Comparison of Macroeconomic Variables and Industries Portfolios Returns in Constructing Systemic Risk Indicator

Zichao Wen[1,a,*]

[1]*School of Applied Mathematics, Beijing Normal University, Zhuhai, China*
a. wenzichao991128@gmail.com
**corresponding author*

Keywords: systemic risk, macroeconomic variables, industries portfolios, principal component analysis, SR, absorption-ratio, VAR

Abstract: Motivated by the difficulty in measuring systemic risk, this paper constructs two systemic risk indicators based on two different set of variables: macroeconomic variables and industries portfolios returns. We examine which one of these two types of variables is better than the other in tracking underlying systemic risk. Furthermore, we investigate the predictability of both indicators for financial asset returns. The Vector Auto Regressing (VAR) analysis shows that systemic risk constructed based on macroeconomic variables has significant predictive power for the future asset returns and is better than the risk indicator based on industry portfolio returns.

1. Introduction

In the aftermath of 2008-2009 financial crisis, systemic has become the focal point reach in finance literature. In terms of risk management perspective, it is important to conduct in-depth research on system risk by constructing proxies for quantifying this latent risk. Existing literature has used two sets of variables to construct systemic risk proxies: macroeconomic variables and industries portfolios returns. The purpose of this paper is to examine which set of these variables, macroeconomic variables or industries portfolios returns, is more suitable to construct systemic risk, via two different statistical approaches. Furthermore, this research utilizes VAR model to investigate the predictability of systemic risk proxies for different asset classes' returns. We will discuss more details step by step in the rest of this paper. This paper consists of 7 sections. Section 1 is the introduction, and section 2 gives a brief literature review on systemic risk. Section 3 describes the data, and section 4 talks about two methodologies. Section 5 and 6 cover horse race analysis of two set of variables used to construct the systemic risk and the predictive regression analysis of the two different indicators. Finally, section 7 concludes.

2. Literature Review

Zhou, Pang and Wang (2018) [4] used Absorption-Ratio to proxy systemic risk, which is constructed by the variance contribution of first three Principal Components to the total variations based on 56 industry portfolios returns in China. They performed Granger Causality Test on the Absorption-Ratio and market return to examine the relationship between them. They also established different investment strategies to test effectiveness of Absorption-Ratio in real trading. Their works shows that the AR could capture the systemic risk in China to a certain degree, and be able to predict the trend of capital market returns in a sensible way.

In order to study the impact of house price volatility on systemic risk in China, Tang (2018) [3] constructed a systemic risk indicators SR using pure macroeconomic variables. Tang (2018) [3] established a VAR model based on four variables growth of average price of commercial housing, growth rate of real estate mortgage, one-year deposit interest rate and SR. The two main findings of his paper are: (1) House price volatility, growth rate of real estate mortgage does Granger cause the systemic risk. (2) Increase interest rate in short period will increase systemic risk while, long-term interest rate regulation policy does not have significant effect on systemic risk.

Another seminal paper, Giglio, Kelly, and Pruitt (2016) [3], extracts a latent factor out of a cross section of systemic risk measures and find that their factor can predict lower quantiles of future macroeconomic shocks instead of the central tendency of those shocks. Motivated by exploring the relationship between systemic risk and the distribution of macro-economic shocks, GKP uses the quantile regression to find that systemic risk can predict a downside quantile of industry production innovations. Moreover, their method of dimension reduction, Partial Quantile Regression, condenses the cross section of predictors according to each predictor's quantile covariation with the forecast target, choosing a best linear combination of predictors that is most fitted to quantile forecast target. So, their methods belong to supervised learning and utilized the information of the forecast target which consists of industry production shocks.

The above references mainly building an indicator reflected systemic risk and exploring relationship between housing market and systemic risk. Different from them, this paper focus on comparing effects of two types of variables in constructing systemic risk indicator, using the method mentioned in the above references.

3. Data Selection

3.1. Data of Macroeconomic Variables and Industries Portfolios Returns

We follow the literatures and use, 13 U.S. macroeconomic variables: GDP growth rate (GDP), M2/GDP (MG), Non-performing loans rate (NL), Federal surplus or deficit (FSD), Leverage (L), Home price index (H1), Median sales price of houses (H2), Investment in government fixed assets (FA), Interest rate (IR), Inflation rate (IF), Federal debt held by foreign (FD), Stock market total value/GDP (SG), and Bank capital to total assets (BC). Among them, MG, NL, L, FD and SG are reverse variables, and it is necessary to reverse these variables. For the industries portfolios, we use the quarterly yields of 49 industries portfolios in US market. Our final samples consist of quarterly observations, covering the period from January 1, 1999 to January 1, 2016.

3.2. Financial Asset Data

In order to study the relationship between systemic risk and asset returns, we focus on four classes of financial assets: S&P500 Index, U.S. 10 Year Treasury Bond, silver futures and cruel oil futures. They are collected at quarterly level covering the same sample period.

4. Methodology

4.1. Principle Component Analysis

The idea of PCA is to reduce the dimensionality of a large data set while maintain and maximize the total variations of the underlying variables.

