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Time series momentum and moving average trading rules

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We compare and contrast time series momentum (TSMOM) and moving average (MA) trading rules so as to better understand the sources of their profitability. These rules are closely related; however, there are important differences. TSMOM signals occur at points that coincide with a MA direction change, whereas MA buy (sell) signals only require price to move above (below) a MA. Our empirical results show MA rules frequently give earlier signals leading to meaningful return gains. Both rules perform best outside of large stock series which may explain the puzzle of their popularity with investors, yet lack of supportive evidence in academic studies.

Keywords: Technical analysis; Time series momentum; Moving average; Return predictability

JEL Classification: G11; G12

1. Introduction

Moskowitz *et al.* (2012) introduce a 'time-series momentum' (TSMOM) trading rule.¶ They find these rules—which generate a buy signal when the price is higher than a historical, say 200 days prior, price—have strong predictive power.‖ We compare and contrast TSMOM rules and moving average (MA) rules that involve buying an asset when its price moves above its average price over a prior period. By comparing these rules, we are able to provide insight into the sources of the returns they generate. While similar, these rules do not always generate buy and sell signals at the same time. Figures 1(a) and 1(b) gives an example of a faster MA buy signal using S&P 500 data. Price moves above the 200-day moving average (signalling a buy) much sooner than the point where the 200-day return turns positive (necessary for a time series momentum buy signal). We investigate TSMOM and MA rules in the US and internationally, in different economic and market states and consider their susceptibility to crash risk.

There is a puzzling disconnect between the popularity of past price-based trading rules with the investment community (e.g. Hutchinson and O'Brien 2014) and academic papers such as Olson (2004) which find these rules have not added value in the last few decades. We investigate whether this may be due to trading rules being less effective on large stock-dominated market indices that many tests have been conducted on.

Brown and Jennings (1989) were among the first to provide theoretical support for technical analysis. They show investors can use past prices to gain insight into private information in situations where there is incomplete information. More recently, Zhu and Zhou (2009) show moving average trading rules can improve asset allocation decisions by capturing return predictability. The theoretical work that underpins cross-section momentum also helps explain TSMOM. Hong and Stein (1999) suggest prices can move in trends when information diffuses slowly into prices as a result of 'news watchers' in the market. Barberis *et al.* (1998) show the behavioural biases of conservatism and

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¶This is different to Jegadeesh and Titman's (1993) momentum anomaly which focuses on cross-sectional return comparisons. Here, an asset would be purchased if it was among those with the strongest past returns, even if the asset's price had declined during the evaluation period and the relative out-performance was simply due to its returns being less negative than its peers. In contrast, a time series momentum strategy would not buy this asset until it had positive past returns.
‖Other papers also find support for time series momentum. Baltas and Kosowski (2013) show volatility estimators can be used to improve the performance of time series momentum strategies and Antonacci (2013) shows time series momentum or 'absolute momentum' as they call it has value as a stand-alone or overlay strategy.

Figure 1(a). S&P 500 Index—200-day moving average trading rule.

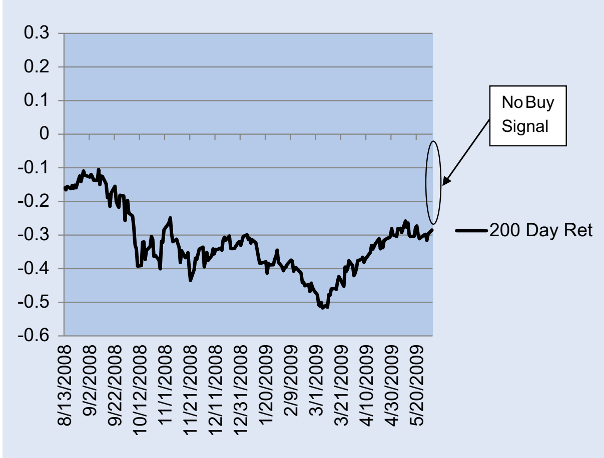

Figure 1(b). S&P 500 Index—200-day time series momentum trading rule.

anchoring lead to under-reaction, while Daniel *et al.* (1998) suggest investors can be overconfident about the accuracy of their private information and this leads to momentum.

TSMOM and MA rules are clearly closely related. TSMOM rules signal a buy (sell) when price moves above (below) a historical price at a certain historical point, while MA rules signal a buy (sell) when price moves above (below) the average price over a historical period. However, there are important differences in the timing of the signals generated by TSMOM and MA rules. We formalize the relation between TSMOM and MA rules and show that TSMOM entry and exit signals are generated when a MA changes direction. Given that a MA is the average of multiple prices, a price change is more likely to result in price moving above (below) the MA, as required for a MA entry (exit) signal, than a MA direction change as required for a TSMOM signal. As such, the signals generated by MA rules are likely to occur before TSMOM signals.

Our empirical results are consistent with these notions. The correlation of the returns generated by long-only TSMOM and MA rules is 0.78 or higher. However, while there is a strong relation between the returns from TSMOM and MA rules, there is a consistent pattern of MA rules generating larger returns, and larger Sharpe ratios and Fama and French (1993)/Carhart (1997) four-factor alphas.† Our core results are from 'long-only' rules which lead to stock market investment following buy signals and T-bill investment following sell signals. However, we verify our results also hold for rules that take short market positions. Our results are consistent with He and Li (2015) who point out that both TSMOM and MA rules capture short-term price trends and Neely *et al.* (2014) who find MA rules outperform TSMOM rules.

We decompose the periods where MA and TSMOM rules are not in the market together and find periods where either MA or TSMOM strategies enter the market before the other rule is characterized by relatively large positive daily returns on average. MA rules generate earlier buy signals more frequently which contribute to its return advantage over TSMOM rules. Moreover, TSMOM strategies are more likely to result in a position remaining open longer than MA strategies. When this occurs, daily returns are negative on average. The earlier closing of MA positions in these instances is of further benefit to MA rules.

The majority of MA rules generate breakeven transaction cost levels that appear to be larger than the actual transaction costs an investor would face. These one-way breakeven costs range from 42 to 69 basis points for rules with 10 to 150 look-back periods. These are larger than the 40 basis points transaction cost which we estimate for our sample period, based on the Jones (2002) estimate of one-way transaction costs (half spread + NYSE commission) of around 100 basis points in 1970 and 20 basis points in 2000. This indicates the rules generate profits after transaction costs. The higher breakeven costs for TSMOM rules reflect the fact that these typically lead to positions being held for longer than their MA equivalents and this lower portfolio turnover results in larger breakeven transaction costs, even though the gross of transaction cost TSMOM returns is lower than their MA equivalents.

We compare and contrast the performance of TSMOM and MA rules on CRSP size quintile indices.‡ Previous empirical tests of MA and TSMOM on equity markets have mostly focused on market indices.§ However, there is good reason to believe these techniques, which capture price continuation, may be more successful on stocks other than the large stocks which dominate market indices. Bhushan (1989) shows analysts focus on large stocks, while Hong *et al.* (2000, p. 267) suggest 'stocks with lower analyst coverage should, all else equal, be ones where firm-specific information moves more slowly across the investing public.'

†These results are not inconsistent. The average monthly return on cross-sectional momentum winner stocks (from Ken French's website) over the 1963–2011 period is 1.51% compared to 0.88% for the CRSP value-weighted index. However, the correlation between these two series is 0.85.

‡We thank Ken French for making these data available on his website.

§MA examples include Brock *et al.* (1992) for the US and Ratner and Leal (1999) for Asian and Latin American markets. The TSMOM paper of Moskowitz *et al.* (2012) is also based on equity indices/futures contracts on these indices. A MA exception is Lo *et al.* (2000) who consider US stocks from different size quintiles.

