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Revisiting the Time Series Momentum Anomaly

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In this study, we re-examine the time series momentum anomaly to address several issues raised in a previous study. We first find that there is a significant and economically meaningful time series momentum anomaly regardless of the volatility scaling method. We also show that the anomaly exists even after considering the characteristics of diversified futures markets and more factors. Lastly, we show that the time series momentum anomaly is still present until recent years.

Key Words: Asset pricing; Time series momentum; Volatility scaling; Futures pricing; International financial markets.
JEL Classification Numbers: G12, F30, F38, Q02.

1. INTRODUCTION

Since Moskowitz, Ooi, and Pedersen (2012) (hereafter, MOP) first documented time series momentum, related strategies have been developed and implemented successfully, along with cross-sectional momentum strategies. For example, Hurst, Ooi, and Pedersen (2017) extend MOP's findings using a consistent long-term time series momentum that began in 1880. Baltas and Kosowski (2017) suggest an advanced time series momentum strategy that reduces turnover and enhances performance. Furthermore, Hurst, Ooi, and Pedersen (2013) show that the performance of commodity trading advisors and that of managed futures funds are explained primarily by their time series momentum strategies.

An investor can make time series momentum returns when buying (selling) an asset if the past cumulative performance of the asset is positive (negative). MOP use 58 liquid and traded futures contracts as individual assets, and construct a time series momentum strategy with a 12-month look-back period, a one-month holding period, and the volatility-scaling

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method. Their time series momentum strategy delivers monthly alphas of 1.09% to 1.58% when measured by the Fama–French three-factor model with a momentum factor and the factor model in Asness, Moskowitz, and Pedersen (2013).

However, Kim, Tse, and Wald (2016) argue that the time series momentum anomaly is driven by the volatility-scaling method used by MOP, rather than by time series momentum itself. They show that there is no significant difference in the alphas of a time series momentum strategy and a passive long strategy without the volatility-scaling method. In addition, they find that time series momentum only statistically exceeds a passive long strategy with the volatility-scaling method during the 1985-2009 period.

There remain two critical issues in their findings. First, no significant difference in the alphas of two strategies does not guarantee that time series momentum represents the same factor in a passive long strategy such as characteristics of diversified futures markets, which means there is no time series momentum anomaly. In other words, rather than just looking at the difference in the size of the alphas, it needs to be tested whether the time series momentum strategy captures a different dimension of excess returns compared to a passive long strategy. The other issue is in the same spirit — it needs to be tested differently whether the existence of the anomaly depends on the volatility scaling. These issues can be important to investors as they will fail to earn a significant excess return from a time series momentum strategy if the anomaly does not exist in accordance with Kim et al. (2016).

To address these issues, we reassess the time series momentum anomaly to test the effect of the volatility-scaling method in three different ways to previous studies. First, we directly regress the excess returns of the time series momentum strategy on the excess returns of the passive long futures market strategy, rather than comparing the alpha differentials, in order to check whether the passive long strategy can explain the time series momentum alpha. Following Fama and French (2008) and Fama and French (2016), it provides us the direct evidence that the existence of time series momentum anomaly which is not stemmed from futures markets itself. Second, we construct the excess return series of futures contracts to take account of first notice day of futures contracts. It gives us more rigorous and appropriate excess returns of the rolling portfolio that can avoid physical inventory problems of futures contracts. Third, we extend the previous data set (1984–2009) to a more recent period (1984–2017) to examine that the time series momentum strategy also works after MOP published the strategy, we also use various factor models, such as the Fama–French five-factor model (Fama and French (2015)) and the Fama–French global factor models (Fama and French (2012) and Fama and French (2017)), to account for factors not included in the MOP and Kim et al. (2016) specifications.

Our results show a significant and economically meaningful time series momentum anomaly, regardless of the volatility-scaling method employed. Furthermore, the anomaly is not explained by a Fama–French three-factor model with a cross-sectional momentum factor, a Fama–French five-factor model with a cross-sectional momentum factor, the factors in Asness et al. (2013), or the diversified futures markets (proxied by the passive long strategy). In addition, this anomaly remains significant and positive in recent years and is not fully explained by both the Fama-French global three-factor model and five-factor model with a global cross-sectional momentum factor.

Since our findings mitigate the issues raised by Kim et al. (2016), this study encourages future research on the time series momentum. We reconfirm the existence of the time series momentum anomaly, which supports the findings of MOP and the previous studies on the time series momentum. To the best of our knowledge, this is the first study to focus on the time series momentum anomaly using rigorously constructed excess returns on futures contracts and testing various factor models in terms of the volatility-scaling method.

The remainder of the paper proceeds as follows. Section 2 describes the data and time series momentum. Then, Section 3 discusses the empirical analysis frameworks and findings. The final section concludes the paper.

