009	0.0105	-0.1236	0.0005	0.1692
PAYEMS	2248	0.0002	0.0069	-0.0806	-0.0001	0.0335
USGOOD	2248	-0.0055	0.0117	-0.1462	-0.0038	0.0368
CES1021000001	2248	0.0074	0.0090	-0.0251	0.0066	0.1175
USCONS	2248	-0.0001	0.0116	-0.2307	0.0008	0.0604
MANEMP	2248	-0.0090	0.0124	-0.0838	-0.0066	0.0188
DMANEMP	2248	-0.0078	0.0125	-0.0952	-0.0053	0.0231
NDMANEMP	2248	-0.0111	0.0123	-0.0808	-0.0089	0.0172
SRVPRD	2248	0.0012	0.0073	-0.0507	0.0007	0.0399
USTPU	2248	0.0006	0.0075	-0.1160	0.0006	0.0350
USWTRADE	2248	0.0048	0.0107	-0.1231	0.0059	0.0841
USTRADE	2248	-0.0003	0.0083	-0.1424	0.0000	0.0321
USFIRE	2248	0.0001	0.0082	-0.0973	0.0004	0.0363
USGOVT	2248	-0.0023	0.0103	-0.0617	-0.0023	0.1081
CES0600000007	2248	-0.0012	0.0104	-0.2242	-0.0017	0.0970
AWOTMAN	2248	-0.0060	0.0152	-0.4395	-0.0060	0.0871
AWHMAN	2248	-0.0008	0.0101	-0.2192	-0.0012	0.0927
HOUST	2248	-0.0050	0.0106	-0.1583	-0.0039	0.0300
HOUSTNE	2248	-0.0027	0.0106	-0.1229	-0.0025	0.0519
HOUSTMW	2248	-0.0072	0.0106	-0.1093	-0.0060	0.0312
HOUSTS	2248	-0.0028	0.0106	-0.1755	-0.0022	0.0398
HOUSTW	2248	-0.0067	0.0104	-0.1549	-0.0053	0.0263

PERMIT	2248	-0.0041	0.0105	-0.1640	-0.0032	0.0332
PERMITNE	2248	0.0028	0.0131	-0.1624	0.0016	0.0750
PERMITMW	2248	-0.0082	0.0106	-0.1260	-0.0068	0.0177
PERMITS	2248	-0.0026	0.0104	-0.1629	-0.0019	0.0400
PERMITW	2248	-0.0066	0.0109	-0.1699	-0.0051	0.0298
ACOGNO	2248	0.0023	0.0106	-0.0567	0.0005	0.0929
AMDMNOx	2248	0.0023	0.0111	-0.2225	0.0018	0.0895
ANDENOx	2248	0.0028	0.0098	-0.1438	0.0026	0.1394
AMDMUOx	2248	0.0088	0.0097	-0.0238	0.0072	0.0637
BUSINVx	2248	0.0034	0.0088	-0.0492	0.0022	0.0592
ISRATIOx	2248	0.0048	0.0090	-0.0731	0.0044	0.0840
M1SL	2248	0.0013	0.0107	-0.0918	0.0011	0.0928
M2SL	2248	0.0023	0.0092	-0.0625	0.0015	0.0629
M2REAL	2248	0.0026	0.0092	-0.0574	0.0019	0.0585
BOGMBASE	2248	0.0059	0.0101	-0.0377	0.0047	0.0723
TOTRESNS	2248	0.0071	0.0105	-0.0380	0.0057	0.0749
NONBORRES	2248	0.0063	0.0106	-0.0579	0.0048	0.0743
BUSLOANS	2248	0.0031	0.0086	-0.0553	0.0022	0.0441
REALLN	2248	0.0061	0.0093	-0.0622	0.0049	0.0614
NONREVSL	2248	0.0025	0.0091	-0.0564	0.0016	0.0523
CONSPI	2248	0.0028	0.0102	-0.0457	0.0015	0.0448
SP 500	2248	0.0015	0.0087	-0.0790	0.0010	0.0620
SP: indust	2248	0.0014	0.0089	-0.0703	0.0009	0.0630
SP div yield	2248	0.0066	0.0145	-0.0941	0.0066	0.3524
SP PE ratio	2248	0.0000	0.0151	-0.2159	0.0018	0.2288
FEDFUNDS	2248	-0.0026	0.0194	-0.0937	0.0037	0.1031
CP3Mx	2248	-0.0039	0.0192	-0.1031	0.0021	0.0980
TB3MS	2248	-0.0019	0.0194	-0.0955	0.0044	0.1069