More recently, Han *et al.* (2013) find that size and volatility indices are closely related and that MA rules are particularly profitable in volatile assets. This is consistent with Zhang (2006) who finds that greater information uncertainty, which can be measured by the standard deviation of returns, leads to greater short-term price continuation. Our results indicate both MA and TSMOM rules perform much better on stocks other than those in the largest quintile. Their good performance is not limited to the smallest stocks but rather is absent in the largest stocks. This finding, which is consistent with Han *et al.* (2013), could help explain why technical analysis remains popular with investors, despite academic studies, which tend to focus on market index data, typically finding these rules add no value.† However, it is important to note that smaller stocks have larger transaction costs, which would impact the net returns received by investor.‡

The issue of data snooping is ever present when investigating return predictability. It is always possible that a trading rule appears to be profitable by chance when it is applied to a particular data series. Lakonishok and Smidt (1988, p. 404) suggest a good way to avoid this is to test anomalies 'in data samples that are different from those in which they were originally discovered.' The important technical analysis paper of Brock *et al.* (1992) finds moving average rules like the ones we test add value when they are applied to the Dow Jones Industrial Average over the 1897–1986 period. We therefore consider the 1987–2013 sub-period to ensure we have an out-of-sample test. The MA alphas for series other than the large stock series remain statistically significant in this period, while the TSMOM alphas are statistically significant on the smallest and middle stock portfolios. MA alphas are larger than their TSMOM equivalents in both sub-periods; however, the differences are more marked in the earlier period. Our results are also robust in the 10 international markets studied by Rapach *et al.* (2013). While MA and TSMOM strategies both generate statistically significant alphas, there is a consistent pattern of larger alphas to MA rules.

Daniel and Moskowitz (2011) and Barroso and Santa-Clara (2014) show cross-sectional momentum is susceptible to periods of persistent negative returns. This 'crash risk' arises following periods of large market declines when the past loser portfolio (where a momentum investor is short) strongly out performs the past winner long portfolio. These momentum crash risk papers are related to the work of Cooper *et al.* (2004) who show momentum returns are positive (negative) when the past three-year market return is positive (negative). We show that neither TSMOM nor MA rules are very susceptible to crash risk. The worst monthly returns from these rules are rarely much worse than those of a buy-and-hold strategy. The worst MA rule returns are frequently better than their TSMOM equivalents so there is no evidence that the larger MA alphas are compensation for crash risk.

†The results of Neely *et al.* (2014) suggest another explanation. They find technical trading rules complement predictions based on fundamental factors.

‡We thank an anonymous referee for highlighting this point.

The rest of this paper is structured as follows: section 2 contains a description of the MA and TSMOM trading rules and data. The key tests are described and the results are presented and discussed in section 3. Additional results are presented and discussed in section 4, while section 5 concludes the paper.

2. Trading rules and data

The MA rules and TSMOM rules we study are both easy to implement. The MA rules are the popular 'moving average' rules. Our base tests are conducted on what Brock *et al.* (1992) refer to as 'variable-length moving average rules', which is calculated as follows§:

$$\mathrm{MA}_{t,n} = \frac{P_{t-n+1} + P_{t-n+2} + \cdots + P_t}{n} \tag{1}$$

A buy signal is generated on day t when:

$$\mathrm{MAR}_{t,n} = P_t - \mathrm{MA}_{t,n} > 0 \quad \text{or} \tag{2a}$$

$$\mathrm{MAR}_{t,n} = P_t - \frac{P_{t-n+1} + P_{t-n+2} + \cdots + P_t}{n} > 0 \tag{2b}$$

where n is the length of the moving average or 'look-back period'. This long equity market position is maintained until price moves below the moving average. The returns following a buy signal are therefore R_{t+1}, R_{t+2}, … , R_{t+k+1}, where k is the number holding days as long as the buy signal still exists. In our core test, we follow Han *et al.* (2013) and invest in the risk-free asset at times when there is no buy signal. An alternative approach, which is also applied in the literature, is to take a short position during these times. This assumes that short sale positions can always be entered, which may not be accurate; so, we limit our analysis of this approach to a robustness check. We also generate results for what Brock *et al.* (1992) call a 'fixed-length moving average' rule. Here, a position is held for a predetermined number of days, regardless of whether price has remained above the moving average of past prices or not.

The TSMOM rule we implement generates a buy signal on day t when:

$$\mathrm{TSMOM}_{t,n} = P_t - P_{t-n} > 0 \tag{3}$$

A sell signals occurs when the price moves below the historical price. This results in the returns R_{t+1}, R_{t+2}, … , R_{t+k+1}.

§We do not attempt to contribute to the literature that considers more sophisticated ways of defining and implementing moving average rule trading strategies (e.g. Hong and Satchell 2015). Rather, we apply basic MA and TSMOM rules that have been widely used in the literature. This allows us to compare and contrast these rules without the suggestion of us tilting the test in the favour of one particular rule by considering a specification that is favourable to it.

While Moskowitz *et al.* (2012) test the statistical significance of trend following strategies using a time series regression model involving the returns in a current period regressed on the returns in a previous period, they implement the trading rule by going long (short) if the returns in the previous period are positive (negative).

Our base test involves an investment in the risk-free asset when there is no buy signal. However, we also test a rule that enters short positions during these periods. This approach is particularly appropriate in markets where short positions are readily established, such as the futures markets studied by Moskowitz *et al.* (2012). We also test a TSMOM rule that leads to investors remaining in the market for a fixed period, regardless of where the current price is in relation to the historical price.

We follow Han *et al.* (2013) and Moskowitz *et al.* (2012) and test rules with a variety of look-back periods. The longest look-back period is 200 days which is consistent with the longest interval in Han *et al.* (2013) and similar to the 12-month look-back period that Moskowitz *et al.* (2012) focus on for the majority of their analysis. We also test periods of 10, 50 and 100 days. A 10-day look-back period is the focus of Han *et al.* (2013). Brock *et al.* (1992) consider periods from 50 to 200 days in their seminal paper.

Equations 4(a), 4(b) and (5) prove it can be shown mathematically that TSMOM rule's buy signals are related to changes in MA direction.†

$$\mathrm{MA}_{t,n} - \mathrm{MA}_{t-1,n} = \frac{P_t - P_{t-n}}{n} \tag{4a}$$

or

$$\mathrm{MA}_{t,n} - \mathrm{MA}_{t-1,n} = \frac{\mathrm{TSMOM}_{t,n}}{n} \tag{4b}$$

so

$$\mathrm{TSMOM}_{t,n} = n \times (\mathrm{MA}_{t,n} - \mathrm{MA}_{t-1,n}) \tag{5}$$

Given equations (3) and (5), we can see a buy signal occurs when there is a movement from:

$$n \times (\mathrm{MA}_{t,n} - \mathrm{MA}_{t-1,n}) < 0 \tag{6a}$$

to

$$n \times (\mathrm{MA}_{t,n} - \mathrm{MA}_{t-1,n}) > 0 \tag{6b}$$

As Equations 6(a) and 6(b) shows, a TSMOM buy signal does not occur until the MA changes direction (passes an inflection point). Since a MA buy signal only requires price to move above the moving average, whereas a TSMOM buy signal requires the MA itself to change direction, MA buy and sell signals are likely to occur before TSMOM buy and sell signals. Moving averages are most likely to change direction following a more sustained change in price over consecutive days.

We use value-weighted size quintile portfolios from Ken French's website for the 1963–2013 period for our base tests. As part of our analysis, we want to document the similarity and differences between the returns to TSMOM and MA rules across the portfolios of different sizes after well-known factors like size, value, cross-sectional momentum and the market factor are accounted for; so, we obtain these data from Ken French's website. We also run tests on the 10 international markets studied by Rapach *et al.* (2013). These include Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland and the United Kingdom. The international sample period is 1973–2013. The equity index data are Thomson Reuters Datastream indices in local currency, while the T-bill data are from Global Financial Data. As a final step, we consider a World ex US index which is the total world market excluding the US from Thomson Reuters Datastream. The risk-free proxy for this analysis is the equal weight of the risk-free rate from the 10 countries we mentioned above.

3. Main results

3.1. *Correlations and raw and risk-adjusted returns' comparison*

In table 1, Panels A and B, we report the monthly return correlations of the long-only MA and TSMOM strategies for the four look-back periods we consider (10, 50, 100 and 200 days). The correlations tend to be larger in the small stock portfolio and for the 10-day look-back period. However, the correlations are all high (0.78 and above). It is evident that MA and TSMOM rules are closely related.

The mean annualized returns in Panels C and D clearly demonstrate that both MA and TSMOM rules generate the largest returns on the smallest quintile, one portfolio, and the smallest returns on the largest quintile, five portfolios. The average raw return across the eight MA and TSMOM rules is 19.6% for the quintile one portfolio compared to 9.6% for the quintile five portfolios. The equivalent average excess returns are 14.6 and 4.6%, respectively. The rules based around shorter look-back periods also produce larger returns than their longer look-back period equivalents. The mean return across the five quintile portfolios for MA and TSMOM is 18.7% for the 10-day look-back period compared to 12.7% for the 200-day look-back period, while the equivalent excess returns are 13.7 and 7.7%, respectively. The mean returns generated by all the MA and TSMOM rules are statistically significantly different to zero. It is also clearly evident that MA rules consistently generate larger returns than their TSMOM equivalents and that these differences are typically statistically significant. We use *, ** and *** to indicate MA and TSMOM means that are statistically significantly different to each other at the 10, 5 and 1% levels, respectively. The out performance of MA rules is stronger in smaller stock series and for shorter look-back

†We are grateful to Henry C. Stern for explaining the equations and discussion in this section to us.