2. DATA

We construct the time series momentum factor using 60 futures contracts, comprising nine equity futures, 13 bond futures, 31 commodity futures, and seven currency futures from January 1984 to August 2017, following MOP and Kim et al. (2016). All data on the futures contracts are obtained from Datastream. For each futures contract and day, we calculate the daily futures excess returns in line with Gorton and Rouwenhorst (2006), Gorton, Hayashi, and Rouwenhorst (2013), and Bakshi, Gao, and Rossi (2017) to take into account the first notice day.[1] To construct a time series momentum factor, the investor should roll over the futures position before first notice day, rather than expiry day. Specifically, the excess return of futures contract i from day t to day $t+1$, $r^i_{t,t+1}$, is given as follows if the initial margin payment is F^i_{t,T_1}:

$$r^i_{t,t+1} = \frac{F^i_{t+1,T_1} - F^i_{t,T_1}}{F^i_{t,T_1}}, \tag{1}$$

[1]See Section 2 of Bakshi et al. (2017) for further details.

where F^i_{t,T_1} is the price of the nearest futures contract i (from among the futures contracts that do not expire during the next month, which before first notice day) at the end of month t, with expiration date T_1. In this way, we can use futures contracts in which the first notice day does not occur to construct the conservative and practical excess returns for the time series momentum strategy and the passive long strategy. We compound the daily excess returns to construct monthly and yearly excess returns to construct a single time series momentum strategy.[2]

For the volatility-scaling method, the ex ante exponentially weighted annualized variance $(\sigma^i_t)^2$ is calculated as follows:

$$(\sigma^i_t)^2 = 261 \sum_{j=0}^{\infty} (1-\delta)\delta^j (r^i_{t-1-j} - \overline{r^i_t})^2, \tag{2}$$

where δ is the centre of the mass of the weights obtained from $\frac{\delta}{1-\delta} = 60$ days, and $\overline{r^i_t}$ is the exponentially weighted average return.

Table 1 shows the summary statistics for the futures contracts. Generally, bond futures have the lowest volatility and currency futures are next. Given the volatility-scaling method, the bond futures and currency futures would have a higher percentage in the volatility scaled strategy than the unscaled one. On the other hand, commodity futures would have the largest percentage in the unscaled strategy in terms of the volatility and the total number of the futures contracts.[3]

Next, we focus on a time series momentum strategy with a 12-month look-back period and a one-month holding period, calculated as follows (hereafter TSMOM):

$$r^{TSMOM}_{t,t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{40\%}{\sigma^i_t} sign(r^i_{t-12,t}) r^i_{t,t+1}, \tag{3}$$

where σ^i_t is the ex ante volatility of futures contract i, and N_t is the total number of available futures contracts at time t. The passive long strategy is calculated by substituting the value one for $sign(r^i_{t-12,t})$ in equation (3). When we construct TSMOM and the passive long strategy ($sign(r^i_{t-12,t}) = 1$) without the volatility-scaling method, we exclude $\frac{40\%}{\sigma^i_t}$ in equation (3). Figure 1 shows the cumulative returns of the unscaled TSMOM and the unscaled passive long strategy. Figure 2 shows the cumulative returns of the volatility-scaled TSMOM and the volatility-scaled

[2]Compounding the daily cumulative excess returns reflects the feature of futures daily settlement. See MOP, Bessembinder (1992), and De Roon, Nijman, and Veld (2000).

[3]The volatility-scaled portfolio is also known as risk parity. See the more details about risk parity in Asness, Frazzini, and Pedersen (2012) and Kazemi (2012).

TABLE 1.

Summary statistics of futures contracts.

	Start date	Mean	Volatility	Volatility (MOP)	Sharpe ratio
AEX	Oct-88	7.38%	18.87%	21.31%	0.39
CAC 40	Nov-98	4.72%	18.12%	23.42%	0.26
DAX	Nov-90	7.36%	20.45%	22.84%	0.36
FTSE MIB	Mar-04	2.98%	20.52%	24.35%	0.15
FTSE 100	May-84	5.30%	15.60%	18.33%	0.34
IBEX 35	Apr-92	7.40%	21.33%	23.96%	0.35
TOPIX	Sep-88	0.72%	19.72%	22.76%	0.04
S&P 500	Jul-82	8.52%	14.88%	19.15%	0.57
ASX SPI 200	May-00	4.32%	13.00%	16.22%	0.33
2-year US Treasury Note	Jun-90	1.51%	1.66%	1.68%	0.91
5-year US Treasury Note	May-88	2.95%	4.09%	4.03%	0.72
10-year US Treasury Note	May-82	4.91%	6.87%	6.74%	0.72
30-year US Treasury Bond	Aug-77	4.30%	11.07%	11.15%	0.39
3-year Australian Bond	May-88	0.60%	1.39%	1.36%	0.43
10-year Australian Bond	Apr-89	0.54%	1.16%	1.24%	0.47
10-year Long Gilt	Nov-82	3.06%	7.52%	7.46%	0.41
10-year CGB	Sep-89	3.73%	6.03%	6.18%	0.62
2-year Euro Schatz	Oct-98	0.93%	1.30%	1.31%	0.71
5-year Euro Bobl	Oct-98	2.54%	3.13%	3.30%	0.81
10-year Euro Bund	Oct-98	3.89%	5.32%	5.55%	0.73
30-year Euro Buxl	Sep-05	6.11%	12.53%	12.33%	0.49
10-year JGB	Dec-86	3.22%	4.98%	4.68%	0.65
Corn	Jan-73	−1.82%	26.46%	23.42%	−0.07
Oats	Aug-73	−0.53%	31.97%	29.22%	−0.02
Rice	Aug-86	−4.11%	27.09%	22.78%	−0.15
Soybean Meal	Jan-78	7.09%	25.46%	23.92%	0.28
Soybean Oil	Jan-74	1.99%	28.43%	24.89%	0.07
Soybean	Jan-79	1.60%	23.35%	22.08%	0.07
Wheat	Jan-78	−4.28%	25.63%	25.33%	−0.17
Feeder Cattle	Jul-78	2.71%	14.66%	14.37%	0.19
Lean Hogs	Nov-73	1.74%	26.02%	24.01%	0.07
Live Cattle	Jan-79	2.95%	14.32%	14.77%	0.21
Aluminium	Jul-93	−0.29%	19.03%	19.98%	−0.02
Copper	Jul-93	10.72%	25.03%	25.06%	0.43
Lead	Jul-93	10.45%	27.79%	29.64%	0.38
Nickel	Jul-93	9.49%	34.10%	34.36%	0.28

