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Time series momentum and volatility scaling ☆

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A B S T R A C T

Moskowitz, Ooi, and Pedersen (2012) show that time series momentum delivers a large and significant alpha for a diversified portfolio of international futures contracts. We find that their results are largely driven by volatility-scaling returns (or the so-called risk parity approach to asset allocation) rather than by time series momentum. Without scaling by volatility, time series momentum and a buy-and-hold strategy offer similar cumulative returns, and their alphas are not significantly different. This similarity holds for most sectors and for a combined portfolio of futures contracts. Cross-sectional momentum also offers a higher (similar) alpha than unscaled (scaled) time series momentum.

1. Introduction

Moskowitz, Ooi, and Pedersen (2012, MOP henceforth) examine time series momentum (TSMOM) in the futures markets, where the TSMOM strategy is determined only by a security's own past returns. Specifically, the TSMOM strategy involves going long a particular security if it has positive returns in some prior period, and short the security if it has negative returns. MOP find that time

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series momentum returns are positive for every one of the 58 contracts they examine. They find that the alpha of a well-diversified futures portfolio with a TSMOM strategy yields an impressive excess return of more than 1% per month over the 1985–2009 period. These significant alphas are consistent with under-reaction stories, and MOP write, "Time series momentum represents one of the most direct tests of the random walk hypothesis and a number of prominent behavioral and rational asset pricing theories." Moreover, whereas prior findings on momentum returns in the stock markets indicate that momentum profits largely appear in the least liquid stocks (e.g., Keim, 2003; Korajczyk and Sadka, 2004; Lesmond, Schill, and Zhou, 2004), MOP find strong momentum returns in the relatively liquid futures market, and they find no correlation between their abnormal returns and measures of liquidity or sentiment.

We revisit the findings of MOP using 55 futures contracts over the 1985–2013 period. One special procedure used by MOP is that they scale the returns of the different futures contracts by a simple lagged estimate of volatility. In particular, an asset with a lower volatility will take a greater position size and have a higher weight in the portfolio. MOP use this procedure so that their returns are not dominated by a particular high-volatility sector. Using the same period as MOP, 1985–2009, and also volatility-scaling returns, we find similar results: a portfolio of 55 futures contracts based on the prior 12-month momentum provides an alpha of 1.08% per month.[1]

Using TSMOM, the alphas of the individual contracts are on average 1.08%, the same as the portfolio alpha. However, if we use unscaled, equal-weighted returns, the portfolio alpha and the average individual alpha drop to 0.39% and 0.40%, respectively. Without scaling, the portfolio alpha is similar in magnitude to (and statistically no different from) the alpha of the buy-and-hold position on the futures portfolio. In addition, similarly scaling a set of buy-and-hold positions also produces a higher alpha, 0.73% per month.

More specifically, MOP scale the volatility of each individual futures contract to correspond to the volatility of an average stock, therefore effectively leveraging the positions. The volatility scale used by MOP is similar to the so-called risk parity approach to asset allocation. A risk parity portfolio is an equally weighted portfolio, where the weights refer to risk (as proxied by MOP with ex ante volatility) rather than dollar amount invested in each asset (Kazemi, 2012). When we scale the futures contracts to a lower (higher) volatility, we obtain smaller (larger) alphas, and scaling the buy-and-hold strategy produces similar results.[2] Thus the magnitude of the TSMOM strategy appears to be largely due to leveraging a strategy that happened to have a positive alpha.

In order to verify that the difference between our results and those of MOP are not due to differences in volatility across sectors, we repeat this analysis for each of the four sectors for which we have futures contracts: commodities, bonds, equities, and currencies. We find that a volatility-scaled TSMOM strategy for the 1985–2009 period generates significant positive alphas for commodities, equities, and currencies; however, the volatility-scaled buy-and-hold strategy also generates significant positive alphas for these three sectors. The difference between a volatility-scaled TSMOM and a volatility-scaled buy-and-hold strategy is significantly different (at the 10% level) from zero only for the currency sector.

We then repeat this analysis considering instead the differences between the unscaled TSMOM and unscaled buy-and-hold strategies. The alphas from the TSMOM strategy are much smaller without volatility scaling for all sectors. Moreover, the unscaled TSMOM strategy does not significantly outperform the unscaled buy-and-hold strategy. Thus, the alphas from both the unscaled TSMOM and buy-and-hold strategies are often significantly greater than zero, suggesting that these futures contracts have generally positive alphas over this period regardless of trading strategy.

MOP also show that time series momentum profits are larger than those from the cross-sectional momentum (XSMOM) strategy of Jegadeesh and Titman (1993). In contrast, examining the foreign

[1] These alpha estimates are based on a seven-factor model that includes the MSCI World Index, the Fama-French and Carhart factors (SMB, HML, and UMD), a global commodity index, a bond index, and a currency index. Our conclusions are stronger if we use the four-factor model (MSCI World Index, SMB, HML, and UMD) reported by MOP.

[2] We refer to the strategy where we go long all of the futures contracts, but buy an amount that scales the expected volatility to the target as a volatility-scaled buy-and-hold position, as this captures the scaling procedure without the time series momentum aspect. However, this strategy is not a pure buy-and-hold as there is rebalancing over time.

exchange market only, Menkhoff, Sarno, Schmeling, and Schrimpf (2012) find that the TSMOM strategy is less profitable than the XSMOM strategy. We note that when implementing the TSMOM strategy, Menkhoff et al. do not volatility-scale their results. In our study, we show that the alpha of XSMOM, 0.92%, lies between the alphas obtained from the non-volatility-scaled (equal-weighted) TSMOM strategy and the volatility-scaled TSMOM strategy. Therefore, the different weighting schemes may explain the conflicting conclusions between MOP and Menkhoff et al.

We also examine the results for several sub-periods: 1985–2000 and 2001–2013, and following the recent financial crisis, 2009–2013. The choice of separating the sample at 2001 is based on a potential structural break in commodity futures markets around the passage of the Commodity Futures Modernization Act (CFMA) in December 2000.[3] We show that the superior performance of the TSMOM strategy is larger in the pre-2001 period. In more recent periods, i.e., from 2009 to 2013, we find that the performance of the TSMOM strategy is worse than that of a buy-and-hold strategy. Baltas and Kosowski (2013, 2015) also report the underperformance of the TSMOM strategy over this post-crisis period when correlations across asset classes substantially increased.

Overall, MOP's results are a major challenge to market efficiency, but we show that their results are significantly influenced by how they scale their position size, and that their results do not persist during more recent time periods. The results we present are consistent with markets that are largely efficient, and more so in recent periods.

We organize the paper as follows. In Section 2, we review prior work on momentum and discuss the volatility scaling used by MOP. We also lay out how risk parity in asset allocation is related to volatility scaling. We describe the data in Section 3 and present the results in Section 4. Concluding remarks are in Section 5.

2. Literature review

2.1. Cross-sectional momentum and time series momentum

Jegadeesh (1990) finds significant time series effects in U.S. stock markets, while Jegadeesh and Titman (1993) show that a strategy that buys winners and sells losers yields a significant monthly return over the following few months. Jegadeesh and Titman (2001, 2002) further document that this momentum effect is more consistent with the behavioral models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) than with the expected return and risk-based model of Conrad and Kaul (1998).

Lesmond, Schill, and Zhou (2004) report that the stocks that generate large momentum profits are also the stocks with high trading costs, and that these costs are sufficient to wipe out the momentum profits. Similarly, Korajczyk and Sadka (2004) show that losers are typically small firms with low liquidity and short sale restrictions. They also find that accounting for the price impact of trading leads to a large decline in the apparent profitability of some previously studied momentum-based strategies.

Chordia, Roll, and Subrahmanyam (2011) find that more recently the U.S. equity markets have been characterized by increased trading activity, lower bid-ask spreads, and lower return serial correlation. Their results are consistent with increased market efficiency due to increased arbitrage activity. The authors suggest that this has reduced the cross-sectional predictability of equity returns. Specifically, they find that the cross-sectional momentum effect is significant in the 1993–2000 period, but insignificant during the more recent 2001–2008 period.

In contrast to prior work, which has focused on cross-sectional momentum, MOP show that momentum profits can be derived purely from an asset's own past returns. MOP term this strategy time series momentum (TSMOM), distinguishing it from the cross-sectional momentum (XSMOM) examined in the above-mentioned papers. This TSMOM strategy is related to other popular

[3] The passage of CFMA made it less costly to trade commodity futures, leading to a substantial increase in institutional investors.

trend-following technical analyses, such as moving average and breakout strategies. However, the TSMOM strategy is particularly simple to implement as it involves buying assets with positive past returns and selling assets with negative past returns regardless of relative performance.

MOP mitigate the problems of illiquidity, transaction costs, and short-sale constraints by applying the TSMOM strategy to 58 liquid futures contracts. MOP find that the prior 12-month time series momentum profits are positive for every contract during the 1985–2009 period. A portfolio of all the future contracts they consider offers a large and significant alpha of 1.58% per month with respect to the MSCI World Index and the standard Fama-French (1993) and Carhart (1997) factors, and an alpha of 1.09% when calculated with the MSCI World Index and the Asness, Moskowitz, and Pedersen (2013) long-short value and cross-sectional momentum factors across asset classes.

