Fixed Income Analytics and Models

Course Project:

Expectation Hypothesis and U.S. Bond Return Predictability

ABSRACTS

- **Objectives:**

  We aim to find a well-performing strategy to extract maximum excess returns. At the same time we use a series of methods to examine the robustness and effectiveness of our model.

- **Methods:**

  We employ both in-sample and out-of-sample tests to ensure the model’s validity. For the in-sample test, we choose representative indexes and use the bootstrap method to evaluate efficiency and effectiveness. For out-of-sample test, we try PLS-Predict Analysis, Blindfolding Analysis and Clusters Analysis to examine the robustness.

- **Results:**

  For in-sample test, the p values of the bootstrap result are all lower than 0.05 and the indexes of both inner and outer models all outperform the minimum threshold. For out-of-sample test, we all get positive Q square which indicates that our model behaves better than OLS model as well as the benchmark.

- **Conclusion:**

  We work out a well-performing strategy based on a long-term profitable model based on both macro and financial data. This strategy is proved to be both effective and robust.

ARTICLE

1 Background Introduction

Bond excess return is the spread between the return of the bonds and risk-free assets. Previous empirical works have come up with different methods to forecast the excess returns of U.S. Treasury Bonds, including lots of predictors.

In order to build our own precise model, we have read many papers. We want to optimize the accuracy in predicting the excess return of U.S. Treasury Bonds.

2 Literature Review

Fama and Bliss (1987) thinks that current 1-year forward rates on 1 to 5-year U.S. Treasury bonds are information about the current term structure of 1-year expected returns on the bonds. More interesting, 1-year forward rates forecast changes in the 1-year interest rate 2 to 4 years ahead, and forecast power increases with the forecast horizon. They put forward the Forward Spread Model:

$$rx^{(n)} = \alpha^{(n)} + \beta^{(n)} \bullet FS^{(n)} + \varepsilon$$

Cochrane and Piazzesi (2005) studied time variation in expected excess bond returns. They found that linear combinations of forward rates could predict the excess return of bonds with different maturities. And they came up with Forward Interest Rate Model:

$$\bar{rx} = \alpha + \beta_1 \bullet y + \beta_2 \bullet f^{(2)} + \beta_3 \bullet f^{(3)} + \beta_4 \bullet f^{(4)} + \beta_5 \bullet f^{(5)} + \varepsilon$$

Ludvigson and Ng (2009) used the dynamic factor analysis to investigate possible empirical linkages between forecastable variation in excess bond returns and macroeconomic fundamentals. The predictive power of the estimated factors is significant and economically important, with factors explaining between 21% and 26% of one-year-ahead excess bond returns. They proposed the Macroeconomic factors model, which is:

$$\bar{rx} = \alpha + \beta_1 \bullet f_1 + \beta_2 \bullet f_1^3 + \beta_3 \bullet f_2 + \beta_4 \bullet f_3 + \beta_5 \bullet f_4 + \beta_6 \bullet f_8 + \varepsilon$$

After combining the macroeconomics factors with Cochrane and Piazzesi's single-factor model, the R^2 becomes larger, which means that the model was further modified. The combined model is:

$$\bar{rx} = \alpha + \beta_1 \bullet CP + \beta_2 \bullet LNF5 + \varepsilon$$

3 Data and Methodology

3.1 Data sources: GPD2017

3.2 Chosen time period: 1964-2011

3.3 Methodology:

In our article, we used OLS, PLS regression. While do Out-of-Sample test, we used Rolling Window and Half Regression.

4 Empirical Findings

4.1 In-Sample Test

4.1.1 Fama and Bliss (1987):

$$rx^{(n)} = \alpha^{(n)} + \beta^{(n)} \bullet FS^{(n)} + \epsilon$$

n	2	3	4	5
β	0.832	1.123	1.344	1.018
Adjusted R^2	0.113	0.125	0.136	0.059

At first, we run the simplest model which has one independent variable in the equation. $FS^{(n)}$ is the forward-spot spread. However, R^2 in different maturity time bonds are all small. Hence, we infer the explanatory variable is not convincing enough. It seems necessary that we should think about more complicated regression equation including more explanatory variables.