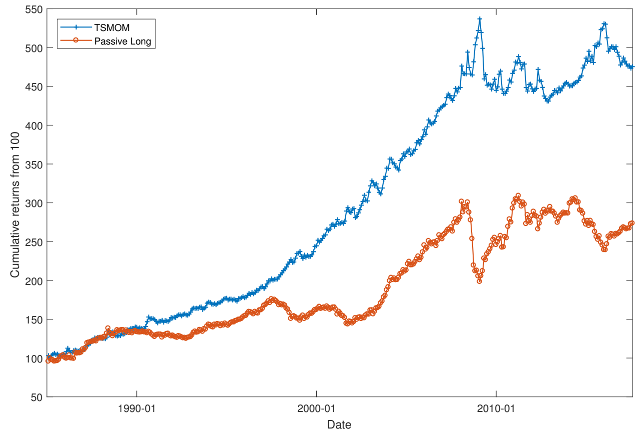
TABLE 1—*Continued*

	Start date	Mean	Volatility	Volatility (MOP)	Sharpe ratio
Tin	Jul-93	8.83%	23.26%	24.90%	0.38
Zinc	Jul-93	3.58%	24.97%	27.17%	0.14
Gold	Oct-78	1.23%	19.20%	19.13%	0.06
Silver	Jan-73	4.51%	32.84%	30.05%	0.14
Platinum	Jan-73	5.72%	27.03%	25.64%	0.21
Palladium	Nov-77	13.31%	35.00%	31.50%	0.38
Cocoa	Aug-73	2.21%	30.53%	29.50%	0.07
Coffee	Nov-77	1.11%	36.87%	34.08%	0.03
Cotton	Oct-77	0.82%	24.25%	22.99%	0.03
Sugar	Aug-73	4.88%	38.11%	35.60%	0.13
Lumber	Jul-78	−6.49%	27.18%	26.15%	−0.24
Light Crude Oil	Mar-83	7.93%	30.79%	31.60%	0.26
Brent Crude Oil	Sep-03	4.32%	29.15%	32.40%	0.15
Heating Oil	Nov-78	7.93%	29.43%	28.30%	0.27
Natural Gas	Apr-90	−3.43%	41.07%	39.23%	−0.08
Gas Oil	Sep-03	7.03%	30.08%	29.40%	0.23
Unleaded Gasoline	Dec-84	14.12%	31.19%	30.20%	0.45
Australian Dollar	Jan-87	3.95%	11.46%	11.88%	0.34
Canadian Dollar	Jan-73	0.31%	6.86%	6.66%	0.05
Swiss Franc	Sep-73	0.77%	12.12%	11.96%	0.06
Euro	Dec-99	1.16%	10.24%	9.95%	0.11
British Pound	Dec-99	0.95%	10.43%	10.27%	0.09
Japanese Yen	Jan-73	0.26%	11.55%	10.80%	0.02
New Zealand Dollar	May-97	3.64%	13.18%	13.31%	0.28

This table shows the annualized mean return and volatility (standard deviation), as well as the volatility calculated from equation (2) and the Sharpe ratio from January 1984 to August 2017.

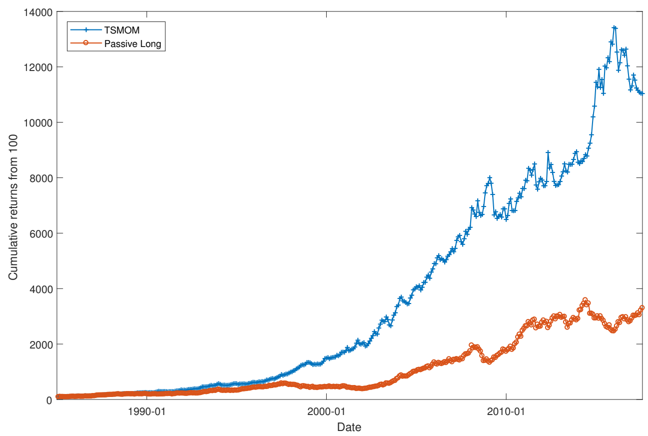
passive long strategy. Regardless of the volatility-scaling method employed, TSMOM outperforms the passive long strategy in terms of the cumulative excess returns.

