Improving Market Timing of Time Series Momentum in the Chinese Stock Market

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Abstract

This paper presents 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 Chinse stock market. We document that the optimal k^* generating the best performance is different across assets and varying 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 that rely on the historical optimal k^*.

Keywords: Technical Analysis; Time-Series Momentum; Market Timing; Chinese Stock Market.

JEL classification: G10; G12

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1. 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[2].

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, Gao et al. (2018) collect the high-frequency ETF data in the US stock market and apply the rule of TSMOM 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 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 et al. (2012) and Marshall et al. (2017) ascertain that the TSMOM strategy over a fixed k of

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[2] 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, Rapach, Tu and Zhou, 2010; Kilgallen, 2012; Huang and Zhou, 2013; Glabadanidis, 2014 and 2015; Han, Zhou, and Zhu, 2016, etc..

12-month can achieve positive excess returns on diverse asset classes. On the other hand, results from some other researchers (e.g., He et al. (2015) and Shi et al. (2017)) show that the performance for TSMOM strategies with different k values is quite different. In addition, 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 be varying both across different assets and over time. We conjecture that the performance of TSMOM depends on k values, which could be different for different assets and over different time 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 efficiency 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 different assets but also varying 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 values, 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 behavior 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**, and 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 to 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 analyze the empirical results. The last section concludes the paper.

2. Methodology
2.1 TSMOM market timing strategies

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

The main signaling

We follow Marshall et al. (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 $TSMOM_t(k)$ is positive (negative), where, $TSMOM_t(k)$ represents the price change of the stock over the past k days:

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

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:

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

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 signaling

We also use alternative signaling 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:

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

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. Portfolio returns are calculated in the same way as shown in equation (2).

2.2 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 the profitability of TSMOM strategies varying with *k*. Moskowitz et al. (2012) use monthly returns of equities and their *k* ranges from 1 to 48 months. Their results show the strategy with a 12-month *k* exhibits better performance across diversified assets. Marshall et al. (2017) explore the profitability of STMOM with daily returns on stocks and their *k* varies from 10 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 *k*s used in the literature. We then document the profits of the TSMOM strategies with each *k* value for each of our sample stocks.

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

For each stock, the performance of the TSMOM strategies with different *k*s 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:

$$k_j^* = \beta_0 + \beta_1 * MV_j + \beta_2 * illiq_j + \beta_3 * turnover_j + \beta_4 * stdmonthly_j + \beta_5 * stdmix + \varepsilon_j \qquad (4)$$

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. 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 change 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).

3. Sample selection

3.1 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 number of observations. For the remaining 289 stocks, we collect the price, market value, trading volume, as well as the CSI 300 index information from 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

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[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.

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.

[Insert Table 1here]

3.2 Performance measure

In this study, we use a risk-adjusted return measure to evaluate the performance of the strategies. In the literature, there are several risk-adjusted performance measures, such as the Sharpe Ratio. However, academic researchers argue that the standard deviation could be an unsuitable measure of risk because it penalizes both the downside and the upside changes in returns of equities. Therefore, in this paper, we use the Sharpe ratio only for robustness check. Our main performance measure is the Modigliani risk-adjusted performance measure (also known as M^2) which is developed on the basis of the Sortino ratio by Modigliani and Modigliani (1997). M^2 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.

Besides the Sharpe ratio, we also calculate the Jensen measure (alpha) for the TSMOM strategies with various k values as a robustness check, and the results are available upon request.

4. Empirical analysis
4.1 Performance of TSMOM trading strategies

We first explore the profitability of the TSMOM strategies with various ks 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.

[Insert Table 2 here]

Table 2 reports the statistics of the first three moments of the returns (the average annualized returns, standard deviation of returns, and skewness 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 ks exhibit positive skewness.

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 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.

[Insert Table 3 here]

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 a further robustness check, we calculate the Jensen's Alpha for each of our sample stocks from each TSMOM strategy. The results[4] are again consistent with those in Table 3.

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.

[Insert Table 4 here]

Table 4 presents the 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.

We also examine an alternative TSMOM strategy signal developed by He and Li (2015) and described in the 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 ratios 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, STMOM strategies using the alternative signaling can achieve the relatively higher M^2 mean through the 20-day to the 250-day ks, compared to the results in table 3.

[Insert Table 5 here]

Overall, our results show the evidence of strong TSMOM profits in the Chinese stock market, supporting a common belief that Chinese market as an emerging one is not yet an efficient

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[4] The results are available upon request.

market. Hence, the Chinese market deserves more attention from technical analysts.