Suppose there are m variables, x_1, x_2, …, x_m, and each variable has n observations. Then, we have a sample matrix X.

$$X = (x_1, x_2, \ldots, x_m) = \begin{pmatrix} x_{11} & \cdots & x_{m1} \\ \vdots & \ddots & \vdots \\ x_{1n} & \cdots & x_{mn} \end{pmatrix} \tag{1}$$

Apply the PCA on this data sample, we can obtain a linear combination of the underlying variable called principal components. Since we are studying m variables, we can obtain m principal components, P_1, P_2, …, P_m. And the form of the principal component i is $P_i = \sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij} x_j$. a_{ij} is the element of the eigenvector of covariance matrix of original data.

4.2.SR

SR is an indicator of system risk which can be constructed by principal components. Suppose we choose n principle components to construct SR, which is defined as

$$SR = \frac{\sum_{i=1}^{n} V_i P_i}{\sum_{i=1}^{n} V_i} \tag{2}$$

Where:

$V_i\ is\ the\ contribution\ proportion\ of\ principle\ P_i$

4.3. Absorption-Ratio (AR)

Dimitrios, Mark, Andrew and Stavros [1] defined AR as the degree of absorption of the total variance of the original variables by a certain number of principal components. In order to calculate the AR at each point in time, the formula is defined as follow:

$$AR = \frac{\sum_{i=1}^{k} \sigma_{E_i}^2}{\sum_{j=1}^{n} \sigma_{a_j}^2} = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{j=1}^{n} \lambda_j} \tag{3}$$

where:

$n\ is\ number\ of\ eigenvectors\ used\ in\ calculating\ AR$

$\sigma_{E_i}^2\ is\ variance\ of\ eignvector\ i$

$\sigma_{a_j}^2$ *is variance of asset j*
λ_i *is eignvalue i*

5. Analysis of SR

5.1. Construction of SR

ADF unit root test of thirteen macroeconomic variables show that, except for GDP growth rate, the other variables are not significant at 5% significance level, which means that 12 out of 13 variables' time series are not stationary. Therefore, we transform these 12 variables by taking the first difference to meet the stationary criteria.

After applying PCA on these variables, we find that the cumulative contributions of the first 8 principal components to the total variations exceeds 90%. We then simply take the first 8 principal components to construct SR.

The expression of each principal component can be obtained according to the eigenvector matrix. Taking principal component 1 as an example, the formula is:

$$\begin{aligned} P1 = 0.40091GDP - 0.40609MG - 0.282698NL + 0.176928FSD - 0.109457 \\ +0.371238H1 + 0.186303H2 + 0.073727FA + 0.252563IR \\ +0.338884IF - 0.263414FD + 0.18637SG - 0.300742BC \end{aligned} \tag{4}$$

SR is the weighted sum of all principal components with the contribution of each PC as the corresponding weight.

We also use the same procedure to generate SR using industry portfolios. The result of the principle component analysis shows that, the cumulative proportion of 14 PCs exceeds 90%, and then the first 14 principal components are chosen to construct the SR.

5.2. Granger Causality Test of SR

In order to determine whether SR has a predictive power for the stock index, a Granger causality test can be performed on two sets of time series data. Before the Granger causality test, it is necessary to determine whether the two sets of series are stationary.

The results of the ADF test show that the time series of the SR pass the unit root test, indicating that the time series of the SR is stationary. In contrast, the original time series of the S&P500 Index does not pass the unit root test. We apply the first difference operation on the S&P500 Index series before performing the unit root test. The test of the difference series shows that the difference series passes the unit root test. Therefore, we adopt the original series of SR and the difference series of S&P500 Index for Granger causality test.

For Granger causality test, 2-8 periods are selected for lags. "S&P500 does not Granger Cause SR of macroeconomic variables" and “S&P500 does not Granger Cause SR of industries portfolios” are accepted at a significance level of 5%. However, “SR of macroeconomic variables does not Granger Cause S&P500” is rejected, while “SR of industries portfolios does not Granger Cause S&P500” is also accepted at a significance level of 10%. It means that SR of macroeconomic variables has a certain predictive power for the S&P500 Index in a statistical sense, but the results do not show strong evidence that SR of industries portfolios has a same effect.

5.3. Impulse Responses Function and Variance Decomposition

In order to study the relationships among SR and stock market, bond market and commodity futures market, we build Vector Autoregression (VAR) model on SR of macroeconomic variables, SR of industries portfolios, yields of S&P500 Index, US 10 Year Treasury Bond, silver futures and cruel oil futures returns.

Before constructing the VAR model, it is also necessary to ensure that all time series are stationary. From the results of the Granger causality test, we can see that the time series of both SR are stationary. After performing ADF unit root test on yields of S&P500 Index, US 10 Year Treasury Bond, silver futures and cruel oil futures, we can see that all time series of these four variables pass the unit root test at a significance level of 5%, which means they are all stationary.

After building the VAR model, we can implement Impulse Responses Function Analysis and Variance Decompositions on these six variables. Impulse response function shows that, for silver futures, shocks of both SR based on macroeconomic variables and industry portfolio returns have not obvious impacts. Regarding to the other three variables, they all have significant responses to a shock of the SR of macroeconomic variables, but not to the shock of SR of industries portfolios. For S&P500 Index, it had positive responses to one unit shock of the SR of macroeconomic variables, and reach the maximum in the first period and then decreased to 0 in the third period and then tended to be stationary. For U.S. 10 Year Treasury, it had negative responses to one unit shock of the SR of macroeconomic variables first fell and then rose, reach the minimum in the second period, and then tended to be 0. For cruel oil futures, it experienced a similar trend as S&P500 Index.

