Chapter 59

Technical Analysis in the Stock Market: A Review

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CHAPTER OUTLINE:

Abstract

Technical analysis is the study for forecasting future asset prices with past data. In this survey, we review and extend studies on not only the time-series predictive power of technical indicators on the aggregated stock market and various portfolios, but also the cross-sectional predictability with various firm characteristics. While we focus on reviewing major academic research on using traditional technical indicators, but also discuss briefly recent studies that apply machine learning approaches, such as Lasso, neural network and genetic programming, to forecast returns both in the time-series and on the cross-section.

Keywords
Technical Analysis, Machine Learning, Genetic Programming, Cross-sectional Returns, Predictability

59.1 Introduction

Why does technical analysis matter? It is about forecasting future asset prices using the past data, and clearly contradicts with market efficiency theory. In an ideal world in which all investors have the same information and the same rational expectations, the asset prices must be a random walk and must be unpredictable by any means. However, the real world is much different. First, no all investors have the same information on stocks. More importantly, even if they do have the same information, not everyone processes the information the same way, and some can view the information as good news and some can view as bad. As a result, how the market collective reacts to the information is never known an ante for sure by anyone, and there is no rational or all agreed equilibrium prices in practice. Therefore, investors have to observe the price path carefully to see how the market price adjusts over time relative to the information and related to their own expectations, resulting in the relevance of past data to future prices, yielding a certain degree of predictability.

There are many other reasons why the path matters (see, Han, Zhou and Zhu (2016) for a review). A simple example of path-dependent asset prices is that investors require greater returns after a big market crash. Another example is that the market is not perfectly liquid, and so larger traders must take time in days or even months to build or unwind their large positions, revealing possibly up or down trends in the market.

Technical indicators have a long history of use by practitioners to predict stock returns. Smidt (1965) surveys amateur traders and finds that over half of them use charts to identify trends. Schwager (1993, 1995) and Lo and Hasanhodzic (2009) show that many top traders and fund managers also rely heavily on technical analysis. Moreover, Covel (2005), citing examples of successful hedge funds, advocates the use of technical analysis exclusively without exploiting any fundamental information on the market. Today, with increasing computing power and data availability, technical indicators are popular and almost all brokerages provide chart analysis. High-frequency trading, algorithmic trading, and systematic trading in general are widespread (see, e.g., Harvey, 2021), which are data-driven and rule-based, sophisticated forms of technical analysis.

In this article, we provide a review on technical analysis. We will focus on the stock market, while briefly discussing other asset classes. We will first survey major advances on time-series predictability, and then on cross-section predictability.

On technical indicators, we focus exclusively on the use of moving averages because they are the most widely used tools for capturing a trend, and trend-following is the major trading strategy in practice. Moreover, they are also the ones on which we have ample evidence. Since technical analysis is in general the study for forecasting prices via past data, it includes machine learning approaches, such as Lasso, neural network and genetic programming, as special cases. We also discuss the latter as they are getting increasing attention and becoming more and more useful in applications.

On time-series predictability, we extend the market predictability study of Brock, Lakonishok, and LeBaron (1992) based on price moving averages to recent years, and find that the early predictability disappears almost completely. Following Schwert (2003) and McLean and Pontiff (2016), we explain this as *publication effect* as many profitable patterns of the stock market tend to disappear, reverse, or attenuate after their publications. Another reason is that the market as a whole is known as very difficult to forecast to begin with, as there are so many factors that can drive the ups and downs unless some other markets such as foreign exchanges of which the predictability is greater. However, using more sophisticated machine learning tools, such as Lasso and a new C-Lasso, Rapach and Zhou (2020) find that the market can still be profitably predicted with the moving averages in conjunction with macro predictor, even in recent years.

59.2 Time-series Predictability

There are both time-series predictability and cross-section predictability. We discuss the former in this section, and the later in the next section.

59.2.1 Market

In this subsection, we focus on time-series predictability of the aggregate stock market such as an index.

59.2.1.1 Empirical studies

Earlier studies on the usefulness of technical analysis concentrate on the market for its data availability. Cowles (1933) is perhaps the first empirical study on the profitability of professional forecasters who presumably use technical analysis and other means. But he finds that they cannot beat the buy-and-hold strategy. Fama and Blume (1966) examine a number of filter rules introduced by Alexander (1961) in the securities in the Dow Jones Industrial Average (DJIA) during 1956 through 1962, and conclude that the trading rules cannot beat the buy-and-hold strategy either. Other popular technical indicators include the moving averages (Cootner, 1962; Van, Horne and Parker, 1967, 1968; James, 1968; Dale and Workman, 1980) and relative strength (Levy, 1967; Jensen and Benington, 1970). The studies also find that technical trading rules fail to generate profitable performance. In short, the majority of earlier studies are skeptical about the usefulness of the technical analysis in the stock market.

With the availability of cheaper computing power and the development of electronic database, later studies generally have improved in terms of the testing procedure with more data and more elaborate strategies. Utilizing the DJIA from 1897 to 1986, Brock, Lakonishok, and LeBaron (1992) examine two of the simplest and the most popular technical trading rules – moving average and trading range break. In contrast to earlier studies, they find that all 26 technical strategies in their study generally exhibit strong profitability. Using the same technical rules, Bessembinder and Chan (1995) also find significant predictability in forecasting index return for a group of Asian stock markets, including Malaysia, Thailand, and Taiwan. Kwon and Kish (2002) extend the work of Brock, Lakonishok, and LeBaron (1992) by including trading volume moving averages indicators. Their results confirm that technical trading rules indeed add value, as compared to a buy-and-hold strategy.

However, there is concern of data snooping bias. Sullivan, Timmermann, and White (1999) find, using the White (2000) reality check bootstrap methodology, weak profitability over the 10 year out-of-sample period, suggesting that efficiency of the stock markets has improved. Our replications of Brock, Lakonishok, and LeBaron (1992) also show diminishing profits. In general, technical strategies are more robust for equity indexes in emerging markets (Bessembinder and Chan, 1995; Ito, 1999; Ratner and Leal, 1999), while that in developed markets are much weaker or have shrink over time (Mills, 1997; Bessembinder and Chan, 1998).

On the other hand, Neely, Rapach, Tu, and Zhou (2014) show that technical indicators, including moving average, momentum and volume-based indicators, can provide complementary information beyond 14 macroeconomic variables collected by Welch and Goyal (2008) to forecast the equity risk premium. They also show that the predictability of technical indicators becomes stronger during recessions. Since the frequency of trend breaks happen more often in recent years, Garg, Goulding, Harvey and Mazzoleni (2020) study the impact of trend breaks on the performance of standard trend-following strategies across several assets and asset classes, and construct dynamic multi-asset trend-following portfolios, with performance more than doubling the standard strategies over the last decade.

While most studies are based on linear models, a growing body of recent research combines traditional technical indicators with non-linear and advanced machine learning techniques, such as genetic programming and neural networks. Genetic programming (Koza, 1992) is a supervised machine learning method based on the principle of Darwinian natural evolution. When applied to technical trading rules, the building blocks of genetic trading rules consist of various functions of past prices, trading volume, numerical and logical constants, and logical functions. Allen and Karjalainens (1999) is among the first to apply genetic programming to examine the profitability of technical trading rules in the stock market. They use the combination of the moving averages of the past prices to find profitable trading rules to beat the S&P 500 index, but unsuccessfully. Neely (2003) also finds no evidence that genetic programming can generate trading rules for the S&P 500 index to beat the buy-and-hold strategy, while Neely, Weller, and Dittmar (1997) and Neely and Weller (2001) show that genetic trading rules produce superior performance in the foreign exchange markets. Recently, however, Brogaard and Zareei (2019), with modified genetic programming algorithms, are able to identify stronger time-series predictability of the S&P 500 index. Berutich, Lopez, Luna, and Quintana (2016) also present a robust genetic programming approach to determine the potential buy and sell conditions, and the resulting method yields robust solutions able to withstand extreme market conditions.

Neural network, based on biological neurosystems, is another commonly used machine learning approach in generating technical trading rules in the stock market. Gencay (1998a) uses a simple feed forward neural network model to explore the non-linear technical trading rules in the DJIA data over 1964 to 1988. The resulting trading rules are shown to outperform easily the buy-and-hold strategy in terms of both return and Sharpe ratio. Utilizing the DJIA data over a longer period from 1897 to 1988, Gencay (1998b) further shows strong and robust evidence of the nonlinear predictability of the trading rules. Gencay and Stengos (1998) further find that incorporating a 10-day volume indicator into the neural network model as an additional indicator help to improve the forecast accuracy on the DJIA return.

