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Improving market timing of time series momentum in the Chinese stock market

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ABSTRACT
This paper is the first study to present firm-level evidence that the time-series momentum (TSMOM) strategies with look-back-period k of 10 to 200 days outperform the buy-and-hold strategy (BH) on individual stocks in the Chinese stock market. We document that the optimal k^* generating the best performance is different across assets and varies over time. We hence propose a model to predict the asset-specific and time-dependent k^*, and examine the performance of the TSMOM strategies with the predicted k^*. Our analysis shows that using the time-varying predicted k^* substantially improves the predictability of the TSMOM strategies. Our new model and findings shed the light on trading strategy for both academia and applied investment practitioners.

KEYWORDS
Technical analysis; time-series momentum; market timing; Chinese stock market

JEL CLASSIFICATION
C32; C53; G11; G12

I. Introduction

Market timing is an active trading strategy that aims to outperform the buy-and-hold (denoted as BH hereafter) strategy. Investors use technical analysis to predict the direction of the markets and decide the timing of moving in and out of the markets or switching between different asset classes. Technical analysis is not only popular among practitioners but also receives wide recognition from academic literature.[1]

Among various technical indicators, trend continuation indicators are widely used by practitioners. Recently, a new trend indicator of equity prices, relating to time-series momentum (denoted as TSMOM), attracts the attention of many researchers. Moskowitz, Ooi, and Pedersen (2012) first document the evidence of TSMOM which is present in diversified markets including equity indices, bonds, currencies, and commodities. They find that the past 12-month excess returns of an instrument can predict its future returns. Marshall, Nguyen, and Visaltanachoti (2017) compare the time-series momentum with the moving average trading rules and suggest that both trading rules create robustly positive returns to stock portfolios in international markets. Moreover, Chakrabarti (2015) finds evidence on the profitability of TSMOM during the period of 2004–2015, which is a global economic cycle, across international stock markets including Asian, European region, and the United States. More recently, Guo et al. (2018) collect the high-frequency ETF data in the US stock market and apply the TSMOM trading rules in intraday trading. They find that the returns of the first half-hour of the trading day can be used to predict the returns of the last half-hour, and both the in-sample and out-of-sample results exhibit statistically and economically significant predictability. Shi and Zhou (2017) look at the Chinese market index and claim that TSMOM exhibits profitability in the strategies with short-term look-back and holding periods. They also find that the TSMOM in China is weaker compared with the evidence found in the US, and their conclusions suggest that these findings are attributed to the data frequency.

Given the mixed empirical evidence from literature, the implementability of the TSMOM strategies for practitioners becomes questionable. Particularly, it is uncertain what the look-back period (denoted k) should be for an optimal TSMOM strategy. On one hand, Moskowitz, Ooi, and Pedersen (2012) and Marshall, Nguyen, and Visaltanachoti (2017) ascertain that the TSMOM strategy over a fixed k of 12-month can achieve

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[1]Such as Brock, Lakonishok, and LeBaron 1992; Blume, Easley, and O'Hara 1994; Zakamulin 2015; Lo, Mamaysky, and Wang 2000; Zhu and Zhou 2009; Neely et al. 2014; Kilgallen 2012; Huang and Zhou 2013; Glabadanidis 2014, 2015; Han, Yang, and Zhu 2016, etc.

positive excess returns on diverse asset classes. On the other hand, results from some other researchers (e.g. He and Li (2015) and Shi and Zhou (2017)) show that the performance for TSMOM strategies with different k values is quite different. Besides, Moskowitz and Pedersen (2013) argue that TSMOM is everywhere, while Huang et al. (2019) show that using the 12-month fixed k for the large cross-section of assets, there is little evidence of TSMOM. A more critical view is expressed in Zakamulin (2014). He does not believe the superior performance based on trading rules including TSMOM and moving average, claiming it 'too good to be true'. He points out that many studies involve data-mining. Given the hot debates in the literature, our study is hence motivated to reconcile these arguments in the literature, by allowing k to vary both across different assets and over time. We conjecture that the performance of TSMOM depends on the value of k, which could be different for different assets and over different periods. Hence, in our test of the profitability of TSMOM, we first employ different k values and identify the optimal value that generates the highest TSMOM profits. We then move one step further from existing literature, by exploring the determinant factors of the optimal k. Such practice helps us to predict the next optimal k in the following trading horizon and establish an empirically implementable trading strategy.

Our paper focuses on the performance of TSMOM strategies with varying k values on the Shanghai and Shenzhen 300 index (CSI300) constituent stocks during the period from 2004 to 2018. Despite the fast-growing importance of the Chinese stock market in the global investment field, few works study the time-series momentum in this market. It is a common belief that the Chinse stock market is far from efficient because a larger proportion of the investors are retail traders who suffer more from information asymmetry and psychological biases. Hence, we expect to see greater underreaction and overreaction that could lead to more pronounced TSMOM in the Chinese stock market which, in turn, may attract more momentum traders. He and Li (2015) show that TSMOM is profitable in markets where the momentum traders dominate, and this conclusion also applies to the market index. Shi and Zhou (2017) present evidence of short-term TSMOM on the market indices in the Chinese stock market, but the effect is weaker than that in the US. In our study, different from Shi and Zhou (2017), we focus on individual stocks as we try to explore the cross-sectional variation in the profitability of TSMOM strategies.

Our main findings are: Firstly, we document strong and robust evidence that TSMOM exists among the individual stocks in Chinese stock markets. The profits are statistically and economically significant with a wide range of k values. Secondly, we find that the optimal look-back-period k^* defined as the one that generates the highest risk-adjusted performance among all the k values, is not only different across assets but also varies over time. Thirdly, based on our findings, we propose a model to explore the determinants of the optimal k^* and find evidence that such value is significantly related to some firm characteristic measures, such as the market value, liquidity, turnover, and volatility of the stocks. Finally, we use our model to predict the optimal k^* and implement the TSMOM strategies with this asset-specific and time-varying k^* in our out-of-sample analysis. The results show that such a practice tremendously improves the profitability of the TSMOM strategies.

We contribute to the literature on technical analysis in the following ways: Firstly, we provide evidence on the existence of TSMOM among individual stocks in the Chinse stock market. And we use alternative trading signals suggested in the literature to ensure the robustness of our evidence. Secondly, we examine a wide range of k values, from 10 days to 300 days, on multiple stocks. Such a practice enables us to reveal the fact that the optimal look-back-period k^* varies across different assets. Prior studies tend to use an arbitrarily determined k to examine the TSMOM on all assets. Our findings suggest that taking into account the heterogeneity of the pricing behaviour of different assets could enhance the profitability of technical trading strategies. Finally, we provide evidence on the time-varying feature of k^*. And more importantly, we propose a model that can successfully capture the variation in k^*. This model can thus be used to predict the updated k^* that practitioners can actually use in implementing their TSMOM trading strategies. And our empirical out-of-sample tests provide strong and robust evidence on the enhanced profitability of our TSMOM trading strategies. These results have important implications for the practitioners and investors, particularly those who are using TSMOM trading strategies.

The remainder of this paper proceeds as follows: Section 2 develops our methods to investigate the profitability of TSMOM strategies. Section 3 describes the sample data. Section 4 reports and analyzes the empirical results. The last section concludes the paper.

II. Methodology

TSMOM market timing strategies

In this study, we first follow the literature and use two signalling methods to explore the performance of TSMOM.

