Bond Market Analyst:

The Secret to Investing Success in U.S. Bond Market

ZJU Investment Management®

Bond Market Analyst

Agenda:

1 Background Introduction

2 Data and Methodology

3 In-Sample Test

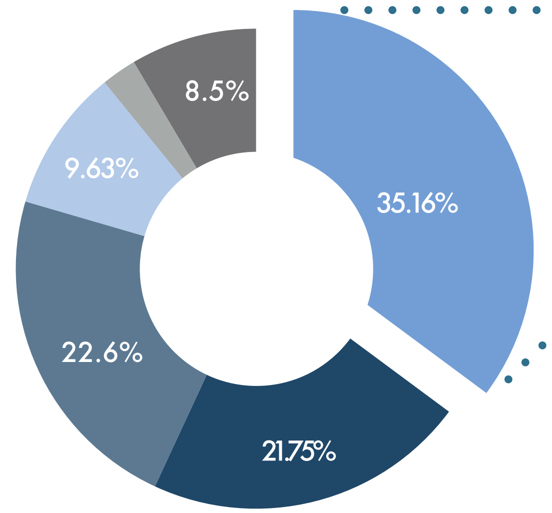
4 Robustness Check

5 Optimal Trading Strategy

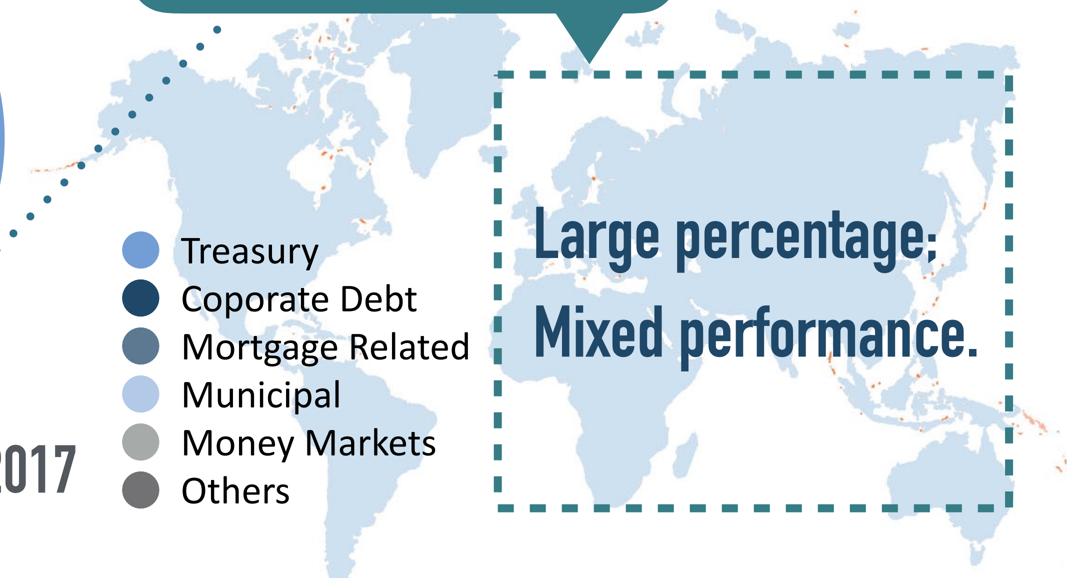
6 Reference

U.S. Bond Market at Odds with Stock Market Optimism

"Trump Reflation Trade"



U.S. Bond Market Size of 2017



Government bonds:

Large percentage;
Mixed performance.

Market Confidence

- U.S. Stock Market

The Federal Reserve raised rate by 0.25%

- U.S. Government Bond

10 year bond yield came in from 2.4% to 2.39%

For years, bond strategists and economists have consistently forecast higher yields on expectations that central banks' stimulus will lead to inflation, which has not materialized.

Next Steps to Consider:

- Research fixed investments
- Optimize trading strategy
- Invest for excess return

Source: Securities Industry and Financial Markets Association (SIFMA), Q1 2017

Research Basis and Orientation

Data

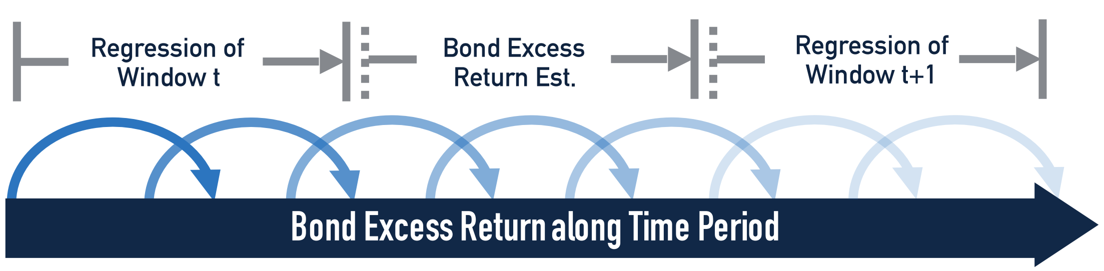
- **Sources:** GPD2017
- **Time Period:** 1964/01-2011/12