Table 1. Time series momentum and technical analysis performance and comparison.

Look-back	Q1 (Small)		Q2		Q3		Q4		Q5 (Large)	
	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM
Panel A: Correlations (Raw Returns)										
10	0.91		0.86		0.85		0.85		0.78	
50	0.90		0.87		0.90		0.88		0.85	
100	0.91		0.89		0.88		0.86		0.89	
200	0.88		0.85		0.83		0.87		0.88	
Panel B: Correlations (Excess Returns)										
10	0.91		0.86		0.85		0.84		0.78	
50	0.90		0.87		0.90		0.88		0.85	
100	0.91		0.89		0.88		0.86		0.89	
200	0.88		0.85		0.83		0.87		0.88	
Panel C: % Mean Returns (Raw)										
10	**27.7*** **	**24.6*** **	**23.4*** **	**19.4*** **	**22.3*** **	**17.4*** **	**19.7*** **	**15.1*** **	**10.5*** **	**7.4*** **
50	**23.1*** **	**18.0*** **	**19.5*** **	**14.7*** **	**17.4*** **	**14.7*** **	**15.6*** **	**13.2*** **	**9.6**	**8.7**
100	**19.2*** **	**15.3*** **	**16.2*** **	**13.1*** **	**15.1* **	**13.8* **	**13.8**	**13.3**	**9.7**	**10.2**
200	**16.3*** **	**12.9*** **	**14.0* **	**12.1* **	**13.2**	**12.4**	**13.3* **	**11.8* **	**10.8**	**10.2**
Panel D: % Mean Returns (Excess)										
10	**22.6*** **	**19.5*** **	**18.3*** **	**14.4*** **	**17.3*** **	**12.4*** **	**14.7*** **	**10.1*** **	**5.5*** **	**2.4*** **
50	**18.1*** **	**12.9*** **	**14.5 *** **	**9.7*** **	**12.4*** **	**9.6*** **	**10.6**	**8.2**	**4.6**	**3.6**
100	**14.2*** **	**10.2*** **	**11.1*** **	**8.1*** **	**10.1**	**8.7**	**8.8**	**8.3**	**4.6**	**5.2**
200	**11.3*** **	**7.9*** **	**9.0**	**7.1**	**8.2**	**7.4**	**8.3*** **	**6.8*** **	**5.7**	**5.2**
Panel E: Sharpe Ratios										
10	**1.59*** **	**1.37*** **	**1.37*** **	**1.08*** **	**1.46*** **	**1.00*** **	**1.28*** **	**0.85*** **	**0.55*** **	**0.23*** **
50	**1.27*** **	**0.88*** **	**1.07*** **	**0.72*** **	**0.99*** **	**0.76*** **	**0.90*** **	**0.68*** **	**0.44* **	**0.34* **
100	**0.97*** **	**0.67*** **	**0.80*** **	**0.56*** **	**0.79* **	**0.67* **	**0.71**	**0.65**	**0.44**	**0.48**
200	**0.74*** **	**0.48*** **	**0.62** **	**0.46** **	**0.61**	**0.52**	**0.67** **	**0.50** **	**0.52**	**0.42**
Panel F: Jensen Alphas (%)										
10	**18.3*** **	**15.0*** **	**14.5*** **	**10.4*** **	**14.1*** **	**8.8*** **	**11.7*** **	**6.8*** **	**3.5*** **	0.2***
50	**13.7*** **	**7.3*** **	**10.5*** **	**4.5*** **	**8.4*** **	**5.2*** **	**7.0*** **	**3.6*** **	**2.2* **	0.3*
100	**8.7*** **	**3.3*** **	**6.1*** **	**2.0*** **	**5.7*** **	**3.0*** **	**4.7* **	**2.8* **	1.4	1.4
200	**3.9*** **	−1.0***	**2.5*** **	−1.4***	2.0*	−0.6	**2.7** **	−0.1**	1.4	−0.1

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. Panels A and B contain monthly correlations of the raw and excess returns produced by the long-only TSMOM and MA strategies for the four look-back periods. The annualized mean of the raw and excess returns are in Panels C and D, respectively. Panel E contains annualized Sharpe Ratios, while Panel F has annualized alphas based on the four-factor model. Statistically significant means, Sharpe ratios and alphas at the 10% level or more are in bold. *, ** and *** denote means, Sharpe Ratios and alphas that are statistically significantly different to the equivalent metric at the 10, 5 and 1% levels, respectively.

periods. This out performance averages 3.9% in the quintile one portfolio and 1.0% in the quintile five portfolios.

MA rules consistently generate larger Sharpe ratios than their TSMOM equivalents and both methods give larger Sharpe ratios when they are applied to smaller stock series and when shorter look-back periods are used. For instance, the annualized Sharpe ratio of MA (TSMOM) rules for a 10-day look-back period on the quintile one portfolio is 1.59 (1.37) compared to Sharpe ratios for MA (TSMOM) rules of 0.74 (0.48) for a 200-day look-back period on the quintile five portfolios.

Panel F contains the alphas from the Fama and French (1993)/Carhart (1997) four-factor model. As such, these alphas are net of market, size, value and cross-sectional momentum effects. These monthly alphas show a similar trend to the Sharpe ratios. MA alphas are consistently larger than their TSMOM equivalents. We highlight in bold alphas that are statistically significant to zero at the 10% level or more, while *, ** and *** indicate MA and TSMOM alphas that are statistically significantly different to each other at the 10, 5 and 1% levels, respectively (based on the Wald test in a system of equations approach). Both rules generate larger alphas on the smaller stock portfolios with shorter look-back periods. The annual MA (TSMOM) alphas for the 10-day look-back period on the quintile one portfolio are 18.3% (15.0%) and these decline to 1.4% (–0.1%) for 200-day look-back periods and the quintile five portfolios. In section 4, we present results which indicate that the conclusions from results of table 1 are robust in different subperiods, across the business cycle, in international markets, when short positions are entered following sell signals and when positions are held for fixed holding periods.

3.2. *Return difference decompositions*

It is clear from the holding period correlations in table 1 that long market or T-bill positions signalled by MA and TSMOM strategies are consistent for the majority of the time. The return differences we document in table 1 come from periods when one rule has signalled a long market position and the other has not; so, we examine these instances in detail in table 2. Both the MA and TSMOM strategies involve a look-back period of 50 days.† The first two scenarios (‘Same Stock’ and

†We present results for the 50-day look-back period as it is in between the shortest (10 days) and longest (200 days) look-back periods. Results for the other look-back periods are available on request.

Table 2. Time series momentum and technical analysis difference decomposition.

Scenario	Same Stock	Same T-bill	MA Early	TSMOM Early	MA Late	TSMOM Late	MA Only	TSMOM Only
Panel A: Q1 (Small)								
Number of Instances	669	334	284	33	85	414	122	60
Number of Days	6793	4321	586	45	109	708	197	79
Proportion of Daily Deviations			34%	3%	6%	41%	11%	5%
Average Return	0.17%	−0.13%	0.42%	0.61%	−0.19%	−0.11%	−0.70%	−0.40%
Panel B: Q2								
Number of Instances	753	335	291	39	104	466	124	59
Number of Days	6738	4213	597	51	141	797	226	75
Proportion of Daily Deviations			32%	3%	7%	42%	12%	4%
Average Return	0.14%	−0.07%	0.51%	0.69%	−0.10%	−0.14%	−0.80%	−0.49%
Panel C: Q3								
Number of Instances	766	348	299	39	99	499	117	55
Number of Days	6813	4065	604	47	135	890	205	79
Proportion of Daily Deviations			31%	2%	7%	45%	10%	4%
Average Return	0.12%	−0.06%	0.49%	0.78%	0.15%	−0.11%	−0.75%	−0.37%
Panel D: Q4								
Number of Instances	790	341	308	40	98	501	118	60
Number of Days	6675	4180	603	52	133	894	220	81
Proportion of Daily Deviations			30%	3%	7%	45%	11%	4%
Average Return	0.11%	−0.04%	0.51%	0.87%	0.04%	−0.12%	−0.72%	−0.33%
Panel E: Q5								
Number of Instances	918	337	301	45	131	543	140	89
Number of Days	6481	4301	558	61	170	913	226	128
Proportion of Daily Deviations			27%	3%	8%	44%	11%	6%
Average Return	0.05%	0.04%	0.51%	0.93%	0.08%	−0.06%	−0.79%	−0.40%