4.1.2 Cochrane and Piazzesi (2005):

$$\bar{rx} = \alpha + \beta_1 \bullet y + \beta_2 \bullet f^{(2)} + \beta_3 \bullet f^{(3)} + \beta_4 \bullet f^{(4)} + \beta_5 \bullet f^{(5)} + \epsilon$$

Variables	y	f(2)	f(3)	f(4)	f(5)
β	-1.717	0.129	-1.012	0.178	-0.056
sig	0.000	0.886	0.000	0.003	0.000
Adjusted R^2	0.220				

The table shows that R^2 results were better than the Fama model. However, we found that $f^{(2)}$ was not significant at all. Also, we found that the 5 variables were highly linear correlated. We thought the regression was not solid enough.

Correlation coefficient	y	f(2)	f(3)	f(4)	f(5)
y	1	0.961	0.919	0.880	0.859
f(2)		1	0.982	0.963	0.947
f(3)			1	0.979	0.968
f(4)				1	0.965
f(5)					1

4.1.3 Ludvigson and Ng (2009):

$$\bar{rx} = \alpha + \beta_1 \bullet f_1 + \beta_2 \bullet f_1^3 + \beta_3 \bullet f_2 + \beta_4 \bullet f_3 + \beta_5 \bullet f_4 + \beta_6 \bullet f_8 + \epsilon$$

Variables	f_1	f_1^3	f_2	f_3	f_4	f_8
β	-1.717	0.129	-1.012	0.178	-0.560	0.777
Adjusted R2	0.224					

After testing the LN model, we found that the R^2 was larger than the previous model, with a more persuasive explanation result. And there is no linear correlation among factors. Therefore, our model will use more of the LN model.

4.1.4 The modified model（CPLN）

$$\bar{rx} = \alpha + \boldsymbol{\beta}_1 \bullet \boldsymbol{CP} + \boldsymbol{\beta}_2 \bullet \boldsymbol{LNF}5 + \varepsilon$$

Variable	f_1	f_1^3	f_3	f_4	f_8	cp
β	-1.276	0.111	0.319	-0.367	0.521	0.907
Adjusted R^2	0.438					

After the analysis on the first 3 basic models, we used the CPLN which shows that the R^2 was larger than CP or LN. In this case, the model is better.

4.2 Out-of-Sample Test

4.2.1 Rolling Window

Under this method, $R^2_{OS} > 0$ ($R^2_{OS} < 0$) implies that the $\hat{rx}^{(n)}_{t+1}$ forecast statistically outperforms (underperforms) the historical average forecast according to the MSPE metric.

FB	Year2	Year3	Year4	Year5
R_{OS}^2	-0.1349	-0.1544	-0.1277	-0.1207

After doing the rolling window, we found that the R^2_{OS} of FB Model is constantly negative, which indicates that it performs under historical mean estimation.

Factors	CP	LN	CPLN
R_{OS}^2	-0.3931	-0.0323	-0.1772

According to the table, we thought that CP and CPLN model are not promising, because the R^2_{OS} are -0.3931 and -0.1772, which has a large negative value.

Compared with above models, LN model has a R^2_{OS} of -0.0323 which is close to 0, which means LN is relatively effective. (In the Appendix we explain why we use half regression).

4.2.2 Half Regression

Out-of-Sample R-Square Test	
LN Model	0.0865

Based on that macro factors are calculated via PCA using previous macro raw data. We run regression of data 1964-1991 and predict rx after 1992.

We found that LN model is effective because it has a large positive value of R^2_{OS}.

5 Optimal Strategy

5.1 The structure of the whole model

We already prove that the LN model have the best R^2_{OS} by using the rolling window method and the half regression method above. To support our assumption, we decide to design two different constructs, which respectively represent the influence of macro and financial data and may help us conclude the optimal strategy. We set 1964/01-2011/12 as the time period.

5.1.1 LN construct

It is a latent variable based on the Principal Component Analysis (PCA) method. By using SPSS, we first transfer raw macro data to Z-score data, then we employ the factor analysis method in order to get main factors. We should do the KMO and Bartlett's test of sphericity as the basis of the factor analysis.

