# Time series momentum: Is it there?

Huang, Dashan, Jiangyuan Li, Liyao Wang, and Guofu Zhou. Journal of Financial Economics (March 2020)

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#### **Outline**

- Introduction
- Research design
  - Univariate time series regression
  - Pooled regression
  - Bootstrap tests
- Empirical results
- Conclusion

#### 1. Introduction-- Motivation

- Time series momentum (TSM) refers to the predictability of the past 12-month return on the next one-month return.
- Moskowitz et al. (MOP, 2012) conclude that time series momentum (TSM) is everywhere: The past 12-month return positively predicts the next one- to 12-month return
- Whether time series predictability is present at the 12-month frequency remains an open question.
- In this paper, using the same data set as MOP (Moskowitz et al., 2012), we reexamine the evidence of TSM, we find that the evidence on TSM is weak.

### 1. Introduction-- Research question

1.How to prove that the evidence on TSM is weak?

 2. Why is the TSM strategy profitable even though the statistical evidence on time series predictability is weak?

#### 1. Introduction-- Framework

We run a **time series regression** of monthly return for each asset on its past 12-month return.

Answers to the first question

We follow MOP's approach and run a **pooled** regression by stacking all asset returns together.

To assess the degree of over-rejection, we use **two bootstrap methods**.

Answers to the second question

We propose a **times series history (TSH)** strategy that buys assets if their historical mean returns are positive and sells them otherwise.

#### 1. Introduction-- Contribution

• 1. This paper proves the evidence on TSM is weak, and explain the phenomenon why the TSM strategy is profitable.

• 2. The predictability in the asset classes, if it exists, is not as simple as a constant 12-month return rule.

#### 2. Data

- Futures prices: 24 commodities, 9 developed country equity indexes, 13 developed government bonds, and 9 currency forwards from the same data sources as MOP(55).
- Sample period: 1985.01 ~2015.12.
- Futures returns: For each day, we calculate the daily excess return
  of each futures contract with the nearest- or next-nearest-to-delivery
  contract and compound the daily returns to a cumulative month
  return index.

### 3. Univariate time series regression

 We run univariate time series regressions to explore the predictability of the past 12-month return for individual assets.

$$r_{t+1}^{i} = \alpha + \beta r_{t-12,t}^{i} + \varepsilon_{t+1}^{i}, \tag{1}$$

• Where  $r_{t+1}^i$  is the return of asset i in month t+1 and  $r_{t-12,t}^i$  is its past 12-month return (i.e., the return between months t-12 and t).

$$R_{OS}^{2} = 1 - \frac{\sum_{t=K}^{T-1} (r_{t+1}^{i} - \hat{r}_{t+1}^{i})^{2}}{\sum_{t=K}^{T-1} (r_{t+1}^{i} - \bar{r}_{t+1}^{i})^{2}},$$

$$\hat{r}_{t+1}^{i} = \hat{\alpha}_{t} + \hat{\beta}_{t} r_{t-12,t}^{i}$$
(2)

Where K is the initial sample size for parameters training.

 $\bar{r}_{t+1}^{i}$  is the sample mean of asset i with data up to month t.

Data spilt:15+16 years

### 3. Univariate time series regression--results

 Table 2 In- and out-of-sample performance of time series momentum (TSM) with time series regression.

Asset	$\beta_i$	t-stat	$R^2$	$R_{OS}^2$
Panel A: Commodity futures				
Aluminum	0.30	0.88	0.28	-1.42
Brent oil	0.34	0.69	0.14	-1.29
Cattle	0.38**	2.23	0.94	-0.62
Cocoa	-0.14	-0.28	0.03	-1.51
Coffee	0.21	0.40	0.04	0.23
Copper	0.77*	1.69	0.97	0.21
Average across asset classes			0.39	-0.67
#(10% significance)	8			3

The evidence of TSM across all the assets is very weak. Of the 55 assets, only eight display significant regression slopes at the 10% level; the significance is not concentrated but disperse among the four asset classes;  $R_{OS}^2$  only three are significant at the 10% level.