The main signalling

We follow Marshall, Nguyen, and Visaltanachoti (2017) in setting up our TSMOM trading rules. In particular, we have a buy or hold (sell or stay out of the market) signal on day *t* when $\mathrm{TSMOM_t}$ (k) is positive (negative), where, $\mathrm{TSMOM_t}$ (k) represents the price change of the stock over the past *k* days:

$$\mathrm{TSMOM_t}(k) = \mathrm{P_{t-1}} - \mathrm{P_{t-1-k}} \tag{1}$$

where *k* is the look-back period, P_{t-1} is the closing price of a stock on day *t-1*, and P_{t-1-k} is the closing price of a stock on day *t-1-k*. On any trading day *t*, if $TSMOM_t$ *(k)* is positive, this generates a buy signal, we then buy the stock or continue holding it if we are already in a long position on day *t-1*. If $TSMOM_t$ *(k)* is negative, this triggers a sell signal, we then sell the stock or stay in cash if we do not hold the stock on day *t-1*. Hence, returns of TSMOM switching strategy can be expressed as follows:

$$\mathrm{MOMR_{jt,,k}} = \begin{cases} \mathrm{R_{jt}}, & \text{if } \mathrm{TSMOM_t(k)>0\&TSMOM_{t-1}(k)>0} \\ \mathrm{R_{jt}} - \tau, & \text{if } \mathrm{TSMOM_t(k)>0\&TSMOM_{t-1}(k)<=0} \\ \mathrm{r_{ft}}, & \text{if } \mathrm{TSMOM_t(k)<=0\&TSMOM_{t-1}(k)<=0} \\ \mathrm{r_{ft}} - \tau', & \text{if } \mathrm{TSMOM_t(k)<=0\&TSMOM_{t-1}(k)>0} \end{cases} \tag{2}$$

where $MOMR_{jt,k}$ is the return of stock *j* at day *t* from the TSMOM switching strategy, R_{jt} is the return of stock *j* on day *t*, r_{ft} is the risk-free interest rate, τ is the one-way transaction cost for buying stocks, and τ' is the one-way transaction cost for buying currency funds which are proxy for the risk free assets. For the one-way transaction cost for stocks, Lynch and Balduzzi (2000) suggest a value of 25 basis points and Glabadanidis (2015) uses 50 basis points. Based on the actual transaction cost in the Chinese stock market, we assume the one-way trading costs are 50 basis points for stocks, (τ = 0.5%), and 0.5 basis points for currency funds (τ'= 0.005%).

An alternative signalling

We also use alternative signalling for the robustness check of the performance of TSMOM strategies, which is suggested by He and Li (2015). The signal of $TSMOM_t$ *(k)* is expressed as:

$$\mathrm{TSMOM_t(k)} = \mathrm{P_{t-1}} - (\mathrm{P_{t-2}} + \mathrm{P_{t-3}} + \ldots + \mathrm{P_{t-1-k}})/\mathrm{k} \tag{3}$$

Similar to the above method, a positive $TSMOM_t$ *(k)* indicates a buy or hold signal, while a negative value suggesting a sell or staying out of the market.[2] Portfolio returns are calculated in the same way as shown in Equation (2).

Selection of the look-back period (*k*)

The look-back period (*k*) is a crucial factor in examining the performance of TSMOM strategies. Previous literature documents that the profitability of TSMOM strategies varies with *k*. Moskowitz, Ooi, and Pedersen (2012) use monthly returns of equities and their *k* ranges from 1 to 48 months. Their results show that the strategy with a 12-month *k* exhibits better performance across diversified assets. Marshall, Nguyen, and Visaltanachoti (2017) explore the profitability of TSMOM with daily returns on stocks and their *k* varies from 10

[2]Such specification is closer to the traditional moving average (MA) trading strategy. Prior literature shows that TSMOM and MA are closely related but different. More details regarding the analysis of these two strategies can be found in Marshall et al. (2017), He and Li (2015) and Zhou and Zhu (2013).

to 200 days. They find the rules that are based on shorter look-back-period generate higher annualized returns. Based on the literature, we select a series of k values that are: 10, 20, 30, 40, 50, 60, 80, 100, 120,160, 200, 250, and 300 days. These values cover most of the ks used in the literature. We then document the profits of the TSMOM strategies with each k value for each of our sample stocks.

Identification of the optimal look-back-period (k^*)

For each stock, the performance of the TSMOM strategies with different ks may be different. We then identify the strategy with the best performance, and the corresponding k is defined as the optimal k (denoted as k^*) for the stock.

We conjecture that the k^* could be stock-specific, and time-varying. Hence, if we can predict the k^* at the beginning of the trading period, we may obtain better performance than using any arbitrary k. In order to predict the k^*, we first need to find out what factors are related to k^*. In so doing, we separate our sample period into two parts – the in-sample and out-of-sample periods. Using the in-sample period data, we identify the k^* as described above. Then we perform the following cross-sectional regression to find out whether and how k^* is related to some stock-specific factors:

$$k_j* = \beta_0 + \beta_1 * MV_j + \beta_2 * illiq_j + \beta_3 * turnover_j + \beta_4 * stdmonthly_j + \beta_5 * stdmix + \varepsilon_j \tag{4}$$

where k_j^* is the optimal k for stock j during the in-sample period, MV_j is the average market value, $illq_j$ is the average Amihud illiquidity ratio, $turnover_j$ is the average daily turnover, $stdmonthly_j$ is the standard deviation of monthly return, and $stdmix_j$ is the standard deviation of monthly returns divided by the standard deviation of weekly returns on stock j over the in-sample period. These firm-specific factors are included because they are used in the factor-based trading strategies documented in the literature (Fabozzi, Focardi, and Kolm 2010). All the values are measured over the in-sample period for stock j.

Then over the out-of-sample period, on each trading day, we calculate the adjusted k_j^* ($adjk_j^*$) as the sum of the original k_j^* obtained from in-sample and the updates in optimal k, Δk_j^*, where Δk_j^* is computed based on the coefficients estimated from regression (4), and the changes in the stock-specific characteristics over the out-of-sample period. Finally based on this updated optimal k, $adjk_j^*$, we determine our TSMOM trading decisions and record our returns as described by Equation (2).

III. Sample selection

Data and sample period

In this study, we focus on examining the TSMOM on individual stocks, in particular, the Shanghai and Shenzhen CSI 300 index constituent stocks.[3] Taking into account that the constituent stocks of CSI 300 were firstly announced in April 2005 and that we need at least 300 days as the look-back period, we set our sample period to be 01/01/2004 to 08/08/2018. We remove 11 stocks that do not have sufficient numbers of observations. For the remaining 289 stocks, we collect the price, market value, trading volume, as well as the CSI 300 index information from China Stock Market and Accounting Research Database (CSMAR).

We split our sample period into the in-sample and out-of-sample sub-periods. To enhance the robustness of our results, we used 6 different splits to create 6 in-sample and out-of-sample subsets. The first split point is 01/01/2012, which is roughly the midpoint of the actual calculation period of 06/2005 to 08/2018. The other 5 split points are selected as 30 days after the previous split point, all concentrating between 2012 and 2013.

Table 1 summarizes the basic characteristics of the 289 stocks during the sample period. Table 1 shows that among the sample stocks the median company has 17,068.9 million in market value (yuan). As the sample stocks are the constituent stocks of an index, it is not surprising to see that they are in general large in size, active in trading and have higher liquidity relative to an average stock in the Chinese stock market.

[3]The CSI 300 is a capitalization-weighted stock market index designed to replicate the performance of top 300 stocks traded in the Shanghai and Shenzhen stock exchanges.

Table 1. Descriptive statistics on sample stocks' main characteristics.