Methodology

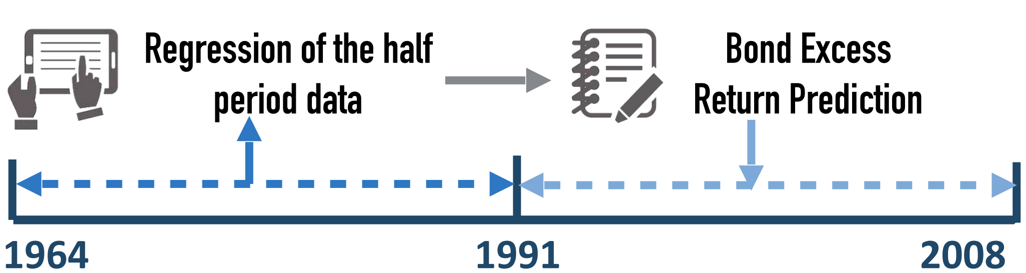
- **OLS Regression** $rx_{t+1}^{(n)} = \alpha + \beta X_t + \varepsilon_{t+1}^{(n)}$
- **PLS Regression** $max\langle X_{p_1}, Y_{q_1}\rangle, \text{s.t.} \|p_1\| = 1, \|q_1\| = 1$

Out-of-Sample

- Rolling Window



- Half Regression



1 Benchmark

$$E_t[r(t+1, t+\tau) - r(t, t+\tau)] = [r(t, t+\tau) - r(t, t+1)/(\tau - 1)]$$

Expectation Hypothesis

- The expected change in yield depends on the slope of the term structure.
- A benchmark predictor is the same as using historical average as the predictor.

2 Predictors

Forward Spread

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

Linear Combination of Forward Rates with Maturities

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

Common Macro Factors

$$\overline{rx} = \alpha + \beta_1 \cdot F_1 + \beta_2 \cdot F_1^3 + \beta_3 \cdot F_2 + \beta_4 \cdot F_3 + \beta_5 \cdot F_4 + \beta_6 \cdot F_8 + \varepsilon$$

Other Factors

Source: Fama-Bliss Price of US Treasury Bond

Regression Results on Previous Models

1 Forward Spreads (FB,1987)

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

n	2	3	4	5
β	0.832	1.123	1.344	1.108
Adjusted R^2	0.113	0.125	0.136	0.059

2 Forward Rates (CP,2005)

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

Variable	y	f^(2)	f^(3)	f^(4)	f^(5)
β	-1.717	0.129	-1.012	0.178	-0.560
sig	0.000	0.886	0.000	0.003	0.000
Adjusted R^2			0.220		

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

- $f^{(2)}$ was not significant: sig = 0.886.
- Multicollinearity among explanatory variables.

3 Common Macro Factors (LN,2009)

$$\overline{rx} = \alpha + \beta_1 \cdot F_1 + \beta_2 \cdot F_1^3 + \beta_3 \cdot F_2 + \beta_4 \cdot F_3 + \beta_5 \cdot F_4 + \beta_6 \cdot F_8 + \varepsilon$$

Variable	F1	F1^3	F2	F3	F4	F8
β	-1.717	0.129	-1.012	0.178	-0.560	0.777
Adjusted R^2				0.224		

- Adjusted R^2 was larger than previous models.
- No linear correlation among factors.
- More feasible.

4 Forward Rates & Macro Factors (CP-LN)

$$\overline{rx} = \alpha + \beta_1 \cdot CP + \beta_2 \cdot LNF_5 + \varepsilon$$

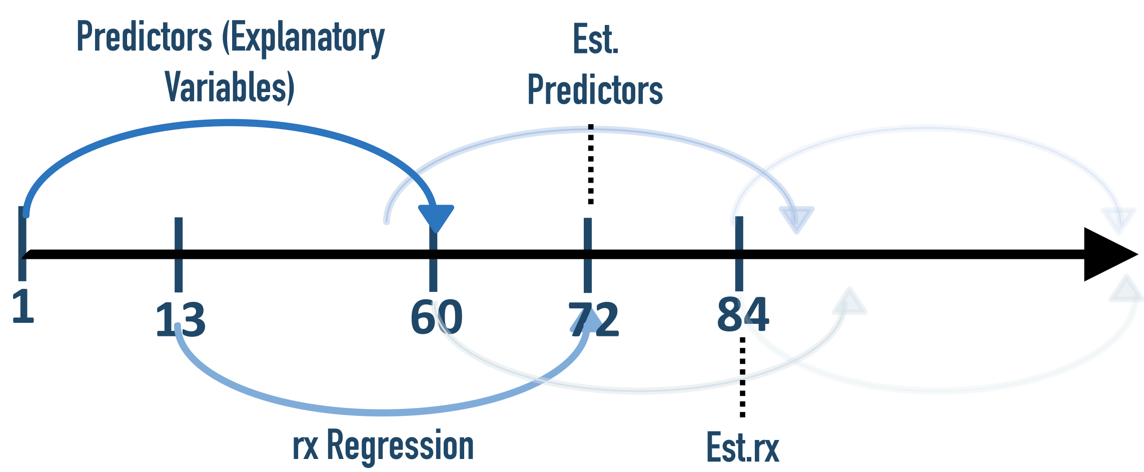
Variable	f1	f1^3	f3	f4	f8	cp
β	-1.276	0.111	0.319	-0.367	0.521	0.907
Adjusted R^2				0.438		

- Adjusted R^2 was larger than the single model of CP or LN.
- Combined the factors from both macro and micro aspects.

