Stock Analysis Using Python

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***Abstract* —** Stock market prediction has always caught the attention of many analysts and researchers. Popular theories suggest that stock markets are essentially a random walk and it is a fool's game to try and predict them. Predicting stock prices is a challenging problem in itself because of the number of variables which are involved. In the short term, the market behaves like a voting machine but in the longer term, it acts like a weighing machine and hence there is scope for predicting the market movements for a longer timeframe. Application of machine learning techniques and other algorithms for stock price analysis and forecasting is an area that shows great promise. In this paper, we first provide a concise review of stock markets and taxonomy of stock market prediction methods. We then focus on some of the research achievements in stock analysis and prediction. We discuss technical, fundamental, short- and long-term approaches used for stock analysis. Finally, we present some challenges and research opportunities in this field.

Keywords: stock exchanges; stock markets; analysis; prediction; statistics; machine learning; pattern recognition; sentiment analysis

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.

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

- ### Market

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

- ### 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).

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.

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.

- **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-analystcoverage 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 w1 and w2 be the fraction of the short- and long-term technical traders. The informed investors observe the dividend Dt , mean growth rate of dividend πt , 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, F i (t) = {Dτ , Pτ , πτ : τ ≤ 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

$A_{it} \equiv Z\ t\ -\infty\ \exp[-\alpha_i(t-s)]P_s ds,$

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, $F_i\ u\ (t) = \{1, D_t , P_t , A_{it}\}$, $i = 1, 2$ is the information sets of the technical traders of type i at time t.

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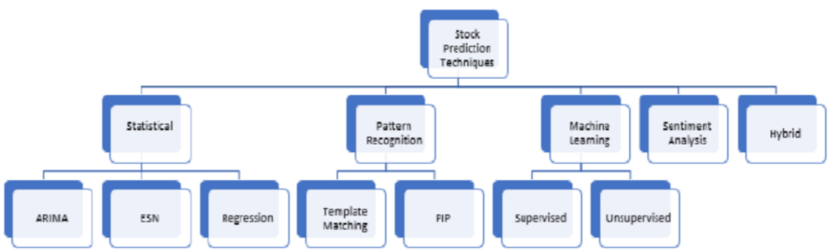
Taxonomy of Stock Market Analysis Approaches

Recent advancements in stock analysis and prediction fall under four categories—statistical, pattern recognition, machine learning (ML), and sentiment analysis. These categories mostly fall under the broader category of technical analysis, however, there are some machine learning techniques which also combine the broader categories of technical analysis with fundamental analysis approaches to predict the stock markets. Figure 1 shows a taxonomy of popular stock prediction techniques. These techniques have gained popularity and have shown promising results in the field of stock analysis in the recent past.



Before the advent of machine learning techniques, statistical techniques which often assumes linearity, stationarity, and normality provided a way to analyse and predict stocks. Time series in stock market analysis is a chronological collection of observations such as daily sales totals and prices of stocks (Fu et al. 2005). According to Zhong and Enke (2017), one group of statistical approaches which fall into the category of univariate analysis, due to their use of time series as input variables, are the Auto-Regressive Moving Average (ARMA), the Auto-Regressive Integrated Moving Average (ARIMA), the Generalized Autoregressive Conditional Heteroskedastic (GARCH) volatility, and the Smooth Transition Autoregressive (STAR) model. The ARIMA model is a widely used technique for stock market analysis (Hiransha et al. 2018). ARMA combines Auto-Regressive (AR) models which try to explain the momentum and mean reversion effects often observed in trading markets and Moving Average (MA) models which try to capture the shock effects observed in time series. A key limitation of the ARMA model is that it does not consider volatility clustering, a key empirical phenomenon in many financial time series. ARIMA is a natural extension to the class of ARMA models and can reduce a non-stationary series to a stationary series. The ARIMA (Box et al. 2015) is fitted to time series data to forecast future points. Zhong and Enke (2017) further describe another group of statistical approaches which usually utilize multiple input variables, these include Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and regression algorithms.

- **Sentiment Analysis**

Sentiment analysis on social media is not an easy task because it is difficult to teach machines all the different contexts of how people express their emotions or opinions. For example, ‘My flight has been delayed, Superb!’, a human can quickly sense the sarcasm in this text, however a machine might identify this as a positive statement. For example, Bollen et al. (2011) used Twitter data to measure the correlations between the public comments and the changes in DJIA. The authors used an effective filtering technique to remove spam tweets, i.e., tweets are discarded if they contain the regular expression ‘www.’ or ‘http://’. The ‘calm’ mood along with the historical prices as input to the SOFNN give 86.7% accuracy. However, the general assumption that the overall public mood affects the stock prices is naive because not all people who tweet invest in the stock markets (Pagolu et al. 2016). Hence a dataset of tweets pertaining to the general stock markets, specifically the DJIA, would be more indicative of the price changes in DJIA. The authors actually discussed these limitations and stated that by no means is the public mood is a good predictor of the changes in DJIA but that it may have some correlation. Mittal and Goel (2012) proposed their approach based on the work of Bollen et al. (2011). The difference between their work and Bollen et al. (2011) is that they chose a much larger dataset and observed that even 'happiness' is indicative of the DJIA prices. They also apply K-fold sequential cross-validation, which is apt for financial data and implemented a basic portfolio strategy which performs well. However, the accuracy achieved was lower than what Bollen et al. (2011) had reported.

- ## 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.

- ### 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.

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.

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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