	Mean	Std	Q3	Median	Q1
Market value (millions ¥)	36,348.6	69,733.0	30,961.6	17,068.9	87,757.6
Daily trade value (millions ¥)	216.61	214.14	256.60	161.46	99.37
Daily log return (%)	0.0433	0.0274	0.0571	0.0401	0.0246
Average illiquidity (daily)	10.5	58.0	34.0	5.43	3.41
Average turnover (daily) %	1.93	0.68	2.34	1.87	1.45

This table presents the descriptive statistics of the 289 sample stocks. Market values of all stocks are measured on the date of 31 December 2017. Daily trade values and return for stocks are averaged over the time range from 1 January 2004 to 31 December 2017. Illiquidity is the liquidity measurer from Amihud and Mendelson (2015), and its equation is expressed as illiquidity = E10*log (1+ abs(return)/dollar trade volume). Turnover is computed by dividing dollar trade volume by market value available for the trading.

Performance measure

In this study, we use a risk-adjusted return measure to evaluate the performance of the strategies. As our investment assets in this study are individual stocks instead of well-diversified portfolios, the total risks rather than the systematic risks alone matter more and should be considered. Hence, performance measures adjusting for systematic risks, such as Jensen's Alpha and Treynor Ratio, would be less appropriate.[4] In this study, we use the standard deviation-based risk-adjusted performance measure, M^2, as our main performance measure and the Sharpe ratio in the robustness checks. M^2 is developed based on the Sortino ratio by Modigliani and Mordigliani (1997), and it measures the difference between the scaled excess return of our portfolio and that of the market, where the scaled portfolio has the same volatility as the market. As we select the market portfolio as our benchmark, M^2 would be the most direct and appropriate performance measure. Intuitively it can be interpreted as how much, in units of percentage returns, the TSMOM portfolios outperform (if $M^2 > 0$) or underperform (if $M^2 < 0$) the market BH portfolio on a risk-adjusted basis.

IV. Empirical analysis

Performance of TSMOM trading strategies

We first explore the profitability of the TSMOM strategies with various *k*s on our 289 sample stocks during the first in-sample period of 01/05/2005 to 31/12/2011. The results are summarized in Table 2.

Table 2 reports the statistics of the first four moments of the returns (the average annualized returns, standard deviation of returns, skewness, and kurtosis of returns) from BH and TSMOM strategies with *k* taking the values of 10, 20, 30, 40, 50, 60, 80, 100, 120, 160, 200, 250, and 300 days, respectively. From Table 2, we can see that: First, the relation between the performance of TSMOM and the look-back period *k* exhibit a U-shape: with much smaller *k* of 10, 20 and 30 days, or with very large *k* of 250 and 300 days, the TSMOM strategies significantly underperform the BH market portfolio; while when *k* is 100 days or 120 days, the TSMOM strategies generate the annualized returns of 31.62% or 28.17%, both significantly higher than the 24.4% return on the BH strategy. Second, from Panel B we can see that the standard deviation of TSMOM strategies is much smaller than that of the BH strategy, suggesting that TSMOM strategies are less risky. This is not surprising as TSMOM strategies switch between the risky stocks and the risk-free assets. Therefore, we cannot purely look at the raw returns of the strategies to evaluate their performance. Third, panel C shows that while the BH returns are negatively skewed, the returns from TSMOM strategies with short to medium look-back period *k*s exhibit positive skewness. Hence, TSMOM captures the positive returns and avoids the negative ones better than the BH strategy. Fourth, panel D suggests that TSMOM strategies tend to have larger kurtosis relative to the BH strategy. Hence, TSMOM produces more extreme returns than the market.

As the risk profiles of the BH and TSMOM strategies are substantially different, a more appropriate way to compare their performance is to look at the risk-adjusted return measures. Table 3 reports the M^2 and Sharpe ratio of TSMOM strategies, to facilitate our comparison of the trading strategies. From Panel A which presents the average M^2 of the TSMOM strategies, we can see that TSMOM strategies significantly outperform the BH strategy in 10 out of the 13 cases, indicated by the significantly positive mean M^2 when *k* takes the

[4]Even though we calculate the Jensen's alpha for the TSMOM strategies with various *k* values as an additional robustness check, and the results are available upon request.

Table 2. Summary statistics of BH and TSMOM returns.

	Mean	Diff	Std	Q3	Median	Q1	Mean	Diff	Std	Q3	Median	Q1
	Panel A: Annualized return μ (%)						Panel B: Annualized standard deviation					
BH strategy	24.4		15.65	34.08	23.02	12.72	53.79		6.23	57.39	53.09	48.66
TSMOM with different *k* (days):												
k = 10	19.22	−5.18***	17.2	30.56	19.22	7.02	38.63	−15.16***	4.87	41.6	39.04	35.43
k = 20	21.38	−3.02**	15.32	31.47	19.91	10.36	39.19	−14.60***	4.67	42.22	39.57	36.06
k = 30	20.94	−3.46***	15.16	30.48	18.97	10.05	39.59	−14.20***	4.81	42.81	40.08	36.40
k = 40	25.68	1.28	16.57	35.59	23.86	13.58	40.11	−13.68***	4.86	43.15	40.56	36.83
k = 50	25.01	0.61	17.32	34.79	22.33	12.01	40.02	−13.77***	4.86	43.31	40.42	37.05
k = 60	22.72	−1.68*	18.14	33.61	20.73	9.25	40.27	−13.52***	4.93	43.45	40.47	37.17
k = 80	25.39	0.99	18.03	36.09	23.93	13.35	40.55	−13.24***	5.17	43.75	40.57	37.41
k = 100	31.62	7.22***	18.02	42.34	29.42	19.93	40.7	−13.09***	5.28	43.97	40.63	37.61
k = 120	28.17	3.77***	17.22	38.67	26.08	17.03	40.82	−12.97***	5.31	44.18	40.84	37.70
k = 160	24.35	−0.05	15.13	34.03	22.97	13.66	41.28	−12.51***	5.43	44.78	41.12	38.00
k = 200	23.97	−0.43	13.36	31.83	23.77	15.15	41.43	−12.36***	5.46	44.89	41.43	38.21
k = 250	18.52	−5.88***	14.26	26.45	17.92	8.80	41.86	−11.93***	5.51	45.43	41.86	38.62
k = 300	14.21	−10.19***	13.62	22.09	12.69	5.09	42.17	−11.62***	5.57	45.62	41.94	38.86
	Panel C: Annualized skewness s						Panel D: Annualized kurtosis					
BH strategy	−0.579		8.19	−0.023	−0.711	−1.499	0.51		2.36	0.32	0.28	0.26
TSMOM with different *k* (days):												
k = 10	1.06	1.64**	11.70	1.80	0.54	−0.46	0.92	0.41***	3.55	0.57	0.50	0.46
k = 20	1.23	1.809***	6.21	1.52	0.23	−0.84	0.70	0.19***	1.38	0.56	0.49	0.45
k = 30	0.97	1.54***	6.11	1.40	0.04	−1.26	0.70	0.19***	1.36	0.57	0.49	0.45
k = 40	0.93	1.505***	6.03	1.19	0.04	−1.08	0.69	0.18***	1.29	0.57	0.49	0.44
k = 50	1.06	1.636***	6.04	1.30	0.08	−1.07	0.69	0.18***	1.26	0.56	0.48	0.43
k = 60	1.06	1.63***	6.04	1.27	0.02	−1.13	0.68	0.17***	1.26	0.56	0.48	0.43
k = 80	0.25	0.83	12.58	1.46	0.07	−1.26	0.88	0.38***	4.11	0.55	0.47	0.42
k = 100	0.41	0.99	12.49	1.29	0.02	−1.15	0.89	0.39***	3.98	0.55	0.47	0.41
k = 120	0.15	0.77	12.40	1.14	−0.27	−1.31	0.88	0.37***	3.98	0.55	0.46	0.41
k = 160	−0.07	0.51	12.62	0.78	−0.07	−1.31	0.87	0.36***	4.12	0.54	0.45	0.39
k = 200	−0.21	0.37	13.04	0.55	−0.49	−1.41	0.88	0.38***	4.31	0.54	0.45	0.39
k = 250	−0.72	−0.14	13.07	0.29	−0.85	−1.82	0.86	0.35***	4.42	0.54	0.45	0.39
k = 300	−0.87	−0.30	13.23	0.04	−0.97	−1.93	0.86	0.36***	4.49	0.54	0.44	0.38