Source: Fama-Bliss Price of US Treasury Bond; Ludvigson S C, Ng S. Macro Factors in Bond Risk Premia[J]

Out-of-Sample Test : Rolling Window

Method and Forecast Evaluation



- Rolling Window Size: 60. Each sample contains data of 5 years.
- First Rolling Window Process: use 1-60 month predictors and 13-72 month rx to run regression. We can forecast the predictors from 72nd month and rx from 84th month.

$$R_{OS}^2 = 1 - \frac{\sum_{j=1}^{T}(rx_j^{(n)} - \widehat{rx}_j^{(n)})^2}{\sum_{j=1}^{T}(rx_j^{(n)} - \overline{rx}_j^{(n)})^2}$$

- $R_{OS}^2 > 0$ ($R_{OS}^2 < 0$) implies that the $\widehat{rx}_{t+1}^{(n)}$ forecast statistically outperforms (underperforms) the historical average forecast according to the MSPE metric.

Result and Comparison

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

▶ **Fama and Bliss Model**

The R_{OS}^2 of Treasury bond with different maturities are constantly negative, indicating it performs under historical mean estimation.

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

▶ **CP and CP-LN Model**

Not promising, because the R_{OS}^2 are -0.3931 and -0.1772 representatively, which has a large negative value.

▶ **LN Model** ✓

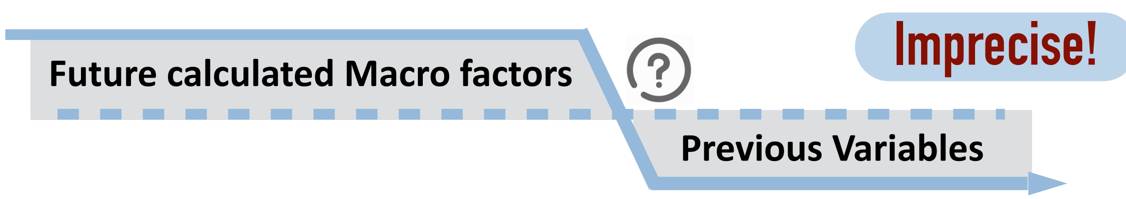
Relatively effective since R_{OS}^2 is close to 0.

Out-of-Sample Test : Half Regression

Validity Test:

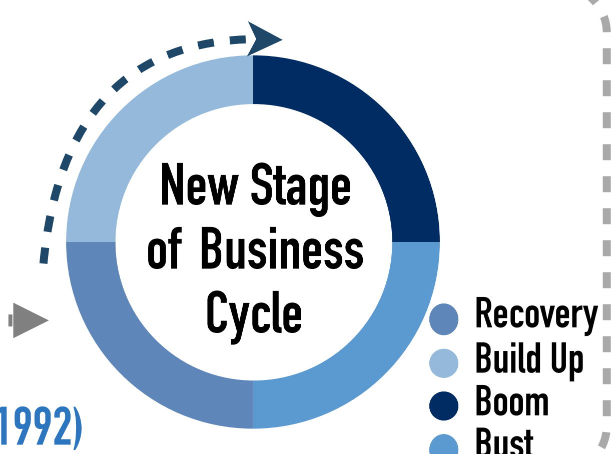
LN-Rolling Window

- Ludvigson and Ng (2009): used PCA method to calculate macro factors based on data generated along the whole time period.
- Previous Out-of-Sample Test: rolling window method used future calculated macro factors to explain previous variables.



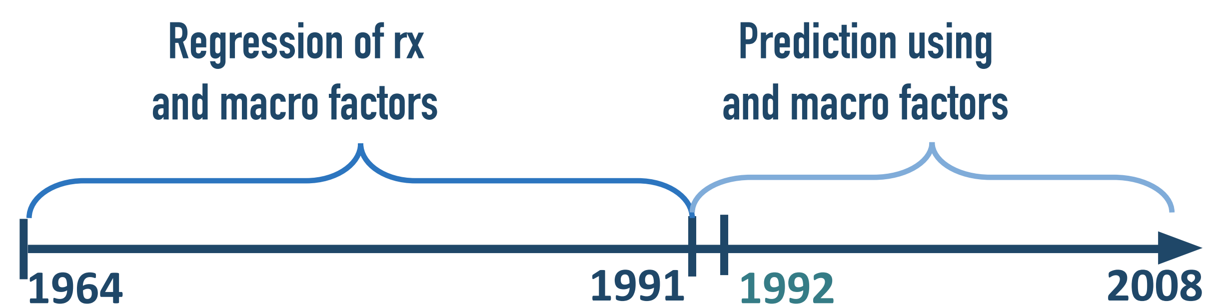
Unusual Time

President Clinton's Inauguration(1992)



If LN model with precise macro factors can well predict rx, especially after change of economy, its validity can be proved.

Half Regression: Method and Forecast Evaluation



- Macro factors are calculated via PCA using previous macro raw data.
- Run regression of data 1964-1991 and predict rx after 1992.
- Good performance of estimated rx among several prediction data.