The result is shown below.

KMO and Bartlett's test of sphericity

KMO Value	0.953
Bartlett Test's significance	0.000

The KMO value 0.953 is very high. Also the result of the significance of the Bartlett test is lower than 0.01. It proves the feasibility of PCA method. We choose first nine principle components because their eigenvalues are larger than 1.

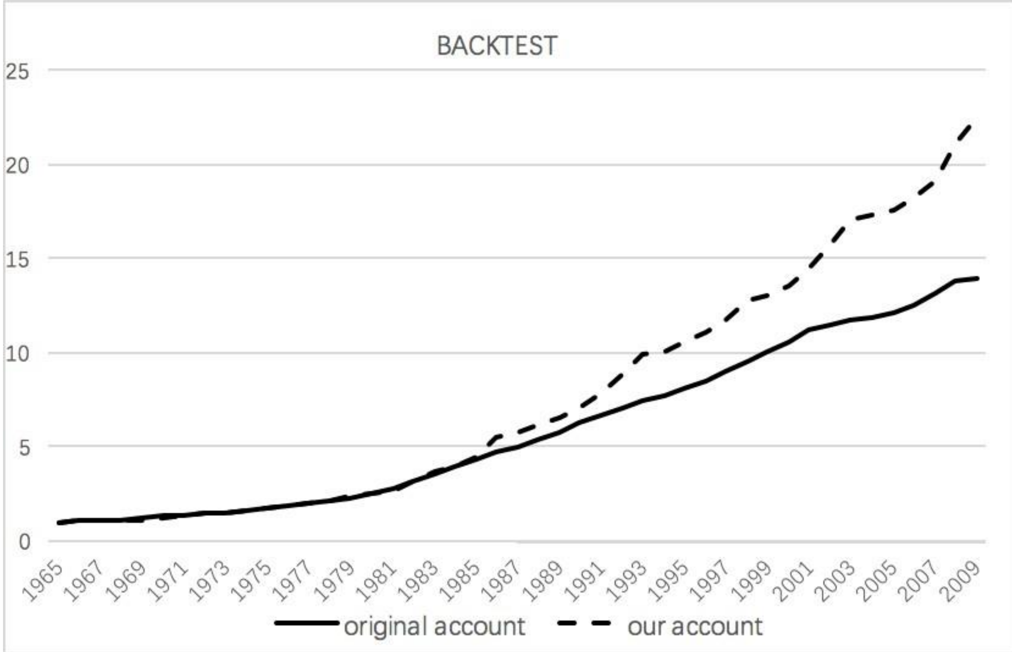
The result is listed here:

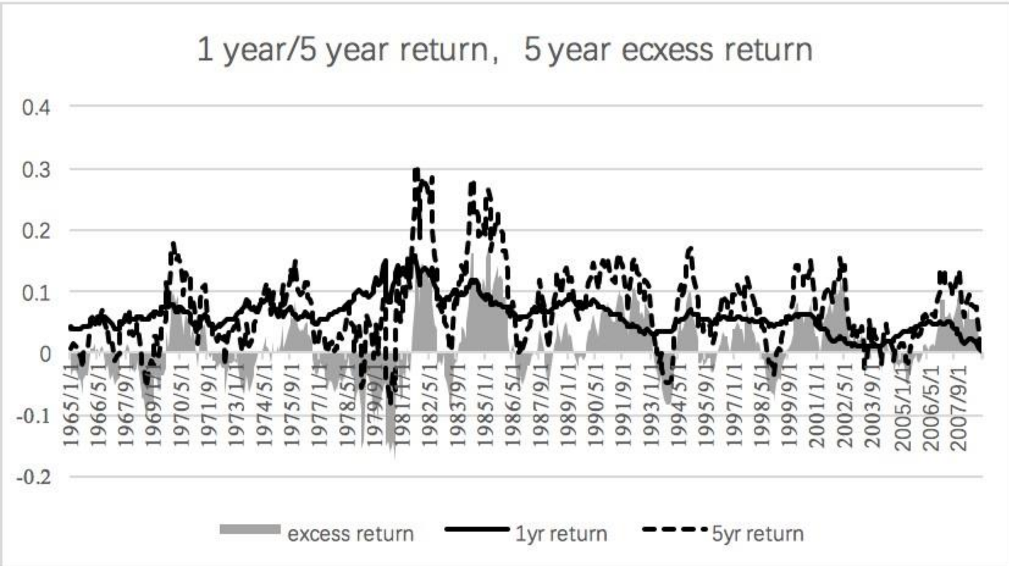
Components	Eigenvalues	Variance %	Variance Accumulation %
1	74.175	56.193	56.193
2	16.165	12.246	68.440
3	13.901	10.531	78.970
4	7.664	5.806	84.776
5	5.160	3.909	88.685
6	3.745	2.837	91.522
7	2.008	1.521	93.043
8	1.506	1.141	94.184
9	1.129	0.855	95.039