Other advanced techniques, such as reinforcement learning and support vector machine, are also utilized to produce technical trading strategies. Lee (2009) develops a prediction model based on support vector machine (SVM) to predict the trend of the stock market. Tan, Quek, and Cheng (2011) use the reinforcement learning (RL) technique, based on the momentum and moving average indicators, to determine the best time to go long and short. Meanwhile, there are also many studies utilizing the above techniques simultaneously to improve the profitability of various technical trading strategies. For example, Kim and Han (2000) propose a hybrid neural network model along with genetic algorithms to predict the stock price index, and show that the combination of the two techniques outperforms the conventional models. Chavarnakul and Enke (2009) develop an intelligent hybrid stock trading system that utilizes neural networks, fuzzy logic, and genetic algorithms to prove the predictability of the volume adjusted moving average indicator.

Recall that our definition of technical analysis is more general. The predictors are not limited to past price and volume information, but allowing for past data of any variables. In the academic literature, there are many economic variables that are well motivated to have predictive power on the stock market.

Welch and Goyal (2008) find that, while numerous economic variables have in-sample predictive ability for the market premium, they fail to deliver consistent out-of-sample forecasting gains relative to the simple historical average. Campbell and Thompson (2008) argue a few predictors can have out-of-sample predictive power, but it is difficult to know ex ante which of the predictors will do well in the future. Without forcing such a choice, Rapach, Strauss and Zhou (2010) show that the market is predictable by using a forecast combination method (averaging all the forecasts), thus providing the first convincing out-of-sample evidence on market predictability. Subsequently, there are many studies that find market predictability. For examples, Li, Ng and Swaminathan (2013) and Kelly and Pruitt (2013) and Rapach, Ringgenberg and Zhou (2016) find, respectively, that the aggregated implied cost of capital, book-market ratio and short interest are powerful predictors of the market, while Huang, Jiang, Tu and Zhou (2015), Jiang, Lee, Martin and Zhou (2019) and Chen, Tang, Yao and Zhou (2020) find investor sentiment, manager sentiment and employee sentiment can predict the market too. Koijen and Van Nieuwerburgh (2011), Rapach and Zhou (2013) and Timmermann (2018) provide reviews of the literature.

Recently, Gu, Kelly, and Xiu (2020) apply a comprehensive set of popular machine learning tools to both macro economic and firm specific predictors in a panel set-up for forecasting firm returns, and then obtain a significant market forecast by summing the component forecasts. Instead of using panel models, Dong, Li, Rapach and Zhou (2021) show, in traditional time-series regressions, that mispricing is related to predictability, and so about 100 asset pricing anomalies become a large set of new time-series predictors on the market beyond the usual dozen macro predictors.

The least absolute shrinkage and selection operator (Tibshirani 1996, LASSO) is one of the most popular machine learning techniques in finance. Rapach, Strauss and Zhou (2013) seems the first to apply it for forecasting returns, and they find that US market leads the world. There does not appear any major LASSO applications until Chinco, Clark-Joseph and Ye (2019) who use the LASSO to predict individual stock returns one minute ahead. Han, He, Rapach and Zhou (2020) propose a C-Lasso approach that can be applied more effectively to combining information from a large number of forecasts. Rapach and Zhou (2020) apply it to both technical indicators and macro variables and show that the market can be profitably predicted.

Since machine learning tools are getting popular and new methods are coming out fast, their application to forecasting the stock market is almost sure to increase substantially over time and may be found effects on the market prices too.

59.2.1.2 The theory

A short survey of theoretical models that justify the use of technical analysis is provided by Han, Zhou and Zhu (2016). Here we focus on the most widely used technical indicators, the moving averages (MAs), which are the foundation of trend-following.

Zhu and Zhou (2009) seems the first to provide a theoretical basis for the MAs. In a partial equilibrium model for a small investor, the MAs are fast learning methods about the underlying true model of asset dynamics. Under uncertainty about predictability or uncertainty about the true parameters, the MA learning can add value to an asset allocation problem in reasonable sample sizes. In contrast, sophisticated econometric methods, though asymptotically optimal, underperform the simple MAs due to not enough data. As an extension, Zhou, Zhu and Qiang (2012) provide an optimal asset allocation strategy using the MAs, and show it makes a significant economic difference empirically.

Han, Zhou and Zhu (2016) propose further an equilibrium model in which there are informed traders and technical traders. In the presence of noise traders, they show that, even in equilibrium, the technical traders can survive in the long-run and the MAs have predictive power on asset prices. However, the fraction of technical traders can matter. When the fraction is small, MAs indicate trend-following, but when the fraction is large, they predict counter-trends. In contrast to Han, Zhou and Zhu (2016) where the technical traders are assumed exogenously, Detzel, Liu, Strauss, Zhou and Zhu (2021) propose a novel equilibrium model in which technical analysis can arise endogenously via rational learning. They document that ratios of prices to their moving averages forecast daily Bitcoin returns in- and out-of-sample, and similar results hold for small-cap, young-firm, and low-analyst-coverage stocks as well as NASDAQ stocks during the dotcom era.

A limitation of the theoretical model of Han, Zhou and Zhu (2016) is that it justifies the use of one MA as a predictor. In practice, multiple MAs may be used at the same time. For simplicity, we consider two MA predictors. We show in what follows that the main conclusion can be extended to allowing for two MAs as predictors.

Consider now three types of investors: the informed, the short-term and long-term technical traders. Let w_1 and w_2 be the fraction of the short- and long-term technical traders. The informed investors observe the dividend D_t, mean growth rate of dividend π_t, the price as well as all history of the variables, while they do not directly observe the supply of asset, the fluctuation of which is due to noise trader behavior. Formally, $\mathcal{F}^i(t) = \{D_\tau, P_\tau, \pi_\tau : \tau \leq t\}$ is the informed investors' information set at time t. On the other hand, technical traders only observe dividend and price, and do not directly observe the mean grow rates of the dividends. The two types of technical investors use

$$A_{it} \equiv \int_{-\infty}^{t} \exp\left[-\alpha_i(t-s)\right] P_s ds, \tag{59.1}$$

with $i = 1, 2$ and $\alpha_1 > \alpha_2 > 0$, to infer information. A_{1t} corresponds to the short-term signal and A_{2t} the long-term signal. Formally, $\mathcal{F}_{\rangle}{}^u(t) = \{1, D_t, P_t, A_{it}\}, \quad i = 1, 2$ is the information sets of the technical traders of type i at time t. The result is summarized as follows.

Theorem: *In an economy defined in above Assumptions, there exists a stationary rational expectations equilibrium. The equilibrium price function has the following linear form:*

$$P_t = p_0 + p_1 D_t + p_2 \pi_t + p_3 \theta_t + p_4 A_{1t} + p_5 A_{2t}, \tag{59.2}$$

where p_0, p_1, p_2, p_3, p_4 and p_5 are constants determined only by model parameters.

Proof: Similar to Equations (A.1) and (A.2) of Han, Zhou and Zhu (2016), the informed investors' optimization problem is

$$\max_{\eta^i, c^i} E\left[-\int_t^{\infty} e^{-\rho s - c(s)} ds | \mathcal{F}_t^i\right] \;\; s.t. \;\; dW^i = (rW^i - c^i)dt + \eta^i dQ. \tag{59.3}$$

Let $J^i(W^i, D_t, \pi_t, \theta_t, A_{1t}, A_{2t}; t)$ be the value function, then it satisfies the HJB equation

$$\begin{aligned} 0 &= \max_{c,\eta}\Big[-e^{-\rho t - c} + J_W(rW^i - c^i + \eta^i e^i_Q \Psi) + \frac{1}{2}\sigma^i_Q \sigma^{iT}_Q \eta^{i2} J_{WW} + \eta^i \sigma^i_Q \sigma^{iT}_\Psi J_{W\Psi} \\ &\quad -\rho J + (e^i_\Psi \Psi)^T J_\Psi + \frac{1}{2}\sigma^i_\Psi J_{\Psi\Psi}\sigma^{iT}_\Psi\Big]. \end{aligned} \tag{59.4}$$

The optimal demand for stock is given by

$$\eta^i = f^i \Psi^i = f^i_0 + f^i_1 D_t + f^i_2 \pi_t + f^i_3 \theta_t + f^i_4 A_{1t} + f^i_5 A_{2t}, \tag{59.5}$$

where $f^i_0, f^i_1, f^i_2, f^i_3$, f^i_4 and f^i_5 are constants.