TB6MS	2248	-0.0026	0.0191	-0.0996	0.0033	0.1014
GS1	2248	-0.0029	0.0186	-0.1065	0.0027	0.0952
GS5	2248	-0.0038	0.0146	-0.1208	-0.0008	0.0604
GS10	2248	-0.0043	0.0123	-0.0896	-0.0024	0.0460
AAA	2248	-0.0053	0.0105	-0.0713	-0.0040	0.0522
BAA	2248	-0.0034	0.0110	-0.0658	-0.0018	0.1127
COMPAPFFx	2248	-0.0172	0.0157	-0.1138	-0.0135	0.0675
TB3SMFFM	2248	0.0057	0.0161	-0.2812	0.0030	0.0893
TB6SMFFM	2248	-0.0022	0.0134	-0.1749	-0.0033	0.0969
T1YFFM	2248	-0.0077	0.0127	-0.1237	-0.0069	0.0815
T5YFFM	2248	-0.0065	0.0143	-0.1023	-0.0091	0.1920
T10YFFM	2248	-0.0058	0.0138	-0.1000	-0.0084	0.1690
AAAFFM	2248	-0.0053	0.0146	-0.1146	-0.0082	0.1882
BAAFFM	2248	-0.0039	0.0143	-0.0993	-0.0063	0.2605
TWEXAFEGSMTHx	2248	-0.0037	0.0090	-0.1128	-0.0036	0.0361
EXSZUSx	2248	-0.0068	0.0119	-0.0653	-0.0041	0.0455
EXJPUSx	2248	0.0031	0.0112	-0.2886	0.0038	0.0348
EXUSUKx	2248	0.0025	0.0105	-0.0439	0.0037	0.1147
EXCAUSx	2248	-0.0059	0.0093	-0.1342	-0.0051	0.0308
WPSFD49207	2248	0.0031	0.0098	-0.0529	0.0018	0.0809
WPSFD49502	2248	0.0028	0.0098	-0.0519	0.0014	0.0820
WPSID61	2248	0.0027	0.0097	-0.0494	0.0013	0.0997
WPSID62	2248	-0.0007	0.0104	-0.0337	-0.0016	0.1056
OILPRICEx	2248	-0.0020	0.0098	-0.0314	-0.0030	0.1199
PPICMM	2248	0.0040	0.0135	-0.0520	0.0048	0.1297
CPIAUCSL	2248	0.0034	0.0094	-0.0591	0.0023	0.0698
CPIAPPSL	2248	0.0012	0.0112	-0.0582	0.0006	0.1157
CPITRNSL	2248	0.0001	0.0102	-0.0506	-0.0013	0.0960

CPIMEDSL	2248	0.0037	0.0093	-0.0545	0.0025	0.0554
CUSR0000SAC	2248	0.0029	0.0102	-0.0484	0.0014	0.0948
CUSR0000SAD	2248	-0.0032	0.0090	-0.0501	-0.0024	0.0620
CUSR0000SAS	2248	0.0034	0.0091	-0.0577	0.0023	0.0579
CPIULFSL	2248	0.0031	0.0094	-0.0607	0.0021	0.0698
CUSR0000SA0L2	2248	0.0038	0.0098	-0.0539	0.0025	0.0783
CUSR0000SA0L5	2248	0.0033	0.0094	-0.0594	0.0023	0.0717
PCEPI	2248	0.0037	0.0094	-0.0577	0.0025	0.0687
DDURRG3M086SBEA	2248	-0.0043	0.0094	-0.0477	-0.0031	0.0508
DNDGRG3M086SBEA	2248	0.0037	0.0104	-0.0457	0.0019	0.0798
DSERRG3M086SBEA	2248	0.0035	0.0091	-0.0580	0.0024	0.0604
CES0600000008	2248	0.0028	0.0092	-0.0625	0.0018	0.0623
CES2000000008	2248	0.0026	0.0092	-0.0594	0.0017	0.0609
CES3000000008	2248	0.0026	0.0093	-0.0666	0.0017	0.0630
UMCSENTx	2248	-0.0003	0.0094	-0.1215	0.0004	0.0297
DTCOLNVHFNM	2248	0.0067	0.0126	-0.0800	0.0043	0.0840
DTCTHFNM	2248	0.0163	0.0157	-0.0241	0.0123	0.0926
INVEST	2248	0.0027	0.0091	-0.0691	0.0020	0.0707
VIXCLSx	2248	-0.0111	0.0115	-0.0725	-0.0098	0.1242