Table 2 presents the summary statistics of moments of returns for the BH and TSMOM switch strategies with different *k* values applied to 289 individual stocks in the sample. The sample period ranges from 01/05/2005 to 31/12/2011. μ, σ and s are the annualized average return, standard deviation, and skewness of returns, respectively. K is the look-back period. A one-way transaction cost of 0.005 is imposed for TSMOM rules. *,**,and *** denote statistically significantly different to the equivalent metric at the 10%, 5%, and 1% levels, respectively.

values of 10 to 200 days. M^2 is significantly negative only when *k* is 300 days. This evidence strongly ascertains a substantial improvement in the performance when using TSMOM switch strategies on stocks, compared to buying and holding the market, given the same risk level. Overall, the range of positive means of annualized M^2 for TSMOM strategies with *k* values from 10 to 200 days is between 3.94% (when $k = 10$ days) to 16.45% (when $k = 100$ days), which are not only statistically but also economically significant.

There has been debate regarding the predictability of technical analysis, including market timing strategies such as TSMOM. Data snooping bias is one of the challenges that technical analysis has to address. Prior literature has suggested ways to address this issue. For example, White (2000) develops a 'reality check' (RC) to rigorously tests the null hypothesis that the best strategy among various related strategies underperforms the benchmark. Hansen (2005) proposes the 'superior predictive ability' (SPA) that is similar to the RC but includes refinements that improve the test power in most cases. In this study, to check the robustness of the profitability of the TSMOM strategies, following Yang et al. (2019) and Hsu and Kuan (2005), we perform the SPA test to generate the p-values of the TSMOM strategies based on bootstrapped samples. These p-values are reported in the last column of Table 3. From the results, we can confirm the outperformance of TSMOM strategies to the benchmark BH when K takes the value of 20 to 200 days.

Panel B of Table 3 also exhibits the Sharpe ratio for BH and TSMOM strategies as an alternative performance measure. The results are consistent with those from Panel A. For almost all the *k* values, that is when *k* varies from 10 to 200, Sharpe ratios on stocks with TSMOM rules are greater than the benchmark's (BH rule) Sharpe ratio. And again, the highest Sharpe ratio of 0.706 appears when *k* takes the value of 100 days. As

Table 3. Risk-adjusted performance of TSMOM strategies.

	Min.	Q1	Median	Mean	Q3	Max.	P^{SPA}
Panel A: Annualized M^2%							
k = 10	−30.85	−8.56	0.56	3.94***	15.04	61.00	0.186
k = 20	−24.97	−5.92	4.73	5.69***	15.03	63.15	0.061
k = 30	−33.87	−5.23	3.57	5.01***	15.12	60.44	0.075
k = 40	−23.08	−1.03	7.78	10.12***	19.8	63.6	0.002
k = 50	−24.8	−1.48	7.49	9.21***	18.61	67.26	0.004
k = 60	−33.02	−4.45	2.56	6.19***	15.1	67.95	0.042
k = 80	−26.39	−1.83	7.45	9.34***	17.98	64.09	0.005
k = 100	−15.91	7.5	15.09	16.45***	23.79	68.54	0.001
k = 120	−22.26	2.6	11.02	12.18***	20.46	71.03	0.001
k = 160	−21.54	−0.9	5.92	7.19***	14.05	49.81	0.046
k = 200	−19.52	−0.13	6.51	6.51***	12.99	45.24	0.059
k = 250	−24.79	−6.32	0.13	−0.31	4.84	27.99	0.855
k = 300	−31.82	−10.29	−4.68	−5.12***	0.24	18.68	0.096
Panel B: Annualized Sharpe ratio %							
BH	−0.33	0.204	0.379	0.412	0.567	1.518	
k = 10	−0.681	0.134	0.401	0.419	0.689	1.854	0.636
k = 20	−0.397	0.227	0.456	0.474*	0.731	1.458	0.101
k = 30	−0.428	0.22	0.451	0.461	0.702	1.497	0.290
k = 40	−0.267	0.25	0.528	0.543***	0.785	1.542	0.005
k = 50	−0.385	0.224	0.456	0.512***	0.779	1.643	0.052
k = 60	−0.547	0.144	0.43	0.464*	0.729	1.713	0.112
k = 80	−0.415	0.26	0.513	0.535***	0.789	1.788	0.015
k = 100	−0.508	0.457	0.657	0.706***	0.927	2.083	0.000
k = 120	−0.426	0.346	0.554	0.589***	0.832	1.834	0.001
k = 160	−0.485	0.278	0.477	0.498***	0.709	1.624	0.087
k = 200	−0.51	0.302	0.483	0.493***	0.668	1.448	0.092
k = 250	−0.467	0.147	0.331	0.348	0.521	1.424	0.897
k = 300	−0.483	0.03	0.16	0.2	0.367	1.155	0.053

Table 3 reports the performance of TSMOM switch strategies using different *k* values, based on the M^2 measure and Sharp ratio which are both reward-risk performance measures. *,**,and *** for Mean denote the mean of M^2 in Panel A or Sharpe Ratio in Panel B for the cross-sectional sample of 289 individual stocks is statistically significantly different from zero at the 10%, 5%, and 1% levels, respectively. P^{SPA} reports the p-values from Hansen (2005)'s 'superior predictive ability (SPA)' test.

a robustness check, we calculate the p-values from the SPA test, and the results suggest that TSMOM significantly outperforms BH in 7 out of 13 cases.[5]

Trading frequencies

One potential reason for the low standard deviation of the TSMOM portfolio returns is that if the strategy does not generate many buying signals, then we are staying out of the market for the majority of the time. To explore this possibility, we look at the trading frequency of our TSMOM strategies that are summarized in Table 4.

Table 4 presents a summary of the trading frequencies of buying stocks under the TSMOM rules with various *k* values. Results in Table 4 indicate that the trading rules with lower values of *k* generate more trading signals. For example, the rule with a 10-day *k* generates 17.12 trading signals per year on average, while the rule with a 300-day *k* on average only generates 2.43 trading signals a year. As we have taken into account the transaction costs for each buying and selling, the trading frequency will not affect the performance of the trading strategies that we documented in the prior session.

Table 4. Trading frequency of TSMOM strategies.

	Trading Frequency					
	Min	Q1	Median	Mean	Q3	Max
k = 10	13.70	16.12	17.21	17.12	18.05	22.23
k = 20	8.52	10.53	11.36	11.48	12.20	16.04
k = 30	5.62	8.35	9.19	9.26	10.19	13.56
k = 40	4.51	6.68	7.52	7.54	8.52	11.87
k = 50	3.08	5.68	6.52	6.67	7.52	10.36
k = 60	2.84	5.35	6.18	6.31	7.19	11.03
k = 80	1.83	4.68	5.16	5.64	6.52	11.03
k = 100	1.67	4.01	4.68	4.76	5.51	9.19
k = 120	1.84	3.34	4.01	4.14	4.85	7.35
k = 160	1.00	2.51	3.18	3.30	4.01	7.35
k = 200	0.67	2.00	2.67	2.83	3.51	7.85
k = 250	0.17	1.84	2.51	2.58	3.18	5.68
k = 300	0.17	1.67	2.33	2.43	3.00	6.35

Table 4 reports the summary of trading frequencies for TSMOM switch strategies with different *k* values applied to 289 individual stocks. Annualized times mean how many times on average a strategy generates buy signals during a year.