Variance Decomposition shows that, the contributions of the SR with macroeconomic variables to S&P500 Index, U.S. 10 Year Treasury Bond and cruel oil futures are prominent, which are above 40 percent, 16 percent and 22 percent, respectively, while the contributions of the SR with industries portfolios are not. Although the contribution of the SR with industries portfolios to silver futures which is above 10 percent is higher than that of SR with macroeconomic variables, the magnitudes of them are both small. Combining the above two analysis, we conclude that, when we use SR to predict systemic risk and construct investment strategy, the SR constructed by macroeconomic variables could be better than the SR constructed by industries portfolios.

6. Analysis of AR

6.1. Granger Causality Test of AR

For industries portfolios, "S&P500 does not Granger Cause AR of industries portfolios” is rejected only with 5 lags and 6 lags at a significance level of 10%, and “AR of industries portfolios does not Granger Cause S&P500” is rejected only with 7 lags and 8 lags at a significance level of 10%. However, for macroeconomic variables, "S&P500 does not Granger Cause AR of macroeconomic variables” is accepted at a significance level of 5%, and “AR of macroeconomic variables does not Granger Cause S&P500” is rejected at a significance level of 5%. In summary, statistical results do not conclude whether AR of industries portfolios is a Granger cause of S&P500 Index, and vice versa. Yet, it supports that AR of macroeconomic variables has a certain predictive power for S&P500 Index.

6.2. Impulse Responses Function and Variance Decomposition

We perform Impulse Responses Analysis and Variance Decomposition on AR. Because the first difference of the two AR variables are stationary, we can construct VAR model based on them and yields of S&P500 Index, US 10 Year Treasury Bond, silver futures and cruel oil futures.

The results of IRF show that, unlike SR, a shock of both AR have significant impacts on S&P500 Index, U.S. 10 Year Treasury and cruel oil futures, but not obvious impacts on silver futures.

For S&P500 Index, it had positive responses to the AR of macroeconomic variables first fell and then rose, reached the maximum in the third period, and then tended to be 0. However, it had negative responses to the AR of industry portfolio returns, which reached the minimum in the first period and increased to 0 in the third period and then tended to be stationary. For U.S. 10 Year Treasury, it had positive responses to the AR industry portfolio returns of first fell and then rose, reached the maximum in the third period, and then tended to be 0. And its responses to the AR of macroeconomic variables had a big fluctuation during the first five periods and eventually tended to be 0. For cruel oil futures, it had negative responses to the AR of industry portfolio returns and reached the minimum in the first period and increased to 0 in the fourth period and then tended to be stationary. And it had positive responses to the AR of macroeconomic variables and reached to maximum in the third period and eventually tended to be 0.

In terms of the results of the Variance Decomposition, it can be clearly seen that both AR have contributions to S&P500 Index which are above 20 percent but they both have very little contributions to Treasury and silver futures. For cruel oil futures, AR of industries portfolios has a large contribution which is above 25 percent to it, yet AR of macroeconomic variables just contribute above 10 percent. Therefore, to construct AR, industries portfolios are better than macroeconomic variables.

7. Conclusion

This paper has presented the difference between systemic risk indicators based on two distinct variables, industries portfolios returns and macroeconomic variables. For macroeconomic variables, we choose 13 variables, and for industries portfolios returns, we choose 49 industries portfolios based on Fama-French approach. We use these two types of variables to construct two systemic risk indicators, SR and AR.

For Granger Causality Test, the results of SR show that SR of macroeconomic variables has a certain predictive power for the S&P500 Index, but SR of industries portfolios does not have. Consistently, for AR, the results show that AR of macroeconomic variables can predict S&P500 Index and AR of industries portfolios has not prominent predictive power.

Furthermore, the results of Impulse Responses Analysis and Variance Decomposition show that macroeconomic variables are better than industries portfolios in constructing SR. The situation is opposite in AR. When we constructing AR, industries portfolios are obviously better.

In summary, according to the above analysis of macroeconomic variables and industries portfolios, we conclude that the systemic risk indicator based on macroeconomic variables is better than industries portfolios.

References

[1] *Dimitrios Bisias, Mark Flood, Andrew W. Lo, Stavros Valavanis. (2012). A Survey of Systemic Risk Analytics. Annual Review of Financial Economics. 1, 255-296*

[2] *Hargreaves, Carol & Mani, Chandrika. (2015). The Selection of Winning Stocks Using Principal Component Analysis. American Journal of Marketing Research. 1. 183-188.*

[3] Stefano Giglio, Bryan Kelly, Seth Pruitt. (2016). Systemic Risk and The Macroeconomy: An Empirical Evaluation. Journal of Financial Economics. 199 (3), 457-471
[4] Tang Aili. (2018). Impact of Housing Price Volatility on Systemic Risk. [D]. Shanghai Academy of Social Science
[5] Zhou Hua, Pang Jiaren, Wang ziyue. (2018). Measurement of China's Systemic Risk Based on Principle Component Analysis. [J]. Insurance Studies. 2018 (04): 3-17.