To solve the technical traders' optimization problem, for $i = 1, 2$, let W^u_i be the wealth of a technical trader i, η^u_i be the holding of stock and c^u_i be the consumption. Then the optimization problem is

$$\max_{\eta^u_i, c^u_i} E\left[-\int_t^\infty e^{-\rho s - c_i(s)} ds | \mathcal{F}^u_{it}\right] \;\; s.t. \;\; dW^u_i = (rW^u_i - c^u_i)dt + \eta^u_i dQ^u_i. \tag{59.6}$$

Let $J^u(W^u_i, \Psi^u_i; t)$ be the value function, then it solves the following HJB equation,

$$\begin{aligned} 0 &= \max_{c^u_i, \eta^u_i}\Big[-e^{-\rho t - c^u_i} + J^u_{W^u_i}(rW^u_i - c^u_i + \eta^u_i e^u_Q \Psi^u_i) + \frac{1}{2}\sigma^u_Q \sigma^{uT}_Q \eta^{u2} J_{W^u_i W^u_i} + \eta^u_i \sigma^u_{iQ} \sigma^{uT}_\Psi J^u_{W^u \Psi^u} \\ &\quad -\rho J^u + (e^u_\Psi \Psi^u)^T J^u_\Psi + \frac{1}{2}\sigma^u_\Psi J^u_{\Psi^u\Psi^u}\sigma^{uT}_\Psi\Big]. \end{aligned} \tag{59.7}$$

The technical traders' optimal demand for stock is given by

$$\eta^u_i = f^{iu}_0 + f^{iu}_1 D_t + f^{iu}_2 P_t + f^{iu}_3 A_{it}, \tag{59.8}$$

where $f^{iu}_0, f^{iu}_1, f^{iu}_2$ and f^{iu}_3 are constants for $i = 1, 2$.

We have now Equations (59.5) and (59.8), the demands of stock by informed and technical investors, the market clearing condition requires

$$(1 - w_1 - w_2)\eta^i + w_1 \eta^u_1 + w_2 \eta^u_2 = 1 + \theta_t,$$

or equivalently,

$$(1-w_1-w_2)[f^i_0 + f^i_1 D_t + f^i_2 \pi_t + f^i_3 \theta_t + f^i_4 A_{1t} + f^i_5 A_{2t}] + \sum_{j=1}^{2} w_j [f^{ju}_0 + f^{ju}_1 D_t + f^{ju}_2 P_t + f^{ju}_3 A_{jt}] = 1 + \theta_t. \tag{59.9}$$

Substitute P_t in (59.2) into above, and by matching coefficients of state variables, we obtain

$$\begin{cases} (1-w_1-w_2)f_0^i + \sum_{j=1}^{2} w_j(f_0^{ju} + f_2^{ju}p_0) = 1, \\ (1-w_1-w_2)f_1^i + \sum_{j=1}^{2} w_j(f_1^{ju} + f_2^{ju}p_1) = 0, \\ (1-w_1-w_2)f_2^i + \sum_{j=1}^{2} w_j f_2^{ju}p_2 = 0, \\ (1-w_1-w_2)f_3^i + \sum_{j=1}^{2} w_j f_2^{ju}p_3 = 1, \\ (1-w_1-w_2)f_4^i + w_1 f_3^{1u} + \sum_{j=1}^{2} w_j f_2^{ju}p_4 = 0, \\ (1-w_1-w_2)f_5^i + w_2 f_3^{2u} + \sum_{j=1}^{2} w_j f_2^{ju}p_5 = 0, \end{cases} \tag{59.10}$$

The solution to Equation (59.10) determines the coefficients p_0, p_1, p_2, p_3, p_4 and p_5 for the price function of (59.2). It is easy to show that a unique solution exists under general conditions. This implies that the Proposition holds. Q.E.D.

If all the investors are informed, i.e., $w = 0$, there is an explicit solution to the problem with the parameters in Equation (59.2) given as

$$p_0 \quad = \Phi + p_0^* = \frac{\alpha_\pi \bar{\pi}}{r(r+\alpha_D)(r+\alpha_\pi)} - \left[\frac{\sigma_D^2}{(r+\alpha_D)^2} + \frac{\sigma_\pi^2}{(r+\alpha_D)^2(r+\alpha_\pi)^2}\right], \tag{59.11}$$

$$p_1 \quad = p_D^* = \frac{1}{r+\alpha_D}, \tag{59.12}$$

$$p_2 \quad = p_\pi^* = \frac{1}{(r+\alpha_D)(r+\alpha_\pi)}, \tag{59.13}$$

with $p_3 < 0$ and $p_4 = p_5 = 0$. Q.E.D.

59.2.1.3 Brock, Lakonishok, and LeBaron (1992): An update

Since Brock, Lakonishok, and LeBaron (1992) is one of the major studies to provide empirical support to technical analysis, it is of interest to examine how the strategies performance after publication. The original sample period is from January 2, 1897 to December 31, 1986, and in this review, we extend the sample period to December 31, 2020.

We consider three trading rules: variable-length moving average (VMA), fixed-length moving average (FMA), and trading range break-out (TRB). To construct these strategies, we first calculate the moving average signals. The moving average (MA) at day t of lag L is defines as

$$A_{t,L} = \frac{P_{t-L-1} + P_{t-L-2} + \cdots + P_{t-1} + P_t}{L}, \tag{59.14}$$

where P_t is the market index level (DJIA) at day t.

The first rule, variable-length moving average (VMA), generates buy (sell) signals when the short moving average is above (below) the long moving average by an amount larger than the band. With a band of zero, this method classifies all trading days into either buys or sells. Mathematically, the returns on VMA strategy are

$$\tilde{R}_{VMA,t} = \begin{cases} MKT_t, & \text{if } \frac{A_{t-1,L_{short}}}{A_{t-1,L_{long}}} \geq 1+b; \\ -MKT_t, & \text{otherwise,} \end{cases} \tag{59.15}$$

where MKT_t is the return on the market index at day t, L_{long} (L_{short}) is the lag window for the long (short) moving average signal, and b is the band.

The second rule, fixed-length moving average (FMA) differs from VMA in the sense that it puts emphasis on the crossing of the moving averages. In specific, FMA trading rule initials a buy (sell) signal when the short moving average cuts the long moving average from below (above). Returns during the next ten days are recorded, and other signals during this period are ignored. As for the final rule, trading range break-out (TRB), a buy signal is initiated if the price penetrates the resistance level, which is defined as the local maximum price. Meanwhile, a sell signal is generated if the price goes below the support level, which is the local minimum. Define $MAX_{t,L}$ and $MIN_{t,L}$ the maximum and minimum price over the past L days include day t, respectively.

$$MAX_{t,L} = max\{P_t, P_{t-1}, \cdots, P_{t-L+1}\}, \tag{59.16}$$

$$MIN_{t,L} = min\{P_t, P_{t-1}, \cdots, P_{t-L+1}\}. \tag{59.17}$$

Then, the returns on TRB strategy are

$$\tilde{R}_{TRB,t} = \begin{cases} MKT_t, & \text{if} \quad \frac{P_{t-1}}{MAX_{t-1,L}} \geq 1 + b; \\ -MKT_t, & \text{if} \quad \frac{P_{t-1}}{MIN_{t-1,L}} \leq 1 - b. \end{cases} \tag{59.18}$$

While numerous variations of the above rules with different parameters are used in practice, we follow Brock, Lakonishok, and LeBaron (1992) to focus on the simplest and the most popular ones. For VMA and FMA, the windows for the short-long moving average are: 1-50, 1-150, 5-150, 1-200, and 2-200. For TRB, the resistance (support) level is defined as the maximum (minimum) price over the past 50, 150, and 200 days. In addition, all the rules are implemented with and without a one percent band.

Table 59.1 reports the summary statistics for the entire series and five subsamples for the daily and 10-day returns on the DJIA. Returns are defined as log differences of the index level. Panel A shows that the index yields the highest average daily return of 0.033% during the most recent subperiod from 1987 to 2020. Meanwhile, the lowest skewness (-1.58) and the greatest kurtosis (41.43) are also observed in this subperiod, indicating that the DJIA return represents a strong non-asymmetric and leptokurtic feature. Panel B reports the statistics for 10-day nonoverlapping returns. It is interesting to note that the resulting kurtosis is much lower than that for the daily returns for all subperiods.

Table 59.2 reports the performance of the 10 variable-length moving average (VMA) trading rules in the full sample and five subperiods. The second column specifies the trading rules. For instance, (1, 50, 0.01) indicates that the short period is one day, the long period is 50 days, and the band is 1%. "N(Buy)" and "N(Sell)" are the number of the buy and sell signals. It is expected to see that the trading rules with zero band generally initiates more trading signals. The last column reports the difference between the buy and sell returns. Panel A shows that during the full sample over 1897 to 2020, all these differences are positive and the resulting t-stats are highly significant. The column of "Buy" and "Sell" shows that the average return for buy and sell signals is positive and negative, respectively, for each of the ten trading rules. Averaging across the rules, the last row shows that the mean buy return is 0.038%, while the mean sell return is -0.01%.