[5]As a further robustness check, we calculate the Jensen's Alpha (the results are available upon request) for each of our sample stocks from each TSMOM strategy. The results are again consistent with those in Table 3.

We also examine an alternative TSMOM strategy signal developed by He and Li (2015) and described in section 2.1 (Equation (3)), as a robustness check of reliability of the TSMOM profitability in the in-sample set. Table 5 reports the results where similar to those in Table 3, we use M^2 and the Sharpe ratio to measure the performance. Results in Table 5 show that TSMOM rules with all k values except for a 10-day k have significantly positive average M^2 across the 289 stocks, and the magnitudes of average M^2 range from 6.02% to 13.13%. The slight difference between the two signals is that the alternative signal displays a less sensitivity in profitability to the look-back period k. In other words, TSMOM strategies using the alternative signalling can achieve the relatively higher M^2 mean through the 20-day to the 250-day ks, compared to the results in Table 3.

Overall, our results show the evidence of strong TSMOM profits in the Chinese stock market, supporting a common belief that the Chinese market as an emerging one is not yet an efficient market. Hence, the Chinese market deserves more attention from technical analysts.

Table 5. Performance of TMOM using alternative signal.

	Min.	Q1	Median	Mean.	Q3	Max.
Panel a: Annualized M^2%						
k = 10	−34.78	−13.91	−3.1	−0.85	8.44	74.55
k = 20	−24.14	−1.98	10	12.98***	25.43	68.22
k = 30	−25.83	−4.06	8.59	9.58***	19.66	72.89
k = 40	−26.76	−2.14	7.68	10.30***	22.52	68.18
k = 50	−19.54	1.95	11.19	12.68***	23.13	72.33
k = 60	−19.79	0.57	10.74	11.69***	21.13	69.4
k = 80	−26.6	−2.75	6.49	8.54***	18.04	71.69
k = 100	−27.43	−0.06	9.89	11.30***	20.34	71.96
k = 120	−20.85	2.8	11.11	13.13***	21.86	66.42
k = 160	−20.33	1.26	10.42	11.81***	19.75	75.33
k = 200	−23.14	1.43	9.36	10.73***	19.97	56.69
k = 250	−16.1	1.88	8.97	9.39***	16.86	47.69
k = 300	−21.91	−0.23	5.99	6.02***	11.97	40.25
Panel b: Annualized Sharpe ratio %						
BH	−0.33	0.204	0.379	0.412	0.567	1.518
k = 10	−0.681	0.134	0.4	0.419	0.689	1.835
k = 20	−0.191	0.287	0.581	0.599***	0.896	1.665
k = 30	−0.413	0.274	0.533	0.542***	0.792	1.539
k = 40	−0.413	0.306	0.53	0.560***	0.788	1.736
k = 50	−0.26	0.368	0.582	0.611***	0.863	1.809
k = 60	−0.207	0.314	0.569	0.596***	0.869	1.762
k = 80	−0.323	0.246	0.516	0.536***	0.782	1.636
k = 100	−0.426	0.311	0.573	0.594***	0.836	1.732
k = 120	−0.471	0.353	0.631	0.635***	0.886	1.91
k = 160	−0.512	0.333	0.595	0.615***	0.879	1.863
k = 200	−0.407	0.341	0.596	0.596***	0.852	1.934
k = 250	−0.512	0.343	0.56	0.573***	0.768	1.672
k = 300	−0.477	0.318	0.486	0.509***	0.706	1.508

Table 5 presents the statistic summary of the performance of TSMOM switch strategies with various k values, based on the alternative signal developed by He and Li (2015). The M^2 measure and Sharp ratio which are both reward-risk performance measures. *,**,and *** for M^2 denote the mean of M^2 for the cross-sectional sample of 289 individual stocks is statistically significantly greater than zero at the 10%, 5% and 1% levels, respectively. *,**,and *** for the Sharpe ratio denote that difference of the mean of the Sharpe ratio between BH and STMOM rules for the cross-sectional sample of 289 individual stocks is statistically significantly greater than zero at the 10%, 5% and 1% levels, respectively.

More analysis on the TSMOM profits

In this session, we look into the TSMOM profits in the Chinese stock market and explore several important issues, such as how it is related to investor sentiment, market states, and its sensitivity to the transaction costs.

TSMOM and investor sentiment

Some researchers posit that sentiment induces systematic deviations from fundamental values and has a long-lasting effect (Brown and Cliff 2005; Baker and Wurgler 2006). Therefore, the demand shocks of uninformed investors may be correlated over time which results in strong and persistent mispricing. Hence, a series of papers look at the return predictability of investor sentiment. For example, Baker and Stein (2004), Brown and Cliff (2005), Baker, Wurgler, and Yuan (2012) show that high sentiment is associated with low market returns in the long run, while Brown and Cliff (2005), Huang et al. (2015), and Han and Li (2017) find mixed evidence on the predictability of sentiment in the short run. In this study, we explore whether the profitability of the TSMOM strategy is linked with the investor sentiment. In so doing, we first collect the investor sentiment data constructed by Cheema, Man, and Szulczyk (2018) for the Chinese stock market. Then following Stambaugh and Yuan (2017), we classify our sample period into high (low) sentiment months where the investor sentiment index is above (below) the median value of the index over the whole sample period. We then compute the returns from the TSMOM strategies for the high- and low-sentiment months. The results are reported in Table 6.

It is interesting to see that the TSMOM strategies significantly underperform the BH strategy during the high sentiment period while significantly outperform during the low sentiment period. And such finding appears in all the TSMOM strategies with different ks. This finding suggests a strong negative link between investor sentiment and TSMOM profits.

Table 6. TSMOM strategies and investor sentiment.

	High-Sentiment				Low-Sentiment			
	Q1	Median	Mean	Q3	Q1	Median	Mean	Q3
k = 10	−31.67	−22.25	−18.71***	−10	−3.23	9.07	12.92***	25.92
k = 20	−27.09	−17.08	−14.96***	−5.65	−3.91	7.37	10.21***	22.1
k = 30	−26.22	−15.91	−14.25***	−5.67	−7.49	4.29	7.3***	19.68
k = 40	−21.35	−12.72	−11.46***	−3.06	−3.63	7.88	12.47***	25.18
k = 50	−20.41	−13.1	−13.16***	−5.82	−4.33	8.11	11.19***	21.53
k = 60	−23.86	−15.52	−14.99***	−7.59	−6.63	3.26	7.05***	17.76
k = 80	−20.49	−12.93	−12.9***	−4.93	−4.47	7.55	11.62***	24.99
k = 100	−19.52	−11.44	−10.73***	−3.15	7.62	22.68	23.39***	35.77
k = 120	−21.18	−13.57	−12.41***	−5.23	4.16	19.33	18.74***	30.91
k = 160	−22.11	−13.95	−13.34***	−3.52	3.2	12.57	14.07***	25.88
k = 200	−21.18	−12.98	−12.66***	−5.04	2.53	13.31	14.73***	25.08
k = 250	−24.65	−15.43	−15.04***	−6.29	−1.71	7.37	8.3***	18.65
k = 300	−26.42	−18.06	−16.24***	−9.01	−6.79	2.12	2.82***	11.05

Table 6 reports the performance of TSMOM switch strategies, measured by annualized M^2, under different investor sentiment states. Investor sentiment data are constructed by Cheema, Man, and Szulczyk (2018) for Chinese stock market. High (low) sentiment months are those where the investor sentiment index is above (below) the median value of the index over the whole sample period. *,**,and *** for M^2 denote the mean of M^2 for the cross-sectional sample of 289 individual stocks is statistically significantly different to the equivalent metric at the 10%, 5%, and 1% levels, respectively.