Out-of-Sample ROS-Square Test	
R^2_{OS} in LN Model	0.0865

CONCLUSION

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

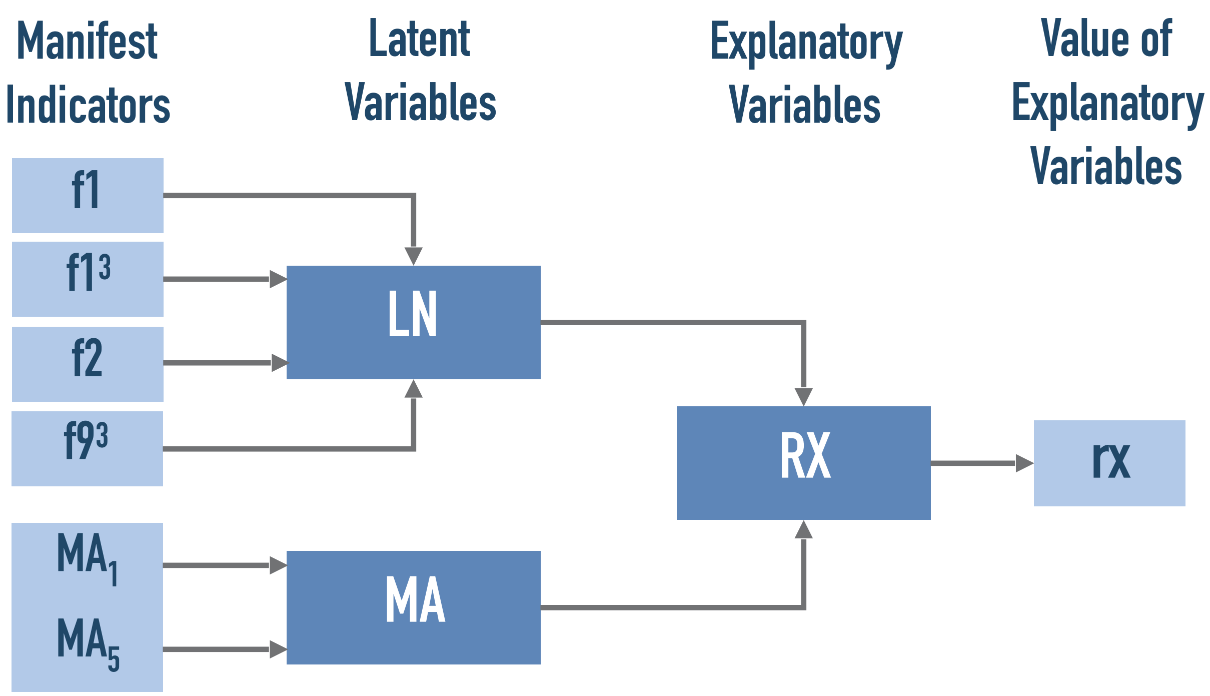
Source: Team Research and Calculation

LN-MA Indicators are Proved Optimal under PLS Method.

Why PLS

- Factors calculated via PCA are linear correlated.
- Historical data is disaccord with normal distribution, which disobeys the assumptions of OLS.

Indicators Structure



- The PLS Path Modeling Method includes two models.
- Inner Model (Measurement Model):
  Latent variables interpret explanatory variable. LN & MA → RX
- Outer Model (Construct Model):
  Manifest indicators explanation. f1, f1³, f2, f9³ & MA1, MA5 → RX

Path Model Validity Evaluation

In-Sample Test

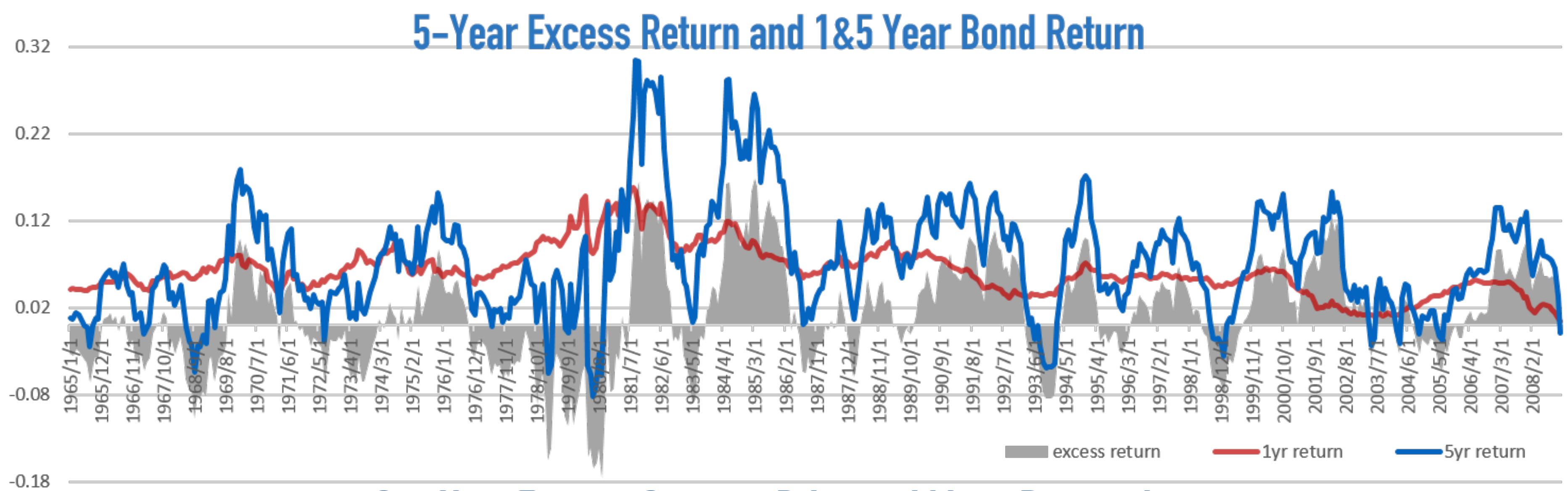
- **HTMT**
  -Discriminant Validity Test
- **Bootstrap**
  -Whether the coefficient β in the test model is accurate.
- **Outer Model Index**
  - Loadings of manifest variables
  - Communality and Average Variance Extracted (AVE)
  - AVE and Correlation Matrix
- **Inner Model Index**
  - Path Coefficient and R-Square
  - Redundancy