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. The MA and TSMOM strategies involve a look-back period of 50 days and investing in the equity market (T-bill) following a buy (sell) signal. Scenarios ‘Same Stock’ and ‘Same T-bill’ are when both MA and TSMOM rules are long the equity market or T-bill, respectively, at the same time. Scenario ‘MA Early’ (‘TSMOM Early’) is a period when MA (TSMOM) rules signal long positions first and TSMOM (MA) rule’s long position signals follow. Scenario ‘MA Late’ (‘TSMOM Late’) is when MA (TSMOM) rules are in the market last following a period when both MA and TSMOM rules have signalled long positions. Scenario ‘MA Only’ (‘TSMOM Only’) is a period when MA (TSMOM) rules have signalled long market positions and TSMOM (MA) rules have not. ‘Number of Instances’ and ‘Number of Days’ are the number of occasions that each scenario occurs and the total number of days of each scenario. The ‘Proportion of Daily Returns’ is the percentage of total days across scenarios 1–6 that each scenario represents. The ‘Average Return’ is the average daily return (as a percentage) across the days in each scenario.

‘Same T-bill’) include days when both MA and TSMOM strategies are longer than the equity market or invested in the T-bill at the same time, respectively.† That MA and TSMOM rules generating the same signal is the most common situation. For example, in the small stock portfolio, Same Stock and Same T-bill occur in 6793 and 4321 out of a total of 12,334 sample days, respectively, which represent 90% of the time. The superior performance of MA and TSMOM rules during periods when they both give the same signal exists following long signals and short signals. For instance, in the small stock US portfolio, the average daily market return following long signals is 0.17%, which equates to 43% p.a. Moreover, the average daily equity market return during periods when the MA and TSMOM rules have both given sell signals is –0.13 or –32% p.a. By being in T-bills, MA and TSMOM investors avoid these large losses. The days when MA and TSMOM rules generate different signals can be classified into six mutually exclusive scenarios. Scenarios ‘MA Early’ and ‘TSMOM Early’ are periods when MA (TSMOM) rules signal long positions first and TSMOM (MA) long position signals follow. Scenarios ‘MA Late’ (‘TSMOM Late’) are periods when just the MA (TSMOM) rule remains in the market following a period when both MA and TSMOM have signalled long positions. Scenario ‘MA Only’ (‘TSMOM Only’) are periods when MA (TSMOM) strategies have signalled long market positions and the other rule has not.

In the small stock portfolio, the average returns on MA Early and TSMOM Early days are 0.42 and 0.61%, respectively, which are much larger than those in the Same Scenario. Establishing a long equity market position early that is subsequently followed by the other strategy leads to positive returns for both strategies. However, the MA rule is far more likely to be in this situation (34% of all days where the strategies signal different positions, compared to just 3% for TSMOM rules). MA Late (TSMOM Late) is when the MA (TSMOM) rule in the market lasts following a period when both MA and TSMOM rules have signalled long positions. It is much more common for TSMOM strategies to stay in the market longer (41% of all days with deviations). Moreover, the market returns are –0.11% on these days on average.

†We thank an anonymous referee for suggesting we consider these two scenarios separately.

Table 3. Breakeven transaction costs.

	Q1	Q2	Q3	Q4	Q5
Panel A: Breakeven Transaction Costs—MA					
10	80	50	46	35	1
50	170	92	55	36	−8
100	147	46	26	17	−10
200	92	−5	−17	11	15
Panel B: Breakeven Transaction Costs—TSMOM					
10	80	36	25	14	−16
50	91	10	16	5	−20
100	37	−29	−1	8	−1
200	−72	−118	−66	−56	−4
Panel C: Holding Periods—MA					
10	8	8	8	7	6
50	27	24	22	19	16
100	41	33	29	30	24
200	60	47	40	45	44
Panel D: Holding Periods—TSMOM					
10	11	10	10	9	8
50	34	26	27	25	18
100	46	39	39	36	29
200	86	83	70	68	62

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. Panels A and B contain one-way breakeven transaction costs which reduce returns to those of the buy-and-hold strategy. Panels C and D show the average number of days each position is held for.

Staying in the market longer tends to hurt TSMOM investors. MA rules are less likely to signal positions staying open longer than TSMOM rules (just 6% of deviation days) so the negative returns associated with these periods have less of an impact. Both MA Only and TSMOM Only occur relatively infrequently (11 and 5% of deviation days, respectively). However, when they do occur, market returns are negative on average (–0.70 and –0.40%, respectively).

It is important to note that the returns in table 2 are not directly comparable to the mean returns in table 1. Returns of table 1 include those earned from being invested in the T-bill and they are monthly returns which have been generated from compounding daily returns. However, returns of table 2 can be used to get insight into the difference between mean MA and TSMOM rule's returns in table 1. These differences are most pronounced for the small stock portfolio and the size of the difference decreases monotonically as the portfolio size increases. There is very little difference between the mean MA and TSMOM rule's returns in the large stock portfolio. As such, we would expect the very apparent differences between MA and TSMOM returns in Panel A of table 2 to reduce in Panels B–E. The results indicate this is the case. The main difference in Panel E over Panel A is that the mean TSMOM return in TSMOM Early is higher. This higher return in periods when the TSMOM rule is first to enter a long position offsets some of the negative relative performance of the TSMOM strategy in the other scenarios. It is also clear that the losses from the unique MA signals are larger those to TSMOM signals. However, the net-weighted average return, which is obtained by multiplying the unique MA strategy returns by the proportion of times they occur and deducting the product of the unique TSMOM strategy return and the proportion of times they occur, is still relatively large.

We also investigate whether a combined strategy that only enters and exits positions when both MA and TSMOM rules are in agreement performs better than individual MA and TSMOM strategies. Appendix 1 results indicate this is not the case. The mean returns and Jensen alphas of the combined strategy are typically lower than those for the stand-alone MA strategy, as documented in table 1.

3.3. Transaction cost analysis

We estimate the one-way breakeven transaction costs by comparing MA and TSMOM rules' returns to the returns to a buy-and-hold strategy and present the results in table 3. These are larger for smaller quintile portfolios and 50-day look-back periods. While the 10-day look-back rules generate the larger pre-transaction cost returns, the more frequent turnover that these rules require often results in lower breakeven transaction costs than rules with longer look-back periods and less frequent trading. Jones (2002) estimates one-way transaction costs (half spread + NYSE commission) of around 100 basis points in 1970 and 20 basis points in 2000 for NYSE stocks. Given transaction costs have likely declined further since 2000, it seems reasonable to assume average transaction costs of around 40 basis points over our sample period. The average breakeven transaction cost for 10-day, 50-day and 150-day look-back periods for MA rules ranges from 42 to 69 basis points so these rules appear to generate positive returns after transaction costs.†

†For example, from table 1, we see the mean excess returns p.a. for the 50-day look-back rule on quartile 3 stocks is 12.4%. The average holding period from table 3 is 22 days which implies 11.3 trades per year. If we assume average one-way transaction costs of 40 basis points, we get a total of 11.3 × 2 × 0.4 = 9.0% of transaction costs, which leaves 3.4% of net profit.

Table 4. Worst day performance.