TSMOM and market states

Another factor that many practitioners and technical traders look at is the market state. Prior literature has documented that the profitability of some trading strategies, such as cross-sectional momentum, depends on the state of the market (Cooper, Gutierrez, and Hameed 2004). To gain a better insight into the profitability of the TSMOM, we then examine whether the TSMOM profits are linked with the market states. Similar to the session above, we separate our sample period into the bull market and the bear market, depending on whether the CSI300 market index is above or below the 250 day moving averages. We then record the TSMOM profits separately under the two market states. The results are reported in Table 7.

From the Table, we can see that TSMOM, in general, underperforms the BH strategy during bull market but outperforms during the bear market, except when *k* takes the value of 250 and 300 days. The results suggest that TSMOM loses its profitability when the look-back period is relatively long, regardless of the market states. The finding that TSMOM significantly outperforms the BH strategy during bear market suggests that the most important advantage of TSMOM strategy is that it helps investors to avoid significant losses by moving out of the market during the market downturns.

TSMOM and transaction cost

One of the issues that investors are concerned about is the transaction cost, which determines the net profits of a trading strategy. In the previous analysis, we assume a fixed transaction cost of 0.5% for the stock investment. In this session, we take

Table 7. TSMOM strategies and market states.

	Bull market				Bear market			
	Q1	Median	Mean	Q3	Q1	Median	Mean	Q3
k = 10	−21.06	−11.73	−7.51***	2.42	−1.71	16.52	20.86***	36.48
k = 20	−13.13	−2.83	−0.3	8.45	−9.01	7.08	9.16***	21.97
k = 30	−13.5	−5.63	−3.38	4.58	−11.04	7.2	11.54***	28.64
k = 40	−17.08	−10.26	−6.14***	−0.27	7.78	29.14	33.7***	55.38
k = 50	−20.85	−13.62	−10.43***	−3.88	12.8	39.02	41.25***	62.97
k = 60	−24.46	−16.45	−13.26***	−6.89	14.22	31.05	38.74***	56.39
k = 80	−16.32	−10.74	−6.61***	−0.05	2.79	22.88	29.07***	44.37
k = 100	−10.06	−3.42	−0.72	5.97	10.15	27.68	34.95***	49.69
k = 120	−11.78	−4.11	−1.68**	4.1	−1.78	15.85	19.43***	34.55
k = 160	−9.85	−3.95	−1.8**	3.2	−15.26	−2.39	1.9***	15.09
k = 200	−8.65	−3.01	−2.26**	2.12	−13.95	−1.71	2.02**	14.99
k = 250	−11.45	−5.94	−5.65***	−0.86	−20.6	−9.15	−6.99***	5.36
k = 300	−13.63	−8.12	−7.25***	−0.78	−25.08	−10.84	−11.79***	0.21

Table 7 reports the performance of TSMOM switch strategies, measured by annualized M^2, under different market states. We separate our sample period into bull and bear market, depending whether the CSI300 market index is above or below the 250-day moving averages. We then record the TSMOM profits separately under the two market states. *, ** and *** for M^2 denote the mean of M^2 for the cross-sectional sample of 289 individual stocks is statistically significantly different to the equivalent metric at the 10%, 5%, and 1% levels, respectively.

a closer look at this issue and examine how the transaction cost would affect the performance of the TSMOM. In so doing, we calculate the break-even transaction costs for each of our trading strategies across all the sample stock and look at the distribution of the costs.[6] The descriptive statistics of the break-even transaction costs show that the mean break-even transaction costs for a unilateral trade range from 0.68% to 1.20% for all TSMOM strategies with different *k*s. Chu, Gu, and Zhou (2019) calculate that the explicit cost of transaction for A-shares in the Chinese stock market is 0.03% for buyers and 0.13% for sellers. Zhang (2018) shows that the average implicit transaction costs for Chinese stocks range from 0.08% to 0.4%. Given that our sample stocks are all the CSI 300 index composite stocks which are nearly the largest and most liquid stocks, the implicit transaction costs are expected to be in the lower end of this range. Hence, the actual transaction costs are much lower than the break-even transaction costs for the TSMOM strategies and lower than the 0.5% fixed cost we used in our previous analysis. Therefore, transaction costs should not be a concern for the TSMOM traders in the Chinese stock market.

Optimal *k** and its persistence

The results so far show that the selection of look-back-period is crucial and to a large extent determines the profitability of the TSMOM strategies. Previous studies use different *k* in examining the performance of TSMOM strategies and show varying profitability under different rules (e.g. Marshall, Nguyen, and Visaltanachoti 2017; Shi and Zhou 2017). Intuitively, there exists an optimal look-back period (k^*) for a specific asset and the strategy with this k^* can exhibit the best performance, compared to any other *k* values. However, a practical question that the technical traders face is which *k* is the optimal one that they should use in implementing the TSMOM trading strategy? In this session, we examine the persistence of the optimal k^* on the individual asset. If an asset has a stable k^* over time, practitioners can easily identify k^* based on historical data and employ it in the trading strategies.

We first identify the optimal look-back period k^* for each individual stock in the in-sample period (01/01/2005 to 31/12/2011), where the optimal criterion is maximizing the M^2 for the stock. Table 8 presents the summary statistics of k^* for 289 individual stocks in the period of 01/05/2005 to 31/12/2011. The mean and median of k^* are 76 days and 84 days, respectively, and the corresponding annualized M^2 are 36.3% and 34.6%, respectively, which are much larger than those displayed in Tables 3 and 5.

Figure 1 shows the distribution of k^* for the 289 sample stocks. Figure 1 indicates that most of the k^*

Table 8. Descriptive statistics of k^* and corresponding M^2 during in-sample period.

	01/05/2005 to 31/12/2011					
Time period:	Min.	Q1	Median	Mean.	Q3	Max.
Optimal K	10	19	84	76	106	281
Annualized M^2%	−4.6	5.3	34.6	36.3***	45.6	83.3

Table 8 reports statistics of k^* values and M^2 for 289 individual stocks over the period of 01/05/2005 to 31/12/2011. *** denotes the mean of annualized M^2 is statistically greater than zero at 1% significance level. The unit of *k* is the day.

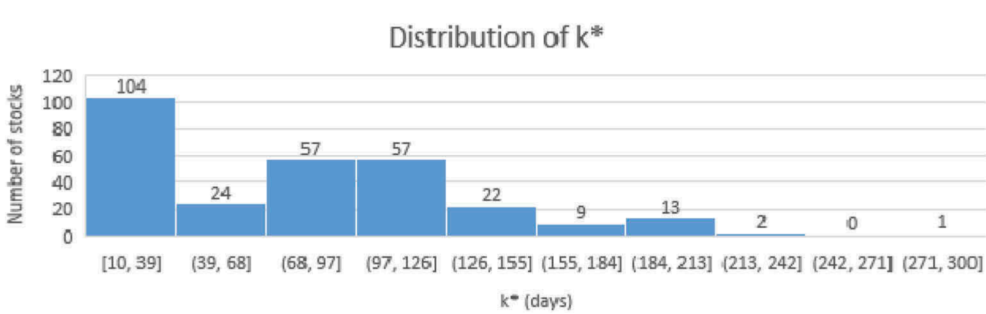

Figure 1. Distribution of k^*.