It is reasonable to include f_1 and f_2 as indicators in our model. Also we cannot deny the fact that f_9 can actually represent some individual influence. Following the logic of the previous LN model, we choose f_1 f_2 f_1^3 f_9^3 as the indicators of our LN construct.

5.1.2 MA construct

This latent variable is comprised of two indicators both based on market financial data. We can easily get the bond prices with different maturities at different time, thus we can also get the difference between the price and the moving average price in the past 12 months. To simplify the assumption, we just choose the 1-year and 5-year bond as our indicators for MA model.





5.2 PLS Method

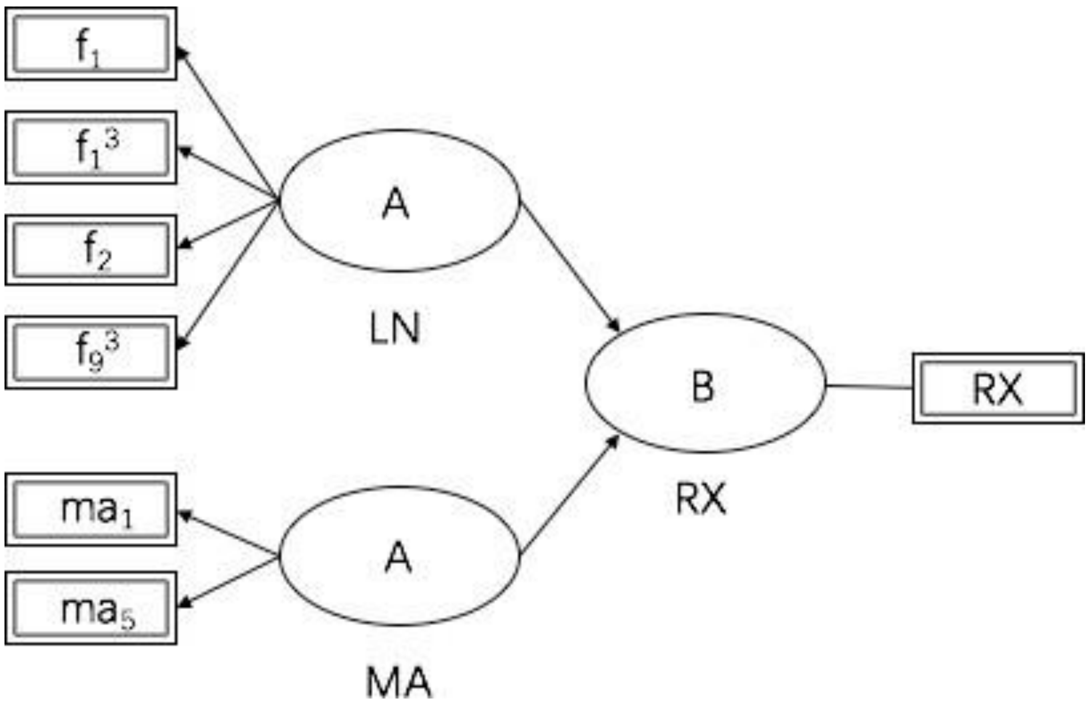
Partial Least Square (PLS) Path Modelling is a popular estimation method. Herman Wold (1966, 1979) suggested both PLS Path Modelling and PLS Regression. He believed that "soft model" (which contains the thought of PLS) might be a better choice for data that didn't obey the normal distribution.