### 4. Pooled regression

We first replicate the Pooled regression in MOP (overstate the presence of TSM):

$$r_{t+1}^{i}/\sigma_{t}^{i} = \alpha + \beta r_{t-h+1}^{i}/\sigma_{t-h}^{i} + \varepsilon_{t+1}^{i},$$
 (3)

$$(\sigma_t^i)^2 = 261 \sum_{j=0}^{\infty} (1 - \delta) \delta^j (r_{t-1-j}^i - \bar{r}_t^i)^2, \tag{4}$$

$$r_{t+1}^i/\sigma_t^i = \alpha + \beta sign(r_{t-h+1}^i) + \varepsilon_{t+1}^i, \tag{5}$$

where sign is the sign function that equals +1 when  $r_{t-h+1}^i \ge 0$  and -1 when  $r_{t-h+1}^i < 0$ . To highlight fixed effects, a possible specification is

$$r_{t+1}^{i}/\sigma_{t}^{i} = \alpha + \beta r_{t-h+1}^{i}/\sigma_{t-h}^{i} + \mu_{i}/\sigma_{i} + \varepsilon_{t+1}^{i},$$
 (6)

$$\hat{\beta} = \beta + \frac{\text{Cov}(r_{t-h+1}^{i}/\sigma_{t-h}^{i}, \mu_{i}/\sigma_{i})}{\text{Var}(r_{t-h+1}^{i}/\sigma_{t-h}^{i})}.$$
(7)

the slope estimate of Eq. (3) is biased upward

### 4. Pooled regression--Bootstrap tests

**Table 3** p-value from the test that all assets have the same mean or Sharpe ratio.

	ANOVA	Welch's ANOVA	Kruskal-Wallis	Bootstrap
Mean Sharpe ratio	0.08 < 10 <sup>-5</sup>	$< 10^{-3}$ $< 10^{-5}$	$< 10^{-10} < 10^{-15}$	0

Two standard bootstrap approaches:

The first is a more restrictive parametric wild bootstrap

The second is a more general nonparametric **pairs bootstrap** that resamples the predictor and the dependent variable simultaneously.

$$\hat{\varepsilon}_{t+1}^{i} = r_{t+1}^{i} / \sigma_{t}^{i} - \hat{\alpha} - \hat{\beta} r_{t-h+1}^{i} / \sigma_{t-h}^{i}.$$
 (8)

wild bootstrap 
$$r_{t+1}^{i*}/\sigma_t^{i*} = \hat{\alpha} + \hat{\beta} r_{t-h+1}^i/\sigma_{t-h}^i + \hat{\epsilon}_{t+1}^i v_{t+1}^i$$
, (9)

$$v_t^i = \begin{cases} 1 & \text{with probability } 1/2, \\ -1 & \text{with probability } 1/2. \end{cases}$$
 (10)

### 4. Pooled regression--results

6

3.29

9.65

Table 4 t-statistic of pooled regression without controlling for fixed effects.

		Bootstrappe	ed t-statistic		Bootstrappe	d <i>t</i> -statistic
h	t-statistic	Wild	Pairs	t-statistic	Wild	Pairs
Panel A	A: Forecast with 1	eturn lagged <i>h</i>	months			
	$r_{t+1}^i/\sigma_t^i =$	$\alpha_h + \beta_h r_{t-h+1}^i / \sigma$	$\varepsilon_{t-h}^i + \varepsilon_{t+1}^i$	$r_{t+1}^i/\sigma_t^i=\alpha_h$	$+\beta_h sign(r_{t-h+1}^i)$	$)+arepsilon_{t+1}^{i}$
1	3.11	9.26	3.63	2.90	8.18	3.41
2	1.31	4.98	1.98	1.62	4.44	2.31
3	2.89	8.61	3.45	2.83	6.84	3.45
4	0.24	2.46	1.06	1.20	2.12	1.99
5	-0.17	1.88	0.60	-0.34	1.83	0.54
6	0.97	4.18	1.71	1.58	3.62	2.28
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Panel I	3: Forecast with [			1 . 1	0 : ( i )	
	$r_{t+1}^i/\sigma_t^i=0$	$\alpha_h + \beta_h r_{t-h,t}^i / \sigma_{t-h}^i$	$-1 + \varepsilon_{t+1}^{\iota}$	$r_{t+1}^i/\sigma_t^i=\alpha_h$	$+ \beta_h sign(r_{t-h,t}^i)$	$+ \varepsilon_{t+1}^{\iota}$
1	3.11	9.26	3.63	2.90	8.18	3.41
2	2.92	9.46	3.46	3.07	8.32	3.61
3	3.74	11.45	4.22	4.15	10.20	4.61
4	3.49	10.71	3.97	4.57	9.49	4.96
5	3.11	9.58	3.63	4.24	8.85	4.72
_						

3.80

At the 5% level ,define the distribution of the *t*-statistic's 97.5% quantile as the simulated *t*-statistic for significance.