4.2 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 et al., 2017; Li, 2015; 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 6 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.

[Insert Table 6 here]

Figure 1 shows the distribution of *k** for the 289 sample stocks. Figure 1 indicates that most of the *k** values concentrate within the ranges of 10-39 days and 68-126 days.

[Insert Figure 1 here]

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 7 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 6. 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 8. Comparing the results in Table 8 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 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.

[Insert Table 7 here]

[Insert Table 8 here]

4.3 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 time 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 9.

[Insert Table 9 here]

Results in Table 9 show that on average, the illiquidity of the stocks, the turnover ratio, standard deviation of the returns have a significant effect on the optimal k^* of the stocks. For example, the average coefficients 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.

4.4 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 9. 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 10 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. 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^*.

[Insert Table 10 here]

5. 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. 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 to 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. We hope that this study is a starting point and more endeavor shall be devoted to exploring the optimal k^* to further enhance the profitability of the TSMOM strategies.

References

Blume, L., Easley, D., O'Hara, M., 1994. Market Statistics and Technical Analysis: The Role of Volume. Journal of Finance 49, 153–81.

Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. Journal of Finance 47, 1731– 64.

Chakrabarti, G., 2015. Time-Series Momentum Trading Strategies in the Global Stock Market. Business Economics 50, 80–90.

Guo, L., Han, Y., Li, S. Z., Zhou, G., 2018. Market intraday momentum. Journal of Financial Economics 129, 394-414.

Glabadanidis, P., 2014. The Market Timing Power of Moving Averages: Evidence from US REITs and REIT Indexes. International Review of Finance 14, 161–202.

Glabadanidis, P., 2015. Market Timing with Moving Averages. International Review of Finance 15, 387–425.

Han, Y., Yang, K., Zhu, Y., 2016. Trend factor: any economic gains from using information over investment horizons? Journal of Financial Economics 122, 352-375.

He, X. Z., Li, K., 2015. Profitability of time series momentum. Journal of Banking & Finance 53, 140-157.

Huang, D., Li, J. Y., Wang, L., Zhou, G. F., 2019. Time-Series Momentum: Is It There? Journal of Financial Economics (JFE), Forthcoming. Available at SSRN: https://ssrn.com/abstract=3165284 or http://dx.doi.org/10.2139/ssrn.3165284

Huang, D., Zhou, G., 2013. Economic and Market Conditions: Two State Variables that Predict the Stock Market. Working paper.

Kilgallen, T., 2012. Testing the Simple Moving Average across Commodities, Global Stock Indices, and Currencies. Journal of Wealth Management 15, 82–100.

Lo, A., Mamaysky, H., Wang, J., 2000. Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation. Journal of Finance 55, 1705–65.

Lynch, A. W., Balduzzi, P., 2000. Predictability and Transaction Costs: The Impact on Rebalancing Rules and Behavior. Journal of Finance 66, 2285–309.

Marshall, B.R., Nguyen, N.H., Visaltanachoti, N., 2017. Time series momentum and moving average trading rules. Quantitative Finance 17, 405-421.

Modigliani, F., Mordigliani, L., 1997. Risk-adjusted performance. Journal of Portfolio Management 23, 45-54.

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. Journal of Financial Economics 104, 228–250.

Moskowitz, T.J., Pedersen, L.H., 2013. Value and momentum everywhere. The Journal of Finance 68, 929-985.

Neely, C. J., Rapach, D. E., Tu, J., Zhou, G., 2014. Forecasting the Equity Risk Premium: The Role of Technical Indicators. Management Science 60, 1772–1791.

Shi, H.L., Zhou, W. X., 2017. Time series momentum and contrarian effects in Chines stock market. Physica A 483, 309–31.

Zakamulin, V., 2014. The real-life performance of market timing with moving average and time-series momentum rules. Journal of Asset Management 15, 261–278.

Zhu, Y., Zhou, G., 2009. Technical Analysis: An Asset Allocation Perspective on the Use of Moving Averages. Journal of Financial Economics 92, 519–44.