FIG. 1. Cumulative excess returns of the time series momentum strategy and the passive long strategy.



Plotted are the cumulative excess returns of the unscaled time series momentum with a 12-month look-back period and a one-month holding period and the unscaled passive long strategy from January 1985 to August 2017.

FIG. 2. Cumulative excess returns of the volatility-scaled time series momentum and the passive long strategy.



Plotted are the cumulative excess returns of the volatility-scaled time series momentum with a 12-month look-back period and a one-month holding period and the volatility-scaled passive long strategy from January 1985 to August 2017.

3. EMPIRICAL EVIDENCE

In this section, we examine whether TSMOM generates a significant alpha regardless of the volatility-scaling method and other factors. First, we investigate how the volatility-scaling method impacts the analysis results by comparing the results of the unscaled TSMOM and those of the volatility-scaled TSMOM. Second, we determine whether the passive long strategy explains the TSMOM alpha. This provides direct evidence that the TSMOM anomaly is not driven by the diversified futures markets. Third, we run two robustness tests by adding a recent dataset and using two different factor models.

TABLE 2.

Performance of the time series momentum strategy with a 12-month look-back period and a one-month holding period from January 1985 to December 2009.

Panel A: Fama-French 3-factor and momentum factor

		Intercept	MSCI World	SMB	HML	WML	Passive Long	*Adjusted* R^2
Passive Long	Unscaled	0.14%	0.31	0.04	0.06	−0.01		0.36
	(t-Stat)	(1.41)	(13.29)	(1.28)	(1.86)	(−0.58)		
	Volatility scaled	0.67%	0.52	−0.04	0.08	0.05		0.30
	(t-Stat)	(3.61)	(12.27)	(−0.57)	(1.23)	(1.27)		
TSMOM	Unscaled	0.38%	−0.01	−0.01	−0.01	0.16		0.17
	(t-Stat)	(4.36)	(−0.46)	(−0.37)	(−0.36)	(8.18)		
	Volatility scaled	1.20%	0.03	−0.06	0.02	0.28		0.15
	(t-Stat)	(7.21)	(0.83)	(−1.11)	(0.36)	(7.62)		
	Unscaled	0.36%	−0.05	−0.02	−0.02	0.16	0.12	0.19
	(t-Stat)	(4.18)	(−1.95)	(−0.56)	(−0.62)	(8.33)	(2.72)	
	Volatility scaled	1.08%	−0.07	−0.06	0.01	0.27	0.19	0.18
	(t-Stat)	(6.48)	(−1.47)	(−1.01)	(0.11)	(7.49)	(4.00)	

Table 2 presents the main results of the empirical analysis. To compare TSMOM and the passive long strategy, we regress the excess returns of the passive long strategy and TSMOM on Fama-French three-factor model and a cross-sectional momentum factor in Panel A, Fama-French five-factor model and a cross-sectional momentum factor in Panel B, and Asness et al. (2013) factor model in Panel C. The sample period is the same as that of MOP and Kim et al. (2016) (i.e. January 1985 to December 2009).[4] [5]

[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5]https://www.aqr.com/Insights/Datasets/Value-and-Momentum-Everywhere-Factors-Monthly

TABLE 2—*Continued*

Panel B: Fama-French 5-factor and momentum factor

		Intercept	MSCI World	SMB	HML	CMA	RMW	WML	Passive Long	*Adjusted* R^2
Passive	Unscaled	0.18%	0.29	0.01	0.08	−0.09	0.00	−0.01		0.36
Long	(t-Stat)	(1.73)	(11.96)	(0.33)	(1.69)	(−1.95)	(0.07)	(−0.33)		
	Volatility scaled	0.69%	0.51	−0.07	0.06	−0.10	0.09	0.05		0.31
	(t-Stat)	(3.64)	(11.32)	(−1.04)	(0.64)	(−1.13)	(0.73)	(1.25)		
TSMOM	Unscaled	0.35%	0.00	0.00	−0.05	0.05	0.06	0.15		0.18
	(t-Stat)	(3.92)	(0.08)	(0.08)	(−1.19)	(1.13)	(1.06)	(7.64)		
	Volatility scaled	1.14%	0.05	−0.03	−0.05	0.11	0.09	0.27		0.15
	(t-Stat)	(6.68)	(1.32)	(−0.46)	(−0.59)	(1.40)	(0.84)	(7.10)		
	Unscaled	0.33%	−0.04	0.00	−0.06	0.06	0.06	0.15	0.13	0.20
	(t-Stat)	(3.68)	(−1.46)	(0.03)	(−1.45)	(1.43)	(1.06)	(7.76)	(2.84)	
	Volatility scaled	1.01%	−0.04	−0.01	−0.06	0.13	0.08	0.26	0.19	0.19
	(t-Stat)	(5.93)	(−0.95)	(−0.24)	(−0.74)	(1.67)	(0.70)	(6.97)	(4.07)	