Date (YYYYMMDD)	Q1 (Small) MA (%)	TSMOM (%)	BH (%)	Q3 Date	MA (%)	TSMOM (%)	BH (%)
Panel A: Rank by BH							
19871019	0.03	0.03	−10.60	19871019	0.03	0.03	−12.79
20081201	0.00	0.00	−10.09	20081201	0.00	0.00	−9.47
19871020	0.03	0.03	−9.15	20081015	0.00	0.00	−8.49
20110808	0.00	0.00	−8.44	19871026	0.03	0.03	−8.39
20000414	0.02	0.02	−8.20	20110808	0.00	0.00	−8.39
20081009	0.00	0.00	−8.07	20081009	0.00	0.00	−7.55
19871026	0.03	0.03	−8.02	20080929	0.01	0.01	−6.97
20081015	0.00	0.00	−7.36	20081119	0.00	0.00	−6.89
19800327	0.06	0.06	−6.50	19871020	0.03	0.03	−6.75
20081119	0.00	0.00	−6.50	20081120	0.00	0.00	−6.57
Panel B: Rank by MA							
19971027	−6.13	−6.13	−6.13	19971027	−6.03	−6.03	−6.03
20090420	−4.97	−4.97	−4.97	20090120	−5.49	0.00	−5.49
20111109	−4.52	−4.52	−4.52	20080922	−4.74	−4.74	−4.74
19791009	−4.24	−4.24	−4.24	20090420	−4.60	−4.60	−4.60
20090513	−4.16	−4.16	−4.16	20010102	−4.51	−4.51	−4.51
19810107	−4.08	−4.08	−4.08	19791009	−4.31	−4.31	−4.31
20090109	−4.07	−4.07	−4.07	20090210	−4.14	−4.14	−4.14
20100811	−4.05	0.00	−4.05	20080915	−4.10	−4.10	−4.10
20100506	−3.97	−3.97	−3.97	20111109	−4.08	−4.08	−4.08
20080915	−3.95	−3.95	−3.95	19891013	−3.92	−3.92	−3.92
Panel C: Rank by TSMOM							
19971027	−6.13	−6.13	−6.13	19971027	−6.03	−6.03	−6.03
20080929	0.01	−5.67	−5.67	20080922	−4.74	−4.74	−4.74
20100520	0.00	−5.02	−5.02	20090420	−4.60	−4.60	−4.60
20090420	−4.97	−4.97	−4.97	20010102	−4.51	−4.51	−4.51
20000403	0.02	−4.70	−4.70	19791009	−4.31	−4.31	−4.31
20000412	0.02	−4.67	−4.67	20080917	0.01	−4.21	−4.21
19791010	0.04	−4.64	−4.64	20090210	−4.14	−4.14	−4.14
20080917	0.01	−4.52	−4.52	20080915	−4.10	−4.10	−4.10
20111109	−4.52	−4.52	−4.52	20111109	−4.08	−4.08	−4.08
19791009	−4.24	−4.24	−4.24	19891013	−3.92	−3.92	−3.92

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. The MA and TSMOM strategies involve a look-back period of 50 days and investing in the equity market (T-bill) following a buy (sell) signal. Panel A contains the lowest 10 daily buy-and-hold returns and the corresponding TSMOM and MA rules' returns. The lowest 10 daily returns for the TSMOM strategy and the corresponding MA strategy and buy-and-hold returns. Panel B contains the lowest daily returns for the MA strategy and the corresponding TSMOM rule and buy-and-hold returns. The lowest 10 daily TSMOM returns and corresponding MA rule and buy-and-hold returns are in Panel C. Each part of the analysis is conducted separately for the small and middle stock portfolios.

The breakeven transaction costs for TSMOM rules are never larger than 28 basis points so these rules do not appear to result in profits after transaction costs. Some rules have negative breakeven transactions which they do not generate returns over and above buy-and-hold returns even before transaction costs are accounted for. The results in Panels C and D indicate TSMOM rules typically lead to positions being held for longer than their MA equivalents. However, in spite of this, TSMOM rules have smaller breakeven transaction costs on account of their lower pre-transaction cost returns. It is also important to note that while the smaller stock breakeven transaction costs are larger, the cost of trading smaller stocks is also larger and this affects the net returns to investors in these stocks.

3.4. Downside and higher moment risk

Daniel and Moskowitz (2011) and Barroso and Santa-Clara (2014) both document that cross-sectional momentum is susceptible to 'crash risk'. These periods of persistent negative returns can be a substantial risk for cross-sectional momentum investors. In table 4, we focus on the lowest daily returns generated by a buy-and-hold investor and by TSMOM (MA) strategies and compare these with the returns earned by an investor using an alternative approach on that day. We present results for a look-back period of 50 days for the small portfolio and the middle size portfolio. As documented previously, neither MA nor TSMOM strategies perform well on the large portfolio. The results also indicate that neither the TSMOM nor MA approaches are particularly susceptible to crash risk. It is clear that both MA and TSMOM rules typically move the investor to the T-bill investment prior to sustained market declines. Moreover, the downside returns of MA rules are less severe than their TSMOM rule equivalents. Crash risk compensation is not driving the higher MA rule returns.

The Panel A results show that both TSMOM and MA approaches have considerably less downside risk than a buy-and-hold strategy. The lowest buy-and-hold return in the small portfolio was 19 October 1987. However, investors adopting a TSMOM or MA trading rule would have been invested in the T-bill on this day and therefore would not have lost any money. A similar pattern is evident in each of the other nine days with the largest market decline. In each instance, both the MA and TSMOM rules have generated sell signals and an investor following these rules would be invested in the T-bill.

In Panels B and C, we compare the downside risk of the MA and TSMOM rules. The largest losses by an investor following these rules occur on days where the rule has signalled a long position in the equity market and the equity market declines. It therefore follows that the downside risk of the MA and TSMOM rules will never be larger than the downside risk of the buy-and-hold strategy. However, it is possible that either MA or TSMOM rules do a better job than each other at avoiding market periods with large downside returns.

The Panel B results indicate each of the then most negative returns experienced by a MA investor in the small stock Q1 index is identical to those experienced by a TSMOM investor. Moreover, in the third quintile portfolio, there is only one instance (12 January 2009) when the TSMOM rule had already signalled an exit from the equity market and the MA rule had not, prior to a large decline. In contrast, an investor using a MA rule on the smallest stock portfolio would have avoided 6 of the 10 largest daily declines experienced by a TSMOM investor. This only occurred in one of the ten days in the third quintile portfolio. However, the overall evidence suggests the MA rule does a better job of minimizing downside risk.

Barroso and Santa-Clara (2014) point out cross-sectional momentum strategies can experience large crashes. Although such strategies may be profitable on average, they may not be appealing to an investor with a reasonable level of risk aversion. They suggest it is therefore important to consider the higher moments of any trading strategy. Results of Table 5 show the MA and TSMOM strategies generate larger returns on the size quintile indices (other than the top two quintiles) than the returns from the size, value or cross-sectional momentum factors. As Barroso and Santa-Clara (2014) document, cross-sectional momentum has large negative skewness, but this is not present in the MA or TSMOM rule's results. Rather, the MA rule generates relatively large positive skewness. MA strategy returns have lower kurtosis than their TSMOM equivalents, but both rules have kurtosis that is considerably lower than that in the cross-sectional momentum rules.

Daniel and Moskowitz (2011) also consider market timing and the sources of crash risk in cross-sectional momentum portfolios using a number of models. We apply the logic behind these models to investigate crash risk in both TSMOM and MA rules. The results are presented in table 6.

$$r_{P,t} - r_{f,t} = [\alpha_0 + \alpha_B I_B] + \left[\beta_0 + \beta_B I_B + \beta_{B,U} I_B I_U\right]\left(r_{m,t} - r_{f,t}\right) + \varepsilon_t \quad (7)$$

$$r_{P,t} - r_{f,t} = \gamma_0 + \gamma_B I_B + \gamma_{mkt}\sigma_m^2 + \gamma_{\text{highstress}} I_B \sigma_{m,t}^2 + \upsilon_t \quad (8)$$

where†:

$r_{P,t}$	is the return on either the TSMOM or MA portfolio in month t
$r_{f,t}$	is the return on the Treasury bill in month t
$r_{m,t}$	is the return on the CRSP VW portfolio in month t
I_B	is an ex-ante indicator variable for bear markets. If the CRSP VW index return is negative (positive) in the prior 24 months prior to month t, the variable is 1 (0)
I_U	is a contemporaneous up-month indicator variable. If the CRSP VW index return is positive (negative) in month t, the variable is 1 (0)
σ_m^2	is an ex-ante market volatility estimate for the next month. We use the standard deviation of the CRSP VW index return over the 50 days prior to month t.

The conditional CAPM in equation (7) examines the alpha and beta differences in bear markets versus other periods.‡ For the TSMOM portfolio, the alpha difference between the bear periods and other periods, α_B, is not significantly different from zero in any of the size quintile portfolios. The changes in alphas driven by the bear periods are also insignificant for the size quintile 1 portfolio for the MA rule. However, the impact of the bear period significantly reduces the alphas of the medium and large size MA strategy portfolios.