The t-statistic from the real data is smaller than the simulated t-statistics respectively, suggesting that the evidence is weak in support of TSM.

3.88

8.88

4.39

### 4. Pooled regression--results

 Table 6 t-statistic of pooled regression without volatility scaling and without controlling for fixed effects

		Bootstrapped <i>t</i> -statistic			Bootstrapped $t$ -	statistic
h	t-statistic	Wild	Pairs	t-statistic	Wild	Pairs
Panel	A: Forecast with	return lagged	h months			
	$r_{t+1}^i =$	$\alpha_h + \beta_h r_{t-h+1}^i +$	$\cdot \varepsilon_{t+1}^i$	$r_{t+1}^i = \alpha$	$\alpha_h + \beta_h sign(r_{t-h+1}^i)$	$+\varepsilon_{t+1}^i$
1	1.80	5.49	2.51	2.20	6.13	2.85
2	0.52	2.58	1.47	1.65	2.67	2.45
3	1.43	4.57	2.19	1.84	4.58	2.58
4	0.67	3.21	1.58	1.47	3.21	2.26
5	-1.33	-0.10	-0.14	-0.89	-0.08	0.28
6	1.03	3.37	1.92	1.77	3.45	2.48
Panel	B: Forecast with	past h-month	returns			
	$r_{t+1}^i =$	$\alpha_h + \beta_h r_{t-h,t}^i +$	$\varepsilon_{t+1}^i$	$r_{t+1}^i =$	$\alpha_h + \beta_h sign(r_{t-h,t}^i)$	$)+\varepsilon_{t+1}^{i}$
1	1.80	5.49	2.51	2.20	6.13	2.8
2	1.39	4.56	2.21	2.57	5.10	3.1
3	1.71	5.26	2.45	3.06	5.81	3.6
4	1.82	5.30	2.59	3.75	5.94	4.2
5	1.27	4.27	2.09	3.23	4.75	3.7
6	1.55	4.85	2.39	2.71	5.38	3.3

The t-statistics without volatility scaling are much smaller than those with volatility scaling. Volatility scaling seems at least partially responsible for the performance of the TSM trading strategy.

### 4. Pooled regression--results

• **Table 7** t-statistic of pooled regression without controlling for fixed effects over **1985:01–2009:12**.

		Bootstrapped	d t-statistic		Bootstrapped	t-statistic
h	t-statistic	Wild	Pairs	t-statistic	Wild	Pairs
Panel	A: Forecast with	return lagged	h months			
	$r_{t+1}^i/\sigma_t^i =$	$\alpha_h + \beta_h r_{t-h+1}^i / \sigma_t^i$	$\varepsilon_{-h}^{i} + \varepsilon_{t+1}^{i}$	$r_{t+1}^i/\sigma_t^i =$	$\alpha_h + \beta_h sign(r_{t-h+}^i)$	$_{1})+\varepsilon_{t+1}^{i}$
1	3.71	10.68	4.20	3.75	9.31	4.19
2	0.97	4.07	1.68	1.34	3.65	2.02
3	2.48	7.43	3.11	2.44	6.09	3.01
4	0.22	2.40	1.14	0.65	2.28	1.59
5	-0.15	1.53	0.67	-0.38	1.56	0.66
6	0.52	3.08	1.30	1.35	2.78	2.15
Panel	B: Forecast with	past h-month	returns			
	$r_{t+1}^i/\sigma_t^i =$	$\alpha_h + \beta_h r_{t-h,t}^i / \sigma_t^i$	$_{-1}+arepsilon_{t+1}^{i}$	$r_{t+1}^i/\sigma_t^i =$	$= \alpha_h + \beta_h sign(r_{t-1}^i)$	$(t_{t+1}) + \varepsilon_{t+1}^i$
1	3.71	10.68	4.20	3.75	9.31	4.19
2	3.09	9.53	3.54	3.19	8.39	3.70
3	3.74	11.53	4.27	4.43	9.96	4.94
4	3.45	10.37	3.98	4.78	9.19	5.19
5	3.06	9.27	3.63	4.36	8.39	4.85
6	3.17	9.31	3.73	4.03	8.52	4.46

For the 1985 to 2009 sample period, the t-statistics from real data are still smaller than the simulated t-statistics.