MOP also apply an XSMOM strategy based on the relative ranking of each asset's past 12-month returns and take long or short positions in proportion to their ranks relative to the median. They report that the TSMOM strategy yields an additional alpha of 0.76% per month not captured by the XSMOM strategy. They write, “Since the cross-sectional correlation of lead-lag effects among assets contributes negatively to XSMOM, it is not surprising that TSMOM, which does not depend on the cross-serial correlations across, produces higher profits than XSMOM” (p. 244).

Menkhoff, Sarno, Schmeling, and Schrimpf (2012) provide an empirical investigation of momentum strategies in foreign exchange (FX) markets. They argue that the liquid FX markets are better than stock markets to examine momentum returns because of higher volume and lower transaction costs. Their sample consists of 48 currencies trading against the U.S. dollar from January 1976 through January 2010. The authors form six portfolios based on lagged returns over the previous one, three, six, nine, and 12 months, and these portfolios are then held for one, three, six, nine, and 12 months. The one-sixth of all available currencies in a given month that have the highest lagged returns make up the winner portfolio, while the lowest one-sixth make up the loser portfolio. Following the equity market literature, they obtain XSMOM profits by buying the winner and shorting the loser.

Menkhoff, Sarno, Schmeling, and Schrimpf (2012) find a significant XSMOM of 10% per annum not explained by traditional risk factors. Although they focus on the XSMOM strategy, they also examine the TSMOM strategy using an equally-weighted portfolio of all currencies. They show that the TSMOM strategy is profitable on average but less profitable than the XSMOM strategy as the latter strategy has a much higher (almost double) average excess return and Sharpe ratio (p. 669).

Although it is difficult to compare the results of MOP with those of Menkhoff, Sarno, Schmeling, and Schrimpf (2012) due to the different time periods and securities, we note these two papers use different weighting schemes. Menkhoff et al. use the standard equal weights to form their portfolios, and most previous papers also use these standard equal weights in portfolio construction. For example, Burnside, Eichenbaum, and Rebelo (2011) use an equally-weighted portfolio of currencies with the total value of the bet normalized to one USD to calculate TSMOM and carry trade profits. In contrast, MOP scale the size of each long or short position of each asset so that it has an ex ante annualized volatility of 40%.

In a concurrent paper, Goyal and Jegadeesh (2015, GJ henceforth) analyze what accounts for the difference in performance between the XSMOM strategy and the TSMOM strategy. GJ analyze both individual U.S. equity positions as well as international stock, bond, commodity, and currency indices. They find that the superior performance of the TSMOM strategy is due to the fact that it is typically net long the underlying assets. They further note that using volatility scaling increases the returns of the TSMOM strategy because it further increases the risk premium and market timing components of TSMOM returns. In contrast to GJ, our analysis focuses on the portion of TSMOM returns due to volatility scaling. We show that for individual contracts, for sectors, or for a diversified portfolio of futures, the TSMOM strategy only significantly outperforms a buy-and-hold strategy when the TSMOM strategy is volatility scaled and the buy-and-hold strategy is not. Thus these results complement GJ's component analysis of what explains the superior returns of the TSMOM strategy.

2.2. Volatility scaling

An important part of MOP's analysis is the way that they scale the returns of each asset by its volatility so that each asset contributes similarly to overall portfolio returns. MOP scale each asset so that the annual volatility matches the average risk of an individual U.S. stock, that is, to a 40% annual volatility. In essence, since the typical futures contract volatility is less than 40%, this corresponds to leveraging most futures contract positions. Thus each security's return is scaled to 40%/σ_{t-1}, where σ_{t-1} is the estimate of the ex ante volatility of each contract given by exponentially weighted lagged squared daily returns as in Eq. (1) of MOP:

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

where r_t is the monthly futures returns and $\bar{r}$ is the exponentially weighted average return. The parameter δ is chosen so that the center of mass of the weights is 60 days.

Therefore, the TSMOM monthly return for each contract s at time t is

$$r_{t,t+1}^{TSMOM,s} = sign(r_{t-12,t}^s) \frac{40\%}{\sigma_t^s} r_{t,t+1}^s, \tag{2}$$

where r_t^s and σ_t^s are the monthly return and ex ante volatility of contract s, respectively.[4] The overall return of the strategy that diversifies across all the assets that are available at time t is

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} \sum_{s=1}^{S_t} sign(r_{t-12,t}^s) \frac{40\%}{\sigma_t^s} r_{t,t+1}^s \tag{3}$$

where S_t is the total number of assets available at month t. Eqs. (2) and (3) show that the size of long or short positions is inversely proportional to the ex ante volatility; accordingly, the position size increases (a more leveraged position) if the volatility is smaller, and the position size is smaller if the volatility is larger.

This volatility scaling is a form of risk parity approach to asset allocation [see Kazemi (2012) for an excellent summary of risk parity].[5] Under the risk parity approach, the more volatile asset classes, like equities, have lower weights in the portfolio than do less volatile assets, like sovereign debt and corporate bonds, until the expected volatility from the position in any asset class is equal. Asness, Frazzini, and Pedersen (2012) argue that risk parity can provide a superior return over typical diversification strategies if investors are averse to leverage. They suggest that as the risk parity portfolio is close to the efficient frontier, investors can leverage the risk parity portfolio to provide superior returns over a more typical unlevered portfolio. While the leveraged risk parity portfolio may outperform other return-volatility combinations along the efficient frontier, it is not expected to outperform a leveraged diversified market (tangency) portfolio.

Empirically, Inker (2010) shows that a position in 10-year Treasury bonds leveraged to the same volatility as the S&P 500 would generate returns over 15% per year from 1982 to 2008, whereas the S&P 500 had returns of 10% per year over the same time period. Asness, Frazzini, and Pedersen (2012) show that the risk parity portfolio would have outperformed either the value-weighted market portfolio or a portfolio with 60% stocks and 40% bonds from 1926 to 2010. However, Inker (2010) discusses several potential problems with realizing additional returns from risk parity portfolios, such as additional risks from leverage, poor estimates of future volatility, negative skewness in certain asset classes, and leveraging positions without significant risk premiums.

The volatility-scaled weights used in MOP follow the logic of risk parity, although they do not explicitly use this term in their paper. They simply weight each position (long or short) to have the same ex ante volatility of 40% in their study. To assess the effect of volatility scaling on the TSMOM profits reported in MOP, we compare the performance of volatility scaled and unscaled TSMOM for individual futures contracts, futures contracts grouped into four sectors, or the entire portfolio of futures contracts in our dataset against the performance of similarly scaled and unscaled buy-and-hold positions. We also compare how different ex ante volatility targets affect the estimated TSMOM and buy-and-hold alphas.

[4] Baltas and Kosowski (2015) consider the effect of using different volatility estimators for TSMOM profits.

[5] With multiple assets, a risk parity approach can also correct for cross-correlation. See Chapter 6 of Roncalli (2014).

Wigglesworth (2015) argues that "risk parity depends on leveraging bond investments, low volatility and modest correlations between different markets over time". To ensure that neither bonds futures nor any other single sector drives our findings, we conduct similar analyses for each individual sector, as well as for the overall portfolio excluding one sector at a time.

2.3. Scaling cross-sectional momentum

Barroso and Santa-Clara (2015) show that a risk-managed XSMOM strategy can substantially increase momentum profits in the equity markets. Barroso and Santa-Clara scale the winners-minus-losers portfolio in order to have constant volatility according to the prior six month realized volatility. Thus, Barroso and Santa-Clara scale the total position, rather than the investment in each individual security in the portfolio. Following Eq. (5) in Barroso and Santa-Clara, we also consider a risk-managed strategy where we calculate monthly realized variance as:

$$\hat{\sigma}^2_{BSC,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}/126, \tag{4}$$

where $r^2_{WML,d_{t-1}-j}$ is the daily return momentum of the winners-minus-losers portfolio during the previous six months for all futures contracts in our sample. Then we scale the monthly momentum returns with (target volatility$/\hat{\sigma}^2_{BSC,t}$). We follow Barroso and Santa-Clara and use an annual 12% target volatility.

3. Data

We obtain daily settlement prices for 55 futures markets for January 1984 (or the start of contract trading) to December 2013 from Commodity Systems, Inc. These 55 futures contracts are actively traded and provide a good representation of four different types of futures contracts: commodities, bonds, stocks, and currencies. Table 1 reports the asset classes, contract symbols, and futures exchanges for these 55 contracts.

The futures contracts in our paper are comparable to the data used by MOP except for some minor differences. MOP use 58 contracts including seven cross-rate currency futures contracts. We also use futures contracts but we do not use cross-rate currency contracts. MOP do not include dollar currency contracts for the Swiss franc, New Zealand dollar, Norwegian krone, or Swedish krona, whereas we do, resulting in a total of 55 futures contracts.

Following Bessembinder (1992), we compute the daily returns as percentage changes using the nearest contracts (until the first trading day of the maturity month), and then roll over to the second-nearest contracts within the delivery month. Monthly returns are calculated by compounding the daily returns. We follow MOP in focusing on a TSMOM strategy with a 12-month lookback period and a one-month holding period, although our tests suggest similar results with other lookback and holding periods. That is, the 12-month returns for 1984 are used to estimate the January 1985 TSMOM profits.