During the bear period, the betas have a statistically significantly decline across all size quintile portfolios for both TSMOM and MA rules, which indicates that the portfolio returns become less sensitive to the downside market movement. This implies the TSMOM and MA strategies tend to switch to the T-bill during bear periods. The coefficient $\beta_{B,U}$ captures the sensitivity of the strategy return to changes in market direction. The significantly positive $\beta_{B,U}$ suggests that the portfolio exposure increases with the contemporaneous positive market movement. This confirms the market timing ability of both TSMOM and MA strategies.

Equation (8) examines the impact of market stress on the TSMOM and MA strategies. When the market volatility is high in bear periods, the estimated coefficients $\gamma_{\text{highstress}}$ in all size quintile portfolios are not statistically different from zero; so, both TSMOM and MA are immune to the high market stress periods in bear markets.

4. Additional results

4.1. Sub-period results

We test the robustness of our claims, based on the full-sample results of tables 1 and 2, in different periods in appendix 2. We consider two sub-periods. The most recent sub-period of 1987–2013 is chosen to ensure we have an 'out-of-sample'

†See Daniel and Moskowitz (2011) for more detail on these variables.
‡Each of the alpha estimates is annualized.

Table 5. Higher moment risks.

	Max	Min	Mean	SD	Skewness	Kurtosis
RM-RF	1.932	−2.789	0.058	0.157	−0.517	4.769
SMB	2.642	−1.967	0.033	0.109	0.515	8.345
HML	1.664	−1.522	0.044	0.101	0.005	5.470
UMD	2.207	−4.166	0.084	0.150	−1.404	13.664
MA1—RF	3.007	−1.108	0.181	0.142	1.160	5.978
MA2—RF	2.074	−2.137	0.145	0.136	0.511	5.140
MA3—RF	1.963	−1.763	0.124	0.125	0.438	4.641
MA4—RF	1.905	−1.559	0.106	0.118	0.575	4.427
MA5—RF	1.302	−1.558	0.046	0.103	0.366	4.354
TSMOM1—RF	3.007	−1.737	0.129	0.147	0.738	6.076
TSMOM2—RF	2.074	−1.342	0.097	0.135	0.468	4.290
TSMOM3—RF	1.883	−1.632	0.096	0.127	0.229	4.263
TSMOM4—RF	1.727	−1.849	0.082	0.121	0.242	4.584
TSMOM5—RF	1.511	−1.418	0.036	0.108	0.097	4.595

Notes: Fama and French's factor data are from Ken French's website. Other data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. All numbers are annualized.

period that follows the 1887–1986 period used by the important moving average technical analysis paper of Brock *et al.* (1992). Lakonishok and Smidt (1988) note that an effective tool to combat data mining bias is to use data-sets different from those researchers use to first document the same anomalies.†

The Panel A results show the correlations are large in both the early sub-period and the more recent one, but they are marginally larger in the earlier sub-period (average = 0.91) than the more recent period (average = 0.86). MA rules are profitable in both sub-periods. The alphas are consistently positive and statistically significantly different from zero in all but the large stock portfolio. The TSMOM alphas are statistically significant in the small and medium portfolios. The lack of robust predictability for MA in the recent period for the large stocks is consistent with Olson's (2004) finding that moving average trading rules are not profitable in the 1990s. MA alphas are larger than their TSMOM equivalents in both sub-periods. These differences are statistically significant for the first four portfolios in the 1965–1986 period and for the small portfolio in the 1987–2013 period.

Henkel *et al.* (2011), Dangl and Halling (2012) and Rapach *et al.* (2013) all find that predictability is stronger in recessions than expansions. Cooper *et al.* (2004) find the cross-sectional momentum strategy is only profitable if the market has been going up over the previous 36 months. Both the MA and TSMOM rules' returns are larger in periods following market increases, which is unsurprising given both rules are trend-following techniques.‡ Moreover, the MA and TSMOM rules' results for these states, which we report in appendix 3, are consistent with the core results. The correlation between MA and TSMOM rules' returns is high in all states and the MA alphas are consistently larger than their TSMOM equivalents. There is also evidence that both MA and TSMOM rules generate large alphas in recessions, which is consistent with Neely *et al.* (2014).

†The international market results we generate also address this issue.

‡We thank an anonymous referee for highlighting this.

4.2. *International results*

We repeat our core analysis for the 10 international markets considered by Rapach *et al.* (2013). These are Australia, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland and the UK. We also include the MSCI World excluding US index. The results are for the long-only strategy and a look-back period of 50 days. Results in Panel A of table 7 indicate the correlation between MA and TSMOM rules' returns is large in each market. The correlations range from 0.81 in Australia to 0.91 in Sweden. Mean returns to MA rules are generally larger than those to TSMOM rules, which is also in accordance with the US results. MA and TSMOM rules perform the best in Sweden, Italy and Australia and the worst in Japan. The Sharpe ratio and Jensen alpha results are similar to the mean results in that they are higher for MA than TSMOM rules in the majority of countries.

Table 8 contains results which decompose return differences between MA and TSMOM rules for the MSCI World excluding US index. These results confirm those documented in table 2 for the US. 'MA Early' is over five times more common than 'TSMOM Early'; so, while the average return on days when the MA rule is long the equity market first are lower than those when TSMOM is in the market first, the fact that 'MA Early' occurs more frequently results in a return advantage to the MA rule. Similar to the US results, 'MA Late' is far less common than 'TSMOM late' and the returns on days when the TSMOM rule is long the equity market and the MA has exited are negative, which contributes to the higher relative MA returns. The 'MA Only' and 'TSMOM Only' results are also similar to their US equivalents in that the average daily equity returns are negative when one rule signals a long equity market position and the other does not.

4.3. *Short position results*

If MA and TSMOM rules are as effective at signalling declines in the equity market as they are at signalling equity

Table 6. Crash risk.

	Market Timing			Market Stress	
	MA	TSMOM		MA	TSMOM
Panel A: Q1 (Small)					
α_0	0.129***	0.091***	γ_0	0.314***	0.344***
α_B	−0.028	−0.024*	γ_B	0.130	0.021
β_0	0.502***	0.530***			
β_B	−0.214**	−0.164**			
$\beta_{B,U}$	0.411**	0.208***			
			γ_{sd}	−0.004***	−0.005***
			$\gamma_{\text{highstress}}$	0.001	0.002
Adjusted R^2	0.317	0.294		0.041	0.055
Panel B: Q2					
α_0	0.097***	0.056***	γ_0	0.267***	0.289***
α_B	−0.088*	−0.056	γ_B	0.191**	0.071
β_0	0.527***	0.584***			
β_B	−0.238**	−0.271**			
$\beta_{B,U}$	0.537***	0.333*			
			γ_{sd}	−0.003***	−0.005***
			$\gamma_{\text{highstress}}$	−0.001	0.001
Adjusted R^2	0.409	0.406		0.050	0.062
Panel C: Q3					
α_0	0.082***	0.055***	γ_0	0.244***	0.266***
α_B	−0.110***	−0.084**	γ_B	0.180**	0.079**
β_0	0.539***	0.580***			
β_B	−0.268***	−0.307***			
$\beta_{B,U}$	0.541***	0.436***			
			γ_{sd}	−0.003***	−0.004***
			$\gamma_{\text{highstress}}$	−0.001	0.001**
Adjusted R^2	0.481	0.466		0.054	0.057
Panel D: Q4					
α_0	0.061***	0.034***	γ_0	0.225***	0.269***
α_B	−0.148***	−0.042	γ_B	0.119	0.045
β_0	0.542***	0.593***			
β_B	−0.386***	−0.318***			
$\beta_{B,U}$	0.723***	0.371**			
			γ_{sd}	−0.003***	−0.005***
			$\gamma_{\text{highstress}}$	0.000	0.002
Adjusted R^2	0.544	0.508		0.046	0.070
Panel E: Q5 (Large)					
α_0	0.006	−0.012	γ_0	0.171***	0.219***
α_B	−0.131***	−0.032	γ_B	0.025	−0.039
β_0	0.515***	0.608***			
β_B	−0.445***	−0.483***			
$\beta_{B,U}$	0.646***	0.377**			
			γ_{sd}	−0.003***	−0.005***
			$\gamma_{\text{highstress}}$	0.001	0.003
Adjusted R^2	0.548	0.564		0.042	0.070

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period. The MA and TSMOM strategies involve a look-back period of 50 days and investing in the equity market (T-bill) following a buy (sell) signal. The equation specifications are as per Daniel and Moskowitz (2011). Statistical significance at the 10, 5 and 1% levels (based on Newey and West (1987) standard errors) is denoted by *, ** and ***, respectively. α_0 and α_B numbers are annualized.

market increases, then entering short equity market positions following market declines rather than investing in T-bills should generate larger returns than those in our base tests. In other words, the gains from short positions in the long/short approach will exceed the returns from being in T-bills in the long-only approach. Appendix 4 results show that both MA and TSMOM rules do typically generate larger returns when short positions are permitted. In particular, the scenarios where the largest returns are generated, such as the 10-day look-back on the small portfolio, show a marked increase.