# 4. Pooled regression $r_{t+1}^i/\sigma_t^i - \overline{r^i/\sigma^i} = \beta(r_{t-h+1}^i/\sigma_{t-h}^i - \overline{r_{-h+1}^i/\sigma_{-h}^i}) + \varepsilon_{t+1}^i$ , (12)

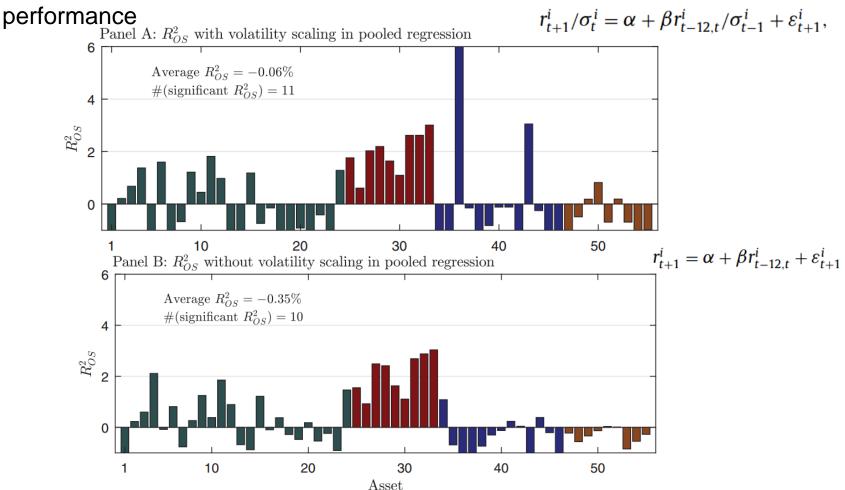
Table 8 t-statistic of pooled regression controlling for fixed effects.

		Bootstrapped <i>t</i> -statistic			Bootstrapped	<i>t</i> -statistic
h	t-statistic	Wild	Pairs	t-statistic	Wild	Pairs
Panel	A: Forecast with	return lagged				
	$r_{t+1}^i/\sigma_t^i=c$	$\alpha_h^i + \beta_h r_{t-h+1}^i / \sigma_t^i$	$\varepsilon_{-h}^{i} + \varepsilon_{t+1}^{i}$	$r_{t+1}^i/\sigma_t^i =$	$\alpha_h^i + \beta_h sign(r_{t-h+}^i)$	$_{1})+\varepsilon_{t+1}^{i}$
1	2.80	8.51	3.39	2.66	7.60	3.19
2	0.96	4.17	1.66	0.94	3.85	1.67
3	2.53	7.77	3.12	2.17	6.36	2.83
4	-0.19	1.56	0.70 0.25	0.36	1.56	1.27
5	-0.56	1.00		-0.94	1.03	0.02
6	0.58	3.26	1.36	1.07	2.90	1.79
Panel	B: Forecast with	past h-month	returns			
	$r_{t+1}^i/\sigma_t^i=\sigma_t^i$	$\alpha_h^i + \beta_h r_{t-h,t}^i / \sigma_t^i$	$_{-1}+arepsilon_{t+1}^{i}$	$r_{t+1}^i/\sigma_t^i$ =	$= \alpha_h^i + \beta_h sign(r_{t-h}^i)$	$(0,t) + \varepsilon_{t+1}^i$
1	2.80	8.51	3.39	2.66	7.60	3.19
2	2.51	8.43	3.07	2.62	7.41	3.19
3	3.23	10.17	3.74	3.56	9.08	4.17
4	2.89	9.24	3.46	3.60	8.36	4.11
5	2.44	7.89	2.99	3.17	7.45	3.66
6	2.53	7.97	3.12	3.15	7.27	3.70

Compared with Table 4, after controlling for the fixed effects, the t-statistic is smaller than that without controlling for fixed effects. Insufficient evidence exists in support of TSM.

# 4. Pooled regression-- Out-of-sample performance

• Fig. 4. Time series momentum (TSM) with pooled regression: out-of-sample



A pooled regression can improve the out-of-sample forecasting power, but such improvement is restricted to international equity markets. it cannot provide significant support for TSM either.