Appendix C. Data detail description

Table C.7: Group1:Output and Income

	id	fred	description
1	1	RPI	Real Personal Income
2	2	W875RX1	Real personal income ex transfer receipts
3	6	INDPRO	IP Index
4	7	IPFPNSS	IP: Final Products and Nonindustrial Supplies
5	8	IPFINAL	IP: Final Products (Market Group)
6	9	IPCONGD	IP: Consumer Goods
7	10	IPDCONGD	IP: Durable Consumer Goods
8	11	IPNCONGD	IP: Nondurable Consumer Goods
9	12	IPBUSEQ	IP: Business Equipment
10	13	IPMAT	IP: Materials
11	14	IPDMAT	IP: Durable Materials
12	15	IPNMAT	IP: Nondurable Materials
13	16	IPMANSICS	IP: Manufacturing (SIC)
14	17	IPB51222s	IP: Residential Utilities
15	18	IPFUELS	IP: Fuels
16	19	NAPMPI	ISM Manufacturing: Production Index
17	20	CUMFNS	Capacity Utilization: Manufacturing

Appendix D. Conventional principal component weights for 120 macro variables

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
RPI	0.08	-0.07	-0.08	0.07	-0.01	0.01	0.00	0.04	-0.02	0.01
W875RX1	0.07	-0.08	-0.07	0.06	0.02	0.01	-0.01	0.03	0.00	-0.01
DPCERA3M086SBEA	0.07	-0.07	-0.06	0.06	0.01	0.05	-0.06	0.01	0.03	-0.03
CMRMTSPLx	0.06	-0.11	-0.04	0.04	0.00	0.01	-0.01	0.00	-0.02	-0.02
RETAILx	0.08	-0.08	-0.05	0.05	-0.04	0.05	-0.04	0.03	0.03	0.01
INDPRO	0.03	-0.16	0.11	-0.01	0.07	-0.03	0.00	-0.02	-0.02	0.01
IPFPNSS	-0.13	-0.18	0.15	-0.01	0.00	0.08	-0.11	-0.01	-0.19	-0.13
IPFINAL	-0.08	-0.17	0.19	0.02	-0.02	0.07	-0.10	-0.05	-0.15	-0.14
IPCONGD	-0.15	-0.11	-0.01	0.00	-0.11	0.05	-0.12	-0.08	-0.14	-0.17
IPDCONGD	-0.01	-0.18	-0.06	-0.11	-0.05	-0.01	-0.03	-0.06	-0.10	-0.17
IPNCONGD	-0.17	0.01	0.04	0.08	-0.08	0.03	-0.15	-0.08	-0.08	-0.06
IPBUSEQ	0.02	-0.09	0.17	0.02	0.10	0.01	-0.02	-0.03	-0.01	0.02
IPMAT	0.07	-0.12	0.06	-0.01	0.09	-0.03	0.03	0.02	0.02	0.03
IPDMAT	0.06	-0.14	0.13	-0.03	0.10	-0.05	0.03	-0.02	-0.03	0.03
IPNMAT	-0.15	-0.07	0.10	0.00	-0.07	0.05	-0.04	0.02	-0.02	0.01
IPMANSICS	-0.06	-0.21	0.19	-0.04	0.05	0.05	-0.05	-0.02	-0.16	-0.09
IPB51222S	0.04	-0.02	-0.02	0.10	-0.02	-0.02	-0.02	-0.06	-0.07	-0.09
IPFUELS	0.03	-0.01	0.06	0.04	0.16	0.09	-0.09	-0.03	0.09	-0.08
CUMFNS	-0.06	-0.21	0.08	-0.09	0.01	0.12	0.01	0.01	-0.09	-0.05
HWI	0.03	-0.11	-0.07	0.01	-0.04	0.06	-0.04	0.05	0.06	0.07
HWIURATIO	-0.01	-0.10	-0.05	0.00	0.04	0.07	-0.06	0.04	0.14	0.09
CLF16OV	0.07	-0.05	-0.05	0.10	0.07	0.03	-0.06	-0.01	0.03	-0.04
CE16OV	0.03	-0.09	-0.03	0.04	0.09	0.04	-0.08	0.03	0.06	-0.02
UNRATE	0.05	0.12	0.01	0.08	-0.10	-0.02	0.12	-0.04	-0.08	0.02
UEMPMEAN	0.08	0.03	0.14	-0.01	-0.05	0.13	0.08	0.05	0.03	-0.07
UEMPLT5	0.01	0.06	-0.03	0.03	0.01	-0.15	0.13	-0.06	-0.20	0.22