Appendix

Tables and Figures

Table 1: ADF Unit Root Test of Macroeconomic Variables.

Variable	1% level	5% level	10% level	t-Statistic	Prob.
GDP	-3.531592	-2.905519	-2.590262	-5.002795	0.0001
MG	-3.531592	-2.905519	-2.590262	0.341057	0.9788
NL	-3.531592	-2.905519	-2.590262	-2.431930	0.1370
FSD	-3.538362	-2.908420	-2.591799	-2.375280	0.1527
L	-3.533204	-2.906210	-2.590628	-2.347453	0.1606
H1	-3.538362	-2.908420	-2.591799	-1.910599	0.3255
H2	-3.530030	-2.904848	-2.589907	-0.564379	0.8709
FA	-3.531592	-2.905519	-2.590262	-1.949000	0.3084
IR	-3.530030	-2.904848	-2.589907	-0.814601	0.8084
IF	-3.546099	-2.911730	-2.593551	-1.603278	0.4746
FD	-3.531592	-2.905519	-2.590262	1.018487	0.9964
SG	-3.531592	-2.905519	-2.590262	-2.832630	0.0591
BC	-3.531592	-2.905519	-2.590262	-2.042135	0.2686

Table 2: PCA of Macroeconomic Variables.

Eigenvalues: (Sum = 13, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.815668	1.586631	0.2935	3.815668	0.2935
2	2.229037	0.773035	0.1715	6.044705	0.4650
3	1.456001	0.425640	0.1120	7.500706	0.5770
4	1.030361	0.101594	0.0793	8.531067	0.6562
5	0.928768	0.119847	0.0714	9.459835	0.7277
6	0.808920	0.048937	0.0622	10.26875	0.7899
7	0.759983	0.062402	0.0585	11.02874	0.8484
8	0.697580	0.265771	0.0537	11.72632	0.9020
9	0.431809	0.074584	0.0332	12.15813	0.9352
10	0.357226	0.111267	0.0275	12.51535	0.9627
11	0.245959	0.093400	0.0189	12.76131	0.9816
12	0.152559	0.066430	0.0117	12.91387	0.9934
13	0.086129	---	0.0066	13.00000	1.0000

Table 3: ADF Unit Root Test of SR of Macroeconomic Variables.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.171058	0.0015
Test critical values:	1% level	-3.533204	
	5% level	-2.906210	
	10% level	-2.590628	

Table 4: ADF Unit Root Test of SR of 49 Industries Portfolios.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.611682	0.0959
Test critical values:	1% level	-3.536587	
	5% level	-2.907660	
	10% level	-2.591396	

Table 5: ADF Unit Root Test of SP500.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.324479	0.9780
Test critical values:	1% level	-3.531592	
	5% level	-2.905519	
	10% level	-2.590262	

Table 6: ADF Unit Root Test of Difference SP500.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.021602	0.0000
Test critical values:	1% level	-3.533204	
	5% level	-2.906210	
	10% level	-2.590628	

Table 7: PCA of 49 Industries portfolios.

Eigenvalues: (Sum = 49, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	20.60537	13.44226	0.4205	20.60537	0.4205
2	7.163112	3.623249	0.1462	27.76848	0.5667
3	3.539863	1.087116	0.0722	31.30834	0.6389
4	2.452747	0.571157	0.0501	33.76109	0.6890
5	1.881590	0.278343	0.0384	35.64268	0.7274
6	1.603246	0.231803	0.0327	37.24593	0.7601
7	1.371444	0.140510	0.0280	38.61737	0.7881
8	1.230933	0.131266	0.0251	39.84830	0.8132
9	1.099667	0.146351	0.0224	40.94797	0.8357
10	0.953316	0.126577	0.0195	41.90129	0.8551
11	0.826739	0.126043	0.0169	42.72803	0.8720
12	0.700696	0.105479	0.0143	43.42872	0.8863
13	0.595217	0.026155	0.0121	44.02394	0.8984
14	0.569062	0.034788	0.0116	44.59300	0.9101
15	0.534275	0.059623	0.0109	45.12728	0.9210
16	0.474652	0.062500	0.0097	45.60193	0.9307
17	0.412152	0.086063	0.0084	46.01408	0.9391
18	0.326089	0.030799	0.0067	46.34017	0.9457
19	0.295290	0.017020	0.0060	46.63546	0.9517
20	0.278271	0.017852	0.0057	46.91373	0.9574
21	0.260418	0.026269	0.0053	47.17415	0.9627
22	0.234150	0.030962	0.0048	47.40830	0.9675
23	0.203187	0.023244	0.0041	47.61149	0.9717
24	0.179944	0.028693	0.0037	47.79143	0.9753
25	0.151251	0.004480	0.0031	47.94268	0.9784
26	0.146771	0.022907	0.0030	48.08945	0.9814
27	0.123864	0.012948	0.0025	48.21331	0.9839
28	0.110915	0.003062	0.0023	48.32423	0.9862
29	0.107853	0.020170	0.0022	48.43208	0.9884
30	0.087683	0.013289	0.0018	48.51977	0.9902
31	0.074395	0.010218	0.0015	48.59416	0.9917
32	0.064177	0.015977	0.0013	48.65834	0.9930
33	0.048200	0.000598	0.0010	48.70654	0.9940
34	0.047602	0.004393	0.0010	48.75414	0.9950
35	0.043209	0.003708	0.0009	48.79735	0.9959
36	0.039502	0.005497	0.0008	48.83685	0.9967
37	0.034005	0.009066	0.0007	48.87086	0.9974
38	0.024939	0.005736	0.0005	48.89580	0.9979
39	0.019202	0.001085	0.0004	48.91500	0.9983
40	0.018117	0.003916	0.0004	48.93312	0.9986
41	0.014201	0.001327	0.0003	48.94732	0.9989
42	0.012875	0.000175	0.0003	48.96019	0.9992
43	0.012700	0.005409	0.0003	48.97289	0.9994
44	0.007291	0.000449	0.0001	48.98018	0.9996
45	0.006842	0.002271	0.0001	48.98703	0.9997
46	0.004571	0.000814	0.0001	48.99160	0.9998
47	0.003756	0.001024	0.0001	48.99535	0.9999
48	0.002733	0.000818	0.0001	48.99809	1.0000
49	0.001915	---	0.0000	49.00000	1.0000