4. Empirical results

4.1. Summary statistics

Table 1 presents summary statistics for annualized futures returns for the 55 different contracts for the January 1984 through December 2013 period. Most futures contracts offer positive returns, with corn having the worst returns (−3.9%), and unleaded gasoline the best returns (23.7%). Annualized volatilities vary widely across contracts, from 1.4% for Australian three-year bonds to 51.1% for natural gas contracts. The average volatility is 19.1%, well below the 40% target volatility used by MOP. Overall, the summary statistics are comparable to those reported by MOP. Bond futures have the lowest

Table 1
Summary statistics for futures contracts.

This table reports information on the futures contracts in our sample including their annualized mean return, volatility (standard deviation), and Sharpe ratio from 1984 to 2013. Daily settlement prices are obtained from Commodity Systems, Inc.

No.	Contract	Symbol	Ex	Class	Start	End	Mean	Volatility	Sharpe Ratio
1	Corn	C	CBOT	Commodity: Grain	Jan-84	Dec-13	−3.87%	24.23%	−0.160
2	Soybeans	S	CBOT	Commodity: Grain	Jan-84	Dec-13	4.10%	22.48%	0.182
3	Soybean meal	SM	CBOT	Commodity: Grain	Jan-84	Dec-13	10.42%	24.49%	0.425
4	Soybean oil	BO	CBOT	Commodity: Grain	Jan-84	Dec-13	−0.89%	23.33%	−0.038
5	Wheat	W	CBOT	Commodity: Grain	Jan-84	Dec-13	−3.27%	26.69%	−0.122
6	Lean hogs	LH	CME	Commodity: Livestock	Jan-84	Dec-13	1.64%	22.40%	0.073
7	Live cattle	LC	CME	Commodity: Livestock	Jan-84	Dec-13	3.79%	14.10%	0.269
8	Cocoa	CC	ICE	Commodity: soft	Jan-84	Dec-13	−0.08%	29.85%	−0.003
9	Coffee	KC	ICE	Commodity: soft	Jan-84	Dec-13	−0.05%	36.10%	−0.001
10	Cotton	CT	ICE	Commodity: soft	Jan-84	Dec-13	2.68%	25.70%	0.104
11	Sugar	SB	ICE	Commodity: soft	Jan-84	Dec-13	3.88%	36.46%	0.106
12	Brent oil	LCO	ICE	Commodity: Energy	Jul-88	Dec-13	19.61%	33.73%	0.581
13	Crude oil	CL	NYMEX	Commodity: Energy	Jan-84	Dec-13	14.30%	36.38%	0.393
14	Gas oil	LGO	ICE	Commodity: Energy	Jan-84	Dec-13	14.03%	31.70%	0.442
15	Heat oil	HO	NYMEX	Commodity: Energy	Jan-84	Dec-13	16.71%	34.73%	0.481
16	Natural gas	NG	NYMEX	Commodity: Energy	Apr-90	Dec-13	−3.04%	51.07%	−0.060
17	Unleaded gasoline	RB	NYMEX	Commodity: Energy	Dec-84	Dec-13	23.74%	36.36%	0.653
18	Aluminum	MHA	LME	Commodity: Metal	July-87	Dec-13	2.65%	20.64%	0.128
19	Copper	HG	NYMEX	Commodity: Metal	Jan-84	Dec-13	11.97%	27.16%	0.441
20	Nickel	MNI	LME	Commodity: Metal	Jan-84	Dec-13	8.79%	32.52%	0.270
21	Zinc	MZS	LME	Commodity: Metal	Sep-88	Dec-13	4.83%	25.83%	0.187
22	Gold	GC	NYMEX	Commodity: Metal	Jan-84	Dec-13	1.01%	16.53%	0.061
23	Platinum	PL	NYMEX	Commodity: Metal	Jan-84	Dec-13	6.51%	22.80%	0.285
24	Silver	SI	NYMEX	Commodity: Metal	Jan-84	Dec-13	2.41%	29.10%	0.083
25	02-yr Treasury note	TU	CME	Bond	Jul-90	Dec-13	1.62%	1.70%	0.953
26	05-yr Treasury note	FV	CME	Bond	Jun-88	Dec-13	3.04%	4.13%	0.736
27	10-yr Treasury note	TY	CME	Bond	Jan-84	Dec-13	4.69%	6.70%	0.700

Table 1 (*continued*)

No.	Contract	Symbol	Ex	Class	Start	End	Mean	Volatility	Sharpe Ratio
28	30-yr Treasury bond	US	CME	Bond	Jan-84	Dec-13	5.85%	10.32%	0.566
29	Australian 03-yr bond	YTT	SFE	Bond	Jun-88	Dec-13	0.71%	1.36%	0.517
30	Australian 10-yr bond	YT2	SFE	Bond	Dec-84	Dec-13	0.47%	1.40%	0.338
31	British Gilt Long Bond	FLG	Eurex	Bond	Jan-84	Dec-13	2.44%	7.44%	0.327
32	Canada 10-yr bond	CGB	ME	Bond	Oct-89	Dec-13	3.82%	6.26%	0.611
33	Euro German 02-yr Schatz	EBS	Eurex	Bond	Apr-97	Dec-13	0.97%	1.38%	0.701
34	Euro German 05-yr Bobl	EBM	Eurex	Bond	Nov-91	Dec-13	2.93%	3.42%	0.858
35	Euro German 10-yr Bund	EBL	Eurex	Bond	Dec-90	Dec-13	3.96%	5.47%	0.725
36	Euro German 30-yr Buxl	EBX	Eurex	Bond	Oct-98	Dec-13	4.31%	10.70%	0.402
37	Japanese Gov't Bond	JGB	OSE	Bond	Apr-90	Dec-13	3.84%	4.39%	0.875
38	AEX (Netherlands)	AEX	EOE	Stock	Nov-92	Dec-13	8.08%	22.39%	0.361
39	CAC 40 Index	FCH	Euronext	Stock	Sep-88	Dec-13	6.24%	22.52%	0.277
40	DAX	FDX	Eurex	Stock	Dec-90	Dec-13	7.74%	23.07%	0.336
41	FTSE/MIB (Italy)	IFS	MIF	Stock	Dec-94	Dec-13	4.32%	24.45%	0.177
42	FTSE 100	FFI	LIFFE	Stock	May-84	Dec-13	5.42%	18.62%	0.291
43	IBEX 35 (Spain)	MFX	MEFF	Stock	May-92	Dec-13	8.54%	24.10%	0.354
44	Nikkei 225	SSI	SGX	Stock	Sep-86	Dec-13	1.91%	25.42%	0.075
45	S&P500	SP	CME	Stock	Jan-84	Dec-13	7.69%	19.54%	0.393
46	SPI ASE 200 Index	YAP	SFE	Stock	Jan-84	Dec-13	6.30%	19.21%	0.328
47	Australian Dollar	AD	CME	Currency	Feb-87	Dec-13	4.49%	12.00%	0.374
48	British pound	BP	CME	Currency	Jan-84	Dec-13	2.68%	10.37%	0.258
49	Canadian dollar	CD	CME	Currency	Jan-84	Dec-13	1.49%	7.26%	0.206
50	Deutschmark/Euro	EU	CME	Currency	Jan-84	Dec-13	2.12%	10.88%	0.195
51	Japanese yen	JY	CME	Currency	Jan-84	Dec-13	0.61%	11.14%	0.055
52	New Zealand Dollar	NE	CME	Currency	Jun-97	Dec-13	4.47%	13.65%	0.327
53	Norwegian Krone	NOK	CME	Currency	Jun-02	Dec-13	4.34%	13.00%	0.334
54	Swedish Krona	SEK	CME	Currency	Jun-02	Dec-13	4.73%	13.11%	0.361
55	Swiss franc	SF	CME	Currency	Jan-84	Dec-13	1.89%	11.99%	0.158

volatility among the different classes of futures and also have the highest Sharpe ratios. For example, the Treasury 2-year bond future has the highest Sharpe ratio, but the fourth lowest volatility. Across all contracts, the correlation coefficient between the volatility and Sharpe ratio is -0.51. This negative