The PLS Path Modeling Method has two main focuses: the estimated latent variable values and the estimated coefficient of influence of the corresponding latent variables. A PLS Path Modeling Method can be divided into the inner model and the outer model, which jointly contribute to the whole model.

The data we used in calculation have already been standardized, i.e. obey N(0,1).

5.3 The Result of PLS Method

5.3.1 The establishment of the PLS Path Model



The PLS Path Model is based on the assumptions in the following:

1) We build two latent variables LN and MA to reflect the manifest variables (indicators) listed above. Specifically, we view f_1, f_2, f_1^3, f_9^3 as direct components of the latent variable LN, and ma1, ma5 as direct components of the latent variable MA. These two sets of individual latent variable and its corresponding manifest variables form two outer models in the PLS Path Model.
2) The inner model is comprised of three latent variables LN, MA and RX, in which RX is explained by LN and MA.
3) In the whole PLS Path Model made up by the inner and outer models, RX is

directly influenced by latent variables as well as indirectly influenced by manifest variables.

4) Bido (2007) suggests that the construct variable (latent variable), which has only one manifest variable, should be represented by “structured order”, therefore: $\eta^{(A)} = \varpi_{RX} RX + \delta$

5.3.2 Heterotrait-Monotrait Ratio (HTMT) Test

We need to ensure that the latent variables we will use is statistically not relevant, so we will use the Heterotrait-Monotrait Ratio (HTMT) Test to examine the discriminant validity. We always refer to the SEM method and we construct the PLS-SEM model.

	LN	MA	RX
LN			
MA	0.265		
RX	0.529	0.186	

We often view HTMT<0.85 as a qualified value of proving that the latent variables are actually independent. The results above shows that out assumption is proved.

5.3.3 Indexes used for model efficiency assessment (in-sample analysis)

5.3.3.1 The Bootstrap test of the model coefficient estimation

In this paper, we use smartPLS 3 to do the Bootstrap test about the Outer Loadings, Outer Weights and the Path Coefficient we get from the model, we set the frequency of resampling equals 200.

	Original Sample (O)	Mean of Sample (M)	Std. Error (STDEV)	T Statistics (|O/STDEV|)	P Value
LN -> RX	0.371	0.377	0.036	10.235	0.000
MA -> RX	0.153	0.159	0.042	3.612	0.000

Outer Weights

	Original Sample (O)	Mean of Sample (M)	Std. Error (STDEV)	T Statistics (|O/STDEV|)	P Value
f_1 <- LN	0.439	0.436	0.034	13.047	0.000
$f_1{}^3$ <- LN	0.406	0.403	0.025	16.353	0.000
f_2 <- LN	0.239	0.237	0.081	2.947	0.003
$f_9{}^3$ <- LN	0.449	0.443	0.068	6.577	0.000
ma1 <- MA	0.670	0.670	0.056	11.985	0.000
ma5 <- MA	0.366	0.366	0.060	6.151	0.000
rx <- RX	1.000	1.000	0.000		

Outer Loadings

	Original Sample (O)	Mean of Sample (M)	Std. Error (STDEV)	T Statistics (|O/STDEV|)	P Value
f_1 <- LN	0.826	0.822	0.055	14.921	0.000
$f_1{}^3$ <- LN	0.825	0.821	0.050	16.428	0.000
f_2 <- LN	0.338	0.335	0.099	3.409	0.001
$f_9{}^3$ <- LN	0.492	0.486	0.080	6.129	0.000
ma1 <- MA	0.981	0.980	0.006	162.768	0.000
ma5 <- MA	0.935	0.934	0.013	72.078	0.000
rx <- RX	1.000	1.000	0.000		

Result

Assumption	Test Result
H_1: Latent variable LN can synthetically reflect 4 manifest variables, which is positively correlated with them	Support
H_2: Latent variable MA can synthetically reflect 2 manifest variables, which is positively correlated with them	Support
H_3: LN has significant positive effect on the RX	Support
H_4: LN has significant positive effect on the RX	Support

5.3.3.2 Efficiency assessment of the outer model

1. Outer loadings of manipulate variables

We use the loadings between manifest variables and latent variables to assess the reliability of each indicator. A widely accepted standard takes 0.7 as the minimum threshold of the loading, which ensures the shared variance would bigger than the error variance (Carmines and Zeller, 1979).