UEMP5TO14	0.03	0.08	-0.04	0.06	-0.01	-0.14	0.11	-0.08	-0.17	0.18
UEMP15OV	0.06	0.11	0.08	0.08	-0.16	0.12	0.09	0.00	-0.02	-0.17
UEMP15T26	0.03	0.11	-0.02	0.05	-0.13	-0.02	-0.01	-0.10	-0.07	-0.16
UEMP27OV	0.06	0.09	0.12	0.08	-0.14	0.18	0.12	0.05	0.01	-0.12
CLAIMSx	0.02	0.04	-0.08	0.07	-0.05	-0.16	0.13	0.04	-0.35	0.25
PAYEMS	0.03	-0.09	-0.04	0.03	0.09	0.02	-0.06	0.05	0.05	0.00
USGOOD	-0.12	-0.08	-0.07	-0.03	0.01	-0.02	-0.02	0.07	0.03	0.09
CES1021000001	0.04	0.01	0.17	0.02	0.13	-0.04	0.00	-0.01	-0.01	0.06
USCONS	-0.07	-0.11	-0.14	0.02	0.01	-0.10	-0.14	-0.10	-0.05	0.03
MANEMP	-0.13	-0.04	-0.01	-0.06	-0.01	0.02	0.04	0.16	0.08	0.13
DMANEMP	-0.13	-0.05	0.00	-0.06	0.00	0.00	0.03	0.15	0.07	0.13
NDMANEMP	-0.13	-0.02	-0.03	-0.06	-0.03	0.06	0.06	0.17	0.11	0.12
SRVPRD	0.05	-0.08	-0.03	0.04	0.09	0.03	-0.06	0.04	0.05	-0.01
USTPU	0.01	-0.11	-0.04	0.00	0.05	0.00	-0.07	0.04	0.04	0.02
USWTRADE	-0.06	-0.12	0.03	0.01	0.18	-0.09	-0.10	0.04	0.05	0.13
USTRADE	-0.02	-0.11	0.01	-0.07	0.09	0.00	-0.12	0.02	0.02	-0.05
USFIRE	0.00	-0.10	-0.11	0.06	0.01	-0.04	-0.06	-0.03	-0.03	0.01
USGOVT	-0.01	0.02	-0.04	0.18	0.17	0.10	-0.24	-0.04	0.08	-0.09
CES0600000007	0.04	-0.12	0.12	-0.04	0.07	0.08	0.13	0.07	-0.01	-0.01
AWOTMAN	-0.02	-0.18	0.15	-0.18	0.09	0.13	0.16	0.08	-0.15	-0.10
AWHMAN	0.03	-0.12	0.13	-0.05	0.05	0.10	0.07	0.06	0.00	-0.06
HOUST	-0.06	-0.11	-0.11	-0.09	-0.10	-0.01	0.05	-0.03	-0.03	0.00
HOUSTNE	-0.03	-0.10	-0.04	-0.14	-0.04	-0.12	0.02	-0.08	0.01	0.08
HOUSTMW	-0.08	-0.06	-0.08	-0.11	-0.11	0.02	0.07	0.09	-0.04	0.04
HOUSTS	-0.04	-0.13	-0.12	-0.07	-0.10	-0.02	0.05	-0.05	-0.04	-0.01
HOUSTW	-0.06	-0.10	-0.11	-0.06	-0.07	0.02	0.06	-0.04	-0.03	-0.02
PERMIT	-0.05	-0.12	-0.12	-0.10	-0.10	-0.03	0.04	-0.04	-0.04	0.01
PERMITNE	0.01	-0.13	-0.03	-0.21	-0.03	-0.20	-0.07	-0.08	0.01	0.14