Panel C: Asness, Moskowitz, and Pedersen (2013) factors

		Intercept	MSCI World	VAL	MOM	Passive Long	*Adjusted* R^2
Passive	Unscaled	0.18%	0.30	−0.03	−0.03		0.35
Long	(t-Stat)	(1.64)	(13.37)	(−0.39)	(−0.44)		
	Volatility scaled	0.66%	0.51	0.03	0.14		0.30
	(t-Stat)	(3.31)	(12.24)	(0.23)	(1.22)		
TSMOM	Unscaled	0.18%	0.00	0.19	0.60		0.37
	(t-Stat)	(2.22)	(−0.21)	(3.13)	(12.54)		
	Volatility scaled	0.80%	0.04	0.42	1.15		0.36
	(t-Stat)	(5.18)	(1.25)	(3.72)	(12.64)		
	Unscaled	0.16%	−0.04	0.19	0.60	0.11	0.39
	(t-Stat)	(1.99)	(−1.81)	(3.22)	(12.72)	(2.83)	
	Volatility scaled	0.69%	−0.04	0.42	1.12	0.17	0.39
	(t-Stat)	(4.50)	(−1.16)	(3.75)	(12.63)	(4.10)	

Panel A shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French size (*SMB*), value (*HML*), and cross-sectional momentum (*WML*) factors. Panel B shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French size (*SMB*), value (*HML*), investment (*CMA*), profitability (*RMW*), and cross-sectional momentum (*WML*) factors. Panel C shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the value everywhere factor (*VAL*) and the momentum everywhere factor (*MOM*) in Asness et al. (2013).

From Panels A to C of Table 2, the passive long strategy (*Passive Long*) shows a significant intercept or alpha only in positions that are volatility

TABLE 3.
Performance of the time series momentum strategy with a 12-month look-back period and a one-month holding period from January 1985 to August 2017.

Panel A: Fama-French 3-factor and momentum factor

		Intercept	MSCI World	SMB	HML	WML	Passive Long	*Adjusted* R^2
Passive	Unscaled	0.11%	0.31	0.04	0.07	−0.02		0.36
Long	(t-Stat)	(1.15)	(14.09)	(1.32)	(2.15)	(−0.92)		
	Volatility scaled	0.62%	0.53	−0.04	0.07	0.04		0.30
	(t-Stat)	(3.56)	(12.79)	(−0.62)	(1.19)	(1.06)		
TSMOM	Unscaled	0.35%	−0.01	−0.01	−0.02	0.16		0.19
	(t-Stat)	(4.33)	(−0.63)	(−0.48)	(−0.73)	(8.97)		
	Volatility scaled	1.12%	0.02	−0.07	−0.01	0.30		0.16
	(t-Stat)	(7.13)	(0.65)	(−1.24)	(−0.14)	(8.35)		
	Unscaled	0.34%	−0.04	−0.02	−0.03	0.16	0.08	0.20
	(t-Stat)	(4.23)	(−1.62)	(−0.61)	(−0.94)	(9.08)	(1.91)	
	Volatility scaled	1.03%	−0.06	−0.06	−0.02	0.29	0.15	0.18
	(t-Stat)	(6.51)	(−1.30)	(−1.15)	(−0.35)	(8.26)	(3.42)	

Panel B: Fama-French 5-factor and momentum factor

		Intercept	MSCI World	SMB	HML	CMA	RMW	WML	Passive Long	*Adjusted* R^2
Passive	Unscaled	0.13%	0.30	0.01	0.07	−0.08	0.03	−0.02		0.37
Long	(t-Stat)	(1.40)	(12.95)	(0.38)	(1.58)	(−1.84)	(0.52)	(−0.78)		
	Volatility scaled	0.62%	0.53	−0.06	0.01	−0.06	0.16	0.04		0.30
	(t-Stat)	(3.49)	(12.14)	(−0.94)	(0.12)	(−0.74)	(1.35)	(0.91)		
TSMOM	Unscaled	0.32%	0.00	0.00	−0.06	0.04	0.07	0.16		0.20
	(t-Stat)	(3.92)	(−0.05)	(0.00)	(−1.58)	(1.16)	(1.25)	(8.46)		
	Volatility scaled	1.06%	0.05	−0.03	−0.10	0.12	0.13	0.28		0.17
	(t-Stat)	(6.60)	(1.25)	(−0.51)	(−1.25)	(1.58)	(1.24)	(7.81)		
	Unscaled	0.31%	−0.03	0.00	−0.07	0.05	0.07	0.16	0.09	0.20
	(t-Stat)	(3.79)	(−1.13)	(−0.04)	(−1.74)	(1.34)	(1.20)	(8.56)	(1.99)	
	Volatility scaled	0.96%	−0.03	−0.02	−0.10	0.13	0.11	0.28	0.15	0.19
	(t-Stat)	(6.00)	(−0.70)	(−0.35)	(−1.28)	(1.73)	(1.02)	(7.75)	(3.42)	

scaled; the alpha ranges between 0.66% and 0.69% per month with respect to the factor models. The passive long strategy loads significantly positively on the excess returns of the MSCI World index (*MSCI World*). Specifically, the first rows in Panels A to C of Table 2 report that *MSCI World* largely explains the excess returns of the passive long strategy when the positions are not scaled.

