INVESTMENT POLICY AND PORTFOLIO MANAGEMENT

Foundations of Technical Analysis: Computational Algorithms, Statistical Inference, and Empirical Implementation

Andrew W. Lo, Harry Mamaysky, and Jiang Wang
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The authors hope to bridge the gulf between technical analysis and quantitative finance by developing an automated, computer-based, systematic and scientific approach to such analysis. Based on the smoothing technique known as "nonparametric kernel regression," this new approach identifies regularities in time series of prices by extracting nonlinear patterns from noisy data. The authors find that certain technical patterns when applied to a large number of U.S. stocks from 1962 to 1996 provide incremental information, especially for Nasdaq stocks. The new approach suggests that traditional technical analysis can be improved by using automated algorithms and that traditional patterns, such as the head-and-shoulders pattern, may not be optimal. Moreover, patterns that are optimal for detecting statistical anomalies need not be optimal for indicating trading profits, and vice versa. In an additional "discussion" section, Narasimhan Jegadeesh provides valuable analysis and commentary regarding the authors' methodology, findings, and conclusions.

Technical analysis has been used by traders and investors for many decades, but it has not received the academic acceptance that fundamental analysis has. One of the main obstacles is the highly subjective nature of technical analysis. The authors examine and evaluate

Andrew W. Lo and Jiang Wang are at the MIT Sloan School of Management. Harry Mamaysky is at the Yale School of Management. The summary was prepared by Joseph D.V. Vu, CFA, DePaul University.

complicated technical trading strategies that are hard to define and implement objectively.

The general goal of technical analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data. The authors propose using smoothing estimators to extract nonlinear relationships by averaging out the noise. They start with quantitative definitions of 10 patterns that are commonly used by technicians, such as the head-and-shoulders, triangle top, and rectangle bottom patterns. They then smooth the price data using kernel regressions and construct an algorithm for automating the detection of technical patterns. The algorithm contains three steps: (1) Define each technical pattern in terms of its geometrical properties, such as local maximums and minimums; (2) construct a kernel estimator of a given time series of prices so that its extreme can be determined numerically; and (3) analyze the kernel estimator for occurrences of each technical pattern. The final steps are simply applications of kernel regression, but the first step is controversial because it requires the skill and judgment of a professional technical analyst.

The authors examine five pairs of technical patterns that are among the most popular patterns of traditional technical analysis: head-and-shoulders and inverse head-and-shoulders, broadening tops and bottoms, triangle tops and bottoms, rectangle tops and bottoms, and double tops and bottoms. These 10 patterns, among other technical indications, are chosen to demonstrate the power of smoothing techniques because these patterns are difficult to quantify analytically.

The authors apply the kernel regression approach to identify technical patterns in the daily returns of individual NYSE/Amex and Nasdaq stocks from 1962 to 1996. They also split the data into NYSE/Amex stocks and Nasdaq stocks and into seven five-year subperiods to reduce the effects of nonstationarities induced by changing market structure and institutions. In each five-year period, 10 stocks from each of five market-capitalization groups are randomly selected. This procedure produces a sample of 50 stocks for each subperiod. The empirical results show that for the entire 1962–96 period, the most common patterns are double tops and double bottoms, followed by head-and-shoulders and inverted head-and-shoulders patterns. Most of the 10 patterns are more frequent for larger stocks than for smaller ones, and they are relatively evenly distributed over the five-year subperiods.

The authors' algorithms allow them to recognize patterns objectively by using a computer rather than visually. They then compare the postpattern distribution of stock returns with the unconditional return distribution to evaluate the effectiveness of technical analysis. They find that certain technical patterns provide useful information, especially for Nasdaq stocks. Although this finding does not imply that technical trading rules can be used for identifying profitable investment opportunities, it raises the possibility that technical analysis can add value to the investment process. The authors conclude that traditional technical analysis can be improved by using automated algorithms, and theirs is one of many possible techniques.

In a separate discussion section by Narasimhan Jegadeesh, he states that the authors' findings are an important contribution to the literature on technical trading. The results indicate that by lessening the subjectivity in technical pattern identification by using an algorithm for pattern recognition, technical analysis can be a useful adjunct to fundamental trading strategies. The evidence, however, does not support the use of technical analysis as a tool to independently identify profitable trading opportunities. Jegadeesh recommends that future research be conducted to build on the study's use of an algorithmic approach to technical pattern recognition. Such research might identify profitable trading rules and then use the algorithm in choosing patterns that can predict future returns.

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