PERMITMW	-0.08	-0.07	-0.09	-0.12	-0.10	0.02	0.09	0.07	-0.02	0.02
PERMITS	-0.04	-0.12	-0.12	-0.07	-0.11	-0.03	0.05	-0.06	-0.05	0.01
PERMITW	-0.06	-0.11	-0.13	-0.07	-0.08	0.02	0.05	-0.04	-0.06	-0.04
ACOGNO	0.09	-0.08	0.12	0.04	0.00	0.01	0.00	-0.02	0.05	0.09
AMDMNOx	0.03	-0.16	0.10	0.02	-0.05	0.03	0.04	-0.03	-0.05	0.07
ANDENOx	-0.01	-0.09	0.15	0.04	-0.07	0.05	0.05	-0.02	-0.04	0.09
AMDMUOx	0.10	-0.04	0.04	0.00	0.12	-0.05	-0.09	-0.03	-0.02	0.02
BUSINVx	0.08	-0.07	-0.03	0.04	0.05	0.00	0.00	0.04	0.01	0.05
ISRATIOx	0.02	0.04	-0.13	-0.01	0.22	-0.12	0.02	0.06	0.01	0.05
M1SL	0.06	-0.06	-0.11	0.06	-0.16	0.06	-0.05	0.10	-0.06	0.06
M2SL	0.08	-0.06	-0.08	0.05	-0.04	0.04	-0.02	0.05	-0.01	0.02
M2REAL	0.09	-0.06	-0.09	0.04	-0.04	0.03	-0.01	0.05	-0.02	0.00
BOGMBASE	0.11	-0.05	-0.05	-0.02	-0.04	0.03	-0.01	0.02	-0.03	0.03
TOTRESNS	0.11	-0.04	-0.03	-0.04	-0.04	0.03	-0.02	0.01	-0.04	0.04
NONBORRES	0.11	-0.06	-0.02	-0.05	-0.04	0.02	0.01	0.01	-0.03	0.04
BUSLOANS	0.08	-0.05	-0.09	0.06	0.02	-0.02	-0.01	0.06	-0.02	0.03
REALLN	0.08	-0.03	-0.08	0.15	0.02	0.02	-0.08	-0.06	-0.02	-0.05
NONREVSL	0.09	-0.07	-0.07	0.04	0.02	0.01	0.00	0.03	0.00	0.01
CONSPI	0.10	-0.06	-0.03	-0.04	0.10	-0.02	0.00	0.00	-0.02	-0.04
SP 500	0.06	-0.09	-0.08	0.03	-0.05	0.04	-0.02	0.06	0.04	0.05
SP: indust	0.07	-0.09	-0.08	0.03	-0.06	0.05	-0.02	0.07	0.04	0.05
SP div yield	0.01	0.17	0.03	0.12	0.30	-0.09	-0.11	0.03	-0.09	-0.04
SP PE ratio	-0.03	0.03	-0.22	-0.04	-0.22	0.13	-0.30	-0.13	0.23	-0.15
FEDFUNDS	-0.21	-0.04	-0.01	0.17	0.06	0.03	0.02	-0.04	0.05	0.06
CP3Mx	-0.21	-0.04	-0.01	0.16	0.06	0.04	0.01	-0.02	0.03	0.09
TB3MS	-0.21	-0.04	-0.02	0.17	0.07	0.05	0.05	-0.09	0.06	0.07
TB6MS	-0.21	-0.04	-0.02	0.16	0.07	0.06	0.04	-0.08	0.06	0.08
GS1	-0.21	-0.04	-0.02	0.14	0.07	0.06	0.03	-0.08	0.05	0.09

GS5	-0.17	0.00	0.00	0.02	0.03	0.04	-0.06	-0.09	0.11	0.14
GS10	-0.14	0.02	0.03	-0.01	0.00	0.04	-0.07	-0.08	0.11	0.11
AAA	-0.11	0.06	0.04	-0.05	0.01	0.03	-0.08	0.00	0.08	0.09
BAA	-0.10	0.09	0.02	-0.02	0.04	0.03	-0.12	0.02	0.02	0.06
COMPAPFFx	-0.09	0.07	-0.10	0.05	0.15	0.32	-0.19	0.23	-0.46	0.15
TB3SMFFM	0.14	0.03	-0.09	-0.07	0.09	0.18	0.23	-0.45	0.08	0.09
TB6SMFFM	0.08	0.06	-0.10	-0.10	0.15	0.32	0.10	-0.36	-0.11	0.12
T1YFFM	0.00	0.08	-0.09	-0.13	0.14	0.39	-0.01	-0.22	-0.16	0.15
T5YFFM	0.07	0.11	0.02	-0.28	-0.03	0.13	-0.25	-0.03	0.01	0.14
T10YFFM	0.09	0.11	0.06	-0.23	-0.07	0.08	-0.20	0.00	0.01	0.05
AAAFFM	0.11	0.13	0.06	-0.22	-0.05	0.03	-0.18	0.09	-0.01	0.02
BAAFFM	0.08	0.17	0.04	-0.17	-0.01	0.02	-0.21	0.09	-0.05	0.04
TWEXAFEGSMTHx	0.00	-0.05	-0.15	-0.12	0.11	-0.03	0.05	0.09	0.05	0.01
EXSZUSx	-0.13	0.03	-0.03	-0.04	0.00	0.03	0.03	0.07	0.05	0.03
EXJPUSx	-0.03	-0.10	-0.10	-0.14	0.07	-0.18	-0.20	-0.16	0.02	0.07
EXUSUKx	-0.09	0.01	0.13	0.02	-0.09	-0.09	-0.14	-0.08	-0.02	0.08
EXCAUSx	-0.01	-0.03	-0.18	-0.12	0.10	0.00	0.03	0.10	0.01	-0.01
WPSFD49207	0.10	-0.06	0.00	0.05	0.00	0.04	-0.02	0.02	0.04	0.07
WPSFD49502	0.10	-0.06	0.02	0.05	-0.01	0.04	-0.02	0.01	0.04	0.08
WPSID61	0.09	-0.06	0.04	0.07	-0.06	0.06	-0.05	0.00	0.04	0.14
WPSID62	0.06	-0.05	0.17	0.05	-0.12	0.05	-0.06	0.00	0.04	0.19
OILPRICEx	0.04	0.00	0.18	0.06	-0.08	0.03	-0.04	0.01	0.09	0.18
PPICMM	-0.01	-0.07	0.11	0.25	-0.28	0.06	-0.08	-0.15	0.01	0.18
CPIAUCSL	0.10	-0.06	-0.04	0.07	0.00	0.03	-0.02	0.02	0.01	0.03
CPIAPPSL	0.05	-0.02	0.14	-0.15	0.16	0.07	0.11	0.15	0.17	0.11
CPITRNSL	0.09	-0.06	0.08	0.05	-0.06	0.06	0.01	0.02	0.08	0.17
CPIMEDSL	0.10	-0.05	-0.06	0.06	0.02	0.01	0.00	0.02	-0.01	-0.01
CUSR0000SAC	0.11	-0.05	0.04	0.05	-0.04	0.04	-0.01	0.01	0.04	0.13