Panel B shows the performance in several subperiods. To save space, we only report the results for (1, 150, 0) rule. During each of the first four subperiods, the average return on buy (sell) signals is positive (negative), and the difference between the buy and sell returns is positive and significant, which is consistent with the results of Brock, Lakonishok, and LeBaron (1992). However, during the most recent subperiod from 1987 to 2020, the average return on buy signals decreases almost by half to only 0.021%. Worse still, the average return on sell signals turns positive (0.064%). As a result, the buy-sell difference is negative, which indicates that the trading rule does not continue to generate a profitable return in this subsequent period.

Table 59.3 provides the results for other VMA trading strategies over 1987 to 2020. The results are similar. All of the ten VMA trading rules generate positive returns on the sell signals, and the resulting buy-sell differences are negative. This result is in stark contrast to the strong profitability of technical trading rules over the early period examined by Brock, Lakonishok, and LeBaron (1992).

Table 59.4 shows the performance of the fixed-length moving average (FMA) rules. Panel A shows that over the full sample from 1897 to 2020, the sell returns are negative, and the buy-sell differences are always positive for all the 10 FMA rules. In sharp contrast to Panel A, Panel B shows that FMA rules have experienced a huge decrease in profitability during the post-1987 subperiod. 9 out of the 10 rules yield positive returns on sell signals, and 7 rules generate negative buy-sell returns. On average, the buy-sell difference is negative (-0.029 %).

Table 59.5 reports the performance of the trading range break (TRB) rules. The results are similar to that of the two moving average rules: although TRB rules show some profitability over the full sample, it fails to generate positive buy-sell return in the post-1987 subperiod.

In short, we confirm Brock, Lakonishok, and LeBaron's (1992) result that the technical trading rules exhibit strong profitability during 1897 to 1986. However, our updated results indicate that it is unlikely that the same strategies can earn any profits during the post-1987 period. The publication effect may be one of the main causes. Today, it seems that different strategies are required to make abnormal profits in the changing world.

59.2.2 Portfolios and Other Assets

There are many studies on the use of technical analysis in other markets besides the stock market. Taylor and Allen (1992) show that currency market seems the next largest place where technical analysis is widely used. However, as shown by Hsu and Taylor (2014), the predictive power, like that in the stock market, tends to decrease over time.

In general, Fung and Hsieh (2001) find that trend-following trading is of great importance for explaining hedge fund returns. Burghardt and Walls (2011) show that a simple mechanical trading rule based on the MAs can yield favorable returns in trading futures contracts and the return correlation with the managed futures index exceeds 70%. Olszweski and Zhou (2014) show that combining both technicals and macro/fundamentals offers a significant improvement in risk-adjusted returns.

59.2.2.1 Related studies

Recently, Moskowitz, Ooi and Pedersen (2012) provide evidence on momentum across asset classes, that is, the past values have predictive power. However, Huang, Li, Wang and Zhou (2020) argue that, while asset classes may have predictability, the predictability is not simply fixed at the 12-month horizon with the past 12-month return as the sole predictor. They show that asset-by-asset time-series regressions reveal little evidence of 12-month momentum, both in- and out-of-sample. From an investment perspective, a strategy of using the 12-month momentum has similar performance with a strategy that is based on historical sample mean and does not require predictability. In other words, while Huang, Li, Wang and Zhou (2020) do not rule out the predictive power of past returns on future values for a wide range of assets, their study merely points out that the predictability can be much more complex than using just the past 12-month return.

Going beyond technical indicators, Filippou, Rapach, Taylor and Zhou (2020) show that the currency market is predictable with country characteristics, global variables, and their interactions, and the predictability yields sizable carry trade profits. For the corporate bond market, Guo, Lin, Wu, and Zhou (2020) provide the first predictability evidence across bond rating along with a survey of the literature.

In summary, technical analysis appears useful not only in the stock market, but also valuable across asset classes. However, as it is in the stock market, the predictability is small and tends to decline over time.

59.2.2.2 Han, Yang and Zhou (2013): An update

Instead of forecasting the stock index which can have too many factors affecting its returns, Han, Yang and Zhou (2013) provide perhaps the first application of a moving average timing strategy to portfolios, which are sorted by volatility or other characteristics of the stocks. We replicate this study below to see whether the publication effct is strong enough to weaken its performance too.

Their study is focused on portfolios sorted by volatility as stock volatility is a simple proxy of information uncertainty. The more uncertain the future information about a stock is, the more volatile the stock price is. The volatility sorted portfolios are also of interest from the theoretical perspectives about technical analysis. Rational models, such as Brown and Jennings (1989), show that rational investors can gain from forming expectations based on historical prices and this gain is an increasing function of the volatility of the asset.

For their major results, they apply the moving average (MA) timing strategy to the CRSP NYSE/Amex volatility decile portfolios constructed based on the NYSE/Amex stocks sorted into ten groups (deciles) by their annual standard deviations estimated using the daily returns within the prior year. The portfolios are rebalanced each year at the end of the previous year. The original sample period for the volatility decile portfolios is from July 1, 1963 to December 31, 2009 to coincide with the Fama-French factors. In this review, we extend the sample period to September 30, 2020.

Denote by R_{jt} ($j = 1, \ldots, 10$) the returns on the volatility decile portfolios, and by P_{jt} ($j = 1, \ldots, 10$) the corresponding portfolio prices (index levels). The moving average (MA) at day t of lag L is defined as

$$A_{jt,L} = \frac{P_{jt-L-1} + P_{jt-L-2} + \cdots + P_{jt-1} + P_{jt}}{L}, \tag{59.19}$$

which is the average price of the past L days include day t. The paper mainly considers 10-day moving averages but also examines 20-, 50-, 100- and 200-day moving averages for robustness.

On each trading day t, if the last closing price P_{jt-1} is above the MA price $A_{jt-1,L}$, the MA strategy will invest in the decile portfolio j for the trading day t, otherwise it will invest in the 30-day Treasury bill. So the MA provides an investment timing signal with a lag of one day. The idea of the MA is that an investor should hold an asset when the asset price is on an uninterrupted up trend, which may be due to a host of known and unknown factors to the investor. However, when the trend is broken, new factors may come into play and the investor should then sell the asset. Mathematically, the returns on the MA timing strategy are

$$\tilde{R}_{jt,L} = \begin{cases} R_{jt}, & \text{if} \quad P_{jt-1} > A_{jt-1,L}; \\ r_{ft}, & \text{otherwise}, \end{cases} \tag{59.20}$$

where R_{jt} is the return on the j-th volatility decile portfolio on day t, and r_{ft} is the return on the risk-free asset, the 30-day Treasury bill.

They define the differences in return between the MA timing strategy and a buy-and-hold strategy, $\tilde{R}_{jt,L} - R_{jt}$, as returns on the MA portfolios (MAPs), which measure the performance of the MA timing strategy relative to the buy-and-hold strategy. With the 10 decile portfolios, we thus obtain 10 MAPs,

$$\text{MAP}_{jt,L} = \tilde{R}_{jt,L} - R_{jt}, \quad j = 1, \ldots, 10. \tag{59.21}$$

A MAP can also be interpreted as a zero-cost arbitrage portfolio that takes a long position in the MA timing portfolio and a short position in the underlying volatility decile portfolio. The abnormal performance of the MAPs indicates the profitability of the MA investment timing strategy.

Table 59.6 reports the updated results of the original Table 1 of the paper. It shows the basic characteristics of the returns on the decile portfolios, R_{jt}, the returns on the 10-day MA timing portfolios, $\tilde{R}_{jt,10}$, and the returns on the corresponding MAPs, $\text{MAP}_{jt,10}$. The updated results are very similar to the old results even with additional 12 year's daily data, which demonstrates the robustness of the MA timing strategy.