Out-of-Sample Test

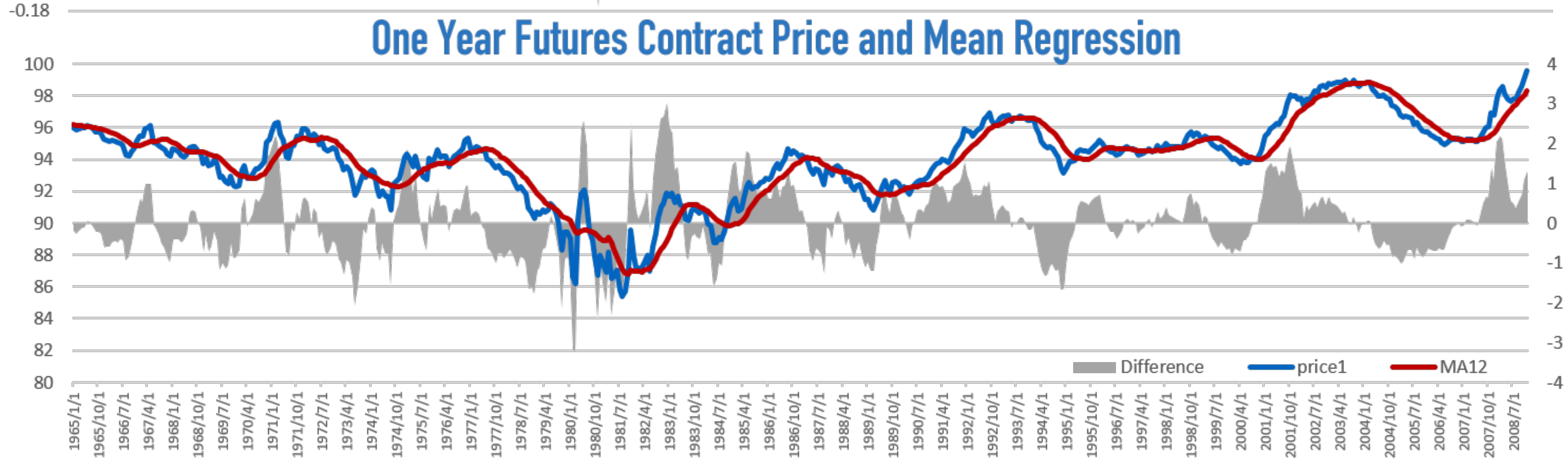
- **PLS Predict & Blindfolding & Cluster Analysis**

MA: Moving Average Indicator

Moving Average Analysis

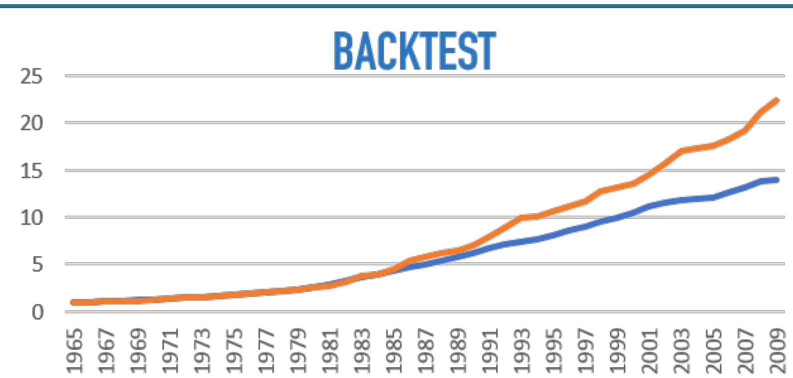


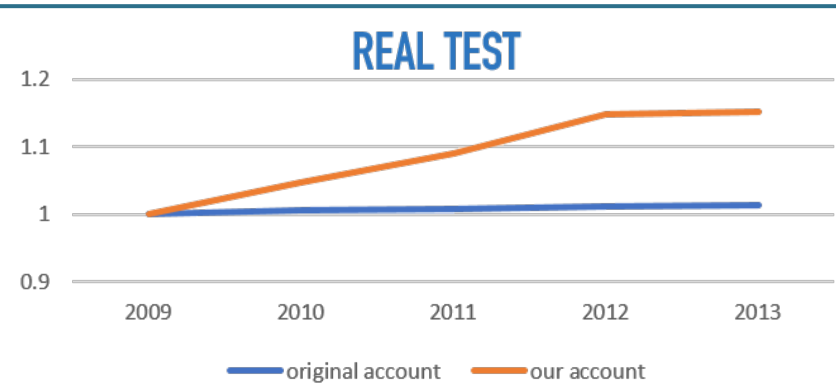
- Interest rate fluctuation results in greater volatility of 5-year bond with longer duration.
- Periodicity in excess return is significant, prediction of which helps market timing.



- Interest rates are inclined to mean regression
- The difference (Price1-MA) has the similar periodicity and high correlation with excess return.

Indicator Test





- When 1-year bond price is lower than MA, buy 1-year bond. Otherwise buy 5-year bond.
- Good performance of backtest and real test.
- MA is a strong indicator.