CUSR0000SAD	-0.04	0.00	0.06	-0.11	-0.20	0.07	-0.01	0.05	0.08	0.19
CUSR0000SAS	0.09	-0.06	-0.07	0.07	0.02	0.02	-0.03	0.02	0.00	0.00
CPIULFSL	0.10	-0.06	-0.04	0.07	0.00	0.03	-0.02	0.02	0.02	0.03
CUSR0000SA0L2	0.11	-0.05	-0.01	0.06	-0.01	0.03	-0.02	0.01	0.02	0.05
CUSR0000SA0L5	0.10	-0.06	-0.04	0.07	0.00	0.03	-0.03	0.02	0.02	0.03
PCEPI	0.10	-0.06	-0.04	0.06	0.00	0.03	-0.02	0.01	0.01	0.02
DDURRG3M086SBEA	-0.10	0.04	0.05	-0.06	-0.08	0.01	0.00	0.01	0.03	0.07
DNDGRG3M086SBEA	0.11	-0.05	0.04	0.05	0.01	0.01	0.00	0.00	0.03	0.09
DSERRG3M086SBEA	0.09	-0.06	-0.06	0.07	0.01	0.02	-0.02	0.02	0.00	0.00
CES0600000008	0.09	-0.05	-0.07	0.07	0.00	0.04	-0.02	0.03	0.01	0.00
CES2000000008	0.09	-0.05	-0.07	0.07	0.00	0.04	-0.02	0.04	0.01	0.00
CES3000000008	0.09	-0.05	-0.07	0.07	-0.01	0.04	-0.02	0.03	0.01	0.00
UMCSENTx	-0.04	-0.08	-0.05	-0.09	0.18	0.00	0.10	-0.05	0.13	-0.09
DTCOLNVHFNM	0.12	-0.11	-0.01	-0.02	-0.03	-0.09	-0.02	-0.08	-0.08	0.02
DTCTHFNM	0.10	-0.05	0.19	-0.04	0.03	-0.31	-0.23	-0.26	-0.14	0.07
INVEST	0.08	-0.06	-0.08	0.06	-0.06	0.06	-0.04	0.05	0.01	0.02
VIXCLSx	-0.04	0.11	-0.10	0.09	-0.01	0.04	-0.10	0.23	-0.23	0.09

Appendix E. Sparse principal component weights for 120 macro variables

Variable	SPC1	SPC2	SPC3	SPC4	SPC5	SPC6	SPC7	SPC8	SPC9	SPC10
AAA	0.14	-	-	-0.06	-	-	-	-	-	-
AAAFFM	-	-	-	-	-	-	0.49	-	-	-
ACOGNO	-0.05	-	-0.08	-	-0.06	-0.27	-	-	-	-
AMDMNOx	-0.02	0.00	-0.29	-	-0.08	-	-	-	-	0.02
AMDMUOx	-0.05	-	-	0.04	-	-0.21	-	-	-	-
ANDENOx	-	0.08	-0.11	-	-0.18	-	-	-	-	-
AWHMAN	-	-	-0.32	-	-	-	-	-	-	-
AWOTMAN	-	0.15	-0.35	-	-	-	-	-	-	0.01
BAA	0.16	-	0.03	-0.02	-	-	-	-	0.11	-
BAAFFM	-	-0.01	0.03	-	-	-	0.42	-	-	-0.05
BOGMBASE	-0.12	-	-	0.07	-	-	-	-	-	-
BUSINVx	-0.16	-	-	-	-	0.00	-	-	-	-
BUSLOANS	-0.15	-	-	-	-	-	-	-	-	-
CE16OV	-0.07	0.02	-0.01	-	-	-	-	-	-	-
CES0600000007	-	-	-0.34	-	-	-	-	-	-	-
CES0600000008	-0.18	-	-	-	-	-	-	-	-	-
CES1021000001	-	-	-0.03	-	-	-0.20	-	-	-	-0.08
CES2000000008	-0.18	-	-	-	-	-	-	-	-	-
CES3000000008	-0.18	-	-	-	-	-	-	-	-	-
CLAIMSx	-	-0.11	-	-	-	-	-	-	-	-
CLF16OV	-0.14	-	-	-	-	-	-	-	-	-
CMRMTSPLx	-0.13	-	-0.04	-	-	-	-	-	-	0.02
COMPAPFFx	-	-	-	-	-	-	-	-	0.89	-
CONSPI	-0.10	-	-0.03	0.07	-	-	-	-	-	-
CP3Mx	-	-	-	-0.33	-	-	-0.14	-	-	-
CPIAPPSL	-	-	-0.24	-	-	-	0.14	-	-	-0.01