Table 8: Granger Causality of SR of Macroeconomic Variables.

Null Hypothesis:	Obs	F-Statistic	Prob.
DSP500 does not Granger Cause SRM	66	2.05202	0.1373
SRM does not Granger Cause DSP500		3.90626	0.0253
DSP500 does not Granger Cause SRM	65	1.88399	0.1423
SRM does not Granger Cause DSP500		3.13551	0.0322
DSP500 does not Granger Cause SRM	64	1.39431	0.2480
SRM does not Granger Cause DSP500		3.28477	0.0174
DSP500 does not Granger Cause SRM	63	1.36745	0.2517
SRM does not Granger Cause DSP500		3.04193	0.0175
DSP500 does not Granger Cause SRM	62	1.12451	0.3621
SRM does not Granger Cause DSP500		2.52112	0.0331
DSP500 does not Granger Cause SRM	61	1.11308	0.3713
SRM does not Granger Cause DSP500		2.22814	0.0489
DSP500 does not Granger Cause SRM	60	1.17644	0.3353
SRM does not Granger Cause DSP500		1.89035	0.0865

Table 9: Granger Causality of SR of 49 Industries Portfolios.

Null Hypothesis:	Obs	F-Statistic	Prob.
DSP500 does not Granger Cause SR49	66	2.55150	0.0863
SR49 does not Granger Cause DSP500		0.29646	0.7445
DSP500 does not Granger Cause SR49	65	2.66887	0.0559
SR49 does not Granger Cause DSP500		0.29560	0.8284
DSP500 does not Granger Cause SR49	64	1.62987	0.1798
SR49 does not Granger Cause DSP500		0.44208	0.7776
DSP500 does not Granger Cause SR49	63	1.42954	0.2292
SR49 does not Granger Cause DSP500		0.74876	0.5907
DSP500 does not Granger Cause SR49	62	1.43265	0.2214
SR49 does not Granger Cause DSP500		0.81280	0.5652
DSP500 does not Granger Cause SR49	61	1.24715	0.2974
SR49 does not Granger Cause DSP500		0.76171	0.6219
DSP500 does not Granger Cause SR49	60	1.59810	0.1538
SR49 does not Granger Cause DSP500		0.66971	0.7150

Table 10: ADF Unit Root Test of Yield of SP500.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.077230	0.0001
Test critical values:	1% level	-3.574446	
	5% level	-2.923780	
	10% level	-2.599925	

Table 11: ADF Unit Root Test of Yield of Treasury.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.826495	0.0000
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 12: ADF Unit Root Test of Yield of Silver Futures.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.480140	0.0000
Test critical values:	1% level	-3.574446	
	5% level	-2.923780	
	10% level	-2.599925	

Table 13: ADF Unit Root Test of Yield of Cruel Oil Futures.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.913765	0.0000
Test critical values:	1% level	-3.574446	
	5% level	-2.923780	
	10% level	-2.599925	

Table 14: ADF Unit Root Test of AR of Industries Portfolios.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.061541	0.7232
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 15: ADF Unit Root Test of Difference AR of Industries Portfolios

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.354472	0.0000
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 16: ADF Unit Root Test of AR of Macro Variables.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.730790	0.4095
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 17: ADF Unit Root Test of Difference AR of Macro Variables.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.786079	0.0057
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 18: Granger Causality of AR of 49 Industries Portfolios.

Null Hypothesis:	Obs	F-Statistic	Prob.
DSP500 does not Granger Cause DAR49	46	0.07783	0.9253
DAR49 does not Granger Cause DSP500		0.39027	0.6794
DSP500 does not Granger Cause DAR49	45	1.56414	0.2139
DAR49 does not Granger Cause DSP500		0.25443	0.8577
DSP500 does not Granger Cause DAR49	44	1.27504	0.2984
DAR49 does not Granger Cause DSP500		0.62809	0.6457
DSP500 does not Granger Cause DAR49	43	2.98144	0.0255
DAR49 does not Granger Cause DSP500		0.71189	0.6190
DSP500 does not Granger Cause DAR49	42	2.35749	0.0562
DAR49 does not Granger Cause DSP500		0.76476	0.6035
DSP500 does not Granger Cause DAR49	41	1.68659	0.1563
DAR49 does not Granger Cause DSP500		2.31304	0.0565
DSP500 does not Granger Cause DAR49	40	1.38176	0.2562
DAR49 does not Granger Cause DSP500		2.03553	0.0873

Table 19: Granger Causality of AR of 49 Macroeconomic Variables.