Panel A provides the average return, the standard deviation, the skewness, and the Sharpe ratio of the buy-and-hold strategy across the ten volatility deciles. The average returns are more or less an increasing function of the deciles, ranging from 10.17% per annum for the lowest decile to 38.13% per annum for the highest decile. The last row in the table provides the difference between the highest and the lowest deciles. For the decile portfolios, the difference is 27.96% per annum, both statistically and economically highly significant. Similarly, the MA timing portfolios, reported in Panel B, also have returns varying (strictly) positively with the deciles, ranging from 17.72% to 53.14% per annum.[1] In addition, the returns on the MA timing portfolios not only are larger than those on the decile portfolios, but also enjoy substantially smaller standard deviations. For example, the standard deviation is 4.21% versus 7.35% for the lowest decile, and 15.06% versus 21.59% for the highest decile. In general, the MA timing strategy yields only about 65% volatility of the decile portfolios. As a result, the Sharpe ratios are several times higher for the MA timing portfolios than for the volatility decile portfolios. Furthermore, while the volatility decile portfolios display negative skewness (except for the highest volatility decile), the MA timing strategy yields either much smaller negative skewness or positive skewness across the volatility deciles. Panel C reports the results for the MAPs. The returns increase monotonically from 7.55% to 15.42% per annum across the deciles (except for the highest volatility decile). While the standard deviations are much smaller than those of R_{jt} in the corresponding deciles, they are not much different from those of $\tilde{R}_{jt,L}$. However, the skewness of the MAPs across all deciles is positive and large.

Table 59.7 is similar to Table 2 of the paper but uses the up-to-date Fama-French five-factor (FF5) model (Fama and French, 2015) instead of the three-factor model (Fama and French, 1993). It reports the results of the daily FF5 regressions of the MAPs formed with 10-day MA timing strategy. Again, the results are very similar. The alphas or risk-adjusted returns are even greater than the unadjusted ones ranging from 9.36% to 20.70% per annum. The alphas also increase monotonically from the lowest volatility decile to higher volatility deciles, except that the highest decile yields a slightly lower alpha than the ninth decile. Nevertheless, the highest volatility decile still generates an alpha that is about twice as large as that generated by the lowest decile (19.49 versus 9.36). The difference is reported in the last row, which is substantial and highly significant.

Table 59.8 reports the daily FF5 regression results using only samples after the publication, i.e., from January 4, 2010 to September 30, 2020. The results are even stronger than the ones reported in the paper for the sample period from July 1, 1963 to December 31, 2009, and the ones reported in Table 59.7 for the extended sample period. For example, the spread between the highest and lowest deciles is 13.38%, while it is 10.13% in the extended sample period.

In summary, the performance of the MA timing on volatility portfolio seems very robust, and even stronger after publication. Hence, the MA timing is an example for which there is most likely no publication effect. One possibility might be that it is much more costly to construct and trade the volatility portfolio than trading the market index.

[1]To put this in perspective, the equal-weighted NYSE/Amex index has an average return of 19.22% per annum, and a standard deviation of 17.14% per annum.

59.3 Cross-section Predictability

Cross-section predictability is about the relative performance of assets, and hence the econometric tools will be different from time-series regressions and the like. Instead, it relies on cross-section regressions, panel models and their extensions.

59.3.1 Fama-MacBeth Regressions

The cross-section predictive power of a firm characteristic can be assessed by sorting the variable across firms, or by running Fama and MacBeth's (1973) regressions, in which asset returns are regressed on firm specific variables across firms. The latter is the most used method for examining the cross-section predictive power of more than one firm characteristics. Haugen and Baker (1996) provide excellent illustration of implementing the latter.

The size and the book-to-market are the earlier well known predictors, and the momentum effect of Jegadeesh and Titman (1993) is the next most well known. Jagannathan, Schaumburg and Zhou (2010), Nagel (2013), and Lewellen (2015) review more predictive variables and related studies. Recent research, however, makes use of more complex models and machine learning tools, to be discussed in the next subsection.

Han, Zhou and Zhu (2016) is the first to study the predictive power of technical indicators in the cross-section. Based purely on the MAs over various horizons, they find that the resulting trend factor earns a high Sharpe ratio, beating almost all known fundamental factors. Because of large individual trading volume in China, Liu, Zhou and Zhu (2021a) propose a new trend factor accounting for the trading volume, and find that it improves the usual trend factor substantially and explains almost all the know anomalies in the Chinese stock market. Avramov, Kaplanski and Subrahmanyam (2021) propose a novel moving average distance as a predictor for the cross-section of stock returns. They find that the resulting spread earns annualized value-weighted alphas around 9%, and the predictability goes beyond momentum, 52-week highs, profitability, and other prominent anomalies.

59.3.1.1 Han, Zhou and Zhu (2016): An update

It is of interest to examine how the trend factor performs after its publication. To construct the trend factor, the paper first calculates the MA prices on the last trading day of each month t, which is defined as

$$A_{jt,L} = \frac{P^t_{j,d-L+1} + P^t_{j,d-L+2} + \cdots + P^t_{j,d-1} + P^t_{j,d}}{L}, \tag{59.22}$$

where P^t_{jd} is the closing price for stock j on the last trading day d of month t, and L is the lag length. Then, the moving average prices are normalized by the closing price on the last trading day of the month,

$$\tilde{A}_{jt,L} = \frac{A_{jt,L}}{P^t_{jd}}. \tag{59.23}$$

To predict the monthly expected stock returns cross-sectionally, a two-step procedure is employed. In the first step, a cross-section regression of stock returns on observed normalized MA signals is run in each month t to obtain the time-series of the coefficients on the signals,

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t}\tilde{A}_{jt-1,L_i} + \epsilon_{j,t}, \quad j = 1, \cdots, n, \tag{59.24}$$

where

$$\begin{aligned} r_{j,t} &= \text{rate of return on stock } j \text{ in month } t, \\ \tilde{A}_{jt-1,L_i} &= \text{trend signal at the end of month } t-1 \text{ on stock } j \text{ with lag } L_i, \\ \beta_{i,t} &= \text{coefficient of the trend signal with lag } L_i \text{ in month } t, \\ \beta_{0,t} &= \text{intercept in month } t, \end{aligned}$$

and n is the number of stocks. It should be noted that only information in month $t-1$ or prior is used above to regress returns in month t. For the signals in the above regressions, the paper considers MAs of lag lengths 3-, 5-, 10-, 20-, 50-, 100-, 200-, 400-, 600-, 800-, and 1,000-days. These MA signals roughly indicate the daily, weekly, monthly, quarterly, 1-year, 2-year, 3-year, 4-year, and 5-year price trends of the underlying stock.

Then, in the second step, as in Haugen and Baker (1996), we estimate the expected return for month $t+1$ from

$$E_t[r_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}]\tilde{A}_{jt,L_i}, \tag{59.25}$$

where $E_t[r_{j,t+1}]$ is our forecasted expected return on stock j for month $t+1$, and $E_t[\beta_{i,t+1}]$ is the estimated expected coefficient of the trend signal with lag L_i, and is give by

$$E_t[\beta_{i,t+1}] = \frac{1}{12}\sum_{m=1}^{12} \beta_{i,t+1-m}, \tag{59.26}$$

which is the average of the estimated loadings on the trend signals over the past 12 months.

Finally, to construct the trend factor, stocks are sorted into five portfolios by their forecasted expected returns. The portfolios are equal-weighted and rebalanced every month. The return difference between the quintile portfolio of the highest expected returns and the quintile portfolio of the lowest is defined as the return on the trend factor. Intuitively, the trend factor buys stocks that are forecasted to yield the highest expected returns (Buy High) and shorts stocks that are forecasted to yield the lowest expected returns (Sell Low).

Table 59.9 reproduces the original Table 1 in the paper with the sample extended to December 2019 and replaces the momentum factor with Fama-French UMD factor. It also includes the trend factor constructed using Fama-French approach (Table 10 in the paper). The trend factor is constructed by excluding stocks with prices below $5 (price filter) and stocks that are in the smallest decile sorted with NYSE breakpoints (size filter) at the end of each month. It reports the summary statistics of the trend factor, short-term reversal factor (SREV), momentum factor (UMD), long-term reversal factor (LREV), as well as the Fama-French three factors, eg, Market, small minus big (SMB), and high minus low (HML).

The average monthly return of the trend factor from June 1930 through December 2019 is 1.56% per month (compared to 1.63% in the paper), more than doubling the average return of any of the other factors including SREV, whose average return is the highest among the other factors but is only 0.77% per month. The standard deviation of the trend factor is unchanged from data up to December 2014 (3.42% versus 3.45%), lower than that of any other factor except SMB. As a result, the Sharpe ratio of the trend factor is much higher than those of the other factors. For example, the trend factor has a Sharpe ratio of 0.46, whereas the next highest Sharpe ratio is only 0.23 generated by SREV. The trend factor constructed using Fama-French approach (Trend(FF)) yields a higher average return of 1.22% per month and lower standard deviation of 2.90%, and thus delivers a higher Sharpe ratio of 0.42. As expected, the momentum factor has a very large negative skewness (-3.02) and very large kurtosis (27.4). In contrast, the trend factor has a large positive skewness (1.44 and 1.61) and large kurtosis (11.3 and 11.2), indicating a fat right tail, and great chances for large positive returns.