Figure 1 plots the distribution of the optimal k^* across the 289 sample stocks. For each of the sample stock, we calculate the M^2 from the TSMOM with different look-back period k. Optimal k^* is the one that produces the highest M^2. The sample period is 01/05/2005 to 31/12/2011.

[6]Descriptive statistics are available upon request.

values concentrate within the ranges of 10–39 days and 68–126 days.

Figure 2 displays the distribution of the corresponding M^2 of portfolios with k^*s. Among the 289 sample stocks, 248 (86% of the sample stocks) achieve an M^2 of above 30% with the optimal k^*, and 288 stocks exhibit positive M^2, indicating their outperformance of the market BH strategy.

To examine whether the optimal k^* for an individual stock is persistent over time, we apply the k^* identified in-sample (01/05/2005 to 31/12/2011) on the out-of-sample data, to see whether the TSMOM strategies with the in-sample k^* can continue outperforming BH as well as other TSMOM strategies during the out-of-sample period of 01/01/2012 to 01/08/2018.

Table 9 reports the descriptive statistics of the M^2 from the TSMOM strategies on the out-of-sample data, while k^* is determined in-sample. The average M^2 is only 2.10%, though statistically significant at the 95% level, it is far below the average M^2 of 36.3% during the in-sample period reported in Table 10. Also, the SPA test fails to reject the null hypothesis of the superior profitability of TSMOM to BH. Such results could be driven by two reasons. The first reason is that TSMOM itself is much weaker in the out-of-sample period than in the in-sample period. To test this possibility, we perform the TSMOM with various ks on the out-of-sample data. The results are summarized in Table 10. Comparing the results in Table 10 with those in Table 3 we can see that the mean M^2 of TSMOM strategies in the out-of-sample period are in general lower than those in the in-sample period, and the number of k (6 out of 13) achieving significantly positive M^2 in the out-of -sample period is less than that (10 out of 13) in the in-sample period. Therefore, the TSMOM does seem to be weaker in the out-of-sample period compared to the in-sample period. The second reason is that the optimal k^* is time-varying. What drives the highest performance during the earlier in-sample period is no longer optimal during the later out-of-sample period. These two explanations are not entirely mutually exclusive, however, there might be a simple way to partially entangle them – while we can do nothing under the

Table 9. Performance of out-of-sample TSMOM with in-sample k^*.

	Annualized M^2%						
	Min.	Q1	Median	Mean.	Q3	Max.	P^{SPA}
TSMOM with in-sample k^*	−31.86	−8.48	1.36	2.10**	10.26	85.57	0.119

Table 9 reports the performance of TSMOM strategies with k^* from the in-sample applied to the out-of-sample covering the period of 01/01/2012 to 01/05/2016. Annualized M^2 is the annual M^2 measure in percent. ** denotes the mean of annualized M^2 is statistically greater than zero at 5% significance level. P^{SPA} reports the p-values from Hansen (2005)'s 'superior predictive ability (SPA)' test.

Table 10. Performance of TSMOM during the out-of-sample period.

	Annualized M^2%						
	Min.	Q1	Median	Mean.	Q3	Max.	P^{SPA}
k = 10	−32.95	−8.56	−0.2	0.69	9.88	47.58	0.741
k = 20	−26.27	−3.31	5.23	7.06***	15.98	74.42	0.045
k = 30	−29.63	−6.51	0.12	1.83*	7.86	45.02	0.184
k = 40	−25.96	−5.96	1.62	2.77***	10.07	47.88	0.064
k = 50	−22.4	−5.67	1.02	1.80*	8.45	54.62	0.202
k = 60	−26.71	−6.89	1.76	2.15**	5.98	39.52	0.089
k = 80	−28.99	−9.55	−2.51	−1.67*	5.16	29.83	0.940
k = 100	−26.86	−6.29	1.3	2.03**	7.72	58.99	0.092
k = 120	−30.7	−9.71	−2.95	−2.51**	4.18	44.77	0.083
k = 160	−23.86	−6.59	−0.49	1.00	7.17	52.66	0.583
k = 200	−26.58	−7.21	−0.31	−0.54	6.36	46.35	0.898
k = 250	−25.43	−5.99	0.05	0.57	6.43	31.56	0.839
k = 300	−31.82	−8.99	−3.25	−2.53**	3.34	29.35	0.059

Table 10 reports the statistics of the performance of TSMOM switch strategies using different look-back period k values for the out-of-sample covering the period of 01/01/2012 to 31/05/2016, based on M^2 measure which is reward-risk performance measure. *,**,and *** for M^2 denote the mean of M^2 for cross-section sample of 289 individual stocks is statistically significantly different to the equivalent metric at the 10%, 5%, and 1% levels, respectively. P^{SPA} reports the p-values from Hansen (2005)'s 'superior predictive ability (SPA)' test.

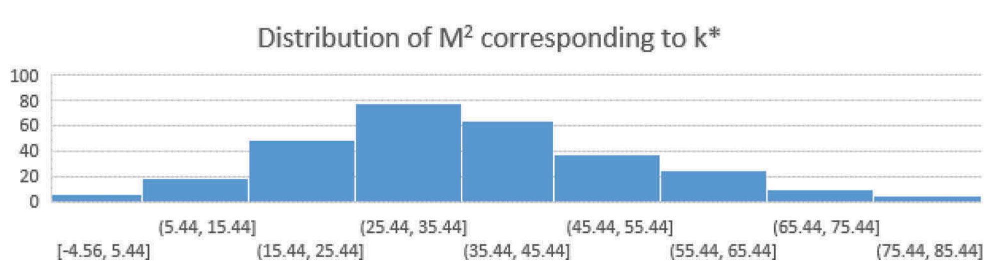

Figure 2. Distribution of corresponding M^2.

Figure 2 plots the distribution of M^2 from the TSMOM with the optimal k^* across the 289 sample stocks. For each of the sample stock, we calculate the M^2 from the TSMOM with different look-back period k. Optimal k^* is the one that produces the highest M^2. The sample period is 01/05/2005 to 31/12/2011.

first possibility, exploring how k^* is time-varying and thus using the time-dependent k^* in the out-of-sample test should enhance the performance of the strategy.

Exploring the optimal look-back periods (k^*)

To explore the determinants of the optimal k^*, we examine the factors that may affect k^* and establish the relation between k^* and these factors. In such a process, we allow the k^* to be not only asset-specific but also time-varying, by adding the time stamp on the firm-specific characteristic variables in our regression model. Based on the literature in technical analysis, we consider the stock-specific characteristic factors which can influence the price movements or reflect the structure of price movements, such as the market value, turnover, liquidity, price range of the stock during various time horizons, and the volatility of the returns. We then perform the following regression on each of the sample stocks:

$$k_{j,t}* = \beta_0 + \beta_1 * MV_{j,t} + \beta_2 * illiq_{j,t} + \beta_3 * turnover_{j,t} + \beta_4 * stdmonthly_{j,t} + \beta_5 * stdmix_{j,t} + \varepsilon_{j,t} \tag{5}$$

where $k_{j,t}{}^*$ is the optimal k for stock j over the period of t, $MV_{j,t}$ is the average market value of the stock, $illq_{j,t}$ is the Amihud illiquidity ratio, $turnover_{j,t}$ is the daily average turnover for the stock, $stdmonthly_{j,t}$ is the standard deviation of monthly returns, and $stdmix_{j,t}$ is the standard deviation of monthly returns divided by the standard deviation of weekly returns on the stock. All values are measured or identified during the in-sample period. The average coefficients from the regressions are reported in Table 11.