Null Hypothesis:	Obs	F-Statistic	Prob.
DSP500 does not Granger Cause DARM	46	1.98418	0.1505
DARM does not Granger Cause DSP500		6.80288	0.0028
DSP500 does not Granger Cause DARM	45	1.62283	0.2001
DARM does not Granger Cause DSP500		5.35310	0.0036
DSP500 does not Granger Cause DARM	44	1.22119	0.3195
DARM does not Granger Cause DSP500		3.74007	0.0123
DSP500 does not Granger Cause DARM	43	1.22765	0.3191
DARM does not Granger Cause DSP500		3.88097	0.0073
DSP500 does not Granger Cause DARM	42	0.83310	0.5543
DARM does not Granger Cause DSP500		3.55081	0.0093
DSP500 does not Granger Cause DARM	41	0.77989	0.6098
DARM does not Granger Cause DSP500		3.32255	0.0116
DSP500 does not Granger Cause DARM	40	0.66817	0.7139
DARM does not Granger Cause DSP500		2.85638	0.0232

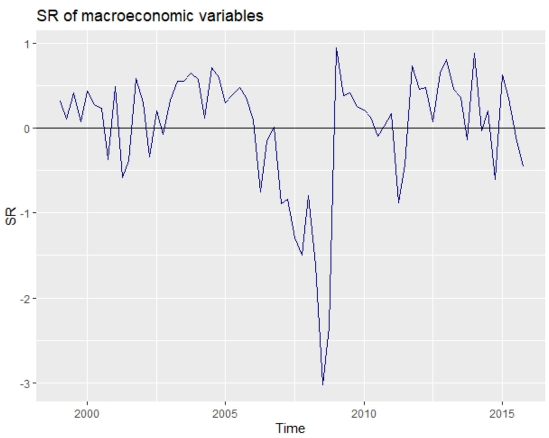

Figure 1: SR of Macroeconomic Variables.

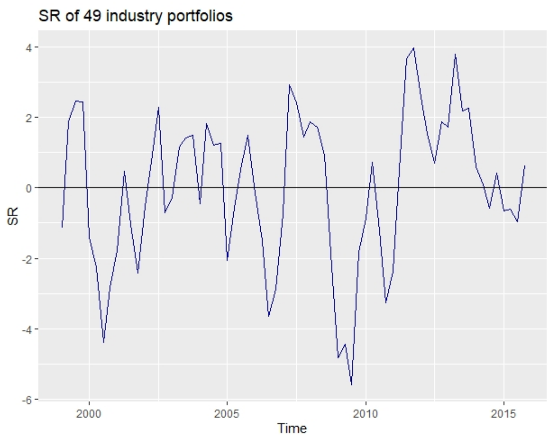

Figure 2: SR of 49 Industries Portfolios.

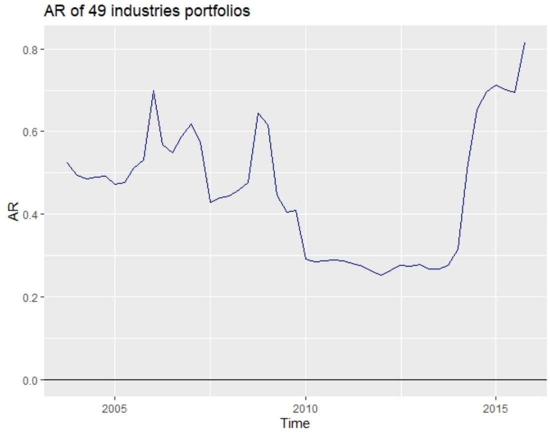

Figure 3: AR of 49 Industries Portfolios.

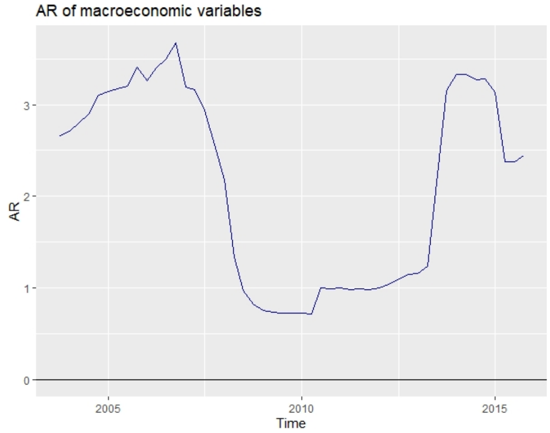

Figure 4: AR of Macroeconomic Variables.