Table 59.10 reports the same summary statistics of these factors after publication of the paper, i.e., from January 2015 to December 2019. In this short five-year period, the trend factor does not perform as well as it used to. It does only slightly better than the momentum factor, but worse than the short-term reversal factor. In contrast, the market performs remarkable well during the last five years, delivering 0.89% a month on average.

What drives the relatively underperformance of the trend factor? The first may be the publication effect emphasized by Schwert (2003), and found true for many anomalies by McLean and Pontiff (2016). While the publication effect may play a role here, there seem to exist other fundamental causes. The long-term reversal factor is particularly bad, losing -0.72% a month. The SMB and HML factors lose money significantly over the years too, whereas the market outperforms all other factors substantially, a very rare phenomenon. The trend now comes down from the usual number one spot to the third. Although it may have something to do with the poor performance of the long-term reversal factor, the impact is likely small since the trend factor captures trends over all horizons. On the other hand, while many anomalies are weakened after publication, do some come back in this extraordinary market environment? Note that our update period here is after the publication of McLean and Pontiff (2016) whose data ends in 2013. These are open questions of future research.

59.3.2 Machine Learning Methods

Machine learning methods, in contrast to the Fama-MacBeth regressions, can incorporate more predictors and can examine nonlinear relations. Freyberger, Neuhierl and Weber (2020), Gu, Kelly and Xiu (2020) and Kozak, Nagel and Santosh (2020) are recent examples of using firm characteristics to predict the cross-section of stock returns, which can easily adapted to using the technical indicators of Han, Zhou and Zhu (2016) or using these in conjunction of the firm characteristics. Typically, such studies assess the economic value of forecasting by examining the performance of a spread portfolio similar to the Fama-MacBeth regression case except that now the estimated expected returns are computed from the new methods rather than from the Fama-MacBeth regression. Liu, Zhou and Zhu (2021b) use a genetic programming approach to maximize the Sharpe ratio of the spread portfolio in estimating the model. As it turns out, this economically motivated objective helps to improve substantially the performance.

The above machine learning methods rely on panel data. Han, He, Rapach and Zhou (2020) propose a C-Lasso approach that allows for missing and adding gradually available new characteristics. This may be particularly useful for applying to high-frequency technical indicators which are available only in recent decades. It will be of interest to apply all these machine learning methods to more pure technical indicators, those depend on price and trading volume only.

59.4 Conclusion

This article reviews primarily the use of technical analysis in the stock market, though we do discuss briefly applications in other asset classes. The empirical evidence shows that technical analysis is useful and has significant predictive power on stock returns both in the time-series and in the cross-section.

However, there are three important caveats. First, the degree of predictability is typically small, and has to be well managed to be exploited profitably. Although cross-section predictability is stronger than time-series predictability, the trading cost of the former is much higher. Second, the predictability is time-varying, and tends to decrease over time. A particular profitable predictability strategy often subjects to a *publication effect* (Schwert, 2003 and McLean and Pontiff, 2016) that, its superior performance often disappears, reverses, or attenuates after its publication. We have updated three major studies with data after publication, and find that two of them have weaker results than before publication. Third, all trading rules, technical strategies included, are subject to a *tournament effect.* No matter what the state of art machine learning tools or artificial intelligence packages all the traders are using, about half of them will fail to beat the market return, while the others will probably outperform.

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Table 59.1

Summary Statistics for Daily and 10-Day Returns

Results are presented for the full sample over 1897 to 2020 and five nonoverlapping subperiods. Returns are measured as log differences of the level of the Dow index. 10-day returns are based on nonoverlapping 10-day periods.

Panel A: Daily Returns						
	Full Sample	1897-1914	1915-1938	1939-1962	1962-1986	1987-2020
N	33583	5272	7165	6570	6283	8545
Mean	0.00021	0.00011	0.00015	0.00022	0.00015	0.00033
Std.	0.01093	0.01001	0.01463	0.00742	0.00849	0.01167
Skew	-0.56880	-0.51406	0.01834	-0.82081	0.23110	-1.57504
Kurtosis	24.27	9.15	12.79	12.69	5.66	41.43
Panel B: 10-Day Returns						
Mean	0.00206	0.00124	0.00142	0.00219	0.00161	0.00324
Std.	0.03549	0.03403	0.04749	0.02729	0.02982	0.03210
Skew	-1.04321	-0.17634	-0.83248	-1.34787	-0.10958	-1.47806
Kurtosis	14.18	4.55	8.81	12.94	4.44	11.82

Table 59.2

Performances of the Variable-Length Moving Average (VMA) Rules: 1897-2020

Results for daily data from 1897-2020. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(Buy)" and "N(Sell)" are the number of buy and sell signals reported during the sample. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. "Buy $>$ 0" and "Sell $>$ 0" are the fraction of buy and sell returns greater than zero. The last row reports averages across all 10 rules. Results for subperiods are given in Panel B.

Period	Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
Panel A: Full Sample								
1897-2020	(1,50,0)	20046	13488	0.00042	-0.00012	0.53662	0.48880	0.00054
				(2.24)	(-2.92)			(4.47)
	(1,50,0.01)	16452	10245	0.00050	-0.00016	0.53805	0.49175	0.00066
				(2.24)	(-3.07)			(4.60)
	(1,150,0)	21184	12250	0.00036	-0.00007	0.53573	0.48955	0.00043
				(1.65)	(-2.37)			(3.48)
	(1,150,0.01)	19338	10486	0.00038	-0.00013	0.53801	0.49199	0.00051
				(1.73)	(-2.60)			(3.75)
	(5,150,0)	21200	12234	0.00033	-0.00001	0.53552	0.48913	0.00035
				(1.32)	(-1.90)			(2.79)
	(5,150,0.01)	19245	10438	0.00036	-0.00006	0.53666	0.49272	0.00041
				(1.40)	(-2.10)			(3.03)
	(1,200,0)	21707	11677	0.00037	-0.00012	0.53577	0.49165	0.00049
				(1.79)	(-2.70)			(3.88)
	(1,200,0.01)	20178	10302	0.00037	-0.00013	0.53717	0.49534	0.00050
				(1.68)	(-2.63)			(3.73)
	(2,200,0)	21722	11662	0.00035	-0.00008	0.53508	0.49082	0.00044
				(1.59)	(-2.41)			(3.47)
	(2,200,0.01)	20150	10287	0.00035	-0.00008	0.53593	0.49344	0.00043
				(1.45)	(-2.25)			(3.21)
	Average			0.00038	-0.00010			0.00048
Panel B: Subperiods								
1897-1914	(1,150,0)	2925	2198	0.00039	-0.00029	0.53231	0.49727	0.00068
				(1.26)	(-1.52)			(2.41)
1915-1938	(1,150,0)	4217	2948	0.00053	-0.00041	0.55229	0.50068	0.00094
				(1.36)	(-1.73)			(2.67)
1939-1962	(1,150,0)	4242	2328	0.00036	-0.00004	0.54267	0.47509	0.00040
				(0.96)	(-1.43)			(2.07)
1962-1986	(1,150,0)	3672	2611	0.00041	-0.00022	0.52206	0.51972	0.00063
				(1.49)	(-1.87)			(2.91)
1987-2020	(1,150,0)	6193	2352	0.00021	0.00064	0.52931	0.45323	-0.00043
				(0.61)	(1.16)			(-1.53)

Table 59.3

Performances of the Variable-Length Moving Average (VMA) Rules: 1987-2020

Results for daily data from 1987-2020. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. "N(Buy)" and "N(Sell)" are the number of buy and sell signals reported during the sample. Numbers in parentheses are standard t-ratios testing the difference of the mean buy and mean sell from the unconditional 1-day mean, and buy-sell from zero. "Buy > 0" and "Sell > 0" are the fraction of buy and sell returns greater than zero. The last row reports averages across all 10 rules.