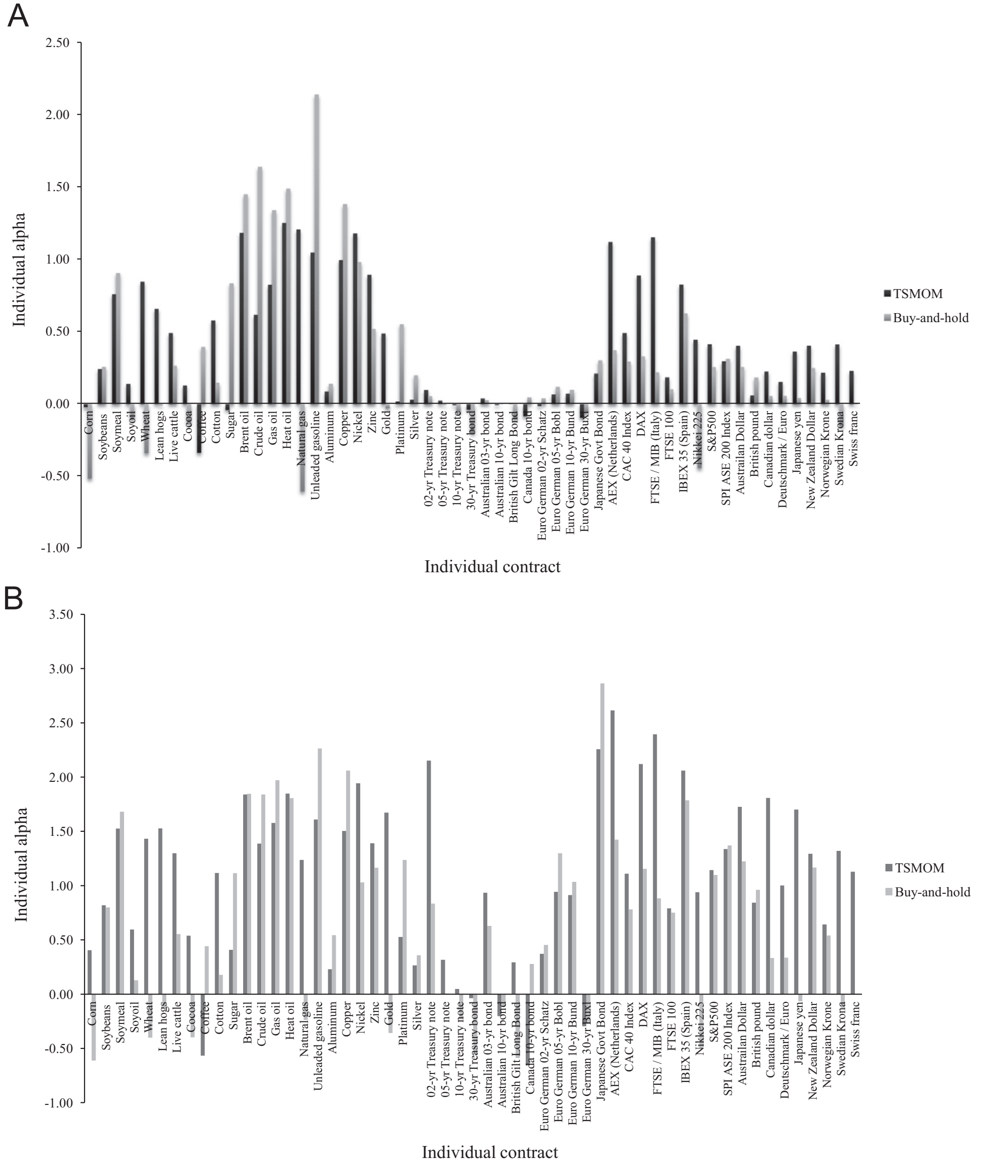

Fig. 1. Panel A. Alphas from individual contracts without volatility-scaling. Alphas of the TSMOM and the passive buy-and-hold strategies of each individual contract without volatility-scaled positions. Fig. 1a reports alphas from the TSMOM and the passive buy-and-hold strategies for individual contracts without volatility scaling for the 1985–2009 period. The alphas are obtained from running Eq. (5) for each individual contract. Panel B. Alphas from individual contracts with volatility-scaling. Alphas of the TSMOM and the passive buy-and-hold strategies of each individual contract with volatility-scaled positions. Fig. 1b reports alphas from the TSMOM and the passive buy-and-hold strategies for individual contracts with volatility scaling for the 1985–2009 period. The alphas are obtained from running Eq. (5) for each individual contract.

correlation suggests that the volatility scaling approach will yield higher returns than the standard equally-weighted returns for both the TSMOM and buy-and-hold strategies.

We also report the alphas of the 12-month TSMOM strategy with a one-month holding period and the passive buy-and-hold strategies of each individual contract without (with) volatility-scaled positions in Panel A (Panel B) of Fig. 1. To compare the results with MOP, we use the same period as

MOP, 1985–2009, in Panels A and B of Fig. 1 and in Tables 2, 3, and 7. The alpha is obtained from estimating the following time series regression:

$$r_t = \alpha + \beta_1 msci_t + \beta_2 gsci_t + \beta_3 aggr_t + \beta_4 dinx_t + \beta_5 smb_t + \beta_6 hml_t + \beta_7 umd_t + \varepsilon_t, \tag{5}$$

where r_t is the time series momentum returns, buy-and-hold returns, and cross-sectional momentum returns. *msci* is the market factor represented by the MSCI World Index and *smb*, *hml*, and *umd* are the Fama-French (1993) and Carhart (1997) factors for size, value, and cross-sectional momentum. To control for the aggregate risk related to each sector's returns, we use additional factors in Eq. (5). We include a global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), and a currency factor (*dinx*, U.S. Dollar Index against the major currencies). As expected, these additional risk factors provide a great deal of explanatory power for the buy-and-hold returns, and the alphas are lower for these buy-and-hold portfolio analyses. Hereafter, we refer to Eq. (5) as the seven-factor model.

Global risks are known to be closely related to the comovements in commodity returns (Yin and Han, 2015). In robustness tests, we therefore consider global equity factors (*gsmb*, *ghml*, and *gumd*) rather than the U.S. equity factors. Since the global equity factors are available from July 1990, we use the North American equity factors before then. Both the global and North American equity factors are obtained from the AQR data library. The results using the global equity factors are qualitatively similar, and we summarize some key four-factor and seven-factor results below.

Fig. 1a shows that, without using volatility scaling positions, the TSMOM alphas are positive for 46 individual contracts. In particular, 33 futures contracts (or 60% of 55 contracts) have higher alphas than those from the buy-and-hold strategy. Volatility-scaling the returns causes the alphas for both the TSMOM and buy-and-hold strategies to be much higher. The volatility-scaled results are displayed in Fig. 1b; 50 contracts (or 91%) have positive TSMOM alphas and 35 contracts (or 63.6%) have higher TSMOM alphas than those from the buy-and-hold strategy. With volatility scaling, the average alpha of the TSMOM returns increases from an unscaled average 0.40% to 1.08%. The average alpha of the scaled buy-and-hold strategies also increases from an unscaled 0.29% to 0.68%. Comparing the Sharpe ratios of individual contracts, we find that the TSMOM strategy has a higher Sharpe ratio than buy-and-hold for 26 contracts when the strategies are volatility scaled, and for 24 contracts when the strategies are not volatility scaled.

Additionally, for each contract, we test whether the alphas from TSMOM and buy-and-hold returns are different from each other. We find that for most of the futures contracts, the individual alphas are not significantly different from each other. For example, 47(51) out of 55 alphas from volatility-scaled (unscaled) TSMOM are not statistically different from those from volatility-scaled (unscaled) buy-and-hold returns. Moreover, we find that we cannot reject the joint hypothesis that all the TSMOM alphas are equal to the buy-and-hold alphas, regardless of using scaled or unscaled returns at any conventional significance level. Overall, there is no clear evidence that a TSMOM strategy outperforms a buy-and-hold strategy for individual contracts.

MOP justify their use of volatility scaling because otherwise certain high volatility asset classes would dominate their analysis. In order to confirm that our results are not driven by differences in volatility across sectors, we divide the futures contracts into four sectors and calculate alphas using the seven-factor model in Eq. (5). We consider scaled and unscaled TSMOM returns, and scaled and unscaled buy-and-hold returns for the 1985–2009 period. We also assess whether scaled and unscaled TSMOM performs better than the cross-sectional momentum strategy, XSMOM. Table 2A presents the results for commodities futures, Table 2B presents the results for bond futures, Table 2C presents the results for equity index futures, and Table 2D presents the results for currency futures. In each of these tables (and in Tables 3–7), we report the results of the TSMOM, buy-and-hold, and XSMOM strategies in Panels A, B, and C, respectively. In Panel D, we present *F*-test results for whether the alphas from scaled and unscaled TSMOM, buy-and-hold, and XSMOM strategies are significantly different from one another.

Tables 2A, 2C, and 2D show that the alphas from the volatility-scaled TSMOM strategy are large and significantly different from zero for commodities, equities, and currencies. In contrast, the alphas for the bond futures contracts in Table 2B are not significantly different from zero for the TSMOM and buy-and-hold strategies, and this holds true whether the returns are scaled or not. The lower alphas

Table 2A
Performance of diversified portfolios for commodity futures (1985–2009).