LV	MV	Outer Weights (w)	Outer loadings
LN	f_1	0.439	0.826
	f_1^3	0.406	0.825
	f_2	0.239	0.338
	f_9^3	0.449	0.492
MA	ma1	0.670	0.981
	ma5	0.366	0.935
RX	rx	1.000	1.000

We can find that the manifest variables f_1, f_1^3, ma1, ma5 can obviously pass the outer loadings test. However, variables f_2, f_9^3 don't meet the requirement we set above. However, we calculate the average outer loadings of LN, and we find that the result is close to 0.7, so we can still take these two variables into account.

2. Communality and Average Variance Extracted (AVE)

For every set of indicators, communality refers to the mean of all square value of correlation coefficients between each indicator and its construct. The mean value of all sets of indicators is the communality of the whole model, which is also called Average Variance Extracted (AVE). It is generally agreed that the communality should be over 0.5 and thus for every outer model, the indicators are able to account for more than fifty percent of total variance. Secondly the square root of AVE of each latent variable larger than the correlation coefficient among all latent variables. This ensures each latent variable is statistically independent from the others.

LV	MV	Average Variance Extracted (AVE)	Average AVE
LN	f_1	0.430	0.674
	f_1^3		
	f_2		
	f_9^3		
MA	ma1	0.918	
	ma5		
RX	rx	---	---

We can also get results according to AVE and the correlation coefficients:

	LN	MA	RX
LN	$\sqrt{AVE}$ =0.656	0.108	0.387
MA	0.108	$\sqrt{AVE}$ =0.958	0.193
RX	0.387	0.193	1.000

5.3.3.3 Efficiency assessment of the inner model

1. Path Coefficient and R square

We get the inner model’s path coefficients and the goodness of fit through OLS regression. R square is an important indicator when evaluating inner relationship.

R	R^2	Adjusted R^2	Std. Error
0.416	0.173	0.170	0.031

We can find that the adjusted R^2 is not so big. However, according to Chin(1998), if R^2 is bigger than 0.17 but not bigger than 0.35, we can say that this model have the weak fitting effect, so we still recognize our result as a acceptable result.

	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	VIF
	B	Std. Error	Beta			

LN	0.371	0.036	0.371	10.235	0.000	1.012
MA	0.153	0.042	0.153	3.612	0.000	1.012

We can find that the Path Coefficient of both latent variable are larger than zero, and the p value (sig.) of both variables are smaller than 0.01, also the VIF (which is used to represent the collinearity of both variables is smaller than 10, so the influence of collinearity is not so big.

2. Redundancy

Redundancy indicates the joint prediction ability of both inner and outer models. It uses the average variance in the outer model and the goodness of fit in the inner model. The minimum standard for redundancy is the multiplication of the minimum communality standard and the minimum R square standard.

Equation: Redundancy = R^2 * Community

Since the AVE is the average of Community, and the Redundancy value is 0.115, which is receivable.

5.4 Robustness Check

5.4.1 PLS Predict

5.4.1.1 Method Explanation

PLS Predict Method allows generating different out-of-sample and in-sample predictions which facilitate the evaluation of the predictive performance when analyzing new data.

The current PLS predict algorithm implementation in the SmartPLS software allows researchers to obtain k-fold cross-validated prediction errors and prediction error summaries statistics such as the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) to assess the predictive performance of their PLS path model for the manifest variables (MV or indicators) and the latent variables (LV or constructs).

In order to evaluate the result of a specific PLS path model, we compare the predictive ability against two naïve benchmarks:

(1) The Q^2 value in PLS Predict compares the prediction errors of the PLS path model against simple mean predictions.