The MA (TSMOM) monthly Jensen alpha increases from 27.7% (24.6%) in the long-only 10-day look-back scenario to 38.5% (32.0%) in the long/short approach. Lower returns are generated by long/short rules for some longer look-back rules on larger stock portfolios. However, what is clear is that the relation between MA and TSMOM strategy returns for any given size portfolio and look-back period is very

Table 7. International evidence.

	Australia	Canada	France	Germany	Italy	Japan	Netherlands	Sweden	Switzerland	UK	MSCI World × US
Panel A: Correlations (Raw Returns)											
Return	0.81	0.86	0.85	0.86	0.88	0.85	0.84	0.91	0.83	0.87	0.86
Holding Period	0.71	0.84	0.82	0.84	0.83	0.82	0.82	0.86	0.80	0.86	0.82
Panel B: Correlations (Excess Returns)											
Return	0.81	0.86	0.85	0.86	0.88	0.85	0.84	0.91	0.83	0.87	0.86
Holding Period	0.71	0.84	0.82	0.84	0.83	0.82	0.82	0.86	0.80	0.86	0.82
Panel C: % Mean Returns (Raw)											
MA	**13.2*** **	**12.1* **	**12.6** **	**10.7** **	**16.3** **	**11.2**	**8.0**	**19.1*** **	**9.3* **	**10.2**	**13.3**
TSMOM	**10.4*** **	**10.5* **	**9.9** **	**8.5** **	**13.1** **	**9.4**	**8.2**	**16.0*** **	**7.7* **	**9.4**	**12.3**
Panel D: % Mean Returns (Excess)											
MA	**5.3*** **	**5.7* **	**6.1** **	**6.4** **	**7.7** **	**8.3**	**3.3**	**12.5*** **	**6.5**	2.9	**7.6**
TSMOM	2.4***	**4.1* **	3.4**	**4.2** **	4.5**	**6.6**	**3.5**	**9.4*** **	**4.9**	2.1	**6.5**
Panel E: Sharpe Ratios											
MA	**0.44*** **	**0.51** **	**0.44** **	**0.49** **	**0.44*** **	**0.67** **	**0.26**	**0.78*** **	**0.61** **	**0.20**	**0.81**
TSMOM	0.19**	**0.35** **	**0.24** **	**0.33** **	**0.24*** **	**0.49** **	**0.27**	**0.57*** **	**0.42** **	0.16	**0.70**
Panel F: Jensen Alphas (%)											
MA	1.6**	1.9	1.7**	**2.9** **	**2.8** **	**5.3**	−0.4	**5.0*** **	**3.3* **	**−1.9**	**3.6**
TSMOM	−1.8**	0.4	−1.1**	0.8**	−0.5**	**3.4**	−0.5	1.8***	1.3*	**−2.3**	**2.6**

Notes: International results are calculated for the countries studied by Rapach, Strauss, and Zhou (2013). Equity data are obtained from Thomson Reuters Datastream. T-Bill Data are from Global Financial Data. The data cover the 1973–2013 period. Returns are in local currency. The results are for the long-only strategy and a look-back period of 50 days. The correlations are based on monthly returns. Mean returns, Sharpe Ratios and Jensen Alphas are annualized. Statistically significant means, Sharpe ratios and alphas at the 10% level or more are in bold. *, ** and *** denote MA and TSMOM means, Sharpe Ratios and alphas that are statistically significantly different to the equivalent MA or TSMOM metric at the 10, 5 and 1% levels, respectively.

Table 8. International time series momentum and technical analysis difference decomposition.

Scenario	Same Stock	Same T-bill	MA Early	TSMOM Early	MA Late	TSMOM Late	MA Only	TSMOM Only
Number of Instances	239	182	59	27	64	155	66	44
Number of Days	6134	3093	324	57	163	574	233	119
Proportion of Daily Deviations			22%	4%	11%	39%	16%	8%
Average Return	0.07%	−0.03%	0.31%	0.62%	−0.04%	−0.07%	−0.35%	−0.22%

Notes: This is as per table 2. MSCI World (Excluding U.S.) equity data are obtained from Thomson Reuters Datastream. T-Bill Data are from Global Financial Data. The data cover the 1973–2013 period.

similar, regardless of whether the long-only or long/short settings are used. MA rules consistently have larger returns, larger Sharpe ratios and larger Jensen alphas than their TSMOM equivalents. The statistical significance of the Jensen alpha differences also shows the same pattern of being stronger for rules with shorter look-back periods on smaller portfolios. Although the results in appendix 4 are more appealing than those in table 1, short selling constraints often limit the ability of investors to take short positions in reality (e.g. Barberis and Thaler 2002).

4.4. Fixed holding period results

Another approach to implementing MA and TSMOM rules is to hold positions for a fixed period, ignoring any sell signals that occur before the end of this period. This period is the minimum holding period as a buy signal at the end of this period would result in the position being maintained, i.e. in reality, an individual would not sell a position one day and open a new position on that day. Rather, they would just keep their position open. Brock *et al.* (1992) also test such a strategy, which they refer to as a 'fixed-length moving average' approach, alongside the more flexible holding period approach we use for our base tests and did not find material differences between the two. We present results for a 50-day look-back period and a 10-day holding period in appendix 5. These results are very similar to those in table 1 in that the MA strategy consistently has higher returns, Sharpe ratios and Jensen alphas than TSMOM.

5. Conclusions

Moving average trading rules and time series momentum have developed as two separate parts of the return predictability literature. Moving averages rules generate a buy signal when the price moves above the average historical price over a defined number of days. Time series momentum rules generate buy signals when the return over a past period is positive. This is distinct from cross-sectional momentum which generates buy signals based on the return of a security relative to the return of other securities.

We show moving average technical trading rules and time series momentum rules are closely related. The returns generated by each method frequently have correlations that are in excess of 0.8. There are, however, important differences between the two. We document the relation between TSMOM and MA rules. TSMOM rule's entry and exit signals are generated when a MA changes direction, which suggests that TSMOM rules tend to take longer than MA rules to give a buy or sell signal. After all, a price change is more likely to result in price moving above (below) the MA, which is required for a MA entry (exit) signal, than it is to cause a MA direction change, as required for a TSMOM signal.

Our empirical results are consistent with this finding. MA rules are more likely to signal a buy signal sooner and exit long positions more quickly, which leads to larger returns on average. MA rules also tend to generate larger Sharpe ratios and larger Jensen alphas than their TSMOM equivalents. We find that both trading rules are most profitable on stocks other than largest quintile stocks. Previous studies have shown moving average rules are not profitable on equities since the mid-1980s. We show this result holds for the largest stocks but not for mid-capitalization or small stocks. This may reconcile the puzzle of the continuing popularity of these rules with the investment community, despite the lack of supportive evidence for these rules in studies using market indices dominated by large stocks.

Unlike cross-sectional momentum, neither MA nor TSMOM strategies are particularly susceptible to crash risk. Both these rules exit long positions prior to sustained market downturns. MA rules are better at this than their TSMOM equivalents so there is no evidence that larger returns accruing to MA rules are compensation for higher crash risk.

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Appendix 1. Combining time series momentum and technical analysis.