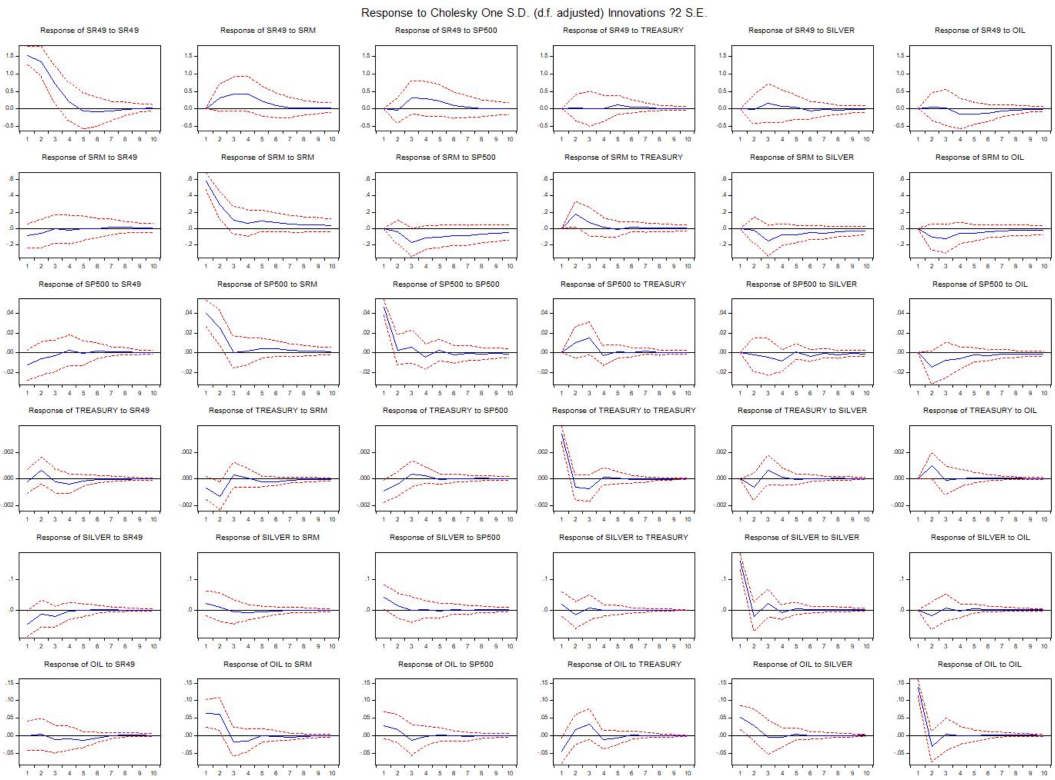

Figure 5: Impulse Responses of SR.

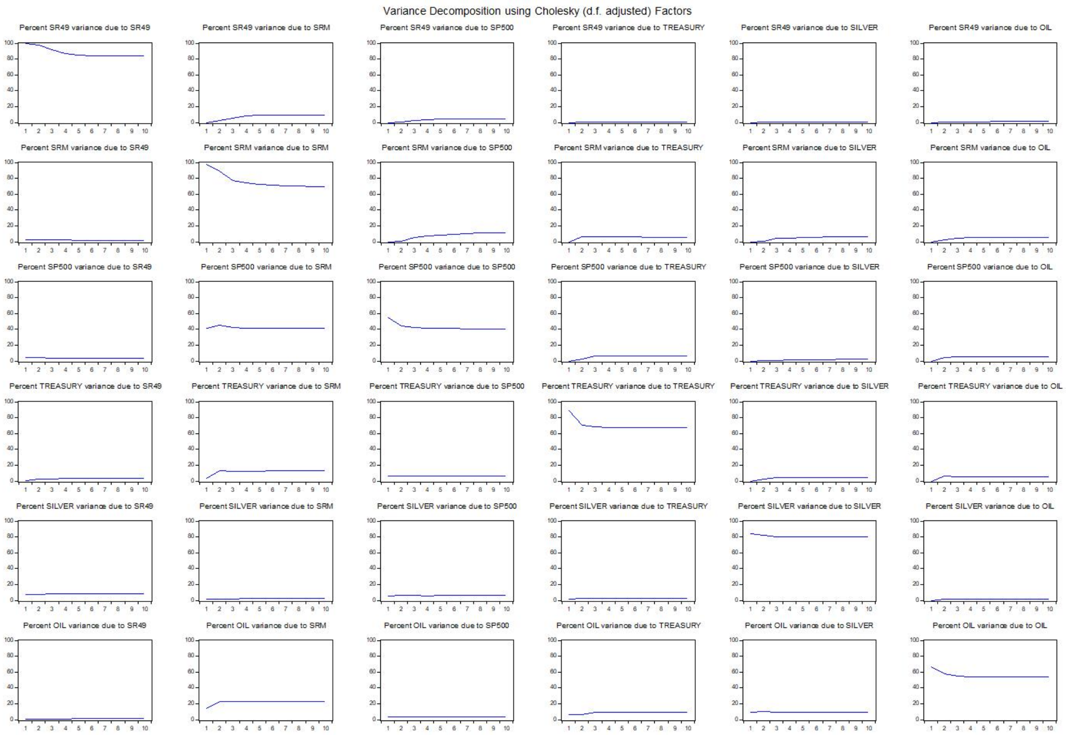

Figure 6: Variance Decomposition of SR.