Period	Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
1987-2020	(1,50,0)	5666	2879	0.00025	0.00048	0.52983	0.45780	-0.00024
				(0.40)	(0.63)			(-0.89)
	(1,50,0.01)	4659	2076	0.00015	0.00052	0.52350	0.45568	-0.00038
				(0.50)	(0.85)			(-1.17)
	(1,150,0)	6193	2352	0.00021	0.00064	0.52931	0.45323	-0.00043
				(0.61)	(1.16)			(-1.53)
	(1,150,0.01)	5661	1874	0.00020	0.00063	0.53030	0.45411	-0.00043
				(0.51)	(1.05)			(-1.35)
	(5,150,0)	6218	2327	0.00021	0.00064	0.53040	0.45552	-0.00043
				(0.60)	(1.13)			(-1.50)
	(5,150,0.01)	5634	1837	0.00022	0.00064	0.53088	0.46053	-0.00042
				(-0.49)	(1.02)			(-1.30)
	(1,200,0)	6398	2147	0.00028	0.00047	0.53329	0.46344	-0.00019
				(0.25)	(0.52)			(-0.67)
	(1,200,0.01)	5949	1771	0.00025	0.00074	0.53169	0.46132	-0.00049
				(0.55)	(1.22)			(-1.54)
	(2,200,0)	6402	2143	0.00026	0.00053	0.53249	0.46104	-0.00027
				(0.36)	(0.73)			(-0.94)
	(2,200,0.01)	5938	1762	0.00025	0.00070	0.53116	0.46254	-0.00045
				(0.50)	(1.11)			(-1.40)
	Average			0.00023	0.00060			-0.00037

Table 59.4

Performances of the Fixed-Length Moving Average (FMA) Rules

Cumulative returns are reported for fixed 10-days periods after signals. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. The last row reports averages across all 10 rules. The sample period in Panel A is from 1897 to 2020. The sample period in Panel B is from 1987 to 2020.

Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
Panel A: Sample period over 1897-2020							
(1,50,0)	452	500	0.0029	-0.0017	0.6150	0.5080	0.0047
			(0.51)	(-2.37)			(2.02)
(1,50,0.01)	411	411	0.0043	-0.0024	0.6253	0.5012	0.0067
			(1.28)	(-2.53)			(2.70)
(1,150,0)	232	271	0.0046	-0.0002	0.5690	0.5609	0.0048
			(1.07)	(-1.07)			(1.52)
(1,150,0.01)	225	206	0.0045	-0.0025	0.6267	0.5728	0.0070
			(1.03)	(-1.83)			(2.04)
(5,150,0)	195	201	0.0061	-0.0011	0.6103	0.5920	0.0072
			(1.58)	(-1.25)			(2.01)
(5,150,0.01)	185	176	0.0048	-0.0030	0.6162	0.5455	0.0078
			(1.05)	(-1.88)			(2.09)
(1,200,0)	174	219	0.0043	-0.0010	0.6034	0.5434	0.0053
			(0.81)	(-1.28)			(1.47)
(1,200,0.01)	173	172	0.0045	-0.0041	0.6243	0.5291	0.0087
			(0.91)	(-2.29)			(2.27)
(2,200,0)	160	203	0.0039	-0.0024	0.6125	0.5517	0.0062
			(0.63)	(-1.78)			(1.66)
(2,200,0.01)	167	159	0.0006	-0.0047	0.5389	0.5220	0.0052
			(0.53)	(-2.38)			(1.33)
Average			0.0040	-0.0023			0.0064
Panel B: Sample period over 1987-2020							
(1,50,0)	110	153	0.0020	0.0042	0.6909	0.6078	-0.0022
			(0.41)	(0.36)			(-0.55)
(1,50,0.01)	115	108	0.0004	0.0059	0.6087	0.6389	-0.0055
			(0.94)	(0.85)			(-1.27)
(1,150,0)	75	84	0.0003	0.0016	0.5200	0.5357	-0.0013
			(0.79)	(0.48)			(-0.25)
(1,150,0.01)	64	59	-0.0021	0.0060	0.5625	0.6610	-0.0081
			(-1.33)	(0.66)			(-1.40)
(5,150,0)	62	61	0.0028	-0.0022	0.5806	0.6066	0.0050
			(0.09)	(-1.32)			(0.87)
(5,150,0.01)	57	51	0.0009	0.0003	0.5088	0.5490	0.0006
			(0.55)	(0.65)			(0.10)
(1,200,0)	60	64	0.0026	0.0029	0.5667	0.5469	-0.0003
			(0.14)	(0.08)			(-0.05)
(1,200,0.01)	47	51	-0.0012	0.0074	0.5745	0.6863	-0.0086
			(-0.95)	(0.93)			(-1.33)
(2,200,0)	51	62	0.0025	0.0020	0.5882	0.5806	0.0005
			(0.16)	(0.30)			(0.09)
(2,200,0.01)	52	45	-0.0025	0.0065	0.5000	0.7111	-0.0090
			(-1.28)	(0.69)			(-1.38)
Average			0.0006	0.0035			-0.0029

Table 59.5

Performances of the Trading Range Break (TRB) Rules

Cumulative returns are reported for fixed 10-days periods after signals. Rules are identified as (short, long, band) where short and long are the short and long moving averages respectively, and band is the percentage difference that is needed to generate a signal. The last row reports averages across all 10 rules. The sample period in Panel A is from 1897 to 2020. The sample period in Panel B is from 1987 to 2020.

Test	N(Buy)	N(Sell)	Buy	Sell	Buy>0	Sell>0	Buy-Sell
Panel A: Sample period over 1897-2020							
(1,50,0)	1031	521	0.0039	0.0012	0.5790	0.5413	0.0027
			(1.65)	(-0.56)			(1.43)
(1,50,0.01)	333	315	0.0073	-0.0005	0.6156	0.5460	0.0079
			(2.69)	(-1.29)			(2.82)
(1,150,0)	761	255	0.0037	0.0005	0.5782	0.5098	0.0032
			(1.23)	(-0.71)			(1.24)
(1,150,0.01)	219	169	0.0073	-0.0008	0.6256	0.4970	0.0081
			(2.17)	(-1.03)			(2.21)
(1,200,0)	699	215	0.0037	0.0006	0.5808	0.5209	0.0031
			(1.18)	(-0.60)			(1.11)
(1,200,0.01)	202	149	0.0066	-0.0001	0.6040	0.5101	0.0067
			(1.82)	(-0.73)			(1.75)
Average			0.0054	0.0002			0.0053
Panel B: Sample period over 1987-2020							
(1,50,0)	299	104	0.0011	0.0062	0.5819	0.5385	-0.0051
			(1.15)	(0.93)			(-1.41)
(1,50,0.01)	83	63	0.0045	0.0030	0.5542	0.5873	0.0015
			(0.35)	(0.07)			(0.28)
(1,150,0)	240	37	0.0010	0.0204	0.5875	0.6216	-0.0195
			(1.08)	(3.25)			(-3.43)
(1,150,0.01)	58	26	0.0035	0.0131	0.5345	0.5769	-0.0096
			(0.07)	(1.57)			(-1.27)
(1,200,0)	224	28	0.0016	0.0208	0.5893	0.6786	-0.0191
			(0.73)	(2.89)			(-2.98)
(1,200,0.01)	53	24	0.0041	0.0229	0.5472	0.7083	-0.0188
			(0.20)	(3.00)			(-2.38)
Average			0.0026	0.0144			-0.0118

Table 59.6

Summary Statistics

We calculate the 10-day moving average prices each day using the last 10 days' closing prices including the current closing price, and compare the moving average price with the current price as the timing signal. If the current price is above the moving average price, it is an in-the-market signal, and we will invest in the decile portfolios for the next trading day; otherwise it is an out-of-the-market signal, and we will invest in the 30-day risk-free Treasury Bill for the next trading day. We use the 10 NYSE/Amex volatility decile portfolios as the investment assets. We report the average excess return (Avg Ret), the standard deviation (Std Dev), and the skewness (Skew) for the buy-and-hold benchmark decile portfolios (Panel A), the moving average timing decile portfolios (Panel B), and the moving average portfolios (MAPs) that are the differences between the MA timing portfolios and the buy-and-hold portfolios (Panel C). The results are annualized and in percentage. We also report the annualized Sharpe ratio (SRatio) for the buy-and-hold portfolios and the moving average timing portfolios, and report the success rate for the MAPs. The sample period is from July 1, 1963 to September 30, 2020. *t*-statistics are in parentheses and significance at the 1% and 5% levels is given by an ** and an *, respectively.