### 5. Trading strategy--TSM versus TSH at asset level

• asset  $i \sim \text{iid} \sim N(\mu^i, \sigma^i)$ , the probability of the past 12-month return being positive is

$$Pr(r_{t-12,t}^{i} > 0) = 1 - Pr\left(\frac{r_{t-12,t}^{i} - 12\mu^{i}}{\sqrt{12}\sigma^{i}} \le -\sqrt{12}\frac{\mu^{i}}{\sigma^{i}}\right)$$
$$= \Phi(\sqrt{12}\mu^{i}/\sigma^{i}), \tag{16}$$

$$r_{t+1}^{\text{TSH},i} = sign(r_{1,t}^i)r_{t+1}^i, \tag{17}$$

$$r_{t+1}^{\text{TSM},i} = sign(r_{t-12,t}^{i})r_{t+1}^{i}. \tag{18}$$

**TSH**: buys the futures contract if its **historical sample mean** is non-negative and sells it if its historical sample mean is negative.

**TSM**: buys the future contract if its **past 12-month return** is non-negative and sells it if its past 12-month return is negative.

### 5. Trading strategy-- TSM versus TSH at asset level

• **Table 9** Time series momentum (TSM) versus time series history (TSH) at the asset level(55).

Asset	TSM return	TSH return	TSM Sharpe ratio	TSH Sharpe ratio	Return difference	<i>p</i> -value of return difference	Sharpe ratio difference	<i>p</i> -value of Sharpe ratio difference
Aluminum	0.27	-0.47	0.05	-0.08	0.74**	0.04	0.13**	0.04
Brent oil	0.80	0.32	0.09	0.04	0.48	0.44	0.05	0.44
Cattle	0.28	0.08	0.07	0.02	0.20	0.48	0.05	0.48
Cocoa	-0.46	0.13	-0.06	0.02	-0.59	0.32	-0.08	0.31
Coffee	0.18	-0.55	0.02	-0.05	0.73	0.30	0.07	0.30
Copper	0.77	0.94	0.10	0.12	-0.17	0.74	-0.02	0.73
JPY/USD	0.46	0.09	0.14	0.03	0.37	0.11	0.11	0.11
NOK/USD	0.06	-0.06	0.02	-0.02	0.12	0.58	0.04	0.58
NZD/USD	0.24	0.02	0.07	0.01	0.22	0.38	0.06	0.38
SEK/USD	0.04	-0.05	0.01	-0.02	0.09	0.70	0.03	0.70
CHF/USD	0.18	0.19	0.05	0.06	-0.01	0.96	-0.01	0.97
GBP/USD	0.00	-0.03	0.00	-0.01	0.03	0.87	0.01	0.87
#(significance)					7		7	

Of the 55 assets, only five(+) show that the TSM strategy generates a higher average return than the TSH strategy.

The TSM strategy does not significantly outperform at the asset level the TSH strategy that does not require predictability.

# 5. Trading strategy-- TSM versus TSH at portfolio level

 Table 10 Time series momentum (TSM) versus time series history (TSH) at the portfolio level.