(2) The linear regression model (LM) offers prediction errors and summary statistics that ignore the specified PLS path model.

(We'll talk about (1) and (2) in the Appendix)

Method: We will divide the sample we used into K folds to check the accuracy of PLS model. The coefficient K can be adjusted by the PLS software so that we can have the multiple results.

5.4.1.2 Result of PLS Predict

1. The Q^2 Value between PLS Model and Mean Value Model

	RMSE	MAE	MAPE	Q^2
RX	0.901	0.666	172.870	0.189

2. The Q^2 Value between LM Model and Mean Value Model

	RMSE	MAE	MAPE	Q^2
RX	0.918	0.704	200.626	0.158

The results showed above shows that the Std. Error of the PLS Model is smaller than the results we get from LM Model. Since we get better results from PLS Predict, we can obviously say that PLS Model are more persuasive.

5.4.2 Blindfolding

5.4.2.1 Method Explanation

Besides evaluating the magnitude of the R^2 values as a criterion of predictive accuracy, researchers may desire to also examine Stone-Geisser's Q^2 value (Stone, 1974; Geisser, 1974) as a criterion of predictive relevance. The Q^2 value of latent variables in the PLS path model is obtained by using the blindfolding procedure.

Blindfolding is a sample re-use technique, which systematically deletes data points according to an omission distance D and provides a prognosis of their original values. A Q^2 value larger than zero for a certain endogenous latent variable indicates the PLS path model has predictive relevance for this construct. For detailed explanations of the blindfolding procedure, see Hair et al. (2017).

Shortcoming: This method may have contingency so that we should use it cautiously.

5.4.2.2 Result of Blindfolding

The Accumulated SSE = 482.149 and SSO = 576.000, we can get $Q^2 = 0.163$, which means that our method is effective.

5.4.3 Cluster Analysis

5.4.3.1 Method Explanation

In the Cluster Analysis, we divide the sample into k clusters and compare the coefficients among different clusters. To ensure the validity we assign a relatively large value of k which leads to overlapping between each adjacent pair. To some extent, the Cluster Analysis seems like a Rolling Window method with a "wider distance". We will employ Student's t test to check if coefficients obey the normal distribution. If the results passed the Student's t test, we would say that the coefficients bear no significant differences with the ones we got from the whole sample.

5.4.3.2 Result of Cluster Analysis

In Student's t test, the significance of LN and MA models are 0.018 and 0.018 respectively. Thus we prove the feasibility of Cluster Analysis.

	N	Mean	Std. Error	Std. Error of the Mean
LN	37	0.449	0.072	0.025
MA	37	0.207	0.050	0.018

T statistic results:

	t statistics	df	sig.	Mean Value Difference	95% Confidence Interval		Test Value
					Lower Limit	Upper Limit	
LN	3.077	36	0.018	0.078	0.018	0.138	0.371
MA	3.031	36	0.019	0.054	0.012	0.095	0.153

6 Conclusion

We draw a conclusion that when we use PLS Regression to cover the six manifest variables we talked above, we can get the best strategy to extract excess return.

REFERENCE

Fama E F, Bliss R R. The Information in Long-Maturity Forward Rates[J]. American Economic Review, 1987, 77(4):680-92.

Cochrane J H, Piazzesi M. Bond Risk Premia[J]. American Economic Review, 2002, 95(1): 138-160.

Ludvigson S C, Ng S. Macro Factors in Bond Risk Premia[J]. Nber Working Papers, 2005, volume 22(12):5027-5067(41).

Goh J, Jiang F, Tu J, et al. Forecasting Government Bond Risk Premia Using Technical Indicators[J]. Ssrn Electronic Journal, 2013.

Eriksen J N. Expected Business Conditions and Bond Risk Premia[J]. Social Science Electronic Publishing, 2015.

Laborda R, Olmo J. Investor sentiment and bond risk premia ☆[J]. Journal of Financial Markets, 2014, 18(1):206-233.

Zhou H. Variance Risk Premia, Asset Predictability Puzzles, and Macroeconomic Uncertainty[J]. Ssrn Electronic Journal, 2010(2010-14).