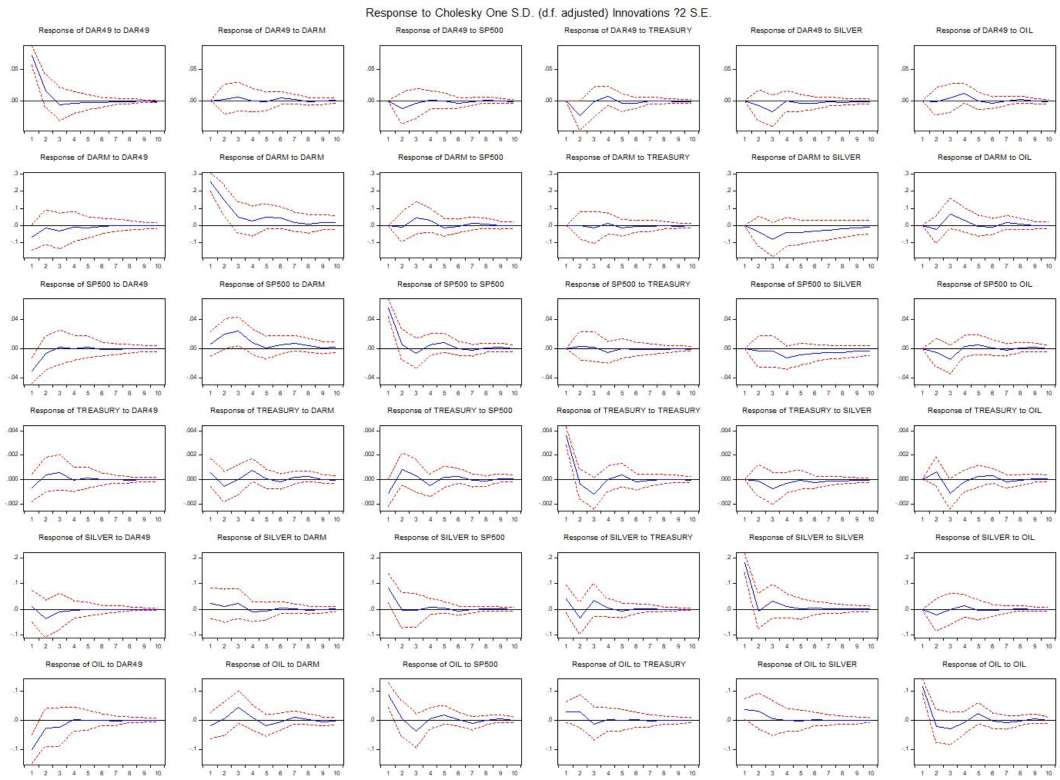

Figure 7: Impulse Responses of AR.

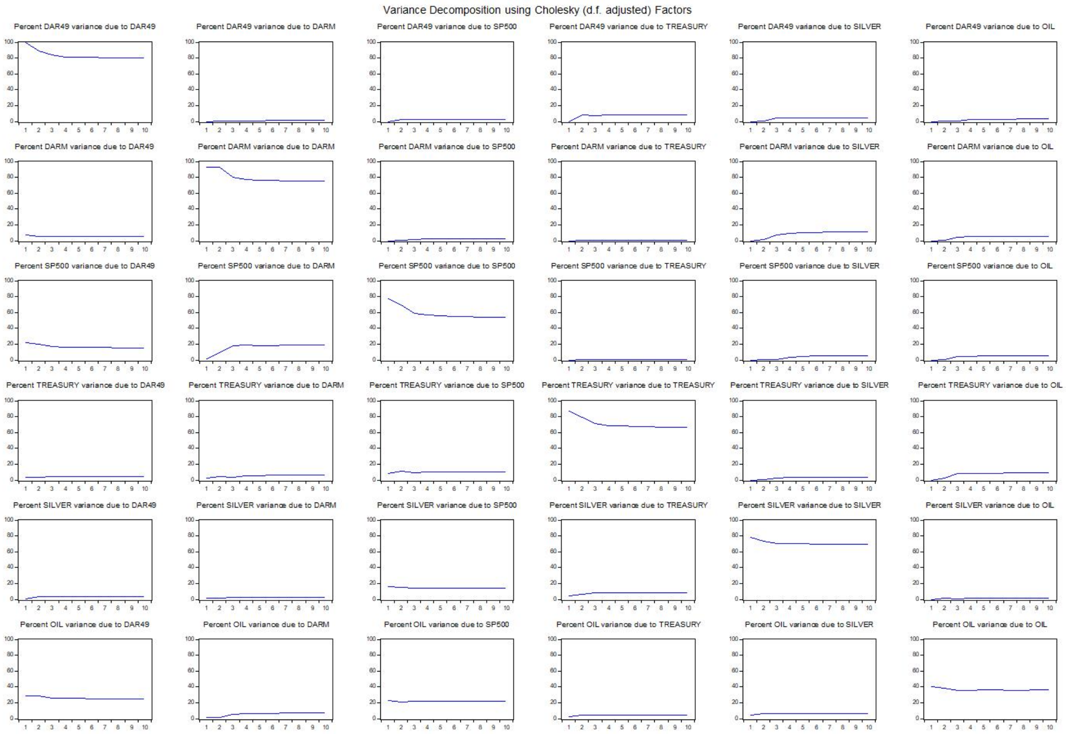

Figure 8: Variance Decomposition of AR.