$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$				Fama-French four-factor model			Asness-Moskowitz-Pedersen three-factor model						
TSM strategy Long leg  0.34*** 0.12** 0.16*** 0.05** 0.09*** 0.32*** 42.57% 0.09 0.16*** 0.14*** 0.14*** 0.14*** 0.38*** 41.92% (4.92) (2.29) (7.73) (2.24) (2.62) (7.19) (1.60) (7.21) (2.99) (7.33)  Short leg -0.05 -0.03 0.14*** 0.11*** 0.03 -0.28*** 48.31% 0.02 0.13*** -0.09 -0.32*** 45.85% (-0.72) (-0.46) (5.30) (4.01) (0.96) (-8.34) (0.23) (5.08) (-1.42) (-6.89)  Long - short 0.39*** (4.73) (1.94) (0.61) (-1.83) (1.01) (9.99) (1.01) (0.93) (2.50) (8.79)  TSH strategy Long leg 0.27*** 0.07 0.28*** 0.14*** 0.14*** 0.10*** 0.08* 49.07% 0.10 0.26*** 0.01 0.26*** 0.01 0.08* 45.30% (2.56) (0.95) (8.79) (4.41) (3.90) (1.93) (1.13) (7.73) (0.24) (1.65)  Short leg 0.02 0.02 0.02 0.03*** 0.03* 0.03* 0.02 -0.04** 8.73% 0.01 0.03*** 0.03 -0.03 8.04% (0.61) (0.52) (3.51) (1.83) (1.47) (-2.01) (0.25) (3.17) (1.15) (-1.04)  Long - short 0.25*** 0.05 0.25*** 0.11*** 0.08*** 0.13*** 44.83% 0.09 0.23*** 0.09 0.23*** -0.00 0.14*** 0.14*** 0.38*** 41.92% 0.16*** 0.16*** 0.16*** 0.14*** 0.38*** 41.92% 0.16*** 0.16*** 0.16*** 0.14*** 0.10*** 0.023) (5.08) (-1.42) (-6.89) 0.03 0.23*** 0.70*** 47.39% 0.10 0.26*** 0.01 0.08* 45.30% 0.24) (1.65) 0.25** 0.02 0.03 0.03 0.03 0.03 0.03 0.03 0.03		Mean	Alpha	World	SMB	HML	UMD	$R^2$	Alpha	World			_
Long leg	Panel A: Equal v	veighting, i.e.	., portfolio	weight =	$\frac{1}{N}$								
Long - short $\begin{pmatrix} -0.72 \\ 0.39^{****} \\ (4.73) \end{pmatrix} \begin{pmatrix} -0.46 \\ 0.15^{**} \\ 0.02 \\ (4.73) \end{pmatrix} \begin{pmatrix} (4.01) \\ 0.02 \\ (0.61) \\ (0.52) \end{pmatrix} \begin{pmatrix} (4.01) \\ 0.02 \\ (0.61) \\ (0.52) \end{pmatrix} \begin{pmatrix} (4.01) \\ 0.06 \\ 0.06 \\ (0.06) \\ (0.06) \end{pmatrix} \begin{pmatrix} (-8.34) \\ 0.06 \\ 0.60^{****} \end{pmatrix} \begin{pmatrix} (0.23) \\ (5.08) \\ (0.27^{***} \\ (0.07) \\ (0.03) \end{pmatrix} \begin{pmatrix} (-1.42) \\ 0.03 \\ (0.07^{***} \\ (0.07^{***} \\ (0.07^{***} \\ (0.08^{**$								42.57%					41.92%
Long - short  0.39***  0.15* 0.02	Short leg							48.31%					45.85%
TSH strategy Long leg  0.27*** 0.07 0.28*** 0.14*** 0.10*** 0.08* 49.07% 0.10 0.26*** 0.01 0.08* 45.30% (2.56) (0.95) (8.79) (4.41) (3.90) (1.93) (1.13) (7.73) (0.24) (1.65)  Short leg 0.02 0.02 0.03*** 0.03* 0.02 -0.04** 8.73% 0.01 0.03*** 0.03 -0.03 8.04% (0.61) (0.52) (3.51) (1.83) (1.47) (-2.01) (0.25) (3.17) (1.15) (-1.04) Long - short 0.25*** 0.05 0.25*** 0.11*** 0.08*** 0.13*** 44.83% 0.09 0.23*** -0.02 0.11* 42.01%	Long - short	0.39***	0.15*	0.02	-0.06*	0.06	0.60***	46.03%	0.07	0.03	0.23**	0.70***	47.39%
Short leg 0.02 0.03 *** 0.03* 0.02 -0.04** 8.73% 0.01 0.03*** 0.03 -0.03 8.04% (0.61) (0.52) (3.51) (1.83) (1.47) (-2.01) (0.25) (3.17) (1.15) (-1.04) Long - short 0.25*** 0.05 0.25*** 0.11*** 0.08*** 0.13*** 44.83% 0.09 0.23*** -0.02 0.11* 42.01%		0.27***	0.07	0.28***	0.14***	0.10***	0.08*	49.07%	0.10	0.26***	0.01	0.08*	45.30%
Long - short 0.25*** 0.05 0.25*** 0.11*** 0.08*** 0.13*** 44.83% 0.09 0.23*** -0.02 0.11* 42.01%	Short leg	0.02	0.02	0.03***	0.03*	0.02	-0.04**	8.73%	0.01	0.03***	0.03	-0.03	8.04%
TSM versus TSH Mean difference $r_{t+1}^{\text{TSM}} = \frac{1}{N_t} \sum_{i=1}^{N_t} $	Long - short	0.25***	0.05	0.25***	0.11***	0.08***	0.13***	44.83%	0.09	0.23***	-0.02	0.11*	
Alpha difference		0.14										$r_t^{T}$	$\sum_{t=1}^{TSM} = \frac{1}{N_t} \sum_{i=1}^{N_t} \sum_{t=1}^{N_t} \sum_{i=1}^{N_t} \sum_{t=1}^{N_t} \sum_{i=1}^{N_t} \sum_{t=1}^{N_t} \sum_{i=1}^{N_t} \sum_{t=1}^{N_t} \sum_$
	Alpha difference											$r_t^{1}$	$\sum_{t+1}^{SH} = \frac{1}{N_t} \sum_{t+1}^{N_t}$