Source: Fama-Bliss Price of US Treasury Bond; Team Research and Calculation

LN-MA Model: Details in Structure and Construction

LN Construct

Principal Component Analysis (PCA)

- **Standardization:** raw data to Z-score data
- **Factor Analysis Method:** get main factors

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

▶ **Factor Selection:** f_1 f_2 f_1^3 f_9^3

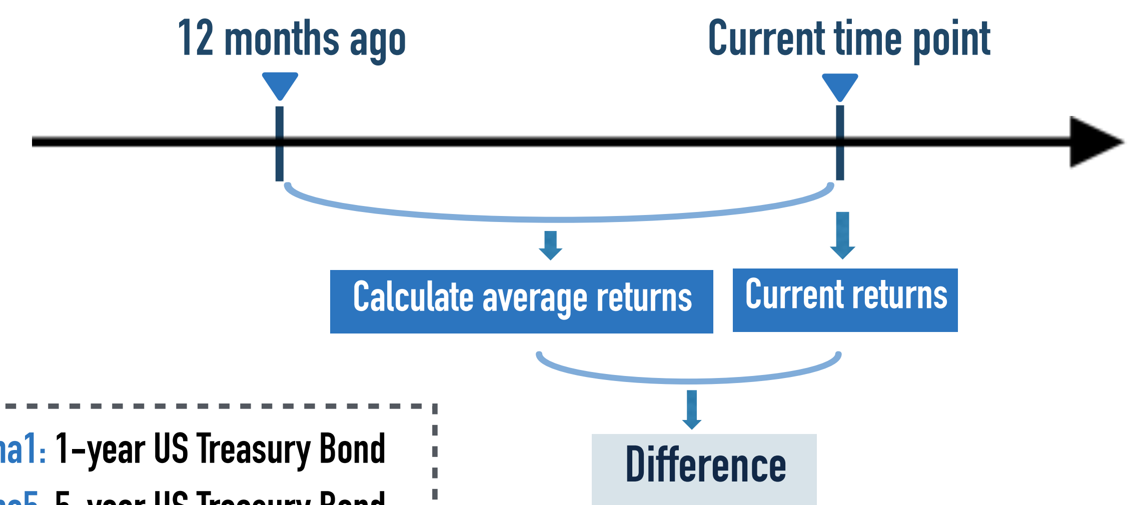
Feasibility Testing

- **Kaiser-Meyer-Olkin (KMO):** sampling adequacy, KMO>0.6
- **Bartlett's Test of Sphericity:** original hypothesis H_0

KMO Value	0.953
Bartlett Test's significance	0.000

MA Construct

How to obtain indicators ma1 & ma5



ma1: 1-year US Treasury Bond
ma5: 5-year US Treasury Bond

Heterotrait-Monotrait Ratio (HTMT) Test

- **Discriminant Validity Examination:** statistically irrelevant latent variables
- **Qualified Value:** HTMT<0.85

	LN	MA	RX
LN	-	-	-
MA	0.265	-	-
RX	0.529	0.186	-

Source: Macro Raw Data; Team Research

LN-MA Model: In-Sample Test

Assessment of the Outer Model

- Outer Loading: minimum threshold: 0.7, shared variance > error variance

LV	MV	Outer Weights (w)	Outer loadings
LN	f1	0.439	0.826
	f1^3	0.406	0.825
	f2	0.239	0.338
	f9^3	0.449	0.492
MA	ma1	0.670	0.981
	ma5	0.366	0.935
RX	rx	1.000	1.000

- Communality & Average Variance Extracted (AVE): minimum threshold: 0.5, indicators account for >50% total variance

LV	MV	Average Variance Extracted (AVE)	Average AVE
LN	f1	0.430	0.674
	f1^3		
	f2		
	f9^3		
MA	ma1	0.918	
	ma5		
RX	rx	---	---

	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

Assessment of the Inner Model

- Path Coefficient & R square: goodness of fit

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

	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

- Redundancy: joint prediction ability of inner and outer models
- Minimum standard = R^2 * Community
- In our model, redundancy value = 0.115 Acceptable √

Bootstrapping: Model Coefficient Estimation

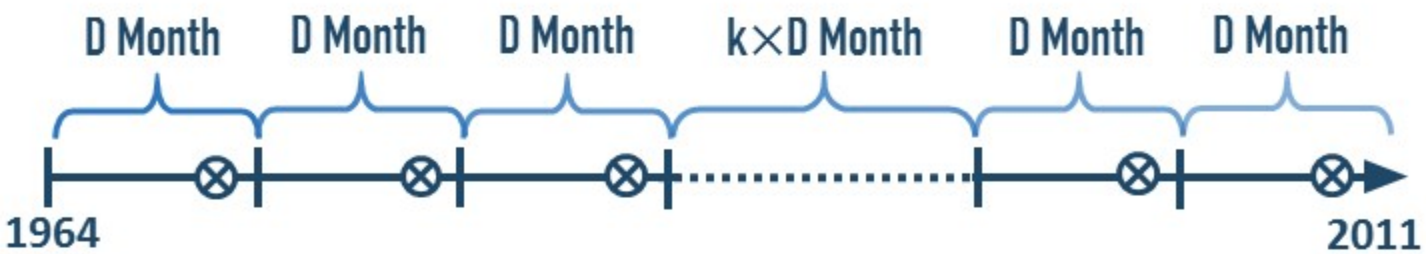
	Original Sample (O)	Mean of Sample (M)	Std. Error (STDEV)	T Statistics (|O/STDEV|)	P Value
LN -> RX	0.371	0.377	0.036	10.235	0.000
MA -> RX	0.153	0.159	0.042	3.612	0.000
f1 <- LN	0.826	0.822	0.055	14.921	0.000
f1^3 <- LN	0.825	0.821	0.050	16.428	0.000
f2 <- LN	0.338	0.335	0.099	3.409	0.001
f9^3 <- LN	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