TABLE 3—*Continued*

Panel C: Asness, Moskowitz, and Pedersen (2013) factors

		Intercept	MSCI World	VAL	MOM	Passive Long	*Adjusted* R^2
Passive Long	Unscaled	0.10%	0.31	0.05	0.00		0.35
	(t-Stat)	(1.05)	(14.33)	(0.61)	(−0.04)		
	Volatility scaled	0.55%	0.52	0.16	0.20		0.30
	(t-Stat)	(2.99)	(12.99)	(1.13)	(1.74)		
TSMOM	Unscaled	0.19%	−0.01	0.14	0.59		0.38
	(t-Stat)	(2.49)	(−0.40)	(2.54)	(13.02)		
	Volatility scaled	0.78%	0.03	0.34	1.15		0.36
	(t-Stat)	(5.39)	(1.06)	(3.11)	(13.07)		
	Unscaled	0.18%	−0.03	0.14	0.59	0.06	0.38
	(t-Stat)	(2.40)	(−1.31)	(2.49)	(13.05)	(1.69)	
	Volatility scaled	0.72%	−0.03	0.32	1.13	0.13	0.38
	(t-Stat)	(4.92)	(−0.85)	(2.96)	(12.89)	(3.22)	

Panel A shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French size (*SMB*), value (*HML*), and cross-sectional momentum (*WML*) factors. Panel B shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French size (*SMB*), value (*HML*), investment (*CMA*), profitability (*RMW*), and cross-sectional momentum (*WML*) factors. Panel C shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the value everywhere factor (*VAL*) and the momentum everywhere factor (*MOM*) in Asness et al. (2013).

TSMOM produces a significant alpha, regardless of whether or not the positions are volatility scaled. The third and fourth rows in Panels A to C of Table 2 report the alpha values with respect to the factor models. In this case, the unscaled TSMOM (third row) produces alphas of 0.18% to 0.38% per month, with *t-stats* of 2.22 to 4.36, respectively. The volatility-scaled TSMOM (fourth row) produces alphas of 0.80% to 1.20% per month, with *t-stats* of 5.18 to 7.21, respectively. In line with the findings of previous studies, the cross-sectional momentum factor in individual equities (*WML*) and the cross-sectional momentum factor in all asset classes (*MOM*) partly explain both the unscaled and the volatility-scaled time series momentum. To sum up, the existence of TSMOM anomaly has little to do with changes in the proportion of assets by the volatility-scaling method.

More importantly, the fifth and sixth rows in Panels A to C of Table 2 report that TSMOM produces a significant alpha, regardless of whether or not the positions are scaled, even if the passive long strategy partly explains the anomaly. For example, the unscaled TSMOM produces alphas of 0.16% to 0.36% per month, with *t-stats* of 1.99 to 4.18, respectively, with respect to the factor models. Similarly, the volatility-scaled TSMOM produces alphas of 0.69% to 1.08% per month, with *t-stats* of 4.50 to 6.48, respectively. Even the volatility scaled passive long strategy delivers significant abnormal returns with respect to the factor models, TSMOM anomaly is not associated with the passive long strategy.

Overall, Table 2 shows a significant and positive TSMOM anomaly, regardless of the concerns claimed by Kim et al. (2016). Nevertheless, in line with the findings of Kim et al. (2016), the scaling method may affect the magnitude of the TSMOM anomaly. Note that the volatility-scaled positions are leveraged. In practice, investors enter into futures contracts with a margin rate of 5% to 20% of the total contract value. Thus, in reality, the unscaled TSMOM anomaly would not be smaller than the volatility-scaled anomaly.

We check our findings in Table 2 using two robustness tests. First, we rerun regressions in Table 2 by adding the recent data from January 2010 to August 2017. Table 3 reports the results. To sum up, TSMOM still produces significant and positive alphas, regardless of the scaled positions, the passive long strategy, or factor model tests.

TABLE 4.

Performance of the time series momentum strategy with a 12-month look-back period and a one-month holding period in terms of Fama–French global factors from January 1990 to December 2009.

Data period is from January 1990 to December 2009								
Panel A: Fama-French global 3-factor and global momentum factor								
		Intercept	MSCI World	SMB	HML	WML	Passive Long	*Adjusted* R^2
Passive Long	Unscaled	0.04%	0.39	0.15	0.08	0.02		0.52
	(t-Stat)	(0.42)	(16.51)	(3.13)	(1.88)	(0.75)		
	Volatility scaled	0.63%	0.56	0.14	0.15	0.11		0.36
	(t-Stat)	(3.15)	(12.30)	(1.51)	(1.83)	(2.13)		
TSMOM	Unscaled	0.24%	0.01	−0.03	0.08	0.23		0.27
	(t-Stat)	(2.58)	(0.24)	(−0.73)	(1.96)	(9.73)		
	Volatility scaled	0.95%	0.05	−0.15	0.18	0.42		0.23
	(t-Stat)	(5.09)	(1.11)	(−1.68)	(2.27)	(8.98)		
	Unscaled	0.23%	−0.06	−0.06	0.06	0.22	0.16	0.29
	(t-Stat)	(2.54)	(−1.94)	(−1.29)	(1.64)	(9.72)	(2.99)	
	Volatility scaled	0.76%	−0.13	−0.20	0.13	0.39	0.31	0.32
	(t-Stat)	(4.20)	(−2.53)	(−2.30)	(1.75)	(8.68)	(5.81)	