Each panel displays the results from time series regressions of monthly returns of the time series momentum (TSMOM) strategy; time series regressions of monthly returns of the buy-and-hold strategy; time series regressions of monthly returns of the cross-sectional momentum (XSMOM) strategy; and the tests of intercepts for alpha for each strategy pair. Panel A reports the results for commodity futures, Panel B for bond futures, Panel C for equity index futures, and Panel D for currency futures. *No scaling* (*Volatility scaled*) indicates without (with) multiplying returns to generate an expected standard deviation of 40% when constructing monthly TSMOM and buy-and-hold returns. For the XSMOM strategy, we scale the volatility using the realized variance as in Barroso and Santa-Clara (2015). Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index) and a currency factor (*dinx*, U.S. Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.54	−0.06	0.07	0.03	−0.01	−0.02	−0.02	0.14	8%
	(3.21)	(−1.49)	(2.62)	(0.19)	(−0.10)	(−0.29)	(−0.34)	(4.00)	
Volatility scaled	1.08	−0.04	0.07	−0.02	−0.03	0.00	−0.02	0.16	5%
	(4.95)	(−0.70)	(1.98)	(−0.12)	(−0.31)	(−0.07)	(−0.21)	(3.64)	

Panel B: Buy and hold strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.56	0.08	0.52	−0.14	−0.13	0.01	0.00	−0.07	71%
	(4.57)	(2.82)	(24.68)	(−1.31)	(−2.70)	(0.26)	(−0.10)	(−2.87)	
Volatility scaled	0.81	0.13	0.61	−0.31	−0.22	0.05	0.01	−0.06	56%
	(3.97)	(2.58)	(17.34)	(−1.85)	(−2.66)	(0.69)	(0.16)	(−1.52)	

Panel C: Cross-sectional momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.99	0.04	0.34	0.07	0.11	−0.07	0.16	0.38	9%
	(1.91)	(0.30)	(3.86)	(0.15)	(0.52)	(−0.44)	(0.95)	(3.67)	
Barroso and Santa-Clara	0.88	0.03	0.26	−0.03	0.05	−0.05	0.13	0.29	8%
	(2.21)	(0.36)	(3.75)	(−0.08)	(0.31)	(−0.43)	(0.95)	(3.58)	

Panel D: Differences in alpha

Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	−0.02	0.882
Scaled time series momentum vs. scaled buy-and-hold	0.28	0.330
Time series momentum vs. cross-sectional momentum	−0.45	0.299
Scaled time series momentum vs. cross-sectional momentum	0.09	0.837
Buy-and-hold vs. cross-sectional momentum	−0.43	0.444
Scaled buy-and hold vs. cross-sectional momentum	−0.19	0.754

for the bond contracts are due to the large factor loadings on the aggregate bond index, *aggr*, for the bond futures strategies. For example, the *aggr* loading for the volatility-scaled TSMOM returns is 3.71 (t=11.0), and this estimate is 6.40 (t=24.9) for the volatility-scaled buy-and-hold returns.[6]

The alphas for the unscaled and scaled buy-and-hold strategies are also significantly different from zero for commodity, equity, and currency futures. In all cases, the scaled strategy alphas are larger than the unscaled strategy alphas. In order to assess whether the high returns generated by MOP are due to volatility scaling, we compare alphas from the scaled buy-and-hold with the scaled TSMOM

[6] If we instead consider a four-factor model, the bond futures TSMOM and scaled buy-and-hold strategies are both significantly different from zero, and not significantly different from each other.

Table 2B
Performance of diversified portfolios for bond futures (1985–2009).
See Table 2A for variable descriptions.

Panel A: Time series momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.04	−0.01	0.01	0.55	−0.01	0.04	−0.02	0.04	31%
	(0.69)	(−0.36)	(0.53)	(10.88)	(−0.41)	(2.31)	(−0.80)	(3.28)	
Volatility scaled	0.55	−0.13	0.07	3.71	0.04	0.34	−0.06	0.25	31%
	(1.37)	(−1.35)	(0.97)	(11.03)	(0.28)	(2.64)	(−0.48)	(3.01)	
Panel B: Buy and hold strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	−0.01	−0.01	−0.01	0.98	0.01	−0.01	−0.01	0.01	79%
	(−0.16)	(−1.01)	(−2.20)	(31.52)	(0.94)	(−0.65)	(−1.06)	(1.61)	
Volatility scaled	0.31	−0.15	−0.07	6.40	0.07	−0.05	−0.04	0.10	70%
	(0.99)	(−2.08)	(−1.37)	(24.90)	(0.60)	(−0.52)	(−0.36)	(1.52)	
Panel C: Cross-sectional momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	−0.21	−0.08	0.03	0.74	−0.10	0.08	0.02	0.04	26%
	(−1.98)	(−3.02)	(1.65)	(7.64)	(−2.20)	(2.58)	(0.58)	(2.09)	
Barroso and Santa-Clara	−0.81	−0.56	0.19	4.57	−0.48	0.39	−0.03	0.16	27%
	(−1.35)	(−3.84)	(1.94)	(8.20)	(−1.85)	(2.13)	(−0.14)	(1.37)	

Panel D: Differences in alpha		
Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	0.05	0.415
Scaled time series momentum vs. scaled buy-and-hold	0.24	0.536
Time series momentum vs. cross-sectional momentum	0.25	0.029
Scaled time series momentum vs. cross-sectional momentum	0.76	0.068
Buy-and-hold vs. cross-sectional momentum	0.20	0.090
Scaled buy-and hold vs. cross-sectional momentum	0.52	0.118

alphas. The results in Tables 2A–2D show that the alphas from TSMOM are not significantly different from the alphas from the scaled buy-and-hold for commodities, bonds, or equities, and significantly different from the alpha of currencies only at the 10% significance level. We further compare the unscaled TSMOM strategy with the unscaled buy-and-hold strategy. For none of the four sector portfolios does the unscaled TSMOM strategy significantly outperform the unscaled buy-and-hold strategy. Thus, the findings from Tables 2A–2D imply that futures contracts performed well on average over this time period; however, there is little evidence that the performance is driven by a TSMOM strategy. Instead, our results indicate that leveraging the positions through volatility scaling is associated with higher alpha.

We also estimate alphas from the cross-sectional momentum strategy, XSMOM, for each sector. To calculate XSMOM, we rank the past 12-month performance of each futures contract into five groups. Following previous studies (e.g., Novy-Marx, 2012), we buy the winners (the top 20%) and sell the losers (the bottom 20%) and hold the portfolio for a month. The futures contracts in the top and bottom performing portfolios are equally weighted. The alphas generated by XSMOM returns for each sector are not significantly different from zero for two sectors (equities and currencies), positive and significant at the 10% level for one sector (commodities), and negative and significant at the 10% level for one sector (bonds).

Table 2C
Performance of diversified portfolios for equity futures (1985–2009).
See Table 2A for variable descriptions.

Panel A: Time series momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.50	0.08	−0.04	−0.02	0.30	0.04	−0.15	0.43	27%
	(2.26)	(1.44)	(−0.98)	(−0.10)	(3.37)	(0.51)	(−1.98)	(9.58)	
Volatility scaled	1.43	0.45	0.00	0.19	0.60	0.10	−0.18	0.70	22%
	(3.35)	(4.38)	(−0.05)	(0.54)	(3.53)	(0.70)	(−1.29)	(8.13)	
Panel B: Buy and hold strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.26	1.03	0.01	−0.08	0.64	0.06	0.07	0.02	87%
	(2.44)	(41.33)	(0.52)	(−0.88)	(15.30)	(1.76)	(1.86)	(0.93)	
Volatility scaled	1.08	1.85	0.03	0.32	1.33	0.06	−0.08	0.18	77%
	(4.10)	(29.37)	(0.61)	(1.47)	(12.66)	(0.75)	(−0.96)	(3.44)	
Panel C: Cross-sectional momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.49	−0.27	−0.06	0.39	−0.11	0.06	0.03	0.14	5%
	(1.33)	(−3.03)	(−1.07)	(1.14)	(−0.68)	(0.57)	(0.23)	(1.92)	
Barroso and Santa-Clara	1.22	−0.53	−0.09	0.39	−0.19	0.11	−0.03	0.20	4%
	(1.75)	(−3.12)	(−0.78)	(0.59)	(−0.64)	(0.50)	(−0.12)	(1.49)	

Panel D: Differences in alpha

Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	0.24	0.373
Scaled time series momentum vs. scaled buy-and-hold	0.35	0.388
Time series momentum vs. cross-sectional momentum	0.01	0.974
Scaled time series momentum vs. cross-sectional momentum	0.94	0.164
Buy-and-hold vs. cross-sectional momentum	−0.23	0.346
Scaled buy-and hold vs. cross-sectional momentum	0.59	0.501

We also include alphas from the Barroso and Santa-Clara risk-managed XSMOM strategy. This does better than the XSMOM strategy for the equity sector (alpha of 1.22% vs. 0.49%) and for the currency sector (alpha of 0.76% vs. 0.22%), but somewhat worse for the commodity sector (alpha of 0.88% vs. 0.99%) and for the bond sector (alpha of −0.81% vs. −0.21%). The alpha from the Barroso and Santa-Clara strategy is significantly different from zero at the 5% level for commodities and significantly different from zero at the 10% level for equities. The alpha from the Barroso and Santa-Clara strategy is significantly different from the XSMOM strategy alpha only for equities.

Table 3 presents the regression analysis for the full portfolio, where we regress the returns of the full portfolio of futures contracts on the seven-factor model for the 1985–2009 period. This table parallels Panels A and B of Table 3 in MOP. As reported in MOP, the *umd* factor has a significant coefficient in the unscaled and scaled TSMOM regressions, as well as in the XSMOM and Barroso and Santa-Clara regressions. Thus, consistent with MOP, time series momentum in the futures markets is tied to the equity momentum factor.

Panels A and B of Table 3 show that the TSMOM and buy-and-hold alphas increase with volatility-scaled positions, from 0.39% (t=4.00) to 1.08% (t=6.02) for TSMOM returns and from 0.34% (t=5.00) to 0.73% (t=4.97) for the buy-and-hold returns. The 1.08% alpha for the TSMOM strategy with

Table 2D
Performance of diversified portfolios for currency futures (1985–2009).
See Table 2A for variable descriptions.