Zhou G, Zhu X. Bond Return Predictability and Macroeconomy: The International Link[J]. Social Science Electronic Publishing, 2015.

Evermann, J. & Tate, M. 2016. Assessing the Predictive Performance of Structural Equation Model Estimators, Journal of Business Research, 69(10): 4565-4582.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., and Chatla, S. B. 2016. The Elephant in the Room: Evaluating the Predictive Performance of PLS Models, Journal of Business Research, 69(10): 4552-4564.

Geisser, S. (1974). A Predictive Approach to the Random Effects Model, Biometrika, 61(1): 101-107.

Stone, M. (1974). Cross-Validatory Choice and Assessment of Statistical Predictions, Journal of the Royal Statistical Society, 36(2): pp 111-147.

Hair, J. F., Hult, G. T. M., Ringle, C. M., and Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2^nd^ Ed., Sage: Thousand Oaks.

Davison, A. C., and Hinkley, D. V. (1997). Bootstrap Methods and Their Application, Cambridge University Press: Cambridge.

Efron, B., and Tibshirani, R. J. (1993). An Introduction to the Bootstrap, Chapman Hall: New York.

Lohmöller, J.-B. (1989). Latent Variable Path Modeling with Partial Least Squares, Physica: Heidelberg.

Dijkstra, T. K. (2010). Latent Variables and Indices: Herman Wold’s Basic Design and Partial Least Squares, in Handbook of Partial Least Squares: Concepts, Methods and Applications (Springer Handbooks of Computational Statistics Series, vol. II), V. Esposito Vinzi, W. W. Chin, J. Henseler and H. Wang (eds.), Springer: Heidelberg, Dordrecht, London, New York, pp. 23-46.

APPENDIX

APPENDIX A FOR CHAPTER 4.2.1 & 4.2.2

The reason why we use half regression to double check the result we get from the rolling window is that we think that the rolling window method is totally not persuasive on testing LN model.

Let us just think about a basic problem we will always meet in PCA method. When we use different time period data, we will find we can get different main components of the raw data, sometimes we even can get different numbers of main components. For example, we find that there are 8 main factors when we use the time period 1964-2007, but we can get 9 main factors when we choose 1964-2011 as a new time period. Nevertheless, when we do rolling window test by use a specific time period data, we are definitely overlook the effects of PCA method. **We are actually using future data to test former time period, it can't be accept since we are doing the robustness check!**

To do a more accurate research, we choose half regression not rolling window.

APPENDIX B FOR CHAPTER 5.1.1

⑴ Bartlett's test of sphericity: We assume that the matrix of correlation equals to the identity matrix (we regard it as the null hypothesis H_0), or we should not use the PCA method.

⑵ KMO (Kaiser-Meyer-Olkin Measure of Sampling Adequacy) is used to observe the difference between the correlation coefficient and partial correlation coefficient. We often use the factor analysis method when KMO>0.6 (0<KMO<1).

APPENDIX C FOR CHAPTER 5.2

Why we choose have PLS not OLS?

(1) The results we get from PCA is linear correlated, so we can't choose OLS since it does not meet the basic assumption of OLS.

(2) The historical data doesn't obey the normal distribution, which also doesn't meet the basic assumption of OLS.

APPENDIX D FOR CHAPTER 5.4.1.1

(1) For this purpose, it uses the mean value of the training sample to predict the outcomes of the holdout sample. The Q^2 value results interpretation is similar to the assessment of Q^2 values obtained by the blindfolding procedure in PLS-SEM. If the Q^2 value is positive, the prediction error of the PLS-SEM results is smaller than the prediction error of simply using the mean values. In that case, the PLS-SEM models offers better predictive performance.

(2) Instead, the LM approach regresses all exogenous indicator variables on each endogenous indicator variable to generate predictions. Thereby, a comparison with the PLS-SEM results offers information whether using a theoretically established path model improves (or at least does not worsen) the predictive performance of the available indicator data. In comparison with the LM outcomes, the PLS-SEM results should have a lower prediction error (e.g., in terms of RMSE or MAE) than the LM. Note that the LM prediction error is only available for the manifest variables and not the latent variables.