TABLE 4—*Continued*

Panel B: Fama-French global 5-factor and global momentum factor

		Intercept	MSCI World	SMB	HML	CMA	RMW	WML	Passive Long	*Adjusted* R^2
Passive	Unscaled	0.01%	0.38	0.17	0.17	0.13	−0.17	0.02		0.53
Long	(t-Stat)	(0.10)	(13.47)	(3.23)	(2.48)	(1.58)	(−2.15)	(0.68)		
	Volatility scaled	0.56%	0.59	0.18	0.11	0.17	0.04	0.10		0.36
	(t-Stat)	(2.68)	(10.47)	(1.78)	(0.81)	(1.09)	(0.25)	(1.88)		
TSMOM	Unscaled	0.20%	0.03	−0.01	0.01	0.10	0.09	0.22		0.28
	(t-Stat)	(2.01)	(1.14)	(−0.15)	(0.17)	(1.32)	(1.22)	(9.20)		
	Volatility scaled	0.82%	0.12	−0.07	0.01	0.32	0.22	0.40		0.25
	(t-Stat)	(4.19)	(2.27)	(−0.76)	(0.07)	(2.15)	(1.46)	(8.36)		
	Unscaled	0.19%	−0.04	−0.04	−0.02	0.08	0.12	0.22	0.17	0.30
	(t-Stat)	(2.02)	(−1.05)	(−0.74)	(−0.28)	(1.04)	(1.63)	(9.21)	(3.07)	
	Volatility scaled	0.65%	−0.06	−0.13	−0.02	0.27	0.20	0.37	0.31	0.33
	(t-Stat)	(3.45)	(−1.04)	(−1.41)	(−0.21)	(1.89)	(1.46)	(8.13)	(5.70)	

Panels A shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French global three-factor model with a global cross-sectional momentum factor. Panels B shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French global five-factor model with a global cross-sectional momentum factor. Panels A and B use the data from January 1990 to December 2009.

Second, we use the Fama–French global three-factor and global five-factor models with a global cross-sectional momentum factor as tests, instead of the previous models. Note that when we use the factor model in Asness et al. (2013) as a test model, Table 2 shows smaller TSMOM alphas than those of the Fama–French models. This is because the Fama–French factor models are derived from U.S. stock markets, whereas the factor model in Asness et al. (2013) is constructed using world financial markets across four asset classes: equity, bond, currency, and commodity markets. Because TSMOM is also constructed from the diversified futures markets such as the equity, bond, currency, and commodity markets, the factor model in Asness et al. (2013) better explains TSMOM than the Fama–French models do. Therefore, we use the Fama–French global three-factor and five-factor models with a global cross-sectional momentum factor to obtain more rigorous results than those derived from the ordinary Fama–French models. The test results show that TSMOM consistently generates a significant and positive alpha, regardless of the scaled positions, the passive long strategy, or data periods as well (see Table 4 and Table 5).

TABLE 5.

Performance of the time series momentum strategy with a 12-month look-back period and a one-month holding period in terms of Fama–French global factors from January 1990 to August 2017.

		Intercept	MSCI World	SMB	HML	WML	Passive Long	*Adjusted* R^2
Data period is from January 1990 to August 2017								
Panel C: Fama-French global 3-factor and global momentum factor								
Passive	Unscaled	−0.02%	0.39	0.15	0.11	0.02		0.51
Long	(t-Stat)	(−0.23)	(17.64)	(3.32)	(2.70)	(0.87)		
	Volatility scaled	0.53%	0.58	0.15	0.18	0.11		0.35
	(t-Stat)	(2.86)	(13.01)	(1.61)	(2.15)	(2.31)		
TSMOM	Unscaled	0.23%	0.00	−0.05	0.05	0.23		0.27
	(t-Stat)	(2.72)	(−0.18)	(−1.27)	(1.23)	(10.21)		
	Volatility scaled	0.92%	0.03	−0.21	0.10	0.44		0.23
	(t-Stat)	(5.24)	(0.62)	(−2.34)	(1.31)	(9.38)		
	Unscaled	0.23%	−0.04	−0.07	0.04	0.23	0.09	0.28
	(t-Stat)	(2.75)	(−1.33)	(−1.57)	(0.97)	(10.15)	(1.71)	
	Volatility scaled	0.79%	−0.12	−0.24	0.06	0.41	0.25	0.28
	(t-Stat)	(4.59)	(−2.33)	(−2.84)	(0.76)	(9.01)	(4.82)	

4. CONCLUSION

In this study, we reassess the time series momentum anomaly using a rigorously constructed return series that considers the physical inventory problems of futures contracts. We review Kim et al. (2016) which argue that the anomaly may result from the volatility-scaled positions or the lack of factor model tests (e.g. the Fama–French five-factor model). We find a significant and economically meaningful time series momentum anomaly, regardless of the volatility-scaling method employed or considering more factors. Specifically, we show that the anomaly is not explained by the Fama-French three-factor, five-factor, or global factor models, the factor model in Asness et al. (2013), or by considering the diversified futures markets as an additional factor (proxied by the passive long strategy). Moreover, the anomaly is still significant and economically meaningful in recent years. Thus, we conclude that time series momentum generates a significant and positive alpha, and that this is not derived from the leverage positions, the diversified futures markets, or the limited set of factors in the previous literature.