Panel A: Time series momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.26	−0.06	−0.04	−0.02	−0.12	−0.05	−0.07	0.04	4%
	(2.06)	(−2.04)	(−1.73)	(−0.15)	(−2.48)	(−1.15)	(−1.60)	(1.70)	
Volatility scaled	1.40	−0.15	−0.06	0.09	−0.48	−0.12	−0.19	0.09	2%
	(3.18)	(−1.41)	(−0.84)	(0.25)	(−2.73)	(−0.84)	(−1.31)	(1.01)	
Panel B: Buy and hold strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.11	0.06	0.04	0.00	−0.81	0.02	0.02	−0.02	91%
	(2.58)	(5.59)	(5.40)	(−0.12)	(−47.87)	(1.63)	(1.21)	(−2.03)	
Volatility scaled	0.51	0.11	0.14	−0.03	−2.81	0.09	−0.03	0.01	83%
	(2.42)	(2.13)	(4.01)	(−0.17)	(−33.65)	(1.36)	(−0.45)	(0.27)	
Panel C: Cross-sectional momentum strategy									
	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.22	0.02	0.01	−0.28	0.01	0.03	−0.01	0.10	0%
	(0.98)	(0.31)	(0.25)	(−1.54)	(0.16)	(0.37)	(−0.17)	(2.22)	
Barroso and Santa-Clara	0.76	0.08	0.06	−0.73	0.09	0.03	−0.04	0.20	0%
	(1.20)	(0.51)	(0.55)	(−1.38)	(0.37)	(0.17)	(−0.18)	(1.57)	

Panel D: Differences in alpha

Strategy pair	diff	p-value
Time series momentum vs. buy-and-hold	0.15	0.276
Scaled time series momentum vs. scaled buy-and-hold	0.89	0.059
Time series momentum vs. cross-sectional momentum	0.04	0.822
Scaled time series momentum vs. cross-sectional momentum	1.18	0.002
Buy-and-hold vs. cross-sectional momentum	−0.11	0.627
Scaled buy-and hold vs. cross-sectional momentum	0.29	0.357

volatility scaling is comparable to the 1.09% alpha reported in MOP when they use the Asness, Moskowitz, and Pedersen (2013) factors. Although the alpha we calculate using scaled TSMOM is larger than the alpha from scaled buy-and-hold returns, the difference between the scaled TSMOM and scaled buy-and-hold is only significantly different at the 10% level. We also note that the alpha for the TSMOM strategy without volatility scaling is similar to the alpha from the buy-and-hold strategy, and the difference between these alphas is not statistically significant. If we instead consider a four-factor model (as in Panel A, Table 3 of MOP), the TSMOM and buy-and-hold alphas are not significantly different from each other for either the scaled or unscaled strategies.

The smaller, but still significant, positive alphas in the unscaled TSMOM and unscaled buy-and-hold strategies may be due to factors not included in the MOP specification, such as Fama and French's (2015) five-factor model, or the downside risk model examined by Lettau, Maggiori, and Weber (2014). In particular, Lettau, Maggiori, and Weber (2014) find that the downside risk capital asset pricing model can explain much of the variation in several asset classes, including commodities and currencies [see Tse (2016) for further evidence from the futures markets].

We also provide the results for the XSMOM strategy in Panel C of Table 3, and that strategy produces an alpha of 0.92 (t=2.51). The risk-managed XSMOM strategy of Barroso and Santa-Clara

Table 3
Performance of diversified futures contract portfolios (1985–2009).

Panel A displays the results from time series regressions of monthly returns of the time series momentum (TSMOM) strategy. Panel B reports the results from time series regressions of monthly returns of the buy-and-hold strategy. Panel C reports the results from time series regressions of monthly returns of the cross-sectional momentum (XSMOM) strategy. *No scaling* (*Volatility scaled*) indicates without (with) multiplying returns to generate an expected standard deviation of 40% when constructing monthly TSMOM and buy-and-hold returns. For Panel C, we scale the volatility using the realized variance as in Barroso and Santa-Clara (2015). Panel D presents the test results of intercepts for alpha for each strategy pair. Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, U.S. Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.39	−0.04	0.02	0.11	0.02	0.00	−0.04	0.14	19%
	(4.00)	(−1.59)	(1.42)	(1.36)	(0.52)	(0.01)	(−1.35)	(7.42)	
Volatility scaled	1.08	−0.02	0.03	0.78	0.01	0.07	−0.07	0.25	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	

Panel B: Buy and hold strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.34	0.19	0.26	0.07	−0.10	0.01	0.01	−0.04	74%
	(5.00)	(11.70)	(21.73)	(1.22)	(−3.50)	(0.46)	(0.48)	(−2.70)	
Volatility scaled	0.73	0.29	0.31	1.11	−0.32	0.02	0.00	0.01	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	

Panel C: Cross-sectional momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.92	−0.04	0.19	0.20	0.18	0.04	0.02	0.43	12%
	(2.51)	(−0.42)	(2.95)	(0.65)	(1.24)	(0.32)	(0.19)	(5.75)	
Barroso and	1.05	0.00	0.20	0.11	0.18	0.01	0.02	0.40	12%
Santa-Clara	(2.92)	(−0.01)	(3.21)	(0.36)	(1.29)	(0.13)	(0.15)	(5.50)	

Panel D: Differences in alpha

Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	0.05	0.718
Scaled time series momentum vs. scaled buy-and-hold	0.35	0.066
Time series momentum vs. cross-sectional momentum	−0.53	0.068
Scaled time series momentum vs. cross-sectional momentum	0.16	0.599
Buy-and-hold vs. cross-sectional momentum	−0.58	0.122
Scaled buy-and hold vs. cross-sectional momentum	−0.19	0.619

(2015) offers only a slightly higher alpha, 1.05 (t=2.92), for our full futures markets sample.[7] Therefore, the TSMOM strategy outperforms (albeit, not significantly as shown in Panel D) the XSMOM strategy only when the TSMOM positions are scaled with predicted volatility. Using a standard equally-weighted approach, like Menkhoff, Sarno, Schmeling, and Schrimpf (2012), the TSMOM strategy does significantly worse than the XSMOM strategy. As previously discussed, these results may explain the conflicting conclusions drawn by MOP and Menkhoff et al. about the relative performance of the TSMOM and XSMOM strategies.

We conduct similar analyses for three subperiods, 1985–2000 (or the pre-2001 period), 2001–2013, and 2009–2013, and report the results in Tables 4, 5, and 6, respectively. The second subperiod

[7] The results in Panel C are similar if the momentum returns are ranked into three groups instead of five.

Table 4
Performance of diversified futures contract portfolios: sub-period analysis (1985–2000).

Panel A displays the results from time series regressions of monthly returns of the time series momentum (TSMOM) strategy. Panel B reports the results from time series regressions of monthly returns of the buy-and-hold strategy. Panel C reports the results from time series regressions of monthly returns of the cross-sectional momentum (XSMOM) strategy. *No scaling* (*Volatility scaled*) indicates without (with) multiplying returns to generate an expected standard deviation of 40% when constructing monthly TSMOM and buy-and-hold returns. For Panel C, we scale the volatility using the realized variance as in Barroso and Santa-Clara (2015). Panel D presents the test results of intercepts for alpha for each strategy pair. Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, U.S. Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.41	0.02	0.03	−0.03	0.04	−0.01	0.00	0.11	5%
	(3.50)	(0.65)	(1.51)	(−0.36)	(0.91)	(−0.26)	(0.11)	(3.41)	
Volatility scaled	1.21	0.07	0.06	0.51	0.08	0.01	−0.06	0.16	11%
	(5.63)	(1.37)	(1.35)	(3.01)	(1.04)	(0.12)	(−0.71)	(2.74)	

Panel B: Buy and hold strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.46	0.18	0.28	0.03	−0.07	0.02	0.02	−0.05	62%
	(5.07)	(7.68)	(15.44)	(0.36)	(−2.23)	(0.78)	(0.66)	(−2.12)	
Volatility scaled	0.77	0.40	0.39	0.93	−0.28	0.07	0.13	−0.05	60%
	(4.05)	(8.26)	(10.46)	(6.20)	(−4.17)	(1.07)	(1.88)	(−1.07)	

Panel C: Cross-sectional momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	1.07	0.06	0.19	−0.36	0.29	0.03	0.07	0.46	7%
	(2.16)	(0.50)	(1.97)	(−0.94)	(1.65)	(0.17)	(0.40)	(3.54)	
Barroso and	1.16	0.08	0.21	−0.39	0.30	0.01	0.05	0.44	7%
Santa-Clara	(2.37)	(0.64)	(2.14)	(−1.01)	(1.71)	(0.03)	(0.29)	(3.42)	

Panel D: Differences in alpha

Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	−0.05	0.735
Scaled time series momentum vs. scaled buy-and-hold	0.44	0.089
Time series momentum vs. cross-sectional momentum	−0.66	0.143
Scaled time series momentum vs. cross-sectional momentum	0.14	0.757
Buy-and-hold vs. cross-sectional momentum	−0.61	0.289
Scaled buy-and hold vs. cross-sectional momentum	−0.30	0.617

coincides with the financialization of commodities, and this analysis starts in the same year, 2001, as the analysis by Chordia, Roll, and Subrahmanyam (2011). For the 2001–2008 period, Chordia, Roll, and Subrahmanyam (2011) find that the XSMOM excess returns are insignificant in the U.S. equity market. The third period is the post-crisis period after the 2007–2009 financial crisis.