Rank	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	SRatio	Avg Ret	Std Dev	Skew	Success
	Panel A				**Panel B**				**Panel C**			
	Volatility Decile Portfolios				**MA(10) Timing Portfolios**				**MAP**			
Low	10.17**	7.35	-2.49	0.77	17.72**	4.21	1.33	3.15	7.55**	5.96	4.81	0.61
	(10.46)				(31.81)				(9.58)			
2	12.13**	10.31	-1.70	0.74	18.92**	6.11	0.55	2.37	6.79**	8.27	3.25	0.58
	(8.89)				(23.40)				(6.21)			
3	13.34**	12.23	-1.39	0.72	19.44**	7.52	-0.16	1.99	6.11**	9.62	2.54	0.57
	(8.25)				(19.56)				(4.80)			
4	13.97**	13.92	-1.00	0.68	21.33**	8.68	-0.38	1.94	7.36**	10.85	1.68	0.57
	(7.59)				(18.58)				(5.12)			
5	14.26**	15.52	-0.86	0.63	22.57**	9.75	-0.28	1.86	8.31**	12.03	1.47	0.57
	(6.95)				(17.51)				(5.22)			
6	15.08**	16.56	-0.71	0.64	23.99**	10.52	-0.17	1.86	8.92**	12.75	1.25	0.57
	(6.88)				(17.25)				(5.29)			
7	14.80**	17.85	-0.63	0.58	24.73**	11.34	-0.00	1.79	9.94**	13.74	1.18	0.57
	(6.27)				(16.49)				(5.47)			
8	14.40**	19.22	-0.48	0.52	27.95**	12.31	0.29	1.91	13.54**	14.68	1.05	0.58
	(5.67)				(17.17)				(6.97)			
9	17.13**	20.24	-0.41	0.62	32.55**	13.21	0.39	2.13	15.42**	15.23	1.01	0.57
	(6.40)				(18.63)				(7.65)			
High	38.13**	21.59	0.07	1.56	53.14**	15.06	1.42	3.23	15.01**	15.30	0.72	0.60
	(13.35)				(26.68)				(7.42)			
High - Low	27.96**	18.46	0.37	0.77	35.42**	13.99	1.40	3.15	7.46**	13.06	0.40	0.61
	(11.45)				(19.14)				(4.32)			

Table 59.7

Fama-French Alphas

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs formed from the 10-day MA timing strategy on the Fama-French five factors. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% and 5% levels is given by an ** and an *, respectively. The sample period is from July 1, 1963 to September 30, 2020.

Rank	α(%)	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}	Adj. R^2(%)
Low	9.36**	-0.19**	-0.05*	-0.04	-0.08**	-0.02	24.51
	(10.50)	(-8.10)	(-2.01)	(-1.19)	(-4.37)	(-0.57)	
2	10.10**	-0.35**	-0.11**	-0.09*	-0.11**	-0.04	42.87
	(9.31)	(-11.76)	(-4.13)	(-2.23)	(-4.72)	(-1.36)	
3	10.29**	-0.44**	-0.16**	-0.09*	-0.15**	-0.07*	49.52
	(9.11)	(-14.41)	(-6.19)	(-2.21)	(-6.04)	(-2.31)	
4	12.20**	-0.51**	-0.22**	-0.10**	-0.16**	-0.08*	52.91
	(10.39)	(-16.79)	(-8.12)	(-2.53)	(-5.92)	(-2.26)	
5	13.64**	-0.57**	-0.28**	-0.14**	-0.16**	-0.03	55.26
	(10.98)	(-19.14)	(-10.71)	(-3.01)	(-5.84)	(-0.95)	
6	14.47**	-0.60**	-0.34**	-0.12**	-0.16**	-0.03	55.28
	(11.07)	(-21.04)	(-11.97)	(-2.73)	(-5.64)	(-0.87)	
7	15.59**	-0.64**	-0.39**	-0.11*	-0.12**	-0.01	55.62
	(11.31)	(-22.66)	(-13.29)	(-2.43)	(-4.02)	(-0.37)	
8	19.25**	-0.67**	-0.44**	-0.07	-0.09**	-0.01	54.28
	(13.19)	(-23.88)	(-13.92)	(-1.48)	(-2.88)	(-0.27)	
9	20.70**	-0.66**	-0.49**	-0.03	-0.02	0.02	51.68
	(13.35)	(-23.21)	(-15.21)	(-0.67)	(-0.73)	(0.51)	
High	19.49**	-0.57**	-0.51**	-0.05	0.06	0.03	42.05
	(11.53)	(-18.99)	(-14.12)	(-0.97)	(1.82)	(0.69)	
High - Low	10.13**	-0.38**	-0.45**	-0.01	0.14**	0.05	
	(6.42)	(-20.56)	(-15.95)	(-0.14)	(4.48)	(1.31)	

Table 59.8

Fama-French Alphas After Publication

The table reports the alphas, betas and the adjusted R-squares of the regressions of the MAPs formed from the 10-day MA timing strategy on the Fama-French five factors. The alphas are annualized and in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1% and 5% levels is given by an ** and an *, respectively. The sample period is after the sample period used in the paper, from January 4, 2010 to September 30, 2020.

Rank	α(%)	β_{mkt}	β_{smb}	β_{hml}	β_{rmw}	β_{cma}	Adj. R^2(%)
Low	5.91*	-0.18**	-0.00	-0.10	-0.08	0.09	18.53
	(2.24)	(-3.98)	(-0.04)	(-1.07)	(-1.52)	(0.79)	
2	4.54	-0.42**	0.03	-0.14	-0.12	0.08	44.34
	(1.36)	(-7.03)	(0.57)	(-1.61)	(-1.81)	(0.71)	
3	2.36	-0.54**	0.01	-0.13	-0.16*	0.04	53.98
	(0.71)	(-8.68)	(0.24)	(-1.74)	(-2.30)	(0.34)	
4	4.82	-0.61**	-0.04	-0.16*	-0.14	0.08	58.80
	(1.47)	(-10.73)	(-0.72)	(-2.05)	(-1.91)	(0.64)	
5	4.64	-0.67**	-0.11	-0.15	-0.16*	0.06	61.16
	(1.37)	(-12.55)	(-1.86)	(-1.83)	(-2.05)	(0.54)	
6	2.78	-0.67**	-0.17**	-0.13	-0.14	0.07	59.62
	(0.78)	(-12.66)	(-2.99)	(-1.70)	(-1.78)	(0.68)	
7	5.24	-0.70**	-0.23**	-0.12	-0.09	0.09	60.17
	(1.41)	(-15.03)	(-4.08)	(-1.68)	(-1.11)	(0.84)	
8	8.41*	-0.69**	-0.28**	-0.08	0.02	-0.02	56.59
	(2.11)	(-15.08)	(-4.42)	(-1.09)	(0.29)	(-0.12)	
9	9.65*	-0.68**	-0.36**	-0.05	0.08	-0.00	53.75
	(2.32)	(-14.13)	(-5.14)	(-0.61)	(1.05)	(-0.02)	
High	19.30**	-0.63**	-0.37**	-0.05	0.24**	-0.06	44.57
	(3.84)	(-12.06)	(-4.83)	(-0.67)	(2.75)	(-0.39)	
High - Low	13.38**	-0.44**	-0.36**	0.04	0.32**	-0.15	
	(2.75)	(-11.96)	(-6.99)	(0.63)	(4.31)	(-1.49)	

Table 59.9

The Trend Factor and Other Factors: Summary Statistics

This table reports the summary statistics for the trend factor (*Trend*), another version of the trend factor following Fama-French approach (*Trend(FF)*), the short-term reversal factor (*SREV*), the umdentum factor (*umd*), the long-term reversal factor (*LREV*), and the Fama-French three factors including the market portfolio (*Market*), *SMB* and *HML* factors. For each factor, we report sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and excess kurtosis. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, an **, and an *, respectively. The sample period is from June, 1930 through December, 2019.

Factor	Mean(%)	Std Dev(%)	Sharpe Ratio	Skewness	Kurtosis
Trend	1.56	3.42	0.46	1.44	11.3
Trend(FF)	1.22	2.90	0.42	1.61	11.2
SREV	0.77	3.43	0.23	1.00	8.38
UMD	0.61	4.74	0.13	-3.02	27.4
LREV	0.28	3.44	0.08	2.92	25.1
Market	0.64	5.31	0.12	0.25	8.13
SMB	0.24	3.19	0.08	2.01	20.0
HML	0.36	3.52	0.10	2.19	19.2

Table 59.10

The Trend Factor and Other Factors After Publication: Summary Statistics

This table reports the summary statistics for the trend factor (*Trend*), another version of the trend factor following Fama-French approach (*Trend(FF)*), the short-term reversal factor (*SREV*), the umdentum factor (*umd*), the long-term reversal factor (*LREV*), and the Fama-French three factors including the market portfolio (*Market*), *SMB* and *HML* factors. For each factor, we report sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and excess kurtosis. The t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, an **, and an *, respectively. The sample period starts after the sample period in the paper, from January, 2015 through December, 2019.

Factor	Mean(%)	Std Dev(%)	Sharpe Ratio	Skewness	Kurtosis
Trend	0.24	2.58	0.09	0.07	3.21
Trend(FF)	0.24	2.22	0.11	-0.51	2.01
SREV	0.47	2.26	0.21	0.40	1.15
UMD	0.22	3.81	0.06	0.12	0.14
LREV	-0.72	2.25	-0.32	0.36	-0.32
Market	0.89	3.59	0.25	-0.59	0.98
SMB	-0.14	2.39	-0.06	0.30	-0.35
HML	-0.36	2.62	-0.14	0.96	1.36