1. The performance of the two strategies mainly stems from the long legs; 2. The alpha differential between the TSM and TSH strategies is always indifferent from zero.

### 5. TSM and TSH forecast comparison: predictive slope

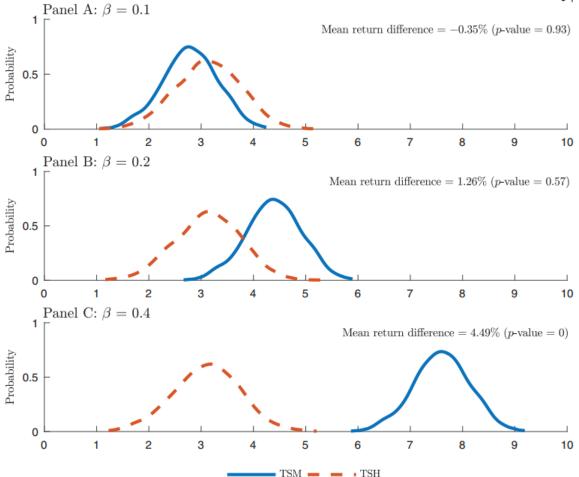
• **Table 11** Time series momentum (TSM) and time series history (TSH) forecast comparison.

	$r_{t+1}^i$ =	$= \alpha + \beta \hat{r}_{t+1}^{TSM,i} + \epsilon$	şi t+1	$\hat{r}_t^{\scriptscriptstyle{ extsf{T}}}$	$\hat{r}_{t+1}^{TSM,i} = d\hat{r}_{t+1}^{TSH,i} + u_t^i$			
Asset class	$\beta$	t-statistic	$R^2$	d	t-statistic	$R^2$		
Panel A: $\hat{r}_{t+1}^{TSM,i}$ is	s estimated	with volatility	scaling					
Overall	0.19	0.61	0.04	1.09***	18.56	40.33		
Commodity	0.15	0.42	0.02	1.24***	11.62	23.53		
Equity	0.07	0.10	0.01	0.84***	14.90	45.06		
Bond	0.23	0.60	0.08	0.99***	68.75	92.27		
Currency	-0.08	-0.12	0.01	1.01***	14.95	4.45		
Panel B: $\hat{r}_{t+1}^{\text{TSM},i}$ is	estimated	without volati	lity scaling	;				
Overall	0.30	0.45	0.03	1.04***	41.89	54.96		
Commodity	0.09	0.11	0.00	1.01***	26.53	37.65		
Equity	-0.37	-0.32	0.07	0.93***	35.34	77.93		
Bond	-0.49	-0.52	0.07	1.00***	72.40	91.38		
Currency	0.03	0.03	0.00	1.64***	19.78	14.32		

The TSM strategy has little predictive power and behaves in a very similar manner to the TSH strategy.

## 5. When does the TSM outperform the TSH?

• **Fig. 5.** Annualized mean return difference between time series momentum (TSM) and time series history (TSH)  $r_{t+1}^i = \alpha^i + \beta \frac{r_{t-12,t}^i}{12} + \varepsilon_{t+1}^i$ ,



When the slope is 0.4, the TSM dominates the TSH in the sense that it does better in almost all the simulated data sets.

#### 6. Conclusion

Firstly, The predictability of the TSM is weak.

 Secondly, The performance of the TSM strategy is likely driven by differences in mean returns, not predictability.