Figure 1 Distribution of k*
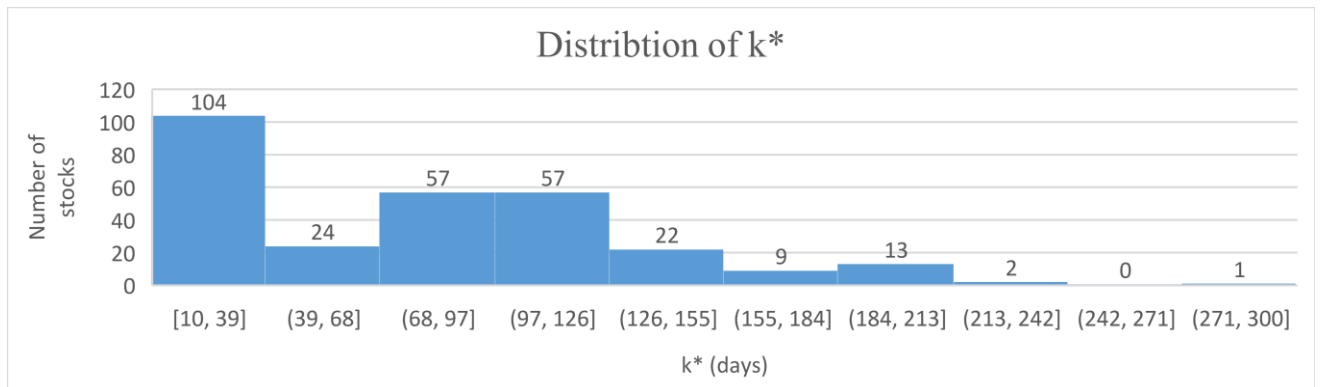
Figure 1: Distribution of k*.

The total number of stocks is 289. The period covers from 01/05/2005 to 31/12/2011. The optimal criterion is to maximize the M^2 for TSMOM switch strategies applied to stocks.

Figure 2 Distribution of corresponding M^2
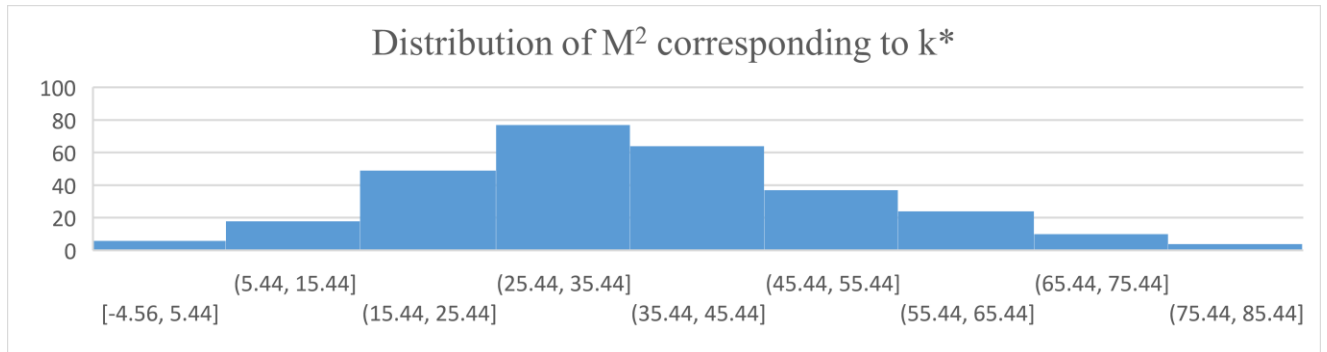
Figure 2: Distribution of annualized M^2

In this figure, the total number of stocks is 289. TSMOM strategies applied to 289 stocks select k* for each stock. Annualized M^2 is the M^2 measure for portfolios

Table 1 Descriptive statistics on sample stocks' main characteristics

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.

	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

Table 2 Summary statistics of BH and TSMOM returns

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.

	Mean	Diff	Std	Q3	Median	Q1	Mean	Diff	Std	Q3	Median	Q1	Mean	Diff	Std	Q3	Median	Q1
panel A: Annualized return μ							**Panel B: annualized standard deviation σ**						**Panel C: annualized skewness s**					
BH strategy	24.4		15.65	34.08	23.02	12.72	53.79		6.23	57.39	53.09	48.66	-0.579		8.19	-0.023	-0.711	-1.499
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	1.062	1.641**	11.7	1.8	0.542	-0.458
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	1.23	1.809***	6.206	1.522	0.229	-0.843
k=30	20.94	-3.46***	15.16	30.48	18.97	10.05	39.59	-14.20***	4.81	42.81	40.08	36.4	0.965	1.543***	6.11	1.396	0.039	-1.259
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	0.926	1.505***	6.032	1.188	0.036	-1.081
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	1.057	1.636***	6.042	1.304	0.076	-1.073
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	1.055	1.634***	6.037	1.27	0.015	-1.129
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	0.249	0.828	12.584	1.46	0.065	-1.264
k=100	31.62	7.22***	18.02	42.34	29.42	19.93	40.70	-13.09***	5.28	43.97	40.63	37.61	0.411	0.99	12.492	1.286	0.015	-1.15
k=120	28.17	3.77***	17.22	38.67	26.08	17.03	40.82	-12.97***	5.31	44.18	40.84	37.7	0.153	0.773	12.397	1.136	-0.265	-1.313
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	-0.074	0.505	12.615	0.781	-0.074	-1.311
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	-0.206	0.373	13.036	0.554	-0.486	-1.412
k=250	18.52	-5.88***	14.26	26.45	17.92	8.8	41.86	-11.93***	5.51	45.43	41.86	38.62	-0.722	-0.143	13.071	0.289	-0.851	-1.819
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	-0.874	-0.295	13.228	0.044	-0.968	-1.934