LN-MA Model: Out-of-Sample Test

PLS-Predict

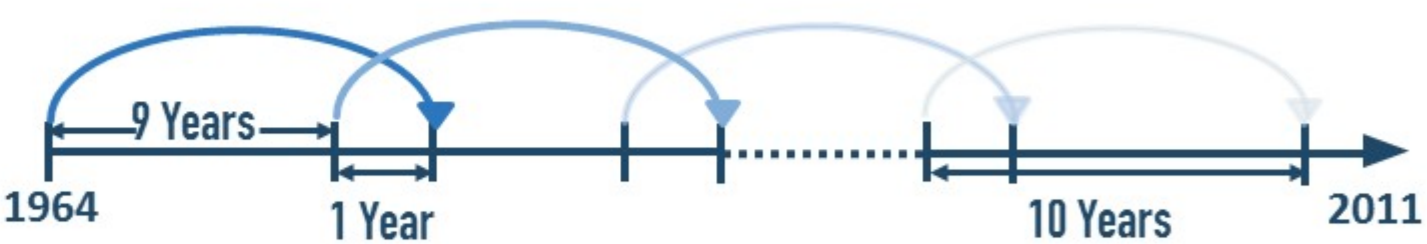
- PLS predict produces more excess return compared to the benchmark (expectation hypothesis).
- PLS method has stronger explanatory ability than the OLS method.

Blindfolding



- Blindfolding analysis makes interval predictions to prove the consistent predictable ability of PLS model at different time intervals.