Look-back	Q1 (Small)	Q2	Q3	Q4	Q5 (Large)
Panel A: Holding Periods					
10	10	8	8	8	7
50	28	23	23	21	16
100	43	36	34	30	25
200	65	48	42	47	46
Panel B: Mean Returns (%)					
10	**26.5**	**21.6**	**19.4**	**17.0**	**8.6**
50	**20.0**	**16.4**	**15.8**	**14.2**	**8.8**
100	**17.4**	**15.0**	**14.8**	**13.5**	**9.9**
200	**14.2**	**12.7**	**12.3**	**12.5**	**10.2**
Panel C: Sharpe Ratios					
10	**1.63**	**1.39**	**1.32**	**1.15**	**0.40**
50	**1.11**	**0.92**	**0.93**	**0.86**	**0.40**
100	**0.91**	**0.78**	**0.83**	**0.75**	**0.49**
200	**0.64**	**0.56**	**0.58**	**0.64**	**0.48**
Panel D: Jensen Alphas (%)					
10	**17.4**	**13.2**	**11.0**	**9.1**	1.7
50	**10.3**	**7.4**	**7.3**	**5.7**	1.3
100	**6.7**	**5.0**	**5.3**	**4.3**	1.9
200	2.0	1.2	1.2	2.0	0.8

Notes: The results are as per table 1, except that buy and sell signals are only implemented when both MA and TSMOM rules are in agreement. Statistical significance at the 10% level or better (based on Newey and West (1987) standard errors) is denoted by bold numbers. Panels B–D are annualized numbers.

Appendix 2. Performance and comparison by period.

Panel A: Correlations	1965–1986	1987–2013
Q1 (Small)	0.93	0.87
Q2	0.91	0.84
Q3	0.92	0.88
Q4	0.91	0.87
Q5 (Large)	0.87	0.84

Panel B: Jensen Alphas by Time Period (%)	MA 1965–1986	MA 1987–2013	TSMOM 1965–1986	TSMOM 1987–2013	MA vs. TSMOM *p*-values 1965–1986	MA vs. TSMOM *p*-values 1987–2013
Q1 (Small)	**16.1#**	**11.9#**	**8.2**	**6.4**	0.00	0.00
Q2	**14.8#**	**7.4#**	**6.9#**	**2.8#**	0.00	0.00
Q3	**12.8#**	**5.4#**	**6.7**	**4.1**	0.00	0.34
Q4	**10.7#**	**4.7#**	**5.7**	2.6	0.00	0.05
Q5 (Large)	**4.2#**	**0.8#**	0.8	0.1	0.04	0.63

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period from Ken French's website. The MA and TSMOM strategies involve a look-back period of 50 days and investing in the equity market (T-bill) following a buy (sell) signal. Panel A contains return correlations by sub-period. Annualized alphas, based on the four-factor model, are in Panel B. Statistical significant alphas at the 10% level or more are in bold. *p*-values from a test of the statistical significance of the differences in MA and TSMOM alphas are also provided. We also run a t-test to determine whether the difference in MA (TSMOM) alphas between the two sub-periods is statistically significant. Those that are (at the 10% level or stronger) are denoted by a #.

Appendix 3. Performance and comparison by economic and market state.

	Recession	Expansion		36-Month up	36-Month down	
Panel A: Correlations						
Q1 (Small)	0.82	0.92		0.91	0.88	
Q2	0.81	0.89		0.89	0.83	
Q3	0.90	0.90		0.90	0.90	
Q4	0.86	0.89		0.89	0.89	
Q5 (Large)	0.76	0.87		0.86	0.82	
Panel B: Jensen Alphas by Business Cycle (%)						
	Recession		Expansion		MA vs. TSMOM *p*-values	
	MA	TSMOM	MA	TSMOM	Recession	Expansion
Q1 (Small)	17.4***	6.0	13.1***	7.5***	0.00	0.00
Q2	15.6***	7.6*	9.6***	3.9***	0.00	0.00
Q3	13.7***	10.2***	7.5***	4.3***	0.26	0.00
Q4	13.9***	9.4***	5.7***	2.5*	0.08	0.00
Q5 (Large)	9.5***	7.4**	0.9	−1.0	0.48	0.07
Panel C: Jensen Alphas by Up and Down Markets (%)						
	Previous 36-Month Up		Previous 36-Month Down		MA vs. TSMOM *p*-values	
	MA	TSMOM	MA	TSMOM	36-Month Up	36-Month Down
Q1 (Small)	18.5***	10.0***	12.4***	6.5***	0.00	0.00
Q2	11.1***	5.8**	10.3***	4.1***	0.03	0.00
Q3	9.8***	8.2***	8.0***	4.4***	0.52	0.00
Q4	10.3***	9.5***	6.0***	1.9	0.69	0.00
Q5 (Large)	7.3***	6.4**	0.7	−1.4	0.60	0.07

Notes: Data are CRSP quintile value-weighted size portfolios for the 1963–2013 period from Ken French's website. The MA and TSMOM strategies involve a look-back period of 50 days and investing in the equity market (T-bill) following a buy (sell) signal. Panel A contains return correlations, NBER business cycle and market return over the prior 36 months. Annualized alphas, based on the four-factor model, are in Panels B and C. Statistical significance at the 10, 5 and 1% levels (based on Newey and West (1987) standard errors) is denoted by *, ** and ***, respectively. *p*-values from a test of the statistical significance of the differences in MA and TSMOM alphas are also provided.

Appendix 4. Long/short time series momentum and technical analysis robustness.

Look-back	Q1 (Small)		Q2		Q3		Q4		Q5 (Large)	
	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM
Panel A: Correlations										
10	0.80		0.71		0.68		0.67		0.56	
50	0.78		0.74		0.78		0.76		0.69	
100	0.79		0.77		0.75		0.70		0.76	
200	0.71		0.67		0.64		0.72		0.75	
Panel B: Mean Returns (%)										
10	38.5	32.0	29.4	21.2	27.4	17.5	22.5	13.3	6.0	−0.1
50	29.2	19.2	21.8	12.2	17.8	12.3	14.7	10.1	4.7	3.1
100	21.6	14.0	15.2	9.4	13.4	10.8	11.4	10.5	5.2	6.6
200	16.2	10.0	11.6	8.2	10.1	9.1	11.0	8.3	8.0	7.3
Panel C: Sharpe Ratios										
10	1.78	1.52	1.33	0.94	1.38	0.75	1.12	0.52	0.07	−0.35
50	1.30	0.72	0.89	0.39	0.74	0.41	0.61	0.31	−0.02	−0.13
100	0.85	0.44	0.54	0.23	0.47	0.33	0.37	0.33	0.01	0.10
200	0.55	0.23	0.33	0.15	0.29	0.21	0.37	0.18	0.20	0.14
Panel D: Jensen Alphas (%)										
10	**35.0*****	**27.9*****	**26.0*****	**17.3*****	**23.9*****	**13.3*****	**18.7*****	**8.9*****	**1.4*****	**−5.1*****
50	**25.5*****	**12.8*****	**17.9*****	**5.8*****	**12.9*****	**6.4*****	**9.5*****	**2.9*****	−0.8*	−4.2*
100	**15.7*****	**5.1*****	**9.2*****	**1.2*****	**7.5****	**2.3****	**5.3**	1.7	−1.8	−1.6
200	**6.3*****	−2.9***	**2.6****	−4.8**	0.6	−4.0	**1.9****	−3.2**	−1.3	−3.6

Notes: The results are as per table 1, except that short equity market positions are entered following sell signals. Means, Sharpe Ratios and Jensen Alphas are annualized numbers. Statistically significant (based on Newey and West (1987) standard errors) alphas at the 10% level or more are in bold. *, ** and *** denote MA and TSMOM alphas that are statistically significantly different at the 10, 5 and 1% levels, respectively.

Appendix 5. 50-day look-back period and 10-day minimum holding periods.

	Q1 (Small)		Q2		Q3		Q4		Q5 (Large)	
	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM	MA	TSMOM
Correlations	0.75		0.71		0.68		0.67		0.65	
Mean Returns	24.9	14.8	19.5	10.2	13.0	10.5	10.7	8.4	5.4	5.0
Sharpe Ratio	1.09	0.49	0.81	0.28	0.44	0.32	0.33	0.21	0.03	0.00
Jensen Alpha	17.5***	5.2	13.1***	1.2	6.4***	2.1	3.7	−0.1	−1.3	−3.0

Notes: The results are as per table 1, except that long equity market positions are held for a minimum of 10 days, regardless of whether there is a sell signal during this time or not. If there is still a buy signal after the 10-day period, the position is maintained. Means, Sharpe ratios and Jensen Alphas are annualized numbers. Statistically significant (based on Newey and West (1987) standard errors) alphas at the 10% level or more are in bold. *, ** and *** denote MA and TSMOM alphas that are statistically significantly different at the 10, 5 and 1% levels, respectively.