CPIAUCSL	-0.17	-	-	0.01	-	-	-	-	-	-
CPIMEDSL	-0.17	-	-	0.01	-	-	-	-	-	-
CPITRNSL	-0.10	-	0.00	-	-0.14	-0.17	-	-	-	-
CPIULFSL	-0.18	-	-	0.00	-	-	-	-	-	-
CUMFNS	-	0.32	-0.10	-	-	-	-	-	-	0.10
CUSR0000SA0L2	-0.15	-	-	0.04	-	-0.03	-	-	-	-
CUSR0000SA0L5	-0.17	-	-	0.01	-	-	-	-	-	-
CUSR0000SAC	-0.10	-	-	0.04	-0.06	-0.13	-	-	-	-
CUSR0000SAD	0.06	-	-	-	-0.11	-	-	-	-	0.02
CUSR0000SAS	-0.17	-	-	-	-	-	-	-	-	-
DDURRG3M086SBEA	0.14	-	-	-0.03	-	-	-	-	-	-
DMANEMP	-	0.00	-	-0.20	-	-	-	-	-	0.05
DNDGRG3M086SBEA	-0.09	-	-	0.06	-	-0.17	-	-	-	-
DPCERA3M086SBEA	-0.16	-	-	-	-	-	-	-	-	-
DSERRG3M086SBEA	-0.17	-	-	-	-	-	-	-	-	-
DTCOLNVHFNM	-0.17	-	-	0.01	-	-0.15	-	-	-0.07	-
DTCTHFNM	-	-	-	-	-	-0.73	-	-	-	-
EXCAUSx	-	-	-	-	0.28	-	-	-	-	0.08
EXJPUSx	-	-	-	-	0.13	-	-	-	-	0.19
EXSZUSx	0.05	-	-	-0.14	-	0.13	-	-	-	-
EXUSUKx	0.09	0.02	-	-0.03	-0.05	-	-	-0.13	-	-
FEDFUNDS	-	-	-	-0.33	-	-	-0.15	-	-	-
GS1	-	-	-	-0.33	-	-	-0.11	-	-	-
GS10	0.07	-	-	-0.17	-	-	-	-	-	-
GS5	-	-	-	-0.28	-	-	-	-	-	-
HOUST	-	-	-	-	-	-	-	-	-	0.26
HOUSTMW	-	-	-	-0.04	-	0.08	-	-	-	0.17
HOUSTNE	-	-	-	-	-	-	-	-	-	0.20

HOUSTS	-	-	-	-	-	-	-	-	-	0.26
HOUSTW	-	-	-	0.00	-	0.04	-0.02	-	-	0.22
HWI	-0.10	-	-	-	-	-	-	-	-	0.08
HWIURATIO	-0.02	0.02	-	-	-	-	-	-	-	0.10
INDPRO	-0.01	0.03	-0.33	-	-	-0.01	-	-	-	-
INVEST	-0.17	-	-	-	-	-	-	-	-	-
IPB51222S	-0.06	-	-	-	-	-	-	-	-	-
IPBUSEQ	-	0.04	-0.18	-	-	-0.11	-	-	-	-
IPCONGD	-	0.16	-	-0.18	-	-	-	-	-	0.11
IPDCONGD	-	-	-0.10	-	-	-	-	-	-	0.26
IPDMAT	-0.01	-	-0.31	-	-	-0.15	-	-	-	-
IPFINAL	-	0.47	-	-	-0.03	-	-	-	-	-
IPFPNSS	-	0.51	-	-0.05	-	-	-	-	-	-
IPFUELS	-	-	-	-	-	-0.09	-	-	-	-0.01
IPMANSICS	-	0.43	-0.13	-	-	-	-	-	-	-
IPMAT	-0.08	-	-0.20	-	-	-0.08	-	-	-	-
IPNCONGD	0.02	-	-	-0.27	-	-	-	-0.02	-	-
IPNMAT	0.03	0.18	-	-0.17	-	-	-	-0.03	-	-
ISRATIOx	-	-0.06	-	-	0.29	-	-	-	-	-
M1SL	-0.14	-	-	-	-	-	-	-	-	0.00
M2REAL	-0.17	-	-	-	-	-	-	-	-	-
M2SL	-0.17	-	-	-	-	-	-	-	-	-
MANEMP	-	-	-	-0.20	-	-	-	-	-	0.05
NDMANEMP	-	-	-	-0.18	-	0.07	-	-	-	0.04
NONBORRES	-0.09	-	-	0.10	-	-	-	-	0.00	-
NONREVSL	-0.17	-	-	-	-	-	-	-	-	-
OILPRICEx	-	-	-	-	-0.29	-0.15	-	-	-	-0.01
PAYEMS	-0.07	-	-0.03	-	-	-	-	-	-	0.02