Results in Table 11 show that on average, the illiquidity of the stocks, the turnover ratio, standard deviation of the returns has a significant effect on the optimal k^* of the stocks. For example, the average coefficient on the turnover ratio is −10.085, suggesting that on average a 1% increase in the turnover ratio of the stock decreases an optimal k^* by 10.085 days. For other factors, illiquidity is positively correlated with k^*, while the standard deviation of the stocks is negatively related to k^*. Such results make intuitive sense. For stocks that are actively traded (with a high turnover ratio), highly liquid, and prices vary frequently with large swings (high volatility), the optimal look-back period tends to be short. And these stocks tend to generate trading signals more frequently.

Table 11. Average coefficients from the regressions.

	Dependent variable: k^*	
	Mean Estimate	t value
Intercept	299.714***	6.905
Market value/1000000	−0.082	−1.220
Illiquidity*1000000	0.065**	1.989
Turnover %	−10.085**	−2.282
1000* Std of monthly return	−0.396***	−2.704
Std of monthly/Std of weekly return	−60.025***	−2.567
Observations	289	
Average R^2	0.259	

Table 11 reports the summary of the multiple linear regression using cross-sectional data sets. k^* is the optimal k in the in-sample period. Market value/1000000 is the stock average market value during the in-sample period (01/01/2005 to 31/12/2011) divided by 1000000. Illiquidity*1000000 is the Amihud illiquidity measure multiplied by 1000000. Turnover is the stock average daily trading turnover in percent in the period of in-sample. 1000*Std of monthly return is the standard deviation of monthly log returns during the in-sample period multiplied by 1000. Std of monthly/Std of weekly log return is the standard deviation of monthly log returns divided by the standard deviation of weekly log returns.

Improving TSMOM strategies with adjusted k^*

Having established the relation between the optimal k^* with the firm characteristics, we can now use the dynamic model to predict the next optimal k^* (adjusted k^*) and implement the TSMOM strategies in the out-of-sample period.

In our model, the adjusted k^* consists of two components. One is the k^* identified from the in-sample period. Another is the delta k^* which is computed according to data from the in-sample and rolling windows, based on the regression results from Table 11. With this method, we assume that the k^* captures the past information on the movement of the prices of the underlying asset, and the delta k^* reflects the updated information on how price movement may vary over time. Intuitively, the change in the latest trading information and the structure of price movement on the asset can enhance the predictability for TSMOM rules.

Zakamulin (2014) emphasizes that the time split points are relevant to the performance of active trading rules. In order to observe the relation between the time-splitting and the performance of TSMOM strategies, and to check the robustness of our tests, we set 6 different in-sample and out-of-sample split points which generates 6 out-of-sample subsets. That is, the first out-of-sample covers the period of 01/01/2012 to 31/05/2016, the second period moves 30 days forward from the first out-of-sample period, and so on.

Table 12 reports the mean and median M^2 of portfolios for TSMOM rules with k^* and adjusted k^* during the 6 different out-of-sample periods across the 289 individual stocks. The results show strong evidence that using adjusted k^* can significantly enhance the performance of the TSMOM profits. Firstly, strategies with the in-sample optimal k^* show significant positive M^2 only in the first out-of-sample period, marginally significant in the second period, the M^2 becomes insignificantly different from zero, or even negative in the other four sub-periods. Such results indicate the optimal k^* identified in-sample loses its predicting power out of the sample. Secondly, the performance of the strategies with in-sample k^* decreases when the out-of-sample period moves away from the in-sample period. This evidence further supports our conjecture that the actual optimal k^* should be time dependent. Hence, the predictability declines when the test period moves further away. Thirdly, in contrast, the strategies with adjusted k^* all show positive M^2, with four of them are significant at above 95% level, and one marginally significant. Moreover, while all the strategies with the in-sample optimal k^* do not pass the more rigorous SPA test, suggesting that we cannot conclude about the outperformance of these strategies relative to the benchmark BH strategy. However, for the TSMOM with adjusted k^*, four of the six strategies pass the SPA test shown by their p-values. Hence, the outperformance of the TSMOM strategies is statistically robust. Finally, the difference in M^2 from the paired strategies are all positive, with three of them are significant, again, indicating the superior performance of the TSMOM strategies with adjusted k^* relative to the ones with in-sample k^*.

V. Conclusion

In this study, we examine the profitability of the TSMOM strategies with various look-back-period k on individual stocks in the Chinese stock market. We provide robust evidence to show that the active TSMOM strategies on average significantly outperform the buy-and-hold strategy with a wide range of k values, and the profitability is market states and investor sentiment dependent. We also find that the optimal k which generates the highest risk-adjusted performance is not only different across different assets, but also varying over time. Based on these findings, we propose a model to predict the asset-specific and time-dependent k^* and examine the performance of the TSMOM strategies with the predicted k^* in the out-of-sample data. Our out-of-sample analysis shows that using the time-varying predicted k^* substantially improves the predictability of the TSMOM strategies that rely on the historical optimal k^*.

Our findings have important implications for the regulators and practitioners. Especially, our study provides an empirically feasible way to explore the profits in the stock market caused by the market inefficiency. By incorporating the characteristics of

Table 12. Performance of TSMOM strategies with k^* and adjusted k^*.

	Annualized M^2%						
	k^*			adjusted k^*			difference
Time period	Midian	Mean	P^{SPA}	Midian	Mean	P^{SPA}	Δ Mean
T1 to T2	1.36	2.10**	0.119	3.24	4.72***	0.028	2.62*
T1 + 30 to T2 + 30 days	1.43	1.93*	0.358	2.79	3.59***	0.051	1.66
T1 + 60 to T2 + 60 days	1.1	1.67	0.682	1.83	2.32**	0.076	0.65
T1 + 90 to T2 + 90 days	−1.01	−0.71	0.898	1.91	2.54**	0.066	3.25**
T1 + 120 to T2 + 120 days	1.08	1.61	0.571	1.27	1.96*	0.103	0.35
T1 + 150 to T2 + 150 days	−0.21	−0.91	0.896	1.04	1.78*	0.183	2.69**

Table 12 presents the statistics of M^2 for TSMOM switch strategies with k^* and adjusted k^* during the 6 different out-of-sample periods. T1 is the date of 01/01/2012, and T2 is the date of 31/05/2016. The cost of the transaction is 0.5%. k^* is computed based on maximizing the M^2 of the portfolio for rules during the period of in-sample. Adjusted k^* equal to k^* plus delta k^* which is calculated according to the estimate results from the Equation (5), based on the changes in coefficients in rolling windows, with a span of 200 days. *, ** and *** denote the means of M^2 for adjusted k^* and the difference means between k^* and adjusted k^* are statistically significantly different at 10%, 5%, and 1% levels, respectively. P^{SPA} reports the p-values from Hansen (2005)'s 'superior predictive ability (SPA)' test.

the assets, practitioners can significantly increase the profitability of their trading strategies. Also, our findings provide more insights into the time-series momentum documented in the literature. Particularly, the decomposition of the profits with respect to the market states and investor sentiment provides direct evidence on the market dependency of the TSMOM strategies. As time-series momentum plays a significant role in explaining the cross-sectional momentum, findings from this study also generate important implications for practitioners and researchers that are interested in cross-sectional momentum. TSMOM strategies sell when the prices go down and buy when the prices go up, and traders profit at the expense of arbitrageurs. Hence, the impact of these trading strategies on market stability and market efficiency is an important question for future research.

Disclosure Statement

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