TABLE 5—*Continued*

Panel D: Fama-French global 5-factor and global momentum factor

		Intercept	MSCI World	SMB	HML	CMA	RMW	WML	Passive Long	*Adjusted* R^2
Passive Long	Unscaled	−0.05%	0.39	0.17	0.19	0.11	−0.16	0.02		0.53
	(t-Stat)	(−0.51)	(14.60)	(3.38)	(3.11)	(1.56)	(−2.09)	(0.83)		
	Volatility scaled	0.41%	0.63	0.22	0.07	0.27	0.13	0.09		0.36
	(t-Stat)	(2.14)	(11.82)	(2.21)	(0.58)	(1.88)	(0.88)	(1.88)		
TSMOM	Unscaled	0.17%	0.03	−0.02	−0.03	0.12	0.11	0.22		0.28
	(t-Stat)	(1.96)	(1.12)	(−0.41)	(−0.54)	(1.84)	(1.59)	(9.59)		
	Volatility scaled	0.74%	0.12	−0.09	−0.12	0.42	0.31	0.40		0.26
	(t-Stat)	(4.05)	(2.47)	(−0.97)	(−1.07)	(3.04)	(2.21)	(8.62)		
	Unscaled	0.18%	−0.01	−0.03	−0.05	0.11	0.12	0.22	0.09	0.29
	(t-Stat)	(2.02)	(−0.25)	(−0.73)	(−0.83)	(1.69)	(1.79)	(9.53)	(1.76)	
	Volatility scaled	0.64%	−0.02	−0.14	−0.14	0.35	0.28	0.38	0.23	0.30
	(t-Stat)	(3.60)	(−0.39)	(−1.55)	(−1.25)	(2.64)	(2.05)	(8.36)	(4.52)	

Panels A shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French global three-factor model with a global cross-sectional momentum factor. Panels B shows the time series regression analysis results of the monthly excess returns of the passive long strategy and the time series momentum strategy on the excess returns of the MSCI World Index (*MSCI World*) and the Fama–French global five-factor model with a global cross-sectional momentum factor. Panels A and B use the data from January 1990 to August 2017.

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REFERENCES

Asness, Clifford S., Andrea Frazzini, and Lasse H. Pedersen, 2012. Leverage aversion and risk parity. *Financial Analysts Journal* **68**, 47–59.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013. Value and momentum everywhere. *The Journal of Finance* **68**, 929–985.

Bakshi, Gurdip, Xiaohui Gao, and Alberto G. Rossi, 2017. Understanding the Sources of Risk Underlying the Cross Section of Commodity Returns. *Management Science.*

Baltas, Nick and Robert Kosowski, 2017. Demystifying time-series momentum strategies: volatility estimators, trading rules and pairwise correlations.

Bessembinder, Hendrik, 1992. Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies* **5**, 637–667.

De Roon, Frans A., Theo E. Nijman, and Chris Veld, 2000. Hedging pressure effects in futures markets. *Journal of Finance* 1437–1456.

Fama, Eugene F. and Kenneth R. French, 2008. Dissecting anomalies. *The Journal of Finance* **63**, 1653–1678.

Fama, Eugene F. and Kenneth R. French, 2012. Size, value, and momentum in international stock returns. *Journal of financial economics* **105**, 457–472.

Fama, Eugene F., and Kenneth R. French, 2015. A five-factor asset pricing model. *Journal of Financial Economics* **116**, 1–22.

Fama, Eugene F. and Kenneth R. French, 2016. Dissecting anomalies with a five-factor model. *The Review of Financial Studies* **29**, 69–103.

Fama, Eugene F. and Kenneth R. French, 2017. International tests of a five-factor asset pricing model. *Journal of financial Economics* **123**, 441–463.

Gorton, Gary, and K. Geert Rouwenhorst, 2006. Facts and fantasies about commodity futures. *Financial Analysts Journal* **62**, 47–68.

Gorton, Gary B., Fumio Hayashi, and K. Geert Rouwenhorst, 2013. The fundamentals of commodity futures returns *Review of Finance* **17**, 35–105.

Goyal, Amit and Narasimhan Jegadeesh, 2017. Cross-Sectional and Time-Series Tests of Return Predictability: What Is the Difference? *The Review of Financial Studies* hhx131.

Hurst, Brian, Yao Hu Ooi, and Lasse Heje Pedersen, 2013. Demystifying Managed Futures. *Journal Of Investment Management* **11**, 42–58.

Hurst, Brian, Yao Hu Ooi, and Lasse Heje Pedersen, 2017. A century of evidence on trend-following investing.

Kazemi, Hossein, 2012. An Introduction to Risk Parity. *Alternative Investment Analyst Review* **1**.

Kim, Abby Y., Yiuman Tse, and John K Wald, 2016. Time series momentum and volatility scaling. *Journal of Financial Markets* **30**, 103–124.

Moskowitz, Tobias J., Yao Hua Ooi, and Lasse Heje Pedersen, 2012. Time series momentum. *Journal of Financial Economics* **104**, 228–250.