PCEPI	-0.17	-	-	0.01	-	-	-	-	-	-
PERMIT	-	-	-	-	-	-	-	-	-	0.27
PERMITMW	-	-	-	-0.03	-	0.10	-	-	-	0.18
PERMITNE	-	-	-	-	-	-0.19	-	-	-	0.25
PERMITS	-	-	-	-	-	-	-	-	-	0.26
PERMITW	-	-	-	-	-	0.06	-0.01	-	-	0.25
PPICMM	-	-	-	-	-0.53	-	-0.17	-	-	-
REALLN	-0.15	-	-	-	-	-	-	-	-	-
RETAILx	-0.16	-	-	-	-	-	-	-	-	-
RPI	-0.16	-	-	-	-	-	-	-	-	-
SP 500	-0.14	-	-	-	-	-	-	-	-	0.03
SP div yield	-	-	-	-	0.25	-	-	-	0.11	-0.32
SP PE ratio	-	-	0.36	-	-	-	-	-	-	0.16
SP: indust	-0.15	-	-	-	-	-	-	-	-	0.01
SRVPRD	-0.11	-	-0.01	-	-	-	-	-	-	-
T10YFFM	-	-	-	-	-	-	0.46	-	-	-
T1YFFM	0.01	-	-	-	-	-	-	0.47	0.25	-
T5YFFM	-	-	-	-	-	-	0.46	-	-	-
TB3MS	-	-	-	-0.33	-	-	-0.15	-	-	-
TB3SMFFM	0.00	-	-	0.09	-	-	-	0.59	-0.12	-
TB6MS	-	-	-	-0.33	-	-	-0.14	-	-	-
TB6SMFFM	-	-	-	-	-	-	-	0.65	-	-
TOTRESNS	-0.08	-	-	0.11	-	-	-	-	-	-
TWEXAFEGSMTHx	-0.01	-	-	-	0.24	-	-	-	-	0.08
UEMP15OV	-	-0.07	-	-	-0.19	-	0.01	-	-	-0.14
UEMP15T26	-	-0.11	0.04	-	0.00	-	-	-	-	-0.04
UEMP27OV	-	0.00	-	0.00	-0.21	-	0.01	-	-	-0.17
UEMP5TO14	-	-0.15	-	-	-	-	-	-	-	-

UEMPLT5	-	-0.08	-	-	-	-	-	-	-	-
UEMPMEAN	-	-	-0.04	0.07	-0.16	-	0.05	-	-	-0.07
UMCSENTx	-	0.07	-0.03	-	0.20	-	-	-	-	0.04
UNRATE	-	-0.15	-	-	-0.03	-	-	-	-	-0.10
USCONS	-	-	-	0.00	0.03	-	-0.12	-	-	0.20
USFIRE	-0.05	-	-	-	-	-	-0.05	-	-	0.10
USGOOD	-	-	-	-0.15	-	-	-	-	-	0.14
USGOVT	-	-	-	-	-	-	-	-	0.18	-0.01
USTPU	-0.04	-	-0.05	-	-	-	-	-	-	0.09
USTRADE	-	0.09	-0.05	-	-	-	-	-	-	0.07
USWTRADE	-	0.21	-	-	0.08	-	-0.06	-	-	-
VIXCLSx	-	-	0.19	-	-	-	-	-	0.27	-
W875RX1	-0.15	-	-	-	-	-	-	-	-	-
WPSFD49207	-0.13	-	-	0.03	-	-0.07	-	-	-	-
WPSFD49502	-0.12	-	-	0.03	-	-0.10	-	-	-	-
WPSID61	-0.12	-	-	0.00	-0.11	-0.11	-	-	-	-
WPSID62	-	-	-0.01	-	-0.30	-0.21	-	-	-	-