Table 3 Risk-adjusted performance of TSMOM strategies

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 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. *,**,and *** for the Sharpe ratio denote that difference of the mean of 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.

	Min.	Q1	Median	Mean.	Q3	Max.
Panel a: Annualized M^2 %						
k=10	-30.85	-8.56	0.56	3.94***	15.04	61.00
k=20	-24.97	-5.92	4.73	5.69***	15.03	63.15
k=30	-33.87	-5.23	3.57	5.01***	15.12	60.44
k=40	-23.08	-1.03	7.78	10.12***	19.80	63.60
k=50	-24.80	-1.48	7.49	9.21***	18.61	67.26
k=60	-33.02	-4.45	2.56	6.19***	15.10	67.95
k=80	-26.39	-1.83	7.45	9.34***	17.98	64.09
k=100	-15.91	7.50	15.09	16.45***	23.79	68.54
k=120	-22.26	2.60	11.02	12.18***	20.46	71.03
k=160	-21.54	-0.90	5.92	7.19***	14.05	49.81
k=200	-19.52	-0.13	6.51	6.51***	12.99	45.24
k=250	-24.79	-6.32	0.13	-0.31	4.84	27.99
k=300	-31.82	-10.29	-4.68	-5.12***	0.24	18.68
Panel b: Annualized Sharpe ratio %						
BH	-0.330	0.204	0.379	0.412	0.567	1.518
k=10	-0.681	0.134	0.401	0.419	0.689	1.854
k=20	-0.397	0.227	0.456	0.474*	0.731	1.458
k=30	-0.428	0.220	0.451	0.461	0.702	1.497
k=40	-0.267	0.250	0.528	0.543***	0.785	1.542
k=50	-0.385	0.224	0.456	0.512***	0.779	1.643
k=60	-0.547	0.144	0.430	0.464*	0.729	1.713
k=80	-0.415	0.260	0.513	0.535***	0.789	1.788
k=100	-0.508	0.457	0.657	0.706***	0.927	2.083
k=120	-0.426	0.346	0.554	0.589***	0.832	1.834
k=160	-0.485	0.278	0.477	0.498***	0.709	1.624
k=200	-0.510	0.302	0.483	0.493***	0.668	1.448
k=250	-0.467	0.147	0.331	0.348	0.521	1.424
k=300	-0.483	0.030	0.160	0.200	0.367	1.155

Table 4 Trading frequency of TSMOM strategies

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.

	Min	Q1	Median	Mean	Q3	Max
			Trading Frequency			
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 5 Performance of TMOM using alternative signal

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.

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Panel a: Annualized M^2 %						
	Min.	Q1	Median	Mean.	Q3	Max.
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 6 Descriptive statistics of k* and corresponding M^2 during in-sample period

Table 6 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.

Time period:	01/05/ 2005 to 31/12/2011					
	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 7 Performance of out-of-sample TSMOM with in-sample k*

Table 7 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.

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

Table 8 Performance of TSMOM during the out-of-sample period

Table 8 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.

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

Table 9 Average coefficients from the regressions

Table 9 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.

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 10 Performance of TSMOM strategies with *k** and adjusted *k**

Table 10 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.

	Annualized M^2 %				
	k*		adjusted k*		difference
Time period	Midian	Mean	Midian	Mean	Δ Mean
T1 to T2	1.36	2.10**	3.24	4.72***	2.62*
T1+30 to T2+30 days	1.43	1.93*	2.79	3.59***	1.66
T1+60 to T2+60 days	1.10	1.67	1.83	2.32**	0.65
T1+90 to T2+90 days	-1.01	-0.71	1.91	2.54**	3.25**
T1+120 to T2+120 days	1.08	1.61	1.27	1.96*	0.35
T1+150 to T2+150 days	-0.21	-0.91	1.04	1.78*	2.69**