Cluster Analysis

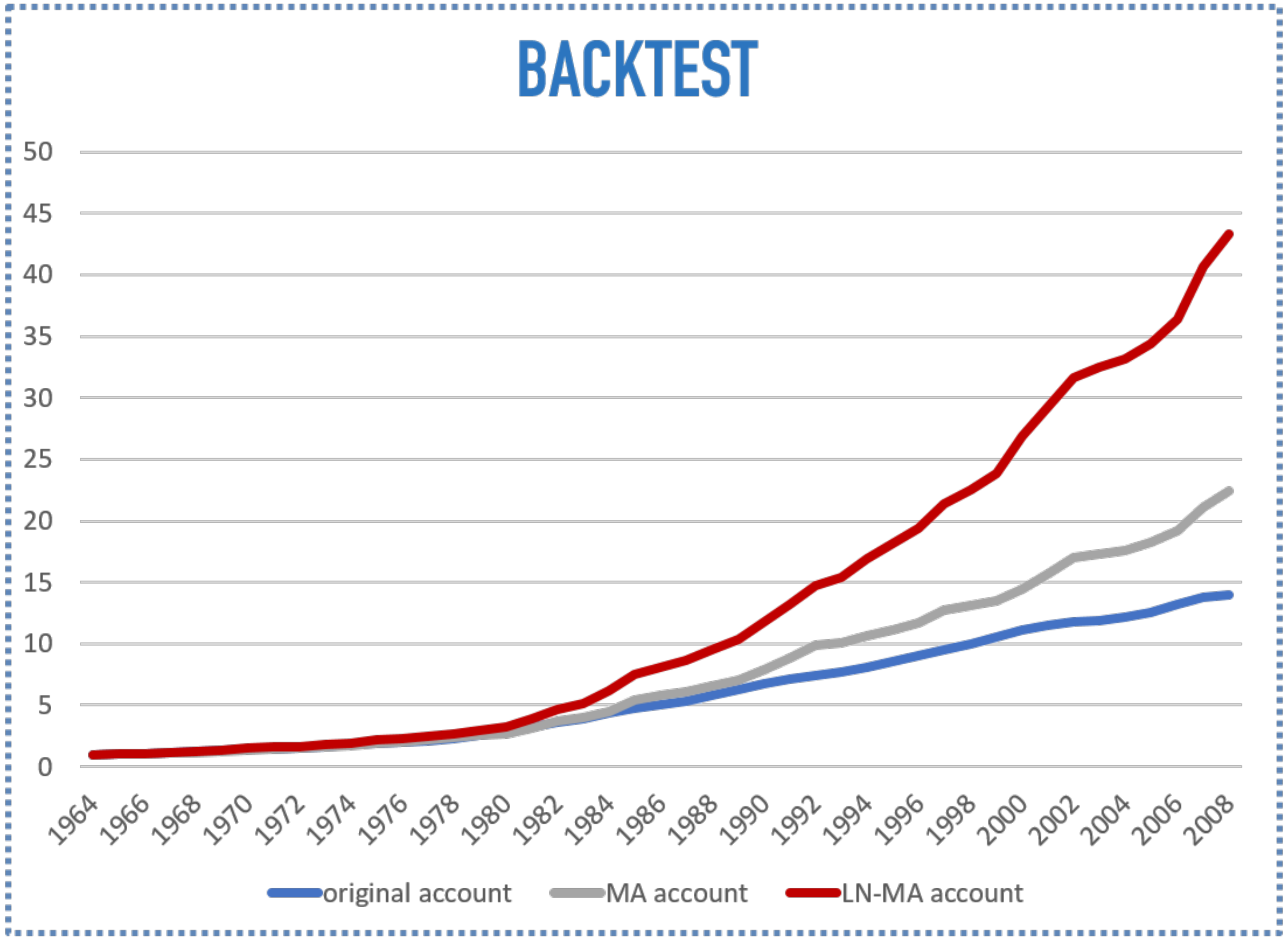


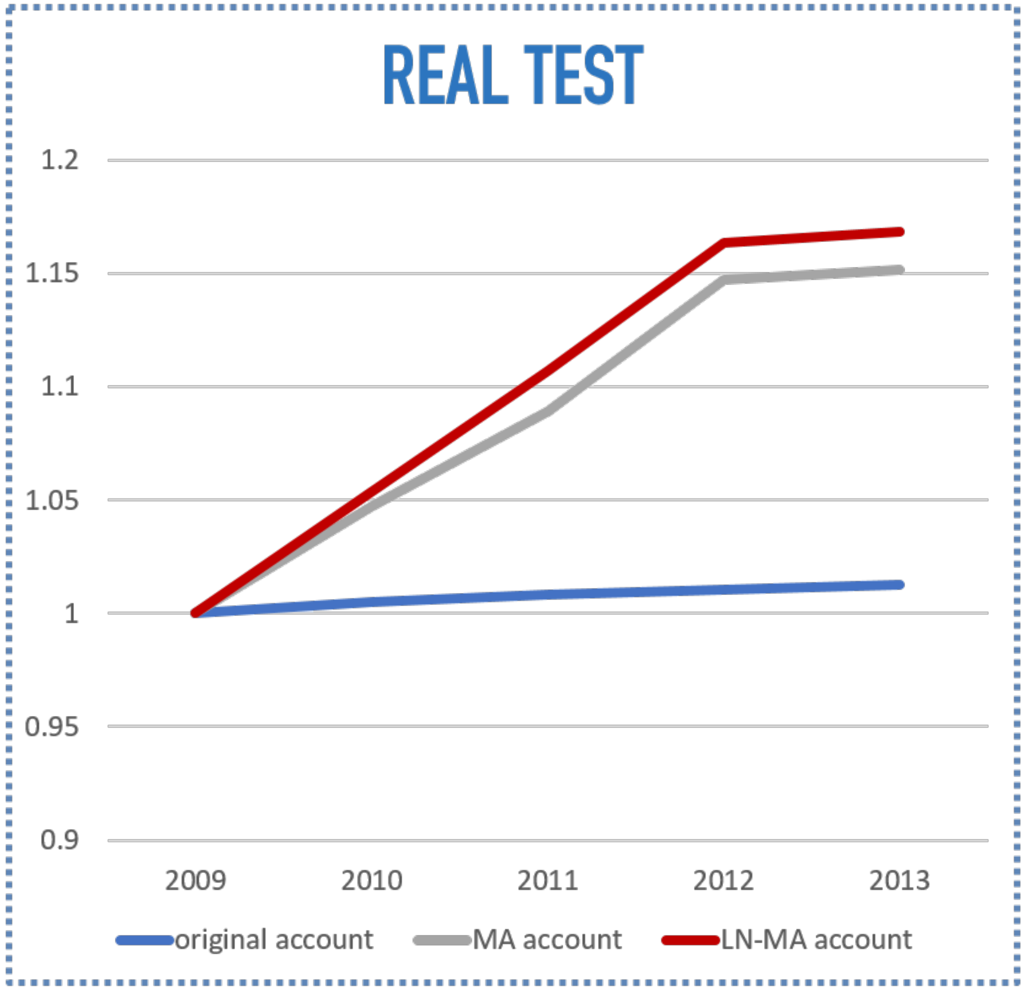
- Conducts single-sample t tests on the coefficients of latent variables in different time intervals
- Prove that coefficients obey the normal distribution with no significant distinction.
- PLS performs well in different time intervals.

Source: Team Research

The Best Future Starts With Us!

LN-MA Model Outperforms MA and 1-Year Bond Return





- Backtest and real test both indicate the outstanding predictability of LN-MA model.
- Our Strategy leads to greater excess return.

Source: Fama-Bliss Price of US Treasury Bond, Team Research and Calculation

The Best Future Starts With Us!

- Start with the principal of $ 1 million and hold for 30 years.

$1 million

- If you invest in 1-year U.S. Treasury Bond continuously, you will get $ 6.05 million.

$6.05 million

- If you employ our MA investing strategy, you will get $ 8.34 million.

$8.34 million

- If you trust our LN-MA Optimal Strategy, you will surely deserve $ 13.06 million in the end!

$13.06 million

Invest for your future!

Source: Team Research and Calculation

Appendix: Reference

- Fama, E. F., & Bliss, R. R. (1987, 9). The Information in Long-Maturity Forward Rates. American Economic Association , pp. 680-692.
- Cochrane, J. H., & Piazzesi, M. (2005, 3). Bond Risk Premia. THE AMERICAN ECONOMIC REVIEW , pp. 138-160.
- Ludvigson, S. C., & Ng, S. (2009, 12). Macro Factors in Bond Risk Premia. The Review of Financial Studies , pp. 5027-5067.
- Goh, J., Jiang, F., Tu, J., & Zhou, G. (2012). Forecasting Government Bond Risk Premia. Ssm Electronic Journal .
- 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.
- 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.
- 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.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