Table 4 shows that for the pre-2001 period, the results are similar to those for the whole period of 1985–2009 reported in Table 3. The alphas for the volatility-scaled TSMOM strategy are 1.21 (t=5.63), 0.77 (t=4.05) for the volatility scaled buy-and-hold strategy, and 1.07 (t=2.16) for the XSMOM strategy. In this period, the alpha from the volatility-scaled TSMOM strategy is larger than the alpha from the volatility-scaled buy-and-hold strategy, and the difference is marginally significant with a *p*-value of 0.09.

Table 5 reports that for the 2001–2013 period, the alpha for the TSMOM strategy with volatility scaled returns, 0.59 (t=2.15), is similar to the alpha from the scaled buy-and-hold strategy, 0.58 (t=3.36). The

Table 5
Performance of diversified futures contract portfolios: sub-period analysis (2001–2013).

Panel A displays the results from time series regressions of monthly returns of the time series momentum (TSMOM) strategy. Panel B reports the results from time series regressions of monthly returns of the buy-and-hold strategy. Panel C reports the results from time series regressions of monthly returns of the cross-sectional momentum (XSMOM) strategy. *No scaling* (*Volatility scaled*) indicates without (with) multiplying returns to generate an expected standard deviation of 40% when constructing monthly TSMOM and buy-and-hold returns. For panel C, we scale the volatility using the realized variance as in Barroso and Santa-Clara (2015). Panel D presents the tests of intercepts for alpha for each strategy pair. Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, US Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.20	−0.02	0.02	0.19	−0.09	0.07	−0.08	0.19	29%
	(1.36)	(−0.50)	(0.91)	(1.28)	(−1.15)	(1.21)	(−1.60)	(6.73)	
Volatility scaled	0.59	−0.07	0.03	1.02	−0.22	0.19	−0.09	0.32	30%
	(2.15)	(−0.86)	(0.59)	(3.72)	(−1.56)	(1.78)	(−1.00)	(5.87)	

Panel B: Buy and hold strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.15	0.25	0.23	0.24	−0.17	−0.01	−0.04	0.00	88%
	(1.89)	(10.96)	(16.77)	(3.03)	(−4.15)	(−0.48)	(−1.30)	(−0.13)	
Volatility scaled	0.58	0.29	0.26	1.53	−0.50	0.02	−0.16	0.06	78%
	(3.36)	(5.81)	(8.73)	(8.83)	(−5.59)	(0.30)	(−2.62)	(1.70)	

Panel C: Cross-sectional momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.33	−0.09	0.17	0.74	−0.04	0.02	0.08	0.42	21%
	(0.75)	(−0.69)	(2.20)	(1.67)	(−0.16)	(0.13)	(0.52)	(4.71)	
Barroso and Santa-Clara	0.60	−0.02	0.16	0.58	−0.01	(0.03)	0.10	0.41	18%
	(1.32)	(−0.15)	(2.07)	(1.28)	(−0.05)	(−0.15)	(0.61)	(4.51)	

Panel D: Differences in alpha

Strategy pair	diff	p-value
Time series momentum vs. buy-and-hold	0.05	0.776
Scaled time series momentum vs. scaled buy-and-hold	0.01	0.969
Time series momentum vs. cross-sectional momentum	−0.13	0.673
Scaled time series momentum vs. cross-sectional momentum	0.26	0.438
Buy-and-hold vs. cross-sectional momentum	−0.18	0.672
Scaled buy-and hold vs. cross-sectional momentum	0.25	0.605

XSMOM strategy has a slightly lower alpha, 0.33 (t=0.75), for this time period. As expected, both the TSMOM and buy-and-hold alphas are smaller if the positions are not scaled. The alphas from the TSMOM and XSMOM strategies are not significantly different from the alpha from the buy-and-hold strategy and not significantly different from each other. These findings are consistent with any superior performance of the TSMOM strategy in the more recent time period being due to the greater use of leverage. In untabulated regressions, we consider this subperiod analysis for each of the four futures sectors. The results are consistent with the full portfolio findings and further support our conclusions.

Table 6 reports that during the 2009–2013 post-crisis period, the alphas for the volatility-scaled TSMOM, 0.23 (t=0.41), for the volatility-scaled buy-and-hold, −0.07 (t=−0.24), and for XSMOM, 0.45 (t=0.60), are all not significantly different from zero. The alphas from the TSMOM and XSMOM strategies are again not significantly different from the buy-and-hold alphas. These results indicate that the

Table 6
Performance of diversified futures contract portfolios: sub-period analysis (2009–2013).

Panel A displays the results from time series regressions of monthly returns of the time series momentum (TSMOM) strategy. Panel B reports the results from time series regressions of monthly returns of the buy-and-hold strategy. Panel C reports the results from time series regressions of monthly returns of the cross-sectional momentum (XSMOM) strategy. *No scaling* (*Volatility scaled*) indicates without (with) multiplying returns to generate an expected standard deviation of 40% when constructing monthly TSMOM and buy-and-hold returns. For panel C, we scale the volatility using the realized variance as in Barroso and Santa-Clara (2015). Panel D presents the tests of intercepts for alpha for each strategy pair. Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, US Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	0.07	0.09	−0.01	−0.30	0.02	0.06	−0.02	0.22	27%
	(0.23)	(0.79)	(−0.23)	(−0.92)	(0.13)	(0.48)	(−0.21)	(4.78)	
Volatility scaled	0.23	0.05	0.00	0.58	−0.03	0.08	0.03	0.33	13%
	(0.41)	(0.27)	(0.03)	(0.96)	(−0.09)	(0.31)	(0.15)	(3.85)	

Panel B: Buy and hold strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
No Scaling	−0.04	0.24	0.24	0.36	−0.17	0.00	−0.05	0.00	91%
	(−0.27)	(4.76)	(7.97)	(2.39)	(−2.05)	(0.06)	(−0.94)	(−0.12)	
Volatility scaled	−0.07	0.35	0.27	2.13	−0.39	0.08	−0.19	0.11	81%
	(−0.24)	(3.09)	(4.02)	(6.24)	(−2.13)	(0.61)	(−1.59)	(2.27)	

Panel C: Cross-sectional momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
Long-Short	0.45	0.40	−0.19	−0.75	0.39	−0.19	0.43	0.41	17%
	(0.60)	(1.45)	(−1.15)	(−0.91)	(0.90)	(−0.58)	(1.53)	(3.52)	
Barroso and Santa-Clara	0.78	0.48	−0.17	−0.88	0.47	−0.32	0.43	0.39	12%
	(0.92)	(1.54)	(−0.91)	(−0.96)	(0.96)	(−0.87)	(1.37)	(3.00)	

Panel D: Differences in alpha

Strategy pair	diff	*p*-value
Time series momentum vs. buy-and-hold	0.11	0.722
Scaled time series momentum vs. scaled buy-and-hold	0.30	0.643
Time series momentum vs. cross-sectional momentum	−0.38	0.524
Scaled time series momentum vs. cross-sectional momentum	−0.22	0.600
Buy-and-hold vs. cross-sectional momentum	−0.49	0.563
Scaled buy-and hold vs. cross-sectional momentum	−0.52	0.577

performance of the TSMOM and XSMOM strategies during this most recent period is worse than their performances for the pre-2001 period and for the whole sample period. Baltas and Kosowski (2013, 2015) attribute the decline in TSMOM profits in more recent years to increased correlations across asset classes. We further find that the Barroso and Santa-Clara strategy does not produce alphas that are significantly different from zero for either the 2001–2013 or the 2009–2013 subperiods.

In Fig. 2, we provide a comparison of the cumulative returns for a $100 investment using either the volatility-scaled TSMOM strategy or a similarly scaled buy-and-hold strategy over the period from January 1985 to December 2013. We plot similar cumulative returns for unscaled TSMOM and unscaled buy-and-hold strategies in Fig. 3. The scaled TSMOM returns are similar to those described by MOP. However, as we instead scale the buy-and-hold strategy in Fig. 2, the TSMOM and buy-and-hold strategies now produce comparable wealth. Similarly, the returns for an unscaled TSMOM strategy are close to the returns for the unscaled buy-and-hold strategy in Fig. 3,

Table 7
Performance of diversified portfolios using different volatility scales (1985–2009).

This table reports the performance of the time series momentum and buy-and-hold strategies using different volatility scales. Panel A and Panel B report the performance of the TSMOM and the buy-and-hold strategies, respectively. For each month, we use a 10%, 20%, 30%, 40%, 50%, and 60% volatility scale to construct the monthly TSMOM and buy-and-hold strategies. Control variables are the returns of the MSCI World Index (*msci*), global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, U.S. Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb* (size), *hml* (value), and *umd* (cross-sectional momentum).

Panel A: Time series momentum strategy

	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
10%	0.27	−0.01	0.01	0.20	0.00	0.02	−0.02	0.06	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	
20%	0.54	−0.01	0.02	0.39	0.00	0.03	−0.04	0.12	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	
30%	0.81	−0.02	0.03	0.59	0.01	0.05	−0.05	0.19	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	
40%	1.08	−0.02	0.03	0.78	0.01	0.07	−0.07	0.25	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	
50%	1.35	−0.03	0.04	0.98	0.01	0.08	−0.09	0.31	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	
60%	1.62	−0.03	0.05	1.17	0.01	0.10	−0.11	0.37	21%
	(6.02)	(−0.49)	(1.11)	(5.25)	(0.11)	(1.18)	(−1.22)	(6.87)	

Panel B: Buy-and-hold strategy

Scale	alpha	msci	gsci	aggr	dinx	smb	hml	umd	Adj. R^2
10%	0.18	0.07	0.08	0.28	−0.01	0.01	0.00	0.00	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	
20%	0.36	0.15	0.15	0.55	−0.16	0.01	0.00	0.00	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	
30%	0.55	0.22	0.23	0.83	−0.24	0.02	0.00	0.01	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	
40%	0.73	0.29	0.31	1.11	−0.32	0.02	0.00	0.01	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−.54)	(0.48)	(0.02)	(0.33)	
50%	0.91	0.36	0.39	1.39	−0.40	0.03	0.00	0.01	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	
60%	1.09	0.44	0.46	1.66	−0.48	0.03	0.00	0.01	64%
	(4.97)	(8.36)	(12.33)	(9.11)	(−5.54)	(0.48)	(0.02)	(0.33)	

although these returns are lower than their scaled counterparts.[8] We also consider similar analyses for each sector, and find similar results.

In Table 7, we consider how different levels of volatility scaling affect monthly time series momentum and buy-and-hold strategy returns. Scaling to a higher volatility, which corresponds to further leveraging a given position, is associated with a higher alpha.[9] A relatively low volatility scale of 10% generates a relatively small alpha of 0.27 for the TSMOM strategy and 0.18 for the buy-and-hold strategy. In contrast, a high volatility scale of 60% produces a very high alpha of 1.62 for the TSMOM strategy and 1.09 for the buy-and-hold strategy. These results are consistent with much of

[8] The difference between the TSMOM returns and buy-and-hold average returns is not statistically different from zero based on a pairwise *t*-test whether using scaled or unscaled returns.

[9] Note that as we only scale the dependent variable in Table 7, the associated *t*-statistics in these different regressions do not change.

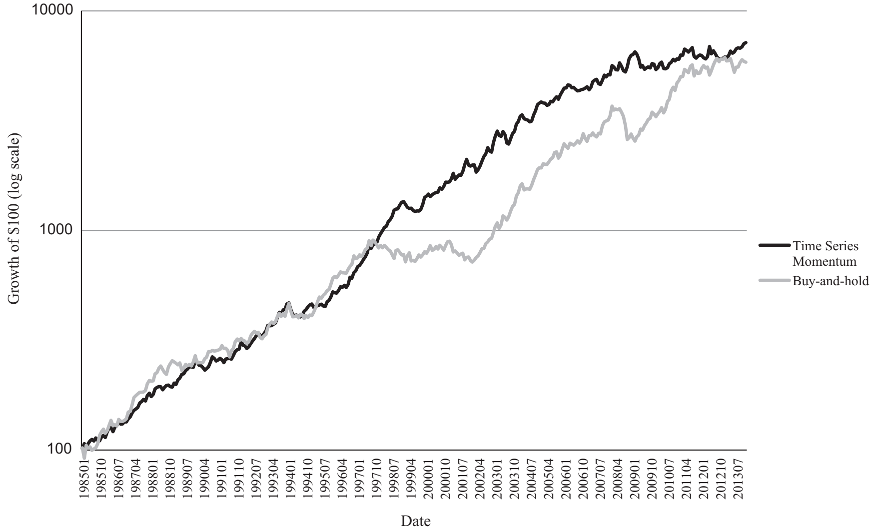

Fig. 2. Cumulative returns (volatility scaled). Cumulative dollar returns for volatility-scaled time series momentum and volatility-scaled buy-and-hold strategies. Plotted are the cumulative returns for volatility scaled time series momentum and volatility scaled buy-and-hold strategies using returns from January 1985 to December 2013.

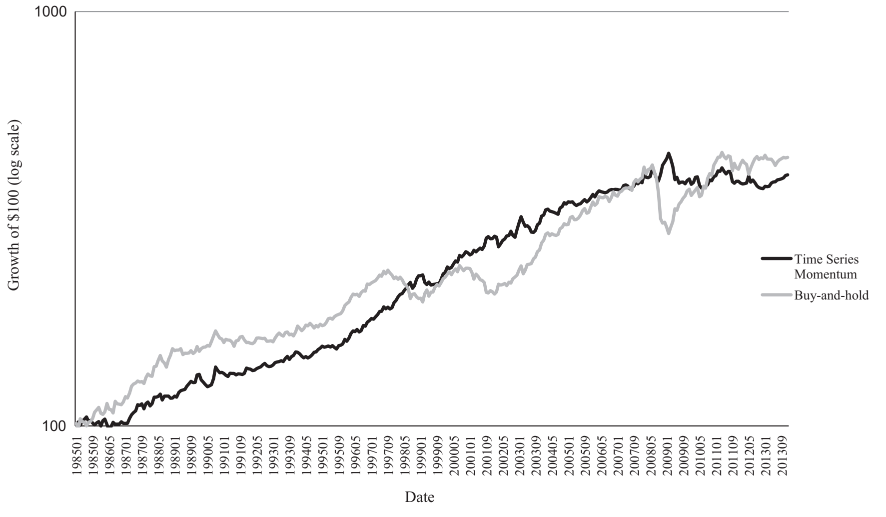

Fig. 3. Cumulative Returns (unscaled). Cumulative dollar returns for unscaled time series momentum, and unscaled buy-and-hold strategies. Plotted are the cumulative returns for unscaled time series momentum and unscaled buy-and-hold strategies using returns from January 1985 to December 2013.

the magnitude of MOP's TSMOM results deriving from effectively levering a strategy with a relatively modest alpha to produce high abnormal returns.

We next consider whether volatility scaling produces significantly higher TSMOM returns than a similar unscaled TSMOM strategy. We summarize the differences in alphas between scaled and unscaled TSMOM for the full portfolio and for each of the four sectors in Panel A of Table 8 for the 1985–2009 period. We report the results using different factor models. For any asset class and factor model used, the difference between scaled and unscaled alphas is larger than 0.5. These results are significant at the 1% level, with the exception of the bond sector for the seven-factor and global-factor models. In Panel B of

Table 8
Summary of differences in alphas between scaled and unscaled time series momentum strategies (1985–2009).

This table reports the differences in alphas between scaled and unscaled time series momentum strategies using different specifications. Panel A reports the differences in alphas for the full portfolio and each sector and Panel B reports the differences in alphas of portfolios excluding one sector at a time. The seven-factor specification is identical to Eq. (4), which includes the MSCI World Index (*msci*), a global commodity factor (*gsci*, the S&P GSCI Index), a bond factor (*aggr*, the Barclays Aggregate Bond Index), a currency factor (*dinx*, U.S. Dollar Index against the major currencies), and the Fama-French and Carhart factors: *smb*, *hml*, and *umd*. The four-factor specification uses the MSCI World Index returns and the Fama-French and Carhart factors. The global equity factor specification is identical to the seven-factor specification except for using global equity factors (*gsmb*, *ghml*, and *gumd*). Since the global equity factors are available from July 1988, we use the North American equity factors before then.

Panel A: Differences in alphas

	7-factor		4-factor		Global factor	
	Diff	*p*-value	Diff	*p*-value	Diff	*p*-value
Full portfolio	0.69	< 0.001	0.86	< 0.001	0.64	< 0.001
Commodity futures	0.54	< 0.001	0.54	< 0.001	0.52	< 0.001
Bond futures	0.51	0.153	1.28	0.004	0.51	0.158
Equity index futures	0.93	< 0.001	0.96	< 0.001	0.84	0.002
Currency futures	1.14	< 0.001	1.20	< 0.001	1.06	0.001

Panel B: Differences in alphas excluding one sector

	7-factor		4-factor		Global factor	
	Diff	*p*-value	Diff	*p*-value	Diff	*p*-value
Commodity futures excluded	0.86	< 0.001	1.19	< 0.001	0.80	< 0.001
Bond futures excluded	0.72	< 0.001	0.72	< 0.001	0.66	< 0.001
Equity index futures excluded	0.65	< 0.001	0.84	< 0.001	0.61	< 0.001
Currency futures excluded	0.62	< 0.001	0.80	< 0.001	0.57	< 0.001

Table 8, we summarize the results of the differences when one of the asset classes is excluded. Regardless of which sector is excluded or which model is used, the scaled TSMOM strategies significantly outperform the unscaled strategies. Again, these results are consistent with our findings that a large portion of the high alphas found by MOP are generated by volatility scaling, not by time series momentum.

5. Conclusion

We re-examine the TSMOM strategy using 55 liquid futures contracts. We find that TSMOM only significantly outperforms the XSMOM strategy and a buy-and-hold strategy during the 1985–2009 period if the TSMOM employs volatility scaling. An unscaled TSMOM strategy does not outperform an unscaled buy-and-hold strategy, and in most cases a scaled TSMOM strategy does not significantly outperform a scaled buy-and-hold strategy. These results hold whether one considers individual futures contracts, sector-specific portfolios, or the full portfolio of futures contracts. Moreover, during the post-crisis period of 2009–2013, the TSMOM strategy does not generate a significant positive alpha regardless of whether the positions are volatility scaled. Overall, the results are consistent with prior TSMOM results being due primarily to the application of leverage to a small positive alpha position. Our findings provide a cautionary warning about using time series momentum